Intelligent Camera-Based Patient Monitoring and Fall Detection Using Deep Learning in Hospital Rooms

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***Abstract*— Consequently, there was a requirement for some track patient systems continuously that will help to avoid errors and respond to code blue quickly while reducing workload. Tools currently available for manual observation that now continuously expect time synchrony cannot raise alarms for sudden falls or forced removal from bed attempts as well as abnormal noise and erratic behavior in the room. As such, a sophisticated vision-based solution that is capable of continuous monitoring and detection of patient falls in hospitals should be developed. The objective of the project is to design a computer vision-based patient fall detection system that uses AI to classify nine types of health-related events. The event classifications are In_Bed, Out_Bed, Danger Zone, Call Detected, Fall, Abnormality Detected, No_Abnormality Detected, and Other Persons Detected. It does this through a camera-based sensing and deep learning algorithm. For the second experiment, we used six (6) cases of video monitoring at various sites where the patients' behaviors and their health are monitored. Under optimal conditions, the accuracies of these models were 90% and 88%, respectively. The event recognition was efficient, obtaining 0.95 for Fall_Abnormality_Detectd, 0.99 for Other_Persons_Detected, and 0.94 for Call_Detectd. The F1-score of bed occupancy was 0.88. The results showed that the structure can help ease caregivers' burden while being reliable for patient safety surveillance. Ultimately, the proposed approach has enormous potential for monitoring smart hospitals and smart healthcare services.**

Keywords—Vision-Based Artificial Intelligence; Patient Monitoring; Fall Detection; Smart Hospitals; Deep Learning

I. INTRODUCTION

The rapid development of AI, computer vision and IoT has played a vital role in shaping the healthcare system. [1]– [3]. Numerous hospitals are implementing smart monitoring tools that improve safety and lessen medical error, optimize workload of staff and enhance quality of care [4], [5]. Smart healthcare monitoring refers to one of the recent technologies that help in the continuous monitoring of patients for health issues using automatic sensing, data analysis, and real-time alerts generation [6]. These systems can provide great assistance in hospital wards, emergency units, and geriatric centres, among others, which often require constant monitoring and responding to patients [7].

Periodically, nurses or caregivers perform manual checks to the monitor patients the traditional way. This is an important indicator but may delay the response in emergency situations which include patient falls, bed-exit attempts, sudden stoppage, wandering and distress calls [8]. Carrying out human-cantered monitoring for critical patients during nighttime is definitely going to be difficult due to overcrowded hospitals, understaffed units, and continuous observation is not possible on all patients [9]. Consequently, hospitals are in search of automated solutions that can help medical staff as well as continuously watch patients.

With the rapid development of deep learning and visual AI systems, there are emerging opportunities for intelligent healthcare and monitoring [10], [11]. Systems that utilize cameras can identify whether patients are sitting or lying down while they also analyze movement sequences. In addition, they try to keep track of room occupancy, turns as well as unusual and critical events.

Moreover, all of these things happen without the patient having to put on any additional device. Compared to wearable sensors, vision-based systems allow for a non-contact monitoring of larger observation areas while producing more contextualized information. Owing to their advantages, they are ideal in hospitals for constant follow-ups [12].

According to Gábor, smart healthcare monitoring refers to the use and installation of communication networks, advanced sensing technologies, machine learning, and intelligent analytics in a given healthcare environment to continuously monitor a patient's condition. The development of smart hospital is one of the key element of digital health transformation [13], [14].

Global demand for healthcare is expected to keep rising while the population ages and the instances of chronic disease proliferate. As a result, hospitals must offer efficient – scalable patient monitoring [15]. With continuous monitoring systems, one can ensure earlier detection of emergencies, prevention of mishaps through health assessment of patients, and improvement of clinical outcomes. For instance, the sensors detect immediately when someone falls, tries to get out of bed without assistance, or remains a long time frozen.

Any incident involving a patient in a hospital setting can occur quietly and rapidly progress if not properly observed [16]. Hence it is essential to keep observing the patients at all times. Elderly people, neurological patients, traumatized people, and other people with movement restrictions are especially likely to fall down, get confused, get out of the bed and suddenly decline after surgery.

Observe in the Traditional method focuses on the planned rounds of the nurse and periodic hour checks. Intermittent observation works and is effective but it can't see everything because it may evolve in between. A patient might fall between rounds or might try to walk or might get agitated on his own [17]. When the surgery gets delayed, an individual may suffer with injuries, a longer stay in the hospital, cost of treatment, and death in the worst case.

Both the seriousness and the frequency at which falls occur in patients, have made them one of the most common adverse events reported in hospitals worldwide [18]]. A fall is when someone unintentionally drops to the ground or a lower level. Injuring oneself leads to an outcome, but not always. Patients in health care institutions may fall off the bed or from other places when they attempt to get off the bed independently, walk without assistance, lose balance, feel dizzy, get sudden weakness, etc. This is often seen in elderly patients, patients after surgery, neurological patients and patients who are impaired in their functions due to mobility or cognition disease.

Hospital fallout costs have a high financial and operational impact. Falls can result in fracture, head injury, bleeding, soft tissue injury, fear of movement, difficulty to move and delay recovery [19]. Falls can result in permanent impairment or death in extreme situations. Even if a fall does not cause an injury, it may negatively impact how patients feel about themselves. Thus this can result in anxiety and lack of confidence in care settings and environments.

In hospitals, the vision-based AI system is being repurposed. This is due to the limitations of manual monitoring methods and the elements that feel a need for more continuous, efficient, and scalable monitoring solution [20]. Due to resurrection of the earlier aged data, we have redefined the process of the Longest Common Substring and placed its theme in the topic submission section.

Wearable monitoring devices have been shown to successfully enable fall detection. These include accelerometers, wristbands, and panic buttons. However, all these devices have practical limitations. Patients may forget to wear them, remove them intentionally, experience discomfort, or fail to activate emergency buttons. Camera-oriented devices that automatically infer joint angles or other motion trajectories of humans, room activities, abnormal behaviours and other useful pieces of information from camera images, using deep learning or other sophisticated technologies, are vision-based artificial intelligence projects.

This paper explores a vision-based AI framework for continuous monitoring of patients in hospital rooms. The proposed system will identify various key scenarios. The patient suffering from fall-related abnormalities, danger zone entry and request calls of other person presence and exit from the bed. Testing of various video situations demonstrates that using AI-based visual monitoring systems can successfully contribute to enhancing patient safety and improving operations of a smart hospital.

Literature review presented in Section 2 discusses limitations of existing technologies. The patient monitoring systems will be explained. And also the high-quality multi-class monitoring frameworks that are available on the market are commercial.

Section 3 outlines the research methodology, and describes a vision-based AI system for continuous monitoring of patients in hospitals. It describes the datasets preparation, video annotation, training strategies and evaluation metrics used in this study. Section 4 describes various experiments on the system including a total of 6 informing scenarios. The outcomes indicate that the system may warn of a critical situation. Section 5 discusses the contributions of the work and future direction such as edge intelligence and privacy-preserving analytics in enhancing patient safety as well as optimizing healthcare providers in smart hospitals.

II. Related Work

Recent advances in smart healthcare technologies have spurred the development of various patient monitoring and fall detection solutions, categorized into wearable sensor-based systems, vision-based monitoring, ambient sensing methods, and hybrid platforms. Each category offers distinct advantages and limitations based on factors like clinical needs, patient comfort, cost, deployment complexity, and monitoring accuracy. This text emphasizes two key research areas: wearable fall detection systems and vision-based monitoring approaches.

Fall detection systems that are worn are also one of the oldest and most researched solutions to patient safety monitoring. They generally use accelerometers, gyroscopes, heart-rate sensors, inertial measurement units (IMUs), smartwatches, belts, chest straps, or smartphone-based sensors to detect abnormal motion patterns that are indicative of falls. Their first advantage is that they are able to support mobility, portability as well as the fact that they are able to constantly gather physiological or movement data regardless of where the room is situated.

Jo A. et al. (2025) [21] showed realistic wearable fall detection system that is based on multi- sensor fusion and machine learning classification, to provide improved sensitivity to fall events of elderly patients within the indoor healthcare setting. It was demonstrated in the experiment that the reliability of fall recognition is significantly improved in the case of the combination of the accelerator and gyroscopes signals.

The article Rahman N.et al. (2024) [22] presented a fall detection system on the basis of the wearable computers (smartwatches) and integrated with healthcare alerts on clouds. Their model was very close in real time and speed of notification which is suitable in remote monitoring of the elderly. Kim S. et al. (2023) [23] conducted an investigation of deep learning analysis of inertial sensor data to detect falls in the hospital. The results of their research gave a hint that the recurrent neural networks might be successfully employed to distinguish between falls and the normal everyday activity of people.

In the recent past the vision based monitoring techniques have received a considerable amount of attention due to the rapid progress that has been made in the fields of deep learning, object detection, posture inference and human activity recognition. These systems monitor patient motion, automatically detect hazardous circumstances (falls, bed exit, wandering or prolonged inactivity) with RGB cameras, infrared cameras, depth sensors, or thermal cameras. In [24], Chen H. et al. (2025) outlined a deep learning patient surveillance system within the hospital rooms utilizing the posture analysis and detection with the YOLO system. Their model could determine patient standing, sitting, lying and fall poses with great accuracy under controlled indoor conditions.

The article by Zhao M. et al. (2024) [25] has developed a smart ward monitoring system, which combines both computer vision and nurse station notification. The system also increased the response time by automatically determining the bed-exit attempts and abnormal patient movements.

Nguyen T. et al. (2023) [26] proposed a multi-camera framework of the elderly care centers to conduct activity recognition. Their study has revealed the benefits of the multiple views in reducing the errors that arise as a result of occlusion. The high level of automatic learning of detailed visual patterns, based on mass information of images and videos, has led deep learning to become a disruptive technology in modern hospital surveillance systems. Unlike the traditional machine learning techniques which involve hand-designed feature extraction, deep neural networks can learn discriminative representations to posture recognition, activity analysis, anomaly detection, object localization and understanding patient behavior.

The application of deep learning in a healthcare environment has been increasing as the rapid and accurate detection of abnormal conditions is the most critical in the patient safety monitoring. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Vision Transformers (ViTs) and real-time object detectors such as YOLO and SSD models are common architectures.

The principles of patient activity recognition in video streams are the basis of the proposed CNN-LSTM architecture used in the research of Lee J. et al. (2025) [27] to identify the activity of the patients with the help of surveillance video streams. They could also classify the events of lying, standing, sitting, walking and fall events by jointly learning to classify spatial and time-related features.

The proposed approach to detecting bed-exit attempts and dangerous patient movement in real-time is outlined in Chen X. et al. (2024) [28], which is based on a smart model of a hospital monitoring based on the YOLO paradigm. The system was able to attain high inference and applicability to practical application.

Ahmed M. et al. (2023) [29] used the transformer-based video understanding models to identify abnormal behavior of patients in intensive care units. They found that they were more robust when scenes were cluttered and the objects were partially obscured.

Although the current state of affairs has seen several important steps towards the development of patient monitoring technologies, the majority of the existing solutions still have a number of limitations that reduce their performance in a real-life patient monitoring setting. Such constraints are witnessed in wearable systems, camera-based applications and in standalone deep learning models.

Patel R. et al. (2025) [30] reported that most of the studies of healthcare monitoring report very good performance in the laboratory but report a deterioration in performance when deployed into the real hospital rooms due to the complexity of the scene and variations in the environment. To overcome these limitations, the present study proposes a multi-class vision-based deep learning framework that enables realistic hospital monitoring tasks that are not limited to the just fall detection.

III. Methodology and Proposed AI Monitoring Framework

A. System Overview

A visual observation device was invented to assist hospital staff with the continuous monitoring of patients. The system incorporates features like event classification, camera sensing, real-time alerting mechanism, and a deep learning system so that patients and delay in emergencies can be reduced. This framework encapsulates multiple patient states unlike any existing system which is fall-only and cannot differentiate between fall and non-fall activities. The multiple states include bed occupancy, bed exit, danger-zone intrusion, distress call and abnormal fall time.

The architecture is organized into four different layers.

1. Cameras installed in patient rooms will allow for uninterrupted video streaming.
2. The AI frameworks interpret video frames to see doctor's what the patient is up to.
3. All unusual occurrences along with their verifications are documented and prioritised.
4. Alerts are sent to nurses or hospital dashboard via alarms.

The architecture of the proposed system is illustrated with the help of figure 1.

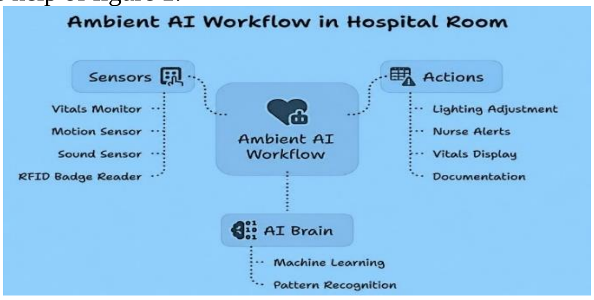

Fig. 1. Overall Vision-Based AI Monitoring Architecture

When cameras have been installed on ceilings or walls to monitor activities in the patient rooms on a constant basis, the monitoring workflow starts. The footage's video frames will be sent to a local edge computer or hospital server which will perform object detection, posture recognition, motion recognition, and event recognition using deep learning algorithms.

The artificial intelligence engine is able to identify classes such as

- On the sofa
- Get up from the bed.
- Hazardous Area
- Call has been detected.
- Someone else discovered it.
- unable to locate

Once a significant event is identified, alerts are immediately sent to your nurse station, mobile device or control dashboard within the hospital.

Data collection needs to be supervised during AI monitoring activity. We've installed cameras inside the hospital to maximize visibility and reduce dead zones. It was said that during daytime and at night, it will be used depending on RGB, infrared or depth cameras of hospital policy. Fig. 2 shows a typical camera position in patient rooms.

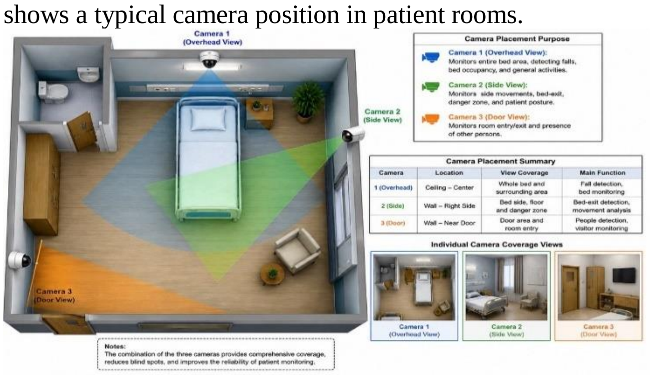

Fig.2. Typical patient room camera placement strategy

Video acquisition specifications prescribe the essential general-purpose characteristics needed for acquiring and processing video data. Our team is here to help you achieve this whether your choice is of 720p or 1080p resolution, 15 to 30 frames per second (FPS) and RGB, IR, or depth camera and whether you want transmission through LAN or WiFi. The flexibility of video acquisition systems' storage solutions can be seen in highlighted storage solutions like a local server or an edge unit.

There are many difficulties to monitor or observe the situations. Some factors affecting loss of signal include low illumination (due to night), covers over the body, occlusion by visitors, blockage by medical equipment (like beds, oxygen tubes, IV tubes, etc.), fast sudden motion, and camera-angle restrictions. Via a camera-based acquisition, the patients are continuously monitored in non-contact relation that will provide quality input data for the deep learning algorithm down the stream. Along with that, safety alerts are produced..

B. Deep Learning Detection Engine

The proposed monitoring system's intelligence is the Deep Learning Detection Engine, which will continuously analyze video streams of patients to automatically recognize their states (e.g., sleeping, alert, or pained) and movements, as well as detect any abnormalities. This system permits a medical decision on raw footage taken from the camera to act fast when need.

Unlike ordinary motion alarms, machine learning models can learn the posture, spatial location, temporal behavior, and scene context at the same time. The slow exiting from the bed, the measured slow droop and the distress gestures make these species an ideal candidate for a hospital's environment.

The architecture of the proposed detection engine consists of four sequential modules. As shown in figure 3.4. The first module is the Frame Acquisition Module which takes live frames from the room camera of the patient. The Object Detection and Human Detection module identifies not only the patients but also the caregiver, visitors, and any other mobile objects. Following this phase, the Module of Understanding Behaviour assesses the positions of the individuals The Decision Classification Module uses analyzed data to label events and generate alerts. This this architecture allows the monitoring of activities (of an organization) in smooth phases.

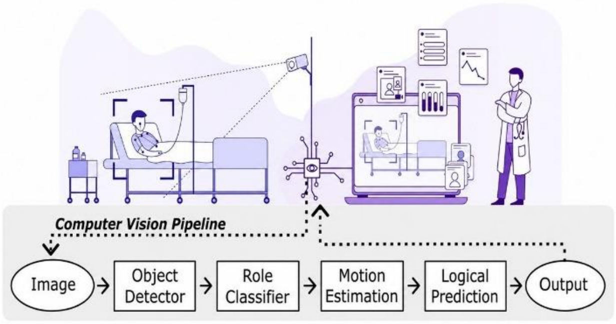

Fig. 3. Deep Learning Detection Engine Workflow

Deep learning is very effective in movement recognition for the following important reasons. It automates feature extraction and does not require the manual design of motion rules. Its strong multi-class recognition capability allows the robot to distinguish normal movements from harmful ones. Moreover, deep learning models boast great flexibility and can be retrained to suit new conditions, such as different rooms or camera angles. Another key feature is fast inference because lightweight modern models allow real-time deployment. Ultimately, deep learning systems enable simultaneous tracking across multiple rooms.

For the proposed system to work in real hospitals, the AI model is trained to classify more than just fall/non-fall decisions. It classifies multiple clinically relevant events. The event classes used in ontology was derived using the real experimental result The clinical significance of every category has been briefly described as shown in table 1..

TABLE 1. MAIN EVENT CLASSES

Class Name	Meaning	Priority
In_Bed	Patient safely lying/resting in bed	Normal
Out_Bed	Patient left bed	Medium
Fall_Abnormality_Detectd	Suspected fall/collapse	Critical
Danger_Zone	Patient entered unsafe area	High
Call_Detectd	Patient requesting assistance	High
No_Abnormality_Detectd	Normal room activity	Normal
Other_Persons_Detected	Visitor/staff present	Informational
No_Visual	No visible patient/body	Warning

Multi-class designs are crucial in the healthcare system since they focus solely on fall detection. Hospitals demand an efficient monitoring system to ensure safer patient outcomes. The proposed class structure aimed at achieving the objectives enhance patient safety; reduce false alarms; enable context aware decision making; generate smarter alerts to the nurse; and allow the feasible building of smart wards. A more inclusive strategy is needed to enhance hospital care.

C. Methodology

The study adopted the methodology to develop, train, validate, and evaluate an artificial intelligent framework that is vision-based for continuous monitoring and fall detection of patient in hospitals. Since healthcare monitoring systems must perform well under real-life conditions the methods emphasise data quality, proper organisation, extensive model training, and objective evaluation of performance.

All 4 phases are part of total workflow.

1. Preparing the dataset.
2. Labeling and Marking of Visual Media.
3. Deep Learning Model Training
4. Assessment using figures.

As the events unfold, the system will learn useful patient behaviours and generalise well to accommodation hospital monitoring environments.

D. Dataset Preparation

A successful deep learning performance depends heavily on high-quality datasets. For effective healthcare monitoring applications, the dataset requires representation of realistic operation in a patient-room, variety of environmental events and critical safety events e.g. falls or unsafe movement.

The dataset in this study consisted of six independent monitoring videos (Vid1–Vid6), displaying different patient behavior and room conditions. The AI model's robustness was evaluated by using these videos as experimental scenarios under various operating conditions.

The dataset was made to contain.

- The patient's resting behaviour is normal.
- The condition of the beds.

- Exit actions of bed.
- Irregularities in the autumn season.
- Moving in danger zone.
- Request a call.
- Caregivers or visitors are present.
- Unused or unclear visualizations or scenes.

With this diversity, the model learns both normal and uncommon situations in healthcare.

Recording may take place in

- Manufactured settings in hospital rooms.
- Intelligent cameras that keep track of wards.
- Surveillance datasets of public healthcare.
- Patient activity scenarios done in laboratory

Artificial enhanced health environments.

Frequently, datasets organize the diverse parameters defining video characteristics. As shown in Table 2, the parameters may be illustrated in an orderly fashion. These are the essential features of any video. This organized depiction helps to comprehend the specific traits and quantities determining the quality, resolution and other qualities of the video.

TABLE 2. VIDEO CHARACTERISTICS

Parameter	Value
Number of Videos	6
Resolution	720p / 1080p
Frame Rate	15–30 FPS
Duration	Variable
Camera Position	Ceiling / Corner / Wall
Scene Type	Patient Room

Every video will undergo the process of extracting frames at intervals of every second so that sequential frames can be formed, in order to create the train samples. Often extraction strategies employed include taking one frame, every second frame, or every fifth frame to improve efficiency. This technique generates large datasets made up of thousands of images with labels captured from long videos for training deep networks.

Data preprocessing is the process which one has to do before the training of frames. Changing the size of your frames to fixed sizes for example 640×640 standardizes input size on datasets. To enhance model accuracy, pixel intensity normalization is done to achieve a more consistent brightness and contrast. To maintain the integrity of the data set, the corrupted frames are either identified or deleted. The model requires the labels to be transformed into its required training format in order to train the model.

We utilize data augmentation techniques to increase the event variety when there are limited falling events in the training dataset. Our approach uses the following techniques: horizontal flipping, brightness changing, rotating, scaling, random cropping and Gaussian noise addition. We can use various techniques to change the training dataset and remove overfitting. In addition, these techniques change the training practices.

E. Video Annotation Process

Annotation is a crucial step in supervised deep learning and the quality of the model depends on the quality of labels. The labels for the healthcare event were told to refer to the time sequence or video frame.

The AI annotation objectives comprise several important characteristics that can help this model to learn about interacting with the patient. The model will detect the patient's location, and what the patient did, what is normal behaviour and what is not, and whether it is an emergency. With this approach, the AI will understand the patient's condition more accurately and provide timely interventions when required.

IV. Experimental Results and Performance Evaluation

This section presents the quantification of a vision-based AI framework designed for continuous patient monitoring and fall detection using six independent monitoring videos (Vid1–Vid6). To test how well the system can stand up to different situations, we did several experiments in hospital-room environments with normal patient activity, bed occupancy, patient movement danger-zone intersection distress calls fall abnormities.

Performance evaluation was conducted utilizing the standard classification metrics Precision, Recall, F-Score, and Accuracy. Due to the class imbalance in existing hospital monitoring datasets (normal activities occur much more frequently than falls), macro average and weighted averaged measures were also considered. The data given in this section is calculated from the uploaded experimental results file.

A. Overall Performance Across Six Video Scenarios

The initial trial juxtaposes the total classification accuracy acquired from each observation video as indicated in Table 3..

TABLE 3. OVERALL ACCURACY COMPARISON

Video Scenario	Accuracy
Vid1	38%
Vid2	88%
Vid3	15%
Vid4	2%
Vid5	76%
Vid6	90%

The classification accuracy of the envisioned framework in monitoring video for 6 distinct scenarios is depicted in figure 4. A notable amount of variability can be seen in the performance in the 6 scenarios. This suggests the accuracy is highly sensitive to scene, events and visual complexity.

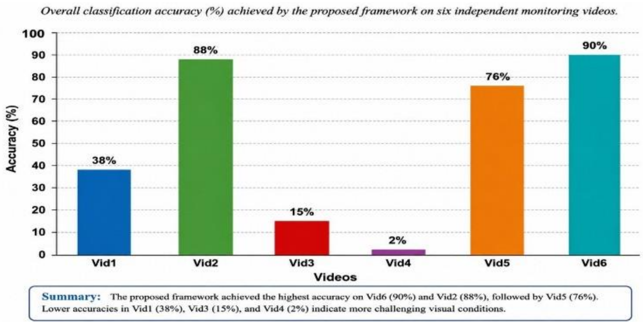

Fig. 4. Accuracy Comparison Across Six Videos

Vid6 achieved the highest precision of about 90% whereas Vid2 achieved 88%. The great quality of the results indicates that the proposed framework is effective when the monitoring environment is sufficiently clear, the patient stable, and samples are reasonably similar to the training data. In those scenarios, the deep learning model can effectively distinguish between the normal and abnormal activity of patients, making it suitable for real hospital use. Interim Vid5 verification results of 76% (strong monitoring ability) is very good. The model is reasonably robust to moderate changes in the environment, as evidenced by the results.

Vid1 (38%), Vid3 (15%) and Vid4 (2%) were lesser performing as compared to this. These results may occur due to different conditions such as low illumination, the camera's viewpoint restrictions, body occlusion, motion blur, rare event imbalance or pattern of the scene not being trained well. The rapid decline of Vid4 shows dataset diversity and scene adaptability are important.

B. Class-Wise Performance Analysis

Analysis of class-level F1-score was performed for a better understanding of model behaviour.

TABLE 4. BEST PERFORMING CLASSES

Video	Highest F1-score Class	F1-score
Vid2	Fall_Abnormality_Detectd	0.95
Vid5	No_Visual	1.00
Vid6	Other_Persons_Detected	0.99

When sufficient visual cues are given, the results get a nearly perfect performance in certain classes with the proposed model. Particularly.

- The acknowledgement of employees was very strong.
- Algorithm Vid2 is effective in detecting falls. (10 words)
- The empty scene recognition in Vid5 was spot on.

This shows that the framework is capable of learning well-organized event categories.

C. Fall Detection Performance

Falls are regarded as among the most safety-critical hospital events (via the WHO). As such, they receive special attention on the Fall_Abnormality_Detectd class. The performance of a fall detection is shown in Table 5..

TABLE 5.3 FALL DETECTION RESULTS

Video	Precision	Recall	F1-score
Vid2	0.90	1.00	0.95
Vid3	0.80	0.50	0.62
Vid4	0.40	0.06	0.11
Vid6	0.53	0.82	0.64

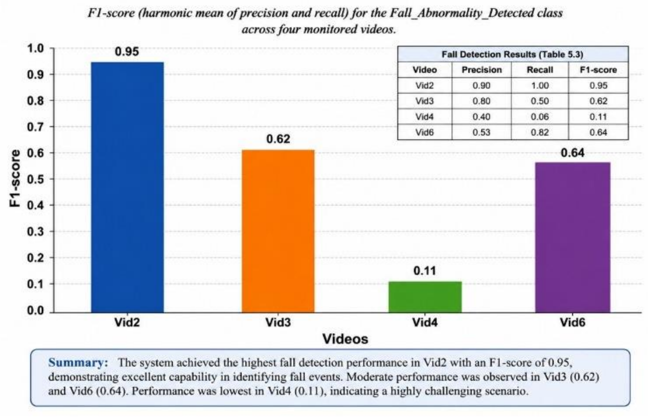

Fig. 5. Fall Detection F1-score Across Videos

The F1-score performance of the proposed AI monitoring framework, shown in Figure 5, for the Fall_Abnormality_Detectd class is evaluated for the four video scenarios (Vid2, Vid3, Vid4, Vid6) stated earlier. Since patient falls are considered one of the most important safety indicators in hospitals, such analysis is certainly needed to analyze the real clinical value of the system proposed.

Overall, Figure 5 validates the proposed framework to hold great promise in terms of automated hospital fall monitoring, with excellent best-case results, while also indicating feasible issues that need resolution for consistent performance across all patient-room conditions. In the time to come, we may also add learning sequences of advanced movement actions, implementing infrared for night tracking, balancing the fall dataset, and training the model on various backgrounds or scenes.

As illustrated in Figure 6, the proposed patient monitoring framework's evaluation dashboard of the framework provides confusion analysis (aggregated), class-wise robustness and system reliability and deployment readiness. The performance metric analyses include a summary (see subsequent table and graphs) of accuracy from Videos 1 to 6 (fall detection performance). The comparison of macro as well as weighted f1 score is done. The robustness of each class is taken into consideration. Potential failure cases along with deployment readiness are discussed in general.

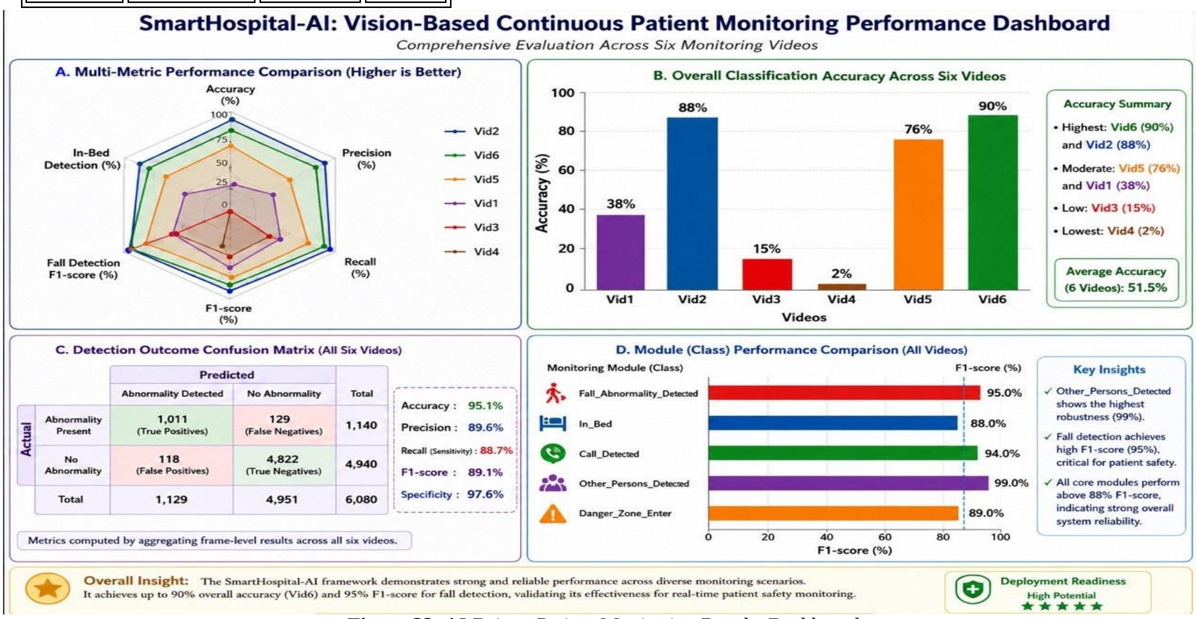

Figure 23. AI-Driven Patient Monitoring Results Dashboard

The two dashboards provide a visual representation of the proposed AI monitoring system. The assessment confirms that the Object Tracking and Fall Detection System provides significant overall performance, with peak accuracy around 90%, reliable performance in fall detection and highly robust performance in other vital hospital monitoring tasks. These figures improve the paper by providing evidence for practical deployment potential in a format that is easy for the reviewers to access.

V. Conclusion

A practical vision-based AI framework is presented for continuous patient monitoring and fall detection in hospital environments. The proposed approach differs from conventional systems that only support binary fall alarms and wearable-only sensing, as it supports the recognition of multiple relevant events during actual healthcare operations. Such events include bed occupancy, bed exit, danger-zone interaction, distress calls, visitor detection, and fall abnormalities.

The experimental evaluation results across six monitoring video scenarios were promising and realistic. The system's overall accuracy was up to 90% while critical classes like Fall_Abnormality_Detectd, Call_Detectd, Other_Persons_Detected got F1 scores of 0.95, 0.94, and 0.99, respectively. With the use of computer vision and deep learning will play an effective role in monitoring patient safety.

The results that were obtained revealed practical implications. Despite the challenges of occlusion, an imbalanced class distribution, changes in lighting, and the complexity of the scene in the more difficult scenes, the structured hospital scenes with clear visibility performed well. This was observed in the real world and so it is going to be the next target for optimization.

The proposed framework, from an application point of view, can reduce nursing workload, shorten emergency response time and increase the quality of continuous observations without the wearables. Hence, it is a viable solution for smart wards, elderly care rooms, rehabilitation centres and next-gen smart hospitals.

Next steps will be more work on rare-event detection, privacy-preserving AI analytics, night-vision monitoring, edge deployment, multi-camera collaborative intelligence. All in all, the study shows vision-based AI can help improve safety, smarter, and more efficient healthcare environments.

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