Problem Statement

PS-07 Innovative Monitoring System for TeleICU Patients Using Video Processing and Deep Learning

Unique Idea Brief (Solution)

Project Overview:

This project aims to enhance the monitoring and safety of ICU (Intensive Care Unit) patients through advanced computer vision techniques. The solution comprises two main components:

1. YOLO Model for ICU Patient Detection :
    - Developed and trained a YOLOv8n (You Only Look Once) a machine learning model which involves three key stages: training, validation, and testing datasets. to detect and identify the presence of ICU patients within the camera frame.
2. Motion Detection and Alarm :
    - Implemented a Python-based system (using openCV) for motion detection to monitor and track patient movements.
    - This system is used to identify unusual or potentially critical movements, such as a patient falling off or attempting bed exits without assistance by generating an alert alarm mechanisms to notify the health care professional for immediate intervention.

The process involves captures video frames at 60 fps, detects people by categorizing them into classes of 0-patient, 1-doctor and 2-fam_member, activates motion detection when the patient is alone, and visualizes motion areas with bounding boxes.

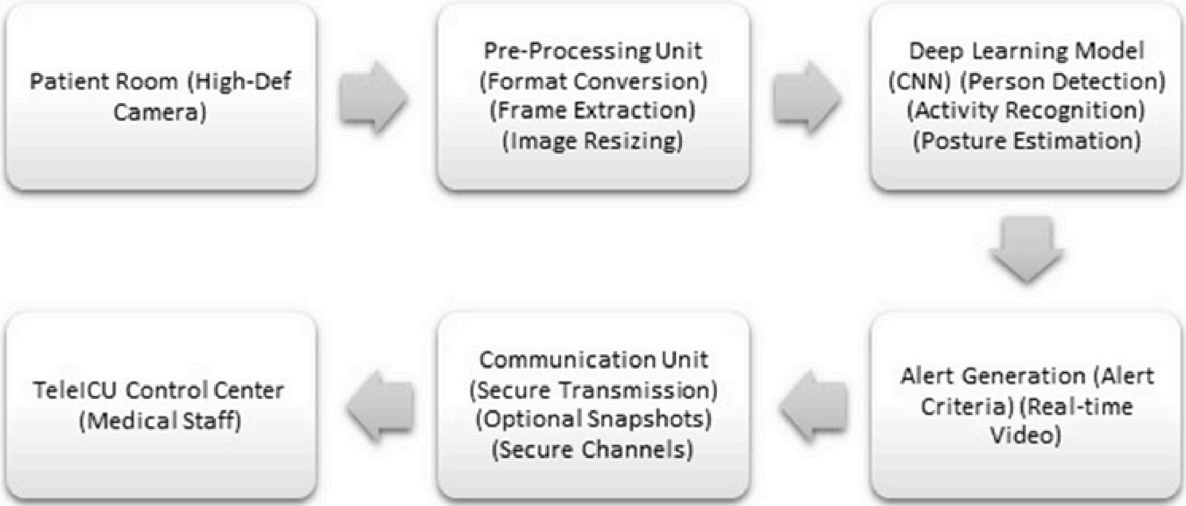
Features Offered

1. Enhanced Patient Monitoring: Utilizes a YOLOv8n model to accurately identify ICU patients, doctors, and family members providing real-time detection of patient which optimizes remote monitoring.
2. Conditional Motion Detection: Conditional motion detection ensuring focused monitoring on the patient’s movements in critical situations, reducing workload on remote healthcare professionals.
3. Real-time Alerts: Improves patient safety which provides timely alerts of critical patient events to medical staff and health care professions for quick life-saving intervention.
4. Integration and Scalability: Seamlessly integrates with existing hospital monitoring and alert systems, designed for scalable deployment across various hospital environments with minimal modifications.
5. Operational Efficiency: Automates the detection process, reducing the need for manual surveillance and allowing medical staff to focus on patient care, thus improving overall operational efficiency and resource utilization.

Process flow

1. Initialization:
   - Start video capture from the camera or video feed.
   - Load the pre-trained YOLOv8n model and configure detection parameters.
2. Frame Acquisition:
   - Continuously capture video frames from the camera.
3. YOLO-based Detection:
   - Operate the YOLOv8n model on each frame to detect and classify individuals (patients, doctors & family members).
4. Analyze Detection Results:
   - Identify if the patient is attended or unattended along with the presences of doctors or family members.
5. Conditional Motion Detection:
   - Activate motion detection if the patient is alone.
   - Deactivate motion detection if doctors or family members are present.
6. Motion Detection of Patient when alone:
   - Compute the absolute difference between consecutive frames to identify changes.
   - Pre-process the frame by converting it to grayscale and applying Gaussian blur filter.

Architecture Diagram



Technologies used

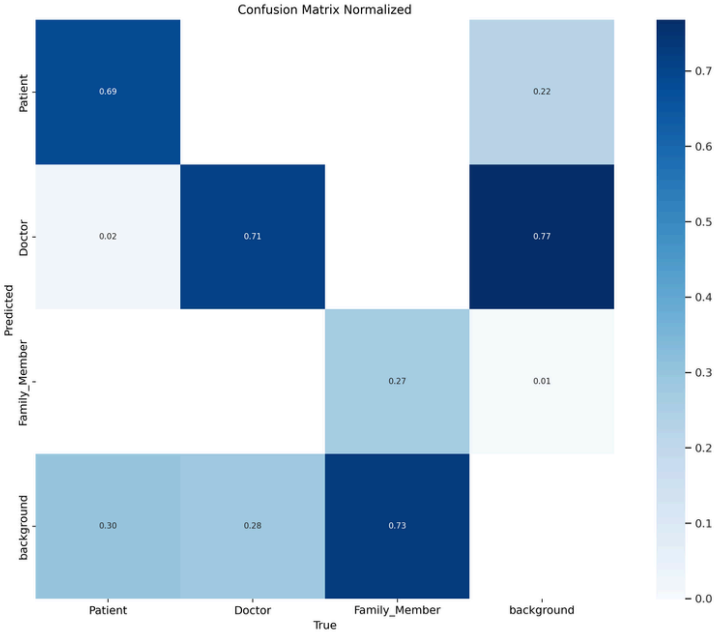
1. Python Libraries:
    - Utilizes libraries such as NumPy, TensorFlow and Ultralytics yolo to handles image data and calculations for custom models.
2. Computer Vision Libraries for video processing:
    - OpenCV: Used for image and video processing tasks, including frame acquisition, preprocessing (grayscale conversion, blurring), and contour detection for motion detection.
3. Deep Learning Frameworks:
    - YOLO (You Only Look Once): Utilizes the YOLOv8n model for real-time object detection to identify ICU patients, doctors, and family members in video frames.
4. Data Annotation Tools:
    - LabelImg/OpenLabeling: Used for annotating training data to label different individuals (patients, doctors, family members) in the collected dataset for YOLOv8n model training.

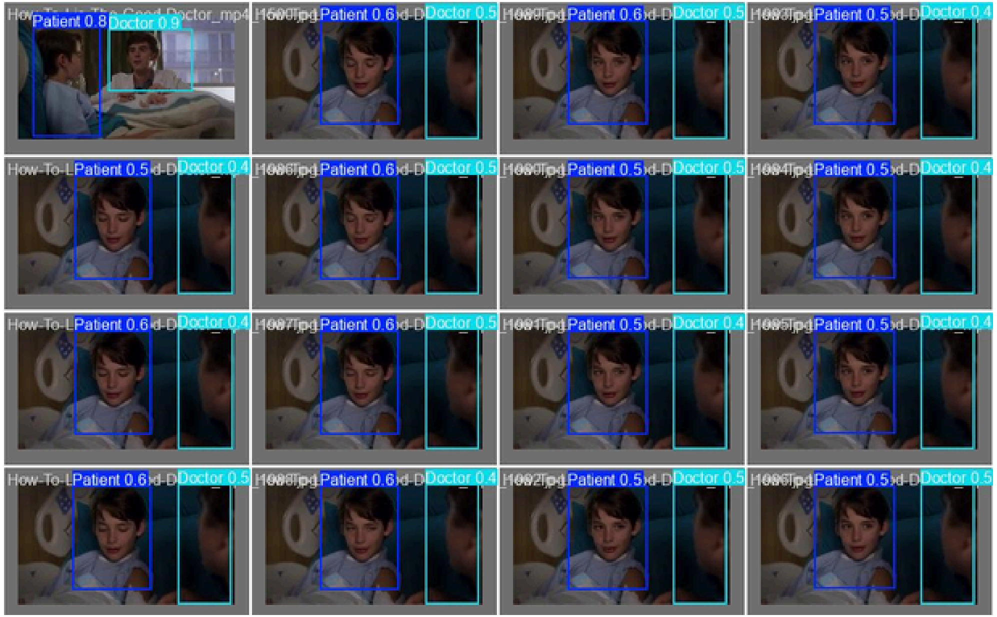
Results and Discussions

The model's training process shows a increasing trend in box, classification, and less difficulty losses over epochs, indicating improvement.

The confusion matrix reveals strong performance for the "Patient" class and significant relation between "Doctor" and "Family Member". The precision-confidence suggests higher precision indicates better leading to model accuracy at identifying correct objects. The precision-recall curves demonstrate varying performance across classes, with "Patient" showing the highest precision. The overall mAP@0.5 threshold suggests better and accurate performance of the model.
Recall measures the model's ability to correctly identify positive instances, hence higher recall indicates better performance in capturing all relevant objects.

Results and Discussions





Team members and contribution

Team Name : Codies
Team Members: Chinmay Sanjay Mahulikar and BS Keerthi

We as a Team have significantly contribute to the project by developing and refining the YOLOv8n model for patient detection. This project is designed and implemented using the Python-based motion detection system, integrating the computer vision model along with the camera. To enhance the system, we’ve additionally developed an alert system with user interface, collected and analysed data to improve model performance and trained machine learning algorithms for recognizing movement patterns and anomalies.

Conclusion

This project significantly advanced our expertise in video processing, deep learning, and system integration for medical applications. We successfully developed a robust, scalable TeleICU solution prioritizing data privacy and ethics. While demonstrating promising results in object detection and initial validation, ongoing refinement of the motion detection model is crucial for comprehensive TeleICU patient monitoring.

A YOLOv8n model was effectively trained on a dataset comprising patients, doctors, and family members. Through extensive training, validation, and testing, the model demonstrated superior performance in patient detection and movement tracking. These accurate results significantly enhance patient safety monitoring, providing invaluable insights and reducing the burden of the healthcare professionals.