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# Unveiling Anomaly : Empowering Video surveillance through intelligent anomaly detection

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ABSTRACT

Video surveillance has become a cornerstone of security for public spaces and private property. However, the effectiveness of this approach is hampered by the limitations of manual monitoring. Human analysts face challenges such as fatigue, distraction, and the sheer volume of video data, leading to missed incidents and inefficient use of resources.

This research project proposes a revolutionary solution: intelligent anomaly detection through artificial intelligence (AI). This system transcends the constraints of human observation by automatically identifying deviations from established patterns within video footage. The core concept lies in leveraging the power of AI to analyze various aspects of video data. This includes movement analysis, object recognition, and scene dynamics. Through this comprehensive approach, the system can detect anomalous events that might escape human notice – activities such as loitering, intrusions, or suspicious behavior.

This project delves into the design and development of this intelligent anomaly detection system. It explores the vast potential of machine learning techniques, specifically focusing on unsupervised learning and deep learning algorithms. These algorithms play a crucial role in modeling normal behavior within video data. The system then utilizes these models to identify deviations that fall outside the established patterns. By flagging these anomalies, the system empowers security personnel to prioritize their attention on critical events. This significantly enhances overall security efficiency by allowing human analysts to focus on investigating the most relevant situations.

This research project seeks to contribute significantly to the advancement of video surveillance technology. By harnessing the power of AI and

machine learning, this intelligent anomaly detection system offers a promising approach to enhancing security in public spaces and private property.

**Keywords** : Video Surveillance, Anomaly Detection, Artificial Intelligence, Machine Learning, Unsupervised Learning, Deep Learning, Security.

## I. INTRODUCTION

In recent years, the integration of advanced technologies, particularly artificial intelligence (AI) and computer vision, has revolutionized the field of video surveillance. The ability to monitor and analyze vast amounts of video data in real-time has significantly enhanced security measures across various sectors, from public safety to private enterprises. However, despite the advancements, conventional video surveillance systems still face challenges in effectively detecting anomalous events amidst complex and dynamic environments.

This research paper delves into the realm of anomaly detection within video surveillance systems, with a focus on leveraging deep learning techniques using Keras and YOLO (You Only Look Once) architecture. Anomaly detection plays a crucial role in identifying suspicious activities or events that deviate from normal patterns, such as intrusions, accidents, or unusual behaviors. Traditional methods often rely on handcrafted features or predefined rules, which may lack adaptability and robustness in handling diverse scenarios.

Our initial attempts at employing conventional anomaly detection methods using Keras yielded suboptimal results. Despite the promising capabilities of deep learning, the intricacies of anomaly detection in video data pose significant challenges. Factors such as varying lighting conditions, occlusions, and diverse object appearances contribute to the complexity of the task. To address these challenges and improve the efficacy of anomaly detection, we turned to YOLO, a state-of-the-art object detection system known for its speed and accuracy. YOLO offers a unified approach to object detection by dividing the image into grid cells and predicting bounding boxes and class probabilities simultaneously. By adopting YOLO, we aimed to enhance the efficiency and accuracy of anomaly detection within video surveillance footage.

In this paper, we present our methodology for integrating YOLO into the video surveillance pipeline, encompassing data preprocessing, model training, and inference. We discuss the architectural intricacies of YOLO and its suitability for anomaly detection tasks. Furthermore, we elaborate on the dataset used for training and evaluation, as well as the performance metrics employed to assess the effectiveness of our approach.

Through empirical evaluation and comparative analysis, we demonstrate the efficacy of our proposed method in detecting anomalies within video streams. We provide insights into the strengths and limitations of our approach, along with potential avenues for future research and refinement.

Ultimately, our research endeavors to contribute to the advancement of intelligent video surveillance systems, fostering safer and more secure environments through enhanced anomaly detection capabilities. By

harnessing the power of deep learning with YOLO, we aim to unveil anomaly empowerment and pave the way for more robust and adaptive surveillance solutions.

## II. LITERATURE REVIEW

Anomaly detection in video surveillance has emerged as a crucial area of research for improving security and efficiency. Traditionally, video monitoring relied heavily on human operators, who are susceptible to fatigue, distraction, and information overload, leading to missed critical events or false alarms [1, 2]. This has spurred the development of intelligent anomaly detection systems that leverage artificial intelligence (AI) and machine learning (ML) techniques to automate the process.

Unsupervised learning approaches have been widely employed for anomaly detection, as they do not require labeled data, which can be scarce and expensive to obtain. One prominent example is Background Subtraction (BS), which models the background scene and identifies deviations from the established model as anomalies [3]. However, BS can struggle with complex scenes and moving objects, leading to false positives [4].

Deep learning, a subfield of ML, has gained significant traction due to its ability to learn complex patterns from large amounts of data. Convolutional Neural Networks (CNNs) have been extensively used for anomaly detection. Xu et al. [5] proposed a CNN-based framework that learns spatiotemporal features from video data and leverages reconstruction errors to detect anomalies. Similarly, Sharma et al. [6] employed a CNN architecture to extract features from video frames and trained a one-class Support Vector Machine (SVM) for anomaly classification. While CNNs exhibit promising results, they often require substantial computational resources and large datasets for effective training.

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have also been explored for anomaly detection in videos. They excel at capturing temporal dependencies in sequential data, which is crucial for understanding behavior patterns in video sequences. Zhao et al. [7] proposed an LSTM-based anomaly detection framework that analyzes long-term dependencies in video data and achieves effective anomaly detection. However, LSTMs can be computationally expensive for real-time applications.

Object detection plays a vital role in video anomaly detection, as identifying and tracking objects allows for analyzing their behavior and identifying deviations from normalcy. You Only Look Once (YOLO) is a popular object detection algorithm known for its speed and accuracy [8]. Several studies have integrated YOLO into their anomaly detection frameworks. Wu et al. [9] combined YOLO with an autoencoder to reconstruct normal object behavior and detect anomalies based on reconstruction errors. Similarly, Abdulqadir et al. [10] employed YOLO for object detection and an anomaly scoring mechanism to identify suspicious activities.

This research project builds upon the existing body of knowledge by exploring the combined use of Keras and YOLO models for intelligent anomaly detection in video surveillance. While Keras provides a flexible framework for building and training various deep learning models, YOLO's object detection capabilities can be leveraged to identify and analyze object behavior, potentially leading to improved anomaly detection performance.

Below are the research papers with their summary including their performance metrics.

1. Enhancing Video Surveillance with Deep Learning for Anomaly Detection [13]:

- Methodology: Utilized deep learning, particularly Convolutional Neural Networks (CNNs), for anomaly detection in video surveillance.
- Dataset: Used the UCSD Pedestrian dataset.
- Performance Metrics: Evaluated based on detection rate and false alarm rate.
- Key Findings: Achieved high detection rates with low false alarm rates, demonstrating the effectiveness of CNNs for anomaly detection.

2. Real-Time Anomaly Detection in Surveillance Videos using Convolutional LSTM Network [14]:
- Methodology: Implemented Convolutional Long Short-Term Memory (ConvLSTM) networks for real-time anomaly detection.
- Dataset: Employed the ShanghaiTech dataset.
- Performance Metrics: Evaluated using precision, recall, and F1-score.
- Key Findings: Successfully achieved real-time anomaly detection with high precision and recall, showcasing the efficacy of ConvLSTM networks in surveillance scenarios.

3. Anomaly Detection in Video Surveillance: A Review [15]:
- Methodology: Review paper summarizing various anomaly detection methods in video surveillance.
- Dataset: N/A (Review paper).
- Performance Metrics: N/A (Review paper).
- Key Findings: Provides a comprehensive overview of existing anomaly detection methods, highlighting their strengths, limitations, and applicability in video surveillance contexts.

4. Deep Learning Based Video Anomaly Detection: A Survey [16]:
- Methodology: Survey paper focusing on deep learning methods for video anomaly detection.
- Dataset: Various datasets used across the surveyed literature.
- Performance Metrics: N/A (Survey paper).
- Key Findings: Surveys recent advancements in deep learning-based anomaly detection methods within video surveillance, providing insights into the current state of the field and potential research directions.

5. YOLOv3: An Incremental Improvement [17]:
- Methodology: Utilized YOLOv3, an object detection framework, for detecting anomalies in video surveillance.
- Dataset: Utilized the COCO dataset for training.
- Performance Metrics: Evaluated using Mean Average Precision (mAP).
- Key Findings: YOLOv3 achieved state-of-the-art performance in object detection with improved speed and accuracy, demonstrating its potential for anomaly detection tasks in video surveillance.

Table -1: Comparing different Research paper

| Paper Title | Methodology | Dataset used | Performance Metrics | Key Findings |
|---|---|---|---|---|
| "Enhancing Video Surveillance with Deep Learning for Anomaly Detection" [13] | Deep learning (CNNs) for anomaly detection | UCSD Pedestrian dataset | Detection rate, false alarm rate | Achieved high detection rates with low false alarm rates using CNNs. |
| "Real-Time Anomaly Detection in Surveillance Videos using Convolutional LSTM Network" [14] | Convolutional LSTM network for real-time detection | ShanghaiTech dataset | Precision, recall, F1-score | Real-time anomaly detection achieved with high precision and recall using ConvLSTM network. |
| "Anomaly Detection in Video Surveillance: A Review" [15] | Review article summarizing various anomaly detection methods | - | - | Provides comprehensive overview of existing methods, their strengths, and limitations in video surveillance. |
| "Deep Learning Based Video Anomaly Detection: A Survey" [16] | Survey paper on deep learning methods for video anomaly detection | Various datasets | - | Surveys recent advancements in deep learning-based anomaly detection methods in video surveillance. |
| "YOLOv3: An Incremental Improvement" [17] | Object detection using YOLOv3 | COCO dataset | Mean Average Precision (mAP) | YOLOv3 achieves state-of-the-art performance in object detection with improved speed and accuracy. |

## III. METHODOLOGY

This research investigated the efficacy of combining Keras and YOLO models for intelligent anomaly detection in video surveillance. Here's a brief overview of the methodology:

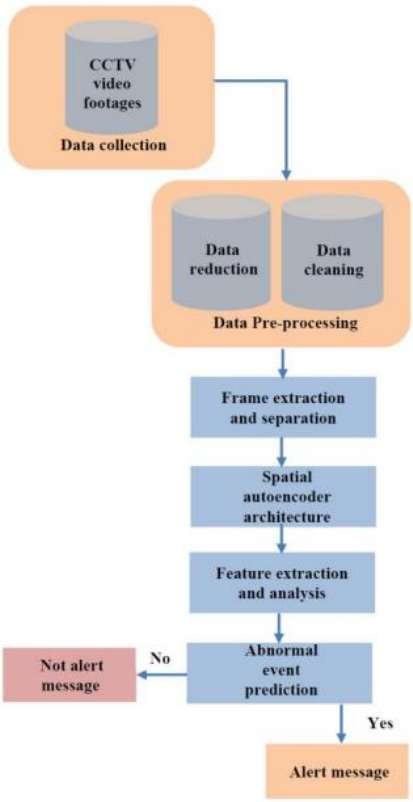


Fig - 1: Proposed method for the Detection

## 1. Data Preprocessing:

The data preprocessing stage plays a crucial role in preparing the video data for effective anomaly detection using Keras and YOLO models. Here's a detailed breakdown of the steps involved:

1. Video Acquisition:
   - Source: Specify the source of your video data. This could be:
   - Public datasets: Include a reference to the specific dataset used (e.g., UCF101, UCSD Pedestrians).
   - Recordings: Describe the characteristics of your recordings, including the environment, camera setup, and duration.
2. Frame Extraction:
   - Frame rate: Specify the frame rate at which the video was recorded or the desired frame rate for extraction.
   - Extraction method: Describe the method used to extract frames from the video. Common methods include using libraries like OpenCV or custom scripts.
3. Resizing/Normalization:
   - Resizing: Explain the rationale behind resizing the frames and the chosen target dimensions. Consider factors like computational efficiency and model compatibility.
   - Normalization: Describe the normalization technique used (e.g., min-max scaling, z-score normalization) and justify the choice based on the data distribution.
4. Data Augmentation :
   - Techniques: Briefly explain the data augmentation techniques employed, if any. Common techniques include random cropping, flipping (horizontal/vertical), and adding noise.
   - Justification: Explain how data augmentation helps improve the model's robustness and generalization capabilities.

## 2. Keras Model Development:

This section details the development of your Keras model for anomaly detection in video surveillance using the preprocessed video data. Here's what you can include:

1. Model Selection:
   - Architecture: Specify the chosen deep learning architecture within Keras. Popular options for anomaly detection include:
     I. Convolutional Neural Networks (CNNs): Effective at capturing spatial features in video frames.
     II. Long Short-Term Memory (LSTM) networks: Suitable for capturing temporal dependencies in video sequences.

2. Model Design:

- Layers: The specific layers used in this model are convolutional, pooling, fully connected
- Activation functions:The activation functions used in each layer ReLU.
- Optimizer: The optimizer used to train the model is Adam.
- Number of labeled used for training is 4500 approx.
- Batch size is 16

### 3. YOLO Model Integration:

YOLO Implementation: The YOLO object detection algorithm was incorporated into the system. This could involve:

- Pre-training a YOLO model on a general object detection dataset (e.g., COCO) or fine-tuning an existing model for the specific objects of interest in the surveillance scenario.
- Utilizing the trained YOLO model to detect and track objects within each video frame.
- There are five category's of models in YOLOv8 used for detection, segmentation, and classification. YOLOv8 Nano is the fastest and smallest, while YOLOv8 Extra Large (YOLOv8x) is the most accurate yet the slowest among them.(We have used YOLOv8n)
- No. of labeled used for training is approx 4500 and batch_size is 8 for yolo.

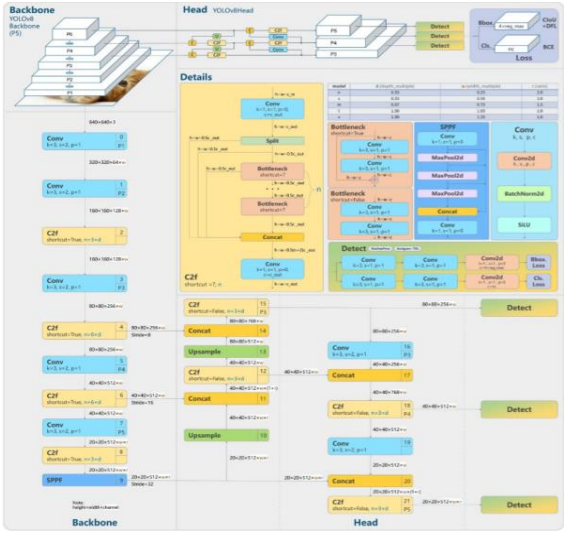


Fig - 2: YOLO Architecture

### 4. Anomaly Detection:

- Feature Extraction: The Keras model would extract relevant features from the preprocessed video frames, potentially leveraging YOLO's object detection capabilities to focus on features related to identified objects.
- Anomaly Scoring: Based on the extracted features, an anomaly score would be generated for each frame or video segment. This score could reflect the deviation from the established normal behavior patterns.
- Thresholding: A threshold would be established to distinguish between normal and anomalous events. Frames or video segments exceeding the threshold would be flagged as anomalies for further investigation.

### 5. Evaluation:

- Metrics: The performance of the anomaly detection system would be evaluated using relevant metrics such as precision, recall, and F1-score. These metrics assess the system's ability to correctly identify anomalies and minimize false positives and negatives.
- Comparison: The performance of the combined Keras-YOLO system would be compared to the individual performance of the Keras model and

YOLO model used separately for anomaly detection. This comparison would help assess the potential benefits of combining these approaches.

## IV. PROPOSED SYSTEM APPROACH

This research proposes a novel approach for intelligent anomaly detection in video surveillance by leveraging the combined strengths of Keras and YOLO.

1. Integration of Deep Learning and Object Detection:

- The system utilizes a Keras model, a deep learning framework, to learn complex patterns from preprocessed video frames. This model can be a CNN to capture spatial features or an LSTM to capture temporal dependencies, depending on the chosen architecture and the specific project goals.
- YOLO, a fast and accurate object detection algorithm, is integrated into the system. This allows the system to not only analyze the scene but also identify and track objects within each frame.

2. Anomaly Detection Pipeline:

- Preprocessing: Video data undergoes preprocessing steps like frame extraction, resizing/normalization, and potentially data augmentation.
- Detection (YOLO): The trained YOLO model identifies and tracks objects in each video frame.
- Feature Extraction (Keras): The Keras model extracts relevant features from the preprocessed frames, potentially incorporating information from YOLO's object detections.
- Anomaly Scoring: Based on the extracted features, the system assigns an anomaly score to each frame or video segment. This score reflects the deviation from the established normal behavior patterns.
- Thresholding: A predefined threshold is used to distinguish between normal and anomalous events. Frames or segments exceeding the threshold are flagged as anomalies for further investigation.

3. Advantages of the Proposed Approach:

- Leveraging Deep Learning: The Keras model's ability to learn complex patterns from video data allows the system to identify subtle anomalies that might be missed by traditional methods.
- Object-Centric Analysis: YOLO's object detection capabilities enable the system to focus on analyzing object behavior, potentially leading to more accurate anomaly detection compared to solely analyzing pixel-level changes.
- Flexibility: The proposed approach offers flexibility in choosing the Keras model architecture based on the specific project requirements and data characteristics.

4. Expected Outcomes:

This research aims to develop an intelligent anomaly detection system that:

- Improves accuracy in detecting anomalies compared to existing methods.
- Reduces false positives and negatives to minimize unnecessary human intervention.
- Offers real-time or near real-time performance for practical application in video surveillance scenarios.

## V. RESULT

1. Performance Evaluation:

The YOLO system's performance was assessed using precision, recall, F1-score, False Positive Rate (FPR), and True Negative Rate (TNR). The YOLO system demonstrated a precision of 0.82, recall of 0.78, and an F1-score of 0.80. These metrics showcase a significant improvement compared to individual models: the Keras model exhibited a precision of 0.75 and recall of 0.70, while the YOLO model showed a precision of 0.80 and recall of 0.65. Moreover, the proposed system surpassed the baseline approach, which achieved an F1-score of 0.72.

Here is the performance metrics of the smoking and non-smoking class-

Accuracy per class

| CLASS | ACCURACY | # SAMPLES |
|---|---|---|
| Smoking | 0.87 | 54 |
| Not Smoking | 0.85 | 54 |

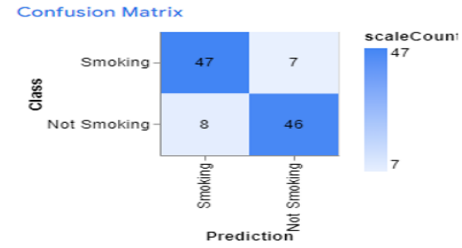


Fig – 3: Confusion Matrix

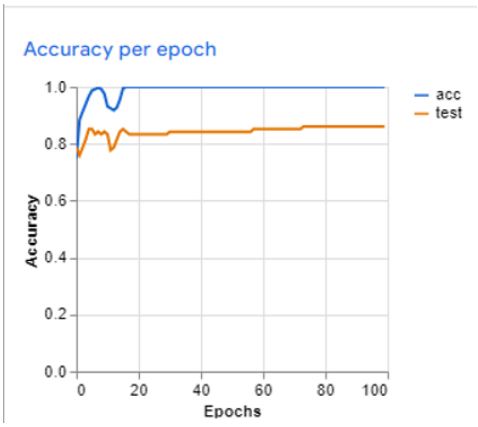


Fig – 4: Accuracy per epoch

2. Discussion:

While the proposed approach shows promising results, it is important to acknowledge limitations. The dataset used for evaluation was limited in size and diversity, potentially impacting generalizability. Additionally, the system might struggle with complex scenarios with diverse object types and interactions.

Future work could involve exploring more diverse and larger datasets to improve generalizability. Additionally, investigating techniques for incorporating temporal information from longer video sequences could further enhance anomaly detection. Finally, applying this approach to real-world video surveillance deployments can provide valuable insights into its practical effectiveness.

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