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Real Time Direction-Sensitive Fall Detection System Using Accelerometer and Learning Classifier

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***Abstract*— Continuous fall recognition framework screens the day by day action of particularly elderly individuals to enroll somebody's assistance as quick as conceivable if there should be an occurrence of crisis. This paper presents a real-time fall detection using a single 3D commercial accelerometer (3DCA) and support vector machine learning algorithm (SVMLA). In past, two machine learning (ML) based calculations SVMLA and k-Nearest Neighbors (K-NN) were executed for mandate fall discovery in reproduction. Among the two strategies, SVMLA give better exhibitions which prompts 96.45% of exactness utilizing PCA mean and standard deviation highlights, surpassing the exhibitions detailed in the writing. The performances of the developed system in real time are also evaluated and they are found same accuracy, precision and recall. When applied to experimental data from 13 male subjects, the real time system discriminates between falls and activities of daily living (ADL) with same level like simulation. The system utilizes privacy preserving sensor. The system is reliable, user friendly and cost effective with less technical error rate and high classification accuracy.**

Keywords—ADL, 3DCA, SVMLA, K-NN, WBSN, IDIL, WS

I. INTRODUCTION

Innovation advances to quicken the quality and sort of administrations accommodated human services and screen. Wearable sensor (WS) frameworks, made out of little and light detecting hubs, can possibly change the medicinal services framework. A critical use of WSs can be the identification of fall with its heading, especially for elderly or generally defenseless individuals. Notwithstanding the recognition of a fall, it is likewise vital to decide its course, which could help find joint shortcoming or post-fall break and help diminish response time. Most wearable fall discovery calculations depend on edges set by observational examination for different fall sorts. In any case, such calculations don't sum up well for inconspicuous informational indexes and their applications in finding the headings of falls are not very much perceived. Utilizing limits, it's anything but difficult to actualize continuously fall recognition, as a result of its number of count low. Be that as it may, it is hard to execute continuously fall identification utilizing learning calculation, in view of colossal estimation to take choice. This paper is worried with continuous ML calculation. We propose a system called "Innovation Dependable Independent Living (IDIL)" for elderly people. In Section III, TRIL is designed and described.

II. RELATED WORK

To identify falls, various calculations in light of camera, WS, encompassing sensor, goniometer 3DCAs and gyrators have been proposed. One approach in like manner utilize is to segregate amongst ADL and falls by limit esteems (for speeding up and rakish speed), set for the most part by observational strategies for both falls and ADL [1-3].

Khawandi et al. [4] utilized various webcams to fall discovery. Their calculation identifies faces and measures the speed with which distinguished confronts push toward the ground. In view of a set limit, it decides whether a fall has happened or not.

Liu and Zuo [5] offered a calculation that analyzes the proportion of the width and tallness of a man while standing and lying, the proportion of the range of a man's figure to the zone of the room and the rate of variety of a picture amid a fall. They presumed that by figuring the three elements on each picture outline, their framework will avoid FPs, and subsequently increment precision. Be that as it may, assessment results were not displayed.

Bashir et al [6] proposed a framework in view of a remote body range arrange. It utilizes a tri-pivotal 3DCA, and a tri-hub gyrator sensor. Three phases are utilized to decide human status to be specific, fall, ADL, and rest. The calculations utilized are edge based and extremely straightforward. It utilizes the stance point, rakish speed, and increasing speed to decide whether a fall has happened. The exactness for ADLs was 100%, while the affectability was 81.6%.

Jantaraprim et al. [7] registered vector size (VM) for a 3D 3DCA mounted on subjects' trunk area. An edge was set by watching the VM flag to segregate amongst falls and ADL.

Ojetola et al. [8] demonstrated that VM alone is adequate to precisely distinguish falls. Sudden developments, moves starting with one stance then onto the next and strolling do produce high VM like falls. Subsequently, calculations in light of edges set for VM alone will trigger false cautions.

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Wang et al. [9] proposed a fall identification framework in view of a 3D 3DCA set behind subjects' ears. Their calculation depended on straightforward guidelines and limits set by observational investigation of increasing speed information. VM of speeding up, extent of level increasing speed, time from begin to end of a fall and speed was figured as a major aspect of their calculation. Amid falls, quickening signals shift extensively from subject to subject and for various fall sorts. Subsequently, edges set for components in view of perception of increasing speed flag just will bring about abnormal state of FPs and FNs.

Shi et al [10] built up a fall discovery framework in view of an android-based cell phone. It coordinates a SVMLA. The proposed procedure utilizes the increasing speed information from the telephone's 3DCA to identify a fall. The fall discovery process is separated into five stages to be specific, typical, insecure, free fall, alteration, and unmoving. A speeding up edge is utilized to trigger the five-stage include extraction technique. A 16-components vector is acquired subsequently of the extraction technique. This vector is sustained into a SVMLA that is utilized to separate tumbles from ADLs. The gained results were the accompanying: review 90% and accuracy 95.7%.

Liu and Cheng [11] proposed the utilization of a SVMLA for fall discovery. Elements were produced utilizing 3D increasing speed information inspected at 200 Hz. The components separated incorporate the VM, the distinction between the most extreme and least speeding up for every hub of quickening, the vertical increasing speed and the tilt point.

Sengto et al [12] proposed a fall discovery framework calculation in light of a back engendering neural system (BPNN). The framework uses a tri-hub 3DCA mounted on the client's midsection keeping in mind the end goal to gather his/her speeding up information conduct. Human exercises are partitioned in three gatherings: falling exercises (forward, in reverse, right and left), moderate movement exercises (strolling, getting up from bed, slumping), and sudden movement exercises (running, hopping). An increasing speed edge is set to separate between moderate movement exercises and different exercises. The general review of the location calculation was 96.25% while the specificity was 99.5%.

Humenberger et al [13] built up a bio-enlivened stereo vision fall identification framework. It uses two optical indicator chips, a field-programmable door exhibit (FPGA), an advanced flag processor (DSP) and a remote correspondence module. The optical chips catch video outlines. The FPGA makes the info information for the DSP by figuring 3D portrayals of the earth. The DSP is stacked with a neural system that is utilized for order purposes. Falls are isolated into 4 states or stages pre-fall, basic, post-fall, and recuperation stage. To run the trials the equipment was mounted on the top corners of a room with a specific end goal to screen the subjects of intrigue. The trial results are 90% of fall discovery.

Takeda et al. [14] built up a foot age appraisal framework that evaluations how likely a man is to fall in light of his/her adjust capacity and stride condition. The framework utilizes tangle sort appropriation sensor to accumulate the SOI's stride qualities. Fluffy rationale the framework can make taught surmises. The fluffy participation capacities were acquired through a learning procedure. The framework was not dependable strategy.

Chen et al [15] built up A human fall identification framework utilizing a PC vision approach is presented. The arrangement is fit for identifying fall-related occasions continuously utilizing skeleton elements and human shape varieties. The framework can separate the human stance and decrease the computational weight by utilizing a 2D show rather than a confounded 3D one. The skeleton (a crossing tree) is obtained by running the outstanding diagram traversal calculation Depth-first inquiry (DFS) on the focal point of the triangular lattices. A separation guide is utilized to compute the separation between two skeletons. A fall is distinguished if the client's movement does not change inside a specific timeframe. The framework can acquire high discovery exactness (90.9%) while keeping up a low false alert rate.

Gjoreski et al [16] proposed consolidates act acknowledgment with limits set by perception examination to identify falls. Their calculation utilizes 3D speeding up information examined at 6 Hz. The extricated components were VM, tilt point, mean of 3DCA x-hub, Root Mean Square (RMS) of VM, standard deviation of VM and change in VM. Stances, (for example, for example, lying or sitting on the floor) are perceived by means of a Random Forest ML calculation. A fall is identified by joining the perceived stance with a limit set for the VM. On the off chance that a subject's stance is lying or sitting and the VM goes over the limit, then a fall is distinguished.

Regardless of various business and research based arrangements (Table I), programmed fall discovery has a few exceptional difficulties. A noteworthy explanation behind low acknowledgment of programmed fall identifiers is the abnormal state of false positive (FP), false negative (FN) and hard to execute progressively [17].

III. System Design

The framework comprises of two principle parts: Wireless Body sensor organize (WBSN) and the checking application (Fig 1).

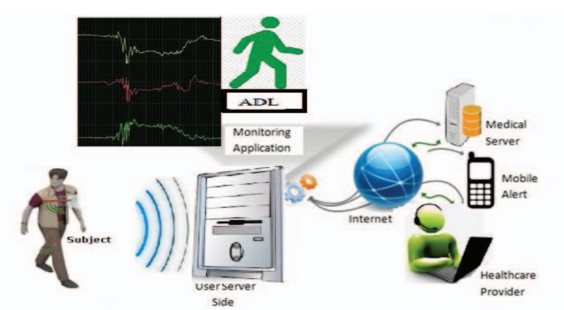

Fig. 1: Real time direction-sensitive fall detection system

The WBSN comprises of WS that gathers 3DCA information. Sensor has a remote Bluetooth to speak with the client's server side. The observing application is introduced in the client's server side (patient's home or wellbeing establishment). The server ought to have the Internet network to send caution to the medicinal services supplier or versatile message to relative and send/recover information from the restorative server. On the off chance that a patient's fall happens, then client server handle the caution by activating alert locally and additionally sending notice to human services supplier by means of web and message to cell phone. Tolerant fall related data will be recorded in the restorative server for further prerequisite. The patient's advisor has particular interface for survey and controlling the tactile information and an organization board is executed to deal with the remarkable information.

IV. METHODOLOGY

Hardware setup: To obtain the increasing speed information of the subject, one SHIMMER [18] sensor hub is utilized for information procurement and transmission from subjects to a remote PC. Sensor hub comprises of a 3D 3DCA, a Bluetooth gadget and a MSP430F1611 microcontroller gadget. The SHIMMER sensor hub is appeared in Fig. 2.

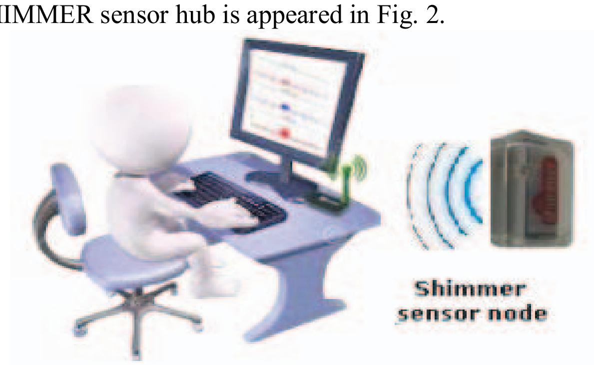

Fig. 2: Data streaming from sensor to server

Placement of sensors: The single 3D 3DCA is connected to body fragment: Chest (Fig 3). The arrangement of the sensor and course of the three tomahawks are kept up the same for every one of the subjects partaken in the trials.

Fig. 3: SHIMMER sensor Placement on subjects

Feature selection: Finding the ideal element subset is as imperative as choosing a fitting calculation. Highlight extraction is otherwise called dimensionality lessening. Principally, we select the most famous components, which are known as a wrapper strategy. The computation and extraction of significant features from the motion signals (Fig 4) start from calculating the 20 common features of signal.

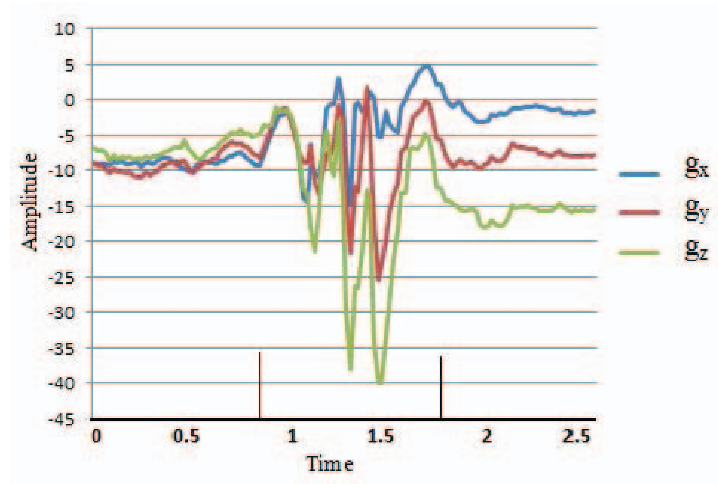

Fig. 4: Acceleration signal

Insignificant info highlights prompt more prominent computational cost. Mean and Standard deviation elements are the main 2 most essential components in the dataset.

Classifier selection: We require a decent calculation to have the capacity to order fall with course by perceiving the flag designs with pre-learned ones. SVMLA demonstrates that [19] the execution among SVMLA, K-NN and Decision Tree is superior to others. Table V demonstrates the perplexity lattice of course touchy fall, utilizing SVMLA classifier.

Table I. Confusion matrix (SVMLA)

Real Group: **Task**	Right_F	Backward_ F	ADL	Left _F	Forward _F
Right_ F	22		1		
Backward_ F	2	26	2	1	1
ADL		3	360	3	
Left_ F		1	3	24	
Forward_ F					27

Assumptions Group

Table II shows the summary results of direction-sensitive fall, using SVMLA classifier.

Table II. Summary results of SVMLA

Task	**Total**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
Right_ F	23	97.60	99.54	95.65
Backward_ F	32	90.17	98.90	81.25
ADL	366	96.47	94.79	98.36
Left_ F	28	92.41	98.96	85.71
Forward_ F	27	99.88	99.77	100

V. REAL TIME FALL DETECTION

As SVMLA classifier is providing better results based on tuning parameters. We implement the SVMLA algorithm in real time. Real time fall detection is developed in MATLAB language to be executed on the SHIMMER MSPP430 microprocessor. Third party software Realterm version 2.0.0.70 is used for PC port scanning (recommended by SHIMMER [20]. Port is scanned every .256s. SVMLA algorithm is implemented using "classificationLearner" of MATLAB R2016a toolkit. We develop a GUI to show the real time directive fall detection result using SVMLA algorithm. A 3D 3DCA is attached to chest of human subjects. 3D 3DCA data is captured by MATLAB and calculate the value. After calculating the functional value (Mean, Std_dev, and PCA), features vector is fed to SVMLA classifier. SVMLA apply its classification logic to find out the class of inputted vector. Twelve types of activities are considered as one class called ADL. A total of five classes are classified (Four type falls and ADL) If directive fall is detected than background color becomes change as red as well as trigger a alarm(Fig 5).

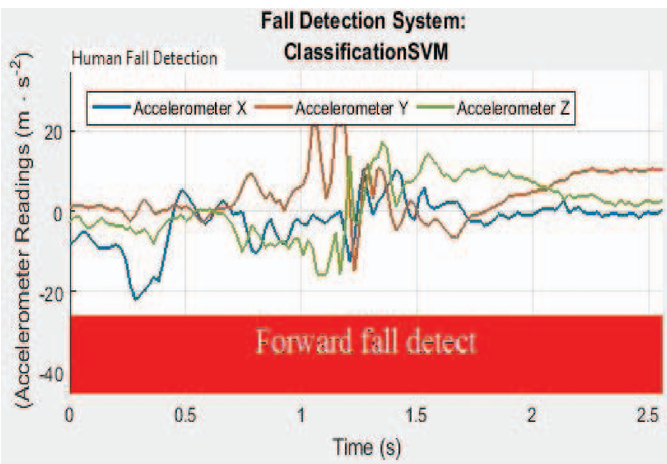

Fig. 5: Fall predict window

In other twelve types of activities , it shows "Activities of daily living" with blue background color and no alarm (Fig 6).

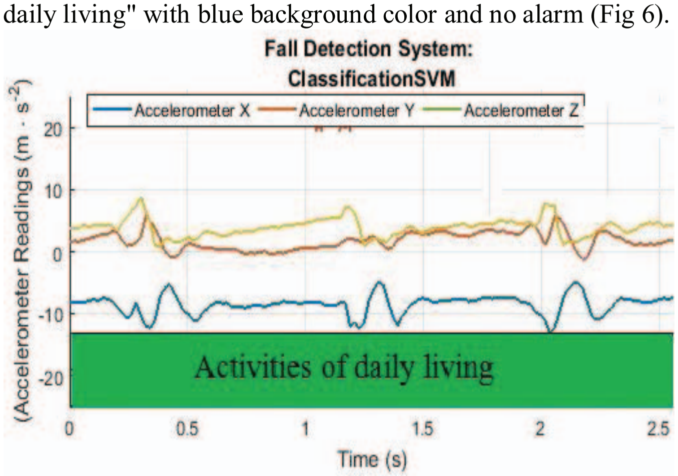

Fig. 6: ADL predict window

VI. RESULTS

After developing the real time system, again thirteen human subjects who are recruited for this testing work. A total of 52times fall and 144 ADL have been performed and we get the result (table III and table IV).

Table III. Confusion matrix (SVMLA)

Real Group: Task	Right_F	Backward_F	ADL	Left_F	Forward_F
Right_ F	12	1			
Backward_ F	1	11	1		
ADL		2	140	1	1
Left_ F			2	10	1
Forward_ F			1		12
	Assumptions Group				

Table IV. Summary results of SVMLA

Task	Total	Accuracy (%)	Precision (%)	Recall (%)
Right_ F	13	95.88	99.41	92.30
Backward_ F	13	91.48	98.09	84.61
ADL	144	94.76	92.66	97.22
Left_ F	13	88.18	99.29	76.92
Forward_ F	13	95.60	98.82	92.30

From the table, we compare the simulation result and real time result table II vs. V. We point out the performance of the real time is very similar to the simulation result. In fact, the similar accuracy (Fig. 7), precision (Fig. 8), recall (Fig. 9) were obtained. These results confirm the quality of the real time system to accurately classify fall and ADL events. Developed real time fall detection system is providing similar result like simulation result with less technical error rate and high classification accuracy.

Fig. 7: Accuracy of simulation & real time directive fall

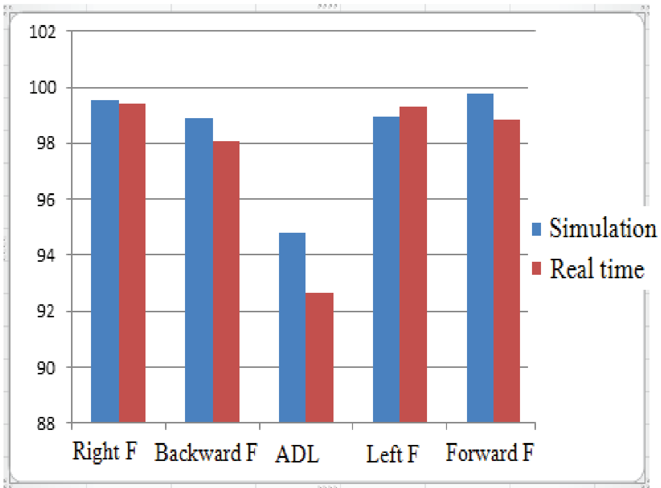

Fig. 8: Precision of simulation & real time directive fall

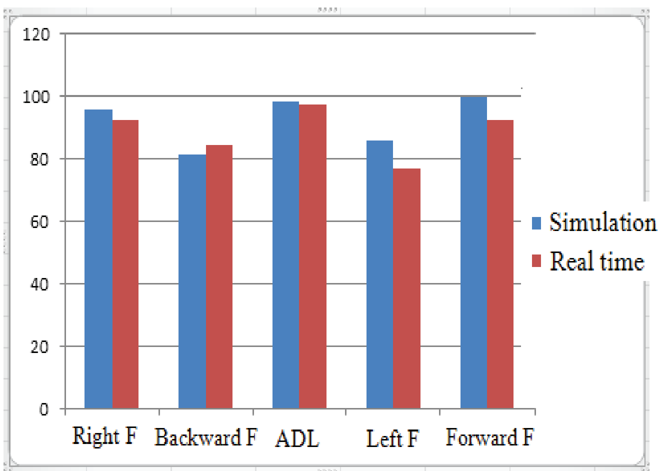

Fig. 9: Recall of simulation & real time directive fall

Comparing the performance with existing works: Four types of falls were tested in real time its performance leads to 96.45 % (Table V) accuracy a sampling rate of 50 Hz, exceeding the performance provided by the literature (Table VII). Existing works can detect only lateral fall not direction. It shows only 'fall' when forward, backward, left, right fall occur.

Table V: Our real time fall detection proposed system

SL	Authors	Hardware	Algorithms	Accuracy (%)
01	Farhad et al.	3DCA	SVMLA	96.45

Table VI: Fall detection existing works

SL	Authors	Hardware	Algorithms	Accuracy (%)
01	Beevi et al [21]	3DCA	prediction	84
02	Ojetola et al [8]	3DCAs	C4.5	90
03	Jantaraprim et al. [7]	3DCA	Threshold based	96.11
04	Anania et al. [22]	3DCA	Threshold based,	90
05	Zhang et al. [23]	3DCA	SVMLA,	93
06	Gjoreski et al. [24]	3 3DCAs	Random Forest,	90
07	Lee et al. [25]	3DCA	-	93.2
08	Noury et al. [26]	2 3DCAs	-	81
09	Noury et al. [27]	3DCA	-	85
10	Tapia et al. [28]	5 3DCAs,	C4.5 Decision Tree	80.6

VII. CONCLUSIONS

We execute the calculation in genuine condition and found the execution of the ongoing is fundamentally the same as the reenactment that builds the acknowledgment of the fall discovery framework. This work not just demonstrates a ML calculation that gives precision past at present accessible calculations additionally indicates course touchy, financially savvy and ongoing fall discovery framework utilizing single 3D 3DCA.

Limitations: The elderly and weak individuals are the essential end-clients of fall identification arrangements. Be that as it may, because of moral concerns, the framework created in this work is just assessed utilizing information from youthful and solid subjects. Consequently, it is important that the proposed ongoing is assessed on information accumulated from the elderly and impaired subjects.

Future Work: There are several areas of future work that can serve to improve the system functionality and provide additional evaluation of its performance. 1. Chest is the best body location for fall detection accuracy but waist is the best comfortable body locations for placement of sensor according to subjects. In future, fall detection studies may be done for a sensor placed in the waist while keeping the accuracy on the same level. 2. Further work may focus on: online focusing and messaging system to mobile phone.

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