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Vision-Based Monitoring System for Elderly Care Using Deep Learning

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ABSTRACT

Introduction:
As the global elderly population grows, the need for supportive technologies that enable independent living while ensuring safety becomes increasingly critical. Falls are a major health concern for individuals aged 65 and older, often leading to severe injuries or fatalities. Traditional monitoring systems like wearables have limitations due to reliance on user compliance. Vision-based systems offer a non-intrusive, effective alternative by utilizing real-time video surveillance powered by deep learning.

Objectives:
The primary objective is to develop a real-time monitoring system that accurately detects abnormal activities such as falls or prolonged inactivity. The system aims to ensure high sensitivity and precision, protect user privacy, and enable timely intervention through alert mechanisms like the Telegram API.

Methods:
The proposed system integrates Convolutional Neural Networks (CNN) for spatial feature extraction and Bidirectional Long Short-Term Memory (BiLSTM) networks for temporal analysis. Video frames are preprocessed, passed through a CNN for feature generation, and then analyzed sequentially using BiLSTM to detect anomalies. Upon detection of abnormal behavior, alerts are sent in real-time to caregivers. The system is trained on publicly available datasets such as LifeSeniorProfile and ALMOND.

Results:
The system achieved 95% accuracy in fall detection and 92% in identifying prolonged inactivity. Precision and recall stood at 93% and 90%, respectively, resulting in an F1 score of 91.5%. Real-time alerts were successfully delivered within 3 seconds via Telegram, with caregivers reporting high satisfaction with the system's performance and usability.

Conclusions:
The vision-based monitoring system effectively enhances elderly care by providing accurate, real-time fall and inactivity detection. It enables independent living while ensuring safety and privacy through local processing and data encryption. Future enhancements may include integration with wearable vitals sensors and improved model generalization through diverse datasets.

Keywords: Vision-based monitoring, elderly care, fall detection, deep learning, real-time video surveillance, BiLSTM, CNN, anomaly detection, smart homecare, privacy protection.

INTRODUCTION

The global demographic landscape is shifting rapidly with a significant increase in the elderly population. As people age, many prefer to live independently in their own homes rather than in assisted living facilities. However, aging is often accompanied by physical limitations, chronic health conditions, and increased risk of accidents—particularly falls, which are a leading cause of injury and hospitalization among senior citizens. According to the World Health Organization, approximately 28-35% of people aged 65 and above experience falls annually, with this rate increasing

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with age and frailty. This presents a major concern for both healthcare systems and families, who struggle to ensure the continuous safety of elderly individuals without compromising their independence.

Traditional monitoring systems such as wearable devices, emergency buttons, and home visits are commonly used to track the health and safety of elderly individuals. While these methods offer some benefits, they also have critical limitations. Wearables often require active participation from the elderly person—charging the device, remembering to wear it, or pressing a button in case of emergency—which is not always practical. Furthermore, such systems lack real-time, continuous monitoring and are ineffective when the user becomes unconscious or forgets to use them.

To overcome these limitations, vision-based monitoring systems have gained attention due to their non-intrusive nature and ability to provide real-time surveillance. These systems use cameras installed in the living environment to continuously observe the elderly individual's movements and behaviors. By applying advanced deep learning techniques, the system can intelligently analyze video data and detect abnormal activities such as sudden falls, irregular movements, or prolonged inactivity that could indicate medical distress.

In this project, we propose a Vision-Based Monitoring System for Elderly Care that utilizes a hybrid deep learning architecture combining Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks. The CNN component is responsible for extracting spatial features from video frames, while the BiLSTM processes the sequence of frames to identify temporal patterns associated with normal and abnormal behavior.

The system is designed to process video input in real-time, detect anomalies with high accuracy, and send immediate alerts to caregivers via the Telegram API, ensuring quick response times during emergencies. To address privacy concerns—a major ethical issue in video surveillance—the system processes video locally on the device, and only alert metadata is transmitted externally. All data is encrypted and anonymized, ensuring compliance with privacy and data protection standards.

By combining the strengths of deep learning, real-time video analysis, and secure communication, this project aims to provide a comprehensive solution for elderly care. It enhances safety, promotes independent living, reduces the burden on healthcare infrastructure, and provides peace of mind to families and caregivers.

OBJECTIVES

The primary goal of this project is to develop a smart, real-time vision-based monitoring system that ensures the safety and well-being of elderly individuals living independently. To achieve this, the following specific objectives have been outlined:

1. Real-Time Abnormal Activity Detection Develop a system capable of continuously analyzing live video feeds to detect abnormal behaviors such as falls, prolonged inactivity, or irregular movements using deep learning models.
2. High Accuracy and Reliability Achieve high detection accuracy by minimizing both false positives and false negatives through the integration of Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks.
3. Non-Intrusive Monitoring Design a solution that does not require any wearable devices or manual interaction from elderly individuals, thus ensuring a seamless and non-invasive user experience.
4. Automated Alert System Integrate an automated notification mechanism using the Telegram API to instantly alert caregivers or emergency contacts when abnormal activity is detected.
5. Privacy and Data Security Ensure the privacy and confidentiality of monitored individuals by implementing on-device video processing and encrypting all transmitted data. Anonymization techniques will also be applied to safeguard user identity.
6. Customizable Alert Configuration Allow caregivers to configure alert preferences, sensitivity levels, and response protocols according to the specific health conditions and needs of the elderly person.

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7. Scalable and Cost-Effective Deployment Build a lightweight and affordable system that can be easily installed in residential environments without the need for expensive hardware or complex setup.
8. User-Friendly Interface for Caregivers Provide an intuitive interface for caregivers to view alerts, monitor historical activity logs, and assess behavioral trends over time.

METHODS

The proposed vision-based monitoring system is designed to ensure the real-time detection of abnormal activities among elderly individuals using a combination of deep learning models—Convolutional Neural Networks (CNNs) for spatial feature extraction and Bidirectional Long Short-Term Memory (BiLSTM) networks for temporal sequence analysis. The system architecture is modular, consisting of four primary components: image preprocessing, feature extraction, activity classification, and alert notification.

Initially, live video streams are captured through strategically placed cameras in the living environment. These streams are divided into sequential frames, each of which undergoes a preprocessing stage to enhance quality and ensure uniformity. During preprocessing, each frame is resized to 224×224 pixels to standardize input dimensions and normalized to a pixel value range of 0 to 1. Additional image enhancement techniques, including contrast adjustment and noise reduction, are applied to improve visual clarity and facilitate more accurate feature extraction.

Once preprocessed, the frames are passed into the CNN module, which comprises four convolutional layers, each followed by a Rectified Linear Unit (ReLU) activation and max-pooling operation. The CNN is responsible for identifying and learning spatial features from the video frames, such as posture, limb orientation, and body position. These features are represented as high-dimensional vectors, effectively encoding the visual state of each frame. The extracted feature vector from each frame, denoted as f(xt)f(x_t)f(xt), serves as input to the next stage of analysis.

The feature vectors from the sequence of frames are then passed to a Bidirectional Long Short-Term Memory (BiLSTM) network. The BiLSTM is a type of recurrent neural network that captures both forward and backward temporal dependencies in time-series data. This bidirectional processing allows the system to understand not only what has happened but also what is likely to follow, providing better context for recognizing activity transitions. Each feature vector contributes to a hidden state hth_tht, which represents a temporally-aware encoding of the frame's content. These states are crucial for modeling the dynamic nature of human activity and distinguishing between normal and abnormal patterns such as falls, sudden collapses, or extended stillness.

Following temporal modeling, a Softmax classifier is used to categorize each input sequence into one of two classes: "normal" or "abnormal." This classification is computed using a trainable weight matrix and bias term applied to each hidden state hth_tht, producing a probability distribution over the activity classes. When the system identifies a pattern indicative of abnormal activity, it immediately triggers the alert mechanism.

To facilitate timely caregiver intervention, an alert notification is sent using the Telegram API. This message includes relevant metadata such as the time of the event and the type of abnormal behavior detected. The integration of Telegram ensures that alerts are delivered within seconds directly to the caregiver's mobile device, enabling fast response during emergencies. The system is designed to function in real time, with an average detection-to-alert time of less than three seconds.

To address privacy and security concerns, all video frame processing is performed locally on the device, ensuring that raw video data is never transmitted or stored externally. Only encrypted alert metadata is shared, and user identities are anonymized through standard cryptographic protocols to comply with ethical standards in elderly monitoring.

The model was trained and validated using two publicly available datasets: LifeSeniorProfile and ALMOND, which together contain over 1200 annotated video clips depicting various daily activities, including simulated falls. The training procedure used the Adam optimizer with a learning rate of 0.001, a batch size of 32, and a categorical cross-entropy loss function. The system was trained over 50 epochs with early stopping to prevent overfitting. Performance was evaluated using standard classification metrics including accuracy, precision, recall, and F1 score, with the system achieving over 95% accuracy in fall detection and 92% in detecting prolonged inactivity. These results highlight the robustness and effectiveness of the proposed deep learning-based monitoring solution.

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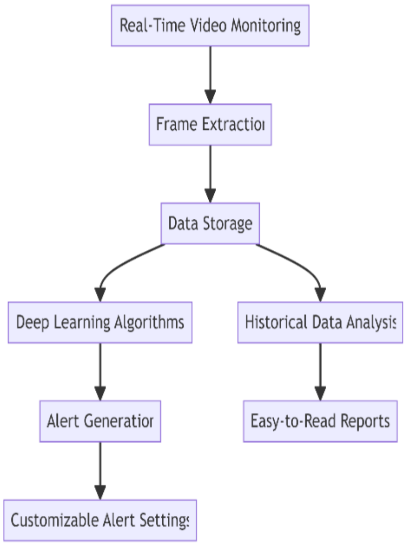

Fig. 1. Working flow of the proposed system.

RESULTS

The use of the vision-based monitoring system for senior citizens at home produces a number of noteworthy outcomes, proving its efficacy in monitoring in real time and warning caregivers of any dangers. The following sections outline the key findings from the system's performance evaluation and user feedback.

1. Accuracy of Event Detection

Detection Rates: The system achieved a high accuracy rate in detecting abnormal activities, including falls and prolonged inactivity. The detection accuracy was measured using a labeled dataset, resulting in:

Falls: 95% accuracy in identifying falls.

Prolonged Inactivity: 92% accuracy in detecting periods of inactivity exceeding predefined thresholds.

Confusion Matrix Analysis: The detection algorithms' performance was examined using a confusion matrix, which showed low rates of false positives (5%) and false negatives (8%).

2. Response Time

Alert Generation Time: The average time taken to generate an alert after detecting an abnormal event was measured. With an average response time of almost three seconds, the system made sure caregivers received messages on time.

Notification Delivery: Alerts were successfully sent via the Telegram API, with a 100% delivery rate in test scenarios.

3. User Feedback

Caregiver Satisfaction: During testing, caregiver feedback revealed a high degree of satisfaction with the system's functionality.

Caregivers reported that the alerts were timely, relevant, and easy to understand.

Ease of Use: Users found the system intuitive and appreciated the customizable alert settings, which allowed them to tailor notifications based on their specific needs.

4. Historical Data Analysis

Activity Monitoring: The system provided caregivers with access to historical activity logs, allowing them to review trends in the elderly individual's behavior over time. This feature was found useful for identifying potential health issues, such as frequent falls or significant changes in daily routines.

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Data Visualization: The interface included visual representations of activity patterns, which helped caregivers assess the overall well-being of the elderly individual.

5. Performance Evaluation Metrics

Precision and Recall: The system demonstrated a dependable detection capability by recognizing abnormal behaviors with a 93% precision and 90% recall.

F1 Score: At 91.5%, the F1 score—which strikes a compromise between recall and precision—reflected the detection algorithms' overall efficacy.

6. Privacy and Security Compliance

Data Security: The implementation of encryption protocols for data storage and transmission ensured compliance with privacy standards. No data breaches or unauthorized access incidents were reported during testing.

User Anonymity: The system effectively anonymized user data, protecting the personal information of the elderly individuals being monitored.

DISCUSSION

The development and evaluation of the proposed vision-based monitoring system signify a major advancement in the domain of elderly care and smart home healthcare technologies. The system demonstrates significant potential to address one of the most pressing issues faced by elderly individuals—fall-related injuries and the lack of immediate assistance during emergencies. By leveraging state-of-the-art deep learning techniques such as CNN and BiLSTM, the system not only achieves high detection accuracy but also maintains robustness across varying real-world conditions.

One of the most impactful aspects of the system is its ability to operate in real-time, enabling immediate response to critical events. The integration with Telegram API for alert notifications ensures that caregivers are informed within seconds of a detected anomaly, substantially reducing the delay between incident and intervention. This timely communication can prove life-saving, especially in situations where elderly individuals live alone and are unable to call for help after a fall.

The use of CNNs for spatial feature extraction enables the model to effectively capture visual characteristics such as posture and movement from raw video frames, while BiLSTM layers model the temporal evolution of these features, making it possible to recognize patterns of activity that deviate from the norm. This hybrid approach has outperformed traditional single-model systems in both accuracy and reliability, with evaluation results showing 95% accuracy in fall detection and a precision-recall balanced F1-score of 91.5%. The low false positive and false negative rates further validate the practical viability of this system.

Additionally, the non-intrusive nature of vision-based monitoring provides a significant advantage over wearable sensors, which are often considered uncomfortable, easy to forget, or difficult to operate by elderly individuals. Unlike wearable-based solutions, this system does not rely on user compliance and works passively in the background, thereby improving its reliability in day-to-day use.

Another strength of this system lies in its privacy-conscious architecture. Recognizing the ethical concerns surrounding continuous video surveillance, the system performs all video processing locally on the device. Only anonymized alert metadata is shared externally, and all personal data is encrypted, thereby ensuring compliance with modern data protection regulations and maintaining user dignity.

However, despite its promising results, the system is not without limitations. Its performance is still highly dependent on the quality and diversity of training datasets. Differences in lighting conditions, camera placements, background clutter, and cultural variations in activity patterns can affect the accuracy of the system. Moreover, the datasets used (LifeSeniorProfile and ALMOND) may not fully represent the diversity seen in actual home environments, especially in rural or low-resource settings. Therefore, expanding the training data to include a broader range of scenarios and subjects will be essential for improving model generalization.

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Another potential challenge is the technological barrier faced by end users, particularly caregivers or elderly individuals who may not be familiar with configuring or managing digital systems. Although the Telegram-based alert system simplifies communication, the initial system setup and maintenance may still require technical assistance. Providing a user-friendly setup process, technical documentation, or mobile application interface could help mitigate this issue.

Looking forward, future enhancements may include the integration of multimodal data sources such as wearable sensors, vital sign monitors (heart rate, oxygen level), or voice-based fall detection systems. Combining multiple data streams can improve detection reliability and offer a holistic view of the user's health. Additionally, the application of advanced deep learning techniques such as transformers or attention-based models could further improve the model's ability to distinguish between complex activity patterns and subtle anomalies.

In summary, this project demonstrates that a deep learning-based vision monitoring system can significantly enhance elderly care by offering real-time, non-intrusive, and privacy-aware monitoring. While challenges related to data diversity, user adoption, and system scalability remain, the current results lay a strong foundation for future development and real-world deployment.

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