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A Self - Supervised Lightweight CNN - LSTM network for violence detection in Low - Labelled Surveillance Video

P.Renugadevi*[1], Mrs.S.Kalpana M.E[2],
*1 PG Student, Department of CSE, SKP Engineering College Tiruvannamalai, Tamil Nadu, India
Email: *[1] renugapalani30@gmail.com
[2]Assistant Professor,Department of CSE, Arunai Engineering College Tiruvannamalai, Tamil Nadu, India

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Abstract:

The detection of violence in surveillance videos is critical for ensuring public safety and enabling rapid response in real-time monitoring systems. However, most existing deep learning approaches demand large amounts of annotated data and computational resources, which limits their deployment in real-world, resource-constrained environments. In this paper, we propose a novel self-supervised framework that integrates a lightweight Convolutional Neural Network (CNN) with a Long Short-Term Memory (LSTM) network for violence detection in low-labelled surveillance video datasets. Our method leverages temporal consistency and motion dynamics through pretext tasks to learn robust spatio-temporal features without relying heavily on manual annotations. The CNN backbone extracts compact spatial representations, while the LSTM captures temporal dependencies, enabling effective identification of violent actions. Experimental evaluations on benchmark violence datasets demonstrate that our model achieves competitive accuracy with significantly reduced model size and training data. This approach presents a scalable and efficient solution for real-time violence detection in practical surveillance systems.

Keywords — **Violence Detection, Self-Supervised Learning, Lightweight CNN, LSTM Network, Surveillance Video, Low-Labelled Data, Spatio-Temporal Features, Deep Learning, Real-Time Monitoring, Action Recognition**

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I. INTRODUCTION

Traditional violence detection methods rely heavily on handcrafted features and rule-based systems, which are often inadequate in capturing the complex dynamics of violent actions. Recently, deep learning-based approaches have demonstrated superior performance in video understanding tasks by automatically learning hierarchical representations. However, these models often require large amounts of annotated video data, which is costly and time-consuming to obtain—particularly for violence, where labelled instances are rare and sensitive in nature.

To address the limitations posed by scarce labelled data and high computational costs, this paper introduces a self-supervised learning framework that leverages both spatial and temporal cues from surveillance videos. Our proposed architecture combines a lightweight Convolutional Neural Network (CNN) for efficient feature extraction with a Long Short-Term Memory (LSTM) network to model temporal dependencies. By employing self-supervised pretext tasks—such as temporal order prediction and motion-based frame sampling—we enable the model to learn meaningful spatio-temporal representations even from low-labelled datasets.

Our method offers two primary advantages: (1) reduced dependency on manual annotations through self-supervised pre-training, and (2) suitability for real-time deployment due to the lightweight design of the model. We evaluate our framework on benchmark violence detection datasets and demonstrate that it achieves competitive performance compared to fully supervised and computationally heavier models.

II. RELATED WORK

The task of violence detection in video surveillance has gained significant attention in recent years, driven by advancements in deep learning and the increasing demand for intelligent security systems. This section reviews existing approaches relevant to three key areas: traditional violence detection methods, deep learning-based models, and recent developments in self-supervised learning and lightweight architectures.

A. *Traditional Methods*

Early approaches to violence detection relied heavily on handcrafted features such as motion vectors, optical flow, and spatio-temporal interest points (STIPs). For example, methods using Histogram of Oriented Gradients (HOG), Histogram of Optical Flow (HOF), and Motion Boundary Histograms (MBH) attempted to describe the motion patterns of violent scenes. While computationally efficient, these methods lacked robustness in complex real-world environments due to their limited ability to generalize across varying scenes, lighting, and actor behaviors.

B. *Deep Learning-Based Approaches*

With the advent of deep learning, Convolutional Neural Networks (CNNs) have become the backbone of modern violence detection models. CNNs are effective in extracting spatial features, while Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been used to model temporal sequences of frames. 3D CNNs and Two-Stream Networks have also shown promising results by simultaneously learning spatial and temporal representations. However, these models typically require large labelled datasets and are computationally expensive, making them unsuitable for real-time deployment or use in low-resource settings.

C. *Self-Supervised Learning in Video Analysis*

Self-supervised learning has emerged as a powerful strategy to overcome the reliance on large annotated datasets. It involves training models using pretext tasks that do not require manual labels, such as frame order prediction, temporal consistency verification, or clip similarity estimation. These tasks allow the model to learn generalizable spatio-temporal representations, which can later be fine-tuned on small labelled datasets. Recent works have explored self-supervised learning for video classification and action recognition, but its application to violence detection remains relatively underexplored.

D. *Lightweight Architectures for Surveillance*

To enable real-time violence detection in resource-constrained environments, researchers have investigated lightweight models using architectures like MobileNet, ShuffleNet, and EfficientNet. These models significantly reduce the number of parameters and computational load without sacrificing much accuracy. However, integrating lightweight design with temporal sequence modeling and self-supervised learning remains an open challenge.

III. PROPOSED METHODOLOGY

The proposed framework aims to detect violent activities in surveillance videos using a lightweight, self-supervised CNN-LSTM architecture. Our methodology is designed to address three main challenges: (1) scarcity of labelled data, (2) need for real-time processing, and (3) capturing both spatial and temporal information effectively. The overall framework consists of four primary stages: preprocessing, self-supervised feature learning, CNN-LSTM modeling, and classification.

A. Overview of Architecture

The model consists of:

- A lightweight CNN backbone for spatial feature extraction.
- An LSTM network to model temporal dynamics across frames.

- A self-supervised pretraining module that learns meaningful spatio-temporal features from unlabelled video segments.
- A final fully connected layer for binary classification (violent vs. non-violent).

B. Data Preprocessing And Frame Sampling

Surveillance videos are first segmented into short clips (e.g., 10–20 frames). To reduce redundancy and computational overhead:

- Frame sampling is performed at uniform intervals or using motion magnitude thresholds (e.g., optical flow-based sampling).
- All frames are resized (e.g., to 112×112 or 128×128) and normalized.
- Data augmentation (e.g., random cropping, flipping, brightness changes) is applied to improve generalization.

C. Self-Supervised Pretext Tasks

To leverage unlabelled video data, we implement self-supervised learning using pretext tasks, which train the CNN-LSTM network to understand spatio-temporal relationships:

- *Temporal Order Prediction:* The model is trained to predict the correct chronological order of shuffled video frames.
- *Future Frame Prediction:* Given a sequence of frames, the model predicts a representation of the next frame.
- *Contrastive Learning:* Embeddings of similar temporal clips (positive pairs) are brought closer, while dissimilar ones (negative pairs) are pushed apart.

These tasks enable the network to learn robust and transferable features without requiring human annotations.

D. Lightweight CNN For Spatial Feature Extraction

A compact CNN (e.g., based on MobileNet or a custom shallow architecture) is used to extract spatial features from each input frame. The goal is to minimize parameters while preserving important visual cues such as posture, movement, and contextual background. The CNN outputs feature vectors for each frame, which are fed into the temporal model.

E. LSTM For Temporal Modeling

The LSTM component receives a sequence of feature vectors and learns temporal dependencies across frames. This is essential for distinguishing violent from non-violent behavior, as certain violent actions (e.g., punching, kicking) are only discernible over time. We use a unidirectional LSTM to maintain causality for real-time applications.

F. Fine-Tuning With Limited Labels

After self-supervised pretraining, the model is fine-tuned on a small labelled dataset using cross-entropy loss for binary classification. This transfer learning step allows the network to specialize in violence detection with minimal labelled data.

G. Classification

The final hidden state of the LSTM is passed through a fully connected layer followed by a sigmoid activation to produce a probability score indicating the presence of violence. A threshold (e.g., 0.5) is used for final decision-making.

Advantages of the Proposed Method

- *Label Efficiency:* Requires fewer labelled examples due to self-supervised learning.
- *Low Latency:* Suitable for real-time applications due to the lightweight model design.
- *Robust Detection:* Effectively captures spatio-temporal patterns of violent behavior.

IV. EXPERIMENTAL SETUP

To validate the effectiveness of our proposed self-supervised lightweight CNN-LSTM framework, we conduct a series of experiments on benchmark violence detection datasets. This section outlines the datasets used, implementation details, evaluation metrics, and training protocols.

A. Datasets

We evaluate our model on two widely-used publicly available datasets for violence detection:

- *Hockey Fight Dataset:* Contains 1,000 video clips (500 violent, 500 non-violent) collected from ice hockey matches. Videos are trimmed to short durations with clearly labeled violent segments.
- *Movies Fight Dataset:* Comprises over 200 short video clips extracted from various movies depicting both violent and non-violent actions in diverse lighting and backgrounds.
- *(Optional):* If available, additional testing can be conducted on real-world surveillance footage datasets such as UCF-Crime (subset), focusing only on violence-related categories.

To simulate a low-labelled environment, we use only a small portion (e.g., 20–30%) of the labelled dataset for fine-tuning and treat the rest as unlabelled for self-supervised pretraining.

B. Data Preprocessing

- All videos are downsampled to 15 FPS and resized to 128×128 resolution.
- Frame sequences are extracted in sliding windows of 16–20 consecutive frames.
- Augmentation techniques include random cropping, rotation, horizontal flipping, and brightness adjustment to improve generalization.

C. Implementation Details

- *Framework:* Implemented using TensorFlow / PyTorch
- *CNN Backbone:* A lightweight CNN (based on MobileNetV2 or custom 6-layer CNN)
- *LSTM:* Single-layer unidirectional LSTM with 128 hidden units
- *Self-Supervised Tasks:* Trained using temporal order prediction and contrastive learning (SimCLR-based loss)
- *Optimizer:* Adam with a learning rate of 1e-4
- *Batch Size:* 32

Epochs:

- Self-supervised pretraining: 100 epochs
- Fine-tuning on labelled data: 50 epochs

Hardware: Experiments are conducted on a system with NVIDIA GTX 1660 GPU, 16GB RAM, and Intel i7 CPU.

D. Evaluation Metrics

To assess the performance of the proposed model, we use standard classification metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- Area Under ROC Curve (AUC)

In addition, we compare inference time per frame to verify the model's suitability for real-time deployment.

E. Baselines For Comparison

We compare our model with the following baseline methods:

- Traditional HOG + SVM-based violence detection
- 2D CNN with fully connected classification head

VI. CONCLUSION

In this paper, we presented a novel approach for real-time violence detection in surveillance videos using a self-supervised lightweight CNN-LSTM network. Our method effectively addresses the challenges posed by limited labelled data, high computational costs, and the need for robust spatio-temporal modeling in practical surveillance environments.

By leveraging self-supervised learning with pretext tasks such as temporal order prediction and contrastive learning, our model learns meaningful feature representations from unlabelled video data. The lightweight CNN extracts efficient spatial features, while the LSTM captures temporal dynamics crucial for identifying violent actions. The integration of these components enables accurate and efficient violence detection with minimal reliance on annotated datasets.

Experimental results on benchmark datasets demonstrate that our approach achieves competitive or superior performance compared to existing methods, while maintaining low model complexity and real-time inference speed. Our method proves especially valuable in resource-constrained surveillance systems where large-scale annotated data and powerful hardware are not available.

VII. FUTURE WORK

Future research will explore:

- **Transformer-Based Temporal Modeling** for improved long-range dependencies.
- **Multimodal Inputs** such as audio or skeletal data for more robust violence detection.
- **Online and Continual Learning Strategies** to adapt the model to new environments without retraining from scratch.
- **Deployment on Edge Devices** using model quantization and pruning.

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