PERFORMANCE ANALYSIS OF VARIOUS MACHINE LEARNING ALGORITHMS FOR FALL DETECTION-A SURVEY

Dr.M.Rajaiah, Dean Academics & HOD, Dept of CSE, AudisankaraCollege of Engineering and Technology, Gudur.

Mr.V.Sreenatha sarma, Dean ICT ,Dept of CSE, Audisankara Collegeof Engineering and Technology, Gudur.

K.Thanuja, UG Scholar,Dept Of CSE,Audisankara College of Engineering and Technology,Gudur.

D.Chaitanya, UG Scholar, Dept of CSE, Audisankara College ofEngineering and Technology, Gudur.

G.Madhuri, UG Scholar, Dept of CSE, Audisankara College ofEngineering and Technology, Gudur.

K.Reddaiah, UG Scholar, Dept of CSE, Audisankara College ofEngineering and Technology, Gudur.

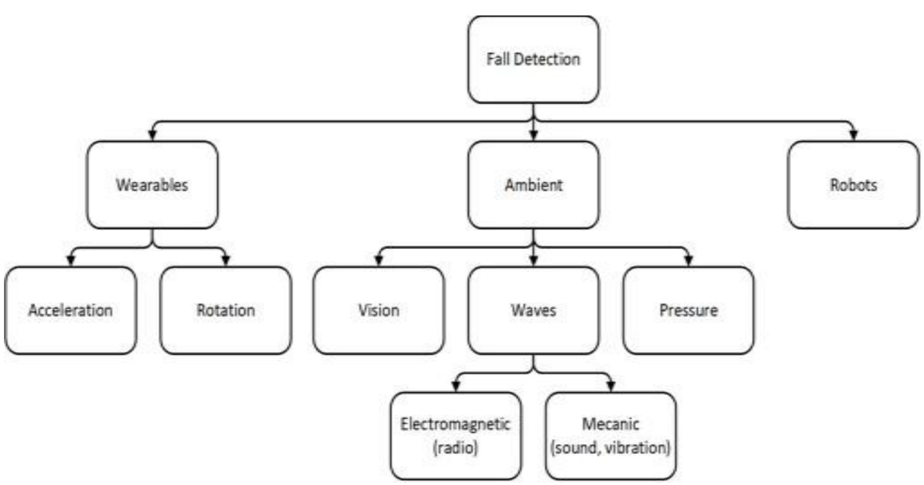
ABSTRACT:

Improper activities appear nowadays for the human (i.e.) falling without aware, and numerous techniques had been developed to reduce them. In this essay, critically analysis of the various proposed methodologies by comparing their strength and their weakness. The complexity and diversity of actions make it difficult to recognise them. The conventional (CCTV) method is ineffective and expensive for monitoring patient activities by using sensor based is also difficult due to drained battery life. So we need real time system for activity recognition with more efficiency and accuracy to avoid people from morality problems or it may lead to causes to major injuries. By comparing various algorithm Support vector machine (SVM) is a discriminative classifier belonging tosupervised learning. Recurrent neural network (RNN) is one of the concepts in deepneural network. The main intention of the RNN is to minimize the preprocessing. This application will seem like visual imagery analysis. The convolutional neural network (CNN) it is more cost expensive compared wearable and ambience based. Diffusion Convolutional Neural Network (DCRNN) is the branch of artificial

intelligence. The neural network was trained by DCRNN algorithm. The goal of the to develop a Diffusion Convolutional Recurrent Neural network-based system for automatically detecting abnormal human activity. and compression of the video in real times it proves to be more effective than otherclassification algorithm.

1.INTRODUCTION:

A broad area of study called "human activity recognition" aims to pinpoint a person's precise movements or actions using data. The aim of activityrecognition is to distinguish between activities of human and seasonal ones. Fall detection is the main issues that handicapped and elderly people face,and_it depends on the environment and the individual's health. Additionally, it is not always possible to fullysupervise a person.
Ambience-based systems can occasionally provide false negative values because they are so sensitive to noise signals. Patient monitoring with wearable sensors is challenging because they occasionally run out of battery when a person forgets to wear their gadgets, it is hard to keep track of their activities. So the best method for observing patient condition is video-based methodology.
Falling elderly or disabled people can result in severe injury and morality problems. They may experience Sevier problems if the caregivers are not present, necessitating immediate medical attention however, the caregiver does not arrive until after they receive a message. Major issuesof dependability and cost-effectiveness are raised bythis. Therefore, from many years, many techniques to overcome this have been developed. Due to this, recently automated.Many innovative automated techniques to detect and control falls have been created utilising the most latest technology to reduce reliance on caregivers and boost security. Numerousdetectors, such as audio sensors, barometers,



picture sensors, and accelerometers, can provide the data. Three distinct types of methodologies have been used to regulate and monitor the patient's actions for fall detection: sensor-based, video surveillance-based, and ambiance device-based.3.PROPOSED SYSTEM:

Algorithms introduced by Guirry using decision tree [1]. Using naive Bayes classifier it's could acquire less accuracy whereas on 100% accuracy for fused data from both sensors i.e. light and GPs sensor. Results from using a magnetometer and gyroscope are approximately 89% and 79%, respectively, while those from a smartphone and smart watch are 95% and 89%, respectively. The fall activities are not being discussed. The threshold-based detection is quite difficult in low cost consumption, according to a fall detection study [1] employing an accelerometer that may be worn. The recurrent neural network [RNN] is helpful to detect falls by using accelerometer technical for collecting datasets in [2]. It evaluated using URFD datasets [3], accelerometer produces 95.71% accuracy.

Training model with random acceleration signal yields 98.57%. The sis Fall dataset was tested and trained by the author [4].The weighted-cross entropy loss function is described by the author depending on the frequency of each class in the dataset used to train their model. Using the ADLs dataset, their model ultimately achieves 97.16% accuracy on falls and 94.14% accuracy on.

The machine learning techniques Support Vector Machine (SVM), Naive Bayes, K Nearest Neighbor (KNN), Decision Trees, and Neural Networks have been applied to fall detection with varying degrees of effectiveness.

4.RESULTS AND DISCUSSION

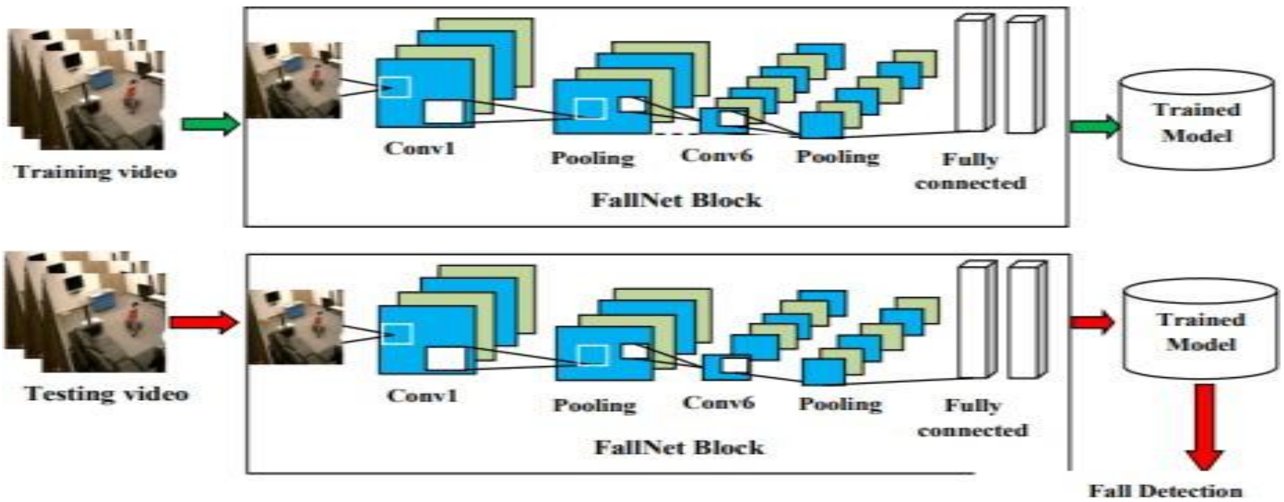


Fig.overall architecture of fall detection

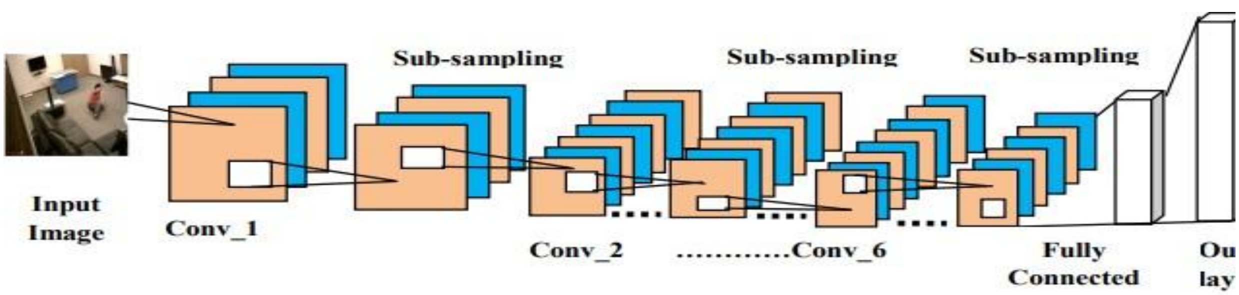


Figure 3: Architecture of CNN

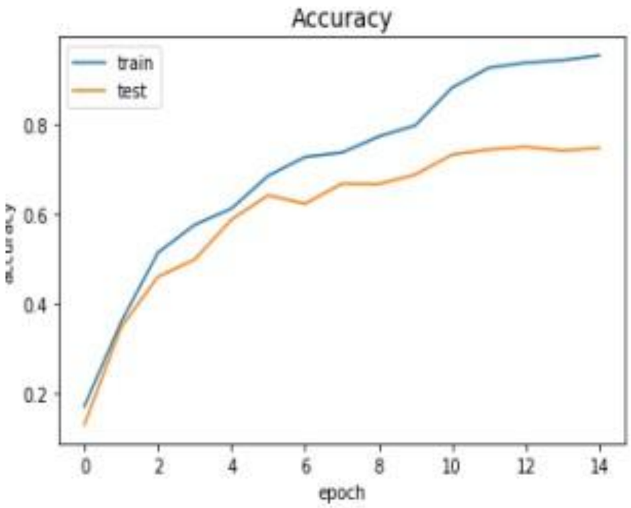
5.TRAINING AND IMPLEMENTATION:

Initialize the FallNet network model's node weights at the beginning. With this model, the weights from the subsequent embedding layer are used to establish the convolutional layer's weights. that possessing zero- mean gaussian distribution (SD= 0.01 and bias=0). For instance, 20 epochs, the trained convolutional layer and embedding layers are from end to another end. Here, the rate at the initial state is set it as 0.01 and

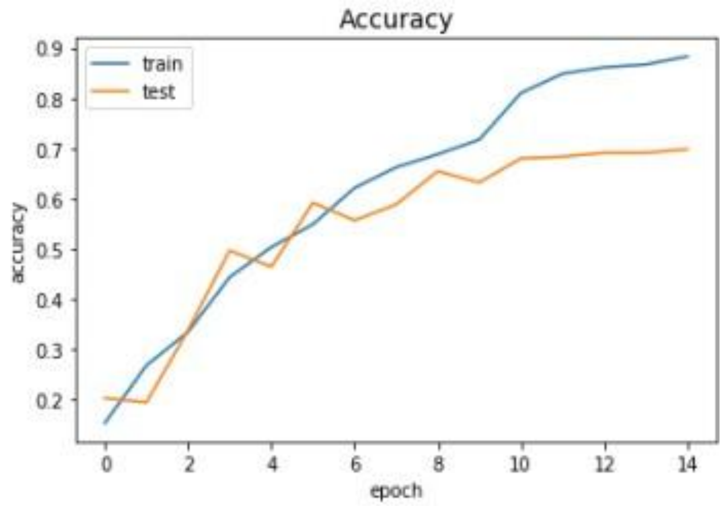
Layer type	Filter size & Stride	Details	Output Shape
Conv1	3x3 & s =1	Conv1 (16)	255,225, 16
Activation	ReLU		255,225, 16
MaxPooling		Pooling Size (2,2)	127,127, 16
Conv2	3x3 & s =1	Conv2 (16)	127,127, 16
Activation	ReLU		127,127, 16
MaxPooling		Pooling Size (2,2)	63,63,16
Conv3	3x3 & s =1	Conv3 (32)	63,63,32
Activation	ReLU		63,63,32
MaxPooling		Pooling Size (2,2)	31,31, 32
Conv4	3x3 & s =1	Conv4 (32)	31,31, 32
Activation	ReLU		31,31, 32
MaxPooling		Pooling Size (2,2)	15,15,32
Conv5	3x3 & s =1	Conv5 (64)	15,15,64
Activation	ReLU		15,15,64
MaxPooling		Pooling Size (2,2)	7,7,64
Conv6	3x3 & s =1	Conv6 (64)	7,7,64
Activation	ReLU		7,7,64
MaxPooling		Pooling Size (2,2)	3,3,64
Flatten	Flatten to a vector		96,756
Dense	Dense Input =256		256
Dense	Input Classes = 6		6
Activation	Softmax		6

(g) Convolution 6

Figure 4: One to six convolution visualization for input image



(a) Accuracy for 'ReLU'



(b) Accuracy for 'ELU'

AUTHOR	SENSOR/ TECHNIQUE	CLASSIFIER	ACCURACY
Xiaogang Li, Tiantian Pang, Weixiang Li, Tianfu Wang et al (2017)	Adaptive video, compressive	Convolutional Neural Network	99.98% average accuracy up to 10 folds
Raksha S,B,G Prasad et al July (2019)	Adaptive video compressive	Cascade, ADA boost	AC:80-90%
Haanvid lee, et al Feb (2019)	Dynamic vision	Convolution Neural Network	AC:95%
Jianyang ding, et al Dec (2019)	Commercial WiFi, CSI, CPV, TFA	Recurrent Neural Network	AC:98%
Miao yu, Liang Wang, et al Nov (2019)	Codebook, background subraction	Online one class Support Vector Machine	AC:95.6%
Chen junli, Jiao lichen, et al Dec (2018)	Kernel function	Support Vector Machine, Structural Risk minimization	AC:90-95%
Bhargavi ,March et al (2018)	State Transition	Multi-Class Support Vector Machine	AC:91%
Enea cippitelli, et al Feb (2017)	RGBD	Support vector Machine	Ac: 98.5%
Sahak kaghyan, et al April (2017)	Accelerometer, Mobile device	KNN	AC:98%

Table1. Analysis of Various Algorithms in Machine Learning

Evaluation Metrics:

The confusion matrix of the given problem is illustrated in figure 5.The matrix comprises of true positive, true negative, false positive and false negative values of fall detection scenario. The success state is considered as the state when the classifier correctly identifies the issue and vice versa denotes the failure state. The overall review of the classifier is obtained by the error rate. It is usually the proportion of the errors over the instances' set.

		Actual Value	
		Positive	Negative
Predicted Value	Positive	TP	FP
	Negative	FN	TN

Figure 5: Confusion Matrix for fall detection

Precision (P) or detection rate defines as the ratio of correctly labeled instances to the total labeled instances. Typically, P can measure the prediction's model which denotes the true positive value which is illustrated below:

$$\text{Precision (P)} = \frac{TP}{TP + FP}$$

Recall (R) or Sensitivity defines as the ratio of labelled instances and the total instances. R measure usually denotes the predictions' model and defined as the true positive figure which is defined by

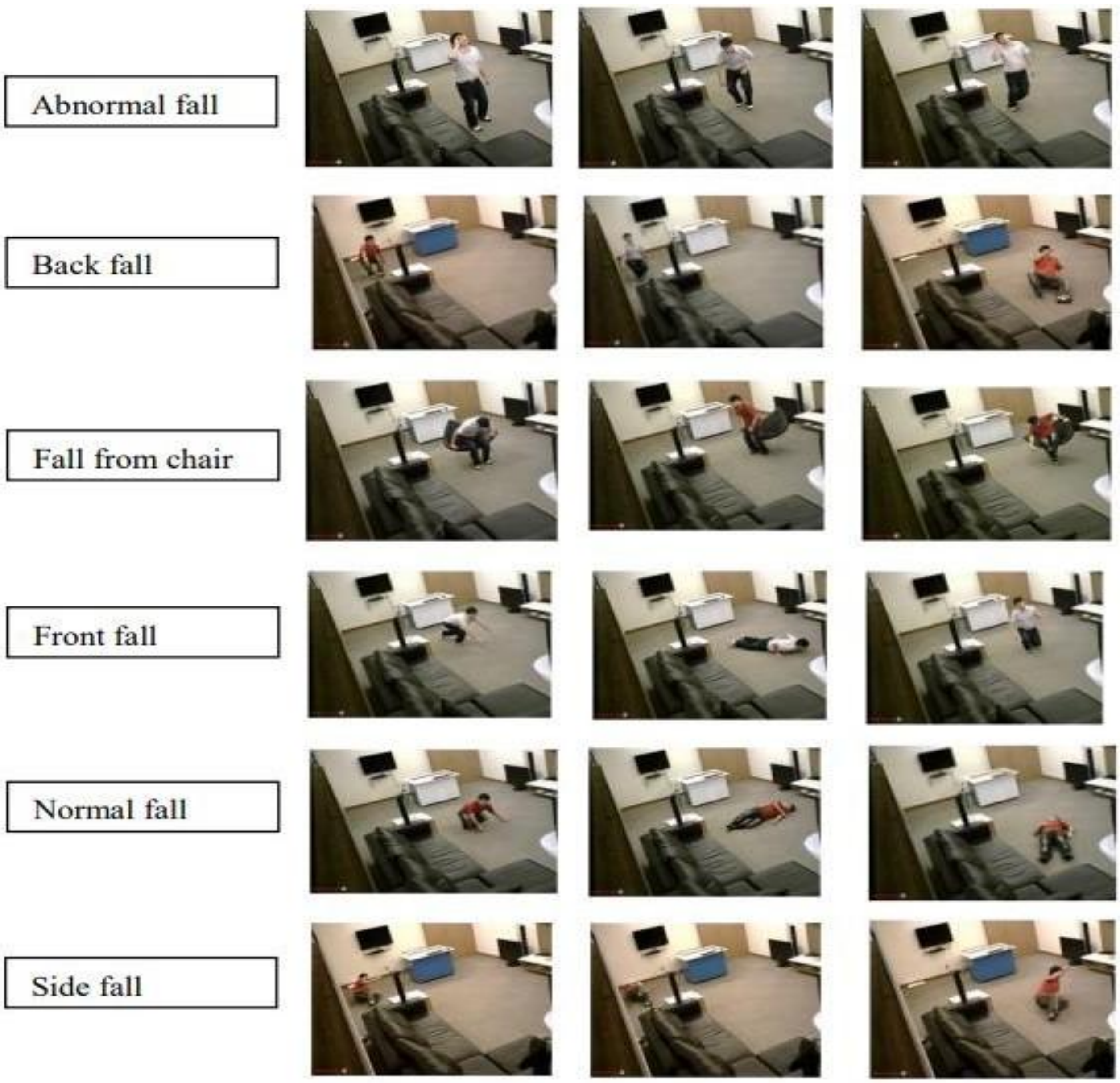


Figure 6: Sample frames for fall detection dataset

CONCLUSION:

From the aforementioned survey work, many fall detection techniques have been examined and verified utilising wearable sensors and environment-based methods, but they aren't sophisticated for users due to numerous battery problems and user-inconvenience. It is impossible to recommend a single technique for their implementation since each approach has its special advantages and limitations. Processing takes the longest time because the scale of the video timestamp is larger to compress. Then it moves on to feature extraction. Therefore, as compared to other systems, the invention of video-based surveillance with Diffusion Convolutional Recurrent Neural Network classification boosts accuracy rate of fall detection. This suggested extension and classificationof the fall and sleep our upcoming research stages involve validating this suggested approach on huge datasets.

References:

[1] Guirry, J.J.; van de Ven, P.; Nelson, J. Sensors 2014, 14, 5687–5701. [CrossRef] [PubMed]

[2] Theodoridis, T.; Solachidis, V.; Vretos, N.; Daras, P. Human fall detection from acceleration measurements using a Recurrent Neural Network. Springer: Singapore, 20[4]; pp. 145–149.

[3] Kwolek, B.; Kepski, M. Human fall detection on embedded platform using depth maps and wireless accelerometer. Comput Meth Prog Biomed. 2014, 117, 489–501. [CrossRef] [PubMed]

[4] RightMinder—Fall Detection for Android Smartwatches and Android Phones. (2014).

[5] Sucerquia, A.; López, J.D.; Vargas-Bonilla, J.F. SisFall: A fall and movement dataset. Sensors 2017, 17, 198. [CrossRef] [PubMed]

[6] Wanru Xu, Zhenjiang Miao, Member, IEEE, Xiao-Ping Zhang, Senior Member, IEEE, Yi Tian. Hierarchical Spatio- Temporal Model for Human Activity Recognition

[7] Yann Lecun, Yoshua Bengio, and Geoffrey Hinton. Deep Learning Nature, 521(7553):436-444, 2015.

[8] Xiaogang, Tiantian Pang, Weixiang Liu, Tianfu Wang Health Science Center,

Shenzhen University. Fall Detection for Elderly Person Care Using Convolutional Neural Networks.

[9] Raksha S, B G Prasad," Anomalous Human Activity Recognition in SurveillanceVideos", (IJRTE) ISSN: 2277-3878, Volume-8, Issue-2S7, July 2019.

AUTHOR PROFILES

Dr.M.Rajaiah, Currently working as an Dean Academics & HOD in the department of CSE at ASCET (Autonomous), Gudur, Tirupathi(DT).He has published more than 35 papers in, Web of Science, Scopus Indexing.

Mr.V.Sreenatha Sharma,Currently working as an Dean ICT in the department of CSE at ASCET (Autonomous),Gudur, Tirupati(DT).

K.Thanuja, B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur. He has pursuing in computer science and engineering.

D.Chaitanya, B.Tech student in the department of CSE at AudisankaraCollege of Engineering and Technology, Gudur. He has pursuing in computer science and engineering.

G.Madhuri ,B.Tech student in the department of CSE at AudisankaraCollege of Engineering and Technology, Gudur. She has pursuing in computer science and engineering.

K.Reddaiah, B.Tech student in the department of CSE at AudisankaraCollege of Engineering and Technology, Gudur. She has pursuing in computer science and engineering.