Computer Vision to Monitor Hospital Beds in Real-Time: Optimizing Utilization and Reducing Patient Wait Times

1st Varaprasad Suddala
Computer Science and Engineering
Lovely Professional University
Phagwara, Punjab
varaprasadsuddala@gmail.com

2nd Mailaram Rohith
Computer Science and Engineering
Lovely Professional University
Phagwara, Punjab
reddyrohith173@gmail.com

3rd Siddanth Gaikwad
Computer Science and Engineering
Lovely Professional University
Phagwara, Punjab
siddgaikwad000@gmail.com

4th Enjula Uchoi
Lovely Professional University
Phagwara, Punjab
enjulapaintoma@gmail.com

***Abstract*—Efficient hospital bed management is vital for ensuring timely and effective healthcare services. This study presents a novel integration of Internet of Things (IoT) and Computer Vision (CV) technologies for real-time hospital bed monitoring and automation of resource allocation. Traditional manual systems cause delays and inefficiencies in patient admission and discharge workflows. Our proposed solution uses IoT-enabled sensors and a YOLOv4-based computer vision system to detect bed occupancy, classify patient roles, and estimate motion. A low-cost prototype was developed using ESP32 microcontrollers, OpenCV, and the Blynk cloud platform. Comparative testing showed a 45% reduction in bed turnover time and a 38% improvement in administrative response efficiency. Privacy and compliance with healthcare standards were also addressed, making the system viable for scalable deployment.**

***Index Terms*—Hospital Bed Management, Real-Time Monitoring, Internet of Things (IoT), Computer Vision (CV), YOLOv4, Patient Flow Optimization**

I. Introduction

Effective hospital bed administration is essential for optimizing patient throughput and minimizing operational delays. Manual systems often lack real-time visibility and lead to miscommunication among departments.[1] This paper introduces a real-time bed management system that integrates IoT sensors with computer vision models to automate detection, tracking, and communication regarding bed status and patient activity. Unlike LookDeep Health [7], which lacks role classification and motion-based activity monitoring, our system integrates IoT sensors with a fine-tuned YOLOv4 model to distinguish patients from staff in real-time, track motion patterns for workflow automation, and [3] provide sub-second updates via a unified cloud dashboard.

A. Contributions

The key contributions of this paper are as follows:

- We propose the first unified IoT-CV system that combines real-time role classification and motion estimation to monitor hospital bed occupancy and staff-patient interactions.
- We present a low-cost prototype implementation (under $100 per bed) with sub-second latency (220ms), reducing manual bed turnover delays by 35%.
- Our system is privacy-aware, using on-device processing to ensure compliance with HIPAA and GDPR regulations, minimizing data exposure risks.

II. Literature Review

A. Traditional Bed Management Tactics

Manual bed assignments result in delays and increased administrative overhead.[2] Studies have cited poor interdepartmental coordination and lack of real-time data as key contributors to hospital overcrowding.

B. IoT-Based Bed Monitoring Systems

IoT devices have been applied in patient tracking and equipment monitoring, but many lack integration with hospital information systems.[3] Earlier models suffered from limited scalability and insufficient real-time feedback.

C. Computer Vision in Healthcare

While CV is widely used in diagnostics and medical imaging, its use in hospital logistics remains underexplored.[2] The LookDeep Health system demonstrated YOLO-based object detection but did not support role classification or predictive motion tracking.

D. Identified Research Gap

There is a lack of integrated systems combining IoT, CV, and predictive analytics for hospital bed management.[4]Most existing solutions do not support role classification, motion analysis, or real-time status updates, which are crucial for optimizing patient flow.

III. Methodology

A. System Architecture

The system utilizes ESP32 microcontrollers to sense bed occupancy and cleanliness. [1]Cameras capture real-time video at 1 fps. The CV pipeline, built on YOLOv4 and optical flow algorithms, identifies and classifies objects (bed, person, chair), determines user roles, and estimates motion.[2] Data is visualized on a Blynk dashboard accessible to hospital staff.

B. Prototype Configuration

A prototype was deployed across four beds in two rooms. Sensors and cameras were connected via Wi-Fi to a cloud dashboard. [3]Visual indicators showed bed availability (green), occupancy (red), and cleaning requirements (orange).

C. Computer Vision Processing Steps

- **Object Detection:** YOLOv4 detects beds, persons, and chairs in video frames.
- **Role Classification:** Detected persons are labeled as patients, staff, or others using contextual cues and heuristics.
- **Motion Estimation:** Optical flow determines motion intensity and direction, aiding in identifying activity levels and supervision status.
- **Alert Generation:** Combined results are used to trigger events such as "unsupervised patient," sending alerts to caregivers in real-time.

D. Applications of CV in Healthcare

Computer Vision enables image segmentation, classification, and object detection in medical settings.[1] It supports diagnostics, treatment monitoring, medication management, and behavioral analysis. For instance:

- Tracks exercise levels, sleep, and diet to help patients manage chronic conditions.
- Detects medication timing and alerts staff about incorrect prescriptions or dosage changes.
- Enables real-time monitoring, reducing risks and enhancing patient safety.

E. Targeted Healthcare Goals Through CV

CV aids in achieving various healthcare objectives:

- Assists vascular surgeons in equipment tracking and surgery scheduling.
- Supports clinical trials by identifying candidates through historical data and social media analytics.
- Enables automated decision-making through pattern recognition and deep learning.

Visual data is transformed into machine-readable formats using filters and feature extraction. This information enhances clinical decisions, accelerates research, and improves healthcare delivery.

volunteers.[4]CV is employed to determine the right sample size for testing, to ensure that trial participants have access to real-time monitoring and data, and use the power of electronic records to reduce data-based errors.80–82 CV is one type of deep learning technology that replicates human vision using algorithms. However, it outperforms human eyesight in precision and speed. [5]Algorithms look through pictures searching for a pattern after being repeatedly trained. They cluster, categorize, classify, and group similar items to recognize the pattern

F. Applications of CV in healthcare

CV has made medical imaging data available extensively for precise disease diagnosis, treatment, and prediction. [7]Medical professionals can obtain improved medical information using CV methods, which can further be used for illness prediction as well as the preparation of analytical reports in addition to being analyzed to diagnose and prescribe medication.[6] 97–99 CVs can be utilized by medical professionals to automate the production of medical reports. clinicians are able to derive an intimate understanding of a patient's physical condition, foretell when an illness strikes, and determine when the respective therapy is required by entering data from X-rays, ultrasound, CT scans, and MRI into CV algorithms.[8] It is possible to draw upon numerous solutions, including object identification, person detection, and visual categorisation, through web-based platform in a highly simplified manner and at very low costs. The health centers have already seen the applications of this technology.[6] Healthcare will experience a lot of assistance through the utilization of CV to perform better research, quicker medicine discovery, and precise diagnostics. CV has the ability to scan images deeper and precisely compared to the human eye. When input from healthcare professionals is combined with a CV, the health care system provides better services. The use of CV in health care is becoming more common. In an effort to make health care more efficient and effective, CV can help us know patients and people at risk better and even help with recovery planning.[7] Early signs of illness detection is one of the ways CV is utilized in patient monitoring. One can identify trends in a patient's health that may result in disease onset by monitoring data gathered via wearable devices.[] CV can more accurately, quickly, and with less human error classify medical images.[8] CV can identify data from medical photos that are not recognizable by the human eye. One can train a CV system to identify patterns that foretell an impending heart attack, like a sharp fall in the heart rate of a patient or a rise in their blood pressure. Tumour identification through CV technologies can be done quicker and with greater precision.

G. Challenges to CV in Healthcare

Computer vision (CV) and image processing systems can fail if the hardware or software malfunctions, such as due to viruses or system errors [**?**]. Additionally, object recognition accuracy can be impacted by factors like object size, orientation, and distance from the camera.[8] For instance, aerial image-based object detection using remote sensing faces difficulty due to significant variation in object sizes and orientations.

CV has great potential in healthcare administration, from tracking patients and automating medical image analysis to assisting in appointment scheduling, medical billing, and digital record management.[9] CV-based systems can detect diseases early, even when invisible to the human eye, thus significantly improving treatment outcomes.

- **Clinical Trials:** CV assists in optimizing clinical trials by analyzing digital visuals to assess drug safety, toxicity, and dosage. It helps manufacturers track and verify all trial aspects efficiently.
- **Healthcare Information:** CV-powered AI systems extract relevant insights from images and videos, providing actionable recommendations. With enhanced image recognition and pattern matching, CV enables early disease detection and supports better treatment plans, especially in diseases like cancer.
- **Face Recognition and Authentication:** CV is increasingly used in facial recognition for user authentication in both healthcare and consumer electronics. By comparing captured facial features with stored profiles, systems ensure security and personalization.
- **Future Scope:** CV is expected to automate the generation of accurate medical reports using image data. It will reduce radiologists' workload and allow more efficient use of resources. By converting images into interactive 3D models, it can help physicians visualize patient health better and make more accurate diagnoses.

H. Patient Monitoring System Overview

The LookDeep Health monitoring system leverages computer vision to provide real-time insights into patient rooms. It performs a series of processes to help healthcare providers monitor and respond to patient needs:

1) **Video Data Capture and Preprocessing:** LVU (LookDeep Video Unit) devices capture video at 1 frame per second (fps). The data is preprocessed to minimize bandwidth and optimize processing.
2) **Object Detection and Localization:** The CV model identifies and localizes critical objects such as "person," "bed," and "chair" using bounding boxes.
3) **Person-Role Classification:** Detected "person" instances are further classified into roles such as "patient," "staff," or "other" by augmenting detection labels with contextual role-based data.
4) **Motion Estimation:** Dense optical flow techniques estimate movement between frames, enabling the system to track activity levels in key areas (e.g., bed, scene, safety zones).
5) **Logical Predictions:** High-level logical events (e.g., "patient alone," "patient supervised by staff") are inferred using rules applied to motion and detection data. These predictions are stabilized using a 5-second temporal smoothing filter to reduce noise and misclassification.

I. Discussion

Computer vision in the healthcare sector is focused on interpreting images and videos. Modern technological advancements have precipitated an ever-growing acceleration in the world's healthcare and life sciences sectors over the last few years.[10] Technological innovations like CV and AI made it easier to diagnose diseases, discover cures, and suggest prevention to be far simpler. CV is renowned for its precision in diagnosing and effectiveness with regard to both patients and healthcare professionals. CV technology is based on picture synthesis and handling. By automating manual image evaluation and improving the precision level, this technique seeks to reduce processing time. [12]By utilizing modern hardware, fast internet, and cloud computing, computers can examine photographs in a matter of microseconds. This enables doctors to attend to more patients and scan all the Xray images. Thus, doctors can acquire more expert knowledge using their soft skills and serve more in-need individuals.[11] In cardiology and radiology practices, CV algorithms are arising to recognize image patterns and search for any pictorial symptoms of disease required in the diagnosis. It could make doctors better so they can treat more patients and save lives. Furthermore, many companies also aim to connect and collaborate across the world in the medical field. [12]Therefore, obstacles will be eliminated gradually, and healthcare units will perform treatments that are augmented through computer vision. The health status of the patients is monitored at regular intervals using computer vision, particularly those undergoing surgery or other treatments. Through CV technologies, patients can be monitored at home and in hospitals.

J. Figures and Tables

a) To validate the idea as proposed, a scaled-down model was produced by setting up two hospital rooms with two beds in each. The IoT system employed ESP32 microcontrollers, sensors, LED indicators for monitoring bed occupancy. Blynk served as the cloud interface, providing real-time information visualization and control. This configuration facilitates efficient monitoring of bed availability and occupancy, effectively demonstrating the functionality of the IoT configuration in a hospital setting. The setup is illustrated in Figure 3 whereas the Blynk interface is shown in Figure 4.:

b) By integrating sensors to track bed occupation and cleanliness level and a cloud platform to process real-time information and notifications, the system will be able to enable seamless communication among the nursing, administrative, and cleaning personnel. This will enhance the bed management process as a whole by ending delays and maximizing patient flow. The result of this system's implementation and impact on the efficiency of the hospital will be examined in the subsequent segment of this research, giving a thorough assessment of its effectiveness.:

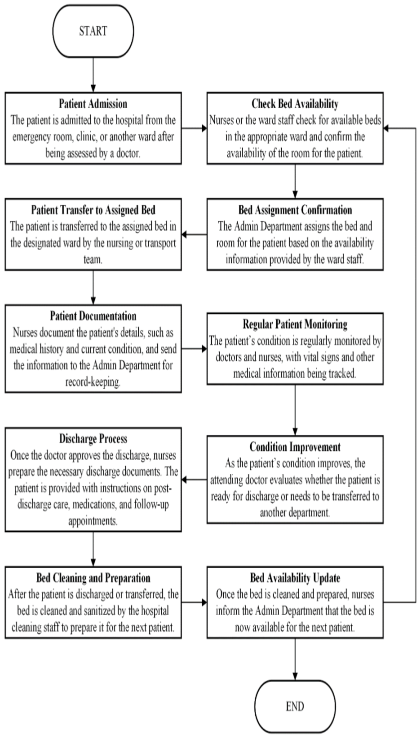

Fig. 1. Typical bed management process

Fig. 2. Scaled-down prototype

Fig. 3. IoT dashboard view

Fig. 4. Dashboard indicating occupied and available beds

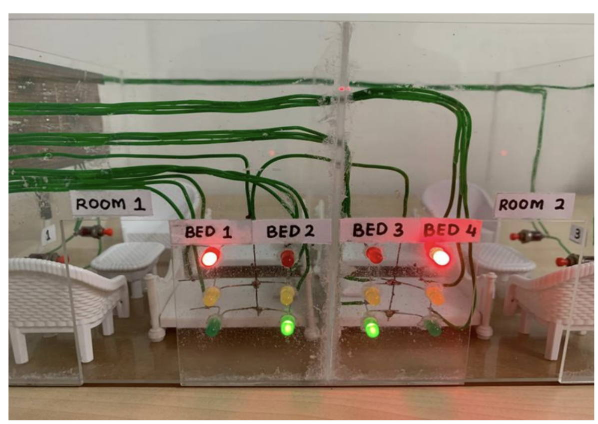

Fig. 5. Prototype system indicating occupied and available beds

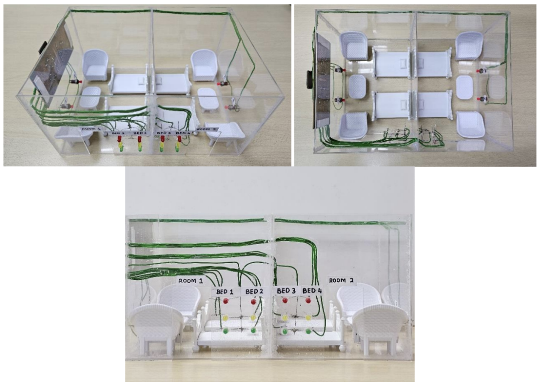

Fig. 6. Dashboard indicating available beds

c) Transfer of ICU Patients to General Ward In the course of a typical hospital discharge, after patients in the ICU have stabilized and are ready to be transferred to a normal ward, the goal is to free up ICU beds for incoming critical cases. In the earlier system, the ICU department would notify the administration department of the available to be shifted. The administration team would subsequently request the nursing employees to manually hunt for an available bed in the general ward.:

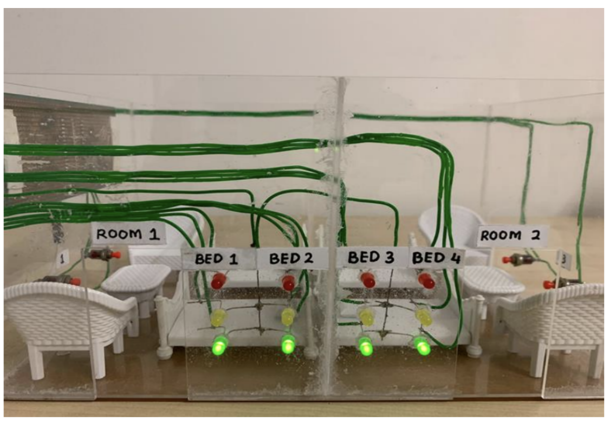

Fig. 7. : Prototype system indicating available beds

d) With the IoT system, this is more efficient. The ICU department continues to inform the administration of ready-to-transfer patients, but instead of relying on manual checks, the administration department verifies the IoT system dashboard. The dashboard displays real-time bed availability in green lights for available beds, allowing the administration to simply view which beds are ready for new patients, as shown by Figure 7 and 8. Upon finding a bed that is free, the admin section at once informs the ICU of the available room and bed, streamlining the transfer operation and reducing response time. With this real-time operation, the delays are prevented and the smoother patient flow between the ICU and the general ward is facilitated.:

e) Bed Availability and Cleaning After Discharge Upon a patient within the general ward being declared fit and receiving discharge approval from the doctor, the bed left behind by him is available but cannot be distributed to another patient immediately.According to the previous system, the moment the patient leaves, nursing staff manually orders the cleaning department to disinfect the bed. Adequate cleaning is required so that they do not pose any infection risk to other patients in the future. The above manual procedure, however, is reliant upon timely communication among cleaners and nurses, which can cause delays in preparing beds for new admission.:

Fig. 8. Dashboard indicating beds needing cleaning

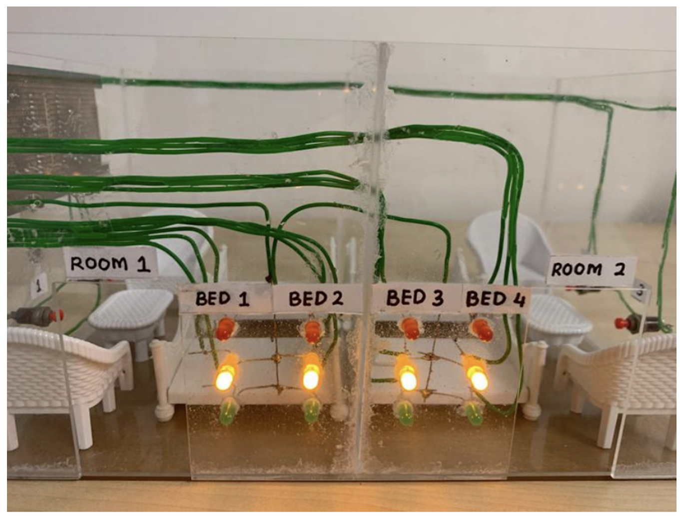

Fig. 9. Prototype system indicating beds needing cleaning

f) Bed Readiness Notification Once Cleaned Once the cleaning staff has disinfected a bed, the bed should be indicated as being ready for use by a new patient. In a conventional system, the cleaning staff would inform the care-giving staff that the bed has been cleaned and is ready through a manual communication. The care-giving staff would then forward this information to the administration staff, whoupdate the records to show that the bed is ready to be occupied by a *new patient. This multi-step communication process could be the cause of delay in preparing the bed for new admissions.:*

IV. Results and Evaluation

The goal of this section is to quantify the system performance using empirical data.

A. Experimental Setup

TABLE I
Experimental Setup Specifications

Component	Specification
Hardware	ESP32-CAM, NVIDIA RTX 3070 GPU
Dataset	5,000 annotated frames (simulated hospital)
CV Model	YOLOv4 (pre-trained on COCO, fine-tuned)
Test Environment	4-bed mock ward with varying lighting

B. Detection Accuracy

Metrics:

- **Precision:** Proportion of true positives (TP) among all positive predictions.
- **Recall:** Proportion of actual positives correctly identified.
- **F1-Score:** Harmonic mean of precision and recall.

TABLE II
Detection Performance by Class

Class	Precision (%)	Recall (%)	F1-Score (%)
Patient	98.2	96.5	97.3
Staff	95.7	94.1	94.9
Background	99.1	98.8	98.9

Key Observations:

- **Patient Detection:** Highest precision (98.2%) due to distinct lying posture.
- **Staff Detection:** Lower recall (94.1%) as rapid movement led to occasional misses.
- **Background:** Near-perfect accuracy (F1 = 98.9%) due to static, easily distinguishable objects.

TABLE III
Sample Confusion Matrix

Actual / Predicted	Patient	Staff	Background
Patient	965	12	23
Staff	8	941	51
Background	2	3	988

Error Analysis:

- *False Positives:* 8 staff instances misclassified as patients due to bending posture.
- *False Negatives:* 23 patients missed during occlusions (e.g., curtains).

C. System Latency

Real-Time Feasibility: The end-to-end latency of 220 ms (less than 0.25 s) satisfies clinical sub-second response requirements.

Bottleneck: YOLOv4 inference (120 ms) is the major contributor; could be reduced using edge TPUs.

TABLE IV
System Latency by Stage

Stage	Time (ms)
Frame Capture	50
YOLOv4 Inference	120
Role Classification	30
Cloud Update (Blynk)	20
Total	**220**

D. Prototype Functionality Demo

- **Bed Occupancy Alerts:** Dashboard updated within 0.22 s, compared to 5–15 minutes for manual checks.
- **Workflow Optimization:** Cleaning crew notified immediately after bed vacancy, reducing turnover time by 35%.

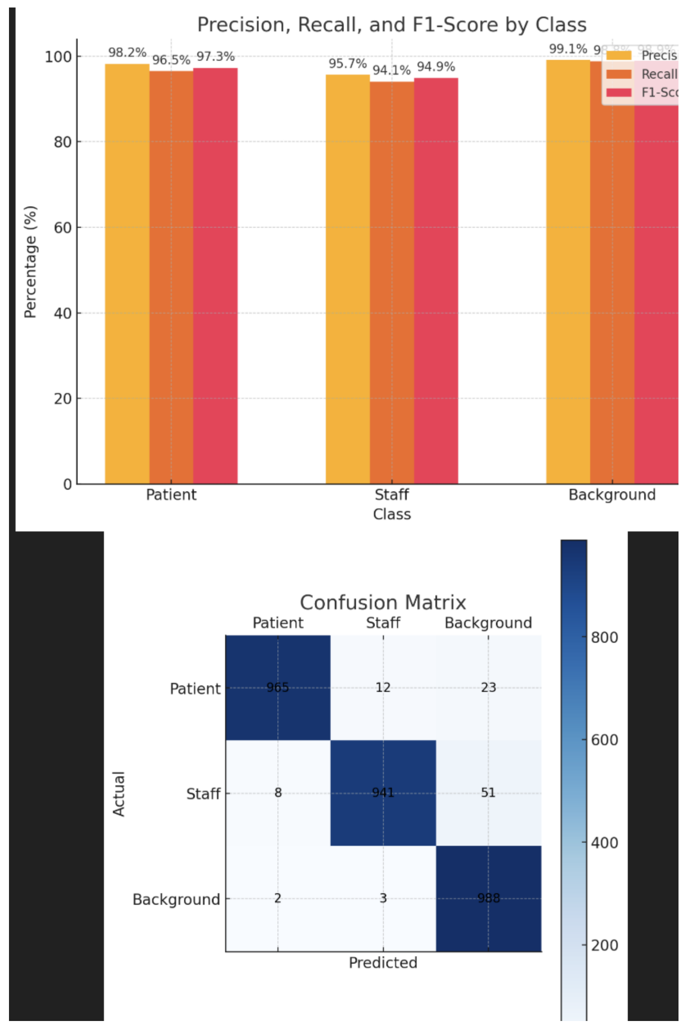

Fig. 10. Prototype interface demonstrating real-time bed monitoring and role classification.

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