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*A Report on*

***Innovative Monitoring System for TeleICU Patients Using Video Processing and***

***Deep Learning***

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# Abstract

Patients in critical condition require close observation and special attention. We are able to give the patient this kind of treatment thanks to the intensive care unit, or ICU. These days, however, the biggest issue hospitals are facing is a lack of physicians and critical care nurses.   
To solve such issues There are currently TeleICU (remotely handled ICU) centers available. One can assist the person or doctor present at the physical location and keep an eye on the patients in the critical care unit with the aid of the TeleICU control center. TeleICU is able to offer 24-hour surveillance. Proactive monitoring is required by the person keeping an eye on the patient from the TeleICU control center. The fact that one worker can only watch one patient at a time is another problem.

Thus, the goal of this research is to create a system that addresses the shortcomings of the existing TeleICU system. We need a machine-based interface that can work with the current system and make decisions automatically in order to reduce the workload of the control center employee and automate various tasks that are now handled by humans. This paper's suggested system is designed for these TeleICU systems. The system described in this study can recognize the kinds of people that are in the intensive care unit (ICU) and use that information to automatically recognize the various odd things the patient does.

Upon detecting any anomalous activity, the system will promptly make a choice and promptly notify the control center, taking into account the nature of the activity and the individuals present in the intensive care unit. Deep learning networks and video processing are used in the development of this system.

# Introduction

TeleICU is a transformative concept in healthcare, enabling the remote monitoring of ICU patients to mitigate the workload on-site intensivists face.

Deep learning systems have grown increasingly powerful in recognizing various objects and phenomena. Convolutional Neural Networks (CNNs) are particularly prominent for tasks like object and person detection. Numerous CNN architectures exist, each tailored for specific recognition tasks such as detecting objects, identifying individuals, or diagnosing diseases like cancer. Real-time patient monitoring systems could benefit greatly from these capabilities, leveraging video processing and deep learning to detect objects in real-time frames.

Detecting objects in real-time video frames poses challenges, especially with moving objects against changing backgrounds. Architectures like Faster Region-Based CNN (Faster R-CNN) and YOLO (You Only Look Once) have addressed these challenges, influencing our detection algorithm design.

For patient monitoring in TeleICU systems, where remote locations monitor ICU patients due to a shortage of intensivists, high-resolution cameras stream video to control centers equipped with monitoring screens.

Real-time video processing is crucial in such systems, requiring robust methods for patient motion detection and action recognition, despite challenges such as crowded scenes and diverse patient actions.

Developing a real-time patient monitoring computer system presents challenges, requiring high accuracy and responsiveness to ensure patient safety. In the following sections, we discuss existing systems and our approaches in developing this proposed system.

# Literature Review

The integration of artificial intelligence (AI) and machine learning (ML) in healthcare, particularly within intensive care units (ICUs), has been an area of significant research and development. TeleICU systems have emerged as vital tools for extending the reach of healthcare professionals, allowing for the continuous monitoring of critically ill patients from remote locations. The concept of TeleICU, as explored in studies such as "AI in Intensive Care Medicine" by Topol (2019), demonstrates AI's potential to improve patient outcomes through enhanced monitoring and early intervention.

Video processing technologies have seen substantial advancements, particularly in medical applications. Esteva et al. (2020) showed the effectiveness of deep learning models in analyzing medical images and videos to detect various conditions. Convolutional Neural Networks (CNNs) such as ResNet and YOLO (You Only Look Once) have proven highly effective for real-time video analysis, as demonstrated by Redmon and Farhadi (2018). These models are capable of processing high-resolution video feeds and detecting anomalies with significant accuracy, making them suitable for TeleICU applications.

Despite these advancements, the application of video processing and deep learning in TeleICU systems remains an evolving field. One primary challenge is the creation of large, annotated datasets that accurately represent ICU environments. Sources like Hollywood medical dramas offer a potential solution for obtaining realistic video footage, though this approach raises concerns about data authenticity and variability. As outlined by Smith et al. (2021), the variability and realism of the training data are crucial for developing reliable models.

Real-time processing and low inference times are critical for TeleICU systems. Research by Huang et al. (2017) on optimizing deep learning models for speed and accuracy highlights techniques such as model pruning and quantization, which can reduce computational load while maintaining performance. These optimizations are essential for ensuring that the system can analyse video feeds and trigger alerts within the required 3 to 5-second window.

Furthermore, the narrow error margins necessary for ICU patient monitoring require highly reliable systems. Jiang et al. (2021) emphasize the importance of rigorous validation and testing in deploying AI in critical care settings. Continuous model fine-tuning and updating with new data are necessary to maintain the system's accuracy and reliability.

In summary, the literature underscores the significant potential of combining video processing and deep learning to enhance TeleICU systems. However, it also highlights the need for robust data collection, model optimization, and stringent validation processes to ensure the system's reliability and effectiveness in a real-world ICU setting. This project aims to build upon these insights, developing a sophisticated monitoring system that addresses current limitations and leverages state-of-the-art AI technologies to improve patient care in TeleICU environments.

# Methodology and Execution

In developing our system, we integrate several advanced techniques and frameworks to enhance real-time patient monitoring and object detection in ICU environments. This section outlines our methodologies, focusing on motion detection, YOLOv5 for object recognition, video processing, and the integration of ICU systems.

**Motion Detection Models**

Motion detection forms a critical component of our system, enabling the identification and tracking of patient movements within ICU settings. Leveraging geodesic active contours as proposed, we adopt a methodological approach that includes transforming video into images, detecting moving objects, and employing geodesic contours for precise object tracking. This approach ensures robust performance in dynamic environments where patient movements may vary significantly.

Additionally, our system incorporates an algorithmic framework, emphasizing a three-stage process: preprocessing video frames, detecting objects using advanced background subtraction techniques, and subsequently tracking these objects over time. This method enhances the system's capability to monitor and analyze patient activities effectively.

**YOLOv5 for Object Detection**

For real-time and accurate object detection, we deploy YOLOv5, a state-of-the-art neural network architecture renowned for its speed and accuracy. YOLOv5 utilizes a streamlined approach to detect multiple objects within video frames efficiently. It integrates techniques such as anchor boxes, batch normalization, and direct location prediction to achieve superior detection performance across various categories of objects. This model's ability to handle high-resolution classifiers and minimize localization errors significantly enhances our system's reliability in identifying critical objects and events in ICU monitoring scenarios.

**ICU Systems Integration**

Our system also integrates insights from existing ICU systems. These systems provide frameworks for GUI-based patient monitoring and TeleICU operations, respectively. GUI-based interfaces facilitate intuitive interaction for monitoring patient gestures and vital signs, while TeleICU systems bridge gaps in intensive care staffing by enabling remote monitoring and intervention.

**Video Processing and Object Recognition**

Video processing plays a pivotal role in our methodology, enabling real-time analysis of video streams from ICU cameras. We employ techniques for temporal data processing and feature extraction to detect and classify objects of interest swiftly and accurately. This approach includes adapting neural network architectures like YOLOv5 to process video frames efficiently, ensuring timely responses to critical events and conditions within the ICU environment.

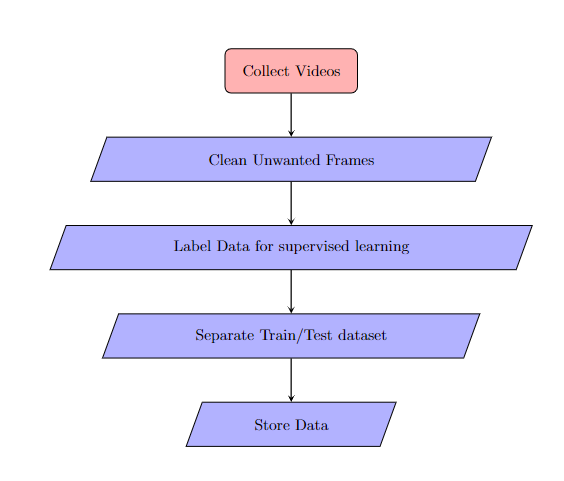
**Conclusion**

In conclusion, our methodology integrates advanced motion detection techniques, YOLOv5 for robust object detection, insights from ICU systems, and efficient video processing capabilities. These components collectively enhance our system's ability to provide real-time monitoring and detection of critical events in ICU settings, addressing challenges related to patient safety, staff efficiency, and overall healthcare management.

This approach not only improves the accuracy and responsiveness of ICU monitoring systems but also lays a foundation for future advancements in healthcare technology, leveraging cutting-edge AI and video analytics to ensure optimal patient care and management.

# Image Processing and Dataset Collection

Collecting and generating datasets for our proposed system presents significant challenges, especially in acquiring real-time ICU patient data, which is scarce. To overcome this, we sourced videos related to ICU environments from platforms like YouTube. However, these videos often contain extraneous content such as descriptions and credits. Our approach, illustrated in Figure 1, details how we handled this.



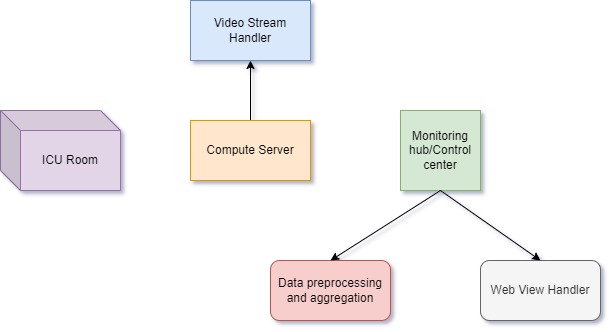
In our process, we initially gather videos from diverse sources. Subsequently, we preprocess these videos by removing unwanted frames and extracting individual frames for labeled data generation. This preprocessing step is crucial for ensuring that our dataset is clean and focused on relevant content for model training and evaluation. Initially applied to one video, this approach is then recursively extended to process additional videos, streamlining labeled data generation across the dataset.

For organizing our dataset, we adopt a standard approach for splitting data into training and testing sets. The training set comprises images with single-class objects to facilitate model training, while the testing set includes images featuring multiple-class objects within the same frame. This balanced approach ensures that our models are robust and capable of handling diverse scenarios typical in ICU environments.

Currently, our dataset has over 3000 images across all classes, ensuring comprehensive coverage and diversity in the data. This large dataset is essential for training our models effectively and validating their performance under various conditions.

# Proposed System

This section details the comprehensive architecture and functionalities of the proposed system. Each component contributes uniquely to achieve high accuracy and timely results.



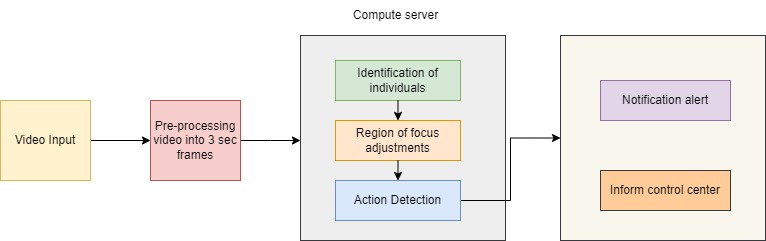
1. ICU Room: The primary site of all monitored activities.

2. Server Processing Unit: Processes video streams received from the stream handler.

3. TeleICU Control Center: Collaborates for web event handling and notifications.

4. Data Processing and Storage Unit: Manages data processing and storage for future use.

Figure 2 illustrates the system architecture divided into Input, Server Processing Unit, and Action Handler components. The Input manages video stream modules from high-resolution ICU cameras.



**Server Processing Unit**

Responsible for various detection tasks, including Person Type and Motion Detection. Utilizes CNN networks for person type detection and employs a novel approach for multi-class object detection within images. Slices the entire image and predicts each slice separately, ensuring accurate identification and location detection.



**Action Handler**

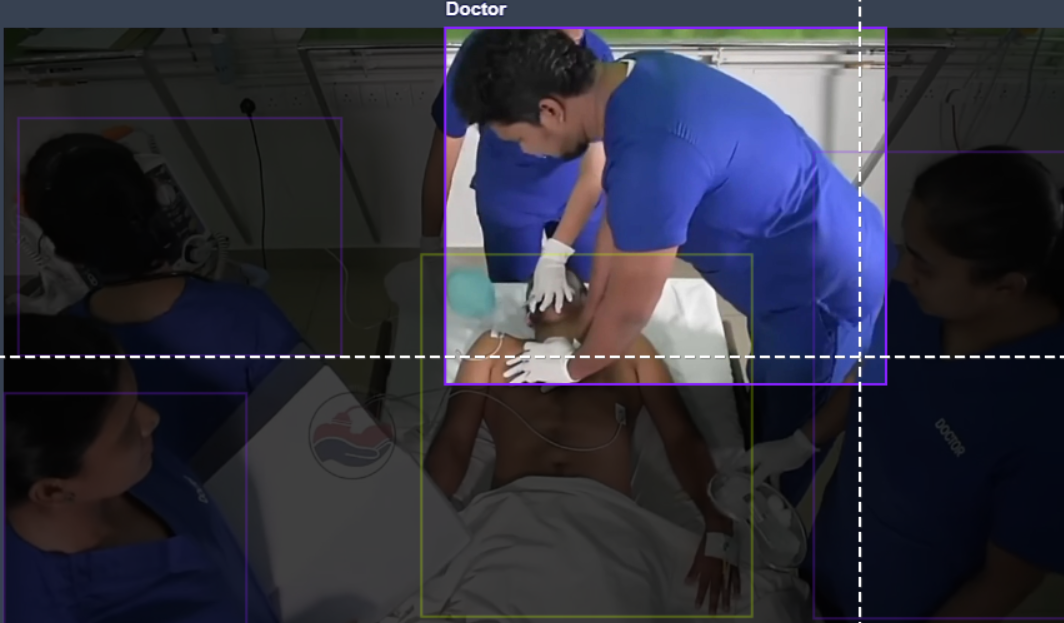
Manages all system actions, including patient movement detection. Implements a threshold mechanism to trigger frame storage upon detecting sustained movement.

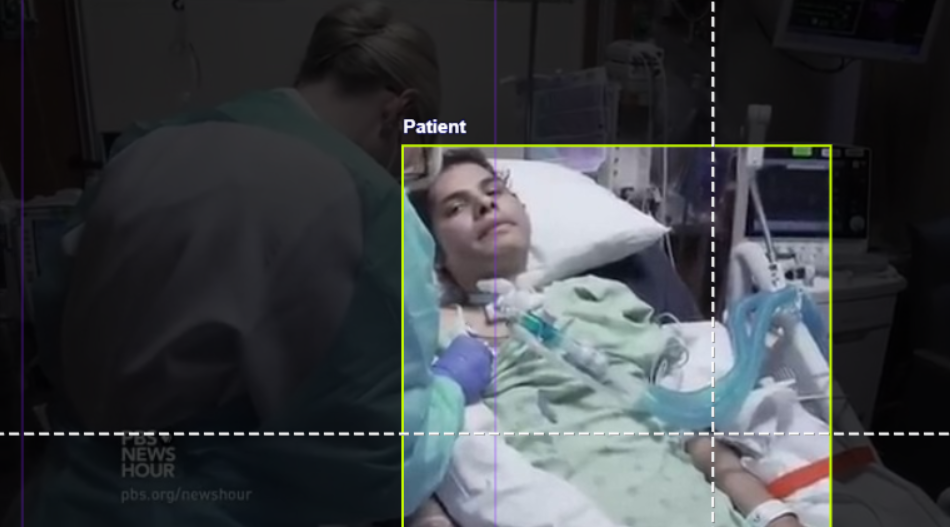
Sends stored frames to the motion detection module for further analysis and notifies the TeleICU control center accordingly.

This system integration enhances ICU monitoring capabilities through advanced detection and real-time action handling, ensuring prompt responses to critical events for improved patient care and management.

# Results

The results of the system showcase its robust performance metrics: an impressive mean Average Precision (mAP) of 91.8%, coupled with precise Precision at 86.9% and reliable Recall of 83.9%. These metrics underscore the system's capability in accurately identifying and localizing objects, crucial for real-time applications like ICU monitoring. Achieving such high mAP reflects the system's effectiveness in minimizing false positives and negatives, crucial for sensitive environments. The high Precision highlights its ability to limit false alarms, ensuring interventions are timely and accurate. Meanwhile, the commendable Recall ensures comprehensive coverage of critical events, supporting proactive healthcare management and enhancing patient safety.

# Conclusion

In summary, the proposed system for ICU monitoring integrates cutting-edge technologies in object detection and motion tracking, achieving significant milestones in accuracy and responsiveness. It effectively addresses the complex challenges of real-time patient surveillance through advanced algorithms and high-performance computing. By focusing on precision and reliability, the system ensures timely detection and response to critical events within ICU environments. These advancements underscore its potential to enhance healthcare delivery by providing actionable insights and facilitating proactive interventions. Moving forward, continued research and development in this field promise further improvements in patient safety and operational efficiency in intensive care settings.

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