A Framework For Fall Activity Detection and Classification using Deep Learning Method

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Abstract. Detecting the fall of a person in indoor environment is a challenging issue especially for elderly and sick living alone. Cameras can continuously observes the scene and require little interaction with the user and therefore, are well suited for fall detection. In this paper, we propose a deep learning based framework for fall detection and classification. Further, different machine learning methods namely, Support Vector Machine (SVM) and decision tree have also been applied, after extracting important features to detect and classify the fall of a person. We compare our deep learning based framework with SVM and decision tree as well as other state-of-the-art methods. Two different publicly available datasets have been considered for performing the experiments. The experimental evaluation of our deep learning based proposed framework gives promising results and is comparable with other state-of-the-art methods.

Keywords: Fall detection, Fall classification, Deep learning, Support Vector Machine, Decision tree, Human Computer Interaction.

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1 Introduction

In this paper, we propose a deep learning based framework for detecting and classifying a fall event from a camera in an indoor environment. We also compare our proposed deep learning method with machine learning based fall detection from a camera. It is assumed that a camera is continuously observing the indoor environment of a room, where a person is present alone. Automated fall detection is important since a fall can lead to major injuries and can also be fatal in some cases. Moreover, a person may not be able to move after falling or become unconscious and may not be able to call for help. Therefore, a camera based automated fall detection system can help by recognizing the fall and alert the caregivers by some communication techniques like sending messages, videos, emails, etc. so that the person can be helped as soon as possible and the life of a person can be saved.

In general, various wearable devices are available for detecting falls in the market. Various research has been carried out [17], [23], [11], [38], [36], [8] to develop these wearable devices and the performance of these devices are good. But there are some issues such as, requiring frequent user interaction, dependency of battery, etc. Most important aspect of these devices is that the user need to continuously wear such devices as well as keep its battery charge. Keeping the battery charge at all time may not also be possible due to lack of forgetful. Therefore, a vision based system is highly suitable in indoor environment for detecting fall since it does not require any human interaction when the system has been installed and set up. However, even in the camera based system, there exists many challenges and issues such as view point variation, illumination-variation, occlusion, etc. It is assumed that a camera is continuously observing the scene such that occlusion is minimum. The camera is placed in an optimum manner so that changes due to illumination-variation and shadows affect the system minimally. Our proposed fall detection framework is based on deep learning, having the advantages that it does not require pre-processing of the data or explicit feature extraction. In the proposed framework, videos for short duration of **t** seconds are recorded and fall detection is carried out on-the-fly after **t** second using this video, thereby, carrying out fall detection in real time. In case, a fall is detected with accuracy greater than a threshold value then the caregivers are immediately informed and an alarm is raised. We use AlexNet neural network for classifying fall in the proposed framework which is trained offline. This neural network consists of 8 convolutional layers which helps to extract deep features needed to accurately detect the fall in the video frame. Our proposed framework is accurate and robust and the results are shown in experimental section. We also explore two machine learning algorithms for detection of fall. In this approach, pre-processing of RGB video frame needs to be carried out before the data given as input to machine learning algorithms. First, Gaussian mixture model has been applied for background subtraction to detect the person under observation. We then extracts various important features to further apply machine learning algorithms to detect a fall.

SVM performs well on high-dimensional data as well as it captures the features of the samples when proper information is not given regarding the data. However, it under performs in the situations where, there is a large number of samples of data as well as it is sensitive to the noise present in image. Therefore, to overcome the above discussed issues, another machine learning method, namely, decision tree, is applied to classify the fall event. In decision tree, there is no need to normalize and scale the data. Also, it works well even if the data contains some missing values. But slight changes in data may lead to incorrect classification, therefore, the decision tree needs to be re-trained from scratch. Also, it takes large amount of time to train the decision tree on large datasets. Our experiential results show that although machine learning based techniques gives fairly good results, however, deep learning based proposed fall detection system is more robust and accurate.

The paper is organized as follows: Section 2 provides an overview of the related work for fall detection. In Section 3, the proposed deep learning based framework is discussed. Furthermore, the machine learning techniques are explained in Section 4. In Section 5, experimental results are shown and discussed. Experimental results show that are proposed deep learning based method successfully distinguishes falls from other activities with higher accuracy when compared with state of the art methods. In Section 6, we conclude and discuss the future directions.

2 Related work

The related work in which deep learning and different machine learning techniques [12, 33, 34, 4, 32, 31, 2, 3, 29, 30, 27] have been applied to detect the fall of a person is discussed in this section. Different features are extracted and then passed to machine learning classifiers. Hamidreza et al. [37] detect the fall event and their system is based on convolutional neural network (CNN) and time frequency analysis. The spectograms are changed into binary images and the features are passed to CNN for classifying the fall activity. Serpa et al. [39] detected fall using connected neural network and pose estimation methods. In this work, the images are passed to pose estimation method and a set of poses are taken as a output. The detected poses are then input to a neural network where the activity is classified either as fall or not. Harrou et al. [13] used the extracted features of reflection variation and apply generalized likelihood ratio (GLR) for fall detection. Jawale et al. [16] proposed a study where they applied two different methods SVM and CNN to compare the classification accuracy of images. Different features section and extraction are done with the help of tensor flow.

Hiroaki et al. [18] detect risk of fall in the video using pose of a person. They detected 24 key points in a human body using OpenPose and calculate the angle of skeleton. Using these features, they used different machine learning techniques to determine the fall activity. Xiangbo et al. [19] detect the fall activity while taking into consideration the privacy of the person. The skeleton data is gathered by using Fast Fourier Transform (FFT). The features are then passed into machine learning algorithms to characterized fall. Muheidat et al. [26] used sensors do detect walking and monitoring health. The gathered data is placed on the cloud and data mining tools are applied for the detection of fall. The fall detection system proposed by Hayat et al. [14] detect the fall while sleeping and for labors who work in buildings. The data is analyzed and compared with the data stored in the system to detect any abnormal activity like fall of a human. Zhou et al. [43] proposed fusion of sensors data and applied deep learning method to detect fall activity. The different human actions are captured with the help of wave radar and optical cameras. Different features are extracted and then multiple CNN are applied to characterized fall. Hamza et al. [10] introduced a system which is based on compressed sensing. The fall and other activities of different people have been captured using shimmer devices. Different machine learning approaches are applied on these data for fall classification.

Shanfeng et al. [15] proposed a motion classification based fall detected method of a person in home. Different machine learning and motion classification techniques are applied in this system. Using sensor, different motions of human are grabbed that is used to build a dataset which contains both fall and other activities of a person. SVM and other functions like linear kernel, Sigmoid, etc. are used to classify fall activity. Basavaraj et al. [7] used a vision based surveillance system to detect a fall activity of a person. They combined motion histogram image and ellipse approximation to detect the fall activity. Chamle et al. [9] detected unusual activity of a person in videos surveillance. The bounding box is fitted on these images and different features such as height of silhouette, fall angle and aspect ratio are extracted. For classification of fall activity, decision tree algorithm is used.

Wang et al. [41] design a system which detect the fall activity of human by applying Hu-moment variation. They detect human body posture and calculate the characteristic matrices. These features are then used in SVM and fall data is classified. Stone et al. [40] used Microsoft kinect to detect the fall in two stages. The 3-D objects from each frame is characterized and tracked. These features are used in decision tree algorithm to characterize the fall activity. Alaoui et al. [5] applied machine learning classifiers to classify fall activity. From the human skeleton, key points are calculated. Then two different features, that is, distance and angle between key points from every pair of images are calculated. These features are input to machine learning techniques and fall activity is detected. Wang [42] detected fall activity using PCANet model and SVM. PCANet model is trained and labeled all the sample images. Again, SVM is applied for the prediction of fall activity in the video. Kumar et al. [21] applied principal component analysis for dimensionality reduction and face recognition and reviews the performance of three different methods which are Singular value decomposition, Eigen decomposition and Hebbian Neural network.

Na Lu et al. [25] detected fall of a person using 3D convolutional neural network. Features are extracted using visual attention model and fall detection is implemented. Liu et al. [24] used multi-layer compressed sensing model for the prediction of fall activity. The different behavior of an object is presented as three orthogonal plane features. They converted fall detection into binary classification problem and fall activity is recognized. Espinosa et al. [1] introduced a vision based framework for the classification of fall activity using convolutional neural networks. Optical flow algorithm is used to find the features and then calculate the relative motion information among consecutive images. Marcos et al. [28] introduced a fall detection method using convolutional neural networks. Rougier et al. [35] applied shape analysis method to characterize fall activity. They applied shape matching algorithm and detected the person's silhouette. At last, they used Gaussian mixture model to detect the fall activity from other normal activities.

In this work, we propose a deep learning based fall detection framework and compare our work with [39], [25], [24] and [1] on datasets [22]. Again, we compare the proposed framework with [28] and [35] on dataset [6]. Experimental result shows that our proposed method achieves better accuracy for fall detection. We also extract relevant features and apply machine learning techniques (SVM, Decision Tree) for the classification of fall activity. Then, compare the machine leaning based frameworks with [13], [5] and [42]. These comparison are discussed in Section 5.

3 Proposed method

In this work, we propose an automated fall detection framework that detect and classify the fall activity of a person inside the home. In the room, a camera is fixed that captures the movement of a person and it is placed in such a way that maximum area of the room is observed and no large occlusion occurs. We propose a deep learning based fall detection framework where, AlexNet [20] neural network is applied to classify fall activity.

The camera continuously observes the area under observation. After every time interval **t**, video of the observed scene during time **t** is sent to the fall classification engine and characterizes whether a fall activity has occurred or not. The video is converted into frames, which are considered as the region of interest (ROI) and are input to the AlexNet neural network for fall classification as shown in Figure 1 using transfer learning. AlexNet neural network has 8 convolutional layers and has been pre-trained on millions of images for classification into 1000 classes. We apply transfer learning to this pre-trained network for faster and improved fall classification using datasets [22] and [6].

Features are extracted after fine-tuning of AlexNet neural network for every input image on datasets [22]

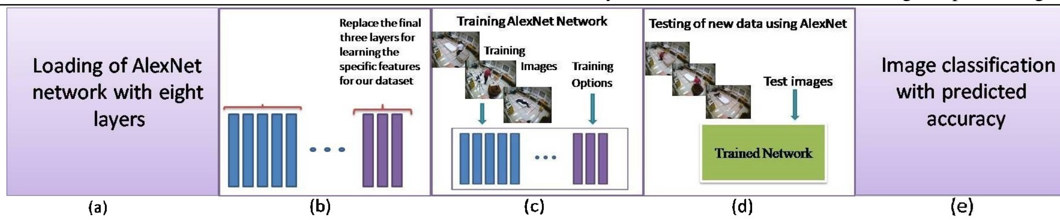

Figure 1: Pictorial representation of AlexNet neural network to classify the image data for fall detection. (a) We load the AlexNet neural network having eight layers, (b) The last three layers are replaced by a classification output layer, soft max layer and fully connected layers in AlexNet neural network for our datasets, (c) We train the AlexNet neural network for our datasets, (d) New Images are tested after training the network, (d) AlexNet neural network classifies the test images and computes the recognition accuracy.

and [6]. We assign the last three layers of this network for solving the problem of fallx classification. These three layers are replaced by a classification output layer, soft max layer and fully connected layers in AlexNet neural network. We fine-tuned our model and use a learning rate 0.00001 and stop after 1000 epochs. At the end, using this fine-tuned network, the fall activity of a person is classified and the accuracy is calculated.

4 Machine leaning methods

For the detection and classification of fall activity from other normal activities, we explore two machine learning algorithms, namely, Support Vector Machine (SVM) and Decision Tree. We first describe the feature extraction steps performed before classification using the above mentioned classifiers.

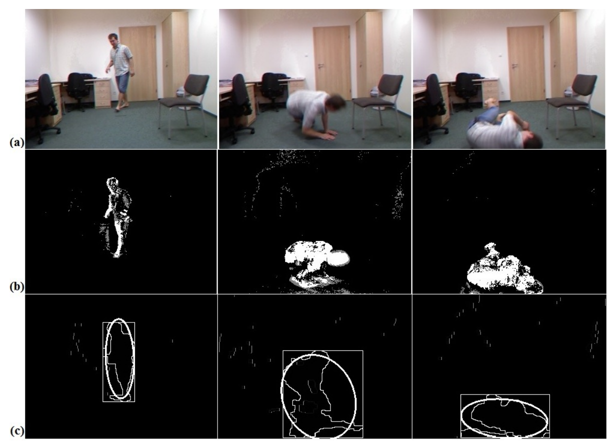

Figure 2: Some sample images are shown from dataset [22] where (a) represents the original image, (b) represents the result of background subtraction, and (c) represents the result of ellipse and rectangle fitting on the foreground region.

4.1 Feature extraction

A camera is placed such that it captures the movement of a person. Then, Gaussian Mixture Model (GMM) is applied for background subtraction to help detect the person in the scene as shown in Figure 2(b). Then, we apply the morphological operations to remove noise from the foreground images and then, apply 8 connected components so that the complete foreground object can be extracted as one component. Then, the contour of the largest connected component that represents the person in the scene is extracted. Then, we fit an ellipse and bounding rectangle to this extracted foreground region as shown in Figure 2(c) for finding out the orientation, area and aspect ratio of the region of interest. We use these features for the classification of fall activity using SVM and decision tree.

An ellipse is defined by its major and minor axes, the orientation, ϕ, and center (x, y). We evaluate the semi-major axis, a, and semi-minor axis, b, of the ellipse and then, the area of the ellipse, A, is calculated using the equation 1.

$$A = \pi * a * b \tag{1}$$

We also compute the height H, width W, and the aspect ratio, AR of the bounding rectangle is calculated which is defined in Equation 2.

$$AR = \frac{W}{H} \tag{2}$$

4.2 Support Vector Machine based classification

We classify the activities of the person under observation as fall and non-fall using Support Vector Machine (SVM). The SVM is trained using the features, that is, orientation, area and aspect ratio of the person, extracted from each frame.

The training dataset of n samples in SVM are given as $(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)$ where, $y_i \in (1, -1)$ denotes the label of training data and x_i is a p-dimensional feature vector. We have to find the hyperplane by maximizing the 'margin' parameter in SVM, which separates the data points x_i into two classes, $y_i = 1$ or $y_i = -1$. The hyperplane for both the classes are defined in Equations 3 and 4.

$$w^T x_i - b \geq 1, if\ y_i = 1 \tag{3}$$

$$w^T x_i - b \leq 1, if\ y_i = -1 \tag{4}$$

where, w represents the vectors normal to the hyperplane. Also, the distance between above two hyperplanes is represented by $2/ \parallel w \parallel$. For deciding the accurate hyperplane, we need to maximize this distance by minimizing the value of $\parallel w \parallel$. Therefore, the optimization problem for deciding the hyperplane can be summarized in Equation 5.

$$\begin{gathered} Minimize \parallel w \parallel \\ subject\ \ to\ \ y_i(w^T x_i - b) \geq 1 \\ for\ \ all\ \ 1 \leq i \leq n \end{gathered} \tag{5}$$

We define two classes in SVM as fall class and non-fall class. Three features, namely, aspect ratio, orientation and area of the object are taken as feature vectors in SVM. The parameters are normalized to its standard range of -1 and 1. -1 denotes the fall class and 1 denotes non-fall class. SVM performs well on high-dimensional data. However, it under performs in the situations where there is large number of samples as well as noise present in the data. Therefore, to overcome these issues, we explore another machine learning method to classify the fall event, namely, decision tree.

4.3 Decision Tree based classification

We further apply another machine learning method, namely, decision tree for fall classification. We build and train a decision tree using the extracted features which are, orientation, area and aspect ratio of the detected person in each frame. Decision tree is the combination of nodes and branches where the leaf node represent the class or label. In our work, only two classes fall and non-fall are considered. In a decision tree, features or attributes are represented as given in Equation 6.

$$(x, y) = (x_1, x_2, x_3, ...x_n, Y) \tag{6}$$

where, Y is the target variable (label) which we want to classify. The vector x represents the features x_1, x_2, x_3, etc. that are used for classification.

The entropy $E(C)$ for each attribute is calculated as given in Equation 7.

$$E(C) = \sum_{i=1}^{n} -p_i\ log_2\ p_i \tag{7}$$

where, C denotes the current state and p_i denotes the probability of an event i of state C. The complete training data is split with the help of features and furthermore, the information gain is calculated as shown in Equation 8.

$$Information\ Gain(C, X) = E(C) - E(C, X) \tag{8}$$

where C represents the current state and X denotes the selected attributes. Entropy for multiple attributes $E(C, X)$ is calculated as shown in Equation 9.

$$E(C, X) = \sum\nolimits_{c \in X} P(c) * E(c) \tag{9}$$

We now compute entropy and information gain for each feature and select the largest value of information gain to split the data. To reach at one of leaf nodes of the tree, the above process is performed repeatedly and in this way, test data is assigned to one of the classes.
The advantages of using decision tree are: (i) it is comprehensible and self-explanatory, (ii) it is able to handle nominal and numeric type attributes as well as continuous and discrete attributes, (iii) it can work for those type of datasets which includes missing values or some other errors. But the slight changes in data may lead to incorrect classification as we need to retrain the decision tree from scratch. Also, it takes a large amount of time to train the decision tree on large datasets. Therefore, we propose a fall detection and classification using AlexNet neural network which is robust, accurate and efficient.

5 Experiment results and discussion

We perform experiments on two different datasets [22] and [6] and these are publicly available. In dataset [22], an elder and two young persons perform different daily activities including fall. There are a total of 70 videos such that in the first 30 videos, the person is falling while doing other activities and in the rest of 40 videos, the person does all activities excluding fall. The dataset [6] has 8 cameras inside the room and contains 24 scenarios. The volunteers perform all activities that include walking, bending on sofa or chair, sitting on chair or some other furniture, and falling while doing all these activities. We treat each camera as a single camera so that we can capture more data related to these activities. A total of 1080 video clips are taken from these

Figure 3: Examples are taken from dataset [22] where the activities of a person are performed in home environment.

Figure 4: Sample images are taken from dataset [6]. Different daily activities and fall of a person has performed in home environment that are captured by 8 cameras.

scenarios such that $2/3^{rd}$ of part contains normal activities and the rest $1/3^{rd}$ part contains fall activity. Some examples of images for both the datasets are shown in Figure 3 and 4. We have used Linux operating system (64 bits) for conducting all the experiments on MATLAB $R2019a$. The desktop contains 26 GB of RAM and Intel $i7-3770$ processor.

5.1 Detection performance of fall activity using AlexNet neural network

To detect the fall activity, we have proposed an AlexNet network based framework. This neural network has 8 layers and it is already trained on millions of images as well as it classifies 1000 different classes. We apply transfer learning to perform classification of activity as fall or non-fall. In AlexNet neural network, we give $2/3^{rd}$ images of dataset for training and remaining $1/3^{rd}$ for testing. We replace the final three layers of the AlexNet neural network for performing our fall classification using transfer learning. Since in transfer learning, it makes the training process faster and require fewer data for training the model. We train our model using cross-validation approach on both the datasets. Our proposed model achieve 98.64% classification accuracy on dataset [22] and 98.89% classification accuracy on dataset [6] as shown in Table 1.

Table 1: Performance of our proposed method using AlexNet neural Network

Performance	Dataset [22]	Dataset [6]
Accuracy	98.64%	98.89%

5.2 Detection performance of fall activity using Support Vector Machine

We resize the images with the resolution of 320×240 on both datasets [22] and [6]. Furthermore, we apply support vector machine for the classification of fall activity. We calculate sensitivity, specificity and accuracy of SVM classifier on these datasets as shown in Table 2. We also draw precision and recall curves for each dataset as shown in Figure 5. If the threshold value is greater than 0.95 only then a fall is detected.

Table 2: Performance of our proposed method using Support vector machine Algorithm

Performance	Dataset [22]	Dataset [6]
Sensitivity	98.15%	99.10%
Specificity	97.10%	98.82%
Accuracy	98.24%	98.75%

5.3 Detection performance of fall activity using decision tree

In order to detect and classify the abnormal behavior of a person such as fall, we further apply decision tree classifier. The extracted features of the person are used as attributes for training the decision tree. Every test data is passed in this model that classifies it to the appropriate class that follow a suitable route from root node to a leaf node. After pruning the decision tree, we improve the classification accuracy of the test data as shown in Table 3.

Table 3: Performance of our proposed method using Decision tree Algorithm.

Performance	Dataset [22]	Dataset [6]
Sensitivity	97.65%	96.40%
Specificity	96.62%	95.48%
Accuracy	96.48%	97.21%

5.4 Comparison of our proposed method with state-of-the-art

We compare our AlexNet based proposed framework with SVM and decision tree and show the comparison

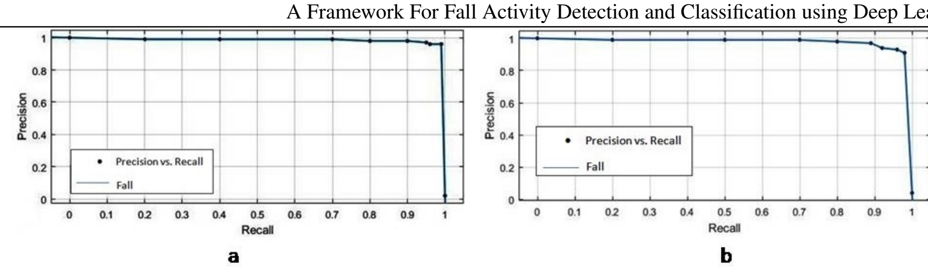

Figure 5: Precision and recall curve for Datasets [22] and [6] where a threshold = 0.95 is selected and fall activity is detected if threshold value is greater than 0.95.

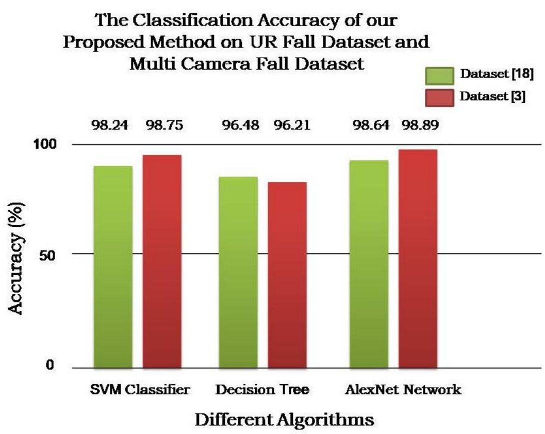

Figure 6: Performance of AlexNet based proposed method for datasets [22] and [6] using different algorithms.

in Figure 6 on the basis of classification accuracy. Also, Table 4 shows that deep learning based proposed fall detection method is more accurate as compared to SVM and decision tree.

Table 4: Accuracy of our proposed method using different algorithms for datasets [22] and [6]

Method	Dataset [22]	Dataset [6]
SVM	98.24%	98.75%
Decision Tree	96.48%	96.21%
AlexNet neural network	98.64%	98.89%

5.4.1 Comparison of our Alexnet based proposed method with state-of-the-art

We compare our deep learning based framework with other state-of-the-art deep learning based fall detection systems [39], [25], [24], and [1] on datasets [22] as shown in Table 5 and with [28], and [35] on dataset [6] as shown in Table 6. Our proposed framework achieves 98.16% sensitivity, 97.50% specificity and 98.64% accuracy on dataset [22]. Furthermore, our proposed deep learning based framework achieves 98.33% sensitivity, 97.16% specificity and 98.89% accuracy on dataset [6]. The results show that our proposed framework is comparable with deep learning based state-of-the-art methods.

Table 5: Comparison of our proposed deep learning based framework on dataset [22]

Method	Sensitivity	Specificity	Accuracy
Serpa et al. [39]	94.50%	**99.90%**	— — —
Na Lu et al. [25]	65.50%	98.37%	97.27%
Liu et al. [24]	**99.20%**	96.84%	98.20%
Espinosa et al. [1]	— — —	— — — —	95.64%
Our Proposed Method	98.16%	97.50%	**98.64%**

Table 6: Comparison of our proposed deep learning based framework on dataset [6]

Method	Sensitivity	Specificity	Accuracy
Marcos et al. [28]	**99.00%**	96.00%	— — —
Rougier et al. [35]	— — —	— — —	98.00%
Our Proposed Method	98.33%	**97.16%**	**98.89%**

5.4.2 Comparison of our SVM based proposed method with state-of-the-art

We have also explored SVM based fall detection and compared it with other SVM based proposed methods for fall classification. The comparison of our explored SVM method with other proposed approaches on dataset [22] and [6] has been shown in Table 7 and 8 respectively.

5.4.3 Comparison of our decision tree based proposed method with state-of-the-art

The next machine learning algorithm we have explored is decision tree to detect and classify the fall activity

Table 7: Comparison Table for SVM based fall classification on dataset [22]

Method	Sensitivity	Specificity	Accuracy
GLR-SVM et al. [13]	94.00%	94.00%	96.66%
PCA + SVM et al. [5]	97.00%	**100.00%**	**98.50%**
Feature extraction + SVM	**98.15%**	97.10%	98.24%

Table 8: Comparison Table for SVM based fall classification on [6]

Method	Sensitivity	Specificity	Accuracy
PCANet + SVM [42]	88.87%	98.90%	− − −
Feature extraction + SVM	**99.10%**	98.82%	**98.75%**

of a person. We compare our decision tree based fall detection method with [5] on dataset [22] and show the comparison in Table 9.

Table 9: Comparison Table for decision tree based fall classification on dataset [22]

Method	Sensitivity	Specificity	Accuracy
PCA + Decision Tree [5]	**98.00%**	**98.00%**	96.00%
Feature extraction + Decision Tree	96.40%	95.48%	**97.21%**

6 Conclusion

We have proposed a deep learning based framework to detect and classify the fall activity of a person using a single camera. The proposed framework has been compared with two machine learning methods, namely, Support Vector Machine and decision tree. For applying machine learning techniques, we develop our own feature extraction process and consider the most relevant features for fall classification. Experiments have been carried out by us on publicly available datasets and show that our deep learning based framework outperforms the machine learning based frameworks. The proposed framework has been compared with other deep learning based methods on the same datasets. Experimental results show that the proposed deep learning based fall detection framework achieves promising results and is comparable with state-of-the-art methods.

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