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Smart Elderly Activity Recognition and Fall Detection Using Machine Learning

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Abstract—The rapidlyincreasing elderly population and the need for their healthcare monitoring systems made a fall detection an important topic for research. Falls are one of the major causes of injury and death in elderly people. Especially the patient with the mobility impairments. Immediate assistance after fall can significantly improve the timely first aid and increase the survival rates. Traditional monitoring systems heavily rely on manual observation or wearable devices, which are not that convenient and prone to failure.

This paper proposes a real-time human fall detection system that uses a deep learning approach that combines spatial feature extraction and temporal sequence modelling. The system uses YOLOv8 for accurate human pose estimation which extract 17 key points of human body form video input. These key points are analysed by Machine Learning Model and passed into a Long Short-Term Memory (LSTM) network to capture and classify human activities into three states which are Normal, Falling, and Fallen.

The proposed architecture design includes backend which uses FastAPI and real-time streaming capabilities, and with a responsive frontend dashboard built using NextJs. The system has an intelligent alert mechanism that triggers Alerts via SMS, voice calls, and email upon detecting a fall event. The experimental results show that the system performs well, giving high accuracy, quick responses (low latency), and reliable performance in correctly differentiating between actual falls and normal daily activities. This work helps in building reliable, scalable, and real-time healthcare monitoring systems that can be used effectively in practical scenarios.

Keywords—Fall Detection, YOLOv8, Pose Estimation, LSTM, Deep Learning, Real-time Monitoring

I. INTRODUCTION

Falls are major risk mostly for older people, patients recovering from surgery, and to those with disabilities. According to global health data, many injuries in older individuals occur due to sudden falls, and many of these falls happen when no one is around to help them. Getting late assistance after fall is one of the main reasons that can lead conditions like fractures, internal bleeding, or even death.

Existing fall detection methods are manual monitoring by caretakers, wearable sensors. Although wearable devices like accelerometer and gyroscope provide useful data that can be helpful, they mostly depend on the user wearing them and wearing them all time is not possible. Most of the time, elderly people may forget to wear these devices, and that makes it less efficient.

Rapid growth in computer vision and deep learning, vision-based systems are now a strong alternative for detecting a human fall. These systems work by analyzing video feeds to detect human activities, and that too without needing any physical interaction from the user side. Algorithms like YOLO (You Only Look Once) are very improved real-time detection and offer high accuracy and speed. Similarly, temporal models such as LSTM (Long Short-Term memory) help in analyzing sequential data, that helps in identifying the pattern over time.

Main objective of this paper is to develop an intelligent model which detect a human fall by integrating YOLOv8-based pose estimation and LSTM-based temporal analysis. The system not only detects persons fall but also automatically alert registered user when fall occur. Using a web-based dashboard this can be easily operated. This makes it ready for real-world use.

II. LITERATURE REVIEW

In the last few decades fall detection has been widely studied using different methods, such as wearable sensors and visionbased systems

A. Wearable Sensor-Based Systems

Wearable devices have accelerometer, gyroscope, and pressure sensor to detect sudden movement of a person. These movements can detect a fall or impact. These systems are comparatively simple and cost-effective but have many limitations:

- Dependence on user compliance
- Battery constraints
- Limited contextual understanding

B. Vision-Based Systems

In this approach cameras are used to observe human activities. Earlier this method used background subtraction and motion detection, but they were easily affected by environmental changes such as lighting noise in surrounding.

C. Deep Learning-Based Approaches

By recent advancement in deep learning, advanced temporal models and special models are increasing and being used for automated fall detection of humans. Models like YOLOv8 model extract features through 2D human pose estimation, and recurrent networks such as LSTMs analyze these biomechanical patterns over time to find patterns. Hybrid approach that is combining these techniques shows highly promising results, for example:

- YOLOv8-Pose for high-performance, real-time 2D skeletal tracking (extracting 17 keypoints).
- PyTorch-based LSTM networks for sequential action recognition over a sliding temporal window.

However, challenges still exist in terms of:

- Real-time processing
- False alarm reduction
- Deployment scalability

The proposed system addresses these challenges by integrating YOLOv8 and LSTM in an optimized pipeline, utilizing strict machine logic (requiring a "FALLING" to "FALLEN" transition).

III. PROBLEM STATEMENT

Even with the available advanced technologies, existing fall detection systems face several limitations:

- High false-positive rates
- Lack of real-time responsiveness
- Limited integration with alert systems
- Inability to distinguish between similar activities

The main objective of this research is to design a system that:

- Detects human falls in real time with high accuracy
- Minimizes false alarms using temporal analysis
- Provides instant alerts through multiple channels
- Supports real-world deployment with scalability

IV. PROPOSED METHODOLOGY

The proposed system is made up of multiple components that work together to achieve real-time fall detection.

A. System Architecture

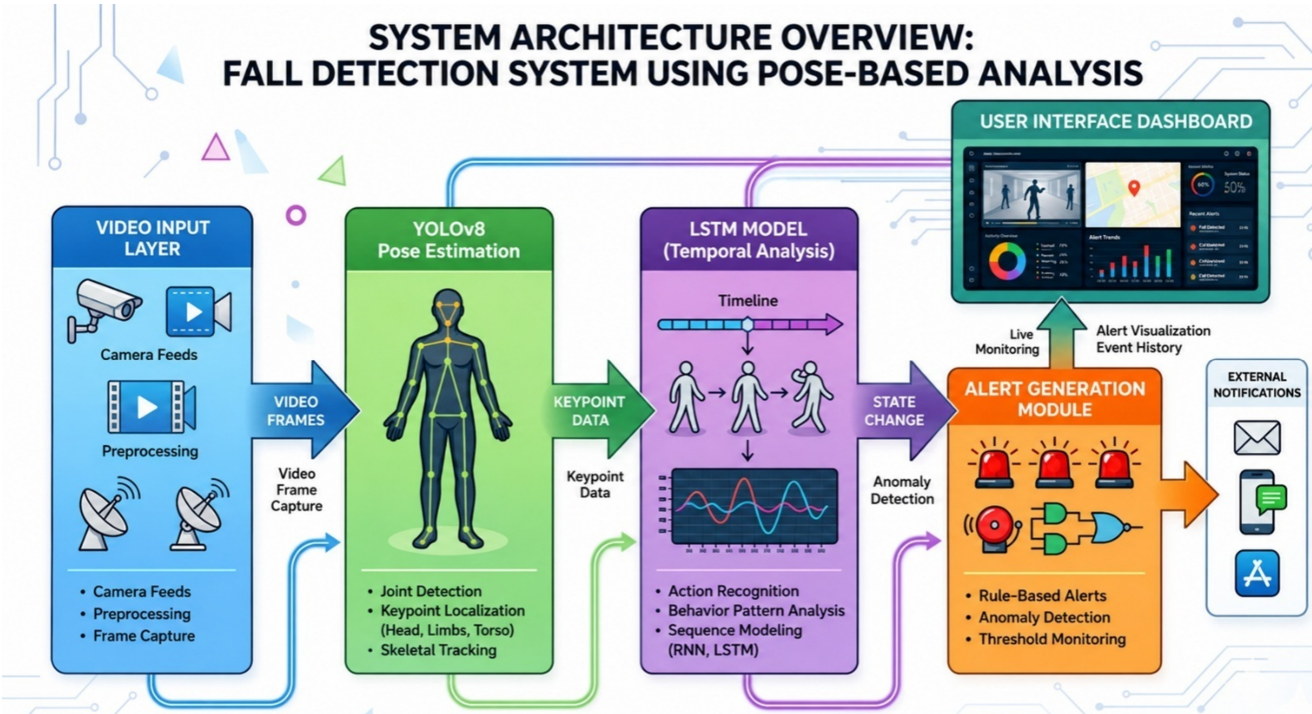

Fig. 1 System Architecture of Fall Detection

- Video Input Layer -takes the video from CCTV.
- Pose Estimation Module – Check for the body pose
- Temporal Analysis Module – Analyse the movement and transition of the pose.
- Alert Generation Module - Generates Alert when matches the condition of Fall.
- User Interface Dashboard - Can check the live feed of camera, check alarm, turn system On/Off, cancel the alarm.

B. Data Acquisition and Preprocessing

The system is mainly designed to work with standard CCTV system for continuous real-world monitoring. For testing validation and demonstration purposes data can also be taken from pre-recorded video dataset or from webcam feed of computer. Video data is captured through dedicated VideoStreamer thread and frames are extracted continuously which is handled by OpenCV to avoid any bottleneck in the pipeline. In preprocessing these frames are passed through YOLOv8-Pose model in real time.

C. Feature Engineering

Extracted key points goes through several steps:

- Pose Estimation: Each frame processed by YOLOv8-pose in real time to extract 2D coordinate for 17 structural key points.
- Key point Normalization: Extracted key points are centered and scaled. This make sure model focus strictly on movement patterns and not the subject size or physical position within frame.
- Temporal Windowing: The normalized data is put into a sliding sequence(15 frames per second) to prepare for temporal classification.

D. Temporal Deep Learning Model

The LSTM model then analyzes sequences of these key points, and learns motion patterns over time for classifying the action of human into three categories:

- Normal: sitting, walking, standing, etc.
- Falling: The transitional phase of a fall.
- Fallen: The final state (person on the ground).

The model architecture includes:

- Input Layer (Keypoint sequences)
- LSTM Layers (Temporal learning)
- Fully Connected Layer
- Softmax Output Layer

E. Decision Logic

A state machine is implemented to track transitions: • Normal
→ Falling → Fallen

- Alerts are triggered only when a valid sequence is detected, reducing false positives.

F. Alert and Notification System

The system integrates multiple communication channels:

- Email notifications with captured images
- SMS alerts using APIs
- Automated voice calls

V. IMPLEMENTATION AND EXPERIMENTAL SETUP

The system's backend is built using Python with FastAPI handling requests efficiently with low latency. OpenCV is used for continuous video processing, while YOLOv8 and PyTorch handle the pose estimation and sequence classification of machine learning. For real time communication, Websocket is used that handles things like sending system status as active, waiting and unavailable, also confidence score of models.

For frontend Next.js is used which is styled with Tailwind CSS. In frontend users will be able to see live video feed along with real-time detection results of fall. The development process includes data extraction from frames, model training, testing, Alert generation using SMS, Call and Email, and System integration.

VI. RESULTS AND DISCUSSION

The proposed system performs well in real-time fall detection and alert generation. The system achieved an accuracy of approximately 92% on the trained dataset, which demonstrate effective performance. By combining pose estimation with temporal modelling improves accuracy and reduce the false alarm. The use of asynchronous processing also helps with smooth video streaming and analysis.

The system works well in normal conditions, but it can face issue in situations like poor lighting, occlusion, or when multiple people are present. These limitations of models show some areas where improvement can be made in near future with better datasets which will have more of these edge cases so the model can become more accurate and model optimization to reduce false positives.

VII. CONCLUSION

Overall, this paper presents a reliable fall detection model that works in real time by using deep learning techniques. The combination of human pose estimation and temporal modeling improves the accuracy and reliability of this system. It is scalable, efficient and suitable for real world healthcare applications. It also provides quick response through multiple automated alert options that make it more reliable, making it useful for elderly care and monitoring vulnerable individuals who require constant watch.

VIII. FUTURE WORK

Future Improvements include:

- Edge deployment on IoT devices
- Multi-person tracking
- Integration with healthcare systems
- Mobile application

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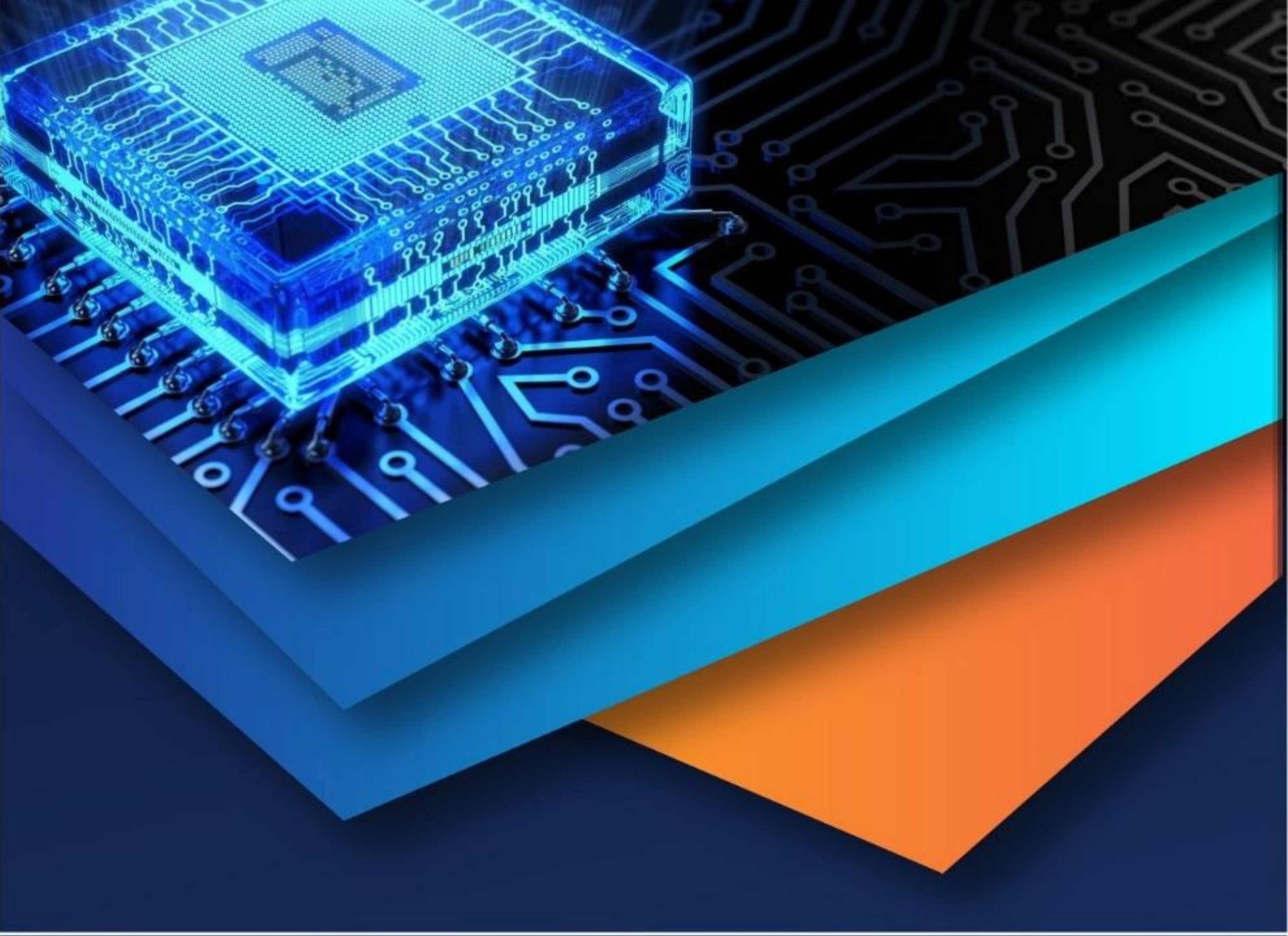

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