Real-Time Detection of Crime and Violence in Video Surveillance using Deep Learning

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Abstract. Since its widespread application, deep learning is a vital part of the machine learning community's toolbox. With so many crimes and wrongdoings going on without adequate oversight in public spaces, various ways have been developed to identify crime and violence in the camera footage. Automated violence detection has become more important in video surveillance research. However, they have several restrictions, and much of the time, it is based on a certain set of circumstances. This research presents a 3D convolutional neural network-based technique for detecting violence in videos. Accuracy is improved by employing machine and deep learning techniques in a suggested manner. Performance evaluations have shown that the suggested technique effectively identifies violence in video clips. ' Experimental data show that the proposed strategy outperforms existing methods for identifying crimes and violence in films. The pre-training models, Inception-V3, InceptionResNetV2, ViolenceNet, and ViolenceNet-OF, were trained on the four datasets. The classification results on the validation data for each model are as follows: ViolenceNet OF 99.40%, InceptionResNetV2 89%, ViolenceNet pseudo 96, and InceptionV3 92%. The DenseNet model was chosen for our application system because it concatenates the feature maps in a simpler method than Inception or InceptionResNet, which are more complicated. It has a more durable design that requires fewer filters and settings to attain high efficiency than other models and achieves the highest accuracy.

Keywords: Crime detection · Violence detection · DenseNet · LSTM · Abnormal detection · Blockchain · InceptionV3 · fight detection

1 Introduction

Even while computer vision has become more interested in identifying human motion in video, identifying criminal behaviour has received far less research attention than other types of human movement. Public and private security can benefit significantly from the capacity to detect criminal activity. There are cameras in almost every public place nowadays, such as schools and jails, hospitals, and retail malls. It's becoming increasingly necessary to have enough staff to monitor these cameras' ever-increasing volume of photos. Usually, this isn't feasible; thus, they lose a lot of their potential.

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Detection of criminal activity is the primary goal of this research. A Spatio-temporal analysis is important to identify criminality and violence in the video because of the abrupt movements associated with strikes and punches. It is possible for violent behaviours to be mistaken for other kinds of actions, leading to false positives. During CPR, for example, quick actions such as punching might be mistaken for punching in a film with minimal motion, leading to a false positive. Detecting these kinds of problems requires a thorough examination of all of the video's temporal context, both before and following the activity.

According to our knowledge, no commercial solution uses artificial intelligence and human operators to identify crimes, despite the fact that substantial research has been done. This is essential from a quality of work standpoint. So that the operators who have to view this sort of film may focus on other productive duties, this method can help alleviate their stress levels. Most importantly, the task cannot be done correctly and effectively because of a basic restriction on the number of movies that can be seen simultaneously and with the required concentration. False positives and false negatives, both of which can lead to the deactivation of a video surveillance system, are the most significant roadblocks to developing a system that can automatically identify violence. A system that has been thoroughly tested across several datasets is thus being considered. There are several sorts of criminal activity, and it is impossible to generalize from a single dataset. Models that have been trained on one dataset may not perform as well when applied to a different dataset. If this is the case, the model cannot be used in production and must be improved.

The following sections depict the flow of this document. Section 2 provides a quick review of the current condition of the problem. Section 3 explains the proposed model's Architecture in great detail. Detailed descriptions of each dataset used to assess the model are provided in Sect. 4. Section 5 includes Training and Validation of the model. Experiment results and discussion are shown in Sect. 6. Finally, in Sect. 7, the most conclusions and probable avenues for future growth are laid bare for the readers.

2 Literature Review

According to this part, an evaluation of the current state of the art in crime and violent action detection using visual characteristics is done. The most generally used references use deep learning techniques, which have consistently produced the best outcomes of any of the other approaches. As a result, there is less control and greater difficulty in creating explainable models utilizing deep learning approaches compared to earlier methods that required manual and typically complex feature extraction.

S. Battiato et al. [1] use a faster version of R-CNN (Region-based Convolutional Neural Network) to identify items within a building in real-time. ImageNet's 12 object classes and Karina dataset were used to assess this study's suggested system's performance. In NvidiaTitanX GPUs, we achieved an average accuracy of 74.33% and a mean detection time of 0.12 s per picture.

L. McClendon et al. [2] The Communities and Crime Dataset were used to develop the linear regression, additive regression, and decision stumbling algorithms utilizing the same limited dataset. The linear regression approach performed the best of the three evaluated algorithms. The study's primary goal is to use machine learning techniques in data mining analysis to forecast violent crime patterns.

A. Chowdhary et al. [3] With feature matching in the videos, this study tries to go beyond simple image-to-image comparisons to locate the query picture in its source image. Recognizing someone or anything is much easier when it comes to this method. It will return just those frames in a given video that meet a specific query characteristic.

S. Chakravarthy et al.; [4] proposed a solution based on neural networks created using the Hybrid Deep Learning (HDL) method. Fragments of video data, such as those showing crowd movement, facial expressions, and object interactions, can be retrieved using this technique. This is done using a Deep Convolutional Neural Network (DCNN) and the HDL method. In conjunction with this feature implementation, a Recurrent Neural Network (RNN) is used to learn object and human recognition. Combining these models and technologies enables an accurate ranking and scoring system for urban crime based on camera footage to be developed. To assess the correctness of the score, the histogram error rate may also be continuously tracked for each instance.

[5] VGGNet19, a pre-trained deep learning model, is used in the proposed system to identify a person aiming a weapon or knife at another person. GoogleNet InceptionV3 was also compared to two other pre-trained models in training. In terms of training precision, the outcomes obtained with VGG19 are superior. For this reason, we decided to use VGG19 with only minor fine-tuning to better detect criminal intent in videos and images than we could with the existing approaches. To construct the bounding box around photos of people, weapons, knives like a knife, guns, and so on, we used the Fast RCNN and RCNN algorithms (also known as Faster RCNN). Object detection and image classification are made easier with the assistance of algorithms.

[6] using SSD and Faster RCNN convolutional neural network algorithms, it implements automatic detection of guns (or weapons). Datasets used in the proposed implementation are split into two types. One dataset contains photographs that have already been labelled, whereas the other contains images that have been labelled manually. When the data is tallied, it turns out that both algorithms produce accurate results. The Faster RCNN has a superior accuracy of 84.6 percent compared to the standard RCNN. For example, SSD has an accuracy of 73.8 percent compared to RCNN, which has a far higher success rate in real-time detection.

[7] The deployed initiative utilizes CCTV video to keep an eye out for any suspicious activity on campus and warns campus security if anything unusual happens. This was accomplished by using CNN to extract characteristics from the frames. Classifying frames as suspicious or regular is done using the LSTM architecture after extraction. For the first 10 epochs of training, the accuracy is 76%. As the number of iterations rises, so does the model's accuracy. For testing, video frames are taken from videos and placed in a single folder. Predicting suspicious or normal behaviour based on our model, the machine classifies the images as either suspicious or normal.

M. K. El den Mohamed et al. [8] Detecting handguns and firearms in video surveillance systems has been made easier with the help of a new method. No intrusive technologies are required for weapon detection in this method. It employs Deep Learning (DL) as part of the classification and detection operations. It employs Deep Learning (DL); using Transfer Learning, the suggested method improves the outcomes that are

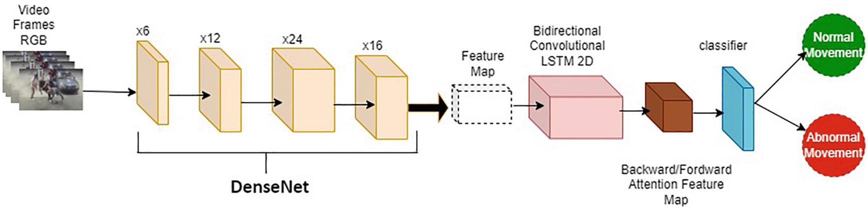

Fig. 1. Model Crime Detection Architecture

generated (TL). Both AlexNet and GoogLeNet are used in this deep learning approach. As demonstrated by experimental data, handguns and weapons may be detected by the same system. Internet Movie Firearms Database (IMFD) was used as a reference point for the tests (IMFDB) (Fig. 1).

P. Sivakumar et al.; [9] Real-Time Crime Detection Technique employing a Deep Learning Algorithm that watches real-time cameras and tells neighbouring cybercrime administrators about the incidence of crime at the current location are suggested. The object detection method utilizes YOLO. In order to compare the proposed YOLO model with the current Fast R-CNN regarding Precision, Recall, and Mean Average Precision, 45 frames per second of real-time processing were used. The suggested work's Mean Average Precision achieved 78.3 percent on the testing set, whereas fast RCNN only achieved 62.4 percent. The proposed work has a final mean average precision of 78.3% in the testing set.

[10] suggested a deep-learning-based real-time violence detector. We present a three-factor (generality, accuracy, and rapid reaction time) CNN-LSTM model that uses spatial feature extraction via CNN and temporal relationship learning via LSTM. The proposed model was 98 percent accurate and ran at a frame rate of 131 frames per second. A comparison of the suggested model's accuracy and speed with earlier studies shows that the proposed model delivers the greatest accuracy and fastest speed in violence detection.

C. S. Sung et al.;[11] suggest constructing an intelligent system for real-time video monitoring without a person's involvement. Once an artificial intelligence server and video surveillance cameras have been constructed, the flaws with the current video surveillance system will be addressed using deep learning technology as part of the data processing model design. In addition, a real-time processing video picture and a notification message will be sent to the web via this design's intelligent surveillance system to promptly and efficiently identify crimes.

3 Model Architecture

Creating a solid video encoding is essential for subsequent classification by utilizing a fully linked network to categorize crime in videos appropriately. To do this, every video is first transformed from RGB into background subtraction. The background subtraction is encoded as a series of feature maps using dense networks [17–19]. Before the attention mechanism is applied spatially and temporally to the video, a multi-head self-attention layer and a bidirectional ConvLSTM layer are applied to these feature maps (forward and backwards pass). Each video's significant spatial and temporal information is extracted using this spatiotemporal encoder's attention algorithm. A four-layer classifier divides the movie into two groups based on the encoded information (normal and abnormal movements).

3.1 DenseNet Convolutional 3D

DenseNet is a 2D convolutional architecture that was created specifically for use with photos [12]. However, it can be extended to handle video. First, the 2D convolutional layers have been replaced with 3D ones, and the 2D reduction layers have been replaced with 3D reduction layers.

For the reduction layers MaxPool2D and AveragePool2D, DenseNet employs (2, 2) as the pool size (7, 7). Maximized Pool3D and Average Pool3D were utilized with a (2, 2, 2)-pool size for the reduction layers (7, 7, 7).

The term "DenseNet" [13] is derived from the dense bricks that form the network's basis. All of a layer's descendants' feature maps are combined in these blocks. To sum it up, we've employed four different-sized dense blocks in our design. This is the succession of layers that make up a dense block: 3-dimensions of batch normalization and convolution -batch normalization-convolution in 3D.

The DenseNet model was chosen from four models, InceptionResNetV2, InceptionV3, and ViolenceNet pseudo-Of, because it concatenates the extracted features more efficiently than models like Inception or InceptionResNet, which are more complicated. It has a more durable design and requires fewer filters and settings to attain high efficiency than other models, unlike others. Compared to previous designs, it has shown superior outcomes when used to handle biomedical pictures. The DenseNet model is more efficient than other models in extracting the features needed to accomplish the detection job in terms of the number of trainable parameters and training and inference times.

3.2 Convolutional LSTM 2d Bidirectional

Bidirectional recurrent cells have two states. The past and the future are the two possible states (forward). Bidirectional recurrent layers are connected to output layers that receive information on both states simultaneously. Bidirectional recurrent layers separate a typical recurrent layer's neurons into two groups, one for positive time and the other for negative time. Having the capacity to go back in time is very helpful when trying to discover crimes and violent acts in the camera footage.

For video and image classification, the bidirectional convolutional LSTM 2D module has been proven to extract Spatio-temporal characteristics. Video gestures may be recognized and classified using long-term Spatio-temporal properties learned from videos. Classification of hyperspectral pictures is accomplished using it; however, spectral characteristics are employed in place of spatial and temporal ones.

One of the most useful features of BiConvLSTM is its ability to concurrently examine time-varying sequences forward and backwards. Layers like BiConvLSTM may look at the video's chronology in both directions. As a result, the video is better understood overall.

3.3 Classification

There are four levels in total in the classifier. There are 1024, 128, 16, and 2 nodes in each layer, arranged in ascending order of a number of nodes. The ReLu activation function is used to activate the layers that aren't visible. An activation function sigmoid is used to classify the input into two classes: Normal Movements and Abnormal Movements. This binary predictor is the last layer's output.

4 Dataset

There were four datasets used in the tests, all of which had been used in previous research on violent action identification. Their usage in comparing methods for identifying aggressive behaviour is widespread. The following are the datasets:

- NHL hockey If you're looking for a selection of games that feature fighting between players, you'll find them here.
- Movies Fights (MFs) A 200-clip compilation of fight and non-fight scenes from action films.
- Violent Flows (VFs): There are a number of videos that feature mob violence. Instead of looking at violence between individuals, this model examines the dynamics between groups of people. It's an intriguing way to see how versatile the model can be.
- A compilation of 1000 violent and 1,000 nonviolent films culled from YouTube, and the violent videos feature numerous genuine street fights in various locales and scenarios. In addition, films of nonviolent human behaviours, such as sports, eating, walking, and so on, are amassed.

They all had the same labels and were split into 80% for training and 20% for testing. Each dataset's details are shown in Table 1. Different weather conditions and indoor and outdoor settings have all been accounted for in these data sets. The Hockey Fights dataset exclusively includes fights that take place in an ice hockey rink. The sequences in the Movies Fights dataset include a mix of indoor and outdoor ones, but none of them is affected by inclement weather. The violence that happens in the open air is what the Violent Flows dataset is focused on. Rain, fog, and even snow may be seen in several of the film's sequences. There are a wide variety of indoor and outdoor settings in the Real-Life Violence Situations dataset, from the street to various sporting event venues, various rooms inside a building, and stages for music shows, among others, and depicts several types of inclement weather, with rain being the most common.

5 Training and Validation of the Model

The weights of all neurons in the model were randomized. In each frame, the pixel values were normalized to be between 0 and 1. All the movies in the dataset had the same number of frames in their input video. This algorithm repeated the previous frame until a satisfactory average was attained [58,59] regardless of whether there were more or fewer frames than average in the input video [58,59]. Using Keras pre-trained models, the frames were scaled to $224 \times 224 \times 3$, the normal size.

Table 1. Dataset Breakdown [14]

Datasets	*Number of videos*	Training	Validation	Frames %
Hockey Fights [14]	1000	**800**	**200**	**50**
Movies Fights [14]	200	**160**	**40**	**50**
"Violent Flows" [15]	246	**196**	**50**	**100**
Real-Life Violence Situations [16]	2000	**1600**	**400**	**100**

Table 2. Results Of The Models

Model Name	*Training Accuracy*	*Validation Accuracy*	Sensitivity	Specificity
InceptionV3	**92%**	**89.23%**	**91%**	**91%**
InceptionResNetV2	**89.12%**	**90.92%**	**91%**	**88%**
ViolenceNet pseudo-Of	**96.23%**	**98.5%**	**98%**	**96%**
ViolenceNet OF	**99.40%**	**100%**	**100%**	**97%**

We settled on a starting learning rate of 14, a batch size of 10 films, and a total of 25 epochs; at 0.1, weight decay was activated. It was also necessary to take advantage of the Adam optimizer's pre-configured settings. A binary cross-entropy loss function and a sigmoid activation function were both selected for use in the classifier's final layer. The training of models has been done using the Python language with deep learning libraries Keras and TensorFlow on a Lenovo laptop named LEGION, which has a GeForce GTX 1650, 4GB GPU.

6 Results and Discussion

By using a robust backbone network in this study, we looked at whether or not the performance might be improved by switching from previous experiments that used optical flow and pseudo-optical flow. It was found that the models with the self-attention module outperformed those without in terms of accuracy and inference time. For those that used only optical flow or pseudo-optical flow input when the attention module was utilized, both accuracy and inference time improved. Convolutional recurrent layer operations required slower to perform on featured maps than on concatenated sequences of attention layers; hence inference time was reduced by the application of attention mechanisms.

It was found that the optical flow input had superior results to the pseudo-optical flow input after the trials were carried out. Table 2 shows the results of a single training and testing iteration for every dataset and type of model input.

Hockey is an extremely fast-paced activity, and our model performed admirably in the HF dataset, where players are constantly moving and occasionally coming into touch with one another. Our model could learn the temporal characteristics of events depending on how energetic they were at the time of their occurrence.

There were differences in the difficulty of generalizing violence in the VF and HF datasets. In the films from the VF dataset, there were instances of violence during large-scale events like marches or concerts. During large-scale events, several acts were taking place at once. Because the vantage points were far away from the action, the images show a large number of individuals in a pixelated form. When seen from a distance, several actions in a single film appear little, making it difficult to tell whether or not a contact motion is aggressive. As a further example, the mass event's setting featured circumstances such as a mob of people grabbing a golf ball (that could seem to be the beginning of a fight). The RLVS dataset also made it impossible to generalize the idea of violence since it is so varied. Because they were not topic-specific, the RLVS scenes

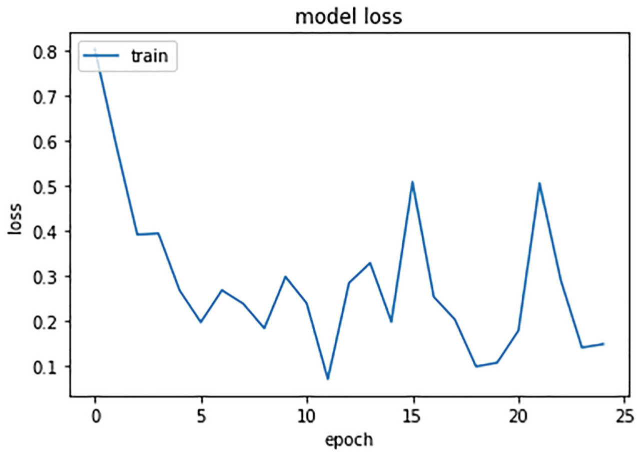

Fig. 2. Training and Validation model loss

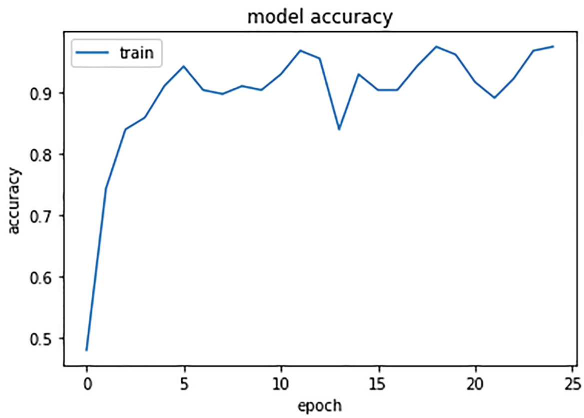

Fig. 3. Training and Validation Accuracy

constituted a unique dataset. The non-violence category showed the most variation in the dataset's heterogeneity, with scenes acting in diverse ways (Figs. 2 and 3).

Violent action detection has benefited more from the model built than from generalizing the idea of violent behaviour. Results from the preceding section show that this is true. It is feasible to increase the generalization of violence in cross-dataset tests if big and diverse cases in a dataset that considers varied settings and circumstances are utilized. The idea of violence cannot be generalized using datasets, For example, whether the input is optical flow or pseudo-optical flow that contains just one context, as in MF and HF.

7 Conclusion and Future Work

Facilities might greatly benefit from this capacity. Using action recognition software, techniques for recognizing individual actors and basic events may now be applied to this more complex scenario. Fight detection on two new datasets is evaluated in this work, including a 1000-video collection of NHL hockey games and a smaller 200-clip collection of action movie sequences. In experiments, researchers have found that the common "bag of words" strategy is 90% accurate in recognizing combat sequences. While accuracy was unaffected by low-level feature descriptors and vocabulary sizes in the hockey dataset, the choice of descriptor was essential for MoSIFT in the second dataset, where it outperformed the top STIP under all circumstances. Because of the encouraging performance of action recognition systems on this difficult job, a commercial and adaptable combat detector appears achievable.

In the future, this research will make use of the decentralised database feature given by blockchain technology [20, 21] to make data available to government for the detection of crime and violence in video surveillance with a high degree of privacy and safety.

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Authors' Contributions. We have been done Real-time detection of crime and violence in video surveillance using Deep learning. In this research author tested the 200 videos for the experiment based on DNN model. The pre-training models, Inception-V3, InceptionResNetV2, ViolenceNet, and ViolenceNet-OF, trained on the four datasets. The classification results on validation data for each model are as follows: ViolenceNet OF 99.40%, InceptionResNetV2 89%, ViolenceNet pseudo 96.

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