OPEN ACCESS International Journal of Innovations in Science & Technology

IJIST
P ISSN : 2618-1630
E ISSN : 2909-6130

Comparative Analysis of Machine Learning Algorithms for Classification of Environmental Sounds and Fall Detection

Farman Hassan [1], Muhammad Hamza Mehmood [2], Babar Younis [3], Nasir Mehmood [4], Talha Imran [5], Usama Zafar [6].
1,2,3,4,5,6 (University of Engineering and Technology Taxila, Punjab Pakistan).
* Correspondence: Farman Hassan, Email ID: farmanhassan555@gmail.com.
Citation | Hassan. F, Mehmood. M. H, Younis. B, Mehmood. N, Imaran. T, Zafar. U. "Comparative Analysis of Machine Learning Algorithms for Classification of Environmental Sounds and Fall Detection". International Journal of Innovations in Science and Technology, Vol 4, Issue 1, pp: 163-174, 2022.
Received | Feb 17, 2022; Revised | Feb 23, 2022 Accepted | Feb 23, 2022; Published | Feb 24, 2022.

Abstract.

In recent years, number of elderly people in population has been increased because of the rapid advancements in the medical field, which make it necessary to take care of old people. Accidental fall incidents are life-threatening and can lead to the death of a person if first aid is not given to the injured person. Immediate response and medical assistance are necessary in case of accidental fall incidents to elderly people. The research community explored various fall detection systems to early detect fall incidents, however, still there exist numerous limitations of the systems such as using expensive sensors, wearable sensors that are hard to wear all the time, camera violates the privacy of person, and computational complexity. In order to address the above-mentioned limitations of the existing systems, we proposed a novel set of integrated features that consist of melcepstral coefficients, gammatone cepstral coefficients, and spectral skewness. We employed a decision tree for the classification performance of both binary problems and multi-class problems. We obtained an accuracy of 91.39%, precision of 96.19%, recall of 91.81%, and F1-score of 93.95%. Moreover, we compared our method with existing state-of-the-art methods and the results of our method are higher than other methods. Experimental results demonstrate that our method is reliable for use in medical centers, nursing houses, old houses, and health care provisions.

Keywords: Decision tree, fall incidents, Environmental Sounds, Machine Learning, Old houses.

INTRODUCTION

The elderly population of the world is growing at an alarming rate, since 2015, the population of the elderly, people aged 60 and above, was estimated to be at 901 million and by 2030, it is expected to reach 1.4 billion people and possibly surpass 2.1 billion by 2050 [1]. The elderly population is increasing, and with it comes a slew of new challenges. In [2], the majority of elderly individuals prefer to live alone and are concerned about their privacy. In [3], the majority of Canadian elderly individuals live on their own. This trend is also being observed in European countries. Elderly people have a higher risk of falling since they can't easily control themselves due to muscle weaknesses. Falls have a serious impact on health and therefore can result in life-threatening injuries or even death. The most devastating problem after an accidental fall is that, in most situations, the patient is unable to ask for help due to unconsciousness [4], which further increases the chances of permanent injuries or even death. In this scenario, the elderly must be adequately cared for, and assistance must be provided immediately [5]. There have been several manual methods of taking care of the elder people, such as nursing at home but at times for a longer period, it is costly and not possible for most people to bear those expenses. The above discussion shows how accidental falls have a financial impact on the elderly population and cause significant health problems for elderly people who live alone. This alarming situation, and the large number of people that die as a result of falls, have motivated researchers to develop means of detecting falls and taking countermeasures after falls to avoid fatal consequences [6].

There are several sensor-based fall detection systems, which include wearable sensors, ambient acoustic sensor-based, and vision sensor-based. [7] Wearable gadgets are worn on the body that detect any unusual activities. There are various wearable gadgets i.e., accelerometer, gyroscope, and smartwatches. They have the following advantages: ease of use, high accuracy, low power consumption, and low weight, among others. However, elderly people tend to forget to wear their devices, or they are obtrusive enough that some people find them difficult to wear. The acoustic-based fall [8] detection system also known as ambient or contactless fall detection system consists of microphones, acoustic sensors, and floor acoustic sensors. A vision-based fall detection system uses surveillance cameras, mobile cameras, 3d, and 2d cameras to monitor a patient or fall vulnerable people [9, 10, 11]. The privacy of elderly individuals is a serious concern, when they are using vision-based sensors, their privacy is violated [13, 14].

There have been numerous studies on wearable fall detection systems. In [15], a wearable sensor placed around the elderly waist is used to detect falls through acceleration analysis. The motion sensor in this method was a triaxial accelerometer named ADXL345. The quaternion algorithm helps in the monitoring of patients' daily activities and the detection of falls. With the use of a universal resource locator (URL), an alert message containing the patient's location was delivered to the respective caretaker once the fall event was detected. In [12], a new smart device was developed for detecting fall events and sending alert messages. 3D acceleration and gyroscope were used for developing this model. At first, activities of daily life (ADLs) and falls were differentiated. In the meantime, a smart device is developed by introducing the k nearest neighbor (KNN) algorithm and sliding window. This smart device is composed of smartphones and wearable motion sensors. The Wearable smart sensor consisted of a Bluetooth, gyroscope, and a triaxial accelerometer [16,17]. The sensor was attached to a vest worn by the elder person. Real-time angular velocity of ADLs and reluctant acceleration was being captured by a smart sensor.

Bluetooth sends this stream data to a phone containing the KNN algorithm and sliding window to analyze data and detect fall events. Accuracy, sensitivity, and specificity achieved by the system are 97.9%, 94%, and 99% sequentially. In [18] a study was performed in which wearable sensors were combined with a location sensor to develop a fall detection system. The developed system aimed to detect fall events in real-life cases and that situation in which fall detection was difficult to distinguish. The performance of context-based reasoning was improved noteworthy. This study concluded that it is better to use a combination of both types of sensors to achieve good results. Wearable sensors were combined with a location sensor to develop a fall detection system in a study published in [19]. The proposed method was designed to detect real-life fall events as well as situations where fall detection was difficult to distinguish. Context-based reasoning performance was significantly enhanced. To attain optimum performance, this study concluded that it is better to use a combination of both types of sensors. The above system performs well in terms of accuracy though accelerometer-based fall detection techniques have several drawbacks, such as sudden changes in acceleration in both the fall event and the activity of daily living (ADL) which in terms, makes it difficult to distinguish between the two incidents.

The acoustic or ambient-based fall detection system includes a microphone that analyzes the surroundings and records human activities information from the environment. The key benefit of using an acoustic sensor-based method is that the elderly would not have to worry about wearing gadgets. Instead, it senses the environment and is passive, which will benefit the elderly because his privacy will be preserved [20]. In [21], an acoustic-FADE system was developed to keep track of the elderly and alert caregivers in the event of a fall. In this system, a circular microphone array is used to record the sound in the room. Based on the source location, the recorded sound is classified as fall or non-fall. The sheered power response is employed to determine position, and the phase transform technique improves the sound's robustness [22]. In [23], a fall event detection system is designed that used MFCC from footsteps. A one-class support vector machine is employed for classification purposes. Similarly, in [24], a machine learning-based approach was developed to detect fall incidents. In [25], MFCC features were used to detect fall incidents.

The proposed technique used SVM to discriminate between incidents involving falls and those involving non-falls. In [26] a supervised fall detection algorithm based on a wireless communication system i.e. smartphone microphone in which falls were executed and subsequently recorded from different participants using a smartphone placed within a distance of 5m from them. This system probably does not work in the case when the volunteer is far from another area. After examining various features and supervised algorithms the author used spectrogram features as the input to an artificial neural network, thus arriving at an accuracy of 98%. Similarly, in [27], a microphone array has been employed in the premises of fall vulnerable people. The initial step in this method is to calculate the energy of the acquired signal. But in case the value goes beyond a threshold a sound localization technique is carried out to eliminate possible false alarms. Finally, the alarm is removed if the sound was noticed from a specific height. Then the author practiced the human falls by experimenting with a single stunt performed falling on a mattress.

Our main contributions are as follows:

- We proposed a novel set of features that capture maximum details from the audio signals.

- To validate our approach, we performed binary class and multi-class experiments to check the effectiveness of the proposed system.
- We conducted extensive experimentations on the daily sounds dataset to validate the superiority of our method.

The remaining paper is organized as follows, Section II discusses the proposed methodology, section III has experimental results and discussion while in Section IV, we conclude our work.

PROPOSED METHODOLOGY

The main purpose of the proposed system is to detect the fall incidents of humans and to detect environmental sounds. Our system comprises mainly of two stages i.e., feature extraction and classification. Initially, we extracted three spectral features from the standard dataset available i.e., The Daily Sounds Dataset. After the feature extraction, we applied different machine learning classifiers such as Naïve Bayes (NB), KNN, linear discriminant analysis (LDA), and decision tree (DT) to differentiate the fall incidents and non-fall incidents. However, DT outperformed all other machine learning classifiers. The illustration of the proposed working mechanism is given in Figure 1.

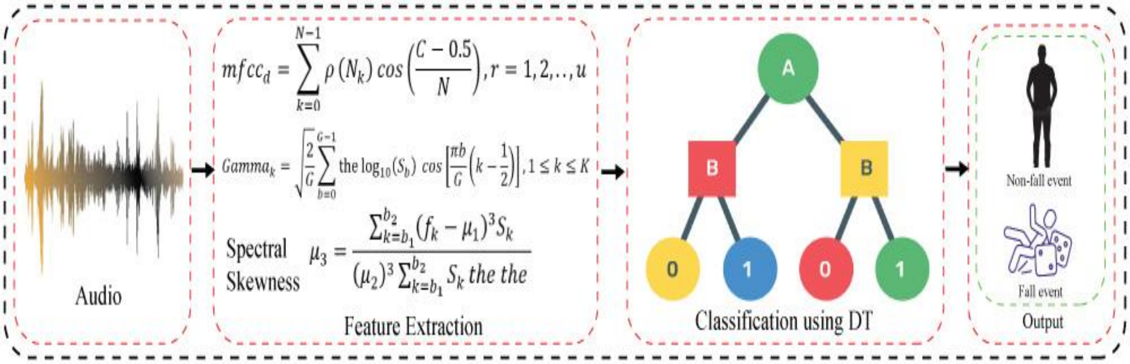

Figure 1. Proposed System.

Dataset

In this paper, we used a standard dataset for experimentation such as The Daily sounds dataset [28]. There is 1049 audio in this dataset. The daily sounds dataset has a total of 18 different classes, which are generated by the human's actions such as breathing, dishes, door clapping, electrical shaver, glass breaking, hairdryer, keys, paper tear, female scream, water falling, yawn, sneeze, male scream, laugh, handclapping, female cry, door opening, and cough that are produced by humans and their actions. To avoid external interference, all the data is recorded during nighttime. We used 898 audio samples for training and 151 audio samples for evaluation purposes. The research community considered the fall and panic sounds as fall class while other environmental sounds as a non-fall class, so, we follow the same standard in this research work.

Features Extraction

Discriminative features extraction is necessary for an efficient and reliable fall incidents detection system. After extensive experimentations, we selected the three spectral features for this research work and selected these manually. We extracted three spectral features such as MFCC, GTCC, and spectral skewness from audio to design a fall incident detection system. The detailed feature extraction mechanism is discussed in the subsequent sections.

MFCC

We extracted fourteen-dimensional MFCC features from the audio by using eq 2. We extracted MFCC as follows: initially, we applied Fourier Transform on the logarithm of the power spectrum of a signal. We used a sampling rate same of 0.5 and audio signals have been used to generate Mel-frequency cepstrum. We achieved this in three steps, first, the entire spectrum is divided into windows, and this is done by using hamming windows technique. Secondly, the square of Mel-spectrum, which is also called power spectrum $|f(w)|^2$, is calculated by the following equation 1 as given below

$$\rho(N_k) = \ln\left[\sum_{k=1}^{x} |S(k)|^2 L_q(k)\right], q = 1, 2, .., r \quad (1)$$

Finally, the acquired Mel frequency coefficient undergoes Discrete Cosine Transform (DCT) technique. We obtained the cepstral coefficients as output after employing DCT. In addition, log operation is involved in the non-linear rectification process which is performed before computing DCT. Therefore, Inverse Discrete Cosine Transform (IDCT) is performed by obtaining features which are given by the following equation.

$$mfcc_d = \sum_{k=0}^{N-1} \rho(N_k) \cos\left(\frac{C - 0.5}{N}\right), r = 1, 2, .., u \quad (2)$$

GTCC

We computed fourteen-dimensional Gammatone Cepstral Coefficient (GTCC) features from the audio of fall and non-fall events. GTCC is a feature extraction technique used for ambulatory EEG signals. This technique is also known as Gammatone Frequency Cepstral Coefficient (GFCC). It has computation difficulty same as MFCC method but higher-level performance. The gammatone filter bank is applied on pre-processed audio signals and sub-band spectrum is obtained as output. Cubic root operation is applied on power spectrum in nonlinear rectification process followed by DCT to obtain GTCC spectral coefficients. We computed the GTCC features by using the following equation.

$$Gamma_k = \sqrt{\frac{2}{G}} \sum_{b=0}^{G-1} \text{the} \log_{10}(S_b) \cos\left[\frac{\pi b}{G}\left(k - \frac{1}{2}\right)\right], 1 \le k \le K \quad (3)$$

In above equation $Gamma_k$ is the kth GTTC, S_b is the energy in the bth sub-band of the spectrum, K is the GTTC cepstral coefficient number and G is gammatone filter number.

Spectral Skewness

Symmetry around the centroid is measured by spectral skewness. Spectral tilt is the other name of spectral skewness in phonetics. Place of articulation is distinguished by using other spectral moments with spectral skewness. The relative strength of lower and higher harmonics is indicated with spectral skewness for harmonic signals. We computed the spectral skewness as follows.

$$\mu_3 = \frac{\sum_{k=b_1}^{b_2}(f_k - \mu_1)^3 S_k}{(\mu_2)^3 \sum_{k=b_1}^{b_2} S_k \, the \, the} \quad (4)$$

In above equation $\mu_1$indicates spectral centroid, $\mu_2$is spectral spread, band edges indicated by b_1 and b_2, S_k is bin k spectral value and f_k is bin k frequency in Hertz.

Classification

Machine learning classifiers are providing promising results for classification problems. In this paper, we focused on using different machine learning classifiers to detect fall incidents. We employed NB, KNN, LDA, and DT, however, the DT outperformed against all other machine learning classifiers. Figure 2 shows the structure of the DT algorithm. DT is a powerful classification algorithm used in numerous fields such as medical, image processing, audio processing, video processing, and other identification problems. DT is a sequential model, which unites a series of small test very effectively and cohesively based on the numeric features that is compared to a specific threshold value in each test. Constructing DT is easier than weights in neural networks of different nodes. DT comprises of nodes and branches, where each node represents a feature to be classified while each branch shows a different value that node takes it. There are two classes in our problem as fall and non-fall, and DT performs well on a binary classification problem. Therefore, we also employed DT to better detect fall incidents.

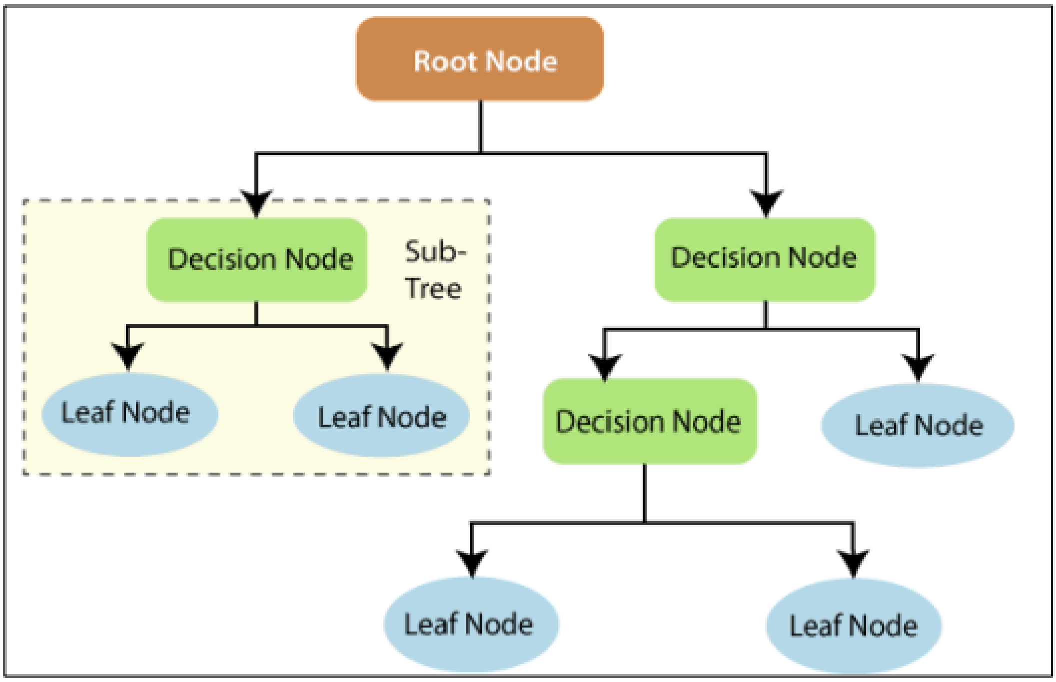

Figure 2. Decision Tree.

EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we have discussed the detailed experimental results and setup for experimentation purposes to detect fall and non-fall events. We evaluated the performance of the proposed system using accuracy, precision, recall, and F1-score. The details of the dataset and experimental results are discussed in the subsequent section.

Comparative analysis of machine learning algorithms

The aim of this experiment is to detect fall incidents. We extracted 29-dim MFCC, GTCC, and spectral skewness features from the audio samples of fall and non-fall incidents. We used 898 samples for training and 151 samples for evaluating the trained model. Moreover, we classified the panic and fall sounds of the dataset as fall incidents while the environmental sounds as non-fall incidents. We applied four different machine learning algorithms such as NB, KNN, LDA, and DT to check the effectiveness of machine learning algorithms in detecting fall incidents. From the results given in Table 1, we can observe that (MFCC-GTCC-spectral skewness-LDA) performed worst and achieved an accuracy of 73.51%, precision of 84.76%, recall of 78.76%, and F1-score of 81.65%. The (MFCC-GTCC-spectral skewness-KNN) performed the second-best in terms of accuracy and achieved an accuracy of 80.79%, precision of 100%, recall of 78.35%, and F1-score of 87.86% while the (MFCC-GTCC-spectral skewness-DT) performs the best and achieved an accuracy of 91.39%, precision of 96.19%, recall of 91.81%, and F1-score of 93.95%. The detailed results are given in Table I. From the results given in Table 1, we concluded that (MFCC-GTCC-spectral skewness-DT) captures maximum information from the audio of the fall and non-fall incidents. This system is reliable and effective to be used for detecting fall incidents.

Table 1. Comparative Analysis of machine learning techniques.

Method	Accuracy%	Precision%	Recall%	F1 score%
NB	73.51	100	72.41	84%
KNN	80.79	100	78.35	87.86
LDA	73.51	84.76	78.76	81.65
DT	**91.39**	**96.19**	**91.81**	**93.95**

Confusion Matrix for Binary class

The confusion matrix is designed to show correct and false prediction results for any classification problem. There are four different values such as false negative, false positive, true negative, and true positive values. We also designed a confusion matrix for DT as shown in Figure 3. We can observe that our method (MFCC-GTCC-spectral skewness-DT) misclassified 4 non-fall incidents as fall incidents while 9 fall incidents as non-fall incidents. Our method (MFCC-GTCC-spectral skewness-DT) correctly classified 101 fall incidents as fall while 37 non-fall incidents as non-fall incidents. From the confusion matrix as shown in Figure 3, we concluded that these show effective results to detect fall and non-fall incidents.

Figure 3. Confusion matrix (1) Fall and (2) non-fall event.

Performance evaluation of Environmental Sounds Classification

The aim of this experiment is to classify ten different classes of the daily sounds dataset. The ten classes are breathing, dishes, door clapping, electrical shaver, glass breaking, hairdryer, keys, paper tear, scream, and water failing. We observe that there is a very high correlation among these ten classes. We extracted 29-dim (MFCC-GTCC-spectral skewness) from the audio samples of these ten classes to train DT. We observe from Table 2 that (MFCC-GTCC-spectral skewness-DT) performed worst to detect the scream and achieved an accuracy of 88%, precision of 94.56%, recall of 99.10%, and F1-score of 96.20%. Our method performed second-best on a paper tear and achieved an accuracy of 98.23%, precision of 97%, recall of 95.21%, and F1-score of 97.88% while our method performed best to detect water failing audio, elegiacal shaver, and glass breaking with an accuracy of 100%, precision of 100%, recall of 100%, and F1-score of 100%. The detailed results of all the classes are given in Table 2. We concluded that (MFCC-GTCC-spectral skewness-DT) is an effective and reliable system to detect the high correlated classes.

Table 2. Performance of environmental sounds classification.

Classes	Accuracy%	Precision%	Recall%	F1-Score%
Breathing	94.12	97	96.2	98.11
Dishes	92.78	98.33	93.89	98
Door Clapping	92.09	99	91.10	94.58
Electrical Shaver	100	100	100	100
Glass Breaking	100	100	100	100
Hair Dryer	96.89	92.41	99	96.98
Keys	96.17	92.56	99	95.89
Paper Tear	98.23	97	95.21	97.88
Scream	88	94.56	99.10	96.20
Water Falling	100	100	100	100

Confusion Matrix for environmental Sounds Classification

The confusion matrix for the ten classes is shown in Figure. 4. The ten classes are breathing, dishes, door clapping, electrical shave, glass breaking, hairdryer, keys, paper tear, scream, and water falling, respectively. From the confusion matrix of multi-class scenarios, as shown in Fig. 4, we observe that our method misclassified only 20 incidents while correctly classifying 204 incidents. We know that these 10 classes are highly correlated, but our method is robust to detect all the ten classes correctly. We concluded that our method is capable to detect complex environmental sounds and can effectively be used for the detection of fall incidents.

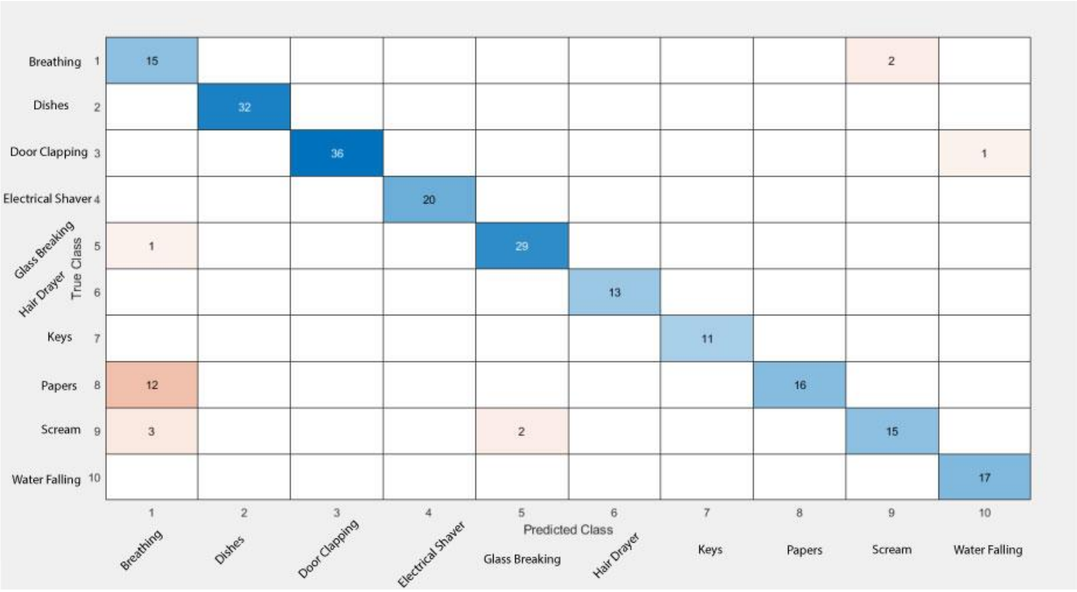

Figure 4. Confusion matrix for Environmental Sounds Classification.

Performance comparison with other methods

The aim of this experiment is to compare the performance of the proposed system with the existing state-of-the-art methods. We compared our method based on accuracy, precision, recall, and F1-score as shown in Table 3. We took direct results from their papers without implementing them. We observed that khan et al. [30] performed worst and achieved an accuracy of 66%, precision of 64%, recall of 76%, and F1-score of 25% while Tuncer et al. [29] performed the second-best and achieved an accuracy of 89.17%. Our proposed method performed best among the existing state-of-the-art methods and achieved an accuracy of 91.39%, precision of 96.19%, recall of 91.81%, and F1-score of 93.95%. This comparative analysis of our method with existing methods demonstrates that our method performed superior and is effective to detect fall incidents. This system can be used in old houses, medical centers, and in the home where old age people are living alone to early detect the fall incidents to save lives and give first aid earlier.

Table 3. Performance comparison with existing techniques.

Authors	Accuracy %	Precision %	Recall %	F1-score %
Tuncer et al. [29]	89.17	-	-	-
Khan et al.[30]	66	100	60	44
Shaukat et al.[31]	77.9	64	76	25
Proposed	**91.39**	**96.19**	**91.81**	**93.95**

CONCLUSION

This paper has presented a novel fall incidents detection system through the fused set of features comprised of (MFCC-GTCC-spectral skewness). We used a standard dataset such as the daily sounds dataset, which is available publicly. We extracted 29-dim features from the fall and non-fall incidents and employed the DT for classification purposes. Comparative analysis of our method with existing state-of-the-art methods demonstrates that our method is superior and effective to detect fall incidents. Our method has the lowest false alarm rate and achieved an accuracy of 91.39%. Moreover, the proposed method can be used in real-time environments such as in medical centers for monitoring of old people, nursing homes, and old houses. In the future, we aim to employ deep learning methods on the fused set of features as well as to send the exact location where the fall incidents happen to the caretakers.

Acknowledgment. Acknowledgments are considered necessary.

Author's Contribution. The corresponding author equally contributed to this work.

Conflict of interest. Authors claim that there exists no conflict of interest for publishing this manuscript in IJIST.

REFERENCES

[1]. United Nations. World Population Ageing; United Nations: New York, NY, USA, 2015.

[2]. Uddin M, Khaksar W, Torresen J (2018) Ambient sensors for elderly care and independent living: a survey. Sensors 18(7):2027.

[3]. Roy N, Dubé R, Després C, Freitas A, Légaré F (2018) Choosing between staying at home or moving: a systematic review of factors influencing housing decisions among frail older adults. PLoS One 13(1): e0189266.

[4]. Burns ER, Stevens JA, Lee R (2016) (2016). The direct costs of fatal and non-fatal falls among older adults — United States. J Saf Res 58:99–103.

[5]. Kistler BM, Khubchandani J, Jakubowicz G, Wilund K, Sosnoff J. (2018). Falls and Fall-Related Injuries Among US Adults Aged 65 or Older With Chronic Kidney Disease. Prev Chronic Dis 2018;15:170518.

[6]. Allali G, Ayers EI, Holtzer R, Verghese J (2017) The role of postural instability/gait difficulty and fear of falling in predicting falls in non-demented older adults. Arch Gerontol Geriatr 69:15–20.

[7]. MubashirM, Shao L, Seed L (2013) A survey on fall detection: principles and approaches. Neurocomputing 100:144–152.

[8]. Wortmann M (2012) Dementia: a global health priority - highlights from an ADI and World Health. Organization report. Alzheimers Res Ther 4(5):40.

[9]. Delahoz Y, Labrador M (2014) Survey on fall detection and fall prevention using wearable and external sensors. Sensors 14:19806–19842.

[10]. Zhong Z, Christopher C, Vassilis A (2015) A survey on vision-based fall detection, Proceedings of the 8th ACM International Conference on PErvasive Technologies Related to Assistive Environments, Corfu, Greece, doi: 10.1145/2769493.2769540.

[11]. Xu T, Zhou Y, Zhu J (2018) New advances and challenges of fall detection systems: a survey. Appl Sci 8: 418.

[12]. Falin Wu, Hengyang Zhao, Yan Zhao, Haibo Zhong, "Development of a Wearable-Sensor-Based Fall Detection System", International Journal of Telemedicine and Applications, vol. 2015, Article ID 576364, 11 pages, 2015.
[13]. Guilherme Gerzson Torres, Renato Ventura Bayan Henriques, Carlos Eduardo Pereira, Ivan Müller, "An EnOcean Wearable Device with Fall Detection Algorithm Integrated with a Smart Home System", IFAC-PapersOnLine, Volume 51, Issue 10, 2018.
[14]. Dharmitha Ajerla, Sazia Mahfuz, Farhana Zulkernine, "A Real-Time Patient Monitoring Framework for Fall Detection", Wireless Communications and Mobile Computing, vol. 2019, Article ID 9507938, 13 pages, 2019.
[15]. He J, Hu C, Wang X. "A Smart Device Enabled System for Autonomous Fall Detection and Alert". International Journal of Distributed Sensor Networks. February 2016.
[16]. J. Wang, Z. Zhang, B. Li, S. Lee and R. S. Sherratt, "An enhanced fall detection system for elderly person monitoring using consumer home networks," in IEEE Transactions on Consumer Electronics, vol. 60, no. 1, pp. 23-29, February 2014.
[17]. Q. Li, J. A. Stankovic, M. A. Hanson, A. T. Barth, J. Lach and G. Zhou, "Accurate, Fast Fall Detection Using Gyroscopes and Accelerometer-Derived Posture Information," 2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks, 2009, pp. 138-143, doi: 10.1109/BSN.2009.46.
[18]. H. Gjoreski, S. Kozina, M. Gams and M. Luštrek, "RAReFall — Real-time activity recognition and fall detection system," 2014 IEEE International Conference on Pervasive Computing and Communication Workshops (PERCOM WORKSHOPS), 2014, pp. 145-147, doi: 10.1109/PerComW.2014.6815182.
[19]. H. Gjoreski, M. Luštrek, M. Gams.: Context-Based Fall Detection using Inertial and Location Sensors. In: International Joint Conference on Ambient Intelligence, Lecture notes in computer science, pp. 1-16, 2012.
[20]. M. Popescu, Y. Li, M. Skubic and M. Rantz, "An acoustic fall detector system that uses sound height information to reduce the false alarm rate," 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2008, pp. 4628-4631, doi: 10.1109/IEMBS.2008.4650244.
[21]. Li Y, Zeng Z, Popescu M, Ho KC. Acoustic fall detection using a circular microphone array. Annu Int Conf IEEE Eng Med Biol Soc. 2010; 2010:2242-5. doi: 10.1109/IEMBS.2010.5627368. PMID: 21096795.
[22]. Li Y, Ho KC, Popescu M. A microphone array system for automatic fall detection. IEEE Trans Biomed Eng. 2012 May;59(5):1291-301. doi: 10.1109/TBME.2012.2186449. PMID: 22532430.
[23]. Khan, Muhammad Salman & Yu, Miao & Feng, Pengming & Wang, Liang & Chambers, Jonathon. (2014). An unsupervised acoustic fall detection system using source separation for sound interference suppression. Signal Processing. 110. 10.1016/j.sigpro.2014.08.021.
[24]. Thiago B. Rodrigues, Débora P. Salgado, Mauricio C. Cordeiro, Katja M. Osterwald, Teodiano F.B. Filho, Vicente F. de Lucena, Eduardo L.M. Naves, Niall Murray, "Fall Detection System by Machine Learning Framework for Public Health", Procedia Computer Science, Volume 141, 2018, Pages 358-365, ISSN 1877-0509.

[25]. A. Chelli and M. Pätzold, "A Machine Learning Approach for Fall Detection and Daily Living Activity Recognition," in IEEE Access, vol. 7, pp. 38670-38687, 2019, doi: 10.1109/ACCESS.2019.2906693.

[26]. Daohua Pan, Hongwei Liu, Dongming Qu, Zhan Zhang, "Human Falling Detection Algorithm Based on Multisensor Data Fusion with SVM", Mobile Information Systems, vol. 2020, Article ID 8826088, 9 pages, 2020.

[27]. Wang S, Chen L, Zhou Z, Sun X, Dong J (2016) Human fall detection in surveillance video based on PCANet. Multimed Tools Appl 75(19):11603–11613.

[28]. M. A. Sehili, D. Istrate, B. Dorizzi, and J. Boudy, "Daily sound recognition using a combination of GMM and SVM for home automation," in *2012 Proceedings of the 20th European Signal Processing Conference (EUSIPCO)*, 2012, pp. 1673-1677.

[29]. T. Tuncer and S. Dogan, "Novel dynamic center based binary and ternary pattern network using M4 pooling for real world voice recognition," *Applied Acoustics,* vol. 156, pp. 176-185, 2019.

[30]. M. S. Khan, M. Yu, P. Feng, L. Wang, and J. Chambers, "An unsupervised acoustic fall detection system using source separation for sound interference suppression," *Signal processing,* vol. 110, pp. 199-210, 2015.

[31]. A. Shaukat, M. Ahsan, A. Hassan, and F. Riaz, "Daily sound recognition for elderly people using ensemble methods," in *2014 11th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*, 2014, pp. 418-423.