Violence Detection using Vision Transformers

A Project Report

submitted by

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BACHELOR OF TECHNOLOGY

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DECLARATION OF ORIGINALITY

I, **Sakthiprian S**, with Roll No: **EC21B1075** hereby declare that the material presented in the Project Report titled **Violence Detection using Vision Transformers** represents original work carried out by me in the **Department of Electronics and Communication Engineering** at the Indian Institute of Information Technology, Design and Manufacturing, Kancheepuram.

With my signature, I certify that:

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- I have not committed any plagiarism of intellectual property. I have clearly indicated and referenced the contributions of others.
- I have explicitly acknowledged all collaborative research and discussions.
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Sakthiprian S

Place: Chennai

Date: 06.05.2025

CERTIFICATE

This is to certify that the report titled **Violence Detection using Vision Transformers**, submitted by **Sakthiprian S (EC21B1075)**, to the Indian Institute of Information Technology, Design and Manufacturing Kancheepuram, for the award of the degree of **BACHELOR OF TECHNOLOGY** is a bona fide record of the work done by him/her under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

The rise in violent incidents in open spaces has pointed at the need for advanced monitoring systems capable of real-time violence detection. Some initial approaches depended on handcrafted features such as optical flow, motion histograms, and local binary patterns. While they are efficient from a computational standpoint, these methods lacked the robustness to variations and perturbations in scene dynamics. The rise of deep learning introduced Convolution-based models, such as Conv3D and ResNet-3D, which improved feature extraction by capturing both the temporal and spacial features in videos. However, CNNs and RNNs struggled with long-term dependencies and higher computational costs, leading to the experimentation of Transformers in this domain. To address these challenges, this work explores the use of Vision Transformers (ViTs) for violence detection in videos. By using the advantages provided by self-attention mechanisms, ViTs can effectively extract temporal and spatial relationships, leading to much better classification accuracy. The model which is used is fine-tuned on an open-source dataset and benchmarked against existing approaches to evaluate its effectiveness. Experimental results demonstrate that ViTs offer significant advantages in identifying violent activities, making them an excellent choice for an alternative solution for intelligent video monitoring and surveillance systems.

KEYWORDS: Violence Detection; Vision Transformers; Self-Attention; Video Surveillance; Deep Learning; Action Recognition.

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ABBREVIATIONS

ViT	Vision Transformer
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
FPS	Frames Per Second

NOTATION

α	Learning Rate
θ	Model Parameters
L	Loss Function
X	Input Data
Y	Output Labels
A	Attention Matrix

CHAPTER 1

Introduction

1.1 Introduction

Violence detection in video surveillance has emerged as a critical area of research, particularly due to the increasing prevalence of violent incidents in public spaces. Traditional methods often struggle to effectively identify such behaviors, especially in complex and dynamic environments. The advancement of deep learning techniques, particularly Vision Transformers (ViTs), offers a promising avenue for enhancing violence detection capabilities. This review synthesizes various research findings related to the application of Vision Transformers in violence detection, highlighting their strengths, potential, and existing gaps in the literature. The initial approaches to violence detection relied on handcrafted features such as optical flow, motion histograms, and local binary patterns. These methods were computationally efficient but lacked robustness to variations in scene dynamics. The advent of deep learning brought CNN-based models, such as Conv3D and ResNet-3D, which improved feature extraction by capturing spatiotemporal information in videos. However, CNNs and RNNs struggled with long-term dependencies and high computational costs, leading to the adoption of Transformers.

1.2 Motivation

The rise in violent incidents in public areas like streets, schools, and transportation hubs has heightened concerns about public safety. This has created an urgent demand for surveillance systems capable of detecting and responding to violent activities in real-time. Traditional methods rely heavily on human monitoring, which can be inefficient due to operator fatigue, while conventional deep learning models, such as CNNs, often struggle with capturing long-range dependencies and accurately recognizing complex

human behaviors. Recent advancements in computer vision, particularly transformer-based architectures, offer a promising alternative. Vision Transformers (ViTs), with their self-attention mechanisms, excel at modeling long-range dependencies and contextual relationships, making them well-suited for improving automated violence detection.

1.3 Problem Statement and Objectives

The main aim of this research is to develop a Vision Transformer based model for detection of violent actions in video feeds with a more improved accuracy. The models which are currently exisiting to solve this problem often fall short in cases where complex human activities are involved. The convolutional network based solutions fail to captue the global context in video sequences. By using Vision Transformers, we can enjoy the advantages given by the self-attention mechanisms and could enhance the detection of violent actions in real time monitoring or surveillance video feeds. The model being developed will be fine tuned on a publicly available open source dataset and the evalutation metrics will be compared to the existing approaches.

1.4 Organisation of the Report

This report is organized into five chapters, each focusing on a key aspect of the project:

Chapter 1: Introduction

Provides an overview of the project, outlining the problem statement, motivation, and objectives.

Chapter 2: Literature Survey

Reviews existing work in the relevant domain, discussing various approaches proposed in prior research and highlighting existing knowledge gaps.

Chapter 3: Dataset and Preprocessing

Describes the publicly available datasets used for this project and details the preprocessing techniques employed to prepare the data for training.

Chapter 4: Training Process

Explains the training methodology, including the two distinct approaches adopted in this study, and the rationale behind them.

Chapter 5: Conclusion and Future Scope

Summarizes the key findings of the project and outlines potential directions for future work based on the current results.

CHAPTER 2

Literature Survey

2.1 Introduction

Violence detection in video surveillance has gained significant attention due to the rising incidents in public spaces. Traditional techniques, such as handcrafted feature extraction, often fail in dynamic environments. The emergence of deep learning, particularly Vision Transformers (ViTs) in the famous paper by google, "An image is worth 16x16 words: Transformers for image recognition at scale" , has introduced new opportunities for improving violence detection [1]. This section explores the evolution of video-based violence detection, highlights the role of ViTs, and reviews advancements in the field.

2.2 Evolution of Video-Based Violence Detection

Early violence detection approaches worked based on handcrafted techniques, including optical flow and motion histograms. While these methods are computationally efficient, lacked robustness to variations in movement and scene complexity. The advent of deep learning led to CNN-based solutions, such as Conv3D and ResNet-3D, which significantly improved spatiotemporal feature extraction [2]. However, CNNs struggle with long-range dependencies, prompting the adoption of Transformers for video analysis.

2.3 Vision Transformers in Violence Detection

ViTs have revolutionized computer vision by effectively processing spatial and temporal information in videos. The original ViT model by Google (2020) demonstrated that transformers could outperform traditional CNNs in image classification tasks, paving the way for their application in video analysis [1]. This foundational work inspired numerous adaptations, including the integration of ViTs for violence detection.

2.4 Advancements in Vision Transformer-Based Violence Detection

2.4.1 Multiscale Vision Transformers (MViTv2)

Following the success of ViTs, researchers developed MViTv2 (2021), which incorporates advanced embeddings and pooling mechanisms, enhancing motion pattern recognition [3]. Such improvements are particularly beneficial in crowded environments where conventional models often fail.

2.4.2 Histogram of Oriented Tracklets (HoT)

In 2022, the HoT approach was introduced to enhance abnormal activity recognition in surveillance videos [2]. While not transformer-based, it provided insights into structured motion features, contributing to the evolution of deep learning models for violence detection.

2.4.3 Video Vision Transformers (ViViT)

An end-to-end framework leveraging ViViT models was proposed in 2022 to enhance violence detection. Data augmentation strategies were applied to mitigate ViT's weaker inductive biases, achieving results comparable to state-of-the-art approaches [4].

2.4.4 CrimeNet: A Deep Learning Approach

CrimeNet (2023) integrates CNNs and LSTMs for violence detection, demonstrating an early attempt to combine deep learning techniques for this task [5]. The CNN extracts spatial features, while the LSTM captures temporal dependencies. The network employs an attention mechanism to enhance motion region focus and minimize false positives. Benchmark datasets, including UCF-Crime and Hockey Fight Dataset, have been used to evaluate its performance. This model laid the groundwork for transformer-

based violence detection approaches.

2.4.5 Edge Deployment of Vision Transformers

A study in 2023 explored pre-trained ViTs for real-time violence detection on edge devices. By optimizing architectures such as DeiT (Data Efficient Vision Transformer) , the research demonstrated an accuracy improvement over traditional CNN-LSTM models [6]. The study highlights the feasibility of deploying ViTs in resource-constrained environments.

2.4.6 Multi-Scale Bottleneck Transformer for Multimodal Analysis

To address multimodal violence detection, researchers introduced a Multi-Scale Bottleneck Transformer (MSBT) in 2023, integrating RGB, optical flow, and audio features. The MSBT employs token-based weighting and contrastive loss to align spatiotemporal representations [7].

2.4.7 Reinforcement Learning-Based Mixture of Vision Transformers

A Mixture of Experts (MoE) model dynamically selects optimal transformer architectures using reinforcement learning. This approach enhances classification accuracy while optimizing computational efficiency, achieving high performance on the RWF dataset [8].

2.4.8 Spatiotemporal Feature Learning for Violence Detection

In 2024, a study introduced spatiotemporal feature learning techniques for violence detection using deep learning. This work further emphasized the importance of ViTs in video-based security applications [9].

2.4.9 JOSE-NET: Joint Spatio-Temporal Encoding Network

JOSE-NET is a lightweight network proposed for violence detection that jointly encodes spatial and temporal features from video clips. It leverages a dual-branch architecture to extract spatial and temporal information separately and then fuses them using a cross-modal attention mechanism to capture dynamic patterns effectively [10].

2.5 Knowledge Gaps and Future Research Directions

Despite the advancements in transformer-based violence detection, challenges remain. Existing models require further evaluation under varied lighting conditions and occlusions. Additionally, incorporating contextual information, such as environmental and social dynamics, could enhance detection accuracy. Ethical concerns, including bias mitigation and false alarms, also require consideration.

2.6 Summary

The adoption of Vision Transformers in violence detection represents a significant leap in surveillance technology. While models like MViTv2 and ViViT have demonstrated promising results, further research is needed to enhance their robustness, scalability, and ethical deployment in real-world applications.

CHAPTER 3

Datasets and Preparation

3.1 Overview of Datasets

In this section, we provide an overview of the datasets used for training and evaluating the Vision Transformer-based violence detection model. The datasets include a diverse set of video samples, with labeled instances of violent and non-violent activities. The diversity in the datasets ensures that the model can generalize effectively across different video sources and real-world conditions.

3.1.1 Dataset Description

The datasets used in this study were carefully selected to ensure a broad coverage of violent and non-violent actions, including various settings such as surveillance footage, public incidents, and controlled environments. These datasets were chosen to reflect the variety of real-world scenarios that the model will encounter during deployment.

The datasets used in this study are summarized in Table 3.1. Each dataset was chosen based on its size, class balance, and relevance to violence detection. The number of hours and video files are provided for reference.

Dataset	Classes	Hours	Files
UCF Crime	14	128	1,900
UBI Fights	2	80	1,000
RWF-2000	2	~3	2,000
XD Violence	7	217	4,754
NTU CCTV Fights	2	1,417.68	1,000

Table 3.1: Summary of datasets used in the study.

UCF Crime

The UCF Crime dataset consists of 1,900 video files, categorized into 14 distinct classes, with a focus on crime-related activities such as assault, robbery, and vandalism. The dataset provides a broad range of video quality and action types, offering valuable diversity for training models aimed at recognizing violence in complex real-world scenarios.

UBI Fights

The UBI Fights dataset contains 1,000 videos, with two classes: Fight and Non-Fight. This dataset specifically focuses on violent altercations and non-violent activities, making it highly relevant for violence detection tasks. With a total of 80 hours of video footage, this dataset ensures ample training data for the model to learn to distinguish between violent and non-violent actions.

RWF-2000

The RWF-2000 dataset is composed of 2,000 videos that are split evenly between Fight and Non-Fight classes. Each video is around 150 frames long, captured under real-world surveillance conditions. This dataset is particularly useful for developing models that are robust to the challenges of real-world environments, such as low-light, motion blur, and occlusions.

XD Violence

The XD Violence dataset contains 4,754 video files, labeled into 7 action classes, including multiple types of violent behavior. With 217 hours of video, this dataset provides a comprehensive set of diverse actions that the model can learn to differentiate, making it a valuable addition to the training process.

NTU CCTV Fights

The NTU CCTV Fights dataset is a large-scale surveillance dataset that consists of 1,000 video clips, totaling 1,417.68 hours of footage. The videos are labeled as either Fight or Non-Fight, with a focus on violence occurring in public settings. This dataset provides high-quality video footage, making it a crucial resource for fine-tuning models on realistic CCTV footage.

3.2 Data Preparation

To prepare the dataset for training, a series of preprocessing steps were applied to segment the videos into fixed-length clips and organize them for model input. These preprocessing steps were designed to ensure that the input data to the model was consistent, meaningful, and contained sufficient temporal context to capture the dynamics of violent events.

3.2.1 Dataset Overview

The RWF-2000 dataset, which is used extensively for training, consists of 2,000 surveillance videos split evenly between two classes: Fight and Non-Fight. Each video is approximately 150 frames long, captured under real-world conditions such as surveillance cameras in public areas. This dataset offers realistic and challenging video clips, with a high level of variability in terms of lighting, camera angles, and background noise.

In this study, the focus was on extracting meaningful temporal features from the video clips, which required segmenting each video into smaller clips that could be processed by the model. Each clip is composed of 16 consecutive frames, providing a snapshot of the temporal dynamics of the video.

3.2.2 Clip Generation

From each video, non-overlapping clips of 16 consecutive frames were extracted to provide temporal context. This approach ensures that the model has access to enough frame-level context to identify both the spatial and temporal aspects of violence. A 16-frame sequence was chosen because it is long enough to capture action dynamics, while still being manageable in terms of computational cost.

For videos that did not have a multiple of 16 frames (which is common towards the end of the video), the remaining frames that did not form a complete 16-frame clip were discarded. In this study, the last 6 frames of each video were not included in the clip extraction process, ensuring that all clips have a uniform size of 16 frames.

This process results in the generation of 16,000 training clips, corresponding to 256,000 frames, and 1,792 validation clips, totaling 28,672 frames. The segmentation ensures that the model can learn temporal patterns without being influenced by the variable length of individual videos.

3.2.3 Directory Structure

To facilitate efficient loading and organization of the dataset, the processed clips were arranged into clearly separated directories based on data split (train/validation) and class (Fight/Non-Fight). The directory structure is as follows:

- `clips16/train/Fight`
- `clips16/train/NotFight`
- `clips16/val/Fight`
- `clips16/val/NotFight`

Each of these directories contains multiple subfolders, with each subfolder representing a single video clip composed of exactly 16 consecutive frames. The clips are organized into the following format:

- `Fight_clip_001`
- `NotFight_clip_001`

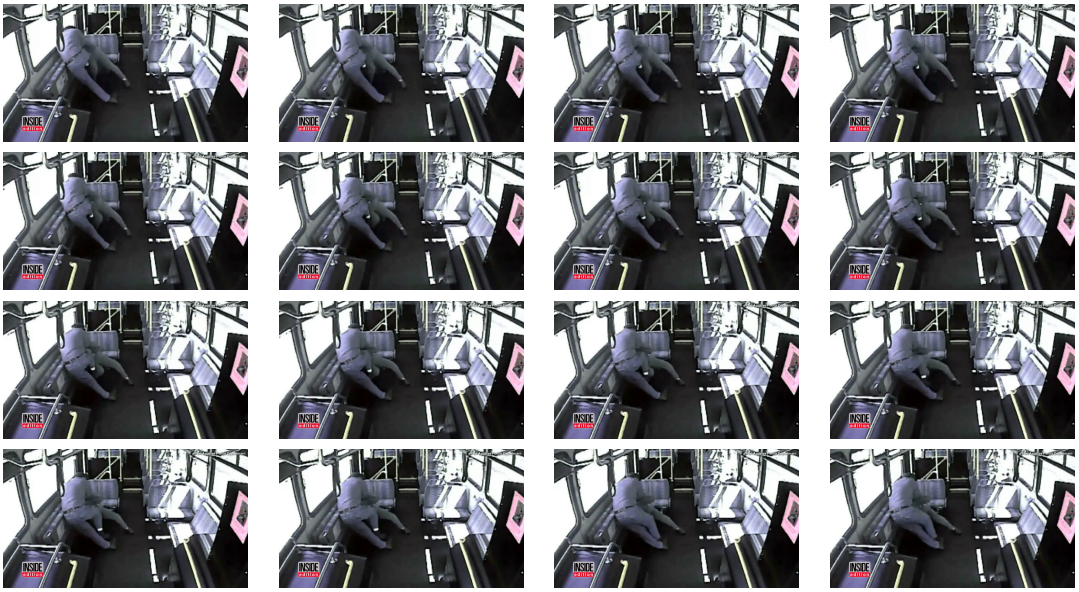

Figure 3.1: Example 16-frame clip showing a temporal segment of a violent event from the Fight folder.

- `Fight_clip_002`
- `NotFight_clip_002`

Each subfolder contains a sequence of 16 frames, saved as image files. This structure ensures that the video clips are easy to access and load during training, allowing the model to efficiently process the data in batches. The use of a fixed-length sequence of frames allows the model to focus on learning temporal dynamics without having to deal with variable-length sequences.

The organization of the dataset also ensures that the model can be trained and validated on the same class distribution, providing a balanced training process. This directory structure is compatible with most deep learning frameworks, making it easy to integrate into the training pipeline.

3.3 Summary

In this chapter, we presented a comprehensive overview of the datasets and preprocessing steps used in this study for violence detection using Vision Transformers. Five key datasets—UCF Crime, UBI Fights, RWF-2000, XD Violence, and NTU CCTV

Fights—were described, each contributing unique characteristics in terms of scene diversity, class labels, and video quality.

We focused particularly on the RWF-2000 dataset for training and validation, detailing the process of segmenting videos into uniform 16-frame clips. These clips were organized into a consistent directory structure that separates training and validation data by class. This setup ensures efficient data loading and supports temporal modeling by maintaining fixed-length sequences.

The combination of diverse datasets and well-prepared, structured inputs forms a solid foundation for training robust models capable of detecting violent activities in real-world scenarios.

CHAPTER 4

Training Process

4.1 Training Setup

This study investigates two distinct transformer-based approaches for detecting violence in video clips, comparing their ability to capture both spatial and temporal dynamics. The first approach integrates optical flow accumulation with the Vision Transformer (ViT) architecture, while the second uses a spatiotemporal attention mechanism through the TimeSformer model.

The specific models explored in this study are:

- **Optical Flow + ViT**
- **Spatiotemporal Attention with TimeSformer**[11]

4.2 Working of Optical Flow + ViT Model

The Optical Flow + ViT model aims to integrate both spatial and temporal information from video frames. It leverages optical flow, which estimates motion between consecutive frames, and combines it with the Vision Transformer (ViT) architecture to capture both motion dynamics and spatial features.

4.2.1 Optical Flow

Optical flow is a computer vision technique that computes the motion of objects between consecutive frames in a video. It estimates the pixel-wise movement (displacement) by tracking intensity changes over time. The flow fields provide directional and magnitude information about how objects move between frames. These optical flow

fields are crucial for detecting motion-based events such as violent actions. Examples for optical flow are shown in this figure 4.1

In this study, optical flow is calculated for a 16-frame video clip. For each consecutive pair of frames, the optical flow is computed to estimate the direction and magnitude of motion between the frames. This process results in a flow field for each frame pair, encoding the motion between the two frames.

4.2.2 Motivation for the Idea

The primary motivation for integrating optical flow with the Vision Transformer (ViT) comes from the JOSE-NET model, which demonstrated the potential of combining motion features with transformer-based architectures for action recognition. However, unlike JOSE-NET, which passes entire streams of optical flow through the network, this work adopts a more computationally efficient method by aggregating the optical flow using a momentum-based strategy.

This aggregation accumulates the motion information across frames while reducing redundancy and computational cost. The momentum aggregation is governed by a parameter β, which controls the balance between the current flow and previously accumulated flow. A value of $\beta = 0.7$ was chosen to ensure that 70% of the contribution comes from the current frame's flow and 30% from prior accumulated motion. This recursive formulation allows the model to retain essential temporal trends without overwhelming the architecture with redundant motion vectors.

Changing the value of β affects the extent of temporal memory retained. A higher β increases reliance on current motion, while a lower β emphasizes longer-term motion history. This trade-off is critical for capturing meaningful temporal dependencies with minimal computational overhead.

4.2.3 Flow Accumulation

A momentum-based technique is used to accumulate the optical flow between frames. This approach helps to capture the motion dynamics over longer durations and ensures

smoother and more stable flow estimation. The accumulated flow is calculated by combining the current flow estimate with the previously accumulated flow using the following formula:

$$\text{acc\_flow} = \beta \cdot \text{curr\_flow} + (1 - \beta) \cdot \text{prev\_acc\_flow}, \quad \beta = 0.7$$

where:

- acc_flow is the accumulated flow.
- curr_flow is the current optical flow estimate.
- prev_acc_flow is the previously accumulated flow.
- β is the momentum parameter, controlling the smoothing effect between the current and previous flow.

This formula ensures that the flow is accumulated in a way that emphasizes long-term motion trends while smoothing out inconsistencies between frame-to-frame flow estimates. Figure showing the working of this approach. 4.2

4.2.4 Model Input and Output

The input to the Optical Flow + ViT model consists of two parts:

- The 16th RGB frame from the video clip, which provides the spatial context for the scene.
- The accumulated optical flow image, which encodes the temporal dynamics and motion information.

These two inputs are concatenated and fed into the Vision Transformer (ViT) architecture. The model outputs a binary classification label indicating whether the video clip depicts a violent action (*Fight*) or not (*NotFight*).

4.2.5 Training Configuration

The training configuration for the Optical Flow + ViT model is as follows:

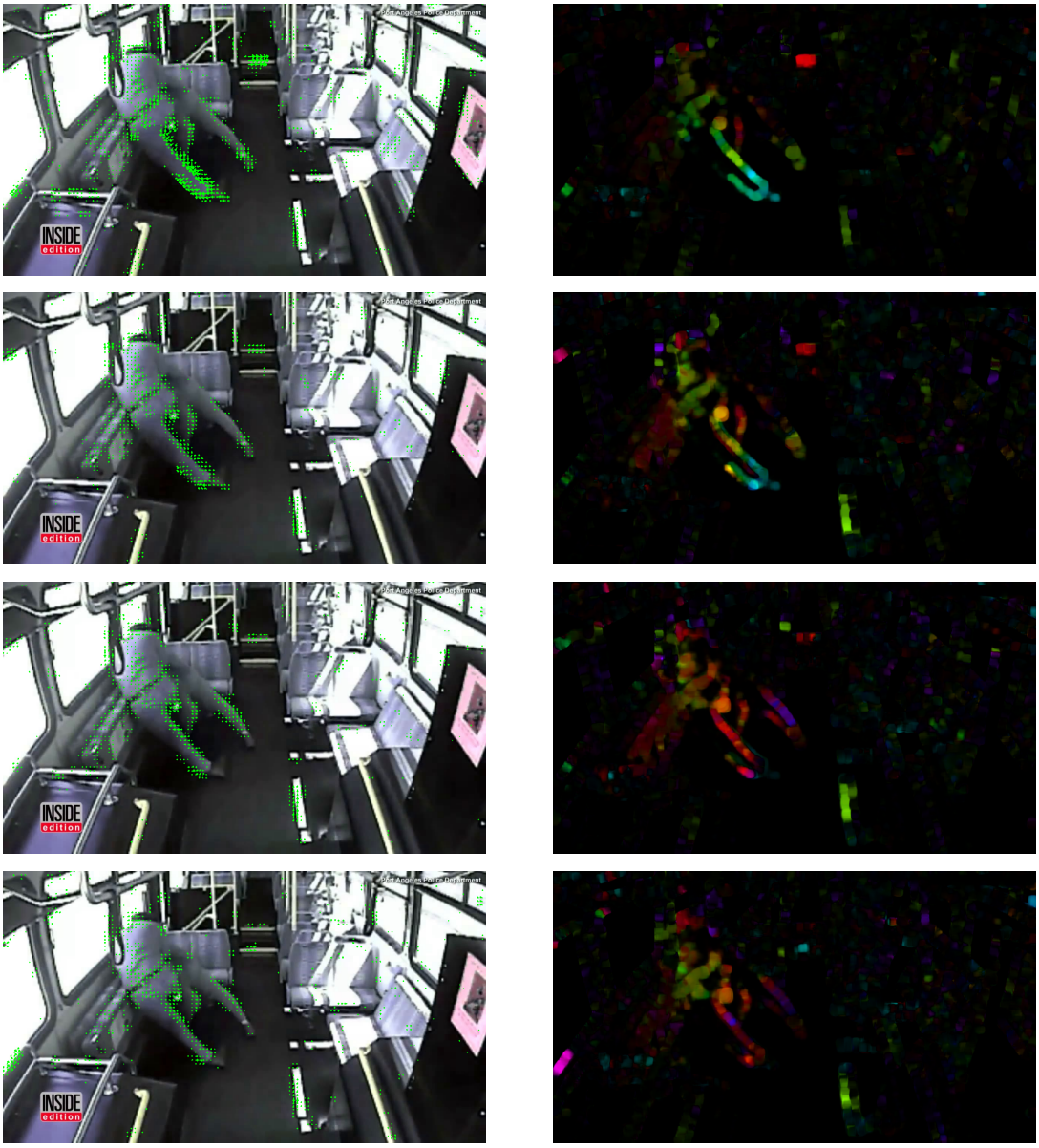

Figure 4.1: Left: Arrow representation of accumulated optical flow. Right: HSV representation for the same 4 video clips.

- **Model:** ViT-Base (Patch size: 16, Image size: 224)
- **Optimizer:** AdamW with a learning rate of $1e^{-4}$
- **Scheduler:** ReduceLROnPlateau
- **Batch Size:** 128
- **Epochs:** 20
- **VRAM Usage:** 22.5 GB
- **Time per Epoch:** 15 minutes
- **GPU:** Google Colab L4

Epochwise training details are shown in table. 4.1Epochwise training graphs for accuracy and loss are shown in this figure 4.3

Table 4.1: Training Results for Optical Flow + ViT Model

Epoch	Train Loss	Train Acc (%)	Val Loss	Val Acc (%)
1	0.6969	57.53	0.6421	63.25
2	0.6251	63.31	0.5994	65.22
3	0.5831	66.55	0.5461	70.23
4	0.5024	74.03	0.4326	79.07
5	0.3840	82.29	0.4071	80.47
6	0.3011	86.87	0.3675	85.03
7	0.2290	90.33	0.2948	85.99
8	0.1799	92.39	0.2522	89.20
9	0.1447	94.17	0.1962	92.68
10	0.1377	94.39	0.1544	94.09
11	0.1023	95.81	0.2694	91.33
12	0.1015	96.00	0.1956	93.47
13	0.0842	96.65	0.1321	95.33
14	0.0714	97.19	0.1403	94.82
15	0.0707	97.43	0.1017	96.29
16	0.0531	97.88	0.1168	95.95
17	0.0607	97.73	0.1620	94.09
18	0.0582	97.71	0.1099	96.23
19	0.0267	98.92	0.1167	96.85
20	0.0207	99.09	0.1046	97.52

4.3 Working of TimeSformer Architecture

The TimeSformer architecture extends the Vision Transformer (ViT) by introducing a spatiotemporal attention mechanism. Unlike traditional ViT models, which process individual frames independently, TimeSformer captures both spatial and temporal dependencies in video data by leveraging separate attention mechanisms for spatial and temporal features.

4.3.1 Spatiotemporal Attention

TimeSformer introduces the novel idea of spatiotemporal attention, where the video input is split into distinct space-time patches. By decoupling spatial and temporal at-

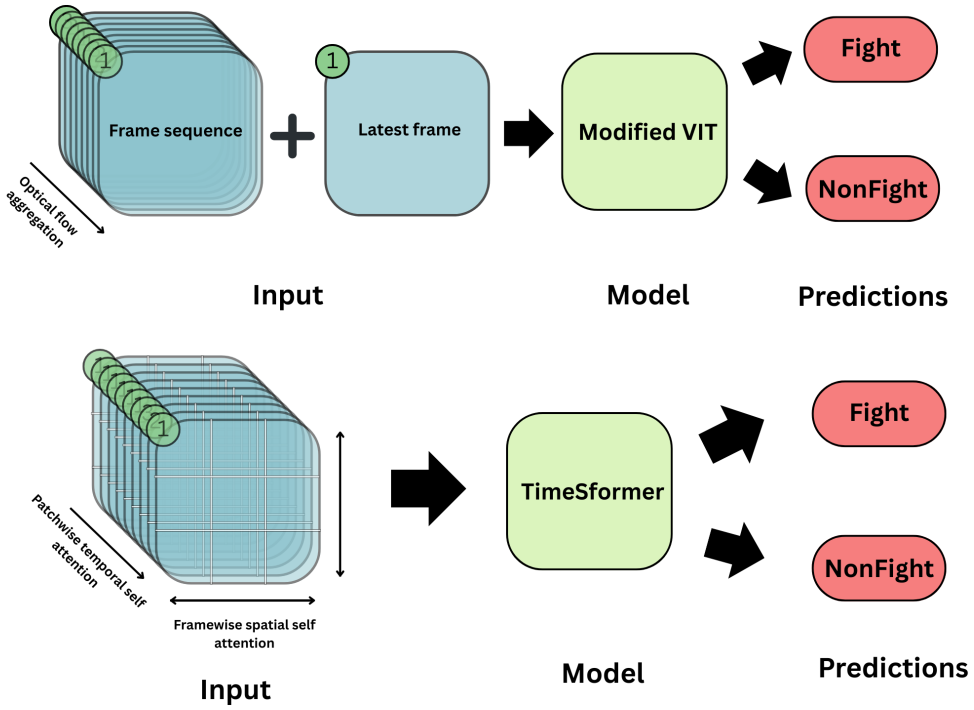

Figure 4.2: Working of Optical Flow + ViT Model and TimeSformer model.

tention, TimeSformer is able to focus on both dimensions independently, which allows it to more effectively capture the complex patterns of motion and structure in video data.

The input video clip is divided into spatial patches, and a separate attention mechanism is applied to these patches across time. This enables the model to learn spatial patterns (within individual frames) as well as temporal dependencies (across frames). This dual attention mechanism enhances the model's ability to detect complex actions, such as violent events, that involve both rapid motion and spatial features. 4.2

4.3.2 Model Input and Output

The input to the TimeSformer model is a 16-frame RGB video clip. Each frame is split into patches, which are then processed by the attention mechanism. The model applies spatiotemporal attention, enabling it to learn both the spatial and temporal relationships between patches.

The model's output is a binary classification: *Fight* or *NotFight*, depending on whether the video clip contains a violent action or not.

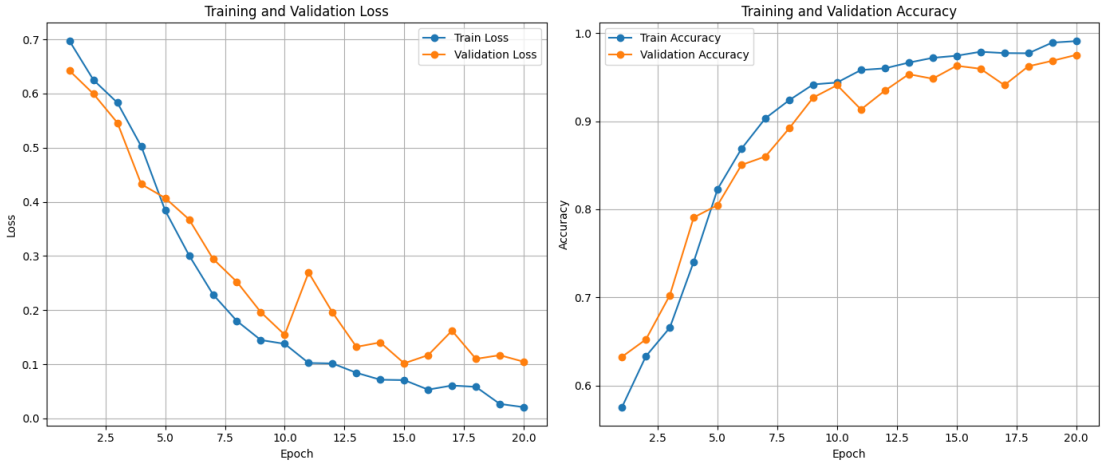

Figure 4.3: Accuracy and loss across epochs for ViT + Optical Flow.

4.3.3 Training Configuration

The training configuration for the TimeSformer model is as follows:

- **Model:** TimeSformer-Base (Patch size: 16, Image size: 224, 16 frames)
- **Optimizer:** AdamW with a learning rate of $1e^{-4}$
- **Scheduler:** ReduceLROnPlateau
- **Batch Size:** 14
- **Epochs:** 14
- **VRAM Usage:** 23.8 GB
- **Time per Epoch:** 50 minutes
- **GPU:** Google Colab L4

Epochwise training loss and accuracy are shown in tables 4.2 and figure 4.4.

Evaluation Metrics

The following metrics are commonly used to assess the performance of machine learning models, particularly for classification tasks:

- **Accuracy**: This measures the percentage of correct predictions made by the model out of all predictions.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Number of Predictions}}$$

Table 4.2: Training Results for TimeSformer Model

Epoch	Train Loss	Train Acc (%)	Val Loss	Val Acc (%)
1	613.5	57.8	125.2	59.4
2	555.0	70.2	121.8	72.0
3	498.3	79.5	132.5	80.8
4	475.1	86.3	128.3	88.1
5	450.2	91.2	125.1	92.4
6	430.0	94.6	119.6	95.0
7	350.0	96.9	109.8	96.3
8	320.5	98.0	113.0	96.7
9	299.8	98.7	120.4	96.6
10	280.6	99.1	128.0	96.3
11	267.1	99.3	132.5	96.0
12	252.0	99.4	135.6	95.7
13	243.5	99.5	138.2	95.4
14	235.0	99.6	140.3	95.0

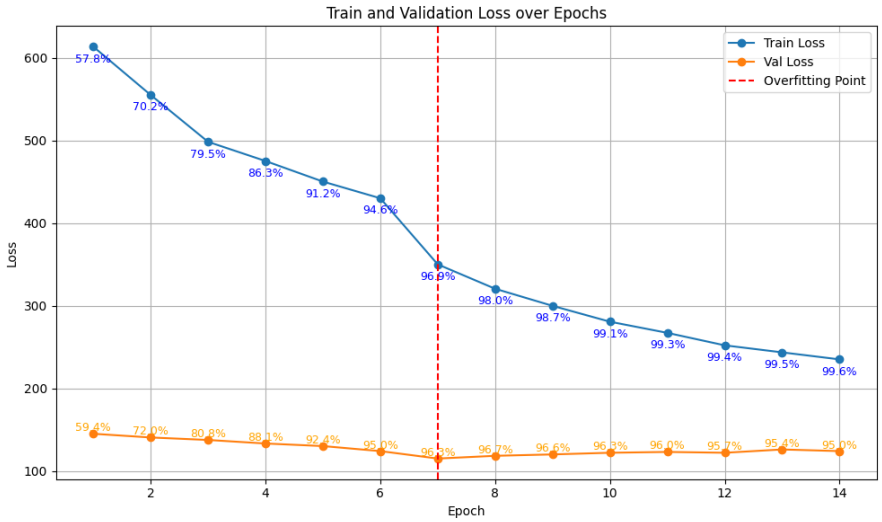

Figure 4.4: Loss and Accuracy across epochs for TimeSformer.

In the context of the models evaluated, **Optical Flow + ViT** achieved a slightly higher accuracy (97.52%) compared to **TimeSformer** (96.60%).

- **Precision**: This indicates the proportion of true positive results in relation to the total predicted positives. It answers the question: "Of all the positive predictions made, how many were actually correct?"

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

The **Optical Flow + ViT** model demonstrated a higher precision (0.9771) than the **TimeSformer** model (0.9630), indicating that the Optical Flow model made fewer false positive predictions.

- **Recall**: Recall measures how well the model identifies positive instances, mean-

Model	Accuracy (%)	Precision	Recall	F1 Score
Optical Flow + ViT	97.52	0.9771	0.9727	0.9749
TimeSformer	96.60	0.9630	0.9410	0.9500

Table 4.3: Evaluation metrics for both models.

ing the proportion of actual positives that were correctly identified.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Optical Flow + ViT also outperforms **TimeSformer** in recall (0.9727 vs. 0.9410), indicating that it correctly identifies more positive instances.

- **F1 Score**: The F1 score is the harmonic mean of precision and recall. It provides a balance between these two metrics, especially when there is an uneven class distribution (i.e., when the classes are imbalanced).

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Optical Flow + ViT also achieves a higher F1 score (0.9749) than **TimeSformer** (0.9500), which indicates that it balances precision and recall more effectively.

Model Comparison and Potential for Improvement

While **Optical Flow + ViT** shows superior performance in terms of all evaluation metrics, it's important to note that **TimeSformer** may perform better with more sequences and data. **TimeSformer** is a transformer-based model that inherently benefits from more data for learning long-term temporal dependencies. Given its architecture, which excels in capturing temporal context over longer sequences, **TimeSformer** could improve its performance in both accuracy and other metrics if trained on a larger dataset with more sequence information.

In contrast, **Optical Flow + ViT** is more focused on leveraging spatial features and temporal motion information through optical flow. However, its performance is somewhat more limited by the smaller dataset and the fact that it relies on frame-wise representations.

Thus, the **TimeSformer** model, with sufficient training data, could outperform **Optical Flow + ViT** in a more realistic, long-term sequence-based scenario.

With more training data, compute, and longer clip durations, **TimeSformer** would outperform the **Optical Flow + ViT** model.

4.4 Observations

- **Convergence:** Both models demonstrate clear convergence during training. The Optical Flow + ViT model converges within 20 epochs, while the TimeSformer model stabilizes within 14 epochs. This indicates that the TimeSformer architecture may require fewer epochs to reach optimal performance compared to the Optical Flow + ViT model, possibly due to the more complex spatiotemporal attention mechanism.
- **Loss Behavior:** In both cases, the training loss steadily decreases over time, which suggests that the models are effectively learning and adapting to the data. The steady decrease in loss without sudden jumps or plateaus suggests that both models are well-regularized.
- **Model Complexity:** TimeSformer requires significantly higher computational resources compared to the Optical Flow + ViT model. This is due to the complexity of the spatiotemporal attention mechanism, which involves processing both spatial and temporal features. As a result, TimeSformer has a longer training time, a smaller batch size, and higher VRAM usage than the Optical Flow + ViT model.
- **Input Design:** The inclusion of optical flow as an additional input modality in the ViT model offers a simpler and computationally less expensive alternative to fully spatiotemporal models like TimeSformer. The flow encoding allows the ViT model to effectively capture motion dynamics over time, making it a viable option for detecting violent actions without the need for complex temporal attention mechanisms.
- **GPU Constraints:** To ensure efficient training without exceeding memory limits, batch sizes for both models were selected to fully utilize the available VRAM on the Google Colab L4 GPU. This optimization allowed the models to process the data efficiently while staying within the computational limits of the hardware.

4.5 Summary

This chapter presented the training process and configuration for two transformer-based models aimed at violence detection in video clips: the Optical Flow + ViT model and the TimeSformer model. The Optical Flow + ViT approach integrates spatial and temporal features by combining the 16th RGB frame with accumulated optical flow, calculated

using a momentum-based method with a decay parameter $\beta = 0.7$. This aggregation strategy allows efficient encoding of motion trends across frames.

The model was trained using the ViT-Base architecture with an input resolution of 224×224, optimized using AdamW and a ReduceLROnPlateau scheduler. Over 20 epochs, the Optical Flow + ViT model demonstrated consistent performance improvement, achieving a final validation accuracy of 97.52%. Detailed results are seen in table 4.3

Additionally, visualizations of arrow-based and HSV representations of the accumulated flow highlighted the model's ability to capture dynamic motion cues effectively. The results validate the efficacy of combining motion and spatial features through transformer-based architectures for video violence detection.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This study explored the effectiveness of Vision Transformer (ViT) models for violence detection in videos using the RWF-2000 dataset. The primary goal was to develop and evaluate two distinct ViT-based architectures for this task: one that combines Optical Flow with ViT and another that uses the spatiotemporal attention mechanism of TimeSformer. The following key conclusions were drawn based on the experimental results:

- **Performance of Optical Flow + ViT:** The model that integrates Optical Flow with ViT achieved **97.52% validation accuracy**, highlighting the power of combining motion information from optical flow with the ViT architecture for detecting violent actions in video clips.
- **Effectiveness of TimeSformer:** The TimeSformer model, which introduces a temporal attention mechanism, achieved **96.6% validation accuracy**. This demonstrates the ability of TimeSformer to capture spatiotemporal relationships in video data, although slightly lower accuracy compared to the Optical Flow-based model.
- **Convergence Behavior:** Both models showed good convergence, with the Optical Flow + ViT model stabilizing after a higher number of epochs (20), whereas TimeSformer achieved convergence within 14 epochs. This suggests that TimeSformer is more efficient at learning spatiotemporal features in the given dataset.
- **Validation and Generalization:** The high validation accuracy for both models indicates their ability to generalize well to unseen video clips. The steady decrease in loss further reinforces the idea that the models are learning meaningful features without overfitting.
- **Computational Considerations:** While both models provided excellent performance, TimeSformer required significantly more computational resources, both in terms of VRAM usage and time per epoch, compared to the Optical Flow + ViT model. This reflects the higher complexity of TimeSformer due to its spatiotemporal attention mechanism.

Overall, the study successfully demonstrated the potential of ViT-based models in detecting violence in video data, validating both the Optical Flow + ViT and TimeS-

former approaches. These findings provide a strong foundation for future improvements and research in violence detection, leveraging the strengths of transformer-based models.

5.2 Future Scope

While the current work has demonstrated promising results in violence detection using ViT-based models, there are several potential areas for further exploration and improvement. The following outlines possible directions for future work:

- **Training on Larger Datasets:** Expanding the training process to other large-scale violence detection datasets could help improve model robustness and generalization. Training on more diverse datasets could also allow the model to learn from a wider variety of scenarios and video conditions.
- **Exploring Larger ViT Architectures:** The use of ViT-base and ViT-large models could potentially lead to better performance. These models offer a greater capacity for feature extraction and attention learning, which could improve the model's accuracy. However, this may come with a significant increase in computational requirements, which would need to be addressed by utilizing more powerful hardware or optimizing the model architecture.
- **Exploring Other Transformer Architectures:** Investigating alternative transformer architectures, such as Swin Transformers or Timesformer, could provide insights into the effectiveness of different self-attention mechanisms in video data. Swin Transformers, for instance, use a hierarchical approach to learn both local and global features, which could be useful for detecting violence in videos with varying scales of action. Similarly, TimeSformer's spatiotemporal attention could be refined and adapted to work more effectively with large-scale datasets.
- **Real-Time Deployment for Surveillance Systems:** Another avenue for future work is adapting these models for real-time video analysis in surveillance systems. Real-time performance is crucial for automatic detection of violent incidents in security and public safety applications. This would require optimizing the models for faster inference times while maintaining high accuracy. Techniques like model pruning, quantization, or distillation could be explored to reduce the model size and computation time.
- **Incorporating Multi-modal Data:** Future work could explore multi-modal approaches that combine video data with audio or sensor data. Audio signals, in particular, could provide complementary information that helps in identifying violent actions, such as shouting or impact sounds. Multi-modal learning could further improve the robustness of violence detection models.

The potential for future improvements in the field of violence detection is vast. By building upon the findings of this study and exploring the outlined areas, researchers can continue to enhance model performance, tackle real-world challenges, and deploy violence detection systems for automated surveillance and public safety applications.

5.3 Note on Tools Used

This report was written with the aid of ChatGPT, which was used to refine the clarity and structure of the content. All ideas, analyses, and conclusions presented are entirely original and reflect my own understanding and work.

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