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Camera-Based Fall Detection System for the Elderly With Occlusion Recognition

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Abstract
We proposed in this paper an algorithm for fall detection using 2D RGB camera. Occlusion, fall, and common daily activities are separated from each other by machine learning algorithms, which were trained on features extracted by a deep learning-based computer vision algorithm. Person dection in videos is done using deep learing algorithm. The experimental validation of the proposed approach was conducted on two datasets, one public, and the second created localy. For evaluation, several assessment measures are computed. This evaluation shown effectiveness of the proposed solution.

Keywords: Fall detection; Camera; Machine learning; Deep learning; e-health

Introduction

Fall is the most issue faced by individuals with special needs like the elderly, disabled, people with Parkinson, overweight and obese, etc. Fall detection has become an active research topic in the e-health field and especially for elderly healthcare. According to a report of the World Health Organization (WHO) [1], 30% of elderly people fall at least once each year and this rate increases to 42% for people over 70 years. Falls are particularly dangerous for older people for two reasons. The first is that they generally live alone, the second reason is related to the first; it is the period between waiting lying on the floor after fall and receiving assistance as it is reported by WHO [1], and Giannakouris et al. [2]. This period can reach several hours. These considerations have increased the number of researches on automatic fall detection to allow fast and proper assistance to the elderly. These kind of systems uses sensing devices to collect data from the observed environment combined with computing technologies to execute algorithms that can detect falls from collected data [3]. Approaches based on wearable small and cheap sensors consist of wearing a device to monitor a person; the problem here is that aged persons tend to forget to wear such devices. On the contrary, vision-based systems do not require any support from the elderly [4]. At the same time, cameras are becoming cheaper, and they are increasingly becoming the most used solution for fall detection.

We can distinguish three major classes to detect a fall: wearable sensors-based methods, ambient sensors-based methods and vision-based methods.

Wearable sensors-based systems are the most used due to their simplicity. They are generally embedded in other devices such as shoes, pendants, belts, or watches. According to literature, gyroscopes and accelerometers are the most commonly used sensors.

Hussain et al. [5] developed machine learning algorithms to detect a fall and to identify the falling pattern and the activity associated with the fall incident. Jefiza et al. [6] collected data from a 3-axis accelerometer and gyroscope and use them by backpropagation neural network (BPNN) for fall detection. This system is supposed to recognize different human positions like sleeping, falling, sitting, squatting, etc. Guvensan et al. [7] implemented an energy-saving mobile application, runs as a background service and monitors the activities of a person in daily life. They propose a three-tier architecture that combines simple thresholding methods with machine learning algorithms. An attached 3D accelerometer was used to generate data. Kwolek and Kepski [8] collected data from a 3D accelerometer and depth maps and used them for fall detection. Measured acceleration is used to detect if there is a high acceleration (higher than an assumed threshold value), an algorithm extracts person features and executes a classifier to identify presence/no presence of a fall.

Ambient devices use external sensors to measure and examine the environment of a subject under surveillance. Usual features for fall detection are pressure, vibration, sound, infrared array [9,10]. In the literature, there are many examples of fall detection systems using ambient sensors. An acoustic fall detection system is proposed by Khan et al. [11].

Fall is detected in three steps. First, the measured acoustic signals are initially processed with a source separation technique to remove the possible noise from other background sound sources. Second, Mel-frequency cepstral coefficient features are next extracted from the processed signals, and finally, a KNN classifier is used to identify if a person walk or in fall situation. The system proposed in [12] uses floor vibration produced by fall downs floor vibration to detect falls of elderly people. The system can recognize who is the fallen person from vibration produced by footsteps. In [13] authors used a pressure sensing triboelectric nanogenerator (TENG) array for ambient-based fall detection. Fan et al. [14] developed a fall detection system using infrared array sensors with several deep learning methods to detect the existence/non-existence of fall. Another interesting approach is the use of Atheros commercial NIC equipment to map the amplitude information in the wireless signal to the human body's fall action [15]. Cheng et al. [16] created a theoretical grid to detect falls. The system is a lased-based, and it consists of using a laser-emitting component in conjunction with a light-sensing component to create many intersections able to detect blocking objects.

An increase in ***Vision-based systems*** was noted because they offer many advantages comparing to wearable-based and ambient-based systems in terms of robustness and non-intervention of humans after installation. In this class of methods, the camera has an important role. We can consider 3 ways to use it taking in consideration the number and the type [3, 17], 2D cameras, multi-cameras and depth cameras. Much work on vision-based systems has been carried out. In [18] authors used a VGGNet, ResNet, DenseNet, InceptionResNet, and Xception as pre-trained CNNs algorithms for human Posture Recognition. Postures were divided into four classes: standing, sitting, lying, and lying crouched. Rougier et al. [19] used a Gaussian Mixture Model (GMM) for falls detection. A person is detected due to a shape matching technique, which is used to track person's silhouette in a video sequence. A Canny edge detector is used to detect any deformation in a silhouette. Redmon et al. [20] used a Convolutional Neural Network (CNN) to analyze images extracted from a video, analyze them and extract features using an optical flow method to detect motion between two consecutive images. Multi cameras are used, and this approach is tested on the UP-Fall Detection dataset. Maldonado-Bascón et al. [17] used a camera placed mobile-patrol robot that can correct its position in case of doubt and an SVM machine learning algorithm for fall detection.

Although these three approaches are interesting, they suffer from some drawbacks. Based on the author's experience the major disadvantage of wereable-based systems a limited energy-dependent and power consumption what limits its usability, sensitivity to body movement which may cause false alarms, undesirable placement of device, forgetfulness or not wanting to wear them especially by elderly people [21, 22, 23].

Ambient sensors work only indoor or where the device is installed, suffer from blind spots, dead spaces, have limited recording area, and can be an expensive setup [24, 25]. Developers of most of the ambient systems, assume that only one person is present in the monitoring room. Background and ambient noise such as falls of everyday objects, certain floor types for vibration-based systems can change the behavior of the system to produce many false alarms.

In ***2D camera-based systems***, only one uncalibrated is used. The advantage of these kinds of systems is simplicity. The main disadvantage is essentially occlusions. The camera cannot capture what is there behind an obstacle such as furniture. Using a multi cameras-based system needs the installation of many cameras in one room. These cameras have to be calibrated and synchronized, which is a real drawback due to the difficulty of this operation [29]. Depth cameras, like Kinect, provide many advantages, they are light-independent, but there are some disadvantages, such as distance detection [26].

We aimed to presents a new vision-based approach for fall detection, with the possibility to monitor in real-time the movements of a person and triggers an alarm if a fall is detected.

Material and Method

The proposed approach deals with two essential drawbacks of fall detection systems using cameras. The system deals with the fall detection problem in the case of having several persons in the same room. This work tackles also the problem of occlusions. In the field of fall detection systems, the term occlusion refers to something that hide a part or entire body of the person. Few researchers have addressed this problem; most studies have focused only on person detection part without taking in consideration obstacles

Proposed Solution

Our main aim was to develop a fall detection based-camera system taking into consideration the weaknesses of previous studies. The proposed algorithm extracts an image from a given video of the person-environment, extracts information, and recognizes its state. To have efficient fall detection system, we put as objective the following challenges (according to literature):

- Different positions and orientation of the subject on the floor
- Noise in the background (different structures and color similarity with the subject)
- Occlusions: when an area of the bottom of a person is covered
- Different person sizes

Resolving these issues ensures a good performance for the system. Steps to follow in our fall detection algorithm are:

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Repeat
-    Extracts a frame from a video stream
-    Person detection by YOLO algorithm in the extracted frame
-    Features extraction from bounding box which is the result of
YOLO detector
-    State identification: using machine learning algorithms
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Person detection: The recent impact of deep learning has considerably changed the scene of the computer vision field, improving the results obtained in many relevant tasks, such as segmentation, object recognition, and image captioning [27]. Deep learning consists of the essential use of artificial neuronal networks such as CNN. The advantage of CNN is that it does not use much-preprocessing treatment, so the absence of initial pretreatment and human intervention is a major advantage of CNNs in comparison to other algorithms in terms of precision and speed. Many CNN algorithms for image detection and classification are available in literature like Region-CNN [28], fast R-CNN [29], faster R-CNN [30], Single Shot Detector (SSD) [31] and You Only Look Once (YOLO) [20]. For the person detection part, we decided to use YOLOv3 [32], which has proven to be an excellent competitor to other algorithms in terms of performance and accuracy. Outputs of YOLOv3 are coordinates of the top left, width and height (x, y, w, h) of a bounding box that surrounds the person. These outputs will be used to calculate other values (features), which will be used as inputs for the classification algorithm. YOLOv3 has the ability to detect many objects/persons in an image and extract coordinates of their respective bounding boxes.

Fall detection: Selection of the right features has an important impact on the accuracy of the classification algorithm. There are many features for person state identification in literature. The most used are ratio [17], fall angle [33], center speed [34] or head motion [35]. In our work used features are:

- The aspect ratio of bounding box (AR): it represents the ratio of width and the height of the bounding box. AR is the most significant parameter for fall detection systems.
- Normalized bounding box width (NBW): represents the ratio between widths of the bounding box and the image. This parameter allows the classification algorithm to work on images with different resolutions, and make state detection independent of the subject's distance to the camera.
- Normalized bottom bounding box (NBB): represents the ratio between the bottom of the bounding box and the whole height of the image. This parameter helps the classification algorithm to make a difference between a person lying on a bed and a person lying on the ground. This parameter allows the classification algorithm also to know if there is an occlusion or no.

The major problem of camera-based systems is occlusions. If an object hides the subject, no analysis can be done about its activity, and the whole system becomes useless [36]. The overcome this problem, the most common solution is to place multiple cameras in different areas of interest to make visible the target from any angle. The disadvantage of this solution, as already mentioned it is cost, the difficulty of cameras calibration and the increase in computing complexity [36]. The proposed solution overcomes the occlusion issue by using only one camera. We started by defining four states of the person after that transitions between these states are used to identify existing/non-existing of a fall to activate an alarm.

The above features (AR, NBW and NBB) are used to identify the following states:

- Fall: if a person is lying on the ground.
- No fall: It corresponds to normal activities in daily life, such as walking, running and lying on a bed.
- Empty: if there is no detected person in the frame. This state can occur if the room is empty or if there is a miss detection by the person detection system.
- Occlusion: when another thing such as furniture hides bottom part of the person. Occlusions affect accuracy significantly in camera-based fall detection systems. Generally, researches ignore this problem, especially if the system is destined to work indoor.

Figure 1 shows different situations that the classification system can meet. The system deals with the bounding box that surrounds a subject to identify its state. Green boxes represent images and blues boxes represent boxes provided by YOLOv3 after a person is detected. Labeling images in a training dataset is made taking into consideration these situations.

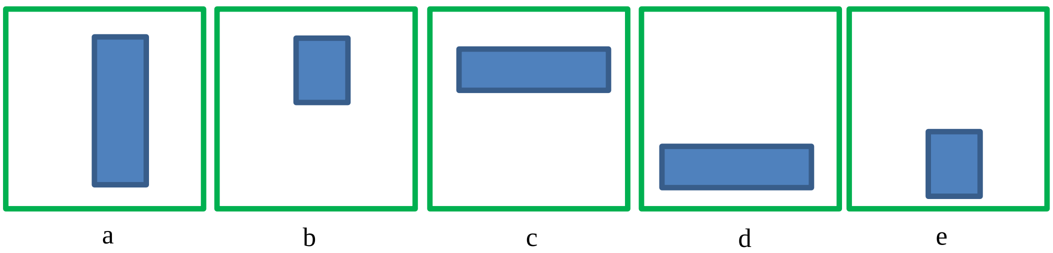


Figure 1. Positions used to identify the subject state. The situation in Figure 1(a) represents a bounding box surrounding a standing person. The box can be in the middle, left or right of the image. Figure 1(b) shows a situation in which another thing occludes a subject, so only the top of the body is detected and surrounded. In Figure 1(c), bounding box surrounds a person in a lying-position but not on the ground (on a bed, for example). In this situation, the classification algorithms consider that the subject is not in a fall state. Figures 1 (d) and (e) represents respectively fall states in which a person is horizontal and vertical positions.

The system can detect many persons in the same image. In image 1, 3 persons were detected (fall in the vertical position, standing and occlusion situations). Figure 2 shows some examples.

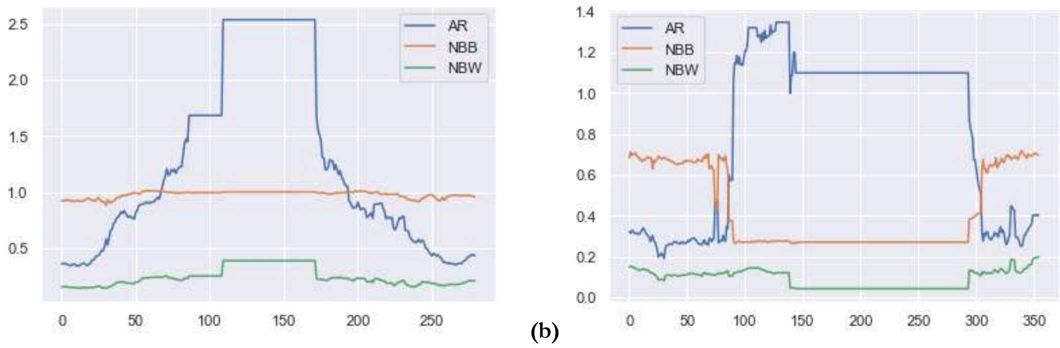
Image 1 Image 2 Image 3

Figure 2. Examples of detected postures

We marked the bounding boxes generated by YOLOv3 in different colors to distinguish between the different postures of the subjects. We marked respectively fall, no fall and occlusion situations, red, green, and blue.

In Figures 3 (a) and (b), the blue, orange, and green lines represent respectively the subject's normalized ratio, NBB and NBW parameters variation from one frame to the next in a video sequence. The graphs in Figure 3 show the subject entering the scene at the beginning of the timeline. During the first part of the timeline, the subject walks inside the room.

In Figure 3 (a) the central area of the graph with stable values corresponds to the stable fall state. Parameters NBB and NBW are almost stable, because the subject has fallen in vertical-pose orientation position.



(a) (b)

Figure 3. Example of fall, occlusion and walking situations (AR = ratio of bounding box, NBB = normalized bottom bounding box, NBW = normalized bounding box width)

During the entire scene, NBB remained high, which means that the bottom of the bounding is almost at the same level as the bottom of the image (there is no occlusion). Even for NBW, its value remained stable because of the subject orientation. Graph in Figure 3 (a) represents situations presented in Figure 1 (a) and (e). During the last stage, the subject stands up after the fall and exits the scene. Figure 3 (c) represents a subject walking at the beginning of the timeline.

At the 85th frame, an obstacle hid the bottom part of the subject until the 300th frame. During this period, NBB is low because the bottom of the bounding box is located above the half of the frame. NBW reminds stable, because the width of the bounding bow did not change.

Fall detection process takes in consideration many parameters and situations to avoid eventual errors comes from person detection and classification systems. Person detection system can miss some frames, and the classification system can misclassify some states.

Through transitions between the four states that our system can decide to send or no an alert about a fall situation. If the system detects/doubts a fall situation, it starts a timer and waits for a period of p seconds. The delay of p seconds avoids sending alerts in precipitation and gives time to the subject to shift to another state. If the state changes, the timer is initialized to zero. Table 1 shows system behavior after each transition. Overall, we have 4 states and 12 transitions.

Table 1. System behavior after each transition

N°	Transition	System behavior	Explanation
1	Fall -> No Fall	Ends the timer	In this case, the person has fallen, but he stands up just after.
2	Fall -> Occlusion	Ends the timer Saves bounding box coordinates	The person is standing behind an obstacle, such as a table. Bounding box coordinates are saved to deal with the situation in which a person falls behind an obstacle, so it will be invisible
3	Fall -> Empty	(Timer is already started in Fall sate) If after ***p seconds***, the state does not change, the system deduces that the person has fallen and sends an alert.	In this situation, the system deduces that there is miss person detection. Because it is impossible that a person disappears just after he was lying on the ground.
4	No Fall -> Empty	Do nothing	The system deduces that the person lefts the room
5	No Fall -> Occlusion	Saves bounding box coordinates	
6	No Fall -> Fall	Starts the timer. If after ***p seconds***, the state does not change, the system deduces that the person has fallen and sends an alert	The person is on the ground
7	Empty -> Fall	Starts the timer. If after ***p seconds***, the state does not change, the system deduces that the person has fallen and sends an alert	The person was invisible before falling.
8	Empty -> Occlusion	Ends the timer. Save bounding box coordinates	The person was behind an obstacle
9	Empty -> No Fall	Ends the timer.	If a timer is started in line 12
10	Occlusion -> Fall	Starts the timer. If after ***p seconds***, the state does not change, the system deduces that the person has fallen and sends an alert	A person behind an obstacle has fallen, and he reminds visible to the camera
11	Occlusion -> No Fall	Do nothing	The person in no longer after an obstacle
12	Occlusion -> Empty	Starts the timer. If after ***p seconds***, state does not change, the system deduces that the person has fallen behind the obstacle and sends an alert.	The person was behind an obstacle and he disappears. The system deduces that a person has fallen, because obstacles are generally situated inside the room. To quit the room, the person has to walk and passes by state No fall

To analyze the efficiency of the proposed model, two fall detection datasets have been conducted: Fallen Person Dataset (FPDS) [17], and our dataset. FPDS dataset was used for training and making the first test of the classification system. All images in FPDS were taken by a robot of 76 cm height. This dataset comprises 2062 images and the resolution is 640 × 480 pixels (1072 falls and 1262 activities of daily living ADL).

Images were taken from different places: office, home, corridor,… could have many actors in same image, and were recorded from different angles and distances. The major advantage of this dataset is having actors with different heights (range of 1.2-1.8 meters).

The problem of FPDS is the absence of situations in which persons are standing behind an obstacle (occlusions). It is why; we have enriched it with additional 700 images that represent occlusion situations. New images were labeled manually in addition to 2062 already labeled.

For the second dataset, a total of 60 videos of 640 x 480 pixels were recorded in two different locations: office and house. This dataset included videos with falls in the main four direction relative to the camera, recovery situations after fall, falls behind an occlusion, standing and walking, standing and walking behind occlusions, sitting events in different orientations, several lying-position perspectives, variable light conditions, and different clothes. Camera was located at an approximate height of 90 to 100cm above the floor.

Parameters used to evaluate the effectiveness of the proposed system are sensitivity, called also recall, (percentage of falls that were identified correctly), and precision (percentage of positive fall identifications that actually fall):

$$\text{Precision} = TP/(TP+FP) \quad (1)$$

$$\text{Sensitivity (Recall)} = TP/(TP+FN) \quad (2)$$

where TP = true positives, number of falls correctly detected, FN = false negatives, number of falls not detected and FP = false positives, number of non-falls detected as falls.

Classifier

For classification we opted to Support Vector Machine algorithm. SVM classifiers are based on two key ideas. The first key idea is the concept of maximum margin. The margin is the distance between the hyperplan and the closest samples. Hyperplan is a line that separates samples of a class from other classes. These closest samples are called support vectors. In SVM, the separation border (hyperplan) is chosen as that it maximizes the margin. The problem is to find this optimal hyperplan, starting from a training set. To be able to deal with cases in which data are not linearly separable, the second key idea of SVM is to transform the representation space of the input data into a space of larger dimension (possibly of infinite dimension), in which it is likely that there is a linear separation. The kernel functions make it possible to transform a scalar product in a large space, which is expensive, in a simple punctual evaluation of a function. This technique is known as kernel trick. To train machine learning algorithm, we split the data into two sets, one for training the machine learning algorithms and one for testing them. Finding the best parameters for classifications algorithms has an essential role to have good results and avoid tendencies to overfitting and underfitting. To find optimal parameters, a 5-fold cross-validation procedure was performed on the training set (the new FPDS of 2762 images was used for training and testing, the set that has produced a higher assessment measures has been selected).

Results and Discussion

As it is mentioned in method secion, we used 60 recorded videos encompassing different situations to evaluate our approach on video sequences. The proposed system was able to detect and predict efficiently fall events, as shown in Figure 4.

We can see a person in a falling situation detected as occlusion. In the second image, YOLOv3 was not able to detect the subject. In this case, a timer is started (transition Occlusion -> Empty). The third image shows the situation after 60 seconds (the waiting period we choose for the system), the system did not detect any movement, and an alert message was sent as it is shown in image 4.

First column in Table 2 shows results without using our approach, which means test each frame separately, while the second column shows results after using our approach. During this experience, YOLOv3 could not detect several persons in lying positions (in 10 videos). Without making link between frames, the classifier could not make a correct prediction. Otherwise, although if there are two false alarms, no fall case was lost (recall 100%).

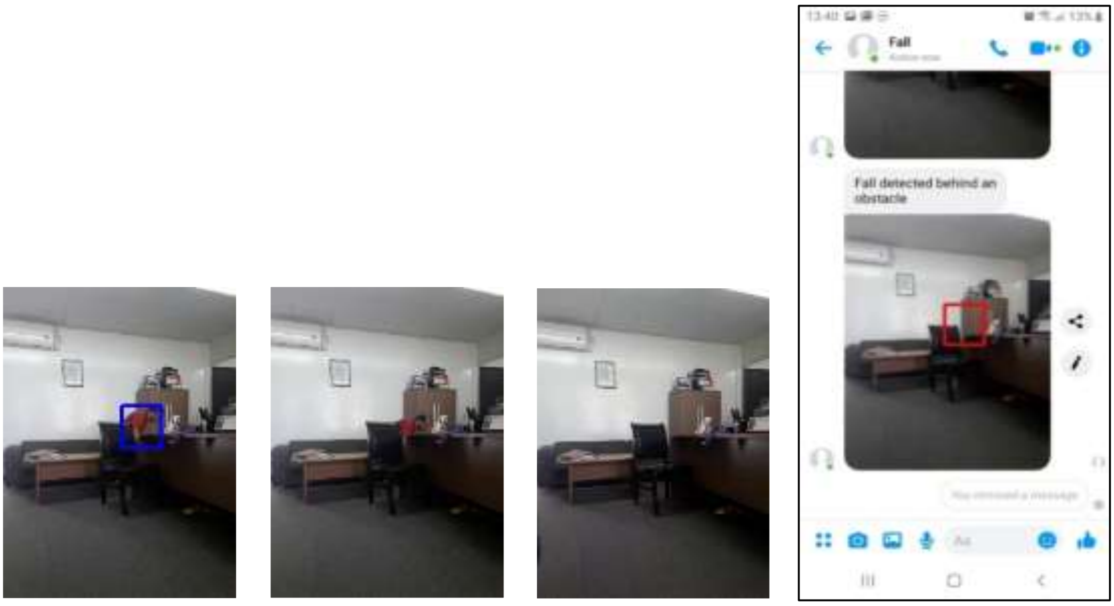


Image 1 Image 2 Image 3 Image 4

Figure 4. Fall alert delivery example.

Table 2. Experiments results without and with the approach

	SVM without approach	**SVM with approach**
TP	21	31
FP	2	2
FN	10	0
Precision (%)	91.30	93.94
Recall (%)	67.74	100.00

We presented in this study a new approach for person detection taking in consideration occlusion situations, which is a problem ignored in the majority of works in the field of camera-based fall detection systems. We proposed a to two stage algorithm. The first part uses CNN algorithm for person detection and features extraction. In the second part, we used SVM classifier for posture recognition. Then, to overcome non-detection person situations that can affect the system effectiveness, we propose a solution based on a transition between four states that the system can recognize. During experiments, detection part could not detect 33% of falls, which contained video sequences. After applying our approach, obtained results showed reliable fall detection. We could see also, there was a homogeneity between values obtained during test phase, and those obtained during experiments. This homogeneity confirms the good choice of parameters' values for the selected features.

One of the limitations of our study was fall detection in dark, because RGB cameras could not detect objects in these conditions.

To measure the real contribution of the present work, comparison with some existing systems is reported in Table 3. Results show a clear advantage of our method. The existing studies had the same assessment measures but without taking into consideration occlusions.

Table 3. Performance comparison between our method and other systems in litterture

Researchers name and year of research [ref]	Feature extraction method	Fall detection method	Occlusion detection	Results (%)
De Miguel et al. [23]	backgroundSubtractorMoG2	K-Nearest Neighbours	No	Sensitivity=96 Precision=96
Antonello et al. [33]	Single-view detector and the multi-view analyser	Support Vector Machine	No	Sensitivity=72 Precision=92
Hsu et al. [37]	Gaussian mixture model	Back propagation neural network	No	Sensitivity=100
Harrou et al. [38]	Multivariate exponentially weighted moving average monitoring scheme	Support Vector Machine	No	Sensitivity=100 Precision=93.55
Our approach	YOLOv3	Support Vector Machine	Yes	Sensitivity=100 Precision=93.94

The main reason of the superiority of our fall detection method is behavior detection and analysis after each transision. The proposed fall detection method can be used for elderly indoor (houses, hospitals,…). Our method gives a boost and improves camera-based fall detection systems due to its novel idea for occlusions detection.

References

1. World Health Organization, W. H.; Unit, L. C. WHO Global Report on Falls Prevention in Older Age; World Health Organization, 2008.
2. Giannakouris K, others. Ageing Characterises the Demographic Perspectives of the European Societies. EUROSTAT Statistics in focus 2008;72:1-11. Available from: https://apapr.ro/wp-content/uploads/2018/04/Eurostat_2008_EU_Population_Projections_2060.pdf
3. Mubashir M, Shao L, Seed L. A Survey on Fall Detection: Principles and Approaches. Neurocomputing 2013;100:144-152. Doi:10.1016/j.neucom.2011.09.037
4. Ramachandran A, Adarsh R, Pahwa P, Anupama K. Machine Learning-Based Fall Detection in Geriatric Healthcare Systems. 2018 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS), Indore, India, 2018, pp. 1-6. Doi: 10.1109/ANTS.2018.8710132
5. Hussain F, Hussain F, Ehatisham-ul-Haq M, Azam MA. Activity-Aware Fall Detection and Recognition Based on Wearable Sensors. IEEE Sensors Journal 2019;19(12):4528-4536. Doi: 10.1109/jsen.2019.2898891.
6. Jefiza A, Pramunanto E, Boedinoegroho H, Purnomo MH. Fall Detection Based on Accelerometer and Gyroscope Using Back Propagation. 017 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), Yogyakarta, 2017, pp. 1-6, doi: 10.1109/EECSI.2017.8239149.
7. Guvensan MA, Kansiz AO, Camgoz NC, Turkmen H, Yavuz AG, Karsligil ME. An Energy-Efficient Multi-Tier Architecture for Fall Detection on Smartphones. Sensors 2017;17(7):1487. Doi: 10.3390/s17071487
8. Kwolek B, Kepski M. Human Fall Detection on Embedded Platform Using Depth Maps and Wireless Accelerometer. Computer Methods and Programs in Biomedicine 2014;117(3):489-501. Doi: 10.1016/j.cmpb.2014.09.005
9. Yang L, Ren Y, Hu H, Tian B. New Fast Fall Detection Method Based on Spatio-Temporal Context Tracking of Head by Using Depth Images. Sensors 2015;15(9):23004-23019. Doi: 10.3390/s150923004.

10. Zigel Y, Litvak D, Gannot I. A Method for Automatic Fall Detection of Elderly People Using Floor Vibrations and Sound—Proof of Concept on Human Mimicking Doll Falls. IEEE Transactions on Biomedical Engineering 2009;56(12):2858-2867. Doi: 10.1109/tbme.2009.2030171
11. Khan MS, Yu M, Feng P, Wang L, Chambers J. An Unsupervised Acoustic Fall Detection System Using Source Separation for Sound Interference Suppression. Signal Processing 2015;110:199-210. Doi:10.1016/j.sigpro.2014.08.021
12. Clemente J, Li F, Valero M, Song W. Smart Seismic Sensing for Indoor Fall Detection, Location and Notification. IEEE Journal of Biomedical and Health Informatics 2020;24(2):524-532. Doi: 10.1109/JBHI.2019.2907498
13. Jeon S-B, Nho Y-H, Park S-J, Kim W-G, Tcho I-W, Kim D, et al. Self-Powered Fall Detection System Using Pressure Sensing Triboelectric Nanogenerators. Nano Energy 2017;41:139-147. Doi: 10.1016/j.nanoen.2017.09.028
14. Fan X, Zhang H, Leung C, Shen Z. Fall Detection with Unobtrusive Infrared Array Sensors. In Multisensor Fusion and Integration for Intelligent Systems; Springer, 2017; pp 253–267.
15. Hao Z, Duan Y, Dang X, Xu H. KS-FALL: Indoor Human Fall Detection Method Under 5GHz Wireless Signals. In IOP Conference Series: Materials Science and Engineering; IOP Publishing, 2019;569:032068. Doi: 10.1088/1757-899x/569/3/032068
16. Cheng AL, Georgoulas C, Bock T. Fall Detection and Intervention Based on Wireless Sensor Network Technologies. Automation in Construction 2016;71:116-136. Doi: 10.1016/j.autcon.2016.03.004
17. Maldonado-Bascón S, Iglesias-Iglesias C, Martín-Martín P, Lafuente-Arroyo S. Fallen People Detection Capabilities Using Assistive Robot. Electronics 2019;8(9):915. Doi: 10.3390/electronics8090915
18. Byeon Y-H, Lee J-Y, Kim D-H, Kwak K-C. Posture Recognition Using Ensemble Deep Models under Various Home Environments. Applied Sciences 2020;10(4):1287. Doi: 10.3390/app10041287
19. Rougier C, Meunier J, St-Arnaud A, Rousseau J. Robust Video Surveillance for Fall Detection Based on Human Shape Deformation. IEEE Transactions on circuits and systems for video Technology 2011;21(5):611-622. Doi: 10.1109/tcsvt.2011.2129370
20. Redmon J, Divvala S, Girshick R, Farhadi A. You Only Look Once: Unified, Real-Time Object Detection. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition 2016; pp. 779-788.
21. Chua J-L, Chang YC, Lim WK. A Simple Vision-Based Fall Detection Technique for Indoor Video Surveillance. Signal, Image and Video Processing 2015;9(3):623-633. Doi: 10.1007/s11760-013-0493-7
22. Ramachandran A, Karuppiah A. A Survey on Recent Advances in Wearable Fall Detection Systems. BioMed Research International 2020;2020: 2167160. Doi: 10.1155/2020/2167160
23. De Miguel K, Brunete A, Hernando M, Gambao E. Home Camera-Based Fall Detection System for the Elderly. Sensors 2017;17(12):2864. Doi: 10.3390/s17122864
24. de la Concepción MÁÁ, Morillo LMS, García JAÁ, González-Abril L. Mobile Activity Recognition and Fall Detection System for Elderly People Using Ameva Algorithm. Pervasive and Mobile Computing 2017;34:3-13. Doi: 10.1016/j.pmcj.2016.05.002
25. Zhang C, Lai C-F, Lai Y-H, Wu ZW, Chao H-C. An Inferential Real-Time Falling Posture Reconstruction for Internet of Healthcare Things. Journal of Network and Computer Applications 2017;89:86-95.
26. Karbasi M, Bilal S, Aghababaeyan R, Rad AE, Bhatti Z, Shah A. Analysis and Enhancement of the Denoising Depth Data Using Kinect Through Iterative Technique. Jurnal Teknologi 2016;78(9):185-193. Doi: 10.11113/jt.v78.5348
27. Liu L, Ouyang W, Wang X, Fieguth P, Chen J, Liu X, et al. Deep Learning for Generic Object Detection: A Survey. International Journal of Computer Vision 2020;128(2):261-318. Doi: 0.1007/s11263-019-01247-4.

28. Girshick R, Donahue J, Darrell T, Malik J. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2014; pp. 580-587.
29. Girshick R. Fast R-Cnn. Proceedings of the IEEE International Conference on Computer Vision 2015; pp. 1440-1448.
30. Ren S, He K, Girshick R, Sun J. Faster R-Cnn: Towards Real-Time Object Detection with Region Proposal Networks. Advances in Neural Information Processing Systems 2015; pp. 91–99.
31. Liu W, Anguelov D, Erhan D, Szegedy C, Reed S, Fu C-Y, et al. Ssd: Single Shot Multibox Detector. In European conference on computer vision; Springer, 2016, pp. 21-37.
32. Redmon J. Farhadi, A. Yolov3: An Incremental Improvement. arXiv preprint arXiv:1804.02767 2018.
33. Antonello M, Carraro M, Pierobon M, Menegatti E. Fast and Robust Detection of Fallen People from a Mobile Robot. 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); IEEE, 2017, pp. 4159-4166. doi: 10.1109/IROS.2017.8206276
34. Debard G, Mertens M, Deschodt M, Vlaeyen E, Devriendt E, Dejaeger E, et al.. Camera-Based Fall Detection Using Real-World versus Simulated Data: How Far Are We from the Solution? Journal of Ambient Intelligence and Smart Environments 2016;8(2):149-168.
35. Lu K-L, Chu ET-H. An Image-Based Fall Detection System for the Elderly. Applied Sciences 2018;8(10):1995. Doi: 10.3390/app8101995
36. Delahoz YS, Labrador M. A. Survey on Fall Detection and Fall Prevention Using Wearable and External Sensors. Sensors 2014;14(10):19806-19842. Doi: 10.3390/s141019806
37. Hsu YW, Perng JW, Liu HL. Development of a vision based pedestrian fall detection system with back propagation neural network. 2015 IEEE/SICE International Symposium on System Integration (SII), Nagoya, 2015, pp. 433-437, doi: 10.1109/SII.2015.7405018
38. Harrou F, Zerrouki N, Sun Y, Houacine A. Vision-based fall detection system for improving safety of elderly people. IEEE Instrumentation & Measurement Magazine 2017;20(6):49-55. doi: 10.1109/MIM.2017.8121952