Violence Detection in Videos

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Declaration of Authorship

I, Praveen Tirupattur, declare that this thesis titled, ‘Violence Detection in Videos’ and the work presented in it are my own. I confirm that:

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■ Where I have consulted the published work of others, this is always clearly attributed.

■ Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.

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Date: 
“Satisfaction lies in the effort, not in the attainment, full effort is full victory.”

Mahatma Gandhi
Abstract

In the recent years, there has been a tremendous increase in the amount of video content uploaded to social networking and video sharing websites like Facebook and Youtube. As a result of this, the risk of children getting exposed to adult and violent content on the web also increased. To address this issue, an approach to automatically detect violent content in videos is proposed in this work. Here, a novel attempt is made also to detect the category of violence present in a video. A system which can automatically detect violence from both Hollywood movies and videos from the web is extremely useful not only in parental control but also for applications related to movie ratings, video surveillance, genre classification and so on.

Here, both audio and visual features are used to detect violence. MFCC features are used as audio cues. Blood, Motion, and SentiBank features are used as visual cues. Binary SVM classifiers are trained on each of these features to detect violence. Late fusion using a weighted sum of classification scores is performed to get final classification scores for each of the violence class target by the system. To determine optimal weights for each of the violence classes an approach based on grid search is employed. Publicly available datasets, mainly Violent Scene Detection (VSD), are used for classifier training, weight calculation, and testing. The performance of the system is evaluated on two classification tasks, Multi-Class classification, and Binary Classification. The results obtained for Binary Classification are better than the baseline results from MediaEval-2014.
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# Abbreviations

| Abbreviation | Full Form |
|--------------|-----------|
| ANP          | Adjective Noun Pair |
| AP           | Average Precision |
| BPM          | Blood Probability Map |
| EER          | Equal Error Rate |
| HSV          | Hue Saturation Value |
| MAP          | Mean Average Precision |
| MFCC         | Mel Frequency Cepstral Coefficients |
| MoSIFT       | Motion Scale Invariant Feature Transform |
| RBF          | Radial Basis Function |
| RGB          | Red Green Blue |
| ROC          | Receiver Operating Characteristic |
| SIFT         | Scale Invariant Feature Transform |
| STIP         | Space Time Interest Points |
| SVM          | Support Vector Machines |
| ViF          | Violent Flows |
| VSD          | Violent Scene Dataset |
| VSO          | Visual Sentiment Ontology |
| XML          | Extended Markup Language |
| ZCR          | Zero Cross Rate |
This thesis is dedicated to my father, for his love, support, and encouragement...
Chapter 1

Introduction

The amount of multimedia content uploaded to social networking websites and the ease with which these can be accessed by children is posing a problem to parents who wish to protect their children from getting exposed to violent and adult content on the web. The number of video uploads to websites like YouTube and Facebook are on the rise. There is an increase of 75% in the number of video posts on Facebook (Blog-FB [3]) in the last one year and more than 120,000 videos are uploaded to YouTube every day (Wesch [56], Gill et al. [26]). It is estimated that 20% of the videos uploaded to these websites contain violent or adult content (Sparks [54]). This makes it easy for children to access or accidentally get exposed to these unsafe contents. The effects of watching violent content on children are well studied in psychology (Tompkins [55], Sparks [54], Bushman and Huesmann [6], and Huesmann and Taylor [32]) and the results of these studies suggest that watching of violent content has a substantial effect on emotions of the children. The major effects are increases in the likelihood of aggressive or fearful behavior and becoming less sensitive to the pain and suffering of others. Huesmann and Eron [31] conducted a study involving children from elementary school, who watched many hours of violence on television. By observing these children into adulthood, they found that the ones who did watch a lot of television violence when they were 8 years old were more likely to be arrested and prosecuted for criminal acts as adults. Similar studies by Flood [25] and Mitchell et al. [40] suggest that exposure to adult content also has detrimental effects on children. This motivated research in the field of automatic violent and adult content detection in videos.

Adult content detection (Chan et al. [8], Schulze et al. [52], Pogrebyak et al. [47]) is well studied and much progress has been made. Violence detection, on the other hand, has been less studied and has gained interest only in the recent past. Few approaches for violence detection were proposed in the past and each of these approaches tried to
detect violence using different visual and auditory features. For example, Nam et al. [41] combined multiple audio-visual features to identify violent scenes. In their work, flames and blood were detected using predefined color tables and various representative audio effects (gunshots, explosions, etc.) were also exploited. Datta et al. [14] proposed an accelerated motion vector based approach to detect human violence such as fist fighting, kicking, etc. Cheng et al. [11] presented a hierarchical approach to locating gun play and car racing scenes through detection of typical audio events (e.g. gunshots, explosions, and car-braking).

More approaches proposed for violence detection are discussed in Chapter 2. All of these approaches focused mainly on detection of violence in Hollywood movies but not in videos from video sharing and social media websites such as YouTube or Facebook. Detection of violence in Hollywood movies is relatively easy as these movies follow some moviemaking rules. For example, to exhibit exciting action scenes, the atmosphere of fast-pace is created through high-speed visual movement and fast-paced sound. But the videos from the video-sharing websites, like YouTube and Facebook, do not follow these moviemaking rules and often have poor audio and video quality. These characteristics of user-generated videos make it very hard to detect violence in them.

Before the approach to detect violence is discussed, it is important to provide a definition for the term “Violence”. All of the previous approaches for violence detection have not followed the same definition of violence and have used different features and different datasets. This makes the comparison of different approaches very difficult. To overcome this problem and to foster research in this area, a dataset named Violent Scene Detection (VSD) was introduced by Demarty et al. [15] in 2011 and the recent version of this dataset is the VSD2014. According to this latest dataset, “Violence” in a video is, “any scene one would not let an 8 year old child watch because they contain physical violence” Schedl et al. [51]. This definition is believed to be formulated based on the research findings from psychology, which are mentioned above. From this definition, it can be observed that violence is not a physical entity but a concept which is very generic, abstract and also very subjective. Hence, violence detection is not a trivial task.

The aim of this work is to build a system which automatically detects violence not only in Hollywood movies, but also in videos from the video-sharing websites like YouTube and Facebook. In this work, an attempt is made to also detect the category of violence in a video, which was not addressed by earlier approaches. The categories of violence which are targeted in this work are the presence of blood, presence of cold arms, explosions, fights, screams, presence of fire, firearms, and gunshots. These represent the subset of concepts defined and used in the VSD2014 for annotating video segments. The categories “gory scenes” and “car chase” from VSD2014 were not selected as there were not many
video segments in VSD2014 annotated with these concepts. Another such category is
the “Subjective Violence”. It is not selected as the scenes belonging to this category
do not have any visible violence and hence are very hard to detect. In this work, both
audio and visual features are used for violence detection as combining both audio and
visual information provides more reliable results in classification.

The advantages of developing a system like this, which can automatically detect violence
in multi-media content are many. It can be used to rate movies depending on the amount
of violence. This can be used by social networking sites to detect and block upload of
violent videos to their platforms. Also, it can be used for scene characterization and genre
classification which helps in searching and browsing movies. Recognition of violence in
video streams from real-time camera systems will be very helpful for video surveillance
in places such as airports, hospitals, shopping malls, public places, prisons, psychiatric
wards, school playgrounds etc. However, real time detection of violence is much more
difficult and in this work no attempt is made to deal with it.

An overview of related work, detailed description of the proposed approach and the
evaluation are presented next. The following chapters are organized as follows. In
Chapter 2 some of the previous works in the area of violence detection are explained
in detail. In Chapter 3, the details of the approach used for training and testing of
feature classifiers are presented. It also includes the details of feature extraction and the
classifier training. Chapter 4 describes the details of datasets used, experimental setup
and the results obtained from the experiments. Finally, in Chapter 5 conclusions are
provided followed by the possible future work.
Chapter 2

Related Work

Violence Detection is a sub-task of activity recognition where violent activities are to be detected from a video. It can also be considered as a kind of multimedia event detection. Some approaches have already been proposed to address this problem. These proposed approaches can be classified into three categories: (i) Approaches in which only the visual features are used. (ii) Approaches in which only the audio features are used. (iii) Approaches in which both the audio and visual features are used. The category of interest here is the third one, where both video and audio are used. This chapter provides an overview of some of the previous approaches belonging to each of these categories.

2.1 Using Audio and Video

The initial attempt to detect violence using both audio and visual cues is by Nam et al. [41]. In their work, both the audio and visual features are exploited to detect violent scenes and generate indexes so as to allow for content-based searching of videos. Here, the spatio-temporal dynamic activity signature is extracted for each shot to categorize it to be violent or non-violent. This spatio-temporal dynamic activity feature is based on the amount of dynamic motion that is present in the shot.

The more the spatial motion between the frames in the shot, the more significant is the feature. The reasoning behind this approach is that most of the action scenes involve a rapid and significant amount of movement of people or objects. In order to calculate the spatio-temporal activity feature for a shot, motion sequences from the shot are obtained and are normalized by the length of the shot to make sure that only the shots with shorter lengths and high spatial motion between the frames have higher value of the activity feature.
Apart from this, to detect flames from gunshots or explosions, a sudden variation in intensity values of the pixels between frames is examined. To eliminate false positives, such as intensity variation because of camera flashlights, a pre-defined color table with color values close to the flame colors such as yellow, orange and red are used. Similarly to detect blood, which is common in most of the violent scenes, pixel colors within a frame are matched with a pre-defined color table containing blood-like colors. These visual features by itself are not enough to detect violence effectively. Hence, audio features are also considered.

The sudden change in the energy level of the audio signal is used as an audio cue. The energy entropy is calculated for each frame and the sudden change in this value is used to identify violent events such as explosion or gunshots. The audio and visual clues are time synchronized to obtain shots containing violence with higher accuracy. One of the main contributions of this paper is to highlight the need of both audio and visual cues to detect violence.

Gong et al. [27] also used both visual and audio cues to detect violence in movies. A three-stage approach to detect violence is described. In the first stage, low-level visual and auditory features are extracted for each shot in the video. These features are used to train a classifier to detect candidate shots with potential violent content. In the next stage, high-level audio effects are used to detect candidate shots. In this stage, to detect high-level audio effects, SVM classifiers are trained for each category of the audio effect by using low-level audio features such as power spectrum, pitch, MFCC (Mel-Frequency Cepstral Coefficients) and harmonicity prominence (Cai et al. [7]). The output of each of the SVMs can be interpreted as probability mapping to a sigmoid, which is a continuous value between [0,1] (Platt et al. [46]). In the last stage, the probabilistic outputs of first two stages are combined using boosting and the final violence score for a shot is calculated as a weighted sum of the scores from the first two stages.

These weights are calculated using a validation dataset and are expected to maximize the average precision. The work by Gong et al. [27] concentrates only on detecting violence in movies where universal film-making rules are followed. For instance, the fast-paced sound during action scenes. Violent content is identified by detecting fast-paced scenes and audio events associated with violence such as explosions and gunshots. The training and testing data used are from a collection of four Hollywood action movies which contain many violent scenes. Even though this approach produced good results it should be noted that it is optimized to detect violence only in movies which follow some film-making rules and it will not work with the videos that are uploaded by the users to the websites such as Facebook, Youtube, etc.
In the work by Lin and Wang [38], a video sequence is divided into shots and for each shot both the audio and video features in it are classified to be violent or non-violent and the outputs are combined using co-training. A modified pLSA algorithm (Hofmann [30]) is used to detect violence from the audio segment. The audio segment is split into audio clips of one second each and is represented by a feature vector containing low-level features such as power spectrum, MFCC, pitch, Zero Cross Rate (ZCR) ratio and harmonicity prominence (Cai et al. [7]). These vectors are clustered to get cluster centers which denote an audio vocabulary. Then, each audio segment is represented using this vocabulary as an audio document. The Expectation Maximization algorithm (Dempster et al. [20]) is used to fit an audio model which is later used for classification of audio segments. To detect violence in a video segment, the three common visual violent events: motion, flame/explosions and blood are used. Motion intensity is used to detect areas with fast motion and to extract motion features for each frame, which is then used to classify a frame to be violent or non-violent. Color models and motion models are used to detect flame and explosions in a frame and to classify them. Similarly, color model and motion intensity are used to detect the region containing blood and if it is greater than a pre-defined value for a frame, it is classified to be violent. The final violence score for the video segment is obtained by the weighted sum of the three individual scores mentioned above. The features used here are same as the ones used by Nam et al. [41].

For combining the classification scores from the video and the audio stream, co-training is used. For training and testing, a dataset consisting of five Hollywood movies is used and precision of around 0.85 and recall of around 0.90 are obtained in detecting violent scenes. Even this work targets violence detection only in movies but not in the videos available on the web. But the results suggest that the visual features such are motion and blood are very crucial for violence detection.

### 2.2 Using Audio or Video

All the approaches mentioned so far use both audio and visual cues, but there are others which used either video or audio to detect violence and some others which try to detect only one a specific kind of violence such as fist fights. A brief overview of these approaches is presented next.

One of the only works which used audio alone to detect semantic context in videos is by Cheng et al. [11], where a hierarchical approach based on Gaussian mixture models and Hidden Markov models is used to recognize gunshots, explosions, and car-braking. Datta et al. [14] tried to detect person-on-person violence in videos which involve only fist fighting, kicking, hitting with objects etc., by analyzing violence at object level rather
than at the scene level as most approaches do. Here, the moving objects in a scene are
detected and a person model is used to detect only the objects which represent persons.
From this, the motion trajectory and orientation information of a person’s limbs are
used to detect person-on-person fights.

Clarin et al. [12] developed an automated system named DOVE to detect violence in
motion pictures. Here, blood alone is used to detect violent scenes. The system extracts
key frames from each scene and passes them to a trained Self-Organizing Map for labeling
the pixels with the labels: skin, blood or nonskin/nonblood. Labeled pixels are then
grouped together through connected components and are observed for possible violence.
A scene is considered to be violent if there is a huge change in the pixel regions with skin
and blood components. One other work on fight detection is by Nievas et al. [42] in which
Bag-of-Words framework is used along with the action descriptors Space-Time Interest
Points (STIP - Laptev [37]) and Motion Scale-invariant feature transform (MoSIFT -
Chen and Hauptmann [10]). The authors introduced a new video dataset consisting of
1,000 videos, divided into two groups fights and non-fights. Each group has 500 videos
and each video has a duration of one second. Experimentation with this dataset has
produced a 90% accuracy on a dataset with fights from action movies.

Deniz et al. [21] proposed a novel method to detect violence in videos using extreme
acceleration patterns as the main feature. This method is 15 times faster than the state-
of-the-art action recognition systems and also have very high accuracy in detecting scenes
containing fights. This approach is very useful in real-time violence detection systems,
where not only accuracy but also speed matters. This approach compares the power
spectrum of two consecutive frames to detect sudden motion and depending on the
amount of motion, a scene is classified to be violent or non-violent. This method does
not use feature tracking to detect motion, which makes it immune to blurring. Hassner
et al. [28] introduced an approach for real-time detection of violence in crowded scenes.
This method considers the change of flow-vector magnitudes over time. These changes
for short frame sequences are called Violent Flows (ViF) descriptors. These descriptors
are then used to classify violent and non-violent scenes using a linear Support Vector
Machine (SVM). As this method uses only flow information between frames and forgo
high-level shape and motion analysis, it is capable of operating in real-time. For this
work, the authors created their own dataset by downloading videos containing violent
crowd behavior from Youtube.

All these works use different approaches to detect violence from videos and all of them
use their own datasets for training and testing. They all have their own definition of
violence. This demonstrates a major problem for violence detection, which is the lack of
independent baseline datasets and a common definition of violence, without which the comparison between different approaches is meaningless.

To address this problem, Demarty et al. [16] presented a benchmark for automatic detection of violence segments in movies as part of the multimedia benchmarking initiative MediaEval-2011 \(^1\). This benchmark is very useful as it provides a consistent and substantial dataset with a common definition of violence and evaluation protocols and metrics. The details of the provided dataset are discussed in detail in Section 4.1. Recent works on violence recognition in videos have used this dataset and details about some of them are provided next.

### 2.3 Using MediaEval VSD

Acar et al. [1] proposed an approach that merges visual and audio features in a supervised manner using one-class and two-class SVMs for violence detection in movies. Low-level visual and audio features are extracted from video shots of the movies and then combined in an early fusion manner to train SVMs. MFCC features are extracted to describe the audio content and SIFT (Scale-Invariant Feature Transform - Lowe [39]) based Bag-of-Words approach is used for visual content.

Jiang et al. [33] proposed a method to detect violence based on a set of features derived from the appearance and motion of local patch trajectories(Jiang et al. [34]). Along with these patch trajectories, other features such as SIFT, STIP, and MFCC features are extracted and are used to train an SVM classifier to detect different categories of violence. Score and feature smoothing are performed to increase the accuracy.

Lam et al. [36] evaluated the performance of low-level audio/visual features for the violent scene detection task using the datasets and evaluation protocols provided by MediaEval. In this work both the local and global visual features are used along with motion and MFCC audio features. All these features are extracted for each keyframe in a shot and are pooled to form a single feature vector for that shot. An SVM classifier is trained to classify the shots to be violent or non-violent based on this feature vector. Eyben et al. [23] applied large-scale segmental feature extraction along with audio-visual classification for detecting violence. The audio feature extraction is done with the open-source feature extraction toolkit openSmile(Eyben and Schuller [22]). Low-level visual features such as Hue-Saturation-Value (HSV) histogram, optical flow analysis, and Laplacian edge detection are computed and used for violence detection. Linear SVM classifiers are used for classification and a simple score averaging is used for fusion.

\(^{1}\)http://www.multimediaeval.org
2.4 Summary

In summary, almost all methods described above try to detect violence in movies using different audio and visual features with an expectation of only a couple [Nievas et al. [42], Hassner et al. [28]], which use video data from surveillance cameras or from other real-time videos systems. It can also be observed that not all these works use the same dataset and each have their own definition of violence. The introduction of the MediaEval dataset for Violent Scene Detection (VSD) in 2011, has solved this problem. The recent version of the dataset, VSD2014 also includes video content from Youtube apart from the Hollywood movies and encourages researchers to test their approach on user-generated video content.

2.5 Contributions

The proposed approach presented in Chapter 3 is motivated by the earlier works on violence detection, discussed in Chapter 2. In the proposed approach, both audio and visual cues are used to detect violence. MFCC features are used to describe audio content and blood, motion and SentiBank features are used to describe video content. SVM classifiers are used to classify each of these features and late fusion is applied to fuse the classifier scores.

Even though this approach is based on earlier works on violence detection, the important contributions of it are: (i) Detection of different classes of violence. Earlier works on violence detection concentrated only on detecting the presence of violence in a video. This proposed approach is one of the first to tackle this problem. (ii) Use of SentiBank feature to describe visual content of a video. SentiBank is a visual feature which is used to describe the sentiments in an image. This feature was earlier used to detect adult content in videos (Schulze et al. [52]). In this work, it is used for the first time to detect violent content. (iii) Use of 3-dimensional color model, generated using images from the web, to detect pixels representing blood. This color model is very robust and has shown very good results in detecting blood. (iv) Use of information embedded in a video codec to generate motion features. This approach is very fast when compared to the others, as the motion vectors for each pixel are precomputed and stored in the video codec. A detailed explanation of this proposed approach is presented in the next chapter, Chapter 3.
Chapter 3

Proposed Approach

This chapter provides a detailed description of the approach followed in this work. The proposed approach consists of two main phases: Training and Testing. During the training phase, the system learns to detect the category of violence present in a video by training classifiers with visual and audio features extracted from the training dataset. In the testing phase, the system is evaluated by calculating the accuracy of the system in detecting violence for a given video. Each of these phases is explained in detail in the following sections. Please refer to Figure 3.1 for the overview of the proposed approach. Finally, a section describing the metrics used for evaluating the system is presented.

3.1 Training

In this section, the details of the steps involved in the training phase are discussed. The proposed training approach has three main steps: Feature extraction, Feature Classification, and Feature fusion. Each of these three steps is explained in detail in the following sections. In the first two steps of this phase, audio and visual features from the video segments containing violence and no violence are extracted and are used to train two-class SVM classifiers. Then in the feature fusion step, feature weights are calculated for each violence type targeted by the system. These feature weights are obtained by performing a grid search on the possible combination of weights and finding the best combination which optimizes the performance of the system on the validation set. The optimization criteria here is the minimization of EER (Equal Error Rate) of the system. To find these weights, a dataset disjoint from the training set is used, which contains violent videos of all targeted categories. Please refer to Chapter 1 for details of targeted categories.
Chapter 3. Proposed Approach

3.1 Feature Extraction

Many researchers have tried to solve the Violence detection problem using different audio and visual features. A detailed information on violence detection related research is presented in Chapter 2. In the previous works, the most common visual features used to detect violence are motion and blood and the most common audio feature used is the MFCC. Along with these three common low-level features, this proposed approach also includes SentiBank (Borth et al. [4]), which is a visual feature representing sentiments in images. The details of each of the features and its importance in violence detection and the extraction methods used are described in the following sections.

3.1.1.1 MFCC-Features

Audio features play a very important role in detecting events such as gunshots, explosions etc, which are very common in violent scenes. Many researchers have used audio features for violence detection and have produced good results. Even though some of the earlier works looked at energy entropy [Nam et al. [41]] in the audio signal, most of them
used MFCC features to describe audio content in the videos. These MFCC features are commonly used in voice and audio recognition.

In this work, MFCC features provided in the VSD2014 dataset are used to train the SVM classifier while developing the system. During the evaluation, MFCC features are extracted from the audio stream of the input video, with window size set to the number of audio samples per frame in the audio stream. This is calculated by dividing the audio sampling rate with fps (frames per second) value of the video. For example, if the audio sampling rate is 44,100 Hz and the video is encoded with 25 fps, then each window has 1,764 audio samples. The window overlap region is set to zero and 22 MFCC are computed for each window. With this setup, a 22-dimensional MFCC feature vector is obtained for each video frame.

3.1.1.2 Blood-Features

Blood is the most common visible element in scenes with extreme violence. For example, scenes containing beating, stabbing, gunfire, and explosions. In many earlier works on violence detection, detection of pixels representing blood is used as it is an important indicator of violence. To detect blood in a frame, a pre-defined color table is used in most of the earlier works, for example, Nam et al. [41] and Lin and Wang [38]. Other approaches to detecting blood, such as the use of Kohonen’s Self-Organizing Map (SOM) (Clarin et al. [12]), are also used in some of the earlier works.

In this work, a color model is used to detect pixels representing blood. It is represented using a three-dimensional histogram with one dimension each for red, green and blue values of the pixels. In each dimension, there are 32 bins with each bin having width of 8 (32 × 8 = 256). This blood model is generated in two steps. In the first step, the blood model is bootstrapped by using the RGB (Red, Green, Blue) values of the pixels containing blood. The 3 dimensional binned histogram is populated with the RGB values of these pixels containing blood. The value in the bin to which a blood pixel belongs to is incremented by 1 each time a new blood pixel is added to the model. Once a sufficient number of bloody pixels are used to fill the histogram, the values in the bins are normalized by the sum of all the values. The values in each of the bins now represent the probability of a pixel showing blood given its RGB values. To fill the blood model, pixel containing blood are cropped from various images containing blood which are downloaded from Google. Cropping of the regions containing only blood pixels is done manually. Please refer to the image Figure 3.2 for samples of the cropped regions, each of size 20 pixels × 20 pixels.
Once the model is bootstrapped, it is used to detect blood in the images downloaded from Google. Only pixels that have a high probability of representing blood are used to further extend the bootstrapped model. Downloading the images and extending the blood model is done automatically. To download images from Google which contain blood, search words such as “bloody images”, “bloody scenes”, “bleeding”, “real blood splatter”, “blood dripping” are used. Some of the samples of the downloaded images can be seen in the Figure 3.3. Pixel values with high blood probability are added to the blood model until it has, at least, a million pixel values.

This blood model alone is not sufficient to accurately detect blood. Along with this blood model, there is a need for a non-blood model as well. To generate this, similar to the earlier approach, images are downloaded from Google which do not contain blood and the RGB pixel values from these images are used to build the non-blood model. Some samples images used to generate this non-blood model are shown in Figure 3.3. Now using these blood and non-blood models, the probability of a pixel representing blood is calculated as follows

\[
P(\text{blood/pixel}) = \frac{P_{\text{blood}}(\text{pixel})}{P_{\text{blood}}(\text{pixel}) + P_{\text{non\text{-}blood}}(\text{pixel})}
\]  

(3.1)

where \( P(\text{blood/pixel}) \) defines the probability of a pixel containing blood, \( P_{\text{blood}}(\text{pixel}) \) refers to the probability of blood for a given pixel and \( P_{\text{non\text{-}blood}}(\text{pixel}) \) corresponds to
the probability of non-blood for a pixel.

Using this formula, for a given image, the probability of each pixel representing blood is calculated and Blood Probability Map (BPM) is generated. This map has the same size as that of the input image and contains the blood probability values for every pixel. This BPM is binarized using a threshold value to generate the final binarized BPM. The threshold used to binarize the BPM is estimated (Jones and Rehg [35]). From this binarized BPM, a 1-dimensional feature vector of length 14 is generated which contains the values such as the blood ratio, blood probability ratio, size of the biggest connected component, mean, variance etc. This feature vector is extracted for each frame in the video and is used for training the SVM classifier. A sample image along with its BPM and binarized BPM are presented in Figure 3.4. It can be observed from this figure that this approach has performed very well in detecting pixels containing blood.
3.1.1.3 Motion-Features

Motion is another widely used visual feature for violence detection. The work of Deniz et al. [21], Nievas et al. [42] and Hassner et al. [28] are some of the examples in which motion is used as the main feature for violence detection. Here, motion refers to the amount of spatio-temporal variation between two consecutive frames in a video. Motion is considered a good indicator of violence as substantial amount of violence is expected in the scenes that contain violence. For example, in the scenes that contain person-on-person fights, there is fast movement of human body parts like legs and hands, and in scenes that contain explosions, there is a lot of movement from the parts that are flying apart because of the explosion.

The idea of using motion information for activity detection stems from psychology. Research on human perception has shown that the kinematic pattern of movement is sufficient for the perception of actions (Blake and Shiffrar [2]). Research studies in computer vision (Saerbeck and Bartneck [50], Clarke et al. [13], and Hidaka [29]) have also shown that relatively simple dynamic features such as velocity and acceleration correlate to emotions perceived by a human.

In this work, to calculate the amount of motion in a video segment, two different approaches are evaluated. The first approach is to use the motion information embedded
inside the video codec and the next approach is to use optical flow to detect motion. These approaches are presented next.

### 3.1.1.3.1 Using Codec

In this method, the motion information is extracted from the video codec. The magnitude of motion at each pixel per frame called the motion vector is retrieved from the codec. This motion vector is a two-dimensional vector and has the same size as a frame from the video sequence. From this motion vector, a motion feature which represents the amount of motion in the frame is generated. To generate this motion feature, first the motion vector is divided into twelve sub-regions of equal sizes by slicing it along the x and y-axis into three and four regions respectively. The amount of motion along the x and y-axis at each pixel from each of these sub-regions are aggregated and these sums are used to generate a two-dimensional motion histogram for each frame. This histogram represents the motion vector for a frame. Refer to the image on the left in Figure 3.5 to see the visualization of the aggregated motion vectors for a frame from a sample video. In this visualization, the motion vectors are aggregated for sub-regions of size 16 × 16 pixels. The magnitude and direction of motion in these regions is represented using the length and orientation of the green dashed lines which are overlaid on the image.

### 3.1.1.3.2 Using Optical Flow

The next approach to detect motion uses Optical flow (Wikipedia [57]). Here, the motion at each pixel in a frame is calculated using Dense Optical Flow. For this, the implementation of Gunner Farneback’s algorithm (Farnebäck [24]) provided by OpenCV (Bradski [5]) is used. The implementation is provided as a function in OpenCV and for more details about the function and the parameters, please refer to the documentation provided by OpenCV (OpticalFlow [43]). The values 0.5, 3, 15, 3, 5, 1.2 and 0 are passed to the function parameters pyr_scale, levels, win-size, iterations, poly_n, poly_sigma and flags respectively. Once the motion vectors at every pixel are calculated using Optical flow, the motion feature from a frame is extracted using the same process mentioned in the above Section 3.1.1.3.1. Refer to the image on the rights in Figure 3.5 to get an impression of the aggregated motion vectors extracted from a frame. The motion vectors are aggregated for sub-regions of size 16 × 16 pixels as in the previous approach to provide a better comparison between the features extracted by using Codec information and Optical flow.

After the evaluation of both these approaches to extract motion information from videos, the following observations are made. First, extracting motion from Codecs is much faster than using optical flow as the motion vectors are precalculated and stored in video codecs. Second, motion extraction using optical flow is not very efficient when there are blurred...
regions in a frame. This blur is usually caused by sudden motions in a scene, which is very common in scenes containing violence. Hence, the use of optical flow for extracting motion information to detect violence is not a promising approach. Therefore, in this work information stored in the video codecs is used to extract motion features. The motion features are extracted from each frame in the video and are used to train an SVM classifier.

3.1.1.4 SentiBank-Features

In addition to the aforementioned low-level features, the SentiBank feature introduced by Borth et al. [4] is also applied. SentiBank is a mid-level representation of visual content based on the large-scale Visual Sentiment Ontology (VSO) \(^1\). SentiBank consists of 1,200 semantic concepts and corresponding automatic classifiers, each being defined as an Adjective Noun Pair (ANP). Such ANPs combine strong emotional adjectives to be linked with nouns, which correspond to objects or scenes (e.g. “beautiful sky”, “disgusting bug”, or “cute baby”). Further, each ANP (1) reflects a strong sentiment, (2) has a link to an emotion, (3) is frequently used on platforms such as Flickr or YouTube and (4) has a reasonable detection accuracy. Additionally, the VSO is intended to be comprehensive and diverse enough to cover a broad range of different concept classes such as people, animals, objects, natural or man-made places and, therefore, provides additional insights about the type of content being analyzed. Because SentiBank demonstrated its superior performance as compared to low-level visual features on the analysis

\(^1\)http://visual-sentiment-ontology.appspot.com
of sentiment Borth et al. [4], it is used now for the first time to detect complex emotion such as violence from video frames.

SentiBank consists of 1,200 SVMs, each trained to detect one of the 1,200 semantic concepts from an image. Each SVM is a binary classifier which gives a binary output 0/1 depending on whether or not the image contains a specific sentiment. For a given frame in a video, a vector containing the output of all 1,200 SVMs is considered as the SentiBank feature. To extract this feature, a python-based implementation is utilized. For training the SVM classifier, the SentiBank features extracted from each frame in the training videos are used. The SentiBank feature extraction takes few seconds as it involves collecting output from 1,200 pre-trained SVMs. To reduce the time taken for feature extraction, the SentiBank feature for each of the frame is extracted in parallel using multiprocessing.

3.1.2 Feature Classification

The next step in the pipeline after feature extraction is feature classification and this section provides the details of this step. The selection of classifier and the training techniques used play a very important role in getting good classification results. In this work, SVMs are used for classification. The main reason behind this choice is the fact that the earlier works on violence detection have used SVMs to classify audio and visual features and have produced good results. In almost all the works mentioned in Chapter 2 SVMs are used for classification, even though they may differ in the kernel functions used.

From all the videos available in the training set, audio and visual features are extracted using the process described in the Section 3.1.1. These features are then divided into two sets, one to train the classifier and the other to test the classification accuracy of the trained classifier. As the classifiers used here are SVMs, a choice has to be made about what kernel to use and what kernel parameters to set. To find the best kernel type and kernel parameters, a grid search technique is used. In this grid search, Linear, RBF (Radial Basis Function), and Chi-Square kernels along with a range of value for their parameters are tested, to find the best combination which gives the best classification results. Using this approach, four different classifiers are trained, one for each feature type. These trained classifiers are then used in finding the feature weights in the next step. In this work, the SVM implementation provided by scikit-learn (Pedregosa et al. [45]) and LibSVM (Chang and Lin [9]) are used.
3.1.3 Feature Fusion

In the feature fusion step, the output probabilities from each of the feature classifiers are fused to get the final score of the violence in a video segment along with the class of violence present in it. This fusion is done by calculating the weighted sum of the probabilities from each of the feature classifiers. To detect the class of violence to which a video belongs, the procedure is as follows. First, the audio and visual features are extracted from the videos belonging to each of the targeted violence classes. These features are then passed to the trained binary SVM classifiers to get the probabilities of each of the video containing violence. Now, these output probabilities from each of the feature classifiers are fused by assigning each feature classifier a weight for each class of violence and calculating the weighted sum. The weights assigned to each of the feature classifiers represent the importance of a feature in detecting a specific class of violence. These feature weights have to be adjusted appropriately for each violence class for the system to detect the correct class of violence.

There are two approaches to finding the weights. The first approach is to manually adjust weights of a feature classifier for each violence type. This approach needs a lot of intuition about the importance of a feature in detecting a class of violence and is very error prone. The other approach is to find the weights using a grid-search mechanism where a set of weights is sampled from the range of possible weights. In this case, the range of possible weights for each feature classifier is \([0,1]\), subjected to the constraint that the sum of weights of all the feature classifiers amounts to 1. In this work, the latter approach is used and all the weight combinations which amount to 1 are enumerated. Each of these weight combinations is used to calculate the weighted sum of classifier probabilities for a class of violence and the weights from the weight combination which produces the highest sum is assigned to each of the classifiers for the corresponding class of violence. To calculate these weights, a dataset which is different from the training set is used, in order to avoid over-fitting of weights to the training set. The dataset used for weight calculation has videos from all the classes of violence targeted in this work. It is important to note that, even though each of the trained SVM classifiers are binary in nature, the output values from these classifiers can be combined using weighted sum to find the specific class of violence to which a video belongs.

3.2 Testing

In this stage, for a given input video, each segment containing violence is detected along with the class of violence present in it. For a given video, the following approach is used
to detect the segments that contain violence and the category of violence in it. First, the visual and audio features are extracted from one frame every 1-second starting from the first frame of the video, rather than extracting features from every frame. These frames from which the features are extracted, represent a 1-second segment of the video. The features from these 1-second video segments are then passed to the trained binary SVM classifiers to get the scores for each video segment to be violent or non-violent. Then, weighted sums of the output values from the individual classifiers are calculated for each violence category using the corresponding weights found during fusion step. Hence, for a given video of length ‘X’ seconds, the system outputs a vector of length ‘X’. Each element in this vector is a dictionary which maps each violence class with a score value. The reason for using this approach is two fold, first to detect time intervals in which there is violence in the video and to increase the speed of the system in detecting violence. The feature extraction, especially extracting the Sentibank feature, is time-consuming and doing it for every frame will make the system slow. But this approach has a negative effect on the accuracy of the system as it detects violence not for every frame but for every second.

### 3.3 Evaluation Metrics

There are many metrics that can be used to measure the performance of a classification systems. Some of the measures used for binary classification are Accuracy, Precision, Recall (Sensitivity), Specificity, F-score, Equal Error Rate (EER), and Area Under the Curve (AUC). Some other measures such as Average Precision (AP) and Mean Average Precision (MAP) are used for systems which return a ranked list as a result to a query. Most of these measures that are increasingly used in Machine Learning and Data Mining research are borrowed from other disciplines such as Information Retrieval (Rijsbergen [49]) and Biometrics. For a detailed discussion on these measures, refer to the works of Parker [44] and Sokolova and Lapalme [53]. The ROC (Receiver Operating Characteristic) curve is another widely used method for evaluating or comparing binary classification systems. Measures such as AUC and EER can be calculated from the ROC curve.

In this work, ROC curves are used to: (i) Compare the performance of individual classifiers. (ii) Compare the performance of the system in detecting different classes of violence in the Multi-Class classification task. (iii) Compare the performance of the system on Youtube and Hollywood-Test dataset in the Binary classification task. Other metrics that are used here are, Precision, Recall and EER. These measures are used as these are
the most commonly used measures in the previous works on violence detection. In this system, the parameters (fusion weights) are adjusted to minimize the EER.

### 3.4 Summary

In this chapter, a detailed description of the approach followed in this work to detect violence is presented. The first section deals with the training phase and the second section deals with the testing phase. In the first section, different steps involved in the training phase are explained in detail. First, the extraction of audio and visual features is discussed, and the details of what features are used and how they are extracted are presented. Next, the classification techniques used to classify the extracted features are discussed. Finally, the process used to calculate feature weights for feature fusion is discussed. In the second section, the process used during the testing phase to extract video segments containing violence and to detect the class of violence in these segments is discussed.

To summarize, the steps followed in this approach are feature extraction, feature classification, feature fusion, and testing. The first three steps constitute the training phase, and the final step is the testing phase. In the training phase, audio and visual features are extracted from the video and they are used to train binary SVM classifiers one for each feature. Then, a separate dataset is used to find the feature weights which minimize the EER of the system on the validation dataset. In the final testing phase, first, the visual and audio features are extracted one per a 1-second video segment of the input test video. Then, these features are passed to the trained SVM classifiers to get the probabilities of these features representing violence. A weighted sum of these output probabilities is calculated for each violence type using the weights obtained in the feature fusion step. The violence type for which the weighted sum is maximum is assigned as a label to the corresponding 1-second video segment. Using these labels, the segments containing violence and the class of violence contained in them are presented as an output by the system. The experimental setup and evaluation of this system are presented in the next chapter.
Chapter 4

Experiments and Results

In this chapter, details of the experiments conducted to evaluate the performance of the system in detecting violent content in videos are presented. The first section deals with the datasets used for this work, the next section describes the experimental setup and finally in the last section, results of the experiments performed are presented.

4.1 Datasets

In this work, data from more than one source has been used to extract audio and visual features, train the classifiers and to test the performance of the system. The two main datasets used here are the Violent Scene Dataset (VSD) and the Hockey Fights dataset. Apart from these two datasets, images from websites such as Google Images\(^1\) are also used. Each of these datasets and their use in this work is described in detail in the following sections.

4.1.1 Violent Scene Dataset

Violent Scene Dataset (VSD) is an annotated dataset for violent scene detection in Hollywood movies and videos from the web. It is a publicly available dataset specifically designed for the development of content-based detection techniques targeting physical violence in movies and videos from the websites such as YouTube\(^2\). The VSD dataset was initially introduced by Demarty et al. [15] in the framework of the MediaEval benchmark initiative, which serves as a validation framework for the dataset and establishes a state of the art baseline for the violence detection task. The latest version of the

\(^1\)http://www.images.google.com
\(^2\)http://www.youtube.com
dataset VSD2014 is a considerable extension of its previous versions (Demarty et al. [19], Demarty et al. [18] and Demarty et al. [17]) in several regards. First, to annotate the movies and user-generated videos, violence definition which is closer to the targeted real-world scenario is used by focusing on physical violence one would not let a 8-year-old child watch. Second, the dataset has a substantial set of 31 Hollywood movies. Third, VSD2014 includes 86 web video clips and their meta-data retrieved from YouTube to serve for testing the generalization capabilities of the system developed to detect violence. Fourth, it includes state-of-the-art audio-visual content descriptors. The dataset provides annotations of violent scenes and of violence-related concepts for a collection of (i) Hollywood movies and (ii) user-generated videos shared on the web. In addition to the annotations, pre-computed audio and visual features and various meta-data are provided.

The VSD2014 dataset is split into three different sub-sets, called Hollywood: Development, Hollywood: Test, and YouTube: Generalization. Please refer to Table 4.1 for an overview of the three subsets and basic statistics, including duration, the fraction of violent scenes (as percentage on a per-frame-basis), and the average length of a violent scene. The content of the VSD2014 dataset is categorized into three types: movies/videos, features, and annotations.

The Hollywood movies included in the dataset are chosen such that they are from different genres and have diversity in the types of violence they contain. Movies ranging from extremely violent to virtually no violent content are selected to create this dataset. The selected movies also contain a wide range of violence types. For example, war movies, such as Saving Private Ryan, contain specific gunfights and battle scenes involving lots of people, with a loud and dense audio stream containing numerous special effects. Action movies, such as The Bourne Identity, contain scenes of fights involving only a few participants, possibly hand to hand. Disaster movies, such as Armageddon, show the destruction of entire cities and contain huge explosions. Along with these, a few completely nonviolent movies are also added to the dataset to study the behavior of algorithms on such content. As the actual movies can not be provided in the dataset due to copyright issues, annotations for 31 movies, 24 in the Hollywood: Development and 7 in the Hollywood: Test set are provided. The YouTube: Generalization set contains video clips shared on YouTube under Creative Commons license. A total of 86 clips in MP4 format is included in the dataset. Along with the video meta-data such as video identifier, publishing date, category, title, author, aspect ratio, duration etc., are provided as XML files.

In this dataset, a common set of audio and visual descriptors are provided. Audio features such as amplitude envelop (AE), root-mean-square energy (RMS), zero-crossing
Table 4.1: Statistics of the movies and videos in the VSD2014 subsets. All values are given in Seconds.

| Name                     | Duration | Fraction of Violence (%) | Avg. Duration |
|--------------------------|----------|--------------------------|---------------|
| **Hollywood: Development** |          |                          |               |
| Armageddon               | 8,680.16 | 7.78                     | 25.01         |
| Billy Elliot             | 6,349.44 | 2.46                     | 8.68          |
| Dead Poets Society       | 7,413.20 | 0.58                     | 14.44         |
| Eragon                   | 5,985.44 | 13.26                    | 39.69         |
| Fantastic Four 1         | 6,093.96 | 20.53                    | 62.57         |
| Fargo                    | 5,646.40 | 15.04                    | 65.32         |
| Fight Club               | 8,004.50 | 15.83                    | 32.51         |
| Forrest Gump             | 8,176.72 | 8.29                     | 75.33         |
| Harry Potter 5           | 7,953.52 | 5.44                     | 17.30         |
| I am Legend              | 5,779.92 | 15.64                    | 75.36         |
| Independence Day         | 8,833.90 | 13.13                    | 68.23         |
| Legally Blond            | 5,523.44 | 0.00                     | 0.00          |
| Leon                     | 6,344.56 | 16.36                    | 41.52         |
| Midnight Express         | 6,961.04 | 7.12                     | 24.80         |
| Pirates of the Caribbean | 8,239.40 | 18.15                    | 49.85         |
| Pulp Fiction             | 8,887.00 | 25.05                    | 202.43        |
| Reservoir Dogs           | 5,712.96 | 30.41                    | 115.82        |
| Saving Private Ryan      | 9,751.00 | 33.95                    | 367.92        |
| The Bourne Identity      | 6,816.00 | 7.18                     | 27.21         |
| The God Father           | 10,194.70 | 5.73                    | 44.99         |
| The Pianist              | 8,567.04 | 15.44                    | 69.64         |
| The Sixth Sense          | 6,178.04 | 2.00                     | 12.40         |
| The Wicker Man           | 5,870.44 | 6.44                     | 31.55         |
| The Wizard of Oz         | 5,859.20 | 1.02                     | 8.56          |
| **Total**                | 180,192.40 | 12.35                  |               |
| **Hollywood: Test**      |          |                          |               |
| 8 Mile                   | 6,355.60 | 4.70                     | 37.40         |
| Braveheart               | 10,223.92 | 21.45                   | 51.01         |
| Desperado                | 6,012.96 | 31.94                    | 113.00        |
| Ghost in the Shell       | 4966.00  | 9.85                     | 44.47         |
| Jumanji                  | 5993.96  | 6.75                     | 28.90         |
| Terminator 2             | 8831.40  | 24.89                    | 53.62         |
| V for Vendetta           | 7625.88  | 14.27                    | 25.91         |
| **Total**                | 50,009.72 | 17.18                  |               |
| **YouTube: Generalization** |          |                          |               |
| Average                  | 109.76   | 31.69                    | 26.62         |
| Std.dev                  | 68.05    | 36.28                    | 50.41         |
| **Total**                | 9,439.39 | 31.69                    |               |
rate (ZCR), band energy ratio (BER), spectral centroid (SC), frequency bandwidth (BW), spectral flux (SF), and Mel-frequency cepstral coefficients (MFCC) are provided on a per-video-frame-basis. As audio has a sampling rate of 44,100 Hz and the videos are encoded with 25 fps, a window of size 1,764 audio samples in length is considered to compute these features and 22 MFCCs are computed for each window while all other features are 1-dimensional. Video features provided in the dataset include color naming histograms (CNH), color moments (CM), local binary patterns (LBP), and histograms of oriented gradients (HOG). Audio and visual features are provided in Matlab version 7.3 MAT files, which correspond to HDF5 format.

The VSD2014 dataset contains binary annotations of all violent scenes, where a scene is identified by its start and end frames. These annotations for Hollywood movies and YouTube videos are created by several human assessors and are subsequently reviewed and merged to ensure a certain level of consistency. Each annotated violent segment contains only one action, whenever this is possible. In cases where different actions are overlapping, the segments are merged. This is indicated in the annotation files by adding the tag “multiple action scene”. In addition to binary annotations of segments containing physical violence, annotations also include high-level concepts for 17 movies in the Hollywood: Development set. In particular, 7 visual concepts and 3 audio concepts are annotated, employing a similar annotation protocol as used for violent/non-violent annotations. The concepts are the presence of blood, fights, presence of fire, presence of guns, presence of cold arms, car chases, and gory scenes, for the visual modality; the presence of gunshots, explosions, and screams for the audio modality.

A more detailed description of this dataset is provided by Schedl et al. [51] and for the details about each of the violence classes, please refer to Demarty et al. [19].

### 4.1.2 Fights Dataset

This dataset is introduced by Nievas et al. [42] and it is created specifically for evaluating fight detection systems. This dataset consists of two parts, the first part (“Hockey”) consists of 1,000 clips at a resolution of 720 × 576 pixels, divided into two groups, 500 fights, and 500 non-fights, extracted from hockey games of the National Hockey League (NHL). Each clip is limited to 50 frames and resolution lowered to 320 × 240. The second part (“Movies”) consists of 200 video clips, 100 fights, and 100 non-fights, in which fights are extracted from action movies and the non-fight videos are extracted from public action recognition datasets. Unlike the hockey dataset, which was relatively uniform both in format and content, these videos depict a wider variety of scenes and
Figure 4.1: Sample frames from the fight videos in the Hockey (top) and action movie (bottom) datasets.
were captured at different resolutions. Refer to Figure 4.1 for some of the frames showing fights from the videos in the two datasets. This dataset is available on-line for download\(^3\).

### 4.1.3 Data from Web

Images from Google are used in developing the color models (Section 3.1.1.2) for the classes blood and non-blood, which are used in extracting blood feature descriptor for each frame in a video. The images containing blood are downloaded from Google Images\(^1\) using query words such as "bloody images", "bloody scenes", "bleeding", "real blood splatter" etc. Similarly, images containing no blood are downloaded using search words such as "nature", "spring", "skin", "cars" etc.

The utility to download images from Google, given a search word, was developed in Python using the library Beautiful Soup (Richardson [48]). For each query, the response contained about 100 images of which only the first 50 were selected for download and saved in a local file directory. Around 1,000 images were downloaded in total, combining both blood and non-blood classes. The average dimensions of the images downloaded are 260 × 193 pixels with a file size of around 10 Kilobytes. Refer to Figure 3.3 for some of the sample images used in this work.

### 4.2 Setup

In this section, details of the experimental setup and the approaches used to evaluate the performance of the system are presented. In the following paragraph, partitioning of the dataset is discussed and the later paragraphs explain the evaluation techniques.

As mentioned in the earlier Section 4.1, data from multiple sources is used in this system. The most important source is the VSD2014 dataset. It is the only publicly available dataset which provides annotated video data with various categories of violence and it is the main reason for using this dataset in developing this system. As explained in the previous Section 4.1.1, this dataset contains three subsets, Hollywood: Development, Hollywood: Test and YouTube: Generalization. In this work all the three subsets are used. The Hollywood: Development subset is the only dataset which is annotated with different violence classes. This subset consisting of 24 Hollywood movies is partitioned into 3 parts. The first part consisting of 12 movies (Eragon, Fantastic Four 1, Fargo, Fight Club, Harry Potter 5, I Am Legend, Independence Day, Legally Blond, Leon, Midnight Express, Pirates Of The Caribbean, Reservoir Dogs) is used for training the

\(^3\)http://visilab.etsii.uclm.es/personas/oscar/FightDetection/index.html
classifiers. The second part consisting of 7 movies (Saving Private Ryan, The Bourne Identity, The God Father, The Pianist, The Sixth Sense, The Wicker Man, The Wizard of Oz) is used for testing the trained classifiers and to calculate weights for each violence type. The final part consisting of 3 movies (Armageddon, Billy Elliot, and Dead Poets Society) is used for evaluation. The Hollywood: Test and the YouTube: Generalization subsets are also used for evaluation, but for a different task. The following paragraphs provide details of the evaluation approaches used.

To evaluate the performance of the system, two different classification tasks are defined. In the first task, the system has to detect specific category of violence present in a video segment. The second task is more generic where the system has to only detect the presence of violence. For both these tasks, different datasets are used for evaluation. In the first task which is a multi-class classification task, the validation set consisting of 3 Hollywood movies (Armageddon, Billy Elliot, and Dead Poets Society) is used. In this subset, each frame interval containing violence is annotated with the class of violence that is present. Hence, this dataset is used for this task. These 3 movies were neither used for training, testing of classifiers nor for weight calculation so that the system can be evaluated on a purely new data. The procedure illustrated in Figure 3.1 is used for calculating the probability of a video segment to belong to a specific class of violence. The output probabilities from the system and the ground truth information are used to generate ROC (Receiver Operating Characteristic) curves and to assess the performance of the system.

In the second task, which is a binary classification task, Hollywood: Test and the YouTube: Generalization subsets of the VSD2104 dataset are used. The Hollywood: Test subset consists of 8 Hollywood movies and the YouTube: Generalization subset consists for 86 videos from YouTube. In both these subsets the frame intervals containing violence are provided as annotations and no information about the class of violence is provided. Hence, these subsets are used for this task. In this task, similar to the previous one, the procedure illustrated in Figure 3.1 is used for calculating the probability of a video segment to belong to a specific class of violence. For each video segment, the maximum probability obtained for any of the violence class is considered to be the probability of it being violent. Similar to above task, ROC curves are generated from these probability values and the ground truth from the dataset.

In both these tasks, first all the features are extracted from the training and testing datasets. Next, the training and testing datasets are randomly sampled to get an equal amount of positive and negative samples. 2,000 feature samples are selected for training and 3,000 are selected for testing. As mentioned above, disjoint training and testing sets are used to avoid testing on training data. In both the tasks, SVM classifiers with Linear,
Radial Basis Function and Chi-Square kernels are trained for each feature type and the classifiers with good classification scores on the test set are selected for the fusion step. In the fusion step, the weights for each violence type are calculated by grid-searching the possible combinations which maximize the performance of the classifier. The EER (Equal Error Rate) measure is used as the performance measure.

4.3 Experiments and Results

In this section, the experiments and their results are presented. First, the results of the multi-class classification task are presented, followed by the results of the binary classification task.

4.3.1 Multi-Class Classification

In this task, the system has to detect the category of violence present in a video. The violence categories targeted in this system are Blood, Cold arms, Explosions, Fights, Fire, Firearms, Gunshots, Screams. As mentioned in the Chapter 1, these are the subset of categories of violence that are defined in the VSD2014. Apart from these eight categories, Car Chase, and Subjective Violence are also defined in VSD2014, which are not used in this work as there were not enough video segments tagged with these categories in the dataset. This task is very difficult as detection of sub-categories of violence adds more complexity to the complicated problem of violence detection. The attempt to detect fine-grained concepts of violence by this system is novel and there is no existing system which does this task.

As mentioned in Chapter 3, this system uses weighted decision fusion approach to detect multiple classes of violence where weights for each violence category are learned using a grid-search technique. Please refer to Section 3.1.3 for more details about this approach. In Table 4.2, the weights for each violence class which is found using this grid-search technique are presented.

These weights are used to get the weighted sum of output values of binary feature classifiers for each violence category. The category with the highest sum is then the category of violence present in that video segment. If the output sum is less than 0.5 then the video segment is categorised as Non-Violent. The video segments in the validation set are classified using this approach and the results are presented in the Figure 4.2. In the figure, each curve represents the ROC curve for each of the violence categories.
Table 4.2: Classifier weights obtained for each of the violence class using Grid-Search technique. Here the criteria for selecting the weights for a violence class was to find the weights which minimize the EER for that violence class.

| Violence Class | Audio | Blood | Motion | SentiBank |
|----------------|-------|-------|--------|-----------|
| GunShots       | 0.50  | 0.45  | 0.00   | 0.05      |
| Fights         | 0.40  | 0.05  | 0.25   | 0.30      |
| Explosions     | 0.90  | 0.00  | 0.00   | 0.10      |
| Fire           | 0.05  | 0.05  | 0.05   | 0.85      |
| Cold arms      | 0.05  | 0.00  | 0.00   | 0.95      |
| Firearms       | 0.05  | 0.30  | 0.05   | 0.60      |
| Blood          | 0.00  | 0.05  | 0.00   | 0.95      |
| Screams        | 0.05  | 0.20  | 0.00   | 0.75      |

Figure 4.2: Performance of the system in the Multi-Class Classification task.

4.3.2 Binary Classification

In this binary classification task, the system is expected to detect the presence of violence without having to find the category. Similar to the previous task, the output probabilities of binary feature classifiers are combined using a weighted sum approach and the output probabilities of the video segment to belong to each of the violence classes are calculated. If the maximum probability for any of the class exceeds 0.5 then the video segment is categorized as violence or else it is categorized as non-violence. As mentioned in Section 4.2, this task is performed on YouTube-Generalization and Hollywood-Test datasets. The Figure 4.3 provides the results of this task on both the datasets. Two
Chapter 4. Experiments and Results

Figure 4.3: Performance of the system in the Binary Classification task.

Table 4.3: Classification results obtained using the proposed approach.

| Test Set     | Precision | Recall | Accuracy | EER  |
|--------------|-----------|--------|----------|------|
| YouTube-Gen  | 51.4%     | 61.3%  | 55.6%    | 45.0%|
| Hollywood-Test| 62.7%     | 85.1%  | 59.2%    | 44.0%|

Table 4.4: Classification results obtained by the best performing teams from MediaEval-2014 (Schedl et al. [51]).

| Test Set     | Precision | Recall | MAP@100 | MAP2014 |
|--------------|-----------|--------|---------|---------|
| YouTube-Gen  | 49.7%     | 85.8%  | 86.0%   | 66.4%   |
| Hollywood-Test| 41.1%     | 72.1%  | 72.7%   | 63.0%   |

ROC curves one for each of the datasets are used to represent the performance of the system. Using 0.5 as the threshold to make the decision of whether the video segment contains violence or not, the precision, recall and accuracy values are calculated. Please refer to Table 4.3 for the obtained results.

4.4 Discussion

In this section, the results presented in Section 4.3 are discussed. Before discussing the results of the Multi-Class and Binary classification tasks, the performance of the
individual classifiers is discussed.

4.4.1 Individual Classifiers

In both the classification tasks discussed in Section 4.3, a fusion of classifier scores is performed to get the final results. Hence, the performance of the system mainly depends on the individual performance of each of the classifiers and partially on the weights assigned to each of the classifiers. For the final classification results to be good, it is important that each of the classifiers have good individual performance. To get best performing classifiers, SVMs are trained using three different kernel functions (Linear, RBF, and Chi-Square) and the classifier with optimal performance on the test set are selected. Following this approach, best performing classifiers for each feature type are selected. The performance of these selected classifiers on the test dataset is presented in Figure 4.4. It can be observed that SentiBank and Audio are the two feature classifiers that show reasonable performance on the test set. Motion feature classifier has a performance which is a little better than chance and Blood has performance equivalent to chance. A detailed discussion on the performance of each of these classifiers in the increasing order of their performance are presented next.

![Individual Classifier Performance](image)

**Figure 4.4:** Performance of individual binary classifiers on the test set.
4.4.1.1 Motion

As it is evident from Figure 4.4, the performance of the motion feature classifier on the test set is only a little better than chance. To understand the reason behind this, the performance of all the motion feature classifiers, trained with different SVM kernels on available datasets are compared. Refer to Figure 4.5 for the comparison. In the figure, the left plot shows the performance of the classifiers on the test set from Hockey dataset and the plot on the right shows the comparison on Hollywood-Test dataset. In both the graphs, the red curve corresponds to the classifier trained on the Hockey dataset and the remaining three curves correspond to classifiers trained on the Hollywood-Dev dataset. From both these plots, it can be observed that the performance of the classifiers trained and tested on the same dataset is reasonably good when compared to the classifiers which are trained on one dataset and tested on another. In the plot on the left (TestSet: Hockey Dataset), the classifier trained on Hockey Dataset has better performance. Similarly, in the plot on the right (TestSet: Hollywood-Test), the performance of classifiers trained on Hollywood-Dev dataset have better performance. From there observations, it can be inferred that the motion feature representation learned from one dataset can not be transferred to another dataset. The reason for this could be to the disparity in video resolution and video format between the datasets. The videos from the Hockey dataset and the Hollywood-Test dataset have different formats, and also, not all videos from Hollywood-Development and Hollywood-Test have the same format. The video format plays an important role as the procedure used to extract motion features (explained in Section 3.1.1.3.1) use motion information from video codecs. Length and resolution of a video will also have some effect, even though the procedure used here tries to reduce this by normalizing the extracted features with the length of the video segment and by aggregating the pixel motions over a pre-defined number of sub-regions of the frame.
Videos from Hockey dataset are very short segments of one second each and have small frame size and low quality. Whereas, the video segments from the Hollywood dataset are longer and have larger frame size with better quality. One solution for this problem could be to convert all the videos to the same format, but even then there could be a problem due to improper video encoding. The other solution could be to use an Optical flow based approach to extract motion features (explained in Section 3.1.1.3.2). But as explained earlier, this approach is tedious and may not work when there is blur due to motion in a video.

### 4.4.1.2 Blood

The performance of blood feature classifier on the test set is just as good as a chance. Refer to Figure 4.4 for the results. Here the problem is not with the feature extraction as the blood detector used for blood feature extraction has shown very good results in detecting regions containing blood in an image. Please refer to Figure 3.4 for the performance of blood detector on images from the web and to Figure 4.6 for the performance of it on sample frames from the Hollywood dataset. From this, it is clear that the blood feature extractor is doing a pretty good job and it is not the problem with the feature extraction. Hence, it can be concluded that the problem is with the classifier training and it is due to the limited availability of training data.

In the VSD2014 dataset which is used for training, the video segments containing blood are annotated with labels (“Unnoticeable”, “Low”, “Medium”, and “High”) representing the amount of blood contained in these segments. There are very few segments in this dataset which are annotated with the label “High”, as a result of which, the SVM classifiers are unable to learn the feature representation of the frames containing blood effectively. The performance of this feature classifier can be improved by training it with a larger dataset with many instances of frames containing a high amount of blood. Alternatively images from Google can also be used to train this classifier.

### 4.4.1.3 Audio

Audio feature classifier is the second best-performing classifier (refer to Figure 4.4) on the test set and this shows the importance of audio in violence detection. Although visual features are good indicators of violent content, there are some scenes in which audio plays more important role. For example, scenes containing fights, gunshots, and explosions. These scenes have characteristic sounds and audio features such as MFCCs and Energy-entropy, can be used to detect sound patterns associated with these violent scenes.
In this work, MFCC features are used to describe audio content (refer to Section 3.1.1.1) as many previous works on violence detection (Acar et al. [1], Jiang et al. [33], Lam et al. [36], etc.) have shown the effectiveness of MFCC features in detecting audio signatures associated with violent scenes. Other audio features such as energy entropy, pitch and power spectrum can also be used along with MFCC features to further improve the performance of the feature classifier. But it is important to note that, audio alone is not sufficient to detect violence and it only plays an important role in detecting few violence classes such as Gunshots and Explosions which have unique audio signatures.

### 4.4.1.4 SentiBank

The SentiBank feature classifier has shown the best performance of all the feature classifiers (Refer to Figure 4.4) and has contributed strongly to the overall performance of the system. This demonstrates the power of SentiBank, in detecting complex visual sentiments such as violence. Figure 4.7 shows the average scores for top 50 ANPs for frames containing violence and no violence. As it can be observed the list of ANPs with

![Figure 4.6](image-url)

**Figure 4.6:** Figure showing the performance of the blood detector on sample frames from the Hollywood dataset. The images in the first column (A and D) are the input images, the second column images (B and E) are the blood probability maps and the images in the last column (C and F) are the binarized blood probability maps.
highest average scores for violence and no-violence class are very different and this is the reason behind the very good performance of SentiBank in separating violence class from no-violence class. Note that, not all the adjectives in the ANP list for violence class describe violence. This could be due to many different reasons, one of which could be the fact that, of the 1,200 ANPs used in SentiBank only a few describe the emotions related to violence (like fear, terror, rage, anger etc..). Please refer to Figure 4.8 which shows the Plutchik’s Wheel of Emotions and the distribution of ANPs for each category of emotion in VSO.

4.4.2 Fusion Weights

As mentioned earlier (Section 3.1.3), the final classification scores are calculated by late fusion of individual classifier scores using weighted sum approach. The weights used here are calculated using a grid-search approach with the goal to minimize the Equal Error Rate (EER). So, weights play an important role in determining the overall classification performance of the system. Note that all these weights are calculated on the test set. In Table 4.2, the weights of the classifiers for each of the eight violence class, obtained using the grid-search technique, are presented. From the weights obtained, the following observations about weight distribution can be made, (i) For most of the violence classes, the highest weight is assigned to SentiBank as it is the most discriminative feature. (ii) Audio has received the highest weight for violence classes such as Gunshots, Explosions, and Fights where audio plays a very important role. (iii) Blood has received high weights for violence classes such as Screams, Gunshots, and Firearms. This is interesting as a video segment belonging to any of these violence classes can also have blood in it. (iv) Motion has received the least weight in most of the violence classes as it the least performing feature. But, it can also be observed that it has a higher weight for the class Fights where a lot of motion can be expected.

If the weights assigned to each of the violence classes are analyzed the following observations can be made, (i) For the class Gunshots, the highest distribution weights is between Audio (0.5) and Blood (0.45). This is expected as audio features play an important role in detecting gunshots and the scenes containing gunshots are also expected to have a lot of blood. (ii) Audio (0.4), and visual features (Motion - 0.25 and SentiBank - 0.30) have received an almost equal amount of weight for the class Fights. This is expected as both audio and visual features are important in detecting scenes containing fights. (iii) For the class Explosions, highest weights are assigned to Audio (0.9) which is expected, as audio features are crucial in detecting explosions. (iv) Fire is a violence class where visual features are expected to have high weights and as expected the best performing visual feature, SentiBank (0.85), is assigned the highest weight. (v) Violence class Cold
Figure 4.7: Graphs showing average scores of Top 50 SentiBank ANPs for frames containing violence and no violence.
arms contain scenes which have the presence of any cold weapon (e.g., knives, swords, arrows, halberds, etc.). For this class, visual features are expected to have high weights. And as expected, SentiBank (0.95) has the highest weight for this class. (vi) “Firearms” is the violence class in which the scenes contain guns and firearms. Similar to the above class, visual features are expected to have high weights. For this class, SentiBank (0.6) and Blood (0.3) have received the highest distribution of weights. The reason for Blood being assigned a higher weight might be due to the fact that most of the scenes containing guns will also contain bloodshed. (vii) For the class Blood, the feature Blood is expected to have the highest weight. But feature Blood (0.05) received only a small weight and SentiBank (0.95) gained the highest weight. This is not an expected result and this could be due to the poor performance of the Blood feature classifier on the test set. (viii) It is intuitive to expect Audio to have higher weights for class “Screams” as audio features play an important role in detecting screams. But, the weights obtained here are against this intuition. Audio has received very less weight whereas SentiBank has received highest weight. Overall, the weights obtained from the grid-search are more or less as expected for most of the classes. Better weight distribution could be obtained if the performance of individual classifiers on the test is improved.
4.4.3 Multi-Class Classification

In this section, the results obtained in the multi-class classification task are discussed. Please refer to Figure 4.2 for the results obtained in this task. From the figure, the following observations can be drawn (i) The system shows good performance (EER of around 30%) in detecting Gunshots. (ii) For the violence classes, Cold arms, Blood and Explosions, the system shows moderate performance (EER of around 40%). (iii) For the remaining violence classes (Fights, Screams, Fire, Firearms) the performance is as good as a chance (EER of more than 45%). These results suggest that there is huge scope for improvement, but, it is important to remember that violence detection is not a trivial task and distinguishing between different classes of violence is, even more, difficult. All the approaches proposed so far have only concentrated on detecting the presence or absence of violence, but not on detecting the category of violence. The novel approach proposed in this work is one of the first in this direction and there are no baseline systems to compare the performance with. The results obtained from this work will serve as a baseline for future works in this area.

In this system, the late fusion approach is followed which has shown good results in a similar multimedia concept detection task of adult content detection (Schulze et al. [52]). Hence, the poor performance of the system can not be attributed to the approach followed. The performance of the system depends on the performance of individual classifiers and the fusion weight assigned to them for each of the violence classes. As the fusion weights are adjusted to minimize the EER using the Grid-Search technique, the overall performance of the system solely depends on the performance of the individual classifiers. So, to improve the performance of the system in this task, it is necessary to improve the performance of individual classifiers in detecting violence.

4.4.4 Binary Classification

The results for the binary classification task are presented in Figure 4.3. This task is an extension to the multi-class classification task. As explained earlier, in this task, a video segment is categorized as “Violence” if the output probability for any one of the violence classes is more than the threshold of 0.5. The performance of the system in this task is evaluated on two datasets, Hollywood-Test, and YouTube-Generalization. It can be observed that the performance of the system on these datasets is a little better than chance. It can also be observed that the performance is better on Hollywood-Test dataset than YouTube-Generalization dataset. This is expected as all the classifiers are trained on data from Hollywood-Development dataset which have similar video content to that of Hollywood-Test dataset. The precision, recall and accuracy values obtained
by the system for this task are presented in Table 4.3. The results obtained by the best performing team in this task from MediaEval-2014 are given in Table 4.4.

These results can not be directly compared, even though the same dataset is used, as the process used for evaluation is not the same. In MediaEval-2014, a system is expected to output the start and end frame for the video segments which contain violence and, if the overlap between the ground truth and the output frame intervals is more than 50% then it is considered as a hit. Please refer to Schedl et al. [51] for more information on the process followed in MediaEval-2014. In the proposed approach, the system categorizes each 1-second segment of the input video to be of class “Violence” or “No Violence” and the system performance is calculated by comparing this with the ground truth. This evaluation criteria used here is much more stringent and more granular when compared to the one used in MediaEval-2014. Here, as the classification is done for each 1-second segment, there is no need for a strategy to penalize detection of shorter segments. MAP metric is used for selecting the best performing system in MediaEval whereas, in the proposed system, the EER of the system is optimized.

Even though the results obtained from this system can not be directly compared to the MediaEval results, it can be observed that the performance of this system is comparable to, if not better than, the best performing system from MediaEval-2014 even though strict evaluation criteria are used. These results suggest that the system developed using the proposed novel approach is better than the existing state-of-art systems in this area of violence detection.

4.5 Summary

In this chapter, a detailed discussion on the evaluation of the developed system is presented. In the Section 4.1, details of the datasets used in this work are explained and in the next section Section 4.2, the experimental setup is discussed. In Section 4.3 the experiments and their results are presented, followed by a detailed discussion on the obtained results in Section 4.4.
Chapter 5

Conclusions and Future Work

In this chapter, the conclusions and the directions in which the existing work can be extended are discussed in the Section 5.1 and Section 5.2 respectively.

5.1 Conclusions

In this work, an attempt has been made to develop a system to detect violent content in videos using both visual and audio features. Even though the approach used in this work is motivated by the earlier works in this area, the following are the unique aspects of it: (i) Detection of different classes of violence, (ii) the use of SentiBank feature to describe visual content of a video, (iii) the Blood detector and the blood model developed using images from the web, and (iv) using information from video codec to generate motion features. Here is a brief overview of the process used to develop this system.

As violence is not a physical entity, the detection of it in a video is not a trivial task. Violence is a visual concept and to detect it there is a need to use multiple features. In this work, MFCC features were used to describe audio content and Blood, Motion and SentiBank features are used to describe visual content. SVM classifiers were trained for each of the selected features and the individual classifier scores were combined by weighted sum to get the final classification scores for each of the violence classes. The weights for each class are found using a grid-search approach with the optimizing criteria to be the minimum EER. Different datasets are used in this work, but the most important one is the VSD dataset, which is used for training the classifiers, calculating the classifier weights and for testing the system.

The performance of the system is evaluated on two different classification tasks, Multi-Class, and Binary classification. In Multi-Class classification task, the system has to
detect the class of violence present in a video segment. This is a much more difficult task than just detecting the presence of violence and the system presented here is one of the first to tackle this problem. The Binary classification task is where the system has to just detect the presence of violence without having to find the class of violence. In this task, if the final classification score from the Multi-Class classification task for any of the violence class is more than 0.5, then the video segment is categorized as “Violence” else, it is categorized as “No Violence”. The results from the Multi-Class classification task is far from perfect and there is room for improvement, whereas, the results on the Binary classification tasks are better than the existing benchmark results from MediaEval-2014. However, these results are definitely encouraging. In Section 5.2, a detailed discussion on the possible directions in which the current work can be extended are presented.

5.2 Future Work

There are many possible directions in which the current work can be extended. One direction would be to improve the performance of the existing system. For that, the performance of the individual classifiers has to be improved. Motion and Blood are the two features whose classifier performance needs reasonable improvement. As explained in Section 4.4, the approach used to extract motion features has to be changed for improving the performance of the motion classifier. For Blood, the problem is with the dataset used for training the classifier but not the feature extractor. An appropriate dataset with decent amount of frames containing blood should be used for training. Making these improvements should be the first step towards building a better system. Another direction for the future work would be to adapt this system and develop different tools for different applications. For example, (i) a tool could be developed which could extract the video segments containing violence from a given input video. This could be helpful in video tagging. (ii) A similar tool could be developed for parental control where the system could be used to rate a movie depending on the amount of violent content in it. Another possible direction for future work is, to improve the speed of the system so that it can be used in the real-time detection of violence from the video feed of security cameras. The improvements needed for developing such a system will not be trivial.
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