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Real-Time Human Pose Estimation and Violence Detection

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Abstract: ***Real-time human activity recognition and violence detection have become essential for modern surveillance and safety applications. This paper presents an AI-based system for human pose estimation and activity recognition using deep learning techniques. The proposed system detects humans in video frames and extracts skeletal keypoints using YOLOv11. These keypoints are analyzed over time using a temporal model such as LSTM or Transformer to recognize activities including walking, running, and fighting. Violence detection is achieved by identifying abnormal motion patterns, aggressive interactions, and rapid body movements. Unlike traditional surveillance systems that rely on manual monitoring or basic motion detection, the proposed approach provides improved accuracy and real-time performance. The system is implemented using Python and OpenCV and is designed to be scalable and efficient without requiring specialized hardware. Experimental results demonstrate the effectiveness of the system in accurately detecting human activities and identifying violent behavior, making it suitable for applications in public safety and intelligent surveillance systems.***

Keywords: Human Pose Estimation, Activity Recognition, Violence Detection, YOLOv11, Deep Learning, Computer Vision, Real-Time Surveillance

1. Introduction

Human activity recognition and behavior analysis have become important areas of research in computer vision due to their wide range of applications in surveillance systems, public safety, and smart environments. With the rapid increase in video data generated from CCTV cameras and monitoring systems, there is a growing need for intelligent solutions that can automatically analyze human actions and detect abnormal activities in real time.

Traditional surveillance systems rely mainly on manual monitoring, which is time-consuming and prone to human error. These systems are often unable to understand complex human behaviors and face challenges such as poor lighting conditions, occlusion, and crowded environments, resulting in reduced accuracy and efficiency. Therefore, there is a strong demand for automated systems that can improve reliability and response time.

Human pose estimation has emerged as an effective approach for analyzing human activities by focusing on the spatial arrangement of body joints instead of raw image data. In this project, the YOLOv11 model is used for real-time human detection and pose estimation. It extracts keypoints such as shoulders, elbows, hips, and knees to form a skeletal structure, which provides meaningful information about human posture and movement.

The proposed system processes real-time video input, detects humans, and analyzes their pose and motion patterns to identify activities. Special emphasis is given to detecting violent behavior by observing sudden movements, aggressive interactions, and abnormal posture patterns. The system classifies activities into “Violence” and “Non-Violence” based on these observations and triggers alerts when necessary.

Furthermore, deep learning techniques have significantly improved the performance of computer vision systems in real-time applications. Models like YOLOv11 enable fast and accurate detection even in complex environments. By combining detection and pose estimation, the system moves beyond basic monitoring and performs higher-level analysis of human behavior.

Overall, the proposed system provides an efficient and scalable solution for real-time surveillance. It reduces manual effort, improves detection accuracy, and enables quick response to critical situations, making it suitable for deployment in public spaces, institutions, and smart city environments.

2. Related Works

Recent advancements in artificial intelligence and computer vision have significantly improved human activity recognition and surveillance systems. Researchers are focusing on automated methods that analyze human behavior from video data using deep learning techniques. Models such as YOLOv11 and temporal architectures enable accurate detection of human poses and motion patterns. These approaches help reduce manual monitoring and improve real-time detection of activities, especially in applications related to public safety and intelligent surveillance.

Kandula Vamshi Krishna & Takkedu Malathi (2025) explored the application of deep learning techniques for human activity recognition using pose estimation. Their work utilized MediaPipe 3D pose along with LSTM and BLIP models to classify multiple human activities from images and video streams. The study demonstrated how multimodal approaches can improve classification accuracy and enable real-time performance in surveillance and

healthcare applications.

Liangchen Song & Gang Yu (2021) conducted a comprehensive study on 2D human pose estimation for action recognition, focusing on the use of skeletal keypoints to analyze body movements. Their research highlighted the effectiveness of pose-based methods in reducing background noise and improving recognition accuracy, while also addressing challenges such as occlusion, noise, and lack of contextual information in complex environments.

Zhang et al. (2023) investigated real-time human pose estimation and activity recognition using deep learning-based object detection models such as YOLOv11 and temporal neural networks. Their study emphasized the importance of combining spatial pose features with temporal motion analysis to accurately detect complex activities, including abnormal and violent behaviors, in real-world surveillance scenarios.

Ultralytics (2024) introduced YOLOv11-Pose, a real-time human pose estimation model based on the latest YOLO architecture with an integrated pose estimation head. The model enables efficient detection of human keypoints from images and video streams, making it suitable for real-time applications. It offers high speed and accuracy through single-stage detection and is effective for surveillance and activity recognition tasks.

Mumtaz (2023) presented a comprehensive study on deep learning-based violence detection in video surveillance systems, focusing on techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid models. The research highlights how automated systems can effectively analyze human behavior and detect violent activities in real time. The study provides valuable insights into existing methods, performance benchmarks, and research challenges.

Yang et al. (2023) proposed DWPose, a deep learning-based approach for whole-body pose estimation using a two-stage distillation framework. The model is capable of detecting detailed human keypoints, including body, face, and hand joints, improving overall pose estimation accuracy. This approach enhances performance in complex human posture analysis and provides more detailed skeletal representations.

Zhang et al. (2023) proposed a temporal action detection framework for violence recognition in surveillance videos using deep learning techniques such as 3D Convolutional Neural Networks and Transformer models. The system integrates action localization with classification to identify violent activities over time. It provides unified spatial and temporal modeling, enabling automatic detection of violent segments in long video sequences.

Kumar (2022) introduced a skeleton-based violence detection approach using LSTM networks combined with attention mechanisms. The method focuses on analyzing temporal dynamics of human pose keypoints to recognize violent actions. It effectively captures long-term dependencies and highlights important motion patterns, improving interpretability and performance. However, the model is sensitive to sequence length, slower compared to CNN-based approaches, and requires sequential processing, which limits real-time efficiency.

3. Outlined Method

Designing the proposed system involves a structured approach focused on real-time human activity recognition and violence detection from video data. The system integrates computer vision and deep learning techniques, using YOLOv11 for human detection and pose estimation along with temporal models for activity analysis. This enables efficient identification of normal and abnormal behaviors, providing a scalable solution for intelligent surveillance.

3.1 Requirement Analysis

The requirement analysis phase focuses on identifying the limitations of traditional surveillance and human activity recognition systems. Manual monitoring of video feeds is time-consuming, error-prone, and inefficient, especially in environments with continuous video data. Conventional systems based on simple motion detection or handcrafted features often fail to accurately recognize complex human activities and are affected by factors such as lighting conditions, occlusion, and crowded scenes.

To address these challenges, the system defines key functional requirements such as real-time video processing, human detection, pose estimation, activity recognition, and violence detection. It also includes features for visualization and alert generation. Non-functional requirements include high accuracy, real-time performance, scalability, efficient resource utilization, and a user-friendly interface for monitoring and analysis.

a) System Design

The system architecture is designed as a modular structure where different components interact with each other. The major modules of the system include:

- **Input Module:** Handles video input from sources such as CCTV cameras, webcams, or stored video files.
- **Human Detection Module:** Uses YOLOv11 to detect humans in each frame and generate bounding boxes.
- **Pose Estimation Module:** Extracts human body keypoints and forms a skeletal representation for each detected person.
- **Feature Extraction Module:** Converts keypoint data into meaningful spatial and temporal features for analysis.
- **Activity Recognition Module:** Uses LSTM or Transformer models to classify human activities based on motion patterns.
- **Violence Detection Module:** Identifies violent actions by analyzing abnormal movements and interactions between individuals.
- **Output and Visualization Module:** Displays pose skeletons, activity labels, and detection results for monitoring.

b) Development

The development of the system is carried out using modern technologies to ensure efficiency and real-time performance.

The system is implemented using Python, which handles the core processing, model integration, and video analysis tasks. OpenCV is used for video capture, frame extraction, and visualization of detection results. Deep learning models such as YOLOv11 are used for human detection and pose estimation, while LSTM or Transformer-based models are applied for activity recognition.

Computer vision and deep learning techniques are used to analyze human body movements and identify patterns over time. These technologies enable the system to automatically detect human activities and identify violent behavior from video streams. The integration of real-time processing and intelligent analysis improves system accuracy, efficiency, and usability for surveillance and safety monitoring applications.

c) Integration & Testing

After development, all modules are integrated into a single system to ensure seamless communication and functionality. Integration testing is performed to verify that components such as human detection, pose estimation, activity recognition, and violence detection work together without errors. Functional testing is conducted to validate key features including real-time video processing, accurate pose detection, activity classification, and correct identification of violent behavior.

Performance testing ensures that the system operates efficiently under real-time conditions with continuous video input, while maintaining accuracy and speed. Usability testing evaluates the clarity of output visualization, including pose skeletons and activity labels, for effective monitoring. These testing processes help identify and resolve issues, ensuring that the final system is reliable, efficient, and suitable for real-world surveillance applications.

4. Evaluation & Optimization

Evaluation and optimization involve analyzing the performance of all modules within the proposed system. This includes measuring the accuracy of human detection, evaluating pose estimation precision, analyzing activity recognition performance, and validating the effectiveness of violence detection. The system is tested on various video inputs to ensure reliable identification of both normal and abnormal human behaviors.

The system performance is assessed based on detection accuracy, classification accuracy, processing speed, and real-time responsiveness. Pose estimation is evaluated based on the correctness of keypoint detection, while activity recognition is analyzed based on the model's ability to correctly classify actions across different scenarios. Violence detection is evaluated by measuring how accurately the system identifies aggressive movements and interactions.

Optimization techniques are applied to improve overall system performance. These include fine-tuning deep learning models such as YOLOv11 for better accuracy, optimizing video processing pipelines to reduce latency, and improving feature extraction methods for enhanced activity recognition. Additional improvements such as efficient memory usage, faster frame processing, and enhanced visualization techniques are implemented to ensure smooth and real-time system operation.

4.1 Machine Learning Approach

The proposed system applies machine learning and deep learning techniques to automate human activity recognition and violence detection from video data. One of the key components of the system is the pose estimation module, which uses advanced computer vision models such as YOLOv11 to detect humans and extract structured skeletal keypoints from images and video frames.

The system processes video input by extracting frames and identifying human body joints such as the head, arms, and legs. These keypoints are then analyzed using temporal models like LSTM or Transformer networks to capture motion patterns across consecutive frames. This enables the system to recognize activities such as walking, running, and fighting with improved accuracy.

In addition to activity recognition, machine learning techniques are used to detect violent behavior by analyzing abnormal motion patterns, sudden movements, and close physical interactions between individuals. The system continuously evaluates these patterns to classify actions as violent or non-violent in real time.

By integrating detection, pose estimation, and temporal analysis, the system provides an efficient framework for intelligent surveillance. The combination of deep learning models and real-time processing enables accurate activity recognition and reliable violence detection, ensuring effective monitoring and analysis.

4.2 Dataset Description

The proposed system utilizes a dataset composed of video inputs and image frames for training and evaluating human detection, pose estimation, and activity recognition models. The data includes various human activities such as walking, running, and sitting, along with violent actions like fighting and pushing. Video data is processed by converting it into frames, from which human body keypoints are extracted using models such as YOLOv11. These keypoints are organized into temporal sequences to capture motion patterns across consecutive frames, enabling accurate activity recognition and violence detection. The dataset can be expanded with diverse samples to improve system robustness, and efficient preprocessing techniques are applied to ensure consistency, faster processing, and reliable performance during both training and real-time execution.

5.2 Sequence Diagram

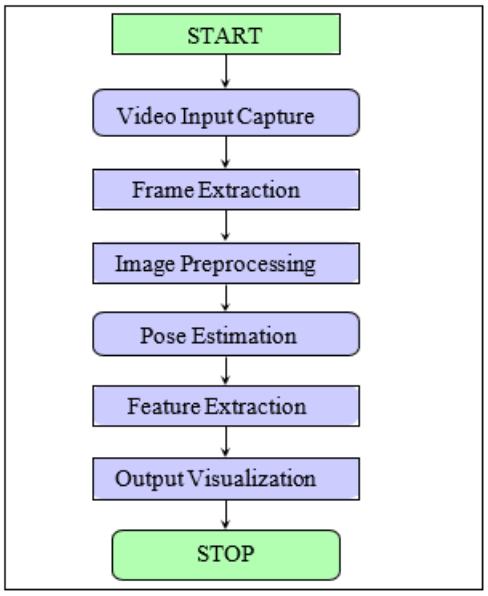

Figure 1: Workflow of Human Pose Estimation System

5. Sequence Diagram

5.1 System Sequence Flow

The sequence diagram illustrates the interaction between different components of the real-time human pose estimation and violence detection system. It shows how video input is processed step-by-step through various modules to detect human activities and identify violent behavior.

The process begins with video input captured from a camera or video file. The frames are extracted and passed to the YOLOv11 model for human detection. Once humans are detected, pose estimation is performed to extract skeletal keypoints. These keypoints are then analyzed to recognize activities and detect violence. If violent behavior is detected, an alert is triggered, and the results are displayed.

Additionally, the sequence diagram highlights the smooth flow of data between each module, ensuring efficient real-time processing and minimal delay in detection. Each component works in coordination to transform raw video input into meaningful insights, improving the system's ability to monitor activities accurately. This structured interaction between modules enhances reliability, scalability, and responsiveness, making the system suitable for real-world surveillance and safety applications.

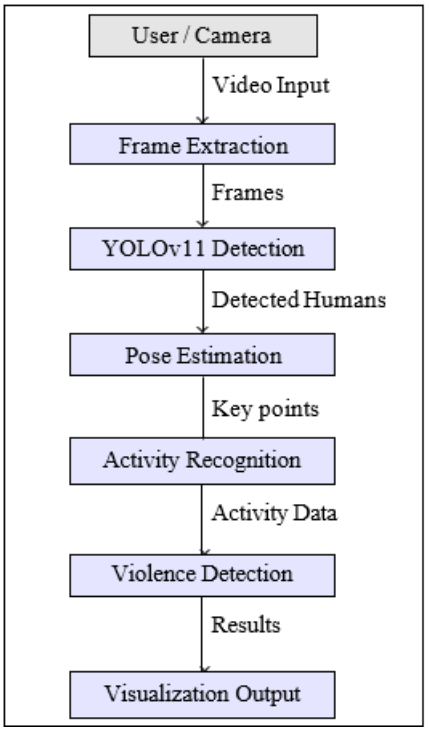

Figure 2: Vertical Sequence Diagram of Human Pose Estimation and Violence Detection System

The sequence diagram represents the step-by-step interaction between different components of the real-time human pose estimation and violence detection system. It begins with the user or camera providing video input to the system. This video is processed by the frame extraction module, which converts the continuous video stream into individual frames for further analysis.

These frames are then passed to the YOLOv11 detection module, where humans present in the frame are identified and localized using bounding boxes. Once the humans are detected, the pose estimation module extracts key body points such as joints and limbs, forming a skeletal representation of each person. This structured representation helps reduce background noise and focus only on human movements.

The extracted keypoints are then forwarded to the activity recognition module, which analyzes movement patterns over time to classify actions such as walking, running, or fighting. Temporal analysis using models like LSTM or Transformers enables the system to understand motion sequences rather than isolated frames, improving accuracy.

Based on this activity data, the violence detection module evaluates whether the behavior is normal or aggressive by identifying sudden movements, abnormal posture, or intense interactions between individuals. If violent behavior is detected, the system can trigger alerts or flags for immediate attention.

Finally, the results are sent to the output visualization module, where the detected activities, pose skeletons, bounding boxes, and alerts are displayed to the user in real time. This sequence ensures a continuous and efficient flow of data between modules, enabling accurate monitoring, quick decision-making, and reliable detection

of human activities and violent behavior in dynamic environments.

6. Result & Discussion

6.1 System Performance

The proposed system demonstrates strong performance in real-time human pose estimation and violence detection using video data. It effectively detects human presence, extracts skeletal keypoints, and analyzes motion patterns to classify activities such as walking, running, and fighting. By leveraging deep learning techniques, the system is able to accurately distinguish between normal and abnormal behaviors with minimal human intervention.

The pose estimation module efficiently identifies key body joints using advanced models such as YOLOv11, enabling precise analysis of human posture and movement. The activity recognition module further processes these keypoints over time using temporal models like LSTM or Transformers, resulting in improved classification accuracy. The violence detection module plays a crucial role by identifying aggressive actions and unusual interactions between individuals, ensuring reliable detection of potentially harmful situations.

The overall performance of the system is enhanced through the use of Python and OpenCV, which support efficient frame processing, real-time visualization, and seamless integration of different modules. The system maintains high responsiveness even with continuous video input, and its modular design ensures scalability and smooth operation. These features make the proposed system highly effective and suitable for real-world applications in intelligent surveillance and public safety monitoring.

6.2 Test Cases and Outcomes

The system was tested under various scenarios to evaluate its functionality, accuracy, and reliability in real-time environments. Multiple test cases were conducted to verify the performance of each module within the system.

The human detection and pose estimation modules successfully identified individuals and extracted body keypoints from different types of video inputs, including live camera feeds and recorded footage. The pose estimation module, implemented using models such as YOLOv11, demonstrated high accuracy in detecting keypoints, although slight variations were observed in challenging conditions such as occlusion, low lighting, or crowded scenes.

The activity recognition module was evaluated using different human actions such as walking, running, and fighting. It effectively classified most activities by analyzing temporal motion patterns derived from skeletal keypoints. The violence detection module was further tested with scenarios involving aggressive behavior and close interactions between individuals, where it was able to identify violent activities with good accuracy and consistency.

The output visualization module was also tested to ensure proper rendering of bounding boxes, skeletal structures, and activity labels in real time. The system maintained smooth visualization without significant delays, even with continuous video streams. Overall, the test results confirm that the system performs reliably across various conditions and provides accurate, consistent outputs, making it suitable for real-time surveillance and safety monitoring applications.

7. Comparison Analysis

A comparison between traditional surveillance systems and the proposed system highlights significant improvements in efficiency, accuracy, and automation.

Criteria	Traditional Method	Proposed System
Monitoring	Manual Surveillance	Automated Detection
Response Time	Delayed	Real-Time
Accuracy	Moderate	High
Automation	Not Available	Fully Automated
Human Effort	High	Low
Violence Detection	Difficult	AI-Based Detection

The traditional surveillance approach depends heavily on manual monitoring, which is inefficient and prone to missed events. In contrast, the proposed system leverages deep learning techniques such as YOLOv11 for human detection, pose estimation, and violence classification, enabling a fully automated and intelligent surveillance framework.

The integration of real-time processing and pose-based analysis significantly enhances the system's ability to detect abnormal activities accurately and respond immediately. This makes the proposed system more reliable, scalable, and suitable for modern smart surveillance applications.

Performance Analysis

To further analyze system performance, a graphical comparison was created based on observed values obtained during system testing.

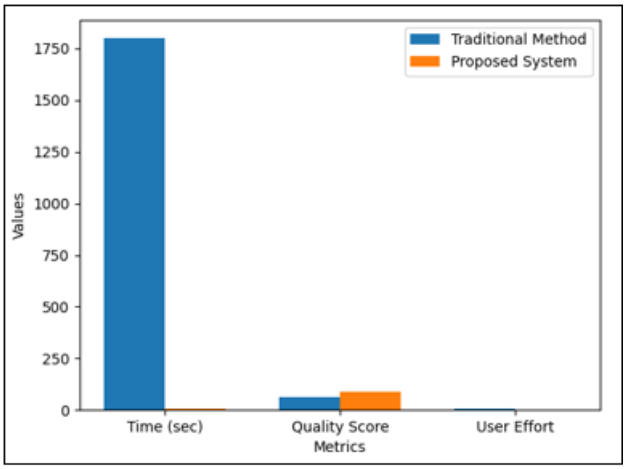

Figure 3: Performance Comparison of Traditional Surveillance and Proposed System

The graph clearly shows that the proposed system significantly reduces response time and improves detection efficiency compared to traditional manual surveillance methods.

8. Conclusion

The proposed system presents an effective and intelligent solution for real-time human activity recognition and violence detection by automating surveillance and behavior analysis processes. The system successfully integrates deep learning techniques to detect humans, estimate body pose, and analyze motion patterns, thereby reducing dependency on manual monitoring and improving accuracy.

By processing video input in real time and extracting skeletal keypoints, the system provides a structured approach to understanding human behavior. The integration of pose estimation using models such as YOLOv11 and temporal models like LSTM or Transformers enables accurate classification of activities and reliable detection of violent behavior. This enhances the system's capability to monitor dynamic environments effectively.

The system demonstrates reliable performance across different modules, including human detection, pose estimation, activity recognition, and violence detection. The use of technologies such as Python and OpenCV ensures efficient video processing, scalability, and smooth system operation.

Overall, the proposed system highlights the potential of combining computer vision and deep learning techniques to improve surveillance efficiency, enhance safety monitoring, and reduce human effort. It represents a step toward intelligent and automated monitoring systems, paving the way for future advancements in AI-based behavior analysis.

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