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Computer Vision-Based Information System for Early Detection of Elderly Patient Falls using YOLOv12

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Abstract

Falls in elderly patients are a significant public health problem due to their high frequency and potential to cause serious injury or even death. Traditional fall detection systems often rely on wearable sensors, which can be intrusive and uncomfortable for long-term monitoring. This study proposes a non-intrusive computer vision-based information system for early fall detection using the YOLOv12 (You Only Look Once version 12) object detection model. The system integrates real-time video processing with a lightweight convolutional neural network architecture to detect falls in indoor care settings. A dataset of 10,793 annotated images, including simulated fall scenarios and daily activities, was used to train and validate the proposed model. The proposed system achieved a Mean Average Precision (mAP) of 90.60%, demonstrating robust performance under various lighting conditions and camera angles when compared with the YOLOv8, YOLOv11, and YOLO-NAS models. This study contributes to the development of intelligent healthcare systems that improve the safety and quality of life of elderly patients through proactive monitoring and rapid response capabilities.

Keywords: computer vision; elderly patients; fall detection; real time; YOLOv12

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1. Introduction

Falls can greatly affect the health and ability of older adults to live independently, often leading to serious injuries, reduced mobility, and an overall decline in quality of life [1]. Statistics show most older adults experience falls each year, with the risk increasing with age and a history of previous falls [2], [3] The consequences of falls go beyond physical harm, often resulting in psychological distress, fear of falling, and social isolation, creating a need for effective fall detection and prevention strategies. The increasing prevalence of elderly individuals living alone further exacerbates the challenges associated with timely fall detection and assistance [4]. In this context, technological solutions that can automatically detect falls and immediately alert caregivers or emergency services have great potential to improve the safety and well-being of older adults [5]. A number of approaches have been researched to develop cost-effective and non-invasive automated fall detection systems that have garnered considerable attention, driven by the increasing aging population and the significant impact of falls on the health and autonomy of older individuals [6].

There are three main categories of existing fall detection systems: those that use wearable sensors, those that rely on ambient sensors, and those that use vision-based technology [7]. Wearable sensor-based systems typically use accelerometers, gyroscopes, and other inertial measurement units to detect sudden changes in motion and orientation that indicate a fall [8]. These systems offer the advantages of being portable and provide continuous monitoring, but may experience limitations related to user compliance, battery life, and potential inconvenience or stigma associated with using the device. Ambient sensor-based systems use environmental sensors like pressure sensors, infrared sensors, and acoustic sensors to identify falls by monitoring changes in the surroundings. These systems offer the benefit of being non-intrusive and do not require the user to wear any device, but may be susceptible to false alarms due to environmental noise and may not be effective in all settings. Vision-based systems use cameras and computer vision algorithms to

analyze video data and detect falls based on movement patterns and posture characteristics [9]. The use of smart home emergency services can also automatically send alerts to the hospital in case of abnormal situations, while smartwatches can also help caregivers track Alzheimer's patients [10]. Vision-based systems offer contactless advantages and provide rich information about the autumn context, but they may be computationally intensive and require careful consideration of privacy concerns. Many fall detection systems primarily focus on detecting falls, but further clinical research is recommended to emphasize fall detection and, much more. important, fall prevention [11].

In line with technological developments, computer vision is increasingly used in fall detection systems due to its ability to provide richer contextual information. Object detection algorithms such as You Only Look Once (YOLO) have evolved into one of the leading approaches due to their high speed and accuracy in real-time processing [12]. Various studies have implemented YOLO variants to detect human activities, including falls, with promising results. For example, a study that used YOLOv8 to detect falls in the elderly [13], while some integrate YOLOv5 with IoT systems for elderly monitoring [14]. Another study adopted a CNN-based method to detect abnormal activity on surveillance video [15]. However, there are still some limitations in terms of computing efficiency [16], the flexibility of integration into real-time information systems, and the ability to display data interactively through web-based platforms.

Based on these gaps, this study proposes the development of a computer vision-based information system for early detection of falls in elderly patients using the YOLOv12 algorithm. The system is designed to: (1) provide real-time fall detection with a high level of accuracy, (2) display detection results through an interactive web interface, including video streaming, and automatic notification features, and (3) enable multi-source integration of both live cameras and video file uploads. The main contribution of the research lies in the integration of the YOLOv12 algorithm with a web-based information system, which not only improves the accuracy of fall detection, but also presents a non-invasive, cost-effective, and accessible solution for elderly monitoring.

The structure of this article is structured as: Part 1 discusses the background, issues and related research; Part 2 explains the methodology used along with the system development method; Part 3 presents the results of the implementation and discussion, and Part 5 summarizes the main findings and the next direction of the research. Thus, this article shows the contribution of research in filling the existing gaps with more integrated, practical, and relevant technological solutions for real application in the field of smart healthcare.

2. Methods

This study uses a computer vision-based experimental approach by integrating the YOLOv12 algorithm into a web-based information system. The research design is focused on developing system prototypes, collecting fall video data, training detection models, and evaluating system performance in detecting fall events in real-time. In this area, we try to describe the proposed strategy for the fall detection process using a combination of hardware and software components. Cameras are strategically placed in the environment to capture real-time video streams of elderly patients [17]. YOLOv12 is implemented using a deep learning framework, utilizing pre-trained models and transfer learning techniques to improve detection accuracy and reduce training time. By providing a pre-trained model to extract the key points of the skeleton from the image. The system incorporates a rule-based decision-making module that analyzes the extracted information and applies predefined rules to detect fall events. The research method will be shown in Figure 1.

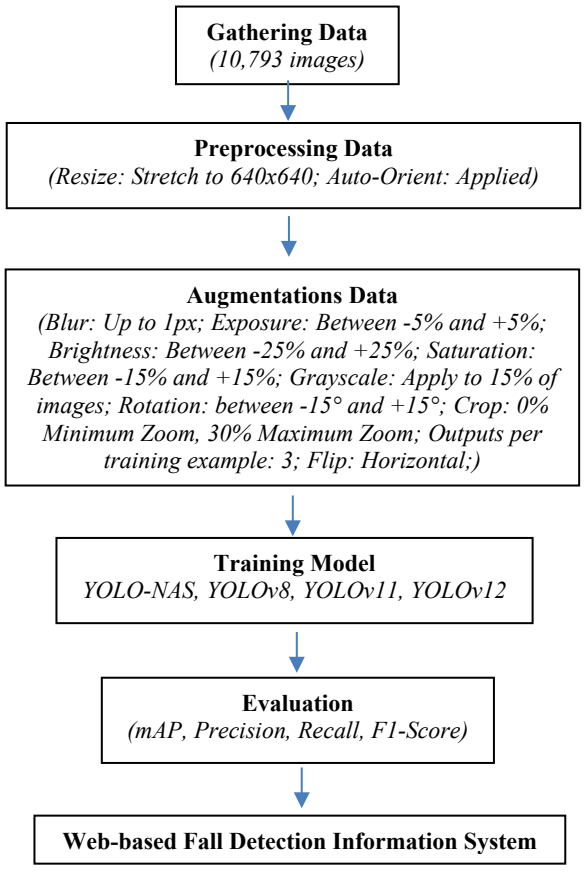


Figure 1. Research methods

2.1 Gathering Data

At the data collection stage, an image acquisition process was carried out as many as 10,793 images consisting of various variations of object conditions, viewing angles, lighting, and backgrounds to ensure diversity and adequate data representation. All images were obtained through a combination of direct field documentation methods using high-quality digital cameras and collection from the online repository

roboflow "fall detection dataset" licensed under CC BY 4.0 [18] which has been curated and adapted to the needs of the study. Each image is then manually labeled using the Roboflow platform, to mark the relevant object area with high accuracy. This process is significant time-consuming as it involves repeated visual validation to guarantee the quality of the training data. The total number of 10,793 images reflects the researcher's efforts in fulfilling the principle of data sufficiency for machine learning models, especially in the context of computer vision-based object detection such as YOLOv12. With a large and varied amount of data, it is expected that the model built has a high level of generalization of new data in the next testing process. The example of a fallen person dataset will be shown in Figure 2.

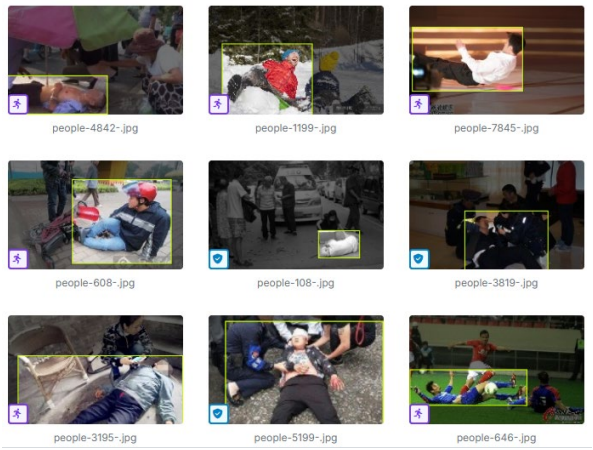


Figure 2 Example of a fallen person dataset

2.2 Preprocesing Data

Data pre-processing is a critical phase in the object detection pipeline, aiming to improve the quality and suitability of input data for training models [19]. Given the inherent variability in real-world images, including variations in viewing angles, poses, occlusion, and lighting conditions, preprocessing techniques play an important role in normalizing and standardizing data [20]. This involves addressing issues such as noise reduction, handling missing values, and ensuring data consistency to improve the robustness and generalizability of object detection models. Preprocessing includes a set of methods designed to refine, modify, and increase the caliber of a dataset [21].

The importance of data preprocessing is reinforced when dealing with unstructured or semi-structured data, as is often encountered in real-world scenarios. In such cases, customized preprocessing steps are essential to extract relevant features and convert the data into a format suitable for model training. Careful preprocessing ensures that the model receives high-quality standard data, leading to improved accuracy, robustness, and overall performance in object detection tasks [22].

Pre-processing can be applied to remove irrelevant data while improving image quality by carefully selecting and processing the right image features [23]. Indeed, the choice of pre-processing techniques and parameters should be chosen wisely based on the specific characteristics of the dataset and the object detection task objectives [24]. Additionally, preprocessing plays a critical role in preparing data for machine learning models, ensuring that duplicates, errors, or gaps in data are minimized [25]. In this study, there are 2 stages of pre-processing, namely: Auto-Orient: Applied; and Resize: Stretch to 640x640.

2.3. Augmentation Data

Augmentation Data serves as a powerful technique to artificially expand the size of the training dataset by applying various transformations to existing images [26]. This approach is especially valuable when dealing with limited data, as it helps improve the generalization capabilities of object detection models by exposing them to a wider range of variations [27]. When annotated data is scarce, data augmentation is an efficient strategy to increase training set variability [28].

Data augmentation is especially useful when Dealing with complex data or high dimensions [29]. In addition, data augmentation serves as a regularization technique, preventing overfitting by exposing the model to a more diverse set of training examples [30]. Traditional data augmentation techniques, such as flipping, rotating, scaling, cropping, and panning, directly manipulate images to increase the amount of training data. Newer and more advanced data augmentation techniques have been developed, including deep-learning augmentation strategies as well as feature-based data augmentation techniques and meta-learning [31].

Data augmentation is a set of techniques that increase the size and quality of training datasets. By creating diverse sets of training samples, data augmentation techniques prevent overfitting and help machine learning models to achieve better generalizations. Data augmentation techniques are usually designed based on prior knowledge of data [32]. Data augmentation is a solution to address the scarcity of labeled data [33]. Basic data augmentation methods have been classified to highlight their strengths and limitations [34]. Data augmentation reduces overfitting, thereby increasing the generalization power of the model.

In this study, the augmentation carried out has several stages, namely: Outputs per training example: 3; Flip: Horizontal; Crop: 0% Minimum Zoom, 30% Maximum Zoom; Rotation: between -15° and +15°; Grayscale: Apply to 15% of images; Saturation: Between -15% and +15%; Brightness: Between -25% and +25%; Exposure: Between -5% and +5%; Blur: Up to 1px.

2.4 YOLOv12 Model

YOLOv12 represents an ongoing evolution in the YOLO series of object detection models, building on the basic principles of its predecessor while incorporating new architectural techniques and training

to improve performance [35]. The YOLO framework revolutionized object detection by introducing a single-stage detection paradigm, avoiding the region proposal stage used by two-stage detectors, thus enabling faster inference speeds [12]. The YOLOv12 architecture is designed around three basic components, similar to previous iterations, providing an efficient framework for the localization and classification of objects [36].

One of the key innovations of YOLOv12 is its attention-centered design, this model addresses the limitations of relying primarily on CNN-based enhancements by utilizing attention power mechanisms to improve modeling capabilities [37]. The model strategically integrates the attention mechanism to refine the representation of features and improve the detection precision of objects, this is done by allowing the model to focus on the most relevant parts of the image, filtering out noise and irrelevant information, ultimately leading to more accurate and powerful detection performance. With the integration of a attention mechanism, YOLOv12 is specifically designed to address the unique challenges of steel surface defect detection, providing adaptability and precision in complex industrial settings. Its main goal is to achieve a balance between detection accuracy and computational efficiency, making it a powerful choice for real-time applications.

2.5 Model Evaluation

The evaluation of an object detection model, such as YOLOv12, relies on a set of metrics that measure various aspects of its performance, including accuracy and efficiency [35]. Mean Average Precision (mAP) stands as a cornerstone metric, offering a comprehensive measure of object detection accuracy across different object categories [36]. The mAP calculates the average precision for each class and then averages these values across all classes, providing a holistic assessment of the model's ability to correctly identify and localize objects [38]. The evaluation matrix of mAP, can be seen in Formula 1.

$$mAP@_{\alpha} = \frac{1}{n}\sum_{i=1}^{n} AP_i \ \ for\ n\ classes \quad (1)$$

Precision and Recall, two basic metrics, offer insights into the trade-off between correctly identified objects and the proportion of actual objects detected. Precision measures the accuracy of positive predictions, indicating the proportion of correctly identified objects among all objects predicted by the model. The evaluation matrix of precisioan, can be seen in Formula 2.

$$precision = \frac{TP}{TP+FP} \quad (2)$$

Remember, on the other hand, recall the completeness of positive predictions, showing the proportion of actual objects correctly identified by the model [39]. The evaluation matrix of mAP, can be seen in Formula 3.

$$recall = \frac{TP}{TP+FN} \quad (3)$$

F1 scores, harmonic averages of precision and memory, provide a balanced measure of accuracy, especially useful when dealing with unbalanced datasets where one class has more significant instances than the other. The evaluation matrix of mAP, can be seen in Formula 4.

$$F1 = 2 * \frac{1}{\frac{1}{precison}+\frac{1}{recall}} \quad (4)$$

3. Results and Discussions

Each of the YOLO models examined in this study has its own strengths and weaknesses in the context of fall detection. YOLO-NAS, with its neural architecture search derivative design, is expected to offer a balance between detection accuracy and computational efficiency. YOLOv8, known for its speed and accuracy, is likely to perform well in real-time fall detection scenarios. The findings of this study have several important implications for the design and deployment of fall detection systems. Identifying the most suitable YOLO model for fall detection can help system developers to optimize the performance and efficiency of their systems.

The findings of this study must be interpreted in light of their limitations. More research is needed to address these limitations and to validate the findings of this study in diverse settings and populations. YOLO's reliance on extensive training data can present limitations, especially in scenarios where data is scarce [12]. Model performance can be affected by variations in posture, with movements such as falling potentially causing false positives [40]. Despite the promising results, challenges remain in achieving ubiquitous and reliable fall detection. Integrating contextual information, such as patient behavior and environmental data, can improve fall prediction [2]. Overcoming these challenges can lead to the development of more robust and practical fall detection systems, thereby promoting independent living and reducing the burden of healthcare. Comparative studies of YOLO-NAS, YOLOv8, YOLOv11, and YOLOv12 for computer vision-based fall detection reveal valuable insights into the performance characteristics of each model.

The study serves as a valuable resource for researchers and practitioners in the field of fall detection, providing a deeper understanding of how the YOLO model can be effectively applied in real-world scenarios. Advances in the YOLO model have had a significant impact on object detection, and the study of its architecture is essential for real-time applications. One of the challenges in using the YOLO model is the absence of official architectural diagrams available to the public, making it difficult to understand the practical operation of these models. The study offers a thorough analysis of the latest YOLO models, offering useful information for academics and practitioners in a variety of domains. This research adds to the growing knowledge of fall

detection and offers practical guidance for the creation of more reliable and efficient systems.

From the experiments carried out using the YOLOv8, YOLOv11, YOLOv12 and YOLO-NAS algorithms, a comparison of the values of mAP, Precision, Recall and F1-Score was produced which can be seen in Table 1.

Table 1. Performance analysis of object detection algorithm on fall dataset

Model	mAP	Precision	Recall	F1 Score
YOLOv8	89,90%	86,00%	86,90%	86,45%
YOLOv11	90,30%	85,90%	87,30%	86,59%
YOLOv12	90,60%	88,90%	84,80%	86,80%
YOLO-NAS	82,50%	83,80%	74,90%	79,10%

3.1 Comparison of Map Values

The evaluation of the comparison of mAP values for the YOLOv8, YOLOv11, YOLOv12 and YOLO-NAS models was 89.90%, 90.30%, 90.60%, 82.50%. A good mAP value is a value close to 100%, so it can be concluded that YOLOv12 has better capabilities compared to other models, while YOLO-NAS has the lowest value. In detail, the comparison of mAP can be seen in Figure 3.

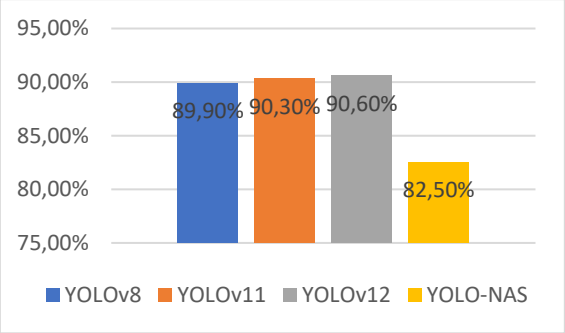


Figure 3. YOLO model detection fall dataset mAP

3.2 Comparison of Precision Values

The evaluation of the comparison of Precision values for YOLOv8, YOLOv11, YOLOv12 and YOLO-NAS models is 83.80%, 88.90%, 85.90%, 86.00%. A good Precision value is a value that is close to 100%, so it can be concluded that the YOLOv12 has better capabilities compared to the other models, while the YOLO-NAS has the lowest value. In detail, the Precision comparison can be seen in Figure 4.

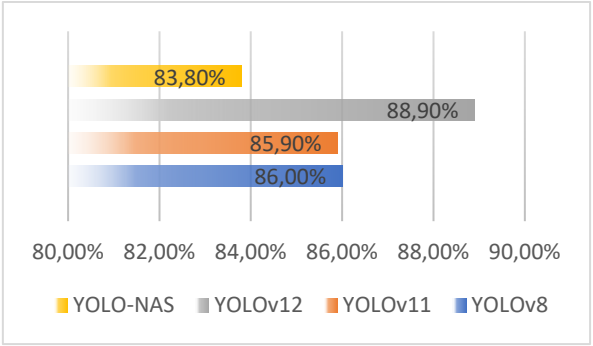


Figure 4. YOLO model detection fall dataset Precision

3.3 Comparison of Recall Values

The evaluation of the comparison of Recall values for YOLOv8, YOLOv11, YOLOv12 and YOLO-NAS models is 86.90%, 87.30%, 84.80%, 74.90%. A good mAP value is a value close to 100%, so it can be concluded that YOLOv11 has better capabilities compared to other models, while YOLO-NAS has the lowest value In detail the Recall comparison can be seen in Figure 5.

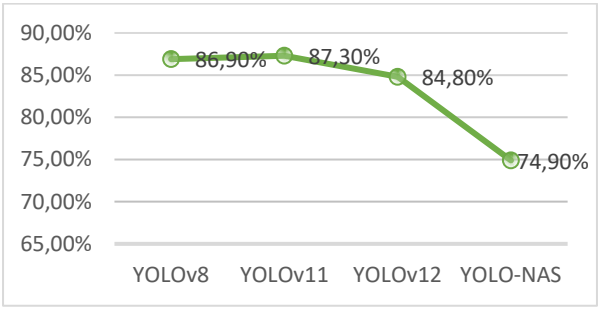


Figure 5. YOLO model detection fall dataset Recall

3.4 Comparison of F1-Score Values

The evaluation of the comparison of Recall values for YOLOv8, YOLOv11, YOLOv12 and YOLO-NAS models is 86.45%, 86.59%, 86.80%, 79.10%. A good mAP value is a value that is close to 100%, so it can be concluded that YOLOv11 has better capabilities compared to other models, while YOLO-NAS has the lowest value. In detail, the comparison of F1-score can be seen in Figure 6.

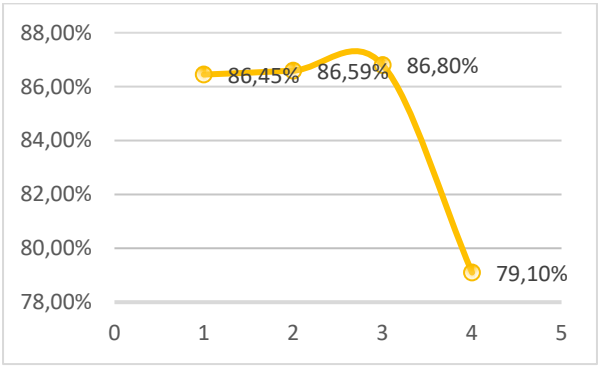


Figure 6. YOLO model detection fall dataset F1-Score

3.5 Fall Detection Information System

The implementation of the fall detection information system can display when a person has fallen and label the object "falling". An example of the implementation of a fall detection information system can be seen in Figure 7.

Apart from that, the history of fall detection is also displayed in the information system, which can be seen in Figure 8.

The results showed that a computer vision-based fainting detection system with the YOLOv12 algorithm was able to identify fainting events in real-time with a high level of accuracy. These findings have some important implications. First, in terms of patient and

elderly safety, this system can be a non-intrusive solution that allows continuous monitoring without the need for wearables. This is especially relevant in the elderly population who often refuse the use of additional devices.

Second, from a technology implementation perspective, the results of this study reinforce the evidence that current deep learning models, such as YOLOv8, not only excel in the domain of general computer vision (e.g. object detection in vehicles or security), but can also be applied to the health and safety domains. Thus, this study expands the scope of the application of the algorithm to a more socially critical domain. Third, the practical implications of this study are the opportunity for integration with smart healthcare and smart home systems. The proposed system could be connected to an existing network of cameras in hospitals, nursing homes or private homes, and then combined with mobile-based notifications to speed up emergency response.



Figure 7. Fall Detection Display

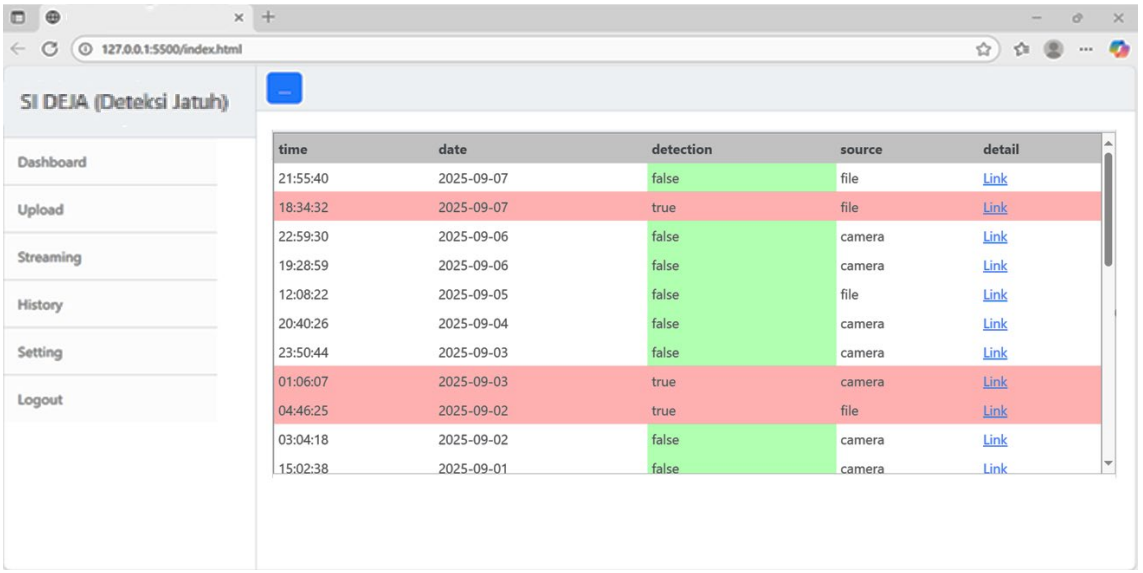


Figure 8. Fall Detection Display

However, it should be underlined that the results of this study should not be considered as a final solution. This model still has limitations, such as sensitivity to lighting, camera angles, and the potential for false detection on certain movements. Therefore, further studies need to be conducted to test these systems under more diverse real-world conditions, as well as evaluate their performance on data with wider demographic and environmental variations.

4. Conclusions

In conclusion, the development of computer vision-based information systems for the early detection of elderly patients falls is a significant advancement in healthcare technology. By leveraging the YOLOv12 object detection model, the system offers a non-intrusive and efficient approach to monitoring elderly individuals and detecting fall events in real-time. The system is a strong and flexible solution that successfully

overcomes issues with power use, connection, and how well it detects falls, making users safer and improving their overall quality of life. Going forward, researchers should look into using advanced machine learning methods to make fall detection more accurate and reliable, as well as combining wearable sensors with other devices around them to create better monitoring systems. More work is needed to find a clear and easy-to-understand way to assess a person's risk of falling using sensing technology.

The development of computer vision-based information systems for the early detection of elderly patients with falls is a significant advancement in healthcare technology. With YOLOv12 having the best mAP, Precision, Recall and F1-Score scores of 90.60%, 88.90%, 84.80%, 86.80%, the system offers the potential to proactively identify and respond to fall events, improve patient outcomes and reduce the burden on healthcare providers. Fall variability, which occurs unconsciously in various shapes and directions, presents a significant challenge in developing reliable fall detection algorithms.

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