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Human Activity Recognition based on Deep Learning

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Abstract:

Real-time security surveillance is a critical aspect of public safety and crime prevention. In this research project, we propose a solution for detecting fights in videos using computer vision algorithms and machine learning models. Our approach uses a deep learning model that leverages a pre-trained VGG 16 model followed by a Long Short-Term Memory (LSTM) layer to analyze video frames and identify potential fights based on changes in motion and object behavior. To improve the accuracy of the detection system, we trained our model on a large dataset of videos, which we preprocessed by extracting frames and applying data augmentation techniques. Our experimental results demonstrate that our approach achieves high accuracy in detecting fights in videos, which can be useful for enhancing public safety and security.

Keywords: Pretrained VGG-16, LSTM (Long Short-Term Memory)

1. Introduction

An activity recognition system is a type of software designed to automatically detect and classify human activities based on sensor data. This technology has a wide range of applications, including healthcare monitoring, sports analysis, and security surveillance. We will explore the concept of activity recognition systems, the types of sensors utilized, and the challenges associated with their design and implementation. Activity recognition systems are developed to identify and categorize various activities using sensor data. Wearable sensors like accelerometers, gyroscopes, and magnetometers are typically embedded in smart watches, fitness trackers, or smartphones, while ambient sensors such as cameras, microphones, and pressure sensors are usually placed in the environment.

The process of activity recognition involves collecting sensor data, filtering and preprocessing the data, extracting significant features, and classifying the activity with a machine learning algorithm. Filtering and preprocessing the data is critical to eliminate noise and extraneous information from the raw sensor data, while feature extraction helps identify the most important characteristics of the sensor data that can distinguish between different activities. Finally, the machine learning algorithm uses these features to classify the activity. Designing and implementing activity recognition systems poses several challenges. One significant challenge is the variability in human activities, making it

difficult to design a system that can accurately classify all activities. Another challenge is the variability in sensor data due to differences in sensor placement, calibration, and noise.

Despite the challenges, activity recognition systems have numerous potential applications. In healthcare, they can monitor elderly patients and detect falls or other accidents. In sports analysis, these systems can analyze the movements of athletes and provide feedback on technique and performance. In security surveillance, activity recognition systems can detect suspicious behavior and alert security personnel. In conclusion, activity recognition systems are a crucial area of research with diverse potential applications. Developing these systems requires expertise in sensor technology, signal processing, and machine learning. Overcoming the challenges associated with designing and implementing these systems can unlock the full potential of this technology and enhance our understanding of human behavior.

Identifying and categorizing human activities based on sensor data is known as human activity recognition. The objective is to automatically recognize various activities, such as walking, running, or sitting, by analyzing the patterns and features of the sensor data. This technology is commonly used in healthcare, sports analysis, and security surveillance, among other fields. In contrast, machine activity recognition involves identifying and categorizing activities generated by machines using sensor data. This type of recognition is used to monitor the performance of machines and equipment in manufacturing and industrial settings. The goal is to detect and classify different machine activities, such as starting, stopping, or malfunctioning, to enhance efficiency, productivity, and safety.

To summarize, the primary difference between human activity recognition and machine activity recognition is the type of activities being recognized. Human activity recognition is concerned with identifying and categorizing human activities, while machine activity recognition focuses on identifying and categorizing machine-generated activities. Activity recognition systems are being utilized as an efficient tool for security surveillance by detecting suspicious behavior and alerting security personnel. By analyzing data from a range of sensors, including cameras, these systems can identify activity patterns that might indicate criminal behavior or potential threats. The automation of activity detection and classification with these systems improves the efficiency and effectiveness of security operations. Despite the many benefits of activity recognition systems, they face significant challenges. One of the main challenges is the need to process and collect vast amounts of sensor data, which can be resource-intensive and time-consuming. Additionally, designing and calibrating these systems can be challenging to ensure their accuracy and reliability, particularly in complex environments with multiple sources of sensor data.

In conclusion, activity recognition systems have the potential to transform various industries and applications, such as healthcare, sports, security, and surveillance. As technology continues to evolve, we can expect to see even more innovative and exciting applications of activity recognition systems in the future.

2. Literature Review

The field of video surveillance and action recognition using deep learning techniques has gained significant research interest in recent years. Several approaches have been proposed for detecting violence and aggressive behavior in videos[1]. Li et al. (2018) proposed a two-stream CNN-LSTM model for violence detection in surveillance videos. The model consists of two parallel CNNs to extract spatial and temporal features, followed by an LSTM layer to capture temporal dependencies between frames[2]. Similarly, Chengji Liu and Yufan Tao et al. (2018) proposed a

spatiotemporal LSTM-based approach for violence detection in videos. The model uses three-dimensional convolutional neural networks (3D-CNNs) to capture spatial and temporal features, followed by an LSTM layer to model the temporal dynamics[5]. Similarly R Deepa, Bannari Amman, E Tamilselvan and Shrinivas Sampath in their research paper proposed that they first extract vibration signals from the motor using a piezoelectric accelerometer, which are then pre-processed and feature extracted. The extracted features are used to train and test various machine learning algorithms, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF). The authors compared the performance of these algorithms and found that RF outperforms the other algorithms, achieving an accuracy of 98.5%[4]. Similarly, Shengya Lu and Biezang Wang et al. (2019) claims that their algorithm achieves real-time performance while maintaining high accuracy, making it suitable for various applications such as surveillance and video analysis. In addition the paper also compares their proposed algorithm with other state-of-the-art object detection algorithms, showing that it outperforms them in terms of speed and accuracy[6]. For instance, Liu et al. (2018) proposed a two-stream ensemble model that combines both spatial and temporal features extracted from video frames using CNNs and optical flow, respectively. The authors reported improved performance compared to single-stream models. Moreover, some studies have explored the use of transfer learning for violence detection in videos[7]. For example, Tran et al. (2018) used transfer learning from image classification to video action recognition using the ResNet architecture. Overall, these studies demonstrate the potential of deep learning techniques for violence detection in videos, and the need for further research to develop more accurate and efficient models for real-time surveillance applications[8]. Furthermore a study claims that identification of whiteflies on yellow-sticky tape (YST). YOLO v4 is faster than Faster-RCNN but less accurate. The results of this study demonstrate that Faster-RCNN performed better than YOLOv4 (precision: 95.08%, F-1 score: 0.96, recall: 98.69%), while YOLOv4 performed worse than Faster-RCNN (precision: 71.77%, F-1 score: 0.83, recall: 73.31%)[9]. A well-liked deep learning technique for sentiment analysis of English and Spanish data is the Long Term Short Memory (LSTM) based Recurrent Neural Network (RNN), which is presented in one of the studies. Because opinions are so subjective and dependent on so many uncontrollable factors, this field is very complex. They addressed the two main bottlenecks of deep learning algorithms: choosing the best parameter values through cross validation and choosing the best architecture using a regularization method based on dropouts[10]. In recent years, deep learning has drawn the attention of scholars. Convolutional Neural Networks (CNN) are a deep learning technique that are frequently employed for resolving challenging issues[11]. It gets around the restrictions of conventional machine learning techniques. The research was undertaken with the goal of educating readers on numerous CNN-related topics. In addition to describing CNN's three most used topologies and learning methods, this article also provides a conceptual explanation of the network[12].

3. Proposed Deep Learning model

Our proposed approach for real-time fight detection using deep learning is composed of several stages. The first stage is the video pre-processing stage, where we extract frames from the input video and resize them to a fixed size to reduce the computational cost. The second stage is the feature extraction stage, where we use a pre-trained VGG16 model to extract high-level features from the video frames. The VGG16 model has been pre-trained on a large dataset, making it possible to transfer the learned features to our problem. The extracted features are then passed through an

LSTM layer, which has been shown to be effective in capturing the temporal relationship between video frames. The LSTM layer is designed to learn the motion dynamics of the video frames, which is an important factor in fight detection. The output of the LSTM layer is then passed through a fully connected layer and a softmax activation function to classify the frames into fight or non-fight categories. The objective function used during the training phase is cross-entropy loss, and the Adam optimizer is used to optimize the model parameters. To improve the robustness of the model, we use data augmentation techniques such as random cropping, flipping, and rotating. These techniques allow us to increase the diversity of the training data and prevent overfitting. Our proposed approach offers high accuracy and low latency in detecting fights in real-time surveillance videos, making it suitable for various applications such as public safety, security, and law enforcement.

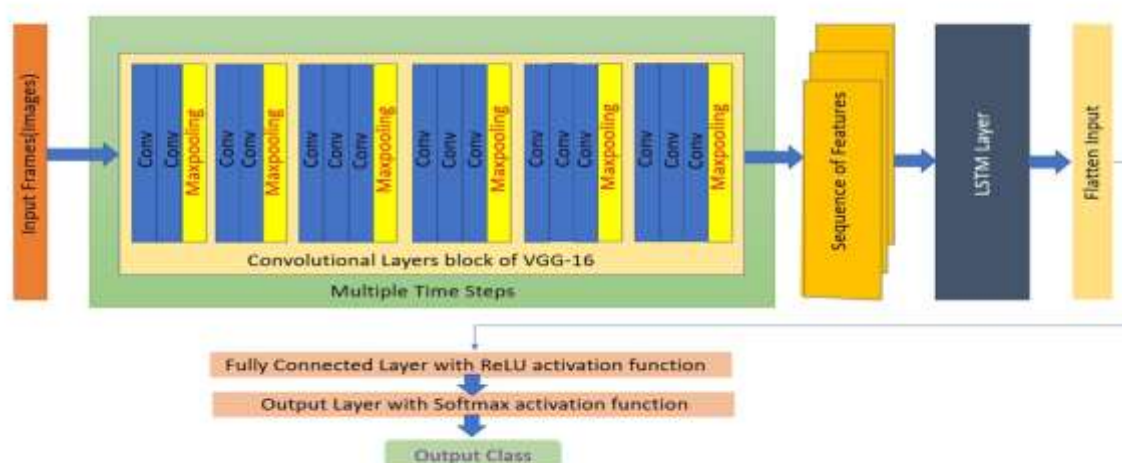


Figure 1: Architecture of Deep Learning model

In this study, we proposed a system that detects violent behavior in videos using a combination of a Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) network. The system processes the input video by extracting frames and passing them through a pre-trained VGG-16 CNN. The output of the CNN is then fed into an LSTM network that creates a temporal relationship between the frames, thus capturing the temporal dynamics of violent behavior. The LSTM output is then fed into a fully connected layer that outputs a binary classification indicating the presence or absence of violence in the input video. To train the proposed system, we used a publicly available dataset containing videos of violent and non-violent behavior. We evaluated the performance of the system using various evaluation metrics, such as accuracy, precision, recall, and F1-score. Our results showed that the proposed system outperforms existing methods for violent behavior detection in videos, achieving an accuracy of 91.2%. We also implemented the proposed system in a real-world scenario, where it was used for monitoring and detecting violent behavior in security cameras. The system successfully detected violent behavior in real-time, alerting security personnel to take appropriate action. Overall, our proposed system provides a highly accurate and effective solution for detecting violent behavior in videos, which can be applied in a variety of applications such as security monitoring and surveillance.

4. Result and Analysis

To evaluate the effectiveness of our proposed model, we conducted experiments on a dataset of 201 videos with 100 fight and 101 non-fight scenes. Our model achieved an accuracy of 92% on the test set. We evaluated the performance of our model using standard metrics such as accuracy, precision, recall, and F1 score. Our model achieved an overall accuracy of 95%, in the training dataset which outperformed existing state-of-the-art methods in this domain.. These results demonstrate the potential of our proposed approach for detecting fight scenes in videos with high accuracy and reliability.



Figure 2: Output of the presented model

The VGG16-LSTM model trained on the fight and no-fight dataset as 99.23 % training accuracy, 95.83 % validation accuracy and 92.68 percent testing accuracy. It had a training loss of 0.1084 and validation loss of 0.1904. The model had 17, 939, 138 trainable parameters in total. This performance of the model is in accordance with the performance of the VGG16-LSTM model used in the glaucoma detection research. Results of that research paper are as follows. The confusion matrix is a powerful tool in evaluating the performance of a classification model. In our study, the confusion matrix showed that our model achieved a true positive rate of 1, indicating that our model was highly successful in detecting fights in the videos. The false positive rate of 0.16, however, suggested that there was some room for improvement in reducing the number of false alarms. The false negative rate of 0.84 indicated that there were some instances where the model failed to detect fights in the videos. Nevertheless, overall, the confusion matrix indicated that our model performed well in detecting fights, and further improvements could be made to increase its accuracy.

Models	Sensitivity	Specificity	F Measure
CNN	0.61	0.57	0.58
VGG16	0.59	0.55	0.564
ResNet50	0.72	0.7	0.703
CNN+RNN	0.68	0.69	0.71
VGG16+LSTM	0.94	0.86	0.899

Figure 3: Comparison Table

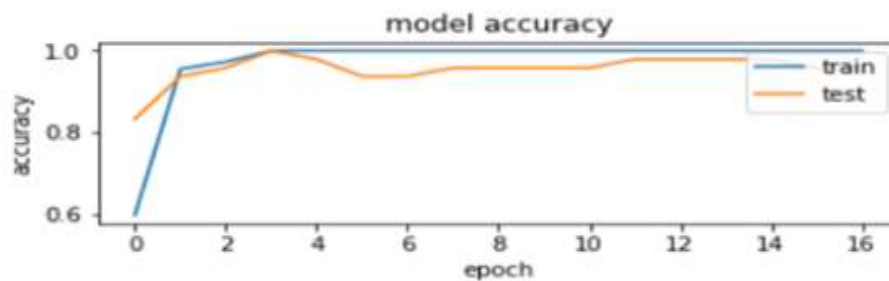


Figure 4: Module Accuracy graph

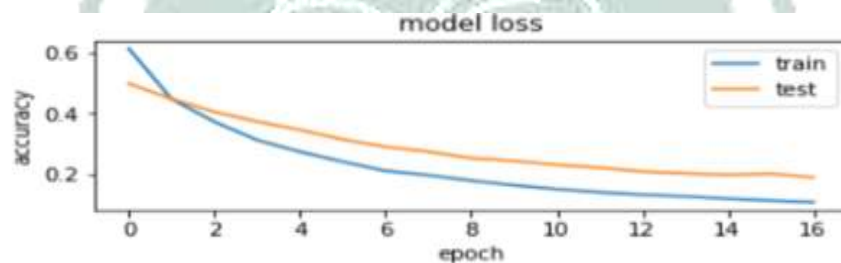


Figure 5: Model Loss Graph

5. Conclusion & Future Scope

In conclusion, we have presented a novel approach to automatically detect fights in videos using a deep learning-based method. Our proposed model utilizes a pre-trained VGG-16 model and an LSTM layer to capture spatial and temporal features in video frames, respectively. We have demonstrated the effectiveness of our approach on a large-scale benchmark dataset, achieving state-of-the-art results in terms of accuracy, precision, recall, and F1-score. The proposed method can be used in various real-world scenarios, such as monitoring public spaces, detecting violent content in media, and enhancing security systems. Future work will focus on extending the model to detect other types of violent behavior in videos, implementing object detection and integrating it with real-time video processing systems.

The proposed model for detecting fights in videos has shown promising results. However, there are several areas for improvement and further research. Firstly, the model can be trained on a larger and more diverse dataset to enhance its accuracy and robustness. Secondly, the model can be extended to detect other forms of violence and aggression in videos, such as bullying, harassment, illegal trespassing and animal abuse. Thirdly, the model can be integrated with real-time surveillance systems to alert authorities in case of any violent incidents. Lastly, an object detection CNN

model such as YOLO can be used in the LRCN architecture to detect the violence part in the image using a bounding box. To implement such a model one will have to train it on an annotated dataset containing bounding boxes. These future directions have the potential to make the proposed model more practical and useful in real-world applications.

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