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An Intelligent Vision-based System for Real-Time Abnormal Behavior Detection in Healthcare Environments

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***Abstract*— Abnormal behaviors among patients, such as falls, sudden collapses, or unusual movements, pose serious safety concerns in healthcare settings and often act as early indicators of medical emergencies. Continuous monitoring is essential, yet traditional systems rely heavily on manual supervision or wearable devices that are uncomfortable, costly, or impractical for long-term use. To address these limitations, this work proposes a low-cost, non-invasive abnormal behavior detection system using deep learning.**

The system integrates USB cameras with a Raspberry Pi running a YOLO-based model for real-time human detection and posture analysis. Upon detecting abnormal activity, alerts are generated through a buzzer, LCD display, and GSM module. The hardware includes onboard memory, communication modules, and audiovisual feedback interfaces. This approach eliminates wearable sensors, reduces caregiver workload, and enables automated monitoring across hospitals, elderly care centers, and home environments. By combining spatial and temporal analysis, the system achieves reliable detection with low power consumption, providing a practical alternative to existing solutions and significantly improving patient safety.

***Index Terms*— Abnormal behavior detection, vision-based patient monitoring, deep learning, YOLO, Raspberry Pi.**

I. Introduction

The possibility of IoT in the healthcare sector is gigantic, and the prospect of constant monitoring of patients and remote control of them is present. The IoT systems can be used to check the chronic diseases and recovery rates with the help of body sensors and other environmental sensors. The future healthcare structure shall involve the optimization of the data stream, which will be facilitated by IoT to support remote healthcare and virtual appointments. Patient safety is one of the main issues in healthcare settings, particularly in the case of the elderly, chronically ill, or post-operative patients who need constant monitoring [1]. The risk of severe injuries is high because of falls, seizures, and wandering, and supervising patients around-the-clock is not an easy task, as it depends on the availability of the workforce and the ineffectiveness of the traditional surveillance solution [2]. Still, manually observed and wearable sensors continue to be popular but are affected by fatigue-induced inaccuracy, inconvenience, calibration error, and emergency lag [3].

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With the increasing complexity of clinical environments, the necessity to switch to automated and intelligent monitoring solutions that can be operated in real time and with little human intervention is increasing [4].
The availability of AI, computer vision, and IoT has facilitated the creation of intelligent vision-based surveillance systems that automatically process the video streams and identify abnormal behaviors [5]. CNN's and RNNs are deep learning models that have the potential to identify intricate postures and movement profiles, triggering warning messages in time in the hospital setting, the home care, the elderly homes, and the rehabilitation centers [6]. Such systems not only guarantee non-invasive monitoring but also lessen the workload of caregivers and facilitate remote healthcare services [7]. The digital healthcare can be transformed in terms of precision and reduced chance of manual surveillance as well as predicted analytics through AI-based surveillance systems [8]. Even the minor changes in the movements of the patients should be regarded as the symptoms of the deterioration of the health conditions that permit preventive measures [9]. The paper proposes a solution of an abnormal behavior detection system on the vision principle in real time utilizing the YOLO algorithm and the corresponding embedded hardware with automated alerts [10]. The following passages will provide the overview of the previous literature, propose the proposed methodology, highlight the integrative mechanisms and conclude with the implications to the actual healthcare deployment.

II. Literature Review

Asif Hashmi et al. [11] have suggested an ICU monitoring system that is IoT-based and uses cheap components like Raspberry Pi and physiological sensors to monitor vital parameters and report alerts to a cloud platform. Although it was useful in minimizing manual monitoring, the system had some difficulties in terms of sensor calibration drift, cybersecurity issues, and lack of large-scale clinical validation.
Gu et al. [12] introduced a multimodal framework of sensing that includes wearable, infrared, Wi-Fi, radar, and vision sensors to detect abnormal behavior in the care of the elderly. Despite the high accuracy, sensor fusion proved ineffective, being computationally complex, consuming more power, and somewhat a privacy threat in addition to being least scalable in real-time.
Ma et al. [13] automated the assessment of Activities of Daily Living (ADL) through CNNs and RNNs and wearable and environmental sensors. The system was able to enhance the accuracy of activity recognition compared to traditional indices, yet needed massive annotated datasets, and was not very flexible to a heterogeneous sensing environment.
Mane et al. [14] designed an ESP8266-based remote patient monitoring system on Arduino and transmitted vital signs using an IoT-based system through a cloud platform. Although telehealth was cost-effective, the use of it was hampered by problems like packet loss, latency, and inadequate data protection to make it usable in the clinical level.
Choudhry et al. [15] conducted a study to investigate the use of two-stream CNNs and autoencoders in detecting abnormal behaviors in surveillance videos. Even though the detection of falls and violent activities was better, there was poor performance in the cluttered environments caused by occlusions and motion blur.
Wang et al. [16] suggested PIR and environmental sensor-based non-visual ambient activity recognition system with the help of a Random Forest classifier. Even though the system was privacy-sensitive, sensor location, room configuration, and false triggering were also sensitive.
Wang et al. [17] presented RF-based camera-free wall-mounted sensing systems that could be used to detect posture and falls. Although these systems were privacy-friendly, they were quite costly and needed to be carefully tuned, as well as being influenced by metal constructions in indoor settings. Patel et al.
[18] developed a multimodal AI model that combines both inertial sensors and camera-based data, and the recognition accuracy is higher with the feature-level fusion. The synchronization requirements, however, added complexity to hardware and real-time processing requirements.
Mehmood et al. [19] proposed a two-stream 3D CNN model using RGB and optical flow for abnormal behavior detection. Although highly accurate, the method was computationally intensive and less effective in crowded scenes.
Arifoglu et al. [20] applied machine learning models to smart home sensor data for detecting cognitive decline. Despite promising results, reliance on labeled datasets and limited interpretability restricted clinical adoption.
The above methods have some recurrent shortcomings, such as reliance on wearable or multi-sensor devices, hardware complexity, requirement to calibrate systems, and power usage in abnormal behavior detection systems. Vision- and RF-based systems have privacy issues, occlusions, and environmental change, whereas cloud-based systems cause latency, security concerns, and untrustworthy alerts. Deep learning models require a high level of computation, which also limits their use on low-power devices in real-time. In order to address

these challenges, there is a need to have a low-cost, non-invasive, edge-based solution, so this work suggests the use of a YOLO-based monitoring system deployed on a Raspberry Pi along with some alert modules, which allows providing real-time, low-latency, and scalable healthcare monitoring.

A. Contributions

- A non-invasive vision-based system of low-cost monitoring is suggested to detect abnormal behavior within a healthcare setting, which requires no wearable sensors or manual oversight.
- A list of the technologies available would include, but is not limited to: |human|>An edge-enabled real-time detection model is built on a Raspberry Pi assembled with a YOLO-based deep learning model, which allows performing efficient on-device inferences at low latency.
- It has a very close alert and communication system that is achieved through the use of GSM, buzzer, and LCD to deliver instant and multi-channel alerts when there is an emergency.
- A scalable and energy-efficient architecture is given, and therefore the system can be applicable in hospitals, geriatric care, and home health care environments.

III. PROPOSED METHODOLOGY

The new framework of monitoring abnormal behavior in geriatric healthcare environments combines computer vision, deep learning, and IoT-based alert systems as a single architecture [21]. The design provides non-invasive, continuous, and automated surveillance based on consumer-grade cameras, giving the opportunity to react to emergencies like falls or long-term immobile state [22].

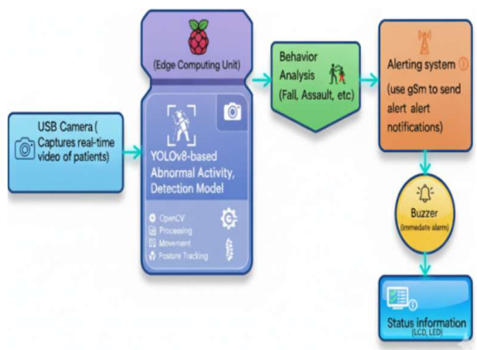


Figure. 1: Proposed Model

Figure 1 (Proposed Model) describes the system, which has two main stages, which include training and testing. Both stages involve preprocessing of the images, features, behavior classification, and alerts generation [23]. The main processing unit is a Raspberry Pi 4B, which is connected to a USB camera, GSM, LCD display, and a buzzer alarm. The Raspberry Pi is used to run the YOLO model (You Only Look Once) and identify and classify in real time the abnormal human activity [24]. The camera captures live video streams, which are processed on the edge device and the GSM module, buzzer, and LCD display issue caregivers with immediate warnings [25]. After booting the Raspberry Pi, the camera loads the YOLO model and starts performing real-time analysis of video frames. Alerts are created instantly on many channels as abnormal patterns are recognized such as falls, immobility, or collapse [26]. All the frames are sent to the Raspberry Pi and preprocessed to ensure consistency. This includes simply scaling frames to 416x416 to make it compatible with YOLO, noise reduction with a Gaussian or bilateral filter, and illumination adjustment with CLAHE when there is low lighting. Normalization establishes the pixel intensities of the same model to have consistency. This preprocessing chain promotes accuracy and reduces the impact of shadows, reflections, and noise.

A. USB Camera and Video Acquisition

The system initiates with a USB camera that captures video streams of the surrounding area of the patient in 720p and 30 fps that is enough to render the space and time definite enough to see motion [27]. Each of the frames is transmitted to the Raspberry Pi where it is processed in a preprocessing fashion, to achieve uniformity. These include resizing the frame to 416x416 pixels to allow YOLO [28], removal of noise by either a Gaussian or bilateral filter [29] and CLAHE to correct the light in low-light conditions [30]. Normalization also causes the pixel intensities to be constant so that the model input is a constant. This pre-processing module boosts accuracy and reduces the impact of shadows, reflections, or noise variation [31].

B. Raspberry Pi: Central Processing and Control Unit

The Raspberry Pi 4B is the heart to process and control the system, which controls the video acquisition, model inference, and communication with peripheral devices [32]. Its ARM Cortex-A72 quad-core and up to 4 GB RAM can be used to make real-time inferences running on both TensorFlow Lite and the Ultralytics YOLOv8 model [33]. Initilaization of cameras, frame capture, detection and execution of the alert and the LCD, buzzer and GSM modules are controlled by Python control scripts and the means through the GPIO pins [34]. The multithreading system architecture reduces the latency time and ensures that the system is operated smoothly [35]. Raspberry Pi has thermal measurement and regulable 5V power to ensure 24/7 reliability in healthcare environment [36].

C. The Feature Extraction and Representation:

In the proposed system, feature extraction is performed using the deep learning model based on the YOLO, and no explicit image segmentation is required. The model will automatically be able to learn spatial features, including human postures, body orientation, and variation of bounding boxes based on video frames. These features vary with the passage of time, comparing normal activities to the abnormal ones such as falls and sedentary lifestyles, among others. This technique makes computationally simpler and is able to identify edge device behavior in real-time.

D. Model Training and Optimization:

Then, the pretrained YOLOv8 model based on COCO is trained on the personal collection of elderly human activities [40]. The dataset has normal (walking, sitting) and abnormal behaviors (falling, collapsing). The image will be augmented with data, rotated, flipped, and the intensity of the brightness will be modified to improve resistance to a wide range of conditions. The hyperparameters that are optimised to increase the detection accuracy are learning rate and batch size. Pruning and quantization reduce the complexity of the models, enabling them to be efficiently run on the Raspberry Pi with minimum quality of detection being reduced [41].

E. Model Training and Optimization

The trained YOLO model works with real-time video feeds during deployment. Every frame is examined in a few milliseconds, and it offers instant detection of abnormal behaviors [34]. The model predicts bounding boxes and the confidence scores, which are judged by decision logic to identify whether the detected activity is normal or requires intervention. A fall, collapse, or long inactivity is detected, and the system automatically switches to the alert mode, thus warranting continuous monitoring and quick response to emergency.

F. Post-Processing and Alert Generation

After an abnormal event is sensed, a multi-layered alert mechanism on the system is activated. The LCD display is a physical sign of a fall detected, whereas the audible alarm is sent to the nearby caregivers by the buzzer [37]. At the same time, the GSM module will send an automated SMS with the type of alert and the time to predetermined contacts [38]. The local and remote alerts package will also provide speed of awareness and does not depend on the proximity of caregivers. The whole alarm process is completed in several seconds to reduce turnaround time.

G. System Integration and Hardware–Software Synchronization:

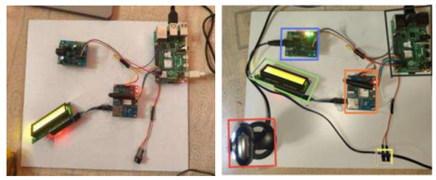
The system combines all hardware and software together by means of synchronized control routines. The camera, GSM module, buzzer, and LCD display are connected to the Raspberry Pi by means of USB and GPIO interfaces, and Python scripts are used to control the flow of data and the logic [39]. OpenCV is involved in handling video streams and TensorFlowLite handles model inference. The GSM communication is managed as a serial protocol. The stable 24/7 operation is equipped with power control and automatic recovery. The scalability of the modular topology gives the ability to monitor more than one patient at a time through any number of cameras or Raspberry Pi units [40].

H. Dataset and Validation

The trained YOLO can be used on real-time video feeds to deploy. Each frame is analyzed within a matter of milliseconds, and it provides real-time detection of abnormal behaviors [34]. The model estimates the bounding boxes and the confidence scores which are evaluated by decision logic to decide whether the identified activity is normal or needs an intervention. A fall, collapse or an extended inactivity is detected, and the system automatically changes to the alert mode hence justifying round-the-clock monitoring and emergency response.

IV. RESULTS

In this section, we will give the findings of the proposed vision-based abnormal behavior detection system in various real-life conditions. The main tasks of the system will be to record constant video streams, transform the streams into frames, and analyze them in real-time with the help of the YOLO-based model running on the Raspberry Pi, and send notifications regarding the critical events only. The outcomes prove that the system is reliable in distinguishing between abnormal and normal everyday activities and creating relevant visual and communication-related notifications.



(a) (b)

Figure. 2 Hardware setup and power initialization of the proposed system.

- Raspberry Pi–based processing and alert modules.
- Complete system integration with camera, LCD, buzzer, and GSM module.

Figure 2 shows the entire hardware configuration that was used in the experiment. After each boot up, the system brings on the camera, processing unit, and alert modules that allow the system to capture videos continuously and monitor the patients in real time. The coordinated structure allows for stable functioning and immediate reaction in the case of the identified abnormal events.

Case 1: Detection of patient self-harm behavior using frame-wise video analysis and YOLO-based classification.

(a) (b)

Figure. 3 Self-harm behavior detection and LCD-based alert indication.

- YOLO-based patient detection and posture analysis from video frame.
- LCD display indicating detected critical self-harm behavior.

Figure 3 shows the detection of patient self-harm behavior using frame-wise video analysis and LCD-based alert indication. The camera records the event when a patient tries to commit suicide in the form of a video stream. Each frame of this video is broken down and identified in order, and the YOLO-based model analyses it. The system identifies the patient subject and assesses changes in posture, the position of limbs, and repetitive abnormal movements between successive frames. According to these visual indicators, it is self-harm. When the confirmation is completed, an LCD displays a self-harm alert, which shows that the critical event had been detected successfully.

Case 2: Sudden posture change and body orientation Fall detection in real time.

(a) (b)

Figure 4 Fall detection and corresponding visual alert on the LCD display.

- Video frame showing sudden posture change detected by YOLO.
- LCD alert indicating fall detection.

Figure 4 shows real-time fall detection based on sudden posture change and body orientation, along with the corresponding LCD alert. A fall scenario will involve recording the abrupt movement of the patient in the form of video data converted into frames, to analyze the image. The system is sensitive to the bounding box of the patient between frames and monitors the fast changes of posture, such as sudden vertical movement and the change of the orientation between the upright and the near-horizontal one. After the identification of such patterns in a short period, the behavior is called a fall, and the LCD presents a message of Fall.

Case 3: Identification of abnormal patient behavior through posture instability and motion irregularities

Figure 5: Abnormal behavior detection and LCD status indication.

- Video frame showing irregular patient posture.
- LCD display indicating abnormal behavior status.

Figure 5 shows the identification of abnormal patient behavior through posture instability and motion irregularities. In the case of general abnormal behavior, the video of the patient captured is recorded frame to examine the stability of posture and continuity of motion. The prolonged lack of movement, the change of the position irregularly, or the unstable orientation of the body in several frames are defined as the deviation from usual activity. The system identifies such conditions as abnormal behavior and changes the LCD display to indicate the state identified.

GSM-based SMS notification generated for critical patient abnormal events.

Figure. 6 GSM-based SMS alert notification for critical abnormal events.

Figure 6 shows the GSM-based SMS alert notification generated for critical abnormal patient events. The GSM module is activated when the behavior of critical patients, including self-harm, falls, or extreme abnormal activity, is detected. To predetermined contacts, an SMS notification with the information about the event is sent. This finding proves effective remote notification only in high-risk cases of the patient.

Case 4: Differentiation of sitting in a stable position and with fewer motion patterns.

(a) (b)

Figure. 7 Sitting activity detected as normal behavior with LCD display output.

- Video frame showing stable sitting posture.
- LCD display indicating sitting activity as normal behavior.

Figure 7 shows the detection of sitting activity classified as normal behavior with LCD display output. In a sitting activity, the camera records the video of the patient and transforms it into frames depicting a sitting stable position. YOLO model identifies similar bounding box sizes with low motion difference. As the behavior is similar to the normal patient activity, the system recognizes the behavior as sitting and indicates the status on the LCD and does not make the alerts.
Case 5: Normal standing activity is detected according to the consistency of upright posture.

(a) (b)

Figure. 8 Normal standing activity detection and LCD status display.

- ➢ Video frame showing upright standing posture.
- ➢ LCD display indicating normal standing activity.

Figure 8 shows the detection of normal standing activity based on consistent upright posture. In the standing case, the system takes the video frame of the patient that has an upright posture with insignificant changes in the time frame. The behavior that has been detected is considered to be normal standing, and the status is reflected on the LCD without the activation of the buzzer and GSM warning.
Case 6: Running activity was classified with the aid of repetitive motion patterns and upright posture.

(a) (b)

Figure 9 Running activity classification and LCD-based activity indication.

- ➢ Video frame showing running motion detected by YOLO.
- ➢ LCD display indicating running activity.

Figure 9 shows the classification of running activity using repetitive motion patterns and upright posture. In the case of a patient who is running, the video stream records fast movements of limbs and higher motion intensity. The frame-wise examination reveals the regular upright posture and patterns of movements. Although the level of movement is increased, the system properly categorizes running as a normal activity, and the visual signal is displayed only on the LCD.
Case 7: Response of the system in case there is no patience in the field of view of the camera.

Figure. 10 No patient detected scenario with LCD display output.

Figure 10 shows the system response when no patient is present in the camera's field of view. In an environment where no one even exists in the picture through the inside of the camera, the frames taken do not have any valid human identifications. This scenario is identified by the system as a no-patient situation and instructs the LCD to suit this, i.e., it does not generate false alerts when the system is not in operation.

Overall, the findings indicate that the suggested system is successful in capturing real-world video data, conducting real time analysis, and correctly classifying normal and abnormal patient behaviors as well as producing alerts when an extreme situation occurs. This shows how reliable and appropriate the system is to continuous healthcare monitoring. The proposed vision-based algorithm is cost-effective and non-discomforting compared to wearable-based and multi-sensors systems because it does not require devices worn by patients. YOLO inference On-device On-device YOLO inference on a Raspberry Pi allows real-time detection with low-latency and no network connectivity. The system has similar accuracy but has benefits in cost of deployment, energy efficiency, and installation ease, and thus it can be employed in keeping a constant check on healthcare.
The suggested system is local processing of the video data on the edge device hence the video streams in the raw form are not delivered and stored in the cloud. This makes it less susceptible to data leakage and promotes privacy of the patients. Other steps like limited placement of cameras, security control, and anonymity of data management can also be taken in practice to further guarantee the adherence to healthcare privacy regulations.

III. CONCLUSION

The paper describes an edge-enabled, vision-based abnormal behavior detection system that can monitor the condition of the patient in real-time (through a Raspberry Pi) and classify the patient behavior (falls, self-harm, abnormal postures and normal daily activities) with a deep learning model based on the open-source framework of YOLO. Experimental findings indicate realistic real-time execution with obvious distinction of critical and non-critical events. A multi-channel alert system based on LCD display and GSM notifications will provide prompt intervention and minimize false alarms and caregiver overload through limited notification to high-risk conditions. The system is applicable in hospitals, elderly care facilities and home health facilities because of its low price, no invasiveness, and power efficiency of implementation. Future directions of the framework will include enhancing resilience to occlusions and high-brightness, support the framework in multi-camera system applications, and introduce explainable AI and secure cloud access as a means to realize scalable and intelligent healthcare monitoring.

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