Fall Detection, Wearable Sensors & Artificial Intelligence: A Short Review

Arslan Ishtiaq
Department of Electrical Engineering
University of Engineering and Technology (UET), Taxila
arslanishtiaq21@gmail.com

Zubair Saeed
Department of Computer Engineering
University of Engineering and Technology (UET), Taxila
zubair.saeed@students.uettaxila.edu.pk

Misha Urooj Khan
Department of Electronics Engineering
University of Engineering and Technology (UET), Taxila
mishauroojkhan@gmail.com

Aqsa Samer
Department of Electronics Engineering
University of Engineering and Technology (UET), Taxila
aqsasamer15@gmail.com

Mamoona Shabbir
Department of Computer Engineering
University of Engineering and Technology (UET), Taxila
addressmamoona.shabbir@students.uettaxila.edu.pk

Waqar Ahmad
Department of Computer Engineering
University of Engineering and Technology (UET), Taxila
waqar.ahmad@uettaxila.edu.pk

***Abstract*— Falls are a major public health concern among the elderly and the number of gadgets designed to detect them has increased significantly in recent years. This document provides a detailed summary of research done on fall detection systems, with comparisons across different types of studies. Its purpose is to be a resource for doctors and engineers who are planning or conducting field research. Following the examination, datasets, limitations, and future imperatives in fall detection were discussed in detail. The quantity of research using context-aware approaches continues to rise, but there is a new trend toward integrating fall detection into smartphones, as well as the use of artificial intelligence in the detection algorithm. Concerns with real-world performance, usability, and reliability are also highlighted.**

Keywords*— Computer vision, Deep learning, Fall detection, machine learning, Wearable sensor.

I. Introduction

Human falling activities (FA) were heard in the past as well as in present times. These activities are mostly found in elderly people whose age is greater than or equal to 65 years old. These actions produce a fear of falling (FF) in them, which leads to disabilities in their physical exercise, work, and mental disorders in the long term. A comparative report about the effect of fear of falling on physical and mental activities and disabilities was performed on more than 673 subjects [1]. The falls caused by environmental hazards and their effects on 1,088 men and 1,088 women were reported in [2]. The FA must be controlled by some algorithms to avoid future falling injuries, lack of confidence at work, bone breakages, and mental disorders. For this, a data set is needed to perform pre-detection and recognition, which is very hard to amass physically in the world. WHO (World Health Organization) reported fall prevention for active and elderly people using multiple awareness approaches like coaching classes, education, and falls-research [3]. A fall can produce fatal and nonfatal injuries. So, the cost estimation for the cure of these events is important and was reported based on medical hospitals, direct cost, gender discrimination based, and age-based in [4]. As such, data collection is hard on an individual basis because the population is growing globally. For this, we are going to review:

i. Fall detection system (FDS)
ii. Types of falls.
iii. how falls can be detection using wearable sensors (WS), machine learning (ML), deep learning (DL) and computer vison (CV).
iv. We also highlighted the limitations faced by each technique and what future direction can be integrated to improve the existing approaches.

II. Fall Detection and Types

Fig. 1 shows how various devices rack up fall data, which is subsequently categorized and delivered to emergency services and family members for medical assistance. With the advancement of technology, the health care industry has improved patient monitoring systems to support patients without physical participation. The most important component of any fall detection system is the accurate distinction between a fall and no fall. Failure in FDS might pose a risk to the lives of older citizens. Researchers face a number of problems in effectively detecting the unintended fall from the rest of daily activities. Effective fall detection equipment should be capable of detecting falls quickly and informing hospitals or family members. Fall detection methods are categorized into two categories, namely wearable device-based and AI-based.

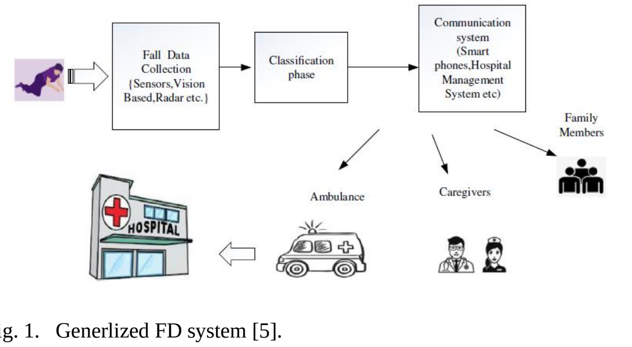

Fig. 1. Generlized FD system [5].

 How to cite: Ishtiaq, A., Saeed, Z., Khan, M. U., Samer, A., Shabbir, M., & Ahmad W. (2022). Fall Detection, Wearable Sensors & Artificial Intelligence: A Short Review. *JAREE (Journal on Advanced Research in Electrical Engineering), 6(2).*

Different kins of fall found in literature are as follows;

1) **Stumbling**: It occurs when a person walks on something that they were unaware of and the center of gravity (CG) continues to move, causing a torso imbalance (Fig. 2a).

2) **Slipping:** This occurs when, the horizontal shear force of the foot is greater than the frictional force opposing the direction of foot motion followed by the heel's contact with the floor. People who already have gait problems slip more easily (Fig. 2b).

3) **Fainting:** Temporary brain hypoxia and reduced cerebral perfusion induce postural tone loss. The head and body drop straight down, while the CG remains aligned with the feet. The torso and knees bend next, and ultimately the entire body stumbles and collapses (Fig. 2c).

4) Falls that result from tripping or sliding are also common. For example, elderly people who use light chairs or stools with wheels frequently fall when getting up from or sitting on them. Tripping over or slipping while walking downstairs, and other similar incidents (Fig. 2 e-f).

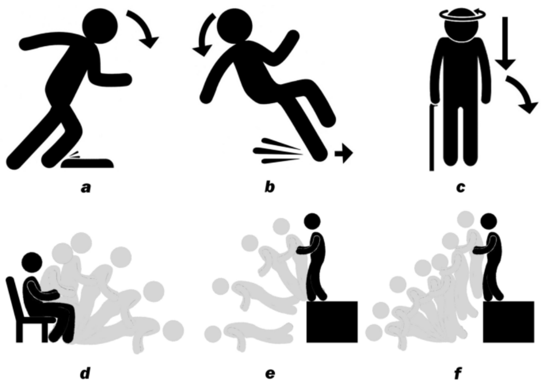

Fig. 2. Different knds of fall (a) Stumbling. (b) Slipping. (c) Fainting. (d) Getting up from a sitting position and falling as in orthostasis. (e) Falling from a high structure (f) Jumping down from a high structure and falling [6].

III. WEARABLE SENSORS BASED FALL DETECTION

In [7], FD relied on sensors placed at various positions places on the human body. The RNN algorithm and TBM are used to identify and classify FD. In [8], a new approach was explored based on a watch tied to the wrist for FD. [9] discussed multiple approaches for FD in detail, i.e., wearable, ambient, multimodal, vision (images & videos), etc., on one platform of smart houses. [10] integrated a wireless approach targeted to predetermine FD with the aid of Bluetooth devices at hardware-level systems. In [11], time-domain, frequency-domain, and Hjorth-domain features are extracted using wearable approach. In [12], FD contains the wearable-sensors where all particulars is based on real-time monitoring with the aid of an IoT-cloud platform configured with MEMS. In [13], three different sensors were placed at various places on the human body and observed the behavior in FD with LIME and XAI methods. In [14], FDS real-time analysis of FDS-Tx and FDS-Rx is performed with a microcontroller as an embedded-system approach along with ADXL335 (accelerometer). The detail is sent to the patient's relatives via the WIFI-Mobile application. A generalized WS-FDS is shown in Fig.3 [15].

A. *Limitations*

We observed following limitations in the wearable's WS-based FD.

1) Poposed research needs to integrate fall detction in a larger range through multi-sensor fusion.

2) Incrased feature caused energy consumption.

3) The battery lifetime afftects the WS and system effeiency.

4) The stabity of WS-FDS must be incrsed.

5) Systems can fail because signals are sensitive to the environment, disturbances, and noises.

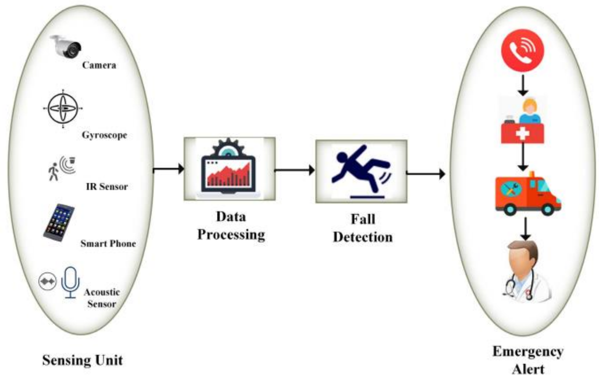

Fig. 3. Genralized WS-FDS [15].

IV. MACHINE LEARNING BASED FALL DETECTION

Artificial intelligence (AI) systems are used to do complex tasks in a way similar to how humans solve problems [16,17,18,19]. Machine learning is a branch of AI, which is usually characterized as a machine's ability to replicate intelligent human behavior [20,21,22,23,24]. A generalized ML-FDS is shown in Fig.3 [30]. [24] used smartphone sensors with cross-correlation event polarity method that makes the operation of the FDS robustly. The categorization of a fall and its deviation from ADL might indicate how well the trained model. This technique outperformed the threshold-based approach on both criteria. Although the performance for differentiating falls from ADL was good and the performance for categorizing falls was mediocre, a modified classifier was constructed in this study. Following ADL identification, the enhanced classification approach gathered the user's posture [25]. They distinguished various classes of the same event which was made possible by collecting a large dataset. [26] proposed a low-cost, high-accuracy machine learning-based fall detection technique. Online feature extraction makes excellent use of the fall's temporal properties. Their system architecture achieved the trade-off between numerical and accuracy complexity. The algorithm's lower computing cost makes it easier to interface with a wearable sensor and minimizes the amount of energy required, boosting the wearable device's autonomy. The occlusion reduction technique based on deep learning is used for PPE evaluation [27]. The process was tested in many settings. The presentations and results of the experiments proved their reliability. A dataset was generated to compute falls. This dataset was congregated by utilizing, the smartphone's gyroscope and accelerometer. [28] elaborated the multiplayer fall prevention gaming platform and fall detection games inspired by the Otago fitness program. The study's findings show how effectively the game performs in senior care facilities. This work improved the Kalman filter-based slip estimation for describing slipping distance. The algorithm's speedy and precise slip onset detection, as well as the sensor's low cost and non-intrusive nature, distinguish it from the competition. Several experiments were performed to confirm and demonstrate that a slip detection and estimation model works as expected. [29] employed a suggested state machine-governed convolutional neural network. Aryokee, a fall detection system, works in unexpected environments and with people who are not in the training set. It also separates diverse motion sources to boost robustness. The dataset comprised 140 people participating in 40 different types of activities in varied circumstances. This FDS showed 92% accuracy and 94% recall.

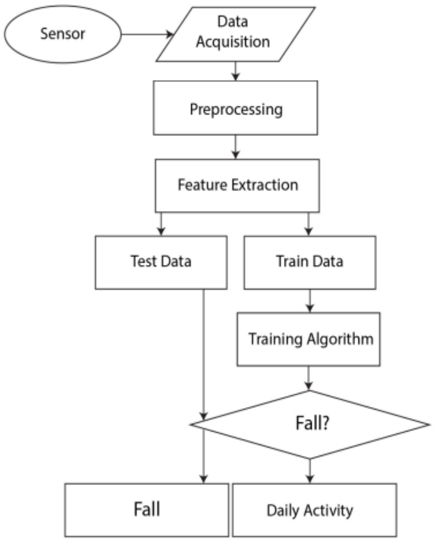

Fig. 4. Genralized ML-FDS [30].

A. *Limitations*

We observed following limitations in the wearable's ML-based FD.

1) Performing well for trained datasets but not for unknown scenarios.

2) The system enhanced the false alarm rate that inhibits their use as a preferred approach

3) The approach classifies fall and non-fall events with less accuracy and without the type of falls.

4) The system requires only a gaming environment. It is for specific uses.

5) The detailed analysis covered different datasets but lacked the performance of the classifier or algorithm.

V. Deep Learning Based Fall Detection

A deep learning model is usually a three-or more-layered neural network and is a type of AI [31,32]. These neural networks attempt, to mimic the functioning of the human brain by "learning" from vast amounts of data as done in [33,34]. Deep learning techniques are becoming increasingly popular in FDS. [38] developed an approach for fall detection that takes into consideration fall direction, severity, and activity identification. Inertial sensor data from the SisFall dataset was utilized to develop the method. Windowing and relabeling is the initial stage in data preparation. Then, for classes with insufficient samples, data augmentation is performed. After that, feature extraction and classification are done. This work treats fall and activity recognition as a whole problem, taking into account various forms of falls and activities, to create more recognition methods for use in cyber-physical systems. A CNN-XGB is proposed for this purpose. A Bi-Directional Long Short-Term Memory (Bi-LSTM) network is used in the research [39]. Missing values are introduced in the data to integrate noise tolerance during training. [40] makes use of data from inertial measurement devices from two separate datasets: SmartFall and MobiAct. The SmartFall dataset have non-fall and fall recordings, whereas the MobiAct stifles data from four falls and nine everyday activities. They compare the performance of a CNN, LSTM, CNN-LSTM combination, and gated recurrent units. [41] displays the spatiotemporal event streams encoded in a conventional sequence of image frames from Dynamic Vision Sensing cameras. These video frames are used to benchmark typical deep learning-based systems. They used the provided strategy to change the cutting-edge vision models for this Dynamic Vision Sensing (DVS) application. [42] presented a 3D Convolutional Neural Network-based architecture that improves the spatial and temporal components to distinguish activities in video frames more accurately than standard 2D-CNN. Using this method, the authors were able to obtain two benefits: the model's optimization was simplified by partitioning the spatial and temporal components, and the model's nonlinearity was enhanced to keep the number of parameters constant.

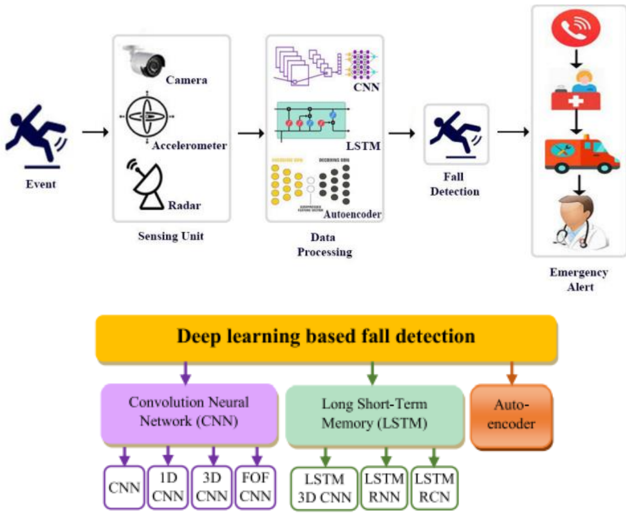

Fig. 5. (a) Genralized DL-FDS (b) Techniques [22].

A. *Limitations*

We observed following limitations in the wearable's DL-based FD.

1) Weights can be assigned by attention networks for possibly higher performance than conventional deep learning methods.

2) The system evaluation is limited to only two datasets, and there must be more real datasets to check the credibility of an algorithm.

3) The evaluation criteria are determined by two simple datasets.

4) Create a novel architecture that can operate in real-time with low latency and limited processing power, then evaluate the effectiveness. This design is not for real-world deployment.

5) More suitable deep learning architectures are needed for the suggested approaches.

VI. COMPUTER VISION BASED FALL DETECTION

Digital images, videos, and other visual inputs can be used to extract information used by computers and systems in computer vision. These systems respond in response to the input [35,36,37]. Aging affects humans' lives severely. The health of elderly people aged more than 55 years becomes prone to many diseases and life-challenging problems. That’s why the falling activities that happened in the past as well as in the present and would happen in the future too. These falling activities cause severe injuries, i.e., deaths, bone breakages, disabilities, etc. To avoid it, infrared and multidimensional fusion-based real-time FDS is designed by an SVM algorithm to identify and classify different injuries [27]. A descriptor MORL-based video fall detection was explained in [28], which took 1300 videos for processing. OC-PCA algorithm is used because it can model activity-daily-life and fall activities. In [29], various position image-based video fall detection algorithms were explored with the use of SVM, TCN, and LSTM algorithms. In [30], Deep-Learning FD is explained and researched with the aid of two approaches, i.e., YOLOK+3DCNN and YOLOK+2DCNN+LSTM. [31] applied FDEP to FallCNN_1, FallCNN_2, Fall_CNN_3, and TLD. [32] FDS using accelerometer-gyro sensors. Thousands of images are taken and played at high speed to make films. A video camera is used whose angle of rotation is 360 degrees to cover the whole area.

A. Limitations

We observed following limitations in the CV-based FD.

1) There are several cases, where monitoring individuals for their protection is quite valuable. However, the requirement for safety must be balanced with privacy.

2) Computer vision programs that process photos of actual people may include very intimate/sesnitive information.

3) Many CV-FDS systems operate on the edge. Edge computing allows inference and data processing to take place on the device itself. That implies no data is transferred to or kept on the cloud. The system simply identifies a fall occurrence and provides an appropriate notice.

4) Data is only transmited to an external source when an event happens.

5) Sections of the images are blurred to obscure people's faces or other sensitive or identifying details.

6) Proper explanation of how the dataset is collected, the number of samples in each class, sampling rate, and format, all are missing.

7) Trained system can't detect challenging abnormal-activities like running, jumping, and going up/down.

VII. COMPARISON

A. Datasets

1) **Wearable sesnors**: [7] piled up data from 18 subjects using an MLX90640 infrared array sensor. [8] obtained data from university students aged 19 to 25. [9] accumulated data with the triaxial Bosch BMA280. [10] employs UP-Fall Detection data. On the user side, [12] forgathered data from wearable devices. [13] utilised the UMAFall dataset to get sensor readings in order to train the algorithms for fall detection. [14] used wearable IoT devices (FDS-Tx) and ADXL335 to cumulate data.

2) **Machine learning:** [25] garnered the dataset by asking the healthy subjects to wear the designed system on their right hip while performing a sequence of tasks. [26] train their models on the publicly available Sisfall dataset. [27] self-collected the data from 31 users. Self-collected data under three different scenarios [28]. [30] piled a large scale dataset of RF signals from both male and female subjects (20–50 years old).

3) ***Deep learning:*** [38] used SisFall dataset. [39] used SisFall dataset and UP-FallDetection dataset. [40] used ADLF and UP-Fall detection dataset. [41] mustered sensory data from 15 individuals' six distinct activities. [42] trained their models on Sports-1M and Kinetics, UCF101 and HMDB51 datasets.

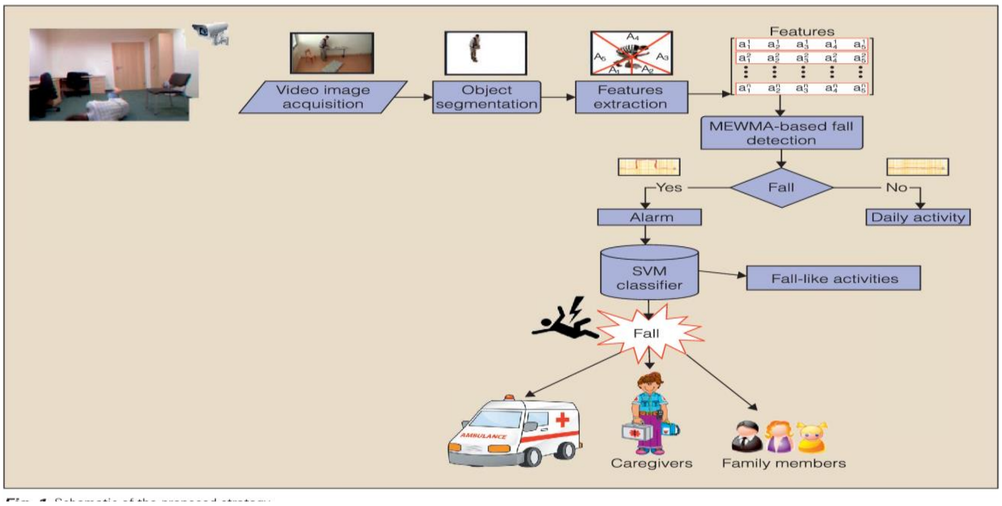

Fig. 6. Genralized CV-FDS [49].

TABLE I. COMPARASION OF FD W.R.T WS,ML,DL & CV TECHNIUQES.

Wearable sensor-based fall detection						
Study By	**Purpose**	**Algorithm**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F1-score (%)**
[7]	Wearable Sensors & Cloud Platform based FD	TBM, RNN	97.68%	98.26%	99.21%	N/G
[8]	Smart Watch based FD	Bica Cubic Hermit Interpolation, KNN	97.09%	95.60%	93..57%	91.99%
[9]	Smart Home FD & Monitoring	CNN, SVM, KNN, GMM, Android GI.	95.34%, 91.63%, 83.95%, 97.78%	88.55%, 87.19%, 96.17%, 100%	96.03%, 93.10%, 94.83%, 97.58%.	N/G
[10]	Bluetooth Based Fall Detection	CNN	93.44%	93.30%	93.43%	93.36%
[11]	PSO Based Wearable approach	RF, J48, k-NN, ANN, SVM	99.51%, 93.79%, 96.41%, 97.28%	99.51%, 93.85%, 96.37%, 97.26%	99.69%, 93.97%, 99.39%, 97.28%	99.51%, 93.63%, 9634%, 97.26%
[12]	Real-time-Wearable FD System	MEMS with IOT cloud	94.88%	95.25%	94.5%	92.01%
[13]	IOT based wearable FD system	ANN	92.5%	91.3%	93.54%	90.10%
[14]	XAI-Fall-wearable FD	LSTM, LIME, XAI	93.45%	92.95%	96.08%	98.95%
[15]	Real-Time-wearable FD based ADXL335	FDS-Tx, FDS-Rx,	83%	97%	69%	90.99%
Machine Learning based fall detection						
Study By	**Purpose**	**Algorithm**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F1-score (%)**
[25]	Smartphone based ADL detector	Threshold +PCA based classification	N/G	91%	100%	N/G
[26]	Low-cost highly accurate FDS	SVM KNN	99.2 99.94	99.17 99.05	99.93 99.95	N/G
[27]	Abnormal Gait Detection	NARX	93.55	90.9	N/G	N/G
[28]	Multi-player fall prevention game platform	Fall Sensing Games	N/G	N/G	N/G	N/G
[30]	RF-Based Fall Monitoring	Aryokee, SVM, LSTM	99.96	93.8	91.9	92.9
Deep Learning-based fall detection						

Study By	Purpose	Algorithm	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
[38]	Severity Aware FDS	CNN-XGB	90.59	88.25	99.36	89.11
[39]	Noise Tolerant FDS	BiLSTM	97.41 97.21	100 99.54	95.45 94.56	94.28 95.41
[40]	latent feature pooling FDS	ARFDNet	96.7	96.69	96.7	96.6
[41]	FDS using smartwatches	BiLSTM	100	N/G	N/G	N/G
[42]	Action Recognition	Spatiotemporal convolutions	98.0	N/G	N/G	N/G
Computer Vision-based fall detection						
Study By	**Purpose**	**Algorithm**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F1-score (%)**
[43]	Fall Detection	SVM	High	93%	90%	92%
[44]	Video based Fall Detection	OC-PCA, SVM, ELM	88.43%	73.21%	96.63%	99.60%
[45]	Body- Geometry & Pose FD in Video	SVM, TCN, LSTM	97.0%	98.3%	97.5%	97.5%
[46]	Image Based FD	YOLOK+3DCNN, YOLOK+2DCNN, +LSTM	99.66%,98.22%	99.92%, 97.9%	N/G	N/G
[47]	Transfer Learning Models based FD	FallCNN, TLM	98%, 97.2%	99%, 98.9%	92.3%	93%
[48]	Multicamera-360 degrees videos-based FD	DSFNN, CNN, SAB-BiLSTM	100%	100%	100%	99.19%

4) **Computer vision:** [43] produced the dataset by utilizing infrared array sensor temperature data. [44] made use of the Le2i FD, the URFD dataset, and the cross-dataset.Using classified movies, a bespoke data set was created [45]. [46] created SimgFall, a signal-based picture dataset. [47] used multi-camera fall datasets, especially UP-Fall and URFD.

B. Challenges

The design of fall detectors entails numerous significant challenges, discussed below.

1) ***Proficiency in real-world settings****:* FD must be as accurate and reliable as possible. A trustworthy FDS should have high sensitivity and specificity. This is occasionally achieved in laboratories, but when applied to real-world situations, the detection rate drops. Also, since there is no standardized procedure or public database to compare, they use data from falls and ADL of young people simulated at the discretion of each author. Furthermore, because fall detectors are intended for the elderly, they should be included in the research. Only a few studies incorporate data from older people, albeit their participation is limited to completing a series of simulated daily life tasks for a few minutes or hours. That is insufficient for assessing the system's actual performance. Users should wear the devices for lengthy periods (at least months).

2) **Usability**: Smartphone-based FDs are popular because of the widespread use of cell phones, particularly among the elderly. This enabled highly standardized measurements, which improved precision but made the results less realistic about how people handle their telephones regularly. Future FD should not be limited to a certain region of the body. Smartphones should be used creatively, with no restrictions on posture or function. This might lead to higher detection rates.

3) ***Acceptance****:* There information available about the viability and acceptability of the techniques is not detailed enough. Acceptance of the elderly is a major challenge due to their unfamiliarity with technical equipment. The operation of the system is crucial in addressing this challenge. The detector should activate and run automatically without human intervention. In this aspect, vision systems, like other non-intrusive techniques, are ahead. However, some wearable devices, such as cellphones, have additional benefits that may help fall detectors gain adoption. They may work inside and outdoors, and they can integrate fall detection with other healthcare applications on the same device. The traditional objection to carrying several gadgets, each with a particular function, would be overcome in this way. However, utilizing smartphones by older people is not without difficulties; these devices, as constructed, present a major use barrier for them. The absence of grading in existing fall detection programs, as well as the lack of real-world application, is proof of this. Potential solutions to improve smartphone usability and accessibility are necessary in this respect. Nonetheless, we noticed that fall detectors are highly valued by the elderly, who displayed a favorable attitude toward smartphone-based solutions following a practical presentation of various assistive technologies as a result of ongoing research.

C. Futurework

Future work presented by the literature is mentioned below.

1) Use multi-sensor fusion to detect falls across a wider area.

2) A novel architecture that combines depth cameras and data from accelerometers or gyroscopes must be developed to enhance fall detection performance and create an HFDS that is not dependent on light.

3) The training pipeline can be improved by better parameter optimization and better training sample selection for classifier input.

4) Advocated algorithms must be capable of working with different sampling frequencies. This function saves electricity by switching to reduced sample frequencies when the user's assessed activity is low.

5) Recognize the dangerous degree of aberrant gait based on the duration and intensity of the abnormality, allowing effective preventative methods to be implemented to avoid significant injury in the event of a hazardous circumstance.

6) Inclusion of new sensor modalities may aid in improving performance for the lowest recognized classes in terms of sensor modalities.

7) The combination of transformer and attention networks can improve accuracy.

8) Multi-sensor fusion strategies frequently outperform single-sensor fusion solutions for both datasets.

9) The DL model may be expanded to include a variety of inertial and visual signals.

10) Reduce the number of data-derived attributes, which should help the wristwatch consume less energy.

11) For feature selection in the future, nature-inspired heuristic optimization feature search must be employed.

12) On the same dataset, different algorithms can be employed to select the best appropriate method.

13) Further system optimization can reduce the time complexity of the prediction models by allowing variable length timestamps for each data input stream and generating predictions based on those timestamps. Because of the changing length timestamp, the LIME-based explainability module may dynamically propose explanations for the resulting predictions, which also speeds up the explanations' inference processes.

14) For future research and analysis in the field of fall detection, the source code and the internal fall dataset must be made available to the research community upon request. To assess the effectiveness of the approach is required to take a cross-view review into account.

15) To develop a realistic understanding of the fall process for evaluating FD performance, one should look at a sizable real-world fall database.

16) Researchers might be able to create a more full profile of people at high risk of falling if they had a good grasp of the neuro-psychological factors that are connected to that risk as well as how they interact. The attempt to predict the fall before it happens may also have significant ramifications. To lessen the severity of fall injuries, it could also allow us to activate specific defensive systems.

17) The subject's biological parameters and fall history may be tracked using the FD system.

VIII. Conclusion

To summarize, fall detection is a challenging procedure that now lacks a standardized solution. Fall detectors are critical for providing rapid assistance as well as minimizing the fear of falling and severe health consequences. This paper categorizes fall detectors based on extensive research findings; assesses their evolution through time; and datasets used for their detection; highlights limitations; and future improvements. The number of studies on vision-based systems is increasing day by day. Furthermore, while there is a current trend toward incorporating fall detectors into cellphones, their use in real-world settings may be impeded by the reasons highlighted in this study. The constraints and potential of fall detection should be understood by both biomedical engineers and doctors.

Some of the major conclusions drawn after the review are as follows:

1) Sensors and algorithms created in the last six years are very different from those projected before 2014. While Kinect has superseded RGB cameras as the most common visual sensor, accelerometers are still the most common sensor in wearable technology.

2) There is currently no standard dataset available for testing and comparing fall detection systems. The development of the field is hampered by this. There are behavioral differences between the elderly and middle-aged adults, despite efforts to employ middle-aged volunteers to simulate falls.

3) It seems like sensor fusion is the way to go. Although it has a higher processing cost than systems that rely on individual sensors, it delivers more reliable fall detection system options. Thus, lowering computer costs is difficult.

4) To create complete and reliable solutions, current research focuses mostly on the data analytics element and pays insufficient attention to IoT platforms. Additionally, an effort is made to analyze data when it is offline. More work needs to be put into developing each component of such systems to create a system that is reliable, stable, and secure, enables (near) real-time processing, and has the elderly's trust.

5) Autonomous health monitoring and support systems based on IoT devices appear to hold the key to discovering early warning signs of physical and cognitive issues ranging from cardiovascular issues to mental ailments such as Alzheimer's and dementia.

Acknowledgment

This work is done under the supervision of community of research and development - CRD.

References

[1] N. Deshpande, E. J. Metter, F. Lauretani, S. Bandinelli, J. Guralnik, and L. Ferrucci, “Activity restriction induced by fear of falling and objective and subjective measures of physical function: a prospective cohort study,” J. Am. Geriatr. Soc., vol. 56, no. 4, pp. 615–620, Apr. 2008, doi: 10.1111/J.1532-5415.2007.01639.X.

[2] T. M. Gill, C. S. Williams, and M. E. Tinetti, “Environmental hazards and the risk of nonsyncopal falls in the homes of community-living older persons,” Med. Care, vol. 38, no. 12, pp. 1174–1183, 2000, doi: 10.1097/00005650-200012000-00004.

[3] WHO, "WHO global report on falls prevention in older age." https://www.who.int/publications/i/item/9789241563536 (accessed Oct. 03, 2022).

[4] E. R. Burns, J. A. Stevens, and R. Lee, "The direct costs of fatal and non-fatal falls among older adults - United States," J. Safety Res., vol. 58, pp. 99–103, Sep. 2016, doi: 10.1016/J.JSR.2016.05.001.

[5] S. Rastogi and J. Singh, "A systematic review on machine learning for fall detection system," Comput. Intell., vol. 37, no. 2, pp. 951–974, May 2021, doi: 10.1111/COIN.12441.

[6] F. Shu and J. Shu, "An eight-camera fall detection system using human fall pattern recognition via machine learning by a low-cost android box," Sci. Reports 2021 111, vol. 11, no. 1, pp. 1–17, Jan. 2021, doi: 10.1038/s41598-021-81115-9.

[7] T. Xu and J. Liu, "A low-power fall detection method based on optimized TBM and RNN," Digit. Signal Process., vol. 126, p. 103525, Jun. 2022, doi: 10.1016/J.DSP.2022.103525.

[8] G. Şengül, M. Karakaya, S. Misra, O. O. Abayomi-Alli, and R. Damaševičius, "Deep learning based fall detection using smartwatches for healthcare applications," *Biomed. Signal Process. Control*, vol. 71, p. 103242, Jan. 2022, doi: 10.1016/J.BSPC.2021.103242.

[9] T. C. Kolobe, C. Tu, and P. A. Owolawi, "A Review on Fall Detection in Smart Home for Elderly and Disabled People," J. Adv. Comput. Intell. Intell. Informatics, vol. 26, no. 5, pp. 747–757, Sep. 2022, doi: 10.20965/JACIII.2022.P0747.

[10] N. De Raeve *et al.*, "Bluetooth-Low-Energy-Based Fall Detection and Warning System for Elderly People in Nursing Homes," *J. Sensors*, vol. 2022, 2022, doi: 10.1155/2022/9930681.

[11] H. L. Le, D. N. Nguyen, Ngo-Thi-Thu-Trang, and H. N. Nguyen, "Applying PSO to improve the pedestrian fall detection rate using wearable sensor data," Int. Conf. Adv. Commun. Technol. ICACT, vol. 2022-February, pp. 453–458, 2022, doi: 10.23919/ICACT53585.2022.9728904.

[12] Z. Qian *et al.*, "Development of a Real Time Wearable Fall Detection System in the Context of Internet of Things," *IEEE Internet Things J.*, 2022, doi: 10.1109/JIOT.2022.3181701.

[13] H. Mankodiya et al., "XAI-Fall: Explainable AI for Fall Detection on Wearable Devices Using Sequence Models and XAI Techniques," Math. 2022, Vol. 10, Page 1990, vol. 10, no. 12, p. 1990, Jun. 2022, doi: 10.3390/MATH10121990.

[14] N. I. M. Amir, R. A. Dziyauddin, N. Mohamed, N. S. N. Ismail, N. S. A. Zulkifli, and N. M. Din, "Real-time Threshold-Based Fall Detection System Using Wearable IoT," 2022 4th Int. Conf. Smart Sensors Appl., pp. 173–178, Jul. 2022, doi: 10.1109/ICSSA54161.2022.9870974.

[15] F. Hussain, F. Hussain, M. Ehatisham-Ul-Haq, and M. A. Azam, "Activity-Aware Fall Detection and Recognition Based on Wearable Sensors," IEEE Sens. J., vol. 19, no. 12, pp. 4528–4536, Jun. 2019, doi: 10.1109/JSEN.2019.2898891.

[16] S. Z. H. Naqvi, M. Arooj, S. Aziz, M. U. Khan, M. A. Choudhary, and M. N. Ul Hassan, "Spectral Analysis of Lungs sounds for Classification of Asthma and Pneumonia Wheezing," *2nd Int. Conf. Electr. Commun. Comput. Eng. ICECCE 2020*, Jun. 2020, doi: 10.1109/ICECCE49384.2020.9179417.

[17] A. Ullah, M. S. Khan, M. U. Khan, and F. Mujahid, "Automatic Classification of Lung Sounds Using Machine Learning Algorithms," Proc. - 2021 Int. Conf. Front. Inf. Technol. FIT 2021, pp. 131–136, 2021, doi: 10.1109/FIT53504.2021.00033.

[18] M. U. Khan, S. Samer, A. Samer, A. Mobeen, A. Arshad, and H. Khan, "Classification of phonocardiography based heart auscultations while listening to Tilawat-e-Quran and music using vibrational mode decomposition," ICAEM 2021 - 2021 Int. Conf. Appl. Eng. Math. Proc., pp. 25–30, Aug. 2021, doi: 10.1109/ICAEM53552.2021.9547150.

[19] M. U. Khan, H. Khan, M. Muneeb, Z. Abbasi, U. B. Abbasi, and N. K. Baloch, "Supervised machine learning based fast hand gesture recognition and classification using electromyography (EMG) signals," ICAEM 2021 - 2021 Int. Conf. Appl. Eng. Math. Proc., pp. 81–86, Aug. 2021, doi: 10.1109/ICAEM53552.2021.9547148.

[20] "(PDF) A Novel Intelligent Model For COVID-19 Detection Using Cough Auscultations and Hjorth Descriptors." https://www.researchgate.net/publication/353636378_A_Novel_Intelligent_Model_For_COVID-19_Detection_Using_Cough_Auscultations_and_Hjorth_Descriptors (accessed Oct. 04, 2022).

[21] M. U. Khan, A. Farman, A. U. Rehman, N. Israr, M. Z. H. Ali, and Z. A. Gulshan, "Automated System Design for Classification of Chronic Lung Viruses using Non-Linear Dynamic System Features and K-Nearest Neighbour," Proc. 2021 Mohammad Ali Jinnah Univ. Int. Conf. Comput. MAJICC 2021, Jul. 2021, doi: 10.1109/MAJICC53071.2021.9526272.

[22] M. U. Khan, S. Zuriat-E-Zehra Ali, A. Ishtiaq, K. Habib, T. Gul, and A. Samer, "Classification of Multi-Class Cardiovascular Disorders using Ensemble Classifier and Impulsive Domain Analysis," Proc. 2021 Mohammad Ali Jinnah Univ. Int. Conf. Comput. MAJICC 2021, Jul. 2021, doi: 10.1109/MAJICC53071.2021.9526250.

[23] "(PDF) Intelligent System Design for Early Diagnosis of Faults in Machine Bearings." https://www.researchgate.net/publication/353636336_Intelligent_System_Design_for_Early_Diagnosis_of_Faults_in_Machine_Bearings (accessed Oct. 04, 2022).

[24] "(PDF) Embedded System Design for Real-time Detection of Asthmatic Diseases Using Lung Sounds in Cepstral Domain." https://www.researchgate.net/publication/353636147_Embedded_System_Design_for_Real-time_Detection_of_Asthmatic_Diseases_Using_Lung_Sounds_in_Cepstral_Domain (accessed Oct. 04, 2022).

[25] B. Andò, S. Baglio, C. O. Lombardo, and V. Marletta, "An Event Polarized Paradigm for ADL Detection in AAL Context," IEEE Trans. Instrum. Meas., vol. 64, no. 7, pp. 1814–1825, Jul. 2015, doi: 10.1109/TIM.2014.2385144.

[26] M. Saleh and R. L. B. Jeannes, "Elderly Fall Detection Using Wearable Sensors: A Low Cost Highly Accurate Algorithm," IEEE Sens. J., vol. 19, no. 8, pp. 3156–3164, Apr. 2019, doi: 10.1109/JSEN.2019.2891128.

[27] M. Hemmatpour, R. Ferrero, F. Gandino, B. Montrucchio, and M. Rebaudengo, "Nonlinear predictive threshold model for real-time abnormal gait detection," J. Healthc. Eng., vol. 2018, 2018, doi: 10.1155/2018/4750104.

[28] J. Silva et al., "Design and Evaluation of a Fall Prevention Multiplayer Game for Senior Care Centres," Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 11112 LNCS, pp. 103–114, 2018, doi: 10.1007/978-3-319-99426-0_9.

[29] TianYonglong, LeeGuang-He, HeHao, HsuChen-Yu, and KatabiDina, "RF-Based Fall Monitoring Using Convolutional Neural Networks," Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol., vol. 2, no. 3, pp. 1–24, Sep. 2018, doi: 10.1145/3264947.

[30] N. Nahar, M. S. Hossain, and K. Andersson, "A Machine Learning Based Fall Detection for Elderly People with Neurodegenerative Disorders," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 12241 LNAI, pp. 194–203, 2020, doi: 10.1007/978-3-030-59277-6_18/COVER.

[31] M. U. Khan et al., "Artificial neural network-based cardiovascular disease prediction using spectral features," Comput. Electr. Eng., vol. 101, p. 108094, Jul. 2022, doi: 10.1016/J.COMPELECENG.2022.108094.

[32] M. U. Khan, Z. Saeed, A. Raza, Z. Abbasi, S. Z.-Z. Ali, and H. Khan, "Deep Learning-based Decision Support System for classification of COVID-19 and Pneumonia patients," JAREE (Journal Adv. Res. Electr. Eng., vol. 6, no. 1, Apr. 2022, doi: 10.12962/JAREE.V6I1.229.

[33] S. Z. H. Naqvi, M. U. Khan, A. Raza, Z. Saeed, Z. Abbasi, and S. Z. E. Z. Ali, "Deep Learning Based Intelligent Classification of Covid-19 Pneumonia Using Cough Auscultations," IMTIC 2021 - 6th Int. Multi-Topic ICT Conf. AI Meets IoT Towar. Next Gener. Digit. Transform., 2021, doi: 10.1109/IMTIC53841.2021.9719740.

[34] Z. Saeed, M. U. Khan, A. Raza, N. Sajjad, S. Naz, and A. Salal, "Identification of Leaf Diseases in Potato Crop Using Deep Convolutional Neural Networks (DCNNs)," ICET 2021 - 16th Int. Conf. Emerg. Technol. 2021, Proc., 2021, doi: 10.1109/ICET54505.2021.9689807.

[35] M. U. Khan, M. A. Abbasi, Z. Saeed, M. Asif, A. Raza, and U. Urooj, "Deep learning based Intelligent Emotion Recognition and Classification System," Proc. - 2021 Int. Conf. Front. Inf. Technol. FIT 2021, pp. 25–30, 2021, doi: 10.1109/FIT53504.2021.00015.

[36] A. Raza, M. U. Khan, Z. Saeed, S. Samer, A. Mobeen, and A. Samer, "Classification of Eye Diseases and Detection of Cataract using Digital Fundus Imaging (DFI) and Inception-V4 Deep Learning Model," *Proc. - 2021 Int. Conf. Front. Inf. Technol. FIT 2021*, pp. 137–142, 2021, doi: 10.1109/FIT53504.2021.00034.

[37] Z. Saeed, M. U. Khan, A. Raza, H. Khan, J. Javed, and A. Arshad, "Classification of Pulmonary Viruses X-ray and Detection of COVID-19 Based on Invariant of Inception-V 3 Deep Learning Model," *2021 Int. Conf. Comput. Electron. Electr. Eng. ICE Cube 2021 - Proc.*, 2021, doi: 10.1109/ICECUBE53880.2021.9628338.

[38] A. S. Syed, D. Sierra-Sosa, A. Kumar, and A. Elmaghraby, "A Deep Convolutional Neural Network-XGB for Direction and Severity Aware Fall Detection and Activity Recognition," Sensors (Basel)., vol. 22, no. 7, Apr. 2022, doi: 10.3390/S22072547.

[39] M. Waheed, H. Afzal, and K. Mehmood, "NT-FDS—A Noise Tolerant Fall Detection System Using Deep Learning on Wearable Devices," Sensors 2021, Vol. 21, Page 2006, vol. 21, no. 6, p. 2006, Mar. 2021, doi: 10.3390/S21062006.

[40] S. K. Yadav, A. Luthra, K. Tiwari, H. M. Pandey, and S. A. Akbar, "ARFDNet: An efficient activity recognition & fall detection system using latent feature pooling," Knowledge-Based Syst., vol. 239, p. 107948, Mar. 2022, doi: 10.1016/J.KNOSYS.2021.107948.

[41] G. Şengül, M. Karakaya, S. Misra, O. O. Abayomi-Alli, and R. Damaševičius, "Deep learning based fall detection using smartwatches for healthcare applications," Biomed. Signal Process. Control, vol. 71, p. 103242, Jan. 2022, doi: 10.1016/J.BSPC.2021.103242.

[42] D. Tran, H. Wang, L. Torresani, J. Ray, Y. Lecun, and M. Paluri, "A Closer Look at Spatiotemporal Convolutions for Action Recognition," Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., pp. 6450–6459, Dec. 2018, doi: 10.1109/CVPR.2018.00675.

[43] Y. Yang, H. Yang, Z. Liu, Y. Yuan, and X. Guan, "Fall detection system based on infrared array sensor and multi-dimensional feature fusion," Measurement, vol. 192, p. 110870, Mar. 2022, doi: 10.1016/J.MEASUREMENT.2022.110870.

[44] B. Hadjadji, M. Saumard, and M. Aron, "Multi-oriented run length based static and dynamic features fused with Choquet fuzzy integral for human fall detection in videos," J. Vis. Commun. Image Represent., vol. 82, p. 103375, Jan. 2022, doi: 10.1016/J.JVCIR.2021.103375.

[45] D. R. Beddiar, M. Oussalah, and B. Nini, "Fall detection using body geometry and human pose estimation in video sequences," J. Vis. Commun. Image Represent., vol. 82, p. 103407, Jan. 2022, doi: 10.1016/J.JVCIR.2021.103407.

[46] M. E. N. Gomes, D. Macêdo, C. Zanchettin, P. S. G. de-Mattos-Neto, and A. Oliveira, "Multi-human Fall Detection and Localization in Videos," Comput. Vis. Image Underst., vol. 220, p. 103442, Jul. 2022, doi: 10.1016/J.CVIU.2022.103442.

[47] M. Vergin, R. Sarobin, and L. J. Anbarasi, "Fall Detection among Elderly Person using FallCNN and Transfer Learning Models," Aug. 2022, doi: 10.21203/RS.3.RS-1884093/V1.

[48] S. Saurav, R. Saini, and S. Singh, "A dual-stream fused neural network for fall detection in multi-camera and $$360^{\circ }$$ 360 ∘ videos," Neural Comput. Appl. 2021 342, vol. 34, no. 2, pp. 1455–1482, Sep. 2021, doi: 10.1007/S00521-021-06495-5.

[49] F. Harrou, N. Zerrouki, Y. Sun, and A. Houacine, "Vision-based fall detection system for improving safety of elderly people," *IEEE Instrum. Meas. Mag.*, vol. 20, no. 6, pp. 49–55, Dec. 2017, doi: 10.1109/MIM.2017.8121952.