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Analysis of ML Algorithm for Geriatric Fall Detection Due to the Effects of Various User Characteristics

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Abstract: Falls are extremely damaging to the elderly. The number of elderly who have experienced falls has increased over the years, several of the elderly stay alone or in in badly maintained elderly homes. This makes a low-cost fall detection system a necessity. There has been huge improvements in terms of IoT systems, ML algorithms. Varied data sets have been collected across the world for fall detection. These data sets have a very little in common among them, in terms of user demographics, sensors used, the ADL and Fall activities Hence in this paper we present a data set that has wide user demographics, we used various sensors – such as accelerometer, gyroscope, magnetometer and hear rate. We used wrist worn sensors to collect data. In this paper we present a detailed analysis of the data set we collected using common ML algorithms such as – Naïve Bayes (NB), K Nearest Neighbor (KNN), Logistic Regression (LR), Random Forest (RF) and Support Vector Machines (SVM). We analyzed the performance of these algorithms for variations in accuracy with respect to age, gender, height, weight and health issues and we have identified outliers by analyzing each incorrect prediction. This paper provides the complete details of the data collection methodology, The methods used for analysis and presents the results of analysis in complete detail.

Keywords: machine learning; geriartic fall detection; dataset; K nearest neighbours; naive bayes; logistic regression; random forest; support vector machine

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1. Introduction

According to WHO statistics [1], people are living longer, and the current population is expected to live well into their sixties. Current statistics (1st October 2022) state the following.

1. The speed of aging is increasing;
2. In the year 2020, people aged more than sixty years outnumbered young kids under the age of five;
3. By 2050 the population of geriatrics is expected to double from 12% to 22%. People over 60 are expected to be around 2.1 billion, and the number of people above 80 is expected to reach 426 million.
4. Two-thirds of the aging population is expected to be in the low- and middle-income range.

The process of aging causes a decrease in physical and mental capacity, other than biological variations, that are a natural part of aging comes retirement and relocation. The elderly are generally considered frail and dependent and hence are shunned. Many of them are forced to live in a low-income retirement home. The changes in their health, financial and social conditions expose them to health risks; especially they become more prone to accidents, including falls.

United Nations has declared 2021 to 2030 as the "UN Decade of healthy aging" and are supporting the use of technology that can improve the quality of life of the elderly.

With recent advances in healthcare systems, specifically with the integration of Internet of Things (IoT) and medical applications, there has been a huge boost in research in medical sensors and machine learning algorithms.

Machine learning and Deep Learning are widely investigated topics in the case of geriatric fall detection to train the ML/DL algorithms, a large amount of data related to fall and non-fall activities is required. Several public datasets for fall are available. The public datasets vary in terms of (a) Sensors used (b) the number of volunteers (c) demographics such as age, gender, and existing health conditions (d) activities performed (e) data gathering techniques. Several researchers [2] have brought out the difficulty of comparing datasets. Therefore, it is also difficult to conclude why certain ML/DL algorithms perform better when compared to others. Most public datasets do not provide the details of data collection. The datasets used for fall detection have a set of daily activities (ADLs) and a set of fall data. Public datasets do not always list the ADL activities, the type of falls, how many times these activities were performed and how long each activity lasted.

Two types of sensing methods are associated with fall detection (a) wearable (b) environmental sensors. The classification is based on the placement of the sensor. The sensors can be placed on the body of the elderly or maybe placed in the environment around them. Body worn sensors usually are accelerometers, gyroscopes, and biometric sensors. Environmental sensors include image, vibration, and audio sensors.

There are several public datasets such as Mobi Fall, K Fall, SiS Fall, and SmartFall, that use body worn sensors that primarily use accelerometer-based sensors. This paper concentrates on data collection using wearable sensors specifically IMU (Inertial Measurement Unit) sensors, gyroscopes, magnetometers. Even with body-worn sensors, there is a considerable variation in the data collected. This is due to the positioning of the sensor on the body. The sensors maybe placed on the torso, thigh, or waist. Based on the placement of the sensors, the data collected, and the performance of the ML algorithms vary.

Raw sensor data is not directly fed to the ML algorithms; sensor data is processed to extract the relevant features; in the case of wearable sensors, these are usually statistical parameters – such as average, mean, maximum, minimum, standard deviation, kurtosis, skew, etc. Public datasets only have the extracted features available. Some of them have only raw accelerometer values; each public dataset produces different accuracies when ML algorithms are applied. This makes it difficult to recommend a single ML algorithm for fall detection. Also, the accuracy of the ML algorithm cannot be coordinated with the data points as no information regarding the volunteers and their individual characteristics are available. Therefore, while using public datasets the following question remains to be answered (A) What is the reason for varying accuracies in ML algorithms (B) Are the volunteered demographics related to varying accuracies, and if so, how? (C) How much data is required to train the algorithms to obtain good accuracies especially since DL algorithms require a large amount of data to converge (D) Can different datasets be used for training and testing and how will the accuracies of the ML algorithms will be affected (E) What will be the actual accuracy obtained when the system is used on the actual target users (i.e.) the elderly. The volunteers cannot be drawn from the geriatric populations due to the health risk involved.

The primary aim of our research work is to build an end device that will be a part of a larger IoT system. The end device will not only collect data but also execute the ML/DL algorithms to detect falls and alert healthcare professionals. The ML algorithms are run on the end device to eliminate network latency and connectivity-related issues. Only long-term health monitoring and analysis will be done on the cloud. The architecture of the proposed system is shown in Figure 1.
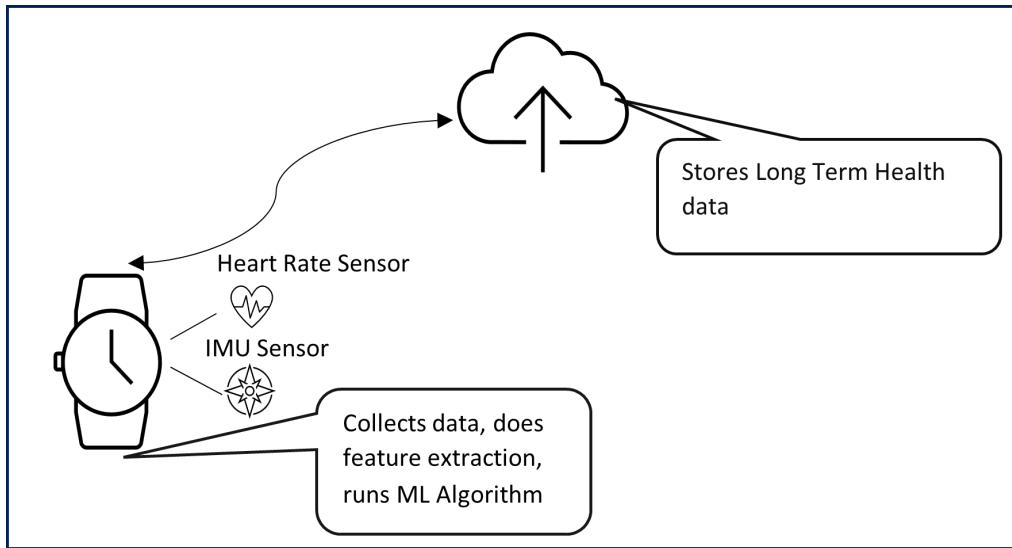
Figure 1. Architectural model of wearable fall detection system.

Such a system would have end devices built around powerful SoCs. The SoC we are using is Snapdragon Qualcomm 820c [3]. The 820c chip has been developed specifically for wearable and IoT applications.In IoT this is termed as Dew Computing.

This device needs to be trained with a large dataset so that we can run compressed ML/DL algorithms on it. The need for compressed algorithms is because running a full-scale algorithm will require a large amount of memory that is not available on SoCs [4]. shows the high latency incurred when running ML algorithms on SoCs. In order to train the system, we started with data collection, cleaning and analysis. This paper elaborates on the process we have used for data collection, cleaning, feature extraction and analysis of the data collected. Various ML algorithms were run on the data collected and analysis was done on various factors and their impact on the ML models. Some of the features considered were (a) Separate test and train data (b) age (c) gender (d) physical condition such as height, weight, and any pore-existing health condition. This paper provides the result of the analysis and also addresses the issue of data collection and the impact of characteristics of the data collected on the performance of the ML algorithms.

2. Background of Work

"Inadvertently coming to rest on the ground, floor, or other lower levels, excluding intentional change in position to rest in furniture, wall or objects", is defined as a fall by WHO [1]. Falls can be detected using multiple mechanisms and methods. This section gives a brief review of the research done in terms of data collection and analysis done for fall detection in the elderly.

2.1. Sensors

The sensors that are used for fall detection can be classified into two categories (a) ambient sensors (b) wearable. The classification is based on the position of the sensor with respect to the user.

2.1.1. Ambient Sensors

Image, Audio and Vibration sensors are the major sensors are the major sensors that fall under this category. Fall detection using vibration sensors [5] is detailed. [6] describes a fall detection system that uses sound sensors. Vibration sensors are usually piezo-electric based and pick up vibrations caused by the fall of a person. The issue with using ambient sensors to detect vibration or audio samples is the large amount of noise present that requires pre-processing of signals using appropriate filters. If the fall detection system is part of the IoT system, then the complexity of the end device will be extremely high. Also, there is a possibility that soft falls may go undetected. Image Sensors [7] analyse images

captured efvery few seconds to find if any person has fallen, in most cases multiple camera frames will be required. Multiple cameras can be placed in a single room and falls can be detected. Using multiple cameras in every room where the elderly live, is not feasible; especially considering that most elderly live on a restricted income.

All these sensors; vibration, acoustic and image are placed in and around the area where the elderly live and hence, they are termed ambient sensors.

2.1.2. Wearable Sensors

Wearable sensors are primarily IMU sensors such as accelerometers, gyroscopes and magnetometers. In some research work [8], GPS has also been used, while in the case of some, biometric parameters such as heart rates, SpO_2 and skin temperature, etc were used.

In many cases, smartphones that already have an IMU sensor or smartwatches equipped with IMU sensors are used. GPS or biometric-based sensors in these devices are generally used for validations.

IMU sensors are made up of three different sensors (a) Accelerometers (b) Gyroscopes (c) Magnetometers.

The accelerometers will experience sudden changes in value during a fall. Based on the position of the sensors, in some cases wrist-worn, thigh-worn or torso worn; The amount of acceleration along the 3 axes will vary. The gyroscope measures the angular velocity along with the 3 axes. The integral gives the angle of the person with respect to the ground. The third part of the IMU sensor, that is the magnetometer provides the orientation with respect to the Earth's magnetic field. In case of falls, there will be a significant change in all these parameters. In some cases, heart rate sensors and skin temperature sensors are used as they may supplement the IMU data. Heart rate may increase in case of a fall, so may the skin temperature. Wearable sensors are preferred over ambient sensors since they can move with the elderly also now IMU sensors are an integral part of smartphones and smartwatches which makes them an ideal choice; they are already available and will cost lesser even if a new system was to be built around them.

2.2. Data-Sets

Generally, to train and test the ML/DL algorithms large amount of data is required. There are multiple datasets available online, but they vary in terms of the type of sensors, manufacturer of the sensors, demographics of the train and test volunteers, the types of ADLs and Falls monitor, Sampling rate, duration of the data collected, number of volunteers and hence the number of data samples. The format of the data may be in terms of simple digital data from sensors, acoustic signals, or images. In the case of some datasets, raw data is available and in the case of some datasets, the features extracted are available. The feature extraction technique may also differ. Different datasets give different accuracies with different ML algorithms. Very little information is provided on why there are variations in accuracies. Does variation in gender, age, height, weight, and previous health issues affect accuracy is something that has not been analysed. Even when we run the ML/DL algorithms it is very difficult to analyse the ac curacies as very little information is provided about the volunteers due to privacy issues. A table analysing various public datasets collected over the last few years is provided in Table 1.

Table 1. An analysis of various public datasets collected over the past few years.

Ref	Year	Dataset used	Sensor used	Sensor placement	Methodology	Performance parameter and details
[9]	2011	UCI dataset	3-Axes accelerometer, 2-axis gyroscope	Chest, thigh	Comparison of ML algorithms for fall detection using single node and two nodes	Accuracy of classification = 99.8% with two nodes(one on waist and one on knee). Naïve Bayes gaves the worst result, others gave comparable
[10]	2012	Generated from experiments	Accelerometer	Smartphones carried along with the user	Comparison of SVM, SMLR, Naive Bayes, decision trees, kNN, and regularized logistic regression for fall detection	Support vector machines and regularized logistic regression were able to identify a fall with 98% accuracy and classify the type of fall (trips, left lateral, slips, right lateral) with 99% accuracy. Naïve Bayes reported least accuracy
[11]	2014	Generated from experiments	Accelerometer gyroscope and magnetometers	6 different positions on the body	Comparison of k-NN, classifier, LSM, SVM,BDM, DTW and ANN algorithms	k-NN classifier and LSM gave above 99% for sensitivity, specificity, and accuracy
[12]	2014	Generated from experiments	Accelerometer	Smartphones carried along with the user	Accelerometer data from wearable sensors to generate alarms for falls, combined with context recognition using sensors in an apartment, for inferring regular ADLs, using Bayesian networks	Provides statistical information regarding the fall risk probability for a subject

Table 1. *Cont.*

Ref	Year	Dataset used	Sensor used	Sensor placement	Methodology	Performance parameter and details
[13]	2015	Publicly available activity recognition dataset	Accelerometer, gyroscope	Smartphone	Comparison of Naive Bayes classifier, decision trees, random forests, classifiers based on ensemble learning (random committee), and lazy learning (IBk) algorithms for activity detection carried along with the user	Naive Bayes classifier performs reasonably well for a large dataset, with 79% accuracy, and it is fastest in terms of building the model taking only 5.76 seconds Random forests are better in terms of both accuracy and model building time, with 96.3% accuracy and 14.65 seconds model building time. k-Means clustering performs poorly with 60% classification accuracy and 582 seconds model building time
[14]	2016	Generated from experiments	3-Axis Accelerometer	Not specified	Comparison of decision tree, decision tree ensemble, kNN, neural networks, MLP algorithms for soft fall detection	Decision tree ensemble was able to detect soft falls at more than 0.9 AUC
[15]	2016	MobiFall dataset	Accelerometer, gyroscope	User's trouser pocket	Comparison of Naive Bayes, LSM, ANN, SVM, kNN algorithms for fall detection	k-NN, ANN, SVM had the best accuracy—results for kNN: Accuracy = 87.5% Sensitivity = 90.70% Specificity = 83.78%
[16,17]	2016	Generated from experiments	3-Axis Accelerometer	Smartwatch	Threshold-based analysis of acceleration	Accuracy = 96.01%

Table 1. *Cont.*

Ref	Year	Dataset used	Sensor used	Sensor placement	Methodology	Performance parameter and details
[17]	2016	Generated from experiments	3-Axis Accelerometer	Different parts of the body	Bayesian framework for feature selection, Naive-Bayes, C4.5	Better accuracy with improved classification than Naive-Bayes and C4.5
[18]	2017	Generated from experiments	Accelerometer gyroscope	Smart - Vest	Kalman filter for noise reduction, sliding window, and Bayes network classifier for fall detection	With Kalman filter Accuracy = 95.67%, Sensitivity = 99.0% Specificity = 95.0%
[19]	2017	Generated from experiments	3-Axis Accelerometer	Smartphone	Combination of threshold-based and ML-based algorithms—K-Star, Naive Bayes, J48	Energy saving = 62% compared with(ML only) techniques Sensitivity =77% (thresholding only), 82% (ML only), 86% (hybrid) Specificity = 99.8% (thresholding only), 98% (ML only), 99.5% (hybrid) Accuracy = 88.4% (thresholding only), 90% (ML only), 92.75% (hybrid)
[20]	2017	Generated from experiments	3-Axis Accelerometer	Waist	Combination of threshold-based and knowledge-based approach based on SVM to detect a fall event	Using a knowledge based algorithm: Sensitivity = 99.79% Specificity = 98.74% Precision = 99.05% Accuracy = 99.33%
[21]	2017	MobiFall dataset	3-Axis Accelerometer	Not specified	Comparison of multilevel fuzzy minmax neural network, MLP, KNN, SVM, PCA for fall detection	Multilevel fuzzy min-max neural network gave best results: Sensitivity = 97.29% Specificity = 98.70%

Table 1. *Cont.*

Ref	Year	Dataset used	Sensor used	Sensor placement	Methodology	Performance parameter and details
[22]	2017	FARSEEING dataset	3-Axis Accelerometer	5 locations on the upper body, neck, chest, waist, right side, and left side	Sensor orientation calibration algorithm to resolve issues arising out of misplaced sensor locations and misaligned sensor orientations, HMM classifiers	Sensitivity = 99.2% (experimental dataset), 100% (real-world fall dataset)
[23,24]	2017	Generated from experiments	3-Axis Accelerometer	Chest	LWT based frequency domain analysis and SVM-based time domain analysis of RMS of acceleration	Accuracy = 100% Sensitivity = 100% Specificity = 100%
[25]	2017	Generated from experiments	3-Axis accelerometer, 3-axis gyroscope	Waist	Back propagation neural network (BPNN) for fall detection	Accuracy = 98.2% Precision = 98.3% Sensitivity= 95.1% Specificity= 99.4%
[26]	2017	Generated from experiments	Accelerometer, radar, depth camera	Wrist	Ensemble subspace discriminant, linear discriminant, kNN, SVM	Overall accuracy of ensemble classifier was the highest, after fusion of radar, accelerometer, and camera = 91.3%. This is an improvement of 11.2% compared to radar-only and 16.9% compared to accelerometer-only results
[27]	2017	Public datasets	3-Axis accelerometer	Not specified	CNN-based analysis on time series accelerometer data converted to images	Accuracy = 92.3%

Table 1. *Cont.*

Ref	Year	Dataset used	Sensor used	Sensor placement	Methodology	Performance parameter and details
[28]	2017	Generated from experiments	Accelerometer, gyroscope, proximity sensor and compass	Right, left, and front pockets	SVM, decision tree, kNN, discriminant analysis	Highest accuracy = 99% for SVM
[29]	2010	Generated from experiments	3-Axis accelerometer	Chest, thigh	Naive-Bayes, SVM, OneR, C4.5 (J48), neural networks	Naive-Bayes gave best results Accuracy = 100%
[30]	2017	Generated from experiments	Accelerometer (MobiAct dataset)	Not applicable	ENN+ kNN (where ENN was applied to remove outliers), ANN, SVM, and J48	For ENN+ kNN: Sensitivity = 95.52% Specificity = 97.07% Precision = 91.83%
[31]	2018	Generated from experiments	Triaxial gyroscope	Waist	Decision tree	Accuracy = 99.52% Precision = 99.3% Recall = 99.5%
[32]	2018	Cogent dataset, SisFall dataset	3D accelerometer , 3D gyroscope- Cogent dataset Accelerometer, gyroscope (SisFall) dataset	Chest, waist	Event-ML, classification and regression tree (CART), kNN, logistic regression, SVM	Better precision and F-scores with Event-ML than FOSW and FNSW-based approaches
[33]	2018	SisFall dataset, generated from experiments	3-Axis accelerometer	Chest/thigh, waist	SVM, kNN, Naïve- Bayes, decision tree	Accuracy and sensitivity of SVM were the highest (97.6% and 98.3%, respectively) for both datasets.
[34]	2018	UMA Datasheet	Accelerometer, gyroscope, magnetometer	Wrist, waist, chest, ankle	kNN, Naive-Bayes, SVM, ANN, decision tree	Without risk categorization: 81% for decision tree With risk categorization: 85% for decision tree
[35]	2018	SisFall dataset original and manually labelled	3-Axis accelerometer	Not specified	RNN	Highest accuracy reported for fall detection: 83.68% (before manual labelling), 98.33% (after manual labelling)

Table 1. *Cont.*

Ref	Year	Dataset used	Sensor used	Sensor placement	Methodology	Performance parameter and details
[36]	2018	Generated from experiments	Accelerometer, gyroscope, magnetometer	Near the waist	kNN	Accuracy = 99.4%
[37]	2018	Generated from Experiments	3-Axis accelerometer	Waist	Decision tree	Accuracy = 91.67% Precision = 93.75%
[38]	2018	SiSFall dataset	3-Axis accelerometer	Waist	RNN with LSTM	Highest accuracy after hyperparameter Optimization (97.16%)
[39]	2018	Generated from experiments	Depth camera, accelerometer	Waist	CNN	Accuracy of fall detection = 100%
[40]	2018	Generated from experiments	Accelerometer, gyroscope, magnetometer	Hip	SVM, random forest	Without sensor fusion: Accelerometer
[41]	2019	Public datasets	Accelerometer, gyroscope	Chest, thigh	ANN, kNN, QSVM, ensemble bagged tree (EBT)	Extraction of new features from acceleration and angular velocity improved the accuracy of all 4 classifiers. Accuracy of EBT was highest (97.7%)
[42]	2019	SisFall dataset	Accelerometer, gyroscope	Waist	kNN, SVM, random forest	Accuracy for fall detection was the highest for kNN (99.8%). Accuracy for recognizing fall activities was the highest for random forest (96.82%)
[43]	2019	Public datasets	Accelerometer	Not specified	CNN-based models for feature extraction	Highest accuracy reported = 99.86%
[44]	2020	SiSfall dataset	Two triaxle accelrometers and gyroscope	Wrist	The XGBoost was implemented on spyder software with a 75-25 train-test split	Overall accuracy using XGBoost = 94.6%

Table 1. *Cont.*

Ref	Year	Dataset used	Sensor used	Sensor placement	Methodology	Performance parameter and details
[45]	2020	SiSFall dataset	Accelerometer and Gyroscope sensors inbuilt with Smartphone	Carrying smartphone on hand or pockets	Features were extracted from raw data and person's correlation was implemented, on the features RF,ANN, SVM and Boosted decision tree was implemented	Accuracies Random Forest = 99.7% ANN = 99.2% SVM = 98.5% Boosted decision tree = 99.9%.
[46]	2020	Generated from experimentation	All IMU sensors and heart-rate sensor	Wrist	Mean and median was calculated from Raw dataset and ANN, KNN, XGB, NB and Random Forest	Accuracy on mean and median ANN = 85.69% KNN = 94.3% XGB = 85.3% NV = 66% Random Forest = 99.7%
[47]	2021	Combination of experimentally Generated and publicly available datset	IMU Based sensor on wristwatch and smartphones	Wrist, waist pelvis	SVM,KNN and ANN was implemented	SVM (wrist placement) = 91.3% (waist placement) = 98% KNN (Wrist placement) = 99% (waist placement) = 99.8% ANN (Wrist placement) = 95.25% (Waist placement) = 92.96%
[48]	2021	UR Fall, MOBIFALL, UP Fall	Accelerometer, magnetometer, gyroscope, ECG sensor	MOBIFALL = trouser, pocket Up Fall = wrist, ankle Ur Fall = pelvis	Feature extraction was performed on the raw dataset and basic ML methods like RF,SVM,KNN, LR,BB and DT were implemented	UR Fall dataset = 99%(RF) UP Fall dataset = 99%(LR) MOBIFALL dataset = 99%(for nearly all mentioned algorithm)

Table 1. *Cont.*

Ref	Year	Dataset used	Sensor used	Sensor placement	Methodology	Performance parameter and details
[49]	2022	Generated from experiments	Accelerometer and gyroscope sensor	Wrist	Data augmentation to solve the imbalance of data set, classification was done by BiLSTM model	Combined sensor accuracy KNN = 74.70% RF = 75.64% SVM = 73.74% BiLSTM = 97.35%
[50]	2022	Generated from experiments	Image based, External placement	Camera based	Multiple images were captured of the subject's skeletal orientation, Standard deviation was calculated and fed into KNN based classifier	Overall accuracy of 95% was obtained
[51]	2022	SisFall, DaLiaC, UMAFall and Epilepsy	IMU based sensors	Wrist and Waist placement	Multiple algorithms were run like ANN, SVM, Decision Trees, Naïve Bayes and Deep learning based	Overall accuracy obtained by the classifier was 92.5%

3. Data Collection Methodology

There are multiple datasets available as described in the background section. There are multiple issues with the datasets:

- Very few public datasets available that have readings from multiple sensors. Most public datasets only have the linear acceleration data.
- Very few datasets available that have wide diversity in terms of age, gender, height, weight and health issues
- Even in datasets where there is diversity, no information is available on the ratio of gender, age, height or weight
- The number of volunteers are usually less. In most cases less than 20.
- The list of ADLs and falls are not completely provided
- The details of how long each activities lasted is not available.
- The data collection methodology is not described
- The details of the sensors used is not provided, hence using multiple datasets becomes a major issue as they cannot be fused together.

Though attempts have been made to compare datasets, not more than three or four [2] datasets are compared and only certain statistical parameters are analysed. Besides all these comparisons are done based only on accelerometer data. Due to these existing issues, we have collected our own data, this section gives the details of the volunteers diversity, the sensors and the data collection methodology.

We also provide the details of the features extracted that are to be used by the various ML algorithms. The datasets are available at "https://shamanx86.github.io/fall_detection_data/".

3.1. Volunteers statistics

- • No of volunteers: 41
- • Age range: 18-50
- • Number of female volunteers: 14.
- • Weight: 50 Kg – 120 Kg.
- • Height: 4ft 11 inches – 6ft 4 inches.

Existing Health issues: High blood pressure, Diabetes, Hypertension Claustrophobia, there were some volunteers who were prone to panic attacks, sinusitis, sinus tachycardia, thyroid, malnutrition, hypochondria, extreme anxiety, low blood pressure, prostate, and early sign of arthritis. The data was collected using a Samsung Galaxy Watch (Series 5) worn by all users on their left wrist. Samsung Galaxy (Series 5) was released in August 2020.

The dimensions of the watch are as follows: 44.4 X 42.3 X 9.8 mm. The watch weighs about 33.5 grams, the processor is a dual-core 1.18 GHz Cortex A55 and the GPU on the watch is Mali-G68.The sensors available on the watch are: Accelerometer, Gyroscope, Magnetometer and Heart-Rate. The Heart-Rate sensor is extremely accurate and comparable to medical grade sensor [52]. IMU sensors are already pre-calibrated for wrist-worn positions and are extremely accurate. Each volunteer was asked to wear the watch on the left wrist while performing the following ADL and Fall activity:

3.1.1. ADL

1. Walking Slowly (2 min)
2. Walking Quickly (2 mins)
3. Jogging (2 min)
4. Jogging (2 min)
5. Climbing up slowly (2 mins)
6. Climbing down slowly (2 mins)
7. Climbing up normal (2 mins)
8. Climbing down normal (2 mins)
9. Slowly sitting on a chair (nil)
10. Rapidly sitting down on a chair (na(not applicable))
11. Nearly Sitting on the chair getting up (na)
12. Swinging Hands (2 mins)
13. Lying on the bed (2 min)
14. Lying on the back and getting up slowly (na)
15. Lying on the back and getting up quickly (na)
16. Transition from sideways to one's back while lying down (na)

3.1.2. Fall

1. Forward fall landing on the knees (30 secs on the ground)
2. Right fall (30 secs on the ground)
3. Left fall (30 secs on the ground)
4. Forward fall (30 secs on the ground)
5. Seated on the bed and falling on the ground (30 secs on the ground)
6. Forward fall body weight on the hand (30 secs on the ground)
7. Backward fall from seated position (30 secs on the ground)
8. Grabbing while falling (30 secs on the ground)

Table 2. Summary of the volunteer statistics.

Sr no.	Parameter	Values and Nos
1	Gender	Male = 27 Female = 14
2	Age-range	20-30 years = 29 30-40 years = 6 >40 years = 6
3	Weight-range	50 Kg – 65 Kg = 21 65 Kg – 80 Kg = 16 80 Kg – 100 Kg = 3 100 Kg – 120 Kg = 1
4	Height Range	5ft – 5ft 5in = 23 5ft 5in – 6ft = 16 >6ft = 2
5	Health Issues	No. of subjects with health issues = 17 No. of subjects without health issues = 24 Health Conditions of subjects: Sinus Tachycardia, High Blood Pressure, Overweight, Folic acid allergy, Obese, Thyroid, Hypochondria, extreme anxiety Low Blood Pressure, Prostrate, Sinusitis and Genetic Diabetes

The data was collected by asking the volunteers to perform the falls within an anechoic chamber. As the anechoic chamber is padded with a thick sponge, during the falls, the volunteers landed on the soft material, and hence they were not injured. As a result, all falls ended up being soft falls. Using 41 volunteers about 1.9 million data points were collected. The features were then extracted from the data. The features were statistical in nature. The statistical parameters derived were mean, standard deviation, variance, minimum, maximum, skew and kurtosis. After feature extraction, we had 100,208 data points that were used for training and testing.

4. Experimental methodology

In order to analyse the data we collected, for efficiency in fall detection, we used five common ML algorithms. (a) Naïve Bayes [53] (b) KNN [54] (c) Logistic regression [55] (d) Random Forest [56] (e)SVM(Suppport vector machine) [57]. To understand the variations in accuracies we used various combinations of the user demographics. This was done to understand the effect of user parameters such as gender, age, height, weight and health issues on the accuracies. We also analysed which of the ADLs and Falls were incorrectly detected with respect to the user parameters. We used a combination of user demographics to understand the behaviour of the algorithm and why there were variations in Accuracies, Sensitivity, Specificity and False Negative rates. We used a combination of varying user parameters for training and testing. For example, to understand the effect of gender on the test accuracies we first ran the ML algorithms separately for male volunteers using their data for both training and testing. We repeated the same for the female volunteers. Then we used the data of the female volunteers for training and the male volunteers for testing and vice-versa. Many of the existing public datasets which are used for training the ML algorithms have similar user demographics. In most cases the volunteers are male and in the age between 20 and 30 years with no known health issues. The actual users of the end product will be people above 60 years, both male and female with several pre-existing health conditions. Under these circumstances, whether the fall prediction algorithms will work accurately needs to be analysed. Hence in this paper, we have tried to analyse the behaviour

of the algorithms with varying user demographics. The combinations that we used for testing and training are given in Table 3.

Table 3. Train and Test Combinations.

Sr no.	User Demographics	Range	Train		Test
1	Age	<30 30-40 40-50	<30 Train) <30 <30 30-40 30-40 40-50	(70%	<30 (30% test) 30 -40 40 - 50 30 - 40 40 - 50 40 - 50
2	Gender	Male Female	Female Male Male Female		Female Male Female Male
3	Health Issues	With Without	Without With With Without		Without With Without With
4	Height	<5.5ft >5.5ft	<5.5ft >5.5ft <5.5ft >5.5ft		<5.5ft >5.5ft <5.5ft >5.5ft
5	Weight	50-65 65-80 80-120	50-65 65-80 80-120 50-65 50-65 65-80 65-80 80-120 80-120		50-65 65-80 80-120 65-80 80-120 50-65 80-120 50-65 65-80

We ran the algorithms with and without the data from heart rate sensors to understand the effects of biometric parameters during falls. In the next section, we give the complete results and the analytics.

We also analysed the behaviour of the algorithms with respect to the ideal "k" value in the case of KNN and found out that it was equal to 9 where we achieved the maximum accuracies, also it was "Minkowski" distance metrics that gave us the highest accuracies at lower "k" values. In the case of Random Forest, we had to find the optimal number of decision trees which yielded the best results which in our case was 170. The results remained the same for with, as well as without heart rate, in the case of Random Forest with 170 decision trees.

5. Results and Discussion

5.1. Overall Performance Analysis for various ML algorithms with varying data sizes

We initially analysed the effect of varying data sizes on the performance of ML algorithms before analysing the effect of user demographics on the performance of the algorithms. As mentioned in earlier sections we have used the common ML models (a) Naïve Bayes (b) KNN (c) Logistic Regression (d) SVM (e) Random Forest.

The accuracy, specificity and sensitivity of various algorithms with (a) 41 users (b) 35 users (c) 30 users (d) 25 users (e) 20 users and (f) 10 users is shown in Figures 2–7.
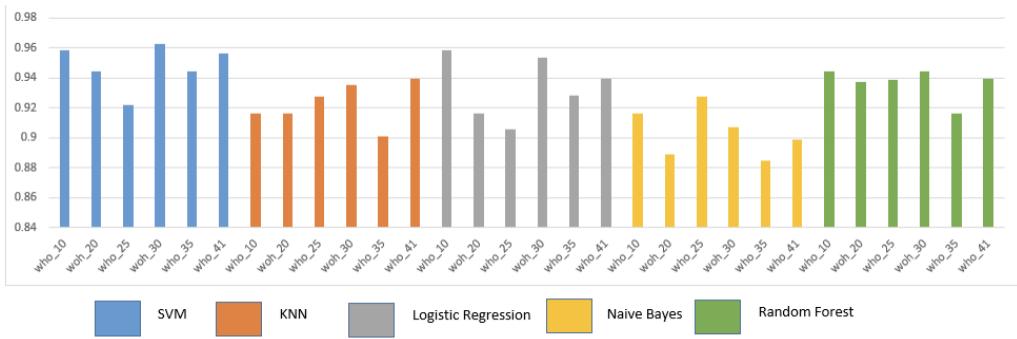
**Figure 2.** Accuracy vs number of users (without heart rate).
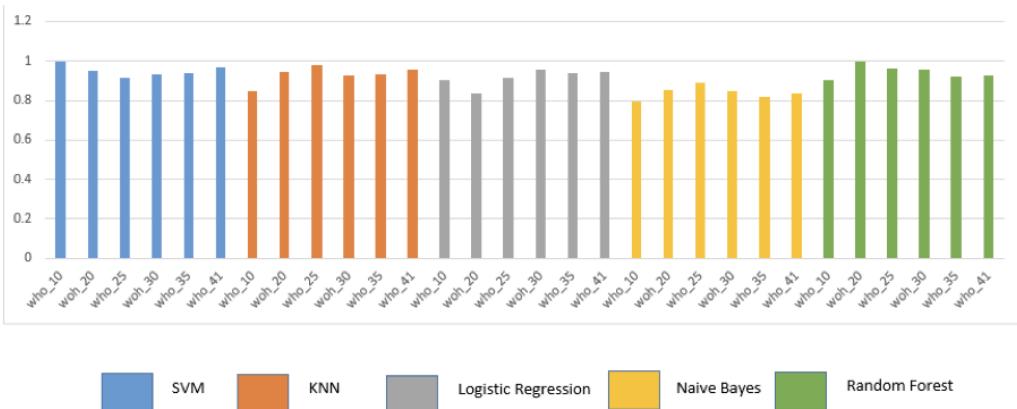
**Figure 3.** Specificity vs number of users (without heart rate).
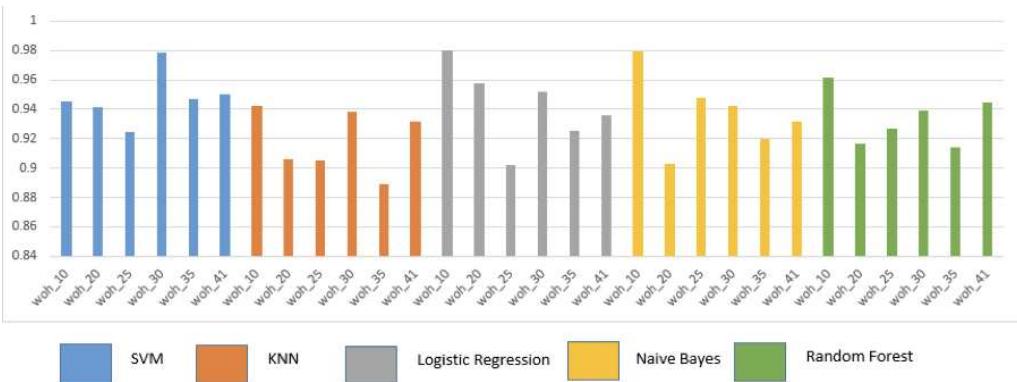
**Figure 4.** Sensitivity vs number of users (without heart rate).
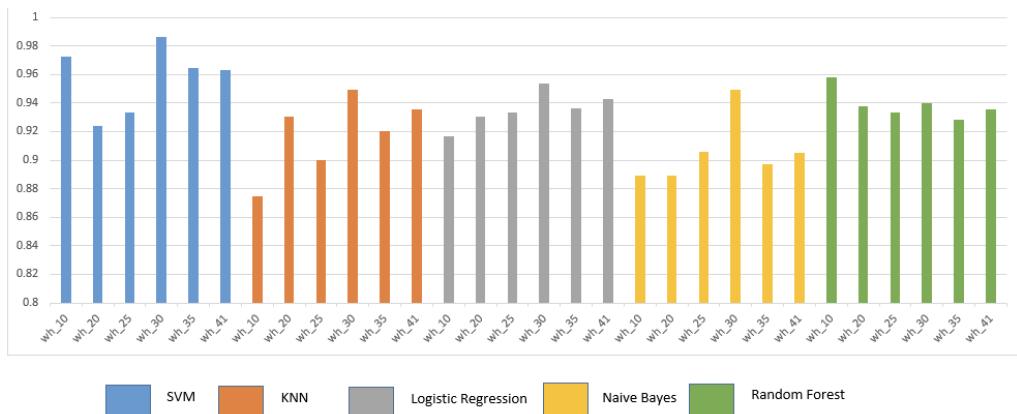
Figure 5. Accuracy vs number of users (with heart rate).
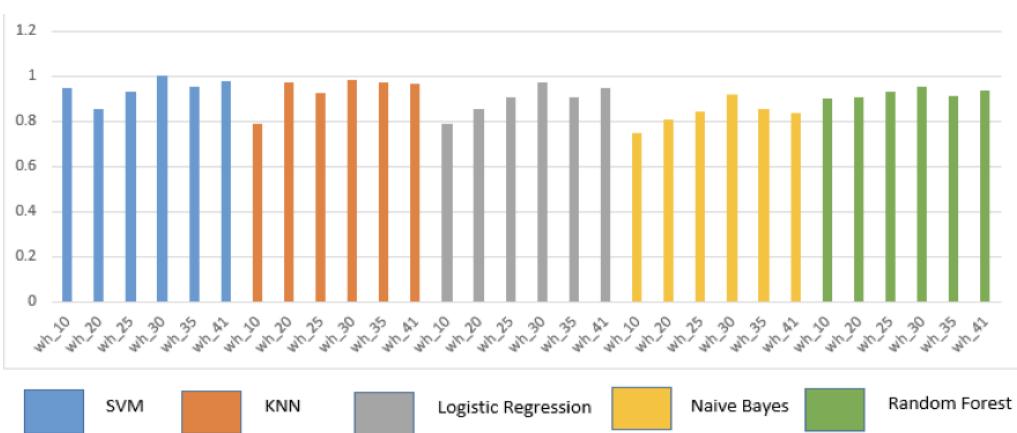
Figure 6. Specificity vs number of users (with heart rate).
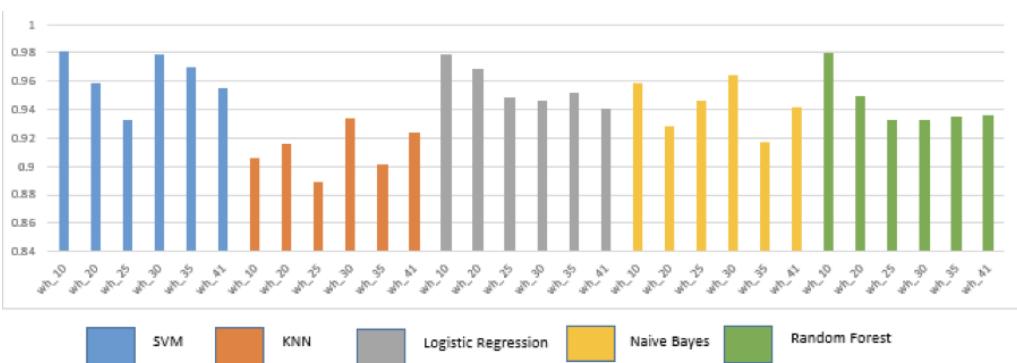
Figure 7. Sensitivity vs number of users (with heart rate).

The best results among all the algorithms were obtained when heart rate was included, as can be seen in Figures 2 and 5. The best result was obtained for 30 users for all algorithms, except for random forest (where the best result was obtained at 10 users), with heart rate the peak accuracy was 98.5% obtained by SVM and 96.5% without heart rate again in SVM. For all user combinations, with and without heart rate the sensitivies were higher than the specificity. This is as per the requirement for Fall detection. Since we are dealing with geriatrics a false positive is better than a false negative. The main activities that were incorrectly detected were those of User-1 as the subject had an erratic heart rate due to a medical condition known as Sinus Tachycardia. In the case of other users, very few ADL or Fall activities failed since we had selected the 10, 20, 25, 30 and 35 users randomly out of the total 41 users. Wherever user 1 was not selected we had better results. When heart rate was ignored several of

the ADL activities which were related to "lying on the bed" or "getting up slowly/quickly from the bed" were incorrectly detected as falls depending purely on the IMU sensor's values. Also "backward falls and falls from the bed" were incorrectly detected as ADL activities for several users. When heart rate was ignored more of User – 1 activities were incorrectly detected especially since several of the ADLs were construed as false positives. This included "lying on the bed", "lying on the back and getting up slowly/quickly" and "transitioning sideways to one's back while lying down". This caused a drop in accuracy from 99% to 98%. Especially due to a drop in specificity values from 0.99 to 0.98. It can be concluded from the results that when we use the heart rate of a volunteer with severe health conditions the accuracies obtained are better especially since there will not be a huge spike in heart rate while performing Fall activities as against performing ADL activities. The sensitivity was higher by almost 1.5% when heart rate was used and the specificity was high when heart rate was ignored.

Tables 4 and 5 show the accuracy, sensitivity and specificity for the various age groups "under 30", "30-40" and "40-50" for individual algorithms with and without heart rate. As usual, Naïve Bayes gives the lowest accuracy and SVM gives the highest accuracy. When training and testing were done with the same age group, it can be observed from the table that the impact of accuracy is not much. The accuracies have dropped in the case of all the algorithms as the size of the dataset would have been reduced as we only considered volunteers under the age of 30. While the accuracies of SVM with the whole dataset went up to 98.5%, here the highest accuracy again being produced by SVM is 95.10% for the age group of >30, in the case of 30-40 it drops to 87.50% as the number of volunteers in this age group was lesser. At 40-50 it was higher at 90.91%. In the case of 40-50, Random Forest and Logistic Regression gave the highest accuracies at 93.18%. Random Forest's Decision trees work equally well with large as well as smaller data sets. When the simulations were run with volunteers being under 30, heart rate had a huge impact for the higher age range which is 40-50 with Random Forest giving an accuracy of 99.31%. But in the case of 30-40, the IMU sensors had the higher impact. Since in most scenarios in practical life, volunteers would be in the age group of below 30 and users will be in the range of 50 and above; The impact of heart-rate is very significant. When we analysed which of the users were causing a fall in accuracy, they were primarily users in the age range of 30-40 but though they were physically fit, they had pre-existing health conditions and were on medications. Primarily user 30 with the pre-existing prostate condition and user 35 with a pre-existing diabetic condition.

Tables 6 and 7 show the accuracy, sensitivity and specificity of the male and female participants for individual ML algorithms with and without heart rate. From the table, it can be seen that we get better accuracies with heart rate in the case of male but in the case of female the accuracies fall with heart rate. In case of females, the accuracies seems to increase or drop erratically because the number of female were only little more than 1/3rd of the entire set of volunteers. When trained with the Male data set and tested with the Female, we got better results both in case of With and Without heart rate, because the training was done with a larger population than the number of test subjects. This shows that the size of the data set has a huge impact while the gender does not have a large impact in accuracy. So its very important to train the models with large datasets with the gender being insignificant. The train set must be larger than the test set.

Table 4. Analysis of the impact of age on accuracies.

Train	Test	Accuracy (%)					Sensitivity (%)					Specificity (%)				
		SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF
< 30	< 30	94.60	92.15	92.64	86.76	92.15	93.38	89.51	93.18	91.80	91.24	97.06	98.36	91.67	79.27	94.03
< 30	30-40	92.50	90.00	89.38	87.50	90.63	92.37	89.34	90.60	89.66	90.76	92.86	92.11	86.05	81.82	90.24
< 30	40-50	96.53	95.14	95.83	93.75	99.31	95.96	93.20	95.92	93.94	98.97	97.78	100	95.65	93.33	100
30-40	30-40	85.42	81.25	83.33	72.92	87.50	84.21	78.57	83.78	85.71	84.62	90.00	100	81.82	55	100
30-40	40-50	90.28	89.58	90.97	88.89	95.83	91.84	86.49	91.92	97.62	94.12	86.96	100	88.89	76.67	100
40-50	40-50	93.18	88.64	93.18	84.09	90.91	90.32	84.85	93.10	92.00	92.86	100	100	93.33	73.68	87.50

* With Heartrate

Table 5. Analysis of the impact of age on accuracies.

Train	Test	Accuracy (%)					Sensitivity (%)					Specificity (%)				
		SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF
< 30	< 30	95.10	91.67	93.14	87.25	92.16	92.81	89.44	93.23	93.28	90.07	100	96.77	92.96	78.82	96.83
< 30	30-40	92.50	90.52	89.38	87.50	90.63	92.37	90.08	90.60	89.66	89.43	92.86	92.31	86.05	81.82	94.60
< 30	40-50	95.83	95.14	95.14	94.44	99.31	95.92	93.20	94.95	96.81	98.97	95.65	100	95.56	90	100
30-40	30-40	87.50	81.25	79.17	72.92	87.50	86.49	78.57	82.86	85.71	84.62	90.91	100	69.23	55	100
30-40	40-50	90.97	88.89	90.28	88.19	93.75	91.09	85.71	91.84	98.77	92.23	90.70	100	86.96	74.60	97.56
40-50	40-50	90.91	86.36	93.18	84.09	93.18	90	82.35	93.10	88.89	93.10	92.86	100	93.33	76.47	93.33

* Without Heartrate

Table 6. Analysis of the impact of gender on accuracies.

Train	Test	Accuracy (%)					Sensitivity (%)					Specificity (%)				
		SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF
Female	Female	93.07	86.14	88.12	84.16	93.07	96.92	92.19	95.16	94.83	95.52	86.11	75.68	76.92	69.77	88.24
Male	Male	93.33	92.82	95.90	89.23	92.82	93.13	90.00	94.70	91.34	91.79	93.75	100.00	98.41	85.29	95.08
Male	Female	94.35	90.48	94.35	89.58	93.45	94.37	88.40	94.76	89.21	93.16	94.29	96.51	93.46	90.53	94.12
Female	Male	91.82	92.59	92.90	91.05	93.83	90.58	91.20	93.47	93.29	92.79	95.03	96.15	91.67	86.57	96.32

*With heart rate gender

Table 7. Analysis of the impact of gender on accuracies.

Train	Test	Accuracy (%)					Sensitivity (%)					Specificity (%)				
		SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF
Female	Female	95.04	89.10	89.10	85.14	93.06	98.46	93.84	95.23	94.91	95.52	88.88	80.55	78.94	71.42	88.23
Male	Male	92.30	92.82	95.38	88.71	92.82	93.02	90.57	94.65	91.26	92.42	90.90	98.24	96.87	84.05	93.65
Male	Female	93.75	92.26	94.05	89.29	92.56	93.94	91.25	94.74	89.17	92.34	93.33	94.79	92.59	89.58	93.07
Female	Male	92.44	92.28	92.44	90.43	94.14	90.83	90.81	93.03	93.43	93.20	96.56	96.11	91.13	84.68	96.35

*Without heart rate gender

Tables 8 and 9 show the accuracy, sensitivity and specificity for subjects with pre-existing health conditions and subjects who did not have any health conditions were used as participants. Table 8 shows the result with heart rate whereas Table 9 shows the result without heart rate.

Of the 41 volunteers, 12 of them had pre-existing health conditions that varied from high blood pressure, diabetes, claustrophobia, vertigo, sinus trachardia, prostate and obesity, etc. To study the effect of health conditions on the prediction we ran the algorithm separately for the volunteers with health issues and without health issues. Performance of the algorithms was better when heart rate was associated with people who did not have any pre-existing health issues. When we tried training the algorithm using people with health issues and testing them with volunteers who did not have any health issues and vice-versa, the heart rate had no such impact in the first case however in the second case there was a slight improvement in accuracies as can be seen in Tables 8 and 9.

Based on this we can come to a conclusion that the presence of health issues does affect the accuracy of fall detection and since erratic heart rate is usually associated with health issues, there is more possibility of errors when heart rate is used as one of the features to detect falls. This will prove to be a major hurdle as we move forward in our research since there are very few elderly who do not have any pre-existing health conditions, in fact in our 40-50 age group only one volunteer had no health issue or was not under any form of medication.

Table 8. Analysis of the impact of Pre-existing health on accuracies.

Train	Test	Accuracy (%)					Sensitivity (%)					Specificity (%)				
		SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF
Without	Without	96.11	93.33	93.89	92.22	95.56	95.80	93.33	94.12	95.54	95.00	96.72	93.33	93.44	86.76	96.67
With	With	91.38	83.62	90.52	84.48	91.38	93.75	82.80	93.67	86.90	91.67	86.11	86.96	83.78	78.13	90.63
With	Without	95.00	91.50	94.17	90.83	94.00	95.12	89.21	95.06	91.17	94.17	94.74	98.06	92.31	90.06	93.62
Without	With	94.27	92.19	92.71	89.06	94.53	94.32	91.85	92.54	91.80	93.04	94.17	92.98	93.10	83.59	98.20

*With heart-rate health issues

Table 9. Analysis of the impact of Pre existing health on accuracies.

Train	Test	Accuracy (%)					Sensitivity (%)					Specificity (%)				
		SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF
Without	Without	93.33	92.22	93.89	94.44	96.11	93.33	91.13	94.87	95.69	95.80	93.33	94.64	92.06	92.19	96.72
With	With	90.52	85.34	88.79	83.62	92.24	93.67	83.87	92.41	86.75	91.76	83.78	91.30	81.08	75.76	93.55
With	Without	96.50	92.00	94.50	90.00	93.83	97.73	90.18	95.76	90.67	94.38	94.09	96.91	91.96	88.46	92.67
Without	With	93.49	92.45	92.71	88.80	93.75	94.25	92.19	92.54	91.44	92.65	91.87	93.04	93.10	83.46	96.43

*Without heart rate health issues

Tables 10 and 11 show the accuracy, sensitivity and specificity for the subjects having height below 5ft 5in and subjects having height above 5ft 5in for data with and without heart rate respectively. The behaviour of the model would definitely be impacted by the height of the person as the amount of change in IMU values would be dependent on the person's height. For a person whose height is above 5ft 5in, which is also the average height of a person of Indian origin, there is no effect of heart rate on the accuracy and the accuracy is completely dependent on the values derived from the IMU sensors. For people who are lesser than 5ft 5in the accuracy drops when heart rate is used. Even otherwise accuracies for people of height more than 5ft 5in are slightly higher than the volunteers whose height is lesser than 5ft 5in. With progression in age, the skeletal structure of a person may change introducing conditions such as hunchbacks which may cause a reduction in height, and hence the accuracies will be affected. When we trained using volunteers of height greater than 5ft5in and tested with volunteers with height less than 5ft 5in, there was a definite drop in accuracy both with and without heart rate. Whereas when we trained with people of height less than 5ft5in and tested using volunteers of height greater than 5ft5in, in the case of some of the ML models, there was a slight increase in accuracy with and without heart rate. This shows that the IMU sensors produce drastically different values that varies with the height of the person. Though we are extracting statistical parameters, the height of the person has a huge impact on the accuracy of the model. Hence, if we use volunteers who are young and in good physical condition and having an above average height to train the ML models and use it on elderly who will have pre-existing health issues, weakening of the muscular structure and reduced height, several of the ADLs may be misinterpreted as falls because the drop in accuracy here is due to the drop in specificity rather than sensitivity. This might be acceptable because in the case of the elderly, it is better to err on the side of caution.

Table 10. Analysis of the impact of varying heights on accuracies.

Train	Test	Accuracy (%)					Sensitivity (%)					Specificity (%)				
		SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF
< 5.5	< 5.5	92.77	91.57	91.57	89.76	91.57	93.69	90.60	92.79	91.82	90.60	90.91	93.88	89.09	85.71	93.88
> 5.5	> 5.5	93.85	90.77	91.54	86.15	93.08	97.56	89.36	97.47	91.46	93.26	87.50	94.44	82.35	77.08	92.68
> 5.5	< 5.5	93.12	90.40	92.93	90.76	91.85	93.19	87.77	92.51	89.92	90.27	92.94	98.52	93.94	92.90	96.03
< 5.5	> 5.5	94.91	92.82	94.68	89.81	93.75	94.93	91.05	95.22	92.36	93.94	94.85	97.48	93.53	84.72	93.33

*With heart rate height

Table 11. Analysis of the impact of varying heights on accuracies.

Train	Test	Accuracy (%)					Sensitivity (%)					Specificity (%)				
		SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF
< 5.5	< 5.5	95.18	93.98	92.17	90.36	91.57	97.20	93.04	93.64	92.66	90.60	91.53	96.08	89.29	85.96	93.88
> 5.5	> 5.5	94.62	90.77	90.00	83.85	93.08	96.47	89.36	96.20	89.16	93.26	91.11	94.44	80.39	74.47	92.68
> 5.5	< 5.5	92.93	90.40	93.12	90.40	93.30	92.73	88.14	92.53	90.28	91.69	93.41	97.12	94.51	90.68	97.42
< 5.5	> 5.5	95.14	93.06	94.68	89.35	93.98	94.95	91.35	95.22	92.01	94.26	95.56	97.50	93.53	84.03	93.38

*Without heart-rate height

Tables 12 and 13 show the accuracy, sensitivity and specificity for the subjects having weight in the range of 50-65 kgs, subjects having weight in the range of 65 to 80, subjects having weight in the range of 80 to 120 Kgs with and without heart rates respectively. The impact of the weight of the subject on accuracies is very high, with accuracies for lower weight range i.e 50-65 Kgs and accuracy drops with an increase in weight. Also, the impact of heart rate on accuracy is visible only in the weight ranges of 80-120 kgs. As the weight of the person will have an impact on the heart rate as he/she performs stressful activities. Again cross-testing and training have the least impact on the weight ranges of 50-65 Kgs. When trained on the weight range of 50-65 Kgs and tested against ranges 65-80 and 80-120, the accuracies are not severely affected. But training with other weight ranges affects the accuracy as can be seen in the table. The drop in the accuracies in the weight range 65-80 is mainly due to the drop in specificity rather than sensitivity. When the weight is in the range of 50-65 which is usually below the Indian average or 80-120 which is above the Indian average, most of the ADL activities are detected correctly except in the case of Naïve Bayes where the sensitivity is better than specificity, but NB is more of a threshold based algorithm and its accuracies are generally very low. Again the elderly are prone to be frail with their weight being less than the average. Hence, we can get better accuracies irrespective of the age group used for training and testing.

Table 12. Analysis of the impact of varying weight on accuracies.

Train	Test	Accuracy (%)					Sensitivity (%)					Specificity (%)				
		SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF
50-65	50-65	96.35	94.89	94.89	89.78	93.43	94.68	93.62	94.57	95.18	92.55	100.00	97.67	95.56	81.48	95.35
65-80	65-80	91.67	87.96	88.89	84.26	92.59	93.75	87.50	95.89	91.89	94.94	85.71	90.00	74.29	67.65	86.21
80-120	80-120	94.12	90.20	90.20	90.20	92.16	92.11	91.67	91.67	96.88	91.89	100.00	86.67	86.67	78.95	92.86
50-65	65-80	93.89	94.17	92.78	91.39	93.61	93.60	92.94	94.21	92.65	92.22	94.55	97.14	89.83	88.70	97.09
50-65	80-120	89.29	90.48	86.90	86.90	88.69	91.23	89.34	88.79	90.91	89.74	85.19	93.48	82.69	79.31	86.27
65-80	50-65	94.74	91.01	93.64	91.45	93.42	95.45	89.25	94.50	92.88	93.35	93.24	95.87	91.84	88.44	93.57
65-80	80-120	94.64	89.29	91.07	88.69	90.48	94.78	87.30	93.69	91.15	90.00	94.34	95.24	85.96	83.64	91.67
80-120	50-65	88.60	87.06	92.54	90.57	92.76	88.41	85.30	93.27	92.23	91.44	89.06	92.66	90.97	87.07	96.12
80-120	65-80	91.94	88.06	92.50	90.00	93.06	92.37	86.08	92.77	92.50	91.19	90.99	94.25	91.89	85.00	97.98

*With heart rate on weight

Table 13. Analysis of the impact of varying weight on accuracies.

Train	Test	Accuracy (%)					Sensitivity (%)					Specificity (%)				
		SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF	SVM	KNN	LR	NV	RF
50-65	50-65	94.89	95.62	94.89	89.78	93.43	93.62	94.62	95.56	95.18	92.55	97.67	97.73	93.62	81.48	95.35
65-80	65-80	92.59	87.04	91.67	83.33	92.59	94.94	85.71	96.05	90.67	94.94	86.21	94.12	81.25	66.67	86.21
80-120	80-120	90.20	88.24	92.16	90.20	92.16	89.47	87.18	94.29	96.88	91.89	92.31	91.67	87.50	78.95	92.86
50-65	65-80	94.44	94.44	93.06	91.11	93.06	94.72	92.97	94.61	91.60	91.19	93.86	98.08	89.92	90.00	97.98
50-65	80-120	90.48	90.48	89.29	87.50	89.29	92.11	90.00	90.52	89.57	89.83	87.04	91.67	86.54	83.02	88.00
65-80	50-65	95.18	92.11	94.30	91.45	93.64	96.08	90.61	94.84	93.44	93.93	93.33	96.03	93.15	87.42	93.01
65-80	80-120	93.45	89.29	89.88	87.50	90.48	93.91	87.30	91.30	89.57	90.00	92.45	95.24	86.79	83.02	91.67
80-120	50-65	90.35	87.72	92.54	89.47	92.54	91.67	86.05	94.41	92.11	91.41	87.50	92.86	88.82	84.21	95.38
80-120	65-80	91.94	86.11	92.50	89.44	92.22	92.37	84.17	92.77	91.74	90.46	90.99	92.68	91.89	84.75	96.94

*Without heart rate on weight

6. Conclusion

Though there a multiple data sets available, and we have used them in our previous works, we were unable to interpret the reasons for the rise or fall in accuracy. Hence we collected our own data and analyzed it. In this paper, we have attempted to analyze the effect of various characteristics such as age, height, weight, gender and health issues on the accuracy of the various well-known ML algorithms. In geriatric fall detection, it is a given that the test volunteers and the actual users will belong to different categories. While the test subjects are usually in the age range of 20-35 in most data sets, we stretched the age range between 20-50, but the actual users would be the elderly or the super elderly. While we did have some users who had serious existing health conditions and were on medication and we did find a fall in accuracy when we trained using healthy volunteers and tested the accuracy for volunteers with health issues. The loss in accuracy was primarily due to a drop in specificity hence some of the ADLs were being incorrectly interpreted. In some cases, the use of heart rate helped improve the accuracy in some cases the impact of heart rate caused a drop in accuracy. But we still recommend the use of heart rate as one of the parameters as any changes in heart rate in the elderly supported by the data from IMU sensors may be indicative of a fall.

The problem with multiple datasets is also that the demographics of the users tend to change with countries. In countries with a good health infrastructure and where healthy living is promoted, the ageing process is more graceful. The average height and weight also vary across countries. In India, healthy living and exercising are new concepts, overindulgence is a norm here; hence most elderly India suffer from various health conditions, and very few of them have access to good healthcare services due to the cost. Falls may times go undetected, repeated falls in the elderly are also very common in India. We need data sets that represent the Indian demographics. We have attempted to create such a database and we have analyzed the database in detail for various user parameters such as age, gender, health issues, height and weight.

The number of features we have is 100,208 after feature extraction, we also plan to add certain parameters such as height and weight that have a huge impact on the accuracy as part of the features. We were also able to identify certain users who were outliers, this could be used to clean the data set further, we have currently retained the outliers as there may be final users who may have similar characteristics.

We plan to run the ML algorithms on the end device built around Qualcomm Snapdragon 820c. This means features have to be pruned and the ML algorithms compressed so that the latency in obtaining the prediction will be much lesser than the sampling rate and timely alerts can be issued.

Understanding the impact of features and user characteristics is the first step to pruning of features which is what we have attempted in this paper. We collected data that is specific to the local user demographics, extracted relevant features and analysed the performance of the ML algorithms on the collected data.

A perfect data set would be one where the demographics are uniform and similar to the end user demographics. While some public data sets have attempted to use the elderly to do a limited number of ADLs, they have not been able to show a significant improvement in accuracy. Hence, we have to proceed with skewed data sets. The application of ranking and pruning of features gains importance, this is the next step in our work. This is required as we plan to use Dew computing IoT model.

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