

An Efficient Deep Learning Approach For Real-Time Threat Detection Using Crowd Behavior Analysis

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Abstract

An efficient deep learning-based approach for real-time anomaly detection in crowded environments using a hybrid model combining Zero-Shot Learning (ZSL) and Teacher-Student Knowledge Distillation. The teacher network transfers knowledge to a lightweight student model, ensuring efficient inference while maintaining accuracy. ZSL enables detecting unseen anomalies without extensive labeled data. A frame selection technique extracts every 10th frame (64×64 pixels) to reduce computational load. Evaluated using accuracy, precision, recall, and F1-score, the model enhances generalization and efficiency, making intelligent video surveillance more practical with minimal computational cost.

Dataset & Data Pre-processing

- The UCF Crime dataset is pre-processed into frames, but additional raw video data was manually processed to enhance training.
- If preprocessing were needed, frames would be extracted using OpenCV, stored by class, and balanced through oversampling or downsampling.
- A systematic pipeline extracts every 10th frame to reduce redundancy while preserving temporal dynamics.
- Frames are resized to 64×64 pixels using bilinear interpolation to optimize efficiency and ensure uniformity.
- A structured naming convention ensures traceability for model debugging.
- Standardized frame sizes facilitate smooth batch processing and model compatibility, making real-time anomaly detection feasible and computationally efficient.

Research Objective

The primary objective of this research is to develop an efficient deep learning-based threat detection system for crowded areas by integrating Zero-Shot Learning (ZSL) and Knowledge Distillation. The focus is on optimizing computational efficiency while maintaining high anomaly detection accuracy. The study seeks to enhance model generalization, enabling the detection of unseen anomalies. Additionally, the proposed framework will be evaluated using benchmark datasets and compared with existing models in terms of accuracy, efficiency, and real-time applicability.

Literature Review

Recent studies explore deep learning for anomaly detection, integrating CNN-LSTM, Zero-Shot Learning (ZSL), and Knowledge Distillation (KD). Innovations include optical flow processing, hybrid architectures, and vision-language models like CLIP. While models achieve high accuracy, challenges include computational costs, dataset bias, and domain adaptation, limiting real-world scalability and generalization.

Methodology

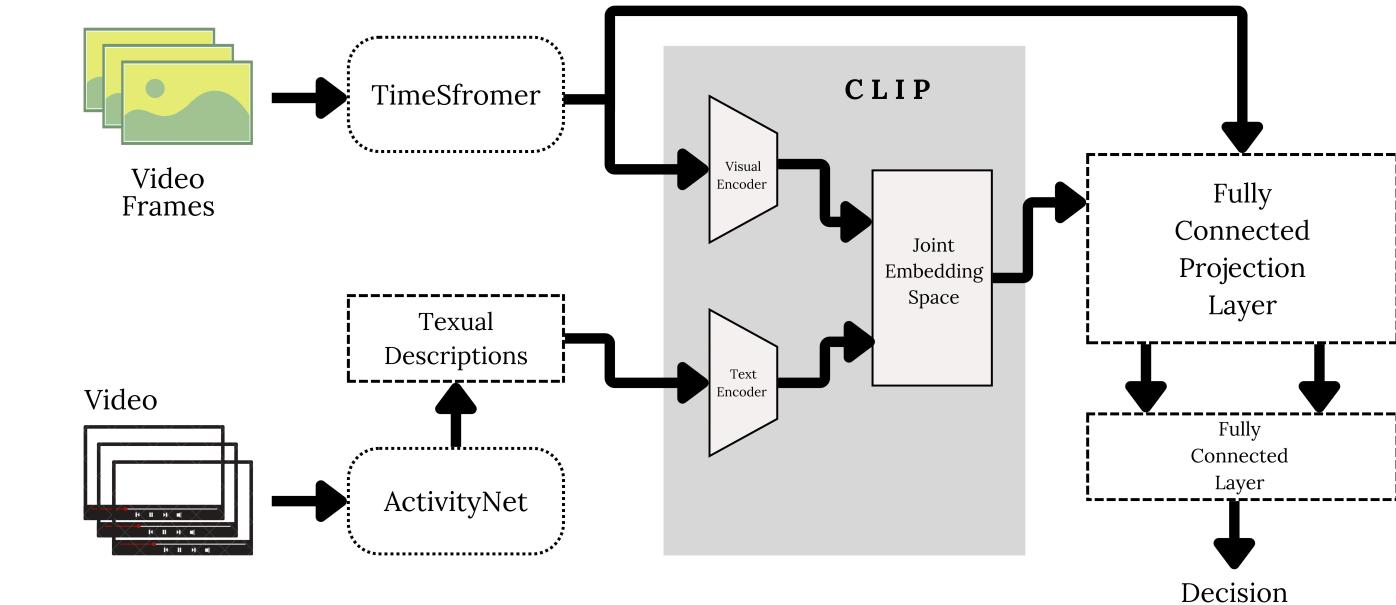
Utilize Zero-Shot Learning (ZSL) and Teacher-Student Knowledge Distillation to enhance anomaly detection efficiency and generalization.

Extract every 10th frame from videos and resize them to 64×64 pixels to reduce computational load.

Train a high-capacity teacher model on normal behaviors and transfer knowledge to a lightweight student model for real-time inference.

Evaluate model performance using accuracy, precision, recall, and F1-score to

Study Pipeline



Result Analysis

The performance evaluation of our proposed for real-time threat detection was conducted using the UCF Crime Dataset. Most data points have anomaly scores concentrated between 0.30 and 0.40, with a gradual decrease in frequency beyond 0.45. The majority of anomaly scores lie within 0.30–0.40, indicating normal behaviors, while higher scores (greater than 0.45) correspond to significant anomalies. It confirms the model's ability to distinguish between normal and abnormal activities effectively.

References

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