Real-World Case Study of a Deep Learning Enhanced Elderly Person Fall Video-Detection System

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Abstract: Recent large and rapid growth in the healthcare sector has contributed to an increase in the elderly population and an increase in life expectancy. One of the important study topics in this field is the automatic fall detection system. Camera-video has been extensively employed recently for applications in surveillance, the home, and healthcare. Therefore a smart fall detection system is focusing on image and video analysis techniques. For that, our scientific work studied an actual vision-based fall detection system. It produces satisfactory outcomes, but there is still room for improvement. The system has a very high recall rate and can detect all falls, but it lacks precision and frequently reports false positives (more than 99 per-cent). In fact, due to the optimum camera quality, several ordinary activities with specific movements, such as wheelchair mobility, or the light changing in an empty room, can be mistaken for falls. To address this problem and increase precision, we propose a post-process approach, hybridizing a CNN model and a Haar Cascade Classifier to determine whether to confirm or reject an alert that has been identified as a fall. The system's effectiveness will increase while the false positives are decreased.

1 INTRODUCTION

The elderly population is growing more in the world recently. The elderly are living longer and are getting more numerous than ever, due to many reasons, including the adoption of modern technologies to lessen health issues. One common and major health problem that elderly people face is falling. Thousands of them are victims of fall incidents. Chan et al. (Chan et al., 2007) estimate that one-third of home-living adults aged 75 or more experience a fall each year. Falls cause variable physical consequences depending on the senior, but they frequently result in serious injuries including hip fractures or even death. In fact, falling is one of the five most common causes of death among the elderly population (Vishwakarma et al., 2007). World Health Organization (World Health Organization,) estimated that 646 000 fatal falls occur each year, making it the second leading cause of unintentional injury death, after road traffic injuries. Furthermore, fall victims suffer from severe psychological effects, such as the loss of self-confidence (Vignat, 2001), which is one of the most reasons that don't encourage the aged population to live alone and maintain an independent lifestyle. As a result, it is highly recommended to adopt technological innovations like smart systems to help address these problems and prevent any dangerous injuries by minimizing the time spent lying down on the cold floor for several hours or even days after a fall incidence has occurred. Because of this, the use of technological advancements, such as smart systems, is strongly recommended to help address these problems and to avoid any dangerous injuries by reducing the period of laying down on the cold floor for several hours or even days after a fall incident has occurred. This makes developing an effective fall detection system a major challenge for the health care research community. That is the primary focus of this paper. There are several types of systems for automatic fall detection, as described in Section 2. There are several types of sys-

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tems for automatic fall detection, which we will describe in Section 2. Including wearable devices and environmental sensors. However, they are unfavorable choices for the people, they consider them blind solutions because they are unable to communicate the severity level of a fall to provide the required assistance. The camera-based system is the most reliable and trustful method of detecting falls and delivering timely aid. Despite the success and the trust of people in this direction, it still faces many challenges. Overcoming one of them is our objective in this study. We based on a real case study in a French company of fall detection camera-based system, to improve it. We found out that because of the video's optimal resolution and room's light condition, there are some daily activities with certain movements such as mobility on a wheelchair or even the light changing in an empty room that can be mistaken for falls, which decreases the system's precision. We focused on how always returning positive falls to maximize the system precision. For this, we proposed to reduce generated false-positive images. We presented an image processing algorithm that hybridizes a Convolution Neural Network model and a Haar cascade classifier, which will be added to the fall detection algorithm to filter the alert image before being sent. The organization of this research paper is as follows. Section 2 will give an overview of fall human detection systems. Section 3 will present a real-use study of a fall video detection system in a French company and discuss one of its weakest points, then we will propose a solution to overcoming this problem and improving this system. Section 5 will cover the experimental results obtained. A conclusion of the work is formulated in section 6.

2 OVERVIEW OF HUMAN FALL DETECTION SYSTEMS

Recently, a huge amount of research is proposed to solve the problem of fall detection. This problem can requires using one of different types of devices in order to collect data when attempting to automatically detect a fall (Gutiérrez et al., 2021; Rastogi and Singh, 2021; Berlin and John, 2021). They can be categorized into invasive devices that must be maintained by the user and passive devices which continue to operate with minimal maintenance.

In the state-of-the-art of fall detection, researchers tend to base there approaches on structured prediction, supervised learning, clustering, outlier detection, dimensional reduction, and neural networks. Through the last decades, many papers reviewed the evolution of existing human fall detection systems. The first survey was published in 2008 by Noury et al. (Noury et al., 2007), they reviewed the sensor-based systems for automatic fall detection by citing all previous works that deal with the accelerometer approach as well as those done with image processing techniques.

Thousands of new techniques have appeared after the survey published by M.A.Habib et al. (Habib et al., 2014) in 2014, and yet no survey paper has been published to group these new approaches until 2018 when T.XU et al. (Xu et al., 2018) updated the survey of fall detection methods focusing on those done from 2014. They have selected the twenty most highly cited articles to discuss profoundly their ideas and theories and analyse them from three aspects: sensors, algorithms, and performance. In the same year, Y. Birku et al. (Birku and Agrawal, 2018) published a survey of various fall detection systems and methods. They detailed the most used approaches in the fall detection system, which include the wearable, ambiance, and camera-based devices. Another survey paper in the human fall detecting domain was written by S.K. Jarraya et al. (Jarraya, 2018). They considered only camera-sensor based approaches because of their performance versus other approaches, they gave an overview of the related works on fall detection that used Kinect camera and discussed their limitation and advantages. Indeed, we will give, in short, a global vision of these different systems and their limits. First, the traditional medical alert systems are manual alarm systems that require the participation of the person. The alarm buttons, existing in the form of a necklace or a bracelet to carry on, allow the person to press on to alert of a fall. The idea behind this type is to avoid false alarms and to allow the person to feel reassured to have at all time a wearing device. But these devices must be worn to function. This is the main cause of their lack of effectiveness. In 1981, Wild et al. (Wild et al., 1981) conducted a study on people over 65 years old for one year. They found that of the nine fallers with an alert system, only two managed to use it to alert after falling. This inability to press the button may be due to the person's unconsciousness or shock. So even though the senior used this system, he remains unprotected and rescued in the event of a sudden fall followed by a loss of consciousness that he could not trigger an alert to the help desk manually. That is what push the researchers to develop an automatic alarm system which can be defined as an assistive device whose main objective is to alert when a fall event has occurred. The most known commercial fall detection systems are mostly classified into three categories; those based on wearable devices, those based on ambiance sensors, and those based on video processing (Yu, 2008; Mubashir et al.,

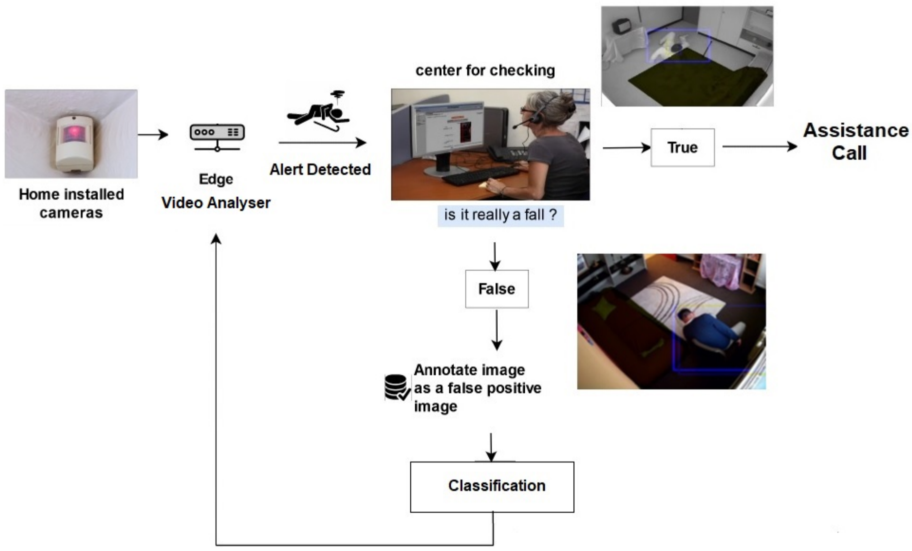


Figure 1: Video fall detection system.

2013). The Wearable device based systems sensitively provide automatic detection, thanks to embedded sensors (accelerometer, triaxial accelerometer, biological signals) and new algorithms which recognize the activities. They allow measuring changes in orientation, motion, and location of the body of the subject to detect the physical activity so that can identify the fall event. Once a fall is recorded and not interrupted by the user, the system immediately contacts the health services to allow early intervention. However, the main drawback of these systems is that they fixed relative relations with the object, which could be easily disconnected. In addition, carrying around devices all the time and wearing them is not convenient, and elderly individuals may simply forget to put them on. The ambiance sensors came to overcome this problem, they detect the plantar pressures exerted by people to ensure that the person is not lying on the floor. They rely on proximity and floor sensors to collect data on the daily living activities of the senior. They use motion, light, and vibration sensors and combine visual and sound information to detect a fall. However, it has the significant disadvantage of sensing the pressure of everything in and around the object and generating false alarms in the case of fall detection, which leads to poor detection accuracy. Furthermore, nothing can guarantee if it is a real fall or not and the degree of severity if so. The last category and not the least is Vision-based systems, which analyse algorithms for images, sounds, and videos. Recently, camera-video has been increasingly popular for surveillance, home, and healthcare applications. Since they tend to deal with intrusion better than other approaches. They can integrate many implemented algorithms and open-source libraries that detect the person's falls. Only this type of system raises the doubt whether it is a real fall or not, so it allows for avoiding unnecessary interventions and minimizes the overall cost of the service and provides the exact cause of human falling. And unlike the others, they make it possible to have an idea about the severity level of a fall event, so that, a necessary rescue will have done. The Cameras must be installed in several rooms to cover the whole area of actuation. When a fall is detected, the system sends the images of this event to the help desk.

3 REAL CASE STUDY OF VISION-BASED FALL DETECTION SYSTEM

3.1 Context and Objective of the Work

Angel Assistance is a French innovative company launched in 2013 to develop a new technique and a complete video fall detection system to help dependent elderly in their home from a camera mounted in a patient room. Once a fall is detected, the system sends automatically and immediately an image alert captured of the senior's situation to the company call center to be treated and verified by human agents, whether is a true fall or a false one to perform the necessary rescue. The false positives are events similar to the characteristics that define the falls.

3.2 Data Acquisition

An RGB camera and an Edge computer are used for data acquisition. In fact, the Hidden RGB camera equipped with infrared LED for night vision used as presence detector (Ismaili-Alaoui et al., 2022; Ismaili-Alaoui et al., 2019). And Edge is a local server that analyzes video feeds from all local cameras. It detects any drop alerts in order to be sent to the operations center. Indeed, the images captured by the camera are analysed in the Edge computer to determine whether or not a fall has occurred. The system alerts the center of the detected fall, which is then checked and stored, by a center agent, in one of four classes: false alerts including empty room, false alerts including active person, true alerts with average risk level including seated person, and true alerts with a high level of risk, which includes people lying down. Figure 1 illustrates the process of video fall.

We studied data gathered by the system over seven months, containing about 26 551 images. We have observed that 99% of received alerts are false positives, and only seven are real alerts. Four falls with a seated person, three falls with a lying person, 16972 images of empty rooms and 9572 images of active people.

3.3 Data Analysis

Various machine learning models were investigated to increase the accuracy of automatic fall detection. For example, (Özdemir and Barshan, 2014) used K-Nearest Neighbor classifier or (Karantonis et al., 2006) used Support Vector Machines (SVM) that accurately detect falls based on wearable motion sensors. However, as mentioned in the section 2, they pose problems because the elderly must always wear them, therefore they are insufficient to provide reliability in real-world circumstances (Galvão et al., 2021). In the other hand, these machine learning classifiers have also been proposed for solutions based on surveillance cameras and computer vision techniques. For example, Feng et al. (Feng et al., 2014) classified human postures identified from extracted silhouettes using a multi-class support vector machine. Also, Galvão et al. (Galvão et al., 2017) tested MLP, KNN and SVM classifiers. All these techniques produced accurate results. However, the current issue is all these studies results represent only reflect the accuracy of sensitivity, which measured the system's capacity to detect falls, and completely ignore the accuracy of specificity, which measures the system's capacity to prevent false alerts (Aziz et al., 2017).
Indeed, sensitivity refers to the ratio of the true positives to the total number of falls as shown in equation 1. Conversely, specificity is determined by the ratio of true negatives to the total number of discarded trials, as shown in equation 2, c .

$$Sensitivity = \frac{TruePositive}{TruePositive + FalseNegative} \quad (1)$$

$$Specificity = \frac{TrueNegative}{TrueNegative + FalsePositive} \quad (2)$$

The false positive rate, which corresponds to the number of false alerts, could also be considered as a significant evaluation metric 3.

$$Falsepositiverate = \frac{FalsePositives}{Time} \quad (3)$$

While Time is given in hours. Aziz O. et al. (Aziz et al., 2017) is one of a few papers that measured all these evaluation performance, like the angel system, they detect falls in elderly datasets, their algorithm based on SVM classifier showed 80% sensitivity, 99.9% specificity and false positive rates from 0.05 to 0.15 false alarms per hour. Similarly, the best performing algorithm reported by Bagalà et al. (Bagala et al., 2012) which showed 83% sensitivity, 97% specificity and 0.21 false alarms per hour. The Angel system gives, for the real-world data set obtained, as previously mentioned, from elderly people, a sensitivity of 100%, a specificity of 95% and 0.02 false alarms per hour.
The primary metrics which determined the system performance are precision and sensitivity/recall (Grandini et al., 2020). The precision is computed as the proportion of the total relevant results returned to the total number of results returned. In other words, the ratio of real falls to the total of falls returned by the system 4. Such a system, with high recall and low precision , is referred in a scientific literature as a recall -oriented system in contrast to the precision -oriented system with low recall but with high precision as they talk a lot but make a lot of mistakes. An "ideal" system provides all the information required and nothing more (high recall and high precision).

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \quad (4)$$

Therefore, the main goal of this work is to enhance the system by increasing precision without reducing sensitivity. Thus, we propose reducing the number of false positives.

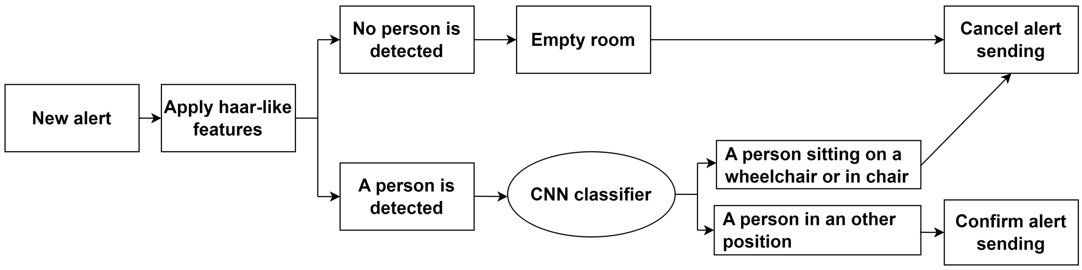


Figure 2: Diagram of error minimizing by alerts filtering using Haar cascade and CNN.

4 PROPOSED IMPROVEMENTS TO THE VISION-BASED FALL DETECTION SYSTEM

In the previous section 3, we noted that many fall detection systems suffer from low performance (high false positive rate 3). An example of these systems is Angel Assistance which suffers from a very high number of false positives (99% of detected images are false). In this section, we propose to help improve this system by reducing the number of these false alarms. Our proposition is defined by a post-processing step that is added after the alert is given by the fall detection system. This approach combines the Haar cascade and a proposed CNN classifier to help determine if the alert is false or not (see figure 2). The combination of the two approaches comes in two integrative steps. First, the haar cascade is applied to determine if the received image contains a person or not (the room is empty). If it does, the image will be transferred to the CNN classifier to determine finally if there is a fall or not.Before we apply this combination of approaches, a data preparation, and processing step is realised.
First, we annotated and visualized false positive data. This phase helped us to more clearly identify the kinds of circumstances that the system has not been able to separate from fall-related ones. We manually labeled roughly 2050 over 9572 images in the category ”active person,” sub-classing them into 4 subcategories: 10 images of people using walkers, 1080 images of people using wheelchairs, 210 images of people using chairs, and the remaining 748 images.

In fact, a prior paper (El Kaid et al., 2019b) examined and offered the idea of reducing false positives by employing a convolutional neural network to get rid of those of a person in a wheelchair. But as indicated in its perspectives, there are still a lot of false positives. For example, none of the CNN models evaluated could distinguish empty room images because of the complexity of the images, variations in the room's lighting, and video resolution. We came up with the notion to further increase the fall detection algorithm's accuracy at that point. Indeed, the idea presented in the earlier paper to address this request will be improved by the proposed method. Since we don't want to affect the main system of the fall detection, we propose an algorithm that will be used as post-processing on the system after the fall detection phase.

This algorithm is applied to the outcomes of the video-based fall detection algorithm or the warnings that have been identified. Post-processing thus analyses the static images, and it is divided into two main components and produces results instantly. The first part uses the Haar-like features method to detect whether an image contains a human or not. If so, a CNN model will process the image and assign it to one of the following two classes: ”person sitting on a wheelchair”, ”person not sitting on chair”, or ”others”. Then, only images from the last class will be assigned to provide desk assistance. They could be true falls or false ones (some images of an active person). But still, a large portion of these alerts (”empty room”, ”a person sitting on a wheelchair”, and ”person sitting on a chair”) are erased.
Human Detection Using Haar-Like Features. The first part of the algorithm, which is based on the human detection technique, aims to distinguish the “Empty room” image from others (“False positive: Active person”, “Real fall”). The goal is to keep only the alerts that include a human and ignore any alerts that do not. First, we tested the most popular algorithm for this task, extracting the features by HOG (Histogram of Oriented Gradients) descriptor and classifying them using SVM. But this machine learning algorithm was unable to detect people in images well due to noise from the surveillance cameras. Then, we attempted to use pre-trained OpenCV classifiers saved in XML files to detect humans using Haar-like features. These files are *haarcascade_fullbody, haarcascade_lowerbody* and *haarcascade_upperbody.*

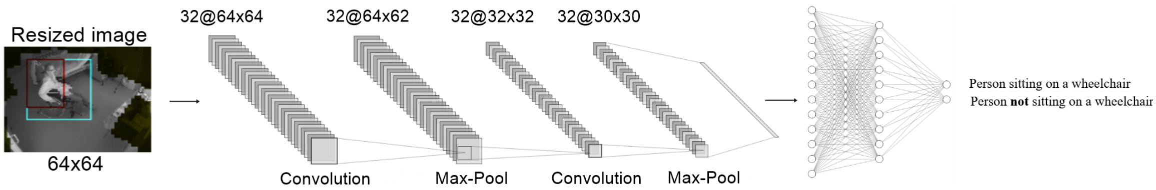


Figure 3: The binary CNN classifier architecture.

Yet, none of these files are compatible with our data. The use of these files necessitates a distinct persona, which does not satisfy our conditions. In practice, after experimenting with numerous OpenCV Haar Cascade Classifiers, we found three XML files that we could use to identify the presence of a person in our images, these files are : *haarcascade_frontalcatface_extended*, *haarcascade_frontalcatface* and *lbpcascade_frontalcatface*.

We employ the *detectMultiScale* technique from *CascadeClassifier* approach to locate the subject in the image. These three detectors are utilized to determine whether or not a person is present in the image. If this classifier indicates that there is no one in the new alert, it is assumed that this image represents an empty room and the warning is canceled. By doing this, we will greatly reduce the number of false positives and enhance the fall detection system.

Convolution Neural Network Model. To build a convolution neural network, we follow the architecture outlined in the graph of the figure 3.

First, we load the CNN model from our previous paper (El Kaid et al., 2019b). It was a binary classifier that was saved in an HDF5 (Hierarchical Data Format version 5) file that was used to determine whether or not an alert contained a person using a wheelchair, which provides a good accuracy of 98%. Using this approach, we can get rid of the images that show a person in a wheelchair, which accounts for around 17% of false positives. Second, we considered creating a new multi-class CNN classifier to categorize alerts into the four categories of ”person sitting on a wheelchair”, ”person sitting on a chair”, ”empty room”, and ”other”. Due to a lack of data, we cannot incorporate the ”images with a walker” class. Several models have been tested, although due to the similarity of the images of the different classes, they generally produce less effective results, as shown in our previous research (El Kaid et al., 2019a). The best performance, in this case, was 89%, which is why we considered including the previously described human detection system. However, we build another multi-class CNN classifier for the three categories above except ”empty room”.

The algorithm 1 explains the proposed post-processing approach to eliminate false positives.

Algorithm 1: Post-processing to filter alerts.

```
Begin
FilterAlert(Mat alert_image)
 faceExtendedCas ← CascadeClassifier
("haarcascade_frontalcatface_extended.xml")
 frontalcatfaceCas ← CascadeClassifier
("haarcascade_frontalcatface.xml")
 frontalcatfaceLbp ← CascadeClassifier
("lbpcascade_frontalcatface.xml")
  detect ← detectMultiScale()
   /* detect contains location and size
   of the bounding box (x,y,w,h)
   if a person is detected */
  d ← 0
  If detect is not None
        Return d ← d+1
  EndIf
  If d > 3 //A person is detected
    model = load(filter_model) // Load CNN
    img_resized = pre-process alert_image
    // Resize the input image
    result ← model.predict(img_resized)
    If result[0][0] = 1
        /*i.e: the image contains
        a person on a wheelchair*/
        Exit //Cancel alert sending
    Else
        send(alert_image) // Confirm
        alert sending
    EndIf
  Else
    /*if no person is detected,
    it is an Empty room.*/
    Exit // Cancel alert sending
  EndIf
  EndFunction
  End
```

5 EXPERIMENTATION RESULTS

This article outlines how an alert is processed and filtered before it is transmitted. This section contains some of the outcomes of the proposed post-process.

When the algorithm is tested on 5254 images, the Haar cascade classifier, which we use as the first step of our approach to filter out alerts containing ”empty room”, provided 76% accuracy.

As can be seen from the figure 5, the Haar cascade classifier succeeds in identifying people in the

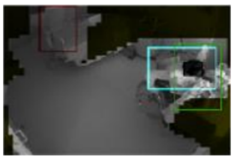
(a) False alarm : A person in a wheelchair

(b) False alarm: An empty room

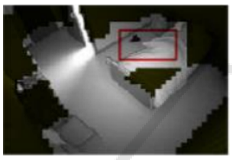
(c) False alarm : A person in a chair

(d) False alarm : A person in a wheelchair

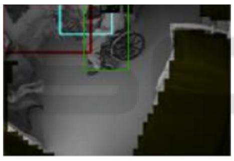
Figure 4: detected Alerts by the fall video detection algorithm[1].



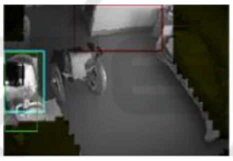
(a) Person detected



(b) Person detected



(c) Person not detected



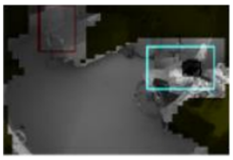
(d) Person detected

Figure 5: The outcomes of a classifier using a Haar cascade classifier.

images and marks their presence with a green rectangle (bounding box) around them while eliminating the image of an "empty room". The second filter, a binary classification model, uses the output of the first step as input and removes the false-positive category of "person sitting in a wheelchair" with an accuracy of 98%, which enhances the fall detection system.

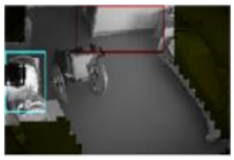
The algorithm's final findings are shown in the figure 6. The categorical model, on the other hand, allows us to do away with the categories of "person sitting in a wheelchair" and also "person sitting in a chair".

Even if its accuracy, 82%, is less than that of the binary classifier, it is still respectable. AlexNet model is the network that was trained for it. We could enhance the elderly person fall video-detection algorithm by hybridizing one of the CNN classifiers with a Haar cascade classifier, maximizing its precision while minimizing the number of false positives sent by eliminating three categories of false alarms: an empty room, a person in a wheelchair, and a person in a chair.



(a) Prediction: person is on a wheelchair

(b) Prediction: person is on a wheelchair



(c) Prediction: person is not on a wheelchair

Figure 6: The final results of Algorithm.

6 CONCLUSION AND PERSPECTIVES

To summarize, when it comes to fall detection devices and methodologies, all sensors, whether worn or embedded in people's environments, are all blind and send fall alerts just like any other detector. Only image-based methods can verify the reality of the fall and avoid unnecessary assistance. However, we recognize that there is room for improvement.

We could enhance the elderly person fall video-detection algorithm by hybridizing a Haar cascade classifier with a CNN classifiers. This improvement could maximize the system's precision by minimizing the number of false positives sent. Indeed, we proposed an algorithm that eliminates three categories of false alarms: an empty room, a person in a wheelchair, and a person in a chair.

In the upcoming work, due to the proximity between images of different classes and to the lighting variation, we propose to develop a video-based fall detection system based on our previous 3D pose estimation approach (El Kaid et al., 2022) to more accurately recognize the fall events .

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