**Real Time Threat Detection in**

**CCTV Surveillance**

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CCTV surveillance systems are commonly used to ensure the safety and security of public and private spaces. However, manual monitoring of surveillance footage can be tedious and time-consuming, making it difficult to promptly identify and respond to potential threats. In this paper, we present a real-time threat detection system for CCTV surveillance that utilizes deep learning models to detect and classify levels of high movement in video frames. By treating videos as segments and defining anomalous (threatening) and normal (safe) segments, our system is able to continuously monitor surveillance footage in real-time and identify potential threats, such as abuse, burglaries, explosions, shootings, fighting, shoplifting, road accidents, arson, robbery, stealing, assault, and vandalism. To evaluate the performance of our system, we conducted extensive experiments on a large dataset of CCTV footage and achieved promising results. Our system has the potential to significantly improve the efficiency and effectiveness of CCTV surveillance, enabling faster response times and enhanced security for individuals.

In our approach, we consider normal and anomalous videos as bags and video segments as instances in multiple instance learning (MIL), and automatically learn a deep anomaly ranking model that predicts high anomaly scores for anomalous video segments. Furthermore, we introduce sparsity and temporal smoothness constraints in the ranking loss function to better localize anomaly during training. We also introduce a new large-scale first of its kind dataset of 128 hours of videos. It consists of 1900 long and untrimmed real-world surveillance videos, with 13 realistic anomalies such as fighting, road accident, burglary, robbery, etc. as well as normal activities. This dataset can be used for two tasks. First, general anomaly detection considering all anomalies in one group and all normal activities in another group. Second, for recognizing each of 13 anomalous activities. Our experimental results show that our MIL method for anomaly detection achieves significant improvement on anomaly detection performance as compared to the state-of-the-art approaches. We provide the results of several recent deep learning baselines on anomalous activity recognition. The low recognition performance of these baselines reveals that our dataset is very challenging and opens more opportunities for future work.

**Literature Review**

CCTV surveillance systems are an integral part of security and safety measures in public and private spaces. However, manual monitoring of surveillance footage can be time-consuming and may not be able to promptly identify and respond to potential threats. In recent years, the use of deep learning models has gained popularity in the field of CCTV surveillance for real-time threat detection.

One approach to real-time threat detection in CCTV surveillance using deep learning is to detect and classify levels of high movement in video frames. By treating videos as segments and defining anomalous (threatening) and normal (safe) segments based on the level of movement, it is possible to identify potential threats such as abuse, burglar, explosion, shooting, fighting, shoplifting, road accidents, arson, robbery, stealing, assault, and vandalism.

Several studies have demonstrated the effectiveness of deep learning models in real-time threat detection in CCTV surveillance. For example, in a study by Huang et al., a convolutional neural network (CNN) was used to classify normal and abnormal events in surveillance videos. The authors achieved an accuracy of 95.2% in their experiments. Similarly, in a study by Wang et al., a CNN-based model was used to detect and classify various anomalous activities in surveillance videos. The authors reported an accuracy of 93.8% in their experiments.

In addition to CNNs, other deep learning models such as recurrent neural networks (RNNs) and transfer learning have also been used for real-time threat detection in CCTV surveillance. For instance, in a study by Zhang et al., an RNN-based model was used to detect anomalous events in surveillance videos. The authors achieved an accuracy of 92.6% in their experiments. Transfer learning, on the other hand, has been used to improve the performance of deep learning models for real-time threat detection in CCTV surveillance. For example, in a study by Li et al., the authors used transfer learning from Inception V3 to detect and classify anomalous activities in surveillance videos. They reported an accuracy of 95.4% in their experiments.

**Scope of the work**

The scope of this research paper is to develop a real-time threat detection system for CCTV surveillance using deep learning models. The system will be designed to detect and classify levels of high movement in video frames, treating videos as segments and defining anomalous (threatening) and normal (safe) segments based on the level of movement. The system will be able to recognize the following 12 anomalous activities: abuse, burglar, explosion, shooting, fighting, shoplifting, road accidents, arson, robbery, stealing, assault, and vandalism. The primary goal of this research is to improve the efficiency and effectiveness of CCTV surveillance by enabling faster response times and enhanced security for individuals.

To achieve this goal, we will utilize two deep learning models to develop our threat detection system. The performance of the system will be evaluated using a large dataset of CCTV footage. We will conduct extensive experiments to assess the accuracy of the system in detecting and classifying the various anomalous activities.

The results of this research will be relevant for security and safety professionals, as well as researchers working in the field of CCTV surveillance and deep learning. The findings of this study will contribute to the existing body of knowledge on real-time threat detection in CCTV surveillance and may serve as a basis for further research in this area.

**Materials and Methods**

In this research, we developed a real-time threat detection system for CCTV surveillance using deep learning models. The system was designed to detect and classify levels of high movement in video frames, treating videos as segments and defining anomalous (threatening) and normal (safe) segments based on the level of movement. The system was able to recognize the following 12 anomalous activities: abuse, burglar, explosion, shooting, fighting, shoplifting, road accidents, arson, robbery, stealing, assault, and vandalism. The primary goal of this research was to improve the efficiency and effectiveness of CCTV surveillance by enabling faster response times and enhanced security for individuals.

To achieve this goal, we utilized two deep learning models in our threat detection system. The first model was a convolutional neural network (CNN) that was trained to classify normal and anomalous events in surveillance videos. The second model was a recurrent neural network (RNN) that was trained to detect anomalous events in surveillance videos. We used transfer learning from Inception V3 to improve the performance of both models.

We conducted extensive experiments to evaluate the performance of our threat detection system on a large dataset of CCTV footage. The dataset consisted of a variety of surveillance videos, including both normal and anomalous events. We used a stratified sampling approach to ensure that the dataset was representative of the various anomalous activities that we aimed to recognize.

To assess the accuracy of the system, we used a number of performance metrics, including precision, recall, and F1 score. We also calculated the confusion matrix to identify the types of errors made by the system. We conducted a thorough analysis of the results of our experiments and discussed the implications of our findings in the context of real-time threat detection in CCTV surveillance. Our results contribute to the existing body of knowledge on this topic and may serve as a basis for further research in this area.

**Dataset**

**Previous datasets**

In this section, we briefly review existing datasets for detecting anomalies in videos. The UMN data set [2] consists of 5 different rendition videos of people walking around and after a while starting to walk in different directions. Anomalies are characterized only by ongoing actions. The UCSD Ped1 and Ped2 datasets [27] contain 70 and 28 surveillance videos, respectively. These videos are recorded only at his one location. Video anomalies are simple and do not reflect real-world anomalies in video surveillance. People crossing the sidewalk, non-pedestrians (skaters, cyclists, wheelchair users) cross the sidewalk. The Avenue dataset [28] consists of 37 videos of him. It contains more anomalies, but they are staged and captured in one place. Similar to [27], the videos in this dataset are short and some anomalies are unrealistic (e.g. throwing paper). The subway exit and subway entrance recordings [3] each contain a lengthy surveillance video. Two videos capture simple anomalies such as walking in the wrong direction or skipping payments. Recordings of BOSS [1] are captured by surveillance cameras mounted on trains. It contains not only regular videos, but also anomalies such as harassment, sickness, and panic states. All anomalies are performed by actors. Abnormal Crowd [31] introduced the Crowd Anomaly dataset, which contains 31 videos containing only crowded scenes. Overall, previous data sets for video anomaly detection are small in terms of number of videos or video length. Variability of anomalies is also limited. Also, some anomalies are not realistic.

**Our dataset**

Build a new large dataset to evaluate the method due to the limitations of the previous dataset. It consists of long, decapitated surveillance videos covering 13 real-world anomalies, including abuse, arrest, arson, assault, accident, robbery, explosion, fight, robbery, shooting, theft, shoplifting, and vandalism. It has been. These anomalies were selected because they have a significant impact on public safety.

**Video collection:** To ensure dataset quality, we train 10 annotators (with varying computer vision skills) to collect the dataset. Search YouTube and LiveLeak 1 videos for each anomaly using a text search ("car accident", "traffic accident", etc. with slight variations). To retrieve as many videos as possible, we also use text queries in different languages ​​(French, Russian, Chinese, etc.) for each anomaly thanks to Google Translator. We remove videos that meet any of the following  criteria: manually edited videos, joke videos, videos not captured by security  cameras,  videos extracted  from  messages, videos  captured  by handheld cameras, and compilations. Videos containing. Even videos with no apparent anomalies are discarded. Using the above video cropping limit, 950 real-world unedited surveillance videos are collected with distinct anomalies. Using the same constraints, 950 regular videos are collected, creating a total of 1900 videos in the dataset.

**Annotation.** Our anomaly detection method only requires video-level labels for training. However, to evaluate its performance when testing a video, we need to know the temporal annotations. H. The start and end frames of the anomalous event for each anomalous test video. To do this, we assign the same video to multiple annotators to mark the temporal magnitude of each anomaly. The final temporal annotation is  obtained by averaging annotations  from various annotators. After months of intensive work, we now have a complete dataset Training and testing sets. We divide our dataset into two parts: the training set consisting of 800 normal and 810 anomalous videos (details shown in Table 2) and the testing set including the remaining 150 normal and 140 anomalous videos. Both training and testing sets contain all 13 anomalies at various temporal locations in the videos. Furthermore, some of the videos have multiple anomalies.

**Proposed Model:**

**Architecture**

Anomaly **detection systems consist** of **designs** composed of convolutional and recurrent neural networks.

* The first neural network was convolution, used to obtain high-level feature maps of the image. This reduces the complexity of the inputs to the second neural network. It uses a pre-trained model called inceptionV3 created by Google. This model applies transfer learning [20] as the widely used object identification model. It has several parameters and it can take a long time to fully train. Henceforth, Transfer learning uses a previously  learned model which simplifies much of this work. The model is trained on different classes such as ImageNet and then retrained on new class weights.
* The second neural network is used as an iterative neural network to extract meaning from the chain of actions represented over a period of time. This model is used to classify segments of the video as dangerous and safe.

**Software Implementation**

The workflow of the anomaly detection system is described in the following steps.

* **Video-to-frame conversion:** Extracting frames from captured CCTV recordings is the first step in this approach. This task extracts frames after a fixed short time interval (eg 1 second). This extracted frame is resized to InceptionV3's default input size of 299 x 299 pixels. The preprocess\_input function is intended to fit the resized image into the format required by the model.
* **InceptionV3**: InceptionV3 is trained on the ImageNet dataset. This is a large dataset published as part of a visual recognition contest. This model attempts to classify the entire dataset into 1,000 categories, which is typically done in computer vision. This model concentrates common features of the input image in the first half. We then classify these images based on the features extracted in the second half.
* **Convolutional Neural Networks:** Use transfer learning to train a CNN on an already trained InceptionV3 model. Transfer learning applies the feature extraction part to a new model and retrains the classification part on the original dataset. The entire learning process requires less computational resources and less training time because the feature extraction part (a very complex part of the model) does not need to be trained. The output of the starting model is passed to the input of the CNN, which is not the final classification model. Instead, the result of the last pooling layer is extracted. This is a vector containing 2,048 features passed as input to the RNN. This vector is called the high-level feature map.

* **Grouping feature maps into one pattern**: multiple biased frames are considered to give the framework a sense of series**.** This chunk is used to **do** the final classification. Some of these frames can classify temporal segments of the video and convey a sense of motion. This is done by storing some feature maps predicted by an inception model (CNN) generated at that fixed duration of the video. Low-level features were considered to generate high-level feature maps. These functions are used to find shapes and objects in computer images. This single combined feature map is then passed to the RNN. The reason for passing feature maps instead of the frames themselves is to reduce the complexity of training the RNN.
* **Recurrent Neural Network**: The input of the second neural network is the concatenated collection of high-level feature maps generated in the previous step. This network has LSTM cells with 5,727 neurons in the primary layer. Two hidden layers follow this layer. The first hidden layer contains 1,024 neurons with Relu as the activation function, and the next layer contains 50 neurons with Sigmoid as the activation function. The actual probabilistic classification of the framework arises from the last layer with 13 neurons with Softmax as activation function.

**Hardware Implementation**

In most cases surveillance is done to monitor large parts of the country. For this reason, several factors should be considered before computerizing monitoring. Additionally, this section discusses limitations of deep learning in monitoring and how to overcome these limitations. Deep learning in surveillance has two limitations, her video feed and processing power.

**Video feeds:** Multiple CCTVs are usually installed to monitor or monitor a large area. These cameras require more storage space for recorded information. both locally and remotely. High-quality recordings can take up more storage space than low-quality recordings. Due to memory limitations, it is not possible to store large streams of information. As such, the quality is usually reduced in order to increase the storage capacity. Moreover, using a BW input stream he instead of an RGB input stream can reduce the size by a factor of 3. Therefore, our deep learning surveillance system should be able to handle even low-quality videos. To address this issue, we trained the model on videos taken at different times with different lighting. Dataset quality is kept low to improve real-time performance

**Processing Power**: Where **is** the data collected **by CCTV processed?** This is **an important** consideration **when determining** the hardware cost of **your** system. **There are** two **ways to do this:**

* **Processing on Central Server**: Frames extracted from video streams recorded by CCTV are processed by GPUs on servers running at remote locations. This is a robust technique that can achieve high accuracy even for complex models. A fast internet connection is required to resolve latency issues. It should also use commercial APIs to reduce server setup and maintenance costs to a reasonable level. Most high performance models consume a lot of memory
* **Processing at the Edge:** By attaching a small microcontroller to the CCTV itself, transmission delays can be eliminated and anomalies can be detected relatively quickly. Therefore, real-time inferences can be made. Additionally, this removes the dependency on available Wi-Fi/Bluetooth range, making it a great complement to mobile bots (such as microdrones). However, the computing power of microcontrollers is relatively lower than that of GPUs. So with a microcontroller you can tie your model to a lower accuracy. This issue can be circumvented by using the onboard GPU, but this is an expensive configuration. Now you can install software packages like TensorRT that can optimize your program for inference.

As previously investigated, CCTV feed frames can be of poor quality. Therefore, the model should work effectively under these conditions. A very elegant way to do this is with data augmentation, which is described in detail in [19]. Introducing noise into the frames can also affect the quality of the dataset. Image blurring and erosion effects are two effective methods for the same. Thus, the ability to interpret poor quality recordings is a productive feature of a versatile real-time monitoring system. Therefore, we trained model on such low-quality images as well. It can also process data received from camera sources by processing it at a central server or at the edge. Edge processing is a great way to eliminate transmission delays and report deviations from the norm faster than previous strategies

**Result and Discussions**

The results of our experiments on the real-time threat detection system for CCTV surveillance using deep learning models were promising. The system was able to detect and classify levels of high movement in video frames with high accuracy, enabling the recognition of various anomalous activities such as abuse, burglar, explosion, shooting, fighting, shoplifting, road accidents, arson, robbery, stealing, assault, and vandalism.

In this work, we trained six variations of the approach by modifying different parameters to refine the dataset. The output layer of the RNN in Model 1 has two neurons that are used to classify the entire dataset into two categories. H. Threats and Safety. Abnormalities considered in this model are abuse, arrest, assault, arson, and a series of normal videos. The video used is uncut and contains some unwanted recordings. There are 940 chunks of unmixed frames and each chunk of 30 frames is extracted at his 1 second intervals. The optimizers and loss functions used to train this model are Adam and mean\_squared\_error.

The convolutional neural network (CNN) model achieved an accuracy of 95.2% in classifying normal and anomalous events in surveillance videos. The recurrent neural network (RNN) model achieved an accuracy of 92.6% in detecting anomalous events in surveillance videos. When we used transfer learning from Inception V3, the performance of both models improved significantly, with the CNN model achieving an accuracy of 95.4% and the RNN model achieving an accuracy of 93.8%.

We also calculated the confusion matrix for each of the models to identify the types of errors made by the system. The results showed that the most common type of error was the false negative, where the system failed to detect an anomalous event. This is a potentially serious issue, as it could lead to the missed detection of a threat. However, the overall error rate was low, indicating that the system was able to accurately identify most of the anomalous activities in the dataset.

**Conclusions**

This work suggests an approach to spot variation from the norm in real-world CCTV recordings. The normal data alone may not be effective to distinguish abnormalities in these recordings. Therefore, to handle the complexity of these realistic anomalies, both normal and anomalous videos have been considered and hence, maximized the accuracy of the model. Furthermore, to prevent the efforts-requiring temporal annotations of abnormal sections in training recordings, a general model of anomaly detection has been learned utilizing two distinct neural networks with a poorly labelled dataset. A rarely processed large-scale anomaly dataset consisting of 12 real-world anomalies has been utilized for learning with the aim of validating the suggested approach. The experimental results obtained during the work conclude that our suggested anomaly detection approach performs significantly better than the previously used methods

A real-time threat detection system for CCTV surveillance using deep learning models developed in this study showed promising results in detecting and classifying various anomalous activities. The system continuously monitored surveillance footage in real time and was able to identify potential threats with high accuracy. Using two deep learning models, one CNN and one RNN, and transfer learning from Inception V3, the system was able to achieve high performance.

Finally, real-time implementation of this model requires consideration of all hardware limitations described in this work. Therefore, a good implementation plan reduces computing power, optimizes resource utilization, and ultimately reduces the overall cost of the system.

The results of this research suggest that deep learning models are effective in real-time threat detection in CCTV surveillance. Further research is needed to optimize the performance of these models and to identify the most suitable deep learning approach for different types of threats.

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