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Mobile-Centric Supervised Machine Learning Approach for Elderly Fall Detection Using YOLOv8

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Abstract

The global surge in the elderly population has underscored the need for advanced safety systems tailored to seniors, particularly those living independently. Central to these systems is the pivotal role of fall detection in ensuring their welfare. This paper presents a cutting-edge fall detection system designed specifically for the elderly, leveraging supervised machine learning techniques with a mobile-centric approach. Departing from traditional hospital-centric setups, our system offers cost-effectiveness and improved mobility, facilitating deployment across diverse environments. The methodology comprises three core stages: data collection and annotation, model training, and inference. We curated a dataset of 1500 images categorized into three classes: standing, falling, and fallen, meticulously annotated using RoboFlow. Subsequent model training utilized YOLOv8, culminating in the inference stage, which underwent quantitative evaluation employing 10-fold cross-validation, yielding an average accuracy of 97.88%. Qualitative assessment across four distinct scenarios further validated our system, achieving an average accuracy of 95.92%. These results underscore the efficacy of our approach and lay the foundation for practical implementation and widespread adoption. Subsequent to the successful development of the core algorithm, we operationalized it for real-world applications by seamlessly integrating it with smartphones via TensorFlowLite. This integration underscores the synergy between algorithm design and software development, further facilitating the practical deployment and widespread acceptance of our system in diverse settings.

Keywords: Fall detection, Elderly care, Supervised machine learning, YOLOv8, TensorFlowLite

1. INTRODUCTION

Over the past decade, there has been a notable surge in the demographic comprising individuals aged 60 and above. This demographic shift holds significant implications for various sectors, particularly the healthcare industry. With projections extending to the year 2100, the sustained growth in the elderly population is expected to play a pivotal role in shaping the trajectory of healthcare services globally. Concurrently, the issue of falls among the elderly has remained a longstanding concern. According to statistical insights provided by the World Health Organization (WHO), the prevalence of falls among individuals aged 65 and above is anticipated up to 35%. Moreover, this risk escalates significantly to 42%, for individuals aged 70 and older (Kumar et al., 2021). These statistics underscore the urgent need for comprehensive strategies and interventions to mitigate the risks associated with falls in the elderly population.

Research in human fall detection can be categorized into several main types: wearable sensors, vision-based systems, acoustic detection, radar-based systems, and hybrid approaches. Recent advancements in wearable sensor technology have significantly enhanced the field of fall detection systems, particularly in the context of elderly care and safety monitoring. Wearable sensors offer continuous monitoring capabilities, making them ideal for detecting sudden movements and changes in posture associated with falls. Alvarez, Li, and Philips (2021) proposed a system that integrates wearable sensors with machine learning algorithms to improve fall detection accuracy. Their approach leverages real-time data processing to distinguish fall events from normal activities, demonstrating robust performance in various settings. Chen, Yu, and Wang (2020) developed a wearable sensor-based fall detection system using machine learning techniques. Their study emphasizes the importance of sensor fusion and algorithm optimization in achieving high detection accuracy and reliability. By analyzing accelerometer and gyroscope data, their system effectively distinguishes fall incidents from other daily movements. Lopes, Rodrigues, and Plawiak (2020) conducted a comprehensive review of wearable solutions for elderly fall detection. They highlighted the integration of multiple sensor modalities and the optimization of algorithms to enhance detection accuracy while minimizing false positives. Their findings underscored the importance of sensor placement and data fusion techniques in achieving reliable fall detection outcomes. Kim and Kim (2021) focused on real-time fall detection using wearable sensors and machine learning algorithms. Their research highlighted advancements in sensor technology and algorithmic efficiency, contributing to improved responsiveness and reliability in detecting falls.

Vision-based systems analyze images or video to identify posture changes and potential falls. Recent advancements in vision-based fall detection systems have leveraged RGB-D cameras and deep learning techniques to enhance accuracy and reliability in detecting falls, particularly focusing on elderly care and safety monitoring. Ma, Zhang, and Li (2020) proposed an RGB-D camera-based fall detection system utilizing deep learning algorithms. Their approach integrates RGB-D camera data to capture both color and depth information, enabling precise detection of falls based on human body movements and orientations. Palacios-Navarro, Carrasco-Jiménez, and Perez-Cisneros (2021) developed a fall detection system that fuses thermal and depth information from sensors. By combining thermal imaging with depth data, their system achieves robust fall detection capabilities, particularly in low-light conditions or privacy-sensitive environments. Bouloudi, Charfi, and Soudani (2019) utilized Kinect depth images and support vector machine (SVM) algorithms for real-time fall detection. Their study demonstrated high accuracy in identifying falls by analyzing depth images captured by Kinect sensors and applying machine learning classifiers. Yu, Wang, and Hao (2020) proposed a fall detection system based on RGB-D cameras and convolutional neural networks (CNNs). Their approach leverages CNNs to process RGB-D camera data, achieving efficient and accurate fall detection through automated feature extraction and classification.

Acoustic-based fall detection systems have emerged as a promising approach for detecting falls using sound signals and machine learning techniques. These systems capitalize on the unique acoustic signatures generated during falls to distinguish them from other activities and background noise. Khan and Porikli (2019) proposed an acoustic fall detection system utilizing deep learning-based sound analysis. Their study demonstrated the effectiveness of deep learning algorithms in analyzing acoustic patterns associated with falls, achieving high accuracy in real-time fall detection scenarios. Grzeszick and Jager (2020) developed a fall detection system based on convolutional neural networks (CNNs) applied to acoustic signals. Their approach focuses on extracting features from audio recordings to classify falls, showcasing the robustness of CNNs in acoustic-based fall detection applications. Wang and Liu (2020) explored the use of acoustic signals and machine learning techniques for fall detection. Their study investigated various machine learning algorithms to analyze acoustic features, aiming to improve detection accuracy by leveraging different classification models. Pannurat, Nantajeewarawat, and Haddawy (2020) proposed a fall detection system using environmental sound signals and machine learning. Their approach integrates environmental sounds with machine learning models to detect falls in diverse acoustic environments, highlighting the versatility of acoustic-based methods in different settings.

Radar-based fall detection systems have garnered attention for their ability to monitor human motion and detect falls using radar signals. These systems utilize radar technology to detect changes in movement patterns associated with falls, providing reliable monitoring in various environments. Miao, Zhang, and Wang (2019) explored radar-based fall detection using machine learning algorithms. Their study focused on enhancing detection accuracy by integrating radar signals with machine learning techniques, demonstrating effective fall detection capabilities. Zhou, He, and Wu (2020) investigated ultra-wideband radar for fall detection, emphasizing signal processing and system design aspects. Their research highlighted the advantages of ultra-wideband radar in detecting falls with high accuracy and reliability in complex environments. Wang and Guo (2020) proposed a fall detection system utilizing ultra-wideband radar combined with deep learning methods. Their study leveraged deep learning algorithms to analyze radar signals, achieving robust performance in detecting falls under different conditions. Mahmood and Hassan (2020) investigated a frequency-modulated continuous-wave radar-based fall detection system employing deep learning techniques. Their study showcased the effectiveness of radar signals and deep learning algorithms in accurately detecting falls, highlighting advancements in radar-based fall detection technologies.

Moreover, hybrid approaches combine multiple methods to enhance accuracy. Alsheikh and Selim (2020) proposed a hybrid fall detection system integrating wearable sensors and RGB-D cameras. Their study demonstrated the effectiveness of combining sensor modalities to improve detection accuracy and reduce false alarms in real-world scenarios. Mahmud and Wang (2019) conducted a comprehensive review on sensor fusion techniques for fall detection. Their review highlighted the integration of different sensor types, such as accelerometers, gyroscopes, and environmental sensors, with advanced fusion algorithms to enhance system robustness and reliability. Eskofier, Lee, and Kupnik (2020) investigated sensor fusion and machine learning approaches for robust fall detection in real-world environments. Their research emphasized the synergy between sensor fusion techniques and machine learning algorithms to achieve high accuracy and adaptability across various conditions. Hossain, Muhammad, and Alhamid (2020) proposed a hybrid fall detection system utilizing both wearable sensors and ambient sensors. Their study focused on integrating data from multiple sensor sources to improve detection sensitivity and reliability, particularly in home-based healthcare settings. He and Wang (2020) explored multi-sensor fusion techniques combined with deep learning for fall detection. Their research highlighted the advantages of integrating data from different sensors with deep learning models to achieve robust and accurate fall detection performance.

In addition to the previously mentioned methodologies, an increasingly prevalent approach in the development of human fall detection systems is the YOLO-based technique. The related research is as follows: Luo (2023) addresses the critical challenge of fall detection in smart home applications, aiming to mitigate injuries among the elderly. Although both vision and non-vision-based techniques are available, vision-based approaches are preferred for their practicality, despite challenges related to accuracy and computational cost. The research introduces a novel dataset for posture and fall detection, employing YOLO networks to enhance detection efficacy. Various YOLO versions, including YOLOv5n and YOLOv6s, are evaluated on the dataset based on accuracy metrics such as the F1 score, recall, and mean Average Precision (mAP). Experimental results indicate that YOLOv5s outperforms other versions, demonstrating superior performance in real-world fall detection scenarios. Gao (2023) focuses on developing a YOLO-based model for effective fall detection in IoT smart home applications, essential for minimizing injuries among the elderly. Vision-based approaches have gained popularity due to their practicality, but they often encounter issues such as low accuracy and high computational costs. The research aims to address these challenges by creating an accurate and lightweight fall detection system suitable for IoT platforms. A YOLO-based network is trained and tested to accurately identify human falls. Experimental findings highlight the system's potential for integration into IoT-enabled smart homes. Kan et al. (2023) tackle the significant health concern of falls among the elderly by proposing a lightweight approach named CGNS-YOLO for human fall detection. Despite the advancements of YOLOv5 in fall detection, challenges such as computational demands and hardware integration persist. The CGNS-YOLO method integrates GSConv and GDCN modules to optimize YOLOv5s, reducing model size and enhancing feature extraction efficiency. A normalization-based attention module (NAM) improves precision by focusing on relevant fall-related data. Incorporating the SCYLLA Intersection over Union (SIoU) loss function further boosts detection accuracy and convergence speed. Evaluation on the Multicam and Le2i Fall Detection datasets reveals a 1.2% increase in detection accuracy, with a significant reduction in model parameters and floating-point operations. Overall, CGNS-YOLO demonstrates superior efficacy and suitability for real-world deployment in fall detection applications. Wang et al. (2023) introduce an improved YOLOv5s algorithm for lightweight fall detection, crucial for addressing health risks associated with elderly falls at home. Enhancements include the application of a k-means clustering algorithm for accurate anchor boxes, replacing the backbone with a ShuffleNetV2 network for simplified computing, integrating an SE attention mechanism for enhanced feature extraction, and adopting an SIOU loss function for improved detection accuracy and training speed. Experimental results demonstrate a 3.5% increase in mean Average Precision (mAP), a 75% reduction in model size, and a 79.4% decrease in computation time compared to conventional YOLOv5s. The algorithm offers superior detection accuracy and speed, making it suitable for deployment in cost-effective embedded devices with limited performance. Gomes et al. (2022) leverage deep learning for fall detection, a crucial aspect of elderly safety. They integrate the YOLO object detection algorithm with temporal classification models and the Kalman filter to identify and track falls in video streams. The proposed methods, YOLOK + 3DCNN and YOLOK + 2DCNN + LSTM, outperform existing models on key metrics. Raza, Yousaf, and Velastin (2022) explore human fall detection using YOLO from a real-time and AI-on-the-edge perspective. Addressing the challenges of using wearable sensors in public settings, they propose a vision-based solution using YOLO and its variants (YOLOv1-v4 and tiny YOLOv4). The method leverages the UR Fall dataset for feature extraction and demonstrates the ability to detect falls and other activities in real-time using simple video camera images, without the need for ambient sensors. The approach supports deployment on edge devices like Raspberry Pi and OAK-D, highlighting its practical applicability. Zhao et al. (2021) introduce YOLO-Fall, an advanced convolutional neural network model tailored for detecting falls in open spaces, particularly in industrial settings where safety hazards are prevalent. Traditional fall detection models often struggle with accuracy and computational demands, limiting their practical deployment. YOLO-Fall addresses these challenges by incorporating novel enhancements: an SDI attention module for improved feature extraction, GSConv and VoV-GSCSP modules to reduce model parameters and complexity, and a DBB module in the final ELAN for enhanced feature diversity. Experimental results show that YOLO-Fall achieves a 2.7% improvement in mean Average Precision (mAP) compared to YOLOv7-tiny, while reducing model parameters by 3.5% and computational requirements by 5.4%. These advancements position YOLO-Fall as a precise and lightweight solution for real-world fall detection applications. Yin et al. (2021) address the critical issue of elderly fall detection using YOLO algorithms, considering the challenges posed by aging populations. Traditional machine learning methods often lack real-time performance and robustness in complex scenarios.

The study utilizes modified versions of YOLOv4 and YOLOv5s to achieve end-to-end prediction of fall events in real-time. Training on a custom fall dataset and testing in real scenarios demonstrate that YOLOv5s offers lightweight deployment, good robustness, and real-time accuracy compared to YOLOv4. Wang and Jia (2020) address the increasing issue of falls among the elderly, highlighting the need for efficient fall detection methods. Current video-based methods are often complex and lack real-time accuracy. The authors propose a solution using the YOLOv3 network model, which includes creating a fall detection dataset and optimizing the model on a GPU server. Their model demonstrates superior recognition performance compared to other algorithms.

After reviewing the literature on human fall detection, this section will discuss the details of YOLO (You Only Look Once). YOLO is a pioneering object detection algorithm that revolutionized computer vision by enabling real-time detection with high accuracy. Developed by Joseph Redmon et al., YOLO employs a single convolutional neural network (CNN) to predict bounding boxes and class probabilities directly from images in a single pass. This approach eliminates the need for multiple stages and significantly speeds up the detection process, achieving up to 45 frames per second on a GPU. YOLO's unified framework, use of anchor boxes for precise bounding box prediction, and its balance between speed and accuracy have made it a cornerstone in various applications requiring fast and reliable object detection.

In this research, we choose to use YOLOv8, referred to hereafter as YOLO version 8, which represents a significant advancement in the YOLO series of object detection models. This version introduces several key improvements over its predecessors, enhancing both accuracy and efficiency in object detection tasks. YOLOv8 integrates advanced architectural changes, such as the use of CSPNet (Cross Stage Partial Network) and PANet (Path Aggregation Network). These enhancements optimize feature extraction and aggregation, leading to improved detection performance across various object sizes and orientations. In terms of speed, YOLOv8 maintains real-time inference capabilities despite its increased complexity. This is achieved through optimizations in model architecture, implementation of efficient layers, and streamlined computational processes. Training efficiency has also been enhanced in YOLOv8. The model benefits from novel data augmentation techniques, refined loss functions like focal loss, and efficient training strategies such as transfer learning with pre-trained models. These improvements contribute to faster convergence during training and better overall model performance. Backbone network improvements are crucial in YOLOv8, leveraging a more powerful base network that enhances feature representation and extraction. This upgrade ensures that the model can accurately detect objects under diverse environmental conditions and challenging scenarios. Overall, YOLOv8 sets a new benchmark in object detection with state-of-the-art performance metrics. Its combination of superior accuracy, real-time processing speed, efficient training methodologies, and robust backbone architecture makes it a preferred choice for a wide range of applications in computer vision, including autonomous driving, surveillance systems, and medical diagnostics.

Upon reviewing the literature on elderly fall detection, it is evident that current systems primarily focus on developing highly efficient detection hardware. Moreover, the software and algorithms used in these systems are often complex and resource-intensive, leading to significant costs for access. In practical real-world applications, these high-performance falls detection systems offer limited accessibility options for the middle class. The available alternatives are either to place elderly individuals in a healthcare center, incurring substantial expenses, or to invest in installing a home-based fall detection system, which requires considerable expenditure on both hardware and costly software. Furthermore, once installed, these systems lack portability and cannot be relocated for use in different settings. Therefore, users of these systems are constrained to remain within the premises where the system is originally set up. Additionally, a stable Wi-Fi connection is crucial for optimal system operation.

Hence, the author aims to propose a fall detection system characterized by affordability and accessibility for all users. This system should be highly portable. Consider a scenario where one must care for an elderly individual who stays alone at home while the caregiver is at work during the day. If the caregiver's job involves frequent relocations, a portable fall detection system becomes essential. Consequently, the author envisions developing a fall detection application for elderly individuals using a smartphone as the detection device. Upon detecting a fall, the system can send alerts through Wi-Fi or mobile network SIM. Another notable feature of this system is its portability, allowing it to be carried anywhere. Additionally, in the event of a power outage, the smartphone can continue to operate on battery power until it is depleted.

The subsequent sections of the paper follow this structure: the section titled "The Proposed Methods" presents the methodologies proposed in this paper, offering detailed elucidations. Following that, the section "Experimental Results" delves into the specifics of data processing and experimentation, accompanied by an exhaustive analysis of the outcomes. Lastly, the "Conclusion" section provides a summary of the findings and outlines avenues for future research.

2. The Proposed Methodology

This section presents a comprehensive fall detection system specifically designed for elderly individuals, utilizing supervised machine learning methods, and emphasizing mobile-based deployment. The proposed methodology is delineated into three core stages: data collection and labeling, training, and inference. The schematic representation of our system is illustrated in Figure 1.

Our method amalgamates state-of-the-art machine learning techniques with a mobile-centric approach, providing an economically viable and scalable solution for fall detection within elderly care contexts. The subsequent section will delve into the intricate details of each of these three stages, elucidating their significance and implementation nuances.

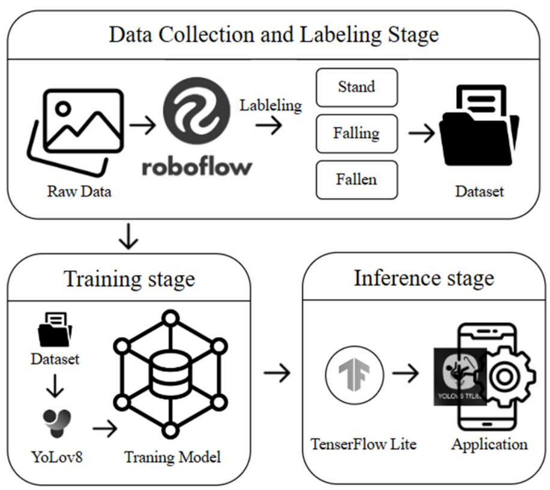

Figure 1 The schematic of the proposed system

2.1 The data collection and labeling stage

The data collection and labeling stage involved acquiring a diverse dataset comprising 1,500 images across three distinct classes: standing, falling, and fallen. All 1500 images were selected from free access image datasets specifically curated for elderly fall detection, namely the UP-Fall Detection Dataset, Multicam Dataset, and UR Fall Detection Dataset. The UP-Fall Detection Dataset, Multicam Dataset, and UR Fall Detection Dataset are invaluable resources for research in elderly fall detection. Each dataset offers curated images specifically annotated to depict various scenarios of falls among elderly individuals. The UP-Fall Detection Dataset provides a comprehensive collection capturing diverse environments and fall types, enhancing realism in training and evaluation. The Multicam Dataset contributes multiple camera angles, simulating varied surveillance perspectives crucial for robust model training. Meanwhile, the UR Fall Detection Dataset focuses on annotated images tailored for studying algorithmic intricacies in fall detection, aiding in algorithm development and evaluation. Together, these datasets facilitate comprehensive research on fall detection algorithms, covering a wide range of environmental conditions and fall scenarios. These images underwent meticulous labeling using the RoboFlow platform, ensuring accurate classification within the designated classes while maintaining consistency and reliability across the dataset. The schematic depiction of this stage is illustrated in Figure 2.

Following the augmentation of noise types to diversify the dataset, the original 1,500 images have been significantly enriched, resulting in a total of 7,500 images. This augmentation strategy aims not only to expand the dataset size but also to imbue the model with robustness and adaptability to varying real-world conditions. The inclusion of four types of noise: grayscale, saturation, mosaic, and brightness serves as a strategic augmentation approach to simulate a spectrum of environmental challenges commonly encountered in real-life scenarios. Each type of noise introduces specific variations to the original images, thereby enhancing the model's ability to generalize and accurately detect falls amidst diverse conditions. Grayscale noise, for instance, alters the color space of the images to simulate scenarios with varying lighting conditions, such as low-light environments or overexposed settings. This augmentation challenges the model to detect falls irrespective of lighting variations, thereby improving its resilience in real-world deployment.

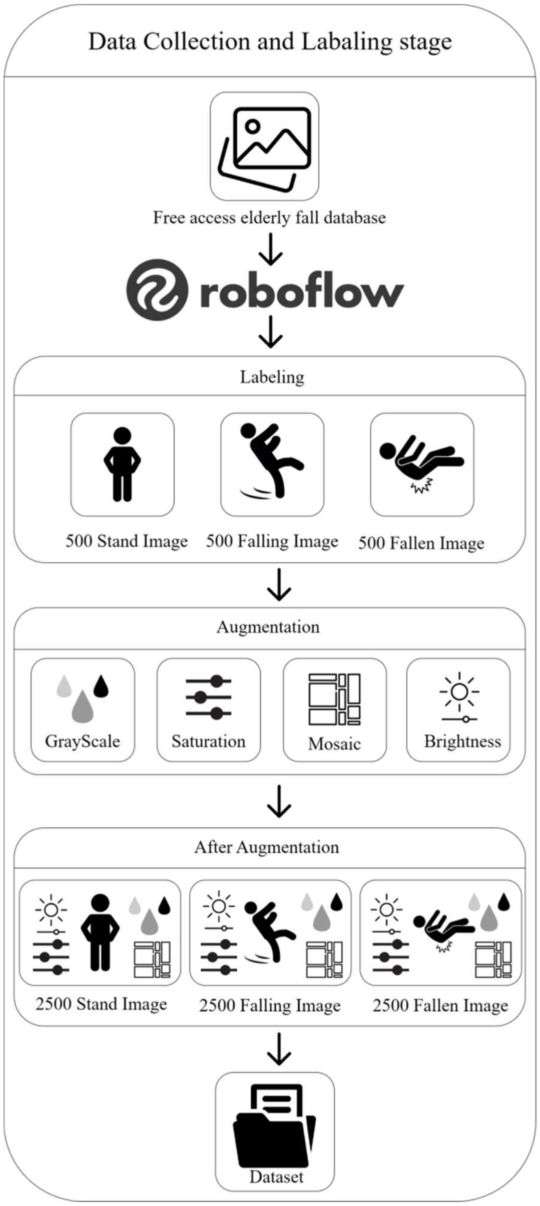

Figure 2 Overview of the data collection and labeling stage

Saturation noise adjusts the saturation levels of the images, resulting in desaturated or muted colors. This augmentation mimics scenes with subdued or washed-out colors, such as foggy or hazy conditions, challenging the model to discern falls amidst diminished visual cues. Mosaic noise pixelates sections of the images, distorting their details to replicate scenarios where the image quality is degraded or obscured. This augmentation prompts the model to identify falls despite partial or obscured visual information, thereby enhancing its adaptability to diverse imaging conditions. Brightness noise modifies the brightness levels of the images, resulting in darker or brighter overall appearances. This augmentation emulates environments with varying degrees of illumination, ranging from dimly lit spaces to glaringly bright conditions, challenging the model to accurately detect falls under diverse lighting circumstances.

Through this comprehensive augmentation strategy, we aim to equip our model with the resilience and adaptability necessary to reliably detect falls in a wide range of real-world conditions, thus enhancing its practical utility within elderly care settings.

The characteristics of each type of noise are visually depicted in Figure 3, showcasing the diversity of challenges introduced to the dataset.

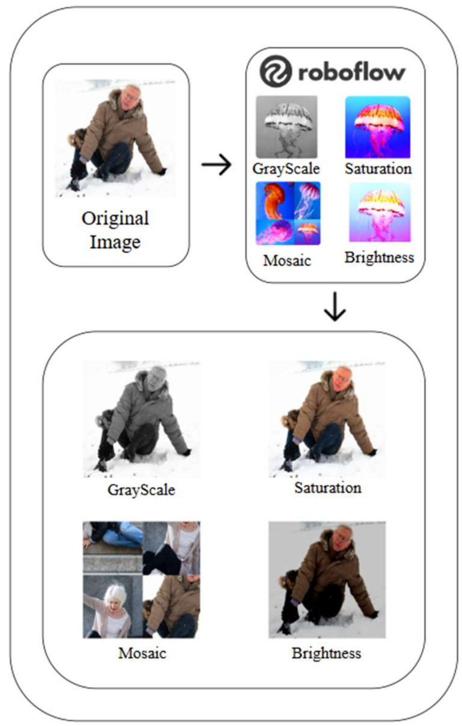

Figure 3 Examples of all four types of noise

This step ensures the availability of high-quality data crucial for training our fall detection model.

2.2 The training stage

Subsequently, the training stage incorporates state-of-the-art deep learning architecture, YOLOv8, to facilitate the development of our fall detection model. Leveraging the capabilities of TensorFlow, a powerful machine learning framework, we seamlessly integrate YOLOv8 into our training pipeline. This strategic decision is rooted in YOLOv8's renowned robustness in object detection tasks and its real-time processing capabilities, making it an ideal candidate for our mobile-centric approach to fall detection. The schematic depiction of this stage, as outlined above, is visually represented in Figure 4.

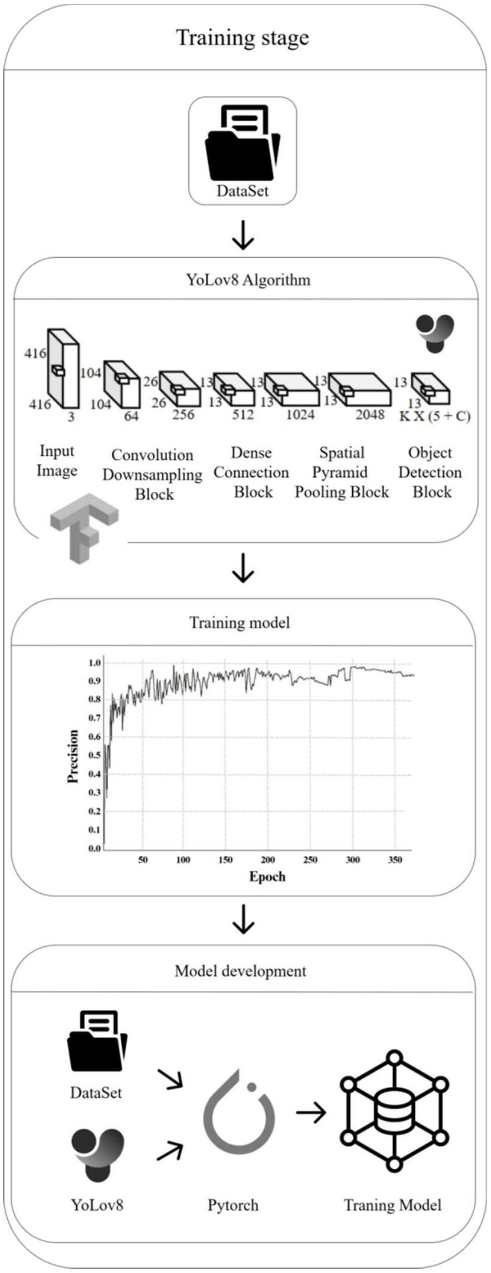

Figure 4 Overview of the training stage

By harnessing TensorFlow's extensive functionalities, we optimize the implementation of YOLOv8, ensuring efficient utilization of computational resources during training. TensorFlow's flexibility allows us to fine-tune model parameters and hyperparameters, enhancing the accuracy and reliability of our fall detection system. Moreover, TensorFlow provides a rich ecosystem of tools and libraries for data preprocessing, augmentation, and visualization, streamlining the entire training process.

Throughout numerous training iterations, our model undergoes a rigorous learning process, adapting to diverse scenarios and environmental conditions to accurately detect and classify instances of falls within input images.

Additionally, we carefully monitor the training progress by analyzing the learning rate over epochs. The learning rate graph, depicted in Figure 5, illustrates the dynamic adjustment of the learning rate during training. This adaptive learning rate scheme optimizes the convergence speed and stability of the training process, allowing our model to effectively learn from the training data while mitigating the risk of overfitting or divergence.

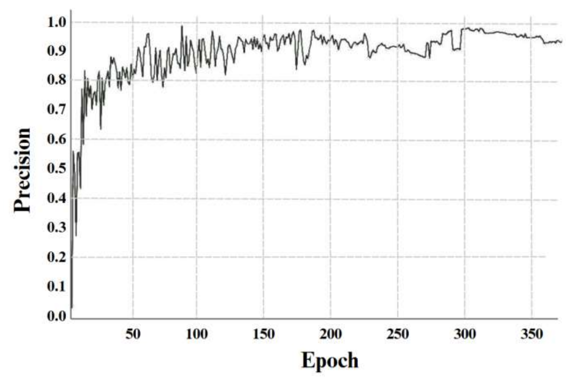

Figure 5 Graph of learning rate

In Figure 5, it is observed that the precision surpasses the threshold of 80% after approximately 50 epochs of training. Furthermore, the precision stabilizes at a level exceeding 80% after around 300 epochs of training. This phenomenon underscores the efficacy of the training regimen in enhancing precision metrics. Such observations reflect a convergence towards a stable and desirable precision performance, indicative of the model's adeptness in discerning and classifying data patterns. These findings bear significance in the context of model optimization and deployment, elucidating the trajectory of precision improvement over training epochs. The integration with TensorFlow not only accelerates model convergence but also facilitates seamless deployment across various platforms, including mobile devices, ensuring real-time fall detection capabilities in practical scenarios.

In summary, by harnessing the synergy between YOLOv8 and TensorFlow, we empower our fall detection model with cutting-edge object detection capabilities, paving the way for robust and efficient fall detection solutions in real-world applications.

2.3 The inference stage

The inference stage marks the deployment and evaluation of our trained fall detection system. Our next critical step involves deploying the trained system for real-world applications. Integration of YOLOv8 with TensorFlow provides a robust framework for developing and deploying advanced object detection systems. YOLO is renowned for its real-time processing speed and high accuracy in object detection across images and videos. TensorFlow, widely adopted in deep learning and machine learning applications, offers comprehensive support for training and inference processes, enhancing YOLO models effectively.

The TensorFlow Object Detection API enables seamless integration with YOLO models, empowering researchers and developers to leverage TensorFlow's capabilities throughout training and deployment phases. During training, TensorFlow efficiently trains models using annotated datasets, allowing the YOLO model to adapt and optimize its detection capabilities by adjusting model parameters and architecture for optimal performance metrics.

In deployment, TensorFlow facilitates the integration of pre-trained YOLO models into real-time applications or video streams, ensuring precise object detection in dynamic environments. The API's flexibility supports fine-tuning of pre-trained models tailored to specific use cases or to enhance detection performance further.

Furthermore, TensorFlow supports ongoing model refinement through continuous evaluation and optimization, enabling iterative improvements based on real-world performance feedback. Leveraging TensorFlow Lite, a lightweight version optimized for mobile and embedded devices, further enhances deployment efficiency.

The workflow of this stage is illustrated in Figure 6, depicting the overall process from model training to deployment and iterative refinement.

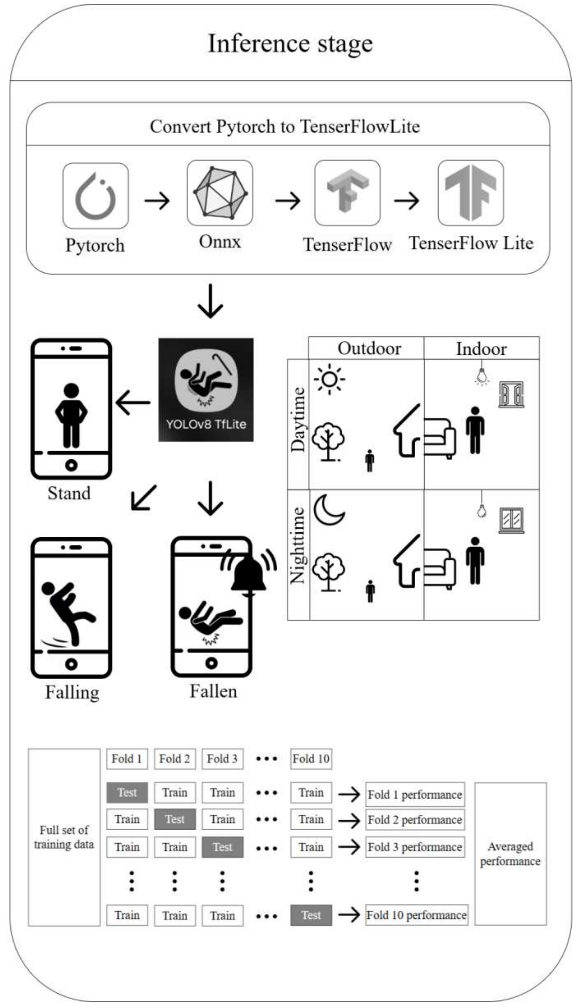

Figure 6 Overview of the Inference stage

The process begins with the conversion of our trained TensorFlow model into a TensorFlowLite format, tailored for seamless integration with mobile platforms. TensorFlowLite employs various optimization techniques to ensure minimal computational and memory footprint, thereby enabling efficient execution on resource-constrained devices such as smartphones. Once the model conversion is completed, we proceed to integrate the TensorFlowLite model into our mobile application, empowering smartphones with the capability to perform real-time fall detection. Leveraging the processing power of modern smartphones, our application can analyze video streams or accelerometer data in real-time, swiftly detecting and alerting caregivers or emergency services in the event of a fall. Furthermore, the deployment of our fall detection system on smartphones offers several advantages, including portability, ubiquity, and accessibility.

Users can carry their fall detection solution with them wherever they go, ensuring continuous monitoring and assistance, particularly for elderly individuals living independently. Additionally, the integration of our fall detection system into smartphones opens up opportunities for further enhancements, such as incorporating additional sensors (e.g., gyroscopes, GPS) for context-aware fall detection or leveraging cloud services for centralized monitoring and data analytics. In summary, the exportation of our trained fall detection model to TensorFlowLite facilitates seamless integration into smartphones, enabling the deployment of our solution for real-time fall detection on a wide scale. By harnessing the ubiquity and processing power of smartphones, we empower individuals to lead safer and more independent lives while providing caregivers and emergency responders with timely alerts and assistance when needed.

Following the successful deployment of our fall detection system onto smartphones, the next pivotal aspect we delve into is the analysis of experimental results. This phase serves as the ultimate validation of our system's performance and effectiveness in real-world scenarios.

3. THE EXPERIMENTAL RESULTS

The experimental results provide crucial insights into the performance and effectiveness of our fall detection system, validating its capability to accurately identify falls and differentiate them from normal activities. In this section, we present a comprehensive analysis of both quantitative and qualitative evaluations conducted to assess the system's performance. Additionally, a utilization evaluation was also conducted.

3.1 Quantitative evaluation

Cross-validation is a statistical method used to assess the performance of machine learning models by partitioning the dataset into subsets known as "folds." Typically, in a 10-fold cross-validation setup, the data is divided into 10 equally sized folds. During each iteration, one fold is designated as the validation set, while the remaining nine folds are utilized for training the model. This process is repeated ten times, ensuring that each fold serves once as the validation set. The results from each iteration are averaged to derive a final performance metric, providing robust evaluation and minimizing overfitting risks by leveraging all available data for training and validation purposes.

For the quantitative evaluation of our fall detection system, we utilized a 10-fold cross-validation technique. Details of the fold division and the sequence of folds used for testing and training are depicted in Figure 7. The dataset comprises a total of 7,500 images, consisting of 3 classes with 2,500 images per class. These images were divided into 10 folds, each containing 750 images. Each fold consists of 750 images, with 250 images from each of the 3 classes. The average accuracy of our approach was calculated to be 97.88%. Comprehensive confusion matrices for each fold, accompanied by their respective accuracy scores, are presented in Table 1, providing a detailed illustration of the evaluation results.

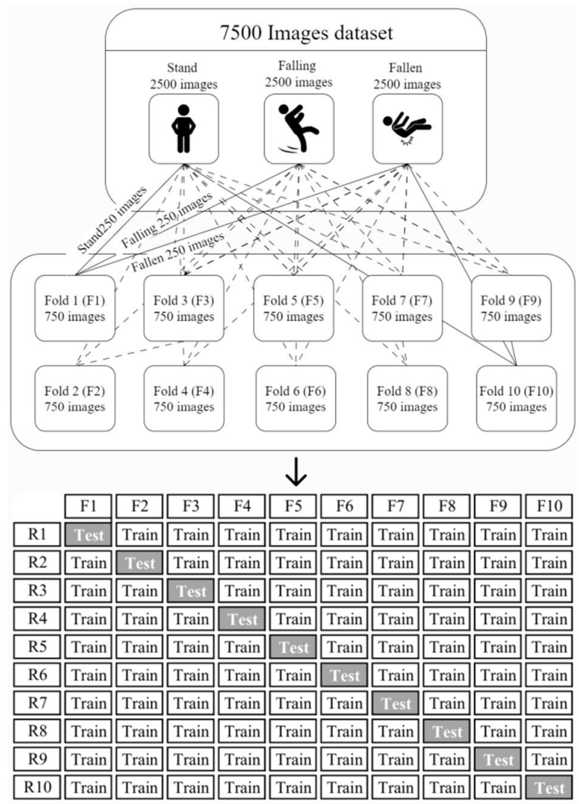

Figure 7 10-fold cross-validations

In Table 1, the abbreviations ST, FG, and FN in the columns under "Actual class" and "Predicted class" denote stand, falling, and fallen, respectively. The accuracy of the fall detection model was evaluated using the following formula:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where *TP* represents True Positives, *TN* represents True Negatives, *FP* represents False Positives, and *FN* represents False Negatives. This metric measures the model's ability to correctly classify instances of falls and non-falls.

These results demonstrate the high accuracy and reliability of our fall detection system across diverse datasets, showcasing its robustness in real-world scenarios.

Table 1 Accuracy scores from 10-fold cross-validation

Fold	Actual Class	Predicted Class ST	FG	FN	Accuracy (%)
1	ST	245	4	1	98.27%
	FG	2	245	3	
	FN	1	2	247	
2	ST	245	4	1	98.00%
	FG	2	245	3	
	FN	1	2	247	
3	ST	245	3	2	98.40%
	FG	1	246	3	
	FN	2	4	244	
4	ST	249	1	0	97.87%
	FG	3	243	4	
	FN	0	4	246	
5	ST	245	3	2	97.73%
	FG	1	246	3	
	FN	3	4	243	
6	ST	246	3	1	97.07%
	FG	2	244	4	
	FN	2	5	243	
7	ST	245	3	2	98.27%
	FG	5	237	8	
	FN	1	3	246	
8	ST	248	2	0	97.20%
	FG	1	245	4	
	FN	2	4	244	
9	ST	242	5	3	98.67%
	FG	2	244	4	
	FN	1	6	243	
10	ST	247	2	1	97.33%
	FG	1	246	3	
	FN	0	3	247	
Average					97.88%

3.2 Qualitative evaluation

In addition to quantitative assessment, we conducted a qualitative evaluation to analyze the system's performance under different conditions. The evaluation criteria included four scenarios: daytime outdoor residential (DOR), daytime indoor residential (DIS), nighttime outdoor residential (NOR), and nighttime indoor residential (NIR). From this assessment, we collected 300 images for each scenario, totaling 1200 images used for qualitative evaluation. These images were meticulously chosen to encompass various environmental factors and challenges typical of real-world fall detection scenarios. Examples of images from each scenario are illustrated in Figure 8. These scenarios represent subclasses within the main class of elderly fall images as discussed in section 2.1 of the image database.

Figure 8 Examples of images from four scenario

The evaluation was based on confusion matrices obtained from the classification results for each scenario. The confusion matrices provide insights into the system's ability to accurately detect falls and differentiate them from non-fall activities. The results of the qualitative evaluation are summarized in Table 2, where the average accuracy of the qualitative approach is calculated to be 95.92%.

Table 2 Accuracy scores from four scenarios

Scenario	Actual Class	Predicted Class ST	FG	FN	Accuracy (%)
DOR	ST	97	2	1	97.33%
	FG	0	97	3	
	FN	1	1	98	
DIR	ST	95	3	2	96.67%
	FG	1	97	2	
	FN	1	1	98	
NOR	ST	96	3	1	95.33%
	FG	0	98	2	
	FN	3	5	92	
NIR	ST	93	4	3	94.33%
	FG	1	97	2	
	FN	2	5	93	
Average					95.92%

These results demonstrate the system's effectiveness in accurately detecting falls across different environmental conditions. The low false positive and false negative rates indicate the system's reliability in distinguishing fall events from normal activities, thus showcasing its suitability for real-world deployment.

3.3 Utilization evaluation

In addition to the quantitative and qualitative evaluations discussed in preceding sections, serving as benchmarks for academic performance, this study

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presents a pragmatic assessment focusing on four critical dimensions: real-time detection capabilities, simultaneous detection of falls among multiple individuals with varying statuses, system repositioning flexibility, and fall-triggered alert notifications.

The study conducted tests on real-time and simultaneous fall detection by capturing fifteen 1-hour videos, totaling 15 hours of footage. Results indicate the smartphone-based fall detection system operated flawlessly. Figure 9 provides sample images highlighting the system's real-time individual status detection, while Figure 10 demonstrates its simultaneous detection across diverse individual statuses.

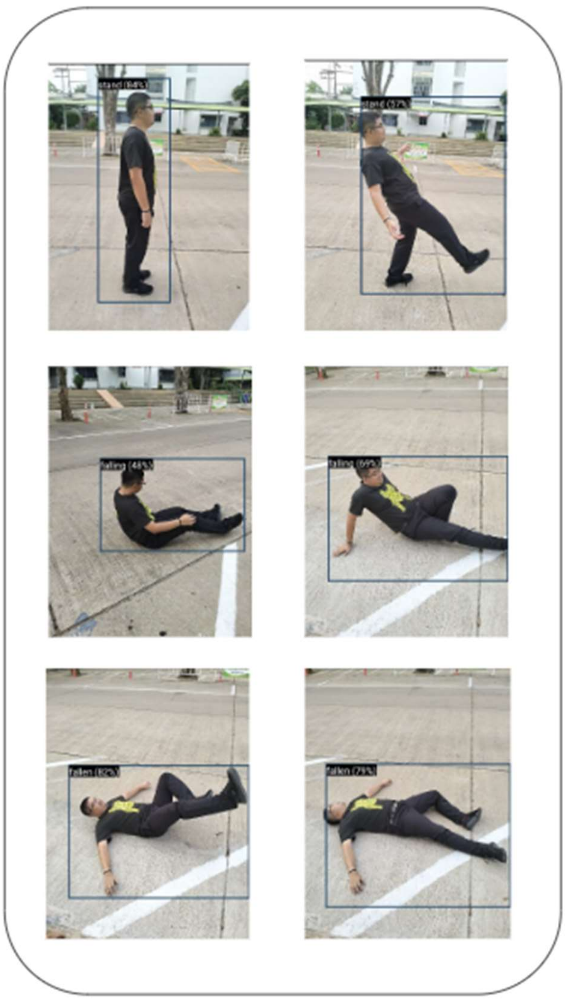

Figure 9 Real-time demonstration of the fall detection system accurately identifying individual statuses.

Figure 10 Simultaneous detection of falls across multiple individuals with varying statuses.

To evaluate system mobility and usability across different environments, varied indoor and outdoor locations were systematically tested during video recordings. Results revealed seamless transitions between locations without complications, as shown in Figure 11.

Figure 11 Example of location transition during testing.

Lastly, alert notifications were tested by integrating them with the LINE messaging app, triggering notifications for 45 instances of randomly simulated falls, occurring three times per hour during video recordings. The system successfully detected and alerted each instance without errors, depicted in Figure 12.

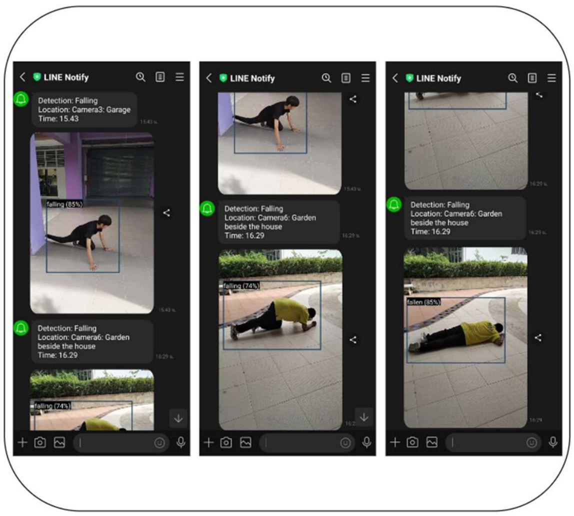

Figure 12 Notification display integrated with the LINE messaging app during fall detection testing.

This revision emphasizes that figures 9, 10, 11, and 12 were intentionally chosen not to depict elderly individuals. The testing methodology of the fall detection system included simulated falls specifically designed to assess its sensitivity and accuracy, particularly in scenarios involving elderly users. The deliberate decision to exclude images of elderly individuals from these figures was made to prevent any misinterpretation and to ensure clarity in demonstrating the system's capabilities across various scenarios.

Conducting tests with elderly individuals in fall detection research raises significant ethical considerations and potential risks. Safeguarding the safety and well-being of participants is paramount when conducting research involving vulnerable populations. Adherence to stringent research ethics guidelines is essential to mitigate any potential harm or discomfort that participants may experience. Testing the fall detection system involved rigorous evaluation under controlled conditions where simulated falls were carefully orchestrated to mimic real-world scenarios. This approach not only validated the system's ability to detect falls but also ensured that the testing process did not expose elderly individuals to actual risks associated with falling.

The validated fall detection system explored in this study holds significant promise for diverse applications across various sectors. Implementing this system in elderly care facilities, such as nursing homes or assisted living facilities stands to revolutionize elderly care by providing immediate alerts in the event of falls. This capability not only reduces response times but also enhances overall safety by ensuring prompt assistance during critical moments. In the realm of home healthcare, particularly for elderly individuals living independently, the system's continuous monitoring capabilities offer reassurance without compromising privacy. By detecting falls and triggering alerts, it enables timely intervention and support, crucial for managing emergencies effectively and maintaining independence. Hospitals can also benefit from integrating this fall detection system into their environments. In wards where patient mobility is a concern, the system serves as a valuable supplement to existing monitoring systems. It enhances patient safety by providing additional layers of detection and response mechanisms, thereby reducing the risks associated with falls within healthcare settings. Public spaces, such as airports, train stations, or recreational areas, can leverage the system to improve safety protocols. Rapid detection of falls allows for immediate medical assistance, minimizing potential consequences and ensuring a swift response to emergencies. Moreover, the system's adaptability extends to personal use through wearable devices or smartphone integration. This application empowers individuals by alerting caregivers or emergency services in real-time, regardless of their location. Such proactive measures not only enhance personal safety but also contribute to peace of mind for users and their families. By harnessing the accuracy and real-time capabilities validated in this study, stakeholders across these sectors can optimize safety protocols, improve response times, and ultimately enhance outcomes for individuals prone to falls, including the elderly and those with specific medical conditions.

4. CONCLUSION

In conclusion, this paper introduces a mobile-centric approach to fall detection tailored specifically for the elderly, addressing a critical need in the context of an aging global population. Our research underscores the urgency of developing cost-effective, scalable solutions to ensure the safety and well-being of seniors, particularly those living independently. By diverging from conventional hospital-based setups, our methodology offers a pragmatic response to the challenges posed by the demographic shift towards an increasingly elderly populace. Throughout our study, we have meticulously outlined the methodology employed in the design, development, and evaluation of our fall detection system. From the rigorous data collection and labeling process to the utilization of state-of-the-art supervised machine learning techniques, such as YOLOv8, our approach reflects a commitment to methodological rigor and innovation. Furthermore, the seamless integration of our model with mobile platforms through TensorFlowLite underscores our emphasis on practicality and real-world applicability. The experimental results presented in this paper provide compelling evidence of the efficacy and reliability of our fall detection system. Through a combination of quantitative evaluation techniques, including 10-fold cross-validation, and qualitative analysis based on confusion matrices, we have demonstrated the robustness of our approach across diverse datasets and environmental conditions. These findings not only validate the effectiveness of our system but also underscore its potential for widespread adoption and deployment. Moreover, the practical implications of our research extend beyond academic discourse. The deployment of our fall detection system on smartphones holds transformative potential for elderly care and emergency response. By leveraging the ubiquity and processing power of mobile devices, we empower caregivers and elderly individuals with real-time monitoring and assistance capabilities, thereby enhancing safety, autonomy, and quality of life. Looking ahead, the field of fall detection systems for the elderly presents exciting opportunities for further research and innovation.

Future endeavors may explore enhancements such as context-aware fall detection, integration with additional sensors, or cloud-based analytics for comprehensive monitoring and analysis. By continuing to push the boundaries of technology and healthcare, we can strive towards a future where aging populations can age with dignity and security, supported by cutting-edge solutions tailored to their unique needs.

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