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Fall Detection for Elderly People Using Machine Learning

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Abstract- Old people are more prone to falls. Since two decades, falls have been greatly investigated by medical institutions to minimize the impact of the fall and also reduce the consequences eg: Cost of hospitalization, etc. However, the problem of elderly falling does not only concern health-professionals but has also drawn the interest of the scientist community. Falls have always been the object of many research studies and the purpose of many commercial products. Recently, researchers have been trying to detect the falls even before they happen. These studies have successfully handled the problem of fall detection keeping sensing methods at bay. Early Fall Prediction systems have come into existence despite minimal clinical studies due to restrictions. In this context, the main contribution of this article is to give a thorough overview on elderly falls and to suggest a general classification of fall-related systems based on their sensor deployment. An extensive research scheme has been done from fall detection to fall prevention systems have been also conducted based on this common ground classification. Data processing techniques for fall detection and fall prevention tracks are also emphasized. The aim of this study is to deliver medical technologists in the field of public health a good understanding regarding fall-related systems.

Keywords - Deep Learning, Transfer Learning, ResNet50, CNN.

I. INTRODUCTION

Falling is one of the most dangerous events that an elderly person can face. With an older population, there is an urgent need for the development of fall detection systems. We tackle this survey from various angles, including data gathering, data transfer, data analysis, security, and privacy. We also go over the benchmark data sets that have been utilised to quantify the performance of the proposed approaches. The survey is intended to provide researchers in the field of senior fall detection using sensor networks with a summary of accomplishments made thus far and to highlight areas where additional effort might be useful. Falls pose a serious risk to the health and independence of persons 65 and older. As there are a wide variety and big number of passive monitoring systems available to identify when an individual has fallen, there is a need to assess and synthesise the evidence regarding their ability to reliably detect falls to decide which systems are most successful. Elderly persons are at a higher risk of death or injury as a result of falls. Every year, more than one-third of the elderly population dies, which can cause fear and loss of independence. The increase in the older population raises the demand for healthcare systems. Pre-processing, feature extraction, feature selection, model training, and classification are the five stages of fall detection classification systems. When all of these procedures are integrated to form the proposed system. The suggested classification system has the advantage of using feature extraction and selection approaches to optimise the classification process. The created classifiers can grow overly complex, resulting in extended computing times with substantial bias . It is critical to select and reduce the features used as classifier inputs . Most studies do not offer a mechanism for determining whether the retrieved features have the information needed to differentiate between ADL and fall activities. Previous work has been done in the fall detection system; new machine learning techniques and feature extraction approaches will be studied in this research. In the present work, the problem of developing such a system for recognizing human movements through the records of CCTV cameras and detecting falls has been considered. The fall of a person can be caused by many factors: loss of balance due to lack of cerebral blood supply, muscle weakness, etc. In any case, a situation when a person has fallen and cannot get up without assistance is dangerous and requires an immediate response.

The problem of detecting falls using video analysis has been studied in a large number of works , which were based on analyzing the shape and position of the person in the frame, gradients in the vertical and horizontal directions, and changes in images in the time domain. In the majority of papers on CCTV cameras records analysis the effectiveness of the fall event classifiers is artificially overestimated because of the limitations of the datasets used for testing and training procedure. These limitations may be described as follows:

Dataset is usually formed by the data recorded in un- changed conditions (most often in the laboratory condi- tions, rather than realistic ones), and for uniform illumi- nation of the entire analyzed scene.
One and the same person acts as test subjects.
Movement artifacts of the "fall" type are similar in pre- ceding actions of the subject and her/his relative position toward the camera at the time of the fall.

In almost all cases, falls are performed on a cushioning mat, which most often has a significant color contrast with respect to the clothing of the subject. All these factors result in a significant overestimation of the classifiers presented in papers based on the analysis of datasets with the above-listed disadvantages. The purpose of this paper was to evaluate the applicability of deep learning and transfer learning techniques in automated detection of falls by analysis of surveillance cameras data gathered in realistic conditions.

1	'data'	Image Input	227x227x3 images with 'zerocenter' normalization
2	'conv1'	Convolution	96 11x11x3 convolutions with stride [4 4] and padding [0 0 0 0]
3	'relu1'	ReLU	ReLU
4	'norm1'	Cross Channel Normalization	cross channel normalization with 5 channels per element
5	'pool1'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
6	'conv2'	Convolution	256 5x5x48 convolutions with stride [1 1] and padding [2 2 2 2]
7	'relu2'	ReLU	ReLU
8	'norm2'	Cross Channel Normalization	cross channel normalization with 5 channels per element
9	'pool2'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
10	'conv3'	Convolution	384 3x3x256 convolutions with stride [1 1] and padding [1 1 1 1]
11	'relu3'	ReLU	ReLU
12	'conv4'	Convolution	384 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
13	'relu4'	ReLU	ReLU
14	'conv5'	Convolution	256 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
15	'relu5'	ReLU	ReLU
16	'pool5'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
17	'fc6'	Fully Connected	4096 fully connected layer
18	'relu6'	ReLU	ReLU
19	'drop6'	Dropout	50% dropout
20	'fc7'	Fully Connected	4096 fully connected layer
21	'relu7'	ReLU	ReLU
22	'drop7'	Dropout	50% dropout
23	''	Fully Connected	2 fully connected layer
24	'prob'	Softmax	softmax
25	''	Classification Output	crossentropyex

II.METHODS

As it is known, deep learning technique is based on the use of convolution neural networks (CNN), which are biologically-inspired variants of multilayer perceptrons. The main drawback of this technique is that its training requires a huge amount of data (more than 100,000 examples) for the successful implementation in practice. As a result, the training process can last for weeks and months, which is not always acceptable.

Transfer learning is the technique which allows over- coming disadvantages of deep learning. It may be described as following: the researcher selects for solving a new problem CNN already trained for another similar problem. That allows transferring knowledge obtained as a result of solving one task (for example, recognition of images of various animal species) to solve another (for example, recognition of interior objects on the image). This approach allows reducing significantly the time required for CNN training on a new dataset comparing to training a neural network from scratch (when initializing the neural network connection with random weights).

In present paper transfer learning procedure was done utiliz- ing MATLAB2017b. We used pre-trained CNN AlexNet which is available by installing Neural Network ToolboxTM Model for AlexNet Network support package. This CNN was trained by its authors on 1.2 millions of images to classify 1000 different classes and significantly outperformed in 2012 all earlier CNN versions by utilizing more filters per layer that previously proposed LeNet-5 , which was a pioneering CNN designed by Yann LeCunn in 1998.

In order to use this network to recognize only two classes of Images (fall and non-fall classes), we need to make changes to the AlexNet CNN architecture. Namely, replace the 23d layer with 2 ”fully connected layers”, since there are two classes, and replace the 25th layer in accordance with the class names for ”fall” and ”non-fall”. After making the appropriate changes, the network architecture has the appearance shown in Fig. 1. Layers that are different from the original AlexNet are underlined. After CNN is designed supervised training procedure should be done by using a dataset with images for both classes (fall and non-fall).

III.EXPERIMENTAL DATA

In present work, an open database of video recordings provided by the Laboratory of Electronics and Imaging of the National Center for Scientific Research in Chalon-sur-Saone was used. In Fig. 2 and 3 examples of frames extracted from the video records both corresponding to fall and non-fall episodes are presented. The merits of this database include the following factors: Video signals are recorded for various environmental conditions.

The illumination of the experimental scene is irregular. The dataset contains records for which contrast of the human over the background objects is rather low due to the limits of the camera dynamic range and presence of regions with high brightness (for example, window area in Fig. 3). 4 different subjects participated in the experiments. Falls were performed at different viewing angles, both from the standing position and from the sitting position.

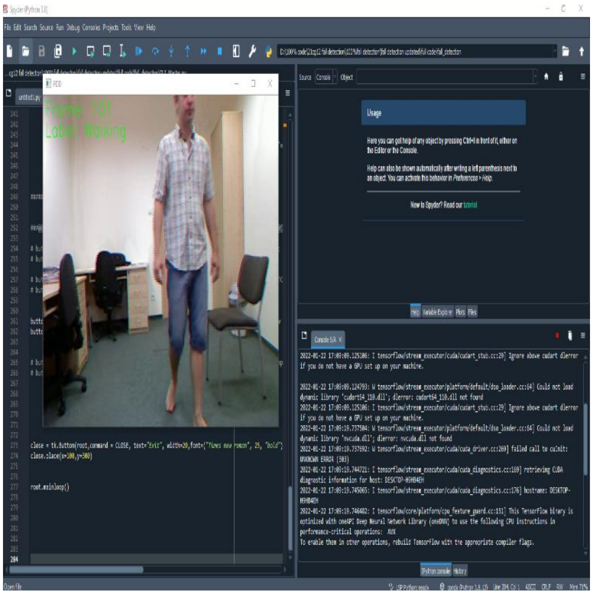

Fig 2. Frame classified as non fall episode

Fig. 3. Frame classified as fall episode

Volunteers were falling both on a specially prepared cushioning base, and directly on the floor.
30 records from the dataset were used in this paper to train and to test classifier. All records contain at least one fall episode. For each record operator visually detected fall episodes, and provide the number of the frame corresponding to the start and the end of the fall episode.

IV.RESULTS AND DISCUSSION

Each record from the data set was divided into separate frames with known class (fall or non-fall), which were used as a training data for the classifier. After that, each frame was re-sampled to make it compatible with CNN AlexNet.

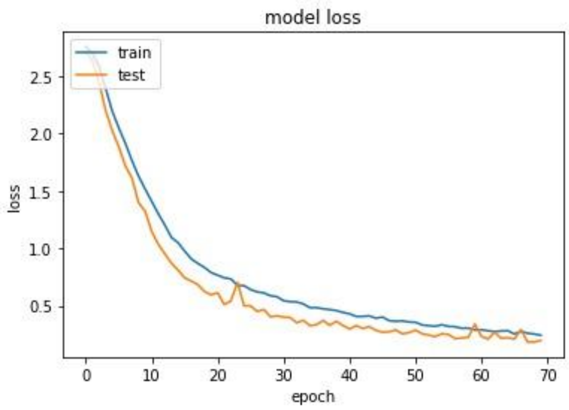

Fig. 4 Model Error

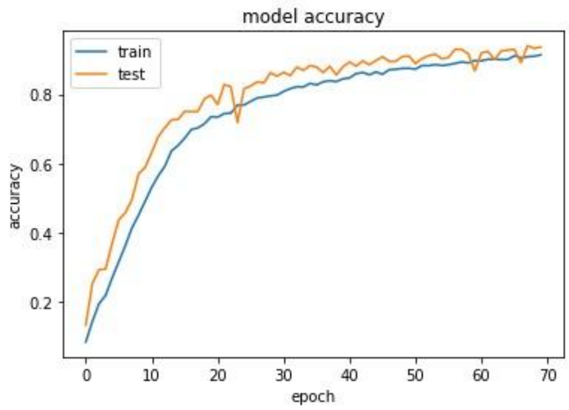

Fig. 5 Model Accuracy.

As transfer learning technique was used to train the CNN, the parameters of the input layer were remained unchanged. That allows using values of connections weights available after CNN pre-training. As a result of CNN training, we had a graph of classification accuracy increasing with each iteration of the CNN training (Fig. 5), while the classification error for a batch with each iteration became smaller, as it is shown in Fig. 4. After completing the training process, the efficiency of the neural network was evaluated on the test sample.

V.CONCLUSION

There is a significant body of material that describes numerous fall detecting technologies. According to this review, technology is growing more capable of doing such a task. More real-world tests, as well as standardisation of the evaluation of these devices, are now required. Age has a direct impact on physical, cognitive, and sensory functioning. As a result, older people find it difficult to complete routine ADLs. Furthermore, these diminished functions increase the likelihood of falls, which can be lethal. As a result, the development of fall detection or prevention technologies is desired to lessen the effects of falls. This paper provides an overview of the most recent fall detection and prevention systems that use machine learning.

REFERENCES

[1]. Weidong Min, Hao Cui , Hong Rao, Zhixun Li,Leiyue Yao, ”Detection of Human Falls on Furniture Using Scene Analysis Based on Deep Learning and Activity Characteristics ,”Recent Advantages of Computer Vision based on Chinese Conference on Computer Vision (CCCV) 2017, IEEE access (vol- ume 6),January 2018.

[2]. X. Ma, H. Wang, B. Xue, M. Zhou, B. Ji and Y. Li, ”Depth-based human fall detection via shape fea- tures and improved extreme learning machine,” IEEE Journal of Biomedical and Health Informatics, vol. 18, no. 6, pp. 1915-1922, Nov. 2014.

[3]. R. Girshick, ”Fast R-CNN,” 2015 IEEE International Conference on Com- puter Vision (ICCV), Santi- ago, 2015, pp. 1440-1448.

[4]. To¨reyin, B. Ugˇur, Y. Dedeogˇlu, and A. E. C¸ etin. ”HMM based falling person detection using both audio and video,” Lecture Notes in Computer Science 3766(2005):211-220.