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Activity Recognition for Elderly Care Using Genetic Search

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Abstract. The advent of newer and better technologies has made Human Activity Recognition (HAR) highly essential in our daily lives. HAR is a classification problem where the activity of humans is classified by analyzing the data collected from various sources like sensors, cameras etc. for a period of time. In this work, we have proposed a model for activity recognition which will provide a substructure for the assisted living environment. We used a genetic search based feature selection for the management of the voluminous data generated from various embedded sensors such as accelerometer, gyroscope, etc. We evaluated the proposed model on a sensor-based dataset - Human Activities and Postural Transitions Recognition (HAPT) which is publically available. The proposed model yields an accuracy of 97.04% and is better as compared to the other existing classification algorithms on the basis of several considered evaluation metrics. In this paper, we have also presented a cloud based edge computing architecture for the deployment of the proposed model which will ensure faster and uninterrupted assisted living environment.

Keywords: Activity Recognition; HAR; Genetic Search Algorithm; HAPT; SMO; Edge Computing; Cloud Computing.

1. Introduction

Old age refers to the critical part of life where a person is more prone to various accidents and life threatening hazards. As per the survey led by World Health Organization (WHO), old age population will grow by 56%, from 962 million in the year 2017 to 1.4 billion speculated in 2030 and the population will be doubled to2.1 billion by the year 2050 [2]. Old age requires proper care, comfort as well as alert monitoring but today's fast-paced lifestyle of family members do not allow them to always stay near and be vigilant. So it is the need of the hour to provide assisted living based on activity recognition. HAR is considered as evolutionary technology listed under the category of pervasive computing which is applicable to lots of real-life-care activities such as assisted living, smart home models, disaster detection, healthcare, fitness tracking, etc. [1]. This assisted living with healthcare monitoring facility can be extended to elderly people without invading their privacy which is a very important aspect. This concern has been addressed with the use of implanting sensors to various wearable gadgets. Now for monitoring and analysis purpose, the HAR is generally obtained by collecting, compiling, and analyzing sensor or visual data [4]. Apart from this for research purpose, many sensor-based datasets such as OPPORTUNITY, MHEALTH, WISHDM, UCI-HAR [7], HAPT [8], etc. are also available in the public domains which are obtained by collecting data from both body-worn sensors and ambient sensors. There are some activity recognitions data collected from subjects in natural out-of-lab settings but do not quantify recognition accuracy [6].

Over last two-decade various research works have been done in the area of HAR. Starting from Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), and Radial Basis Function (RBF) to knowledge based approach, Convolutional Neural Network (CNN) based models [37, 38, 39], Dual-Path CNN-RNN models are used to classify activities [31]. The dire necessity is to find a method to classify the activities that minimizes the cost involved while maximizing the production efficiency [5, 40]. In this regard the use of smart phones embedded with built-in sensors such as microphones, dual cameras, accelerometer, gyroscopes, etc. can be considered as a pertinent option to enable cost minimization objective.

1.1. Motivation

After studying the various works done in the field of HAR, we could find the following limitations:

- The use of vision-based activity recognition hampers the privacy of elderly people.
- Some authors use environmental sensors which defy portability to achieve mobility, and also might give trouble if multiple people are in the same space.
- The use of wearable sensors might be uncomfortable and irritable for elderly persons.
- Scarcity of data in ontological, knowledge-driven method fails to define abnormality in the data.
- A variant of accuracies and time complexities were found by using different classification techniques. We can say that the quest to achieve higher accuracy gives

rise to higher time complexity [27] which can be a big problem in the implementation of Mobile-based health application.

In all the works done in the literature, basically two challenges arise those have motivated us towards our proposed work such as:

As data acquisition through these smart phones contains a large number of features; it makes classification susceptible to over-fitting and increases the training and testing time of classification [18]. To avoid this, feature selection contributes a lot in getting the essential features as a subset of original features to avoid over-fitting. It can be filter-based, wrapper-based, and embedded. In the case of elderly activity recognition, filter-based feature selection is preferred as it preserves the original features and finds a subset of best features by keeping accuracy as a threshold [36]. Even though, the classification algorithms those have their primary potential as features selection are used in embedded feature selection, the demand for resource usage is huge when computed [9]. After dimensionality reduction, the next task performed is activity classification for which many Machine Learning based algorithms have been used.

Utilizing wearable gadget's limited resources such as memory, energy, embedded sensors may lead to a decrease in computation performance and efficiency of the system. It is also important to develop a model which is movable, consumes low-battery, uses low-cost sensors, gives high accuracy, and preserves the privacy of the user [11]. So the amalgamation of Edge computing with Mobile Cloud computing can be a feasible solution.

1.2. Contributions

Keeping into consideration the above mentioned limitations and challenges; we propose a model that has a threefold contribution:

- We have proposed a cost efficient feature selection based approach for HAR classification.
- A comparison of obtained results of activity recognition with and without implementation of feature selection was performed.
- We have also proposed a cloud-based architecture for the development of a mobile application of HAR for elderly care.

Section 2 presents a summarization of related works done in this area with the limitations The proposed methodology is discussed in Section 3 and the experimentation with results is stated in Section 4. In Section 5, proposed cloud architecture is described and Section 6 presents the conclusion and future work.

2. Related Work

HAR has a crucial functionality towards the management of several health risks and diseases and providing an assisting environment is the purpose of an activity recognition system. So many works have been proposed by several researchers regarding activity recognition in the last two decades. In this section, we have discussed the major works done in the field of HAR to develop elderly care applications along with the corresponding limitations and research gaps.

Most recently, a hybrid LSTM was implemented with the Bayesian optimizer which achieved 99.39% of accuracy when experimented with the UCI-HAR dataset [28], but the model does not contain any postural transitions (sit-to-stand, stand-to-sit, sit-to-lie, etc.). A CNN-LSTM model integrated with Adam optimizer, when tested for HAR with datasets WISDM and UCI-HAR, obtained an accuracy of 95.85% and 95.78% respectively [27], but the computation is mentioned to be slow as the dependency in between does not allow parallel processing. Researchers have also used the Sequential Floating Forward Search (SFFS) feature extraction technique and SVM classification algorithm and achieved 96.81% accuracy. Using deep embedding derived from a fully convolutional neural network to classify the activities of several datasets and the WISDM dataset gave an accuracy of 91.3% with Personalized Triplet Network (PTN) [3]. A binary classification dataset has been proposed to achieved an accuracy of 96.81% by applying Random Forest [26].

MLP which implements Xavier's algorithm for random weight initialization [12] has been used for HAR using off-the-shelf smart-watches as well as location was added using movement information. For feature extraction and classification, histogram of gradient, and Fourier Descriptor based on Centroid signature, were adopted [17] respectively with UCI-HAR dataset. But in these contexts, researchers mentioned that the continuity of an activity, and unintended movements of the lower body part can introduce noise in the dataset which might lead to misclassification. A Dual-Path CNN-RNN that was integrated with Adam optimizer, for the purpose of achieving multi-size receptive field for better feature extraction the CNN was used. Next Recurrent Neural Network(RNN) and fully connected layers has been used to learn map between given feature and to produce output for HAR [16]. Implementation of classifiers such as MLP, SVM, and RBF which gave 81.52%, 72.18%, and 90.23% respectively [1].Various decision trees like Random Forest, Random Tree, Hoeffding Tree, Decision Stump, J48, and REP Tree were used as the parameters for the MetaAdaboostM1 classifier [19].The use of various sensors could capture contextual information which monitored and reflected one side of a situation using a knowledge-based approach. Thus both coarse-grained and fine-grained activity recognition were enabled [14]. However, the problem is that use of body-worn sensors [1, 19-20] can be exasperating to the elderly, and also environmental [13] sensors can create problems if more than one person is in the same space.

Khan *et al.* [34] collected 12 activity data from 20 participants and implemented 1D CNN for feature extraction, which uses spatial and discriminative features of the data. Then features are forwarded to LSTM having softmax activation function, which exhibited an accuracy of 90%. Yang *et al.* [35] used CSAS datasets, which segregated the data according to the number of members in the family to implement a sensor data contribution significance analysis. They used a Wide time-domain Convolutional Neural Network (WCNN) on all segregated groups, which gave 97% accuracy for Kyoto8.

A summary of all the major sensor-based algorithms used by several researchers is presented in Table 1.

Table 1. Summary of major sensor based algorithms used

Author	Year	Optimizer and Feature Extractor	Classifier	Accuracy in %
Sakorn[28]	2021	Bayesian Optimizer	CNN-LSTM	99.4
Xia[27]	2020	Adam Optimizer	CNN	95.8
Ahmed[33]	2020	SFFS	SVM	96.8
Burns[3]	2020	--	PTN	91.3
Taylor[26]	2020	--	Random Forest	96.8
Kwon[12]	2018	Xavier's Algorithm(Weight Initialization)	MLP	95.0
Jain[17]	2017	Histogram of gradient	Fourier Descriptor based on Centroid Signature	97.1
Yang[16]	2019	Adam optimizer and CNN feature Extractor	Dual path CNN-RRNN(DPCRN)	99.9
Chermbumroong[1]	2012	--	RBF	90.2
Walse[19]	2016	J48(Parameter)	MetaAdaboostM1	97.8
Khan[34]	2022	1D CNN	LSTM	90
Yang[35]	2022	--	HAR_WCNN	95

Vision-based methods were also used by researchers to detect the target's posture, then the movement and speed value of the target has been determined and finally, the target's interaction with objects in the environment concluded the activity recognition [15]. A sequential Deep Trajectory Descriptor (sDTD) with CNN-RNN and CNN for feature extraction with MLP classifier has been used for vision-based action recognition [23, 24]. Researchers found three problems in vision-based data namely background changes with the self-occlusion, changing size or orientation of the subject, and different activities with similar postures. In this concern, a person-tracking system was used to control self-occlusion, multi-features to solve change in size and orientation of the subject, and embedded Hidden Markov Models (HMMs) to eliminate unnecessary data usage during testing time improve computational processing, and also increase recognition performance [25].

3. Methodology

Providing assisted living requires recognizing the activities of daily living to be most accurate. In this concern, we propose the following Genetic algorithm method for efficient selection of features and then classify them. GA is considered as a speculative global search heuristic that is inspired by the analogy of natural theory of evolution. It works faster in comparison to other methods as instead of a single point, it has the capacity to search a population of points in parallel. The diagrammatic representation of the steps involved in activity recognition is shown in Figure 1.

Our proposed method can be broadly divided into the following three steps:

- Data Acquisition
- Feature Selection
- Classifier

3.1. Data Acquisition

After conducting a study on the datasets available in public repository for the purpose of HAR, we found *Human Activities and Postural Transition (HAPT)* to be more suitable for our work as it includes a variety of activities along with different Postural transitions. HAPT is a publicly available dataset for human activity recognition that includes postural transitions. Postural transitions are transitory movements that describe the change of movement from one static posture to another [8]. This dataset has three static postures ('standing'(Sd), 'sitting'(Sn), 'lying'(L)), three ambulation activities ('walking'(W), 'walking downstairs'(WD), and 'walking upstairs'(WU)), and Postural Transition (PTs) that occur between the three existing static postures ('stand-to-sit'(SdtSn), 'sit-to-stand'(SntSd), 'sit-to-lie'(SntL), 'lie-to-sit'(LtSn), 'stand-to-lie'(SdtL), and 'lie-to-stand'(LtSd)'). To make a data collection more convenient to use and readily available smart phones are used with embedded sensors [7]. An example of a dataset collection from a postural change in sit to stand position is given in Table 2.

Use of embedded gyroscope as well as Tri-axial accelerometer in a proper frequency collected the data captured when the human body is in motion. Tri-axial linear acceleration and angular velocity signal at a sampling rate of 50Hz has been used for data collection process. To reduce the data volume, the collected data has been pre-processed by using a 3rd order low-pass Butter-worth filter with a cut-off frequency of 20Hz. In total there are 12 activity labels. For the usage of the ground truth for manual labeling, a synchronization of the experimental videos was made with the signals. The dataset contains 561 attributes and 10929 instances. The description of the dataset is given in Table 3.

3.2. Feature Selection

Feature selection is used to eliminate redundant and irrelevant data from a huge dataset which makes the classification less time-consuming. We used Genetic Algorithm (GA) as a filter-based feature selection for activity recognition. This algorithm was proposed by John Holland which is based on Darwin's survival of the fittest theory. The genetic algorithm follows natural selection and natural genetics. It focuses on an optimized solution from a population of possible solutions to a particular problem. The implemented GA's reproduction follows simple roulette wheel algorithm where each feature/attribute is given a slot size according to the fitness value. This method passes highly reproductive features to the mating pool where several combinations of features are made known as crossover to yield the best set of highly performing features.

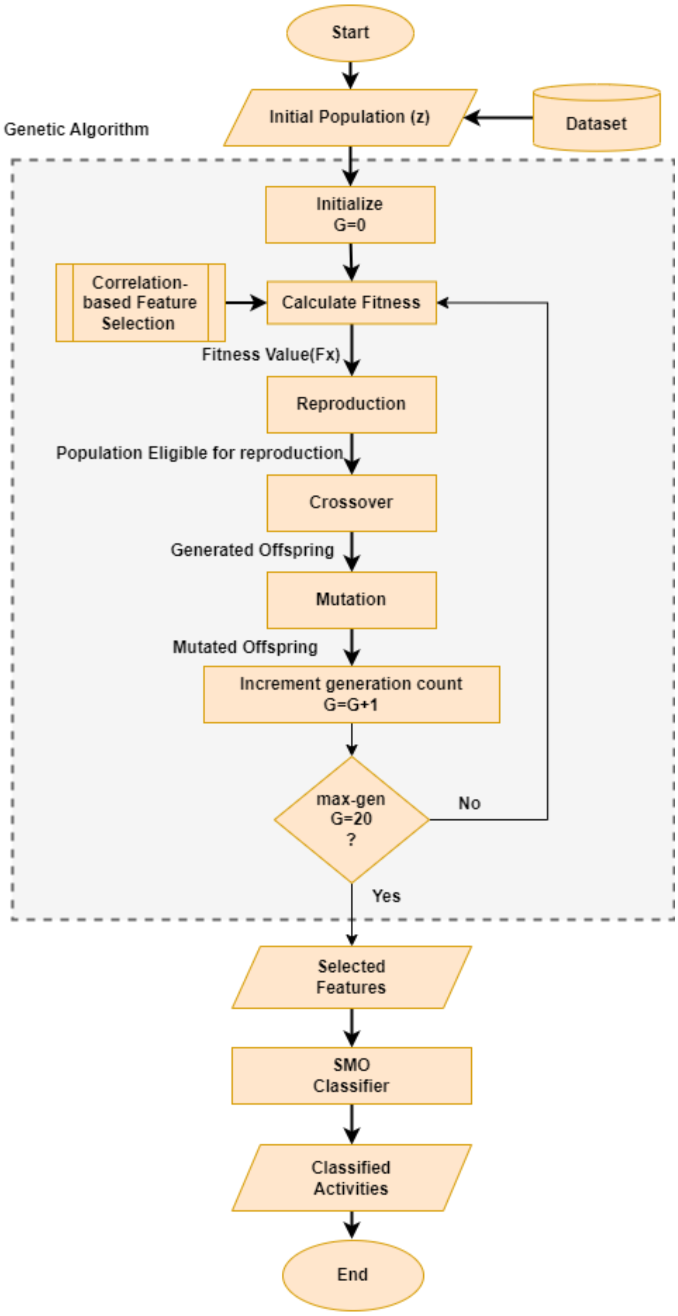


Fig. 1. Flowchart of the proposed feature section model

Table 2. Sample Dataset Collection from Sit-to-Stand posture change

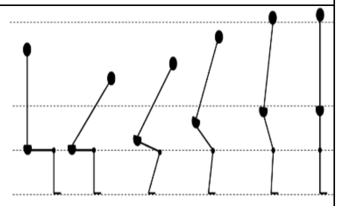
Sl. No	Attributes	Value	Pictorial Instance
1	tBodyAcc-mean()-X	0.207213	
2	tBodyAcc-mean()-Y	-0.58208	
3	tBodyAcc-mean()-Z	-0.399343892	
4	tGravityAcc-correlation()-X,Y	-0.982534872	
5	tBodyAccJerk-mean()-Y	-0.068908792	
6	tBodyAccJerk-iqr()-Z	-0.9287475	
7	tBodyAccJerk-entropy()-X	0.09645113	
8	tBodyAccJerk-arCoeff()-Y,1	-0.338437577	
9	tBodyGyro-mad()-Z	-0.020437	
10	tBodyGyro-arCoeff()-Z,3	0.145486046	
11	tBodyGyroJerk-mad()-Z	-0.776968802	
12	tBodyGyroJerk-sma()	-0.85979946	
13	tBodyAccMag-max()	-0.01035274	
14	fBodyAcc-bandsEnergy()	-0.99676242	
15	fBodyAccJerk-energy()-X	-0.978527667	
16	fBodyGyro-bandsEnergy()	-0.990614018	
17	fBodyBodyGyroMag-mean()	-0.527555664	
18	angle(Z,gravityMean)	-0.27074774	
19	CLASS	SIT_TO_STAND	

Table 3. Dataset Description

Human Activities and Postural Transitions Recognition Dataset		
Instances		10929
Attributes		561
Activities	Static Postures	3
	Ambulation Activities	3
	Postural Transitions	6
	Total	12

The steps involved in GA are described as follows:

(i) **Calculate Fitness:** Selection of pairs those will be participating in the reproduction process is selected on the basis established by the objective function. We have used Correlation-based feature selection (CFS) based fitness function for evaluation of subset and subsequent selection of optimal features. Using a heuristic evaluation function that uses correlation, ranking of attributes are done in CFS [10]. The independent attributes, those correlate with each other with the class label are first put into a separate subset using attribute vector. Now these subsets are evaluated by the function. As per the CFS method only relevant attributes show a higher degree of correlation. At the same time the probability of surfeit attributes need to be identified as being derived features they will also show a higher degree of correlation with the original attribute. The Eq. (1) is used for assessment of subset comprising 'n' features evaluating the goodness of the feature subset. Our genetic feature selection performs a search through the space of feature.

$$F_x = \frac{n\overline{C_{fl}}}{\sqrt{n + n(n-1)\overline{C_{ff}}}} \quad (1)$$

Where, F_x represents the evaluation of a subset of x that has n features in it. $\overline{C_{fl}}$ and $\overline{C_{ff}}$ represent the average correlation value between features, class labels and between two feature respectively.

(ii) **Reproduction**: The term reproduction is used GA for the purpose of selecting the fittest item from the population of strings hinge on the fitness value F_x calculated. In the reproduction process, based on the value F_x generated by the objective function (also called fitness function), the individual strings are copied. Here, F_x refers to the fitness value that indicates some measure of goodness, utility, or profit, that is needed to be maximized. It is the raw performance measure of the individuals provided by the fitness function based on which selection is biased. Now, these selected individuals are recombined to produce the next generation. From the participating individuals, the string values get copied according to their fitness values indicates that the string with a higher value has a higher probability of contributing one or more offspring in the next generation. Genetic information between pairs or larger groups is exchanged using the recombination operator.

(iii) **Crossover**: The technique used to produce the offspring or the new generation string is termed as crossover. It is a process where two of the fit individuals are used for creating a fitter next generation individual. In this process any two individuals are selected from the selection pool created in the reproduction phase, and a part of their gene gets exchanged to create the new individual [21]. The crossover process uses probability index for choosing pairs from the population pool for the purposes of breeding. If a single point crossover is implemented then the value in the $\boldsymbol{i^{th}}$ position gets exchanged in between the participating pair of parents. The position $\boldsymbol{i}$ is chosen randomly anywhere within the string length, i.e., within 1 and ***len***-1 where ***len*** represents the length of the string. This chosen value for $\boldsymbol{i}$ remains constant throughout the entire crossover process. For example, let's consider the following two parents represented in the form of binary strings:

P_a1 = 1 0 1 1 1 0 1 0,
P_a2 = 1 0 0 1 0 1 0 0.
And let's assume the value of $\boldsymbol{i}$=6.
After applying single-point crossover the offspring created will be
O_f1 = 1 0 1 1 1 1 1 0,
O_f2 = 1 0 0 1 0 0 0 0.

(iv) Mutation: Mutation operates in the background towards ensuring the probability of appearance of a subspace within a total population to never become zero. The effect of mutation tends towards impeding the risk of convergence to a local optima in lieu of reaching the global optima. The crossover process after repeatedly applied there is a lot of chance that the resultant offspring in the successive generations would become identical to the initial pool. To avoid this, mutation process is responsible for the key functionality of making changes in the genetic pool. It makes minor changes to the offspring's genome chosen in random, thus ensuring only a small portion of the total population getting affected. Now this change applied may or may not be beneficial to the individual. Once the recombination and mutation process are applied, the newly generated mutated strings are decoded again, applied with the objective function to get a fitness value $\boldsymbol{F_x}$ that is assigned to each individual. If the applied mutation is advantageous, then the fitness gets increased and the selection mechanism approves the gene to remain in the pool but in case it is the other way, then the mutated gene is removed from the population pool by the selection process itself. With this the performance of individuals are always expected to be on rise as only fit participants are preserved and reproduce to create an ever fitter generation removing the participants who are less fit.

The selected features are repeatedly tested and exchanged to produce best set of features. Mutation is a secondary variable with small probability alters the value of a feature's position. The mutation step might seem secondary but it helps us to prevent premature loss of important features.

Each chromosome consists of genes and the genes have a specific value and position to represent a feature. The terminology of biological genetic for AI is given in Table 4. We obtained the best feature by applying reproduction, crossover, and mutation on the initial features. This feature selection approach is more effective as the searching is applied using stochastic operators instead of deterministic rules. It searches for the solution from the population instead of a single point. These strings follow three simple operators to yield an improved result.

Table 4. Comparative terminology between Biology and AI

Biological terminology	AI terminology
Chromosome	String
Gene	Feature, Character, Or Detector
Allele	Feature Value
Locus	String Position
Genotype	Structure
Phenotype	Parameter set, Alternative solution, Decoded structure
Epistasis	Nonlinearity

3.3. Classifier

After selecting the features in this work, for the classification of 12 activities ranging from Static Postures to Postural Transitions, we used Sequential Minimal Optimization (SMO) algorithm. A divide and conquer technique is applied in SMO, where in order solve to a big Quadratic Programming (QP) problem, it is first divided into a series of smaller QP problems. These problems are further subdivided into still smaller sub-problems till the smallest possible QP is attained. Then each of these sub-problems is solved analytically. In order to avoid numerical those are time consuming, SMO approach uses an inner loop for QP optimization. The consumption of memory in SMO is linear in the training set size.

Usually, support vector classifiers are trained using SMO where the scaled polynomial kernels are applied on them. Next, standard sigmoid function is applied on the non-fitting results those are obtained from SVM for transforming them into probabilities [29]. The typical functionality of SMO involves missing value handling and replacements, conversion of attributes from nominal to binary ones and normalization of all numeric attributes. To train a SVM, large QP requires an optimization problem.

4. Experimentation and Results

The proposed model is implemented using Waikato Environment for Knowledge Analysis (WEKA) tool of version 3.9.5 for experimentation and used python in Google collaboratory for result analysis. A random partitioning of the HAPT dataset used is done in 70:30 ratios towards training and testing purpose respectively. The experimentation is based on two parts: one is classification without feature selection, and the second is classification with feature selection.

4.1. Classification without Feature Selection Model

The classifiers DL4jmlp, Decision table, Simple logistic, J48, and SMO algorithm were applied on the HAPT dataset and it was found that SMO performs best in terms of accuracy and model building time in comparison to other algorithms. The details of the test results are given in Table 5.

Table 5. Comparison between other approaches and the proposed approach

Algorithm	Accuracy with 561 features (%)	Model Building time (in Seconds)
DL4jmlp	96.27	228.3
Simple Logistic	96.91	106
Decision Table	80.60	119.9
J48	92.77	18.42
SMO	97.07	10.4

Analysis of the confusion matrix of the above algorithms showed that the classifiers made similar misclassifications except for SMO. The training time of DL4jmlp, Simple Logistic, Decision Table, J48, and SMO are 178.07s, 101.82s, 82.14s, 12.30s, and 5.62s respectively. All these measures led us to implement SMO in our final model for Activity classification. A Polynomial kernel function was used. We set SMO’s complexity parameter to 1.0 and € to 1.0E-12 which we found to be the optimum parameters. The validation sets were carried out using 70% training and 30% testing percentage split.

4.2. Classification with Feature Selection Model

The dataset contains 561 attributes from where we tried to reduce some irrelevant and redundant features by applying the genetic search algorithm based on its parallelism and wide space search capabilities. In the Feature Selection Model whole volumetric data with 561 features was given as input to the feature selection algorithm i.e., Genetic algorithm. Each attribute in the dataset is considered as an individual feature which is referred to as a gene in the biological system. From the search space, a population (Z) of size 20 is chosen randomly in each batch then the fitness of the genes is calculated using the CFS. Reproduction is performed on these genes according to the fitness value after that crossover and then the mutation is performed on the chosen population. In Table 6, we have described the parameters used in the genetic search algorithm.

Our population type is numeric and a total of 20 generations (G) of off-springs are generated. We changed the value of Crossover Probability (CP) and Mutation Probability (MP) from 0.1 to 0.5 and 0.011 to 0.055 respectively to find the optimal subset of features. In the first row of Table-5, the CP and MP are 0.1and 0.011 respectively suggests that 10% of the offspring of the next generation is created through the crossover by increasing the mutation by 1.1% in each iteration of subspace in the current generation's population. Finally, we generate 20 G of offspring, and then the final set of fittest features was selected. The details of the experimentation results are given in Table 7.

Table 6. Parameters used in Genetic Algorithm

GA Parameters	Values
Total Features	561
Population Size(Z)	20
Population Type	Numeric
Generations(G)	20
Crossover Probability(CP)	0.1-0.5
Mutation Probability(MP)	0.33-0.77

The testing of selected attributes was carried out for activity recognition using the SMO algorithm. SMO was set to Polynomial Kernel function and every selected feature set were tested with the selected classification algorithm where we can see that the feature selected using CP and MP with .3 and .033 respectively gives us the best result with minimal time.

4.3. Result Analysis and Discussion

We used performance metrics such as True Positive Rate (TPR), Precision, Recall, F1-measure, and Receiver operating Curve to analyze the efficacy of the proposed model. We also presented the performance metrics for each activity to analyze the classification and misclassification results of the proposed model.

Figure 2 shows a comparison of model building time between the original dataset and the dataset that was produced after feature selection was applied. It was observed from the experimental results that SMO and J48 take less model-building time as compared to other classifiers. DL4jMLP is an extension of MLP, which means it is capable of fitting a wide range of smooth, nonlinear functions with higher accuracy, but due to fully connected layers, Dl4jMLP has a very high number of parameters, and it tends to increase the model building time hence making it cost-effective.

Table 7. Feature Selection and classification

CP	MP	Attributes	Accuracy (In %)	Model Building Time(seconds)
0.1	0.011	262	96.09	5.00
	0.022	269	96.43	5.03
	0.033	276	96.76	4.22
	0.044	285	96.18	4.12
	0.055	271	96.06	4.7
0.2	0.011	176	95.42	3.90
	0.022	278	96.58	4.16
	0.033	264	96.61	5.08
	0.044	237	96.37	3.87
	0.055	265	95.91	4.31
0.3	0.011	275	95.76	4.95
	0.022	267	96.46	4.61
	0.033	281	97.04	4.75
	0.044	287	96.24	4.69
	0.055	270	95.91	3.66
0.4	0.011	190	96.04	2.75
	0.022	212	96.34	4.91
	0.033	231	96.24	3.64
	0.044	225	96.00	4.25
	0.055	250	96.34	3.34
0.5	0.011	218	96.49	4.33
	0.022	228	95.85	3.94
	0.033	211	96.46	3.33
	0.044	259	95.73	3.25
	0.055	249	96.03	3.33

Simple Logistic performs well with linear data but our dataset contains non-linear data so the model building time is higher in comparison to J48 and SMO. The calculation of decision table is a complex multiclass classification and hence it increases the model building time. So we considered only SMO and J8 classifiers for comparison of activities in the context of postural transition. The ROC between SMO and J48 is shown in Figure 3 which indicates that SMO outperforms J48.

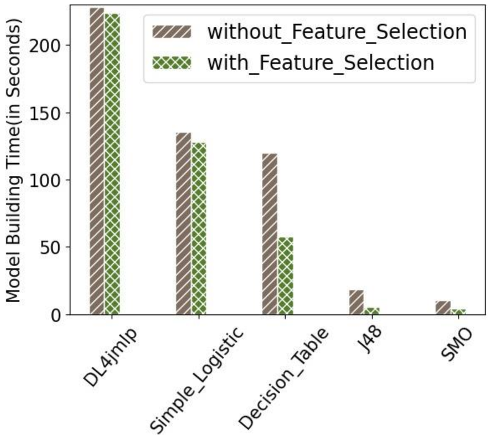


Fig. 2. Model building time analysis of the models with and without feature selection

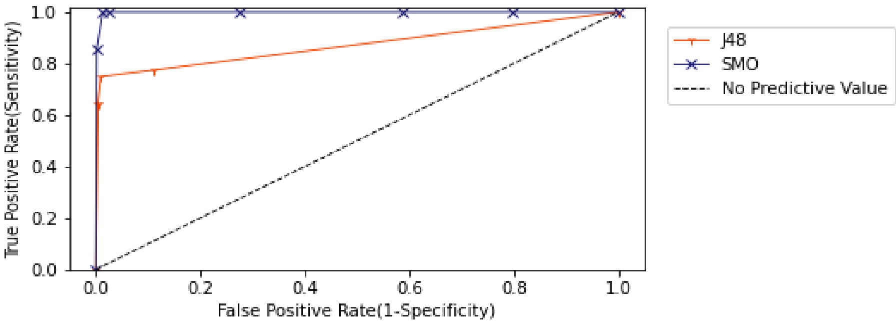


Fig. 3. ROC between J48 and SMO with 281 attributes (Sn_T_L)

The accuracy percentage of the considered classifiers was computed and is shown as in Table-6. It is found that the time complexity and accuracy performance of the SMO algorithm outperforms all other algorithms. The proposed model achieved an accuracy of 97.04% with a standard deviation of 0.22, and a mean absolute error of 0.14.

The comparison of obtained TPR, Precision, Recall, and F-measure for all the considered algorithms using selected attributes is presented in Table 8. Accuracy is the most intuitive performance measure but the ratio of correctly predicted classes to the total predicted observation i.e. precision helped to find out the percentage of our results that are relevant. From the experimental results, it was found that SMO achieved a precision of 95.7%, recall of 94.4% which indicates the ratio between correctly predicted positive observation and all observation in an actual class, and weighted average of precision and recall i.e. F-measure of 95.07%.

Table 8. Comparative results of considered classification algorithms

Algorithms	Accuracy (%)	True positive rate (%)	Precision (%)	Recall (%)	F-measure (%)
Dl4jMlp Classifier	95.21049	85.66	98.64	85.66	91.69
Simple Logistic	96.79683	94.09	96.20	94.09	95.14
Decision Table	78.76754	83.30	69.57	83.30	75.82
J48	92.31239	91.39	92.64	91.39	92.02
SMO	97.04088	94.43	95.72	94.43	95.07

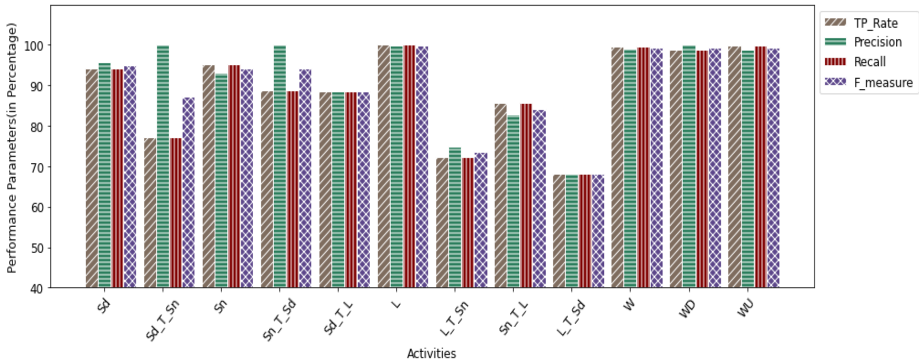


Fig. 4. Performance analysis of the SMO for all 12 activities

The efficiency of the proposed model for each of the 12 activities in terms of TP Rate, precision, recall, and F-measure is shown in Figure 4. In previous researches the higher accuracy giving algorithms, Postural Transitions were not considered. Our proposed model gives an average TP Rate of 80.01% in postural transitions. Average percentage of other performance measures such as Precision, F-measure, and Recall obtained are 85.76%, 82.66%, and 80.18% respectively.

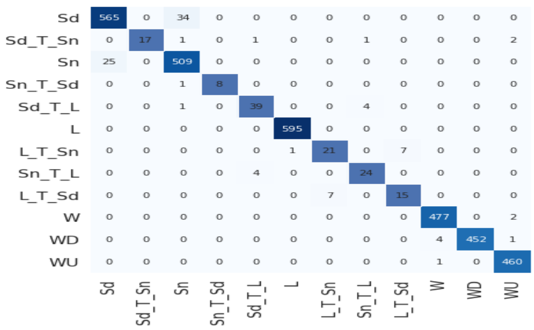


Fig. 5. Confusion matrix of the proposed model

The obtained confusion matrix is shown in Figure 5. From Figure 4 and Figure 5, it was observed that SMO performs well even after reducing the attributes to 50%. The confusion matrix indicates that more than 80% of postural transitions are true positives with least number of attributes.

5. Proposed Cloud Architecture

Utilizing a mobile's limited resources, such as memory, energy, and embedded sensors, may lead to a decrease in the computation performance and efficiency of the system. It is also important to develop a model that is movable, consumes low battery, uses low-cost sensors, gives high accuracy, and preserves the privacy of the user. So, the use of Mobile Cloud computing is a feasible solution as it combines mobile computing, cloud computing, and wireless networks [32]. This architecture provides an environment to continuously track and monitor the activities of elderly people irrespective of the availability of an Internet connection without invading their privacy. Figure 8 shows an overview of the proposed architecture. This proposed architecture has three Layers: Data Acquisition Layer (DAL), Edge Layer (EL), Cloud Computing Layer (CCL), and Output Layer (OL). The process starts with the collection of data from various wearable gadgets continuously, offloading it to the cloud after passing it through the Edge layer for pre-processing and partial computation where the emergency situation is detected. After localizing the source of the signal, an alert is sent to the family member, caretaker, or medical practitioner with the status.

DAL: This layer deals with collecting the data that is continuously get generated from the wearable devices used by the elderly person. Functionalities for sensing real-time data and a user interface for easy status access are provided. Based on the involvement of users with the proposed system, two categories of users are identified - Active Users and Passive Users [30]. The Active User module works on the elderly person's side and activates their wearable sensors for real-time data collection. The current day's advanced wearable devices embedded with sensors have been found to be instrumental in providing personalized health services. They can be classified based on the area of usage as follows. Head-mounted devices like helmets, glasses, etc., wearable for the wrist, which includes bracelets, watches, and gloves, etc., various e-textiles such as cloths, inner wares, etc. and somatosensory modulators like various sensory control devices [22]. These devices are helpful in monitoring cardiovascular signals, salivary contents, sweat contents, physical activities, and the physiological signals of the active user. Through this monitoring, various physiological parameters such as heart rate, pulse rate, level of glucose, sodium in the blood, amount of uric acid, lactate, and potassium, as well as physical parameters such as sleep time, sitting time, daily activity, stets counts can be obtained for analysis. The collected data from the Active user module will be sent to EL directly if the Internet connection is available. In case of unavailability of the Internet, the collected data are streamed to a Local Repository, with the help of Wi-Fi or Bluetooth. Next, on availability of Internet, when the device gets network access, the data collected are uploaded to the EL and the repository is flushed. Passive User is a part of OL. This category refers to the family members/ care givers or medical practitioners who need to access the collected sensor data and are to be contacted immediately in case of any anomalous situation identified with the activities for the active user.

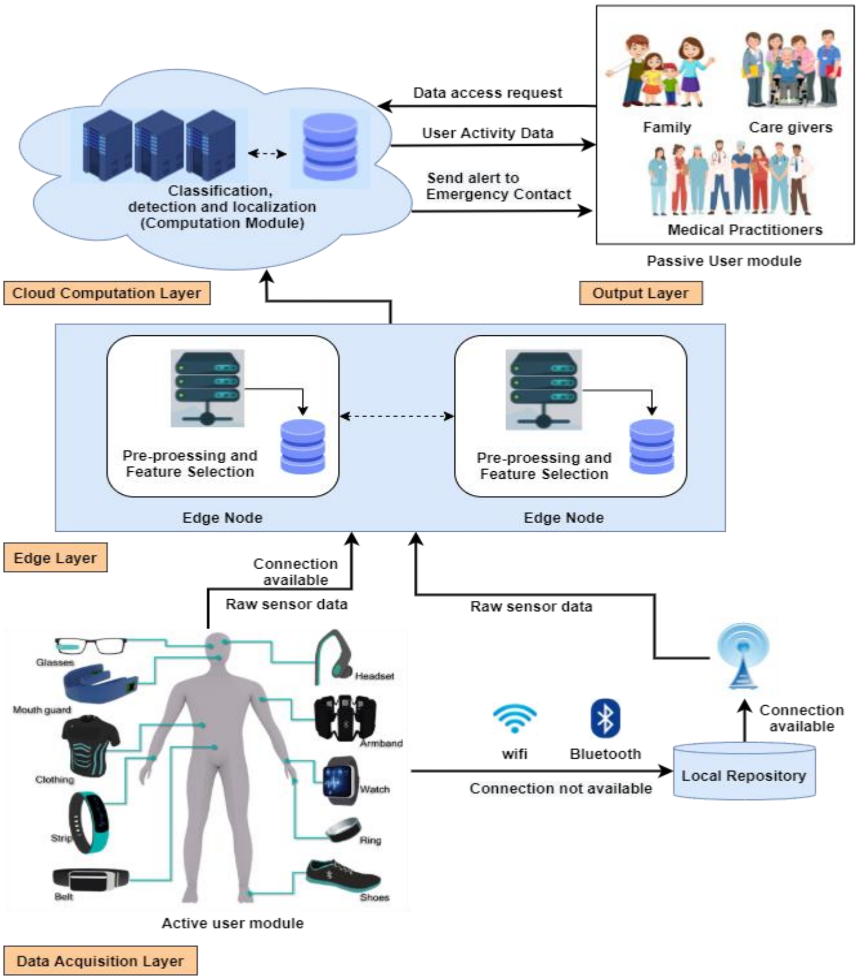


Fig. 6. Proposed HAR model in cloud architecture

EL: This layer is responsible for carrying out the following functionalities.

1) Pre-processing and cleaning: The received raw sensor data are pre-processed and data cleansing is applied for producing a usable dataset.

2) Feature Selection: From all the features available in the dataset, only relevant features are selected for further processing to ensure smoother and faster analysis of the data in the later phases.

CCL: In this layer of the proposed architecture, the data for selected features is stored, managed, and computed for activity recognition. The data is stored in the Cloud Server after the offloading from the EL. In the Computation module, the proposed classification model is deployed. When a request is sent for the status check of the elderly or patient from any passive user module, computation is performed on the stored data, and activity status is sent to the user via the network selection module. If any unusual activity is recognized, then an alert is sent to the Passive user.

OL: This layer is responsible for all the communication between passive users and the cloud server. When the associated medical practitioners or caregivers request the user activity data for analysis, so that information regarding any improvement or deterioration in health can be derived, the data is sent to the requester in OL post-authentication process. Similarly, if any deviation in the regular pattern of received data is observed, the cloud server, after localization of the anomaly, generates an alert and sends it to the OL.

6. Conclusion and Future Work

Due to the busy lifestyle of the current generation, assisted living has become almost the need for all elderly people who spend most of their time alone at home. This paper focuses on a cost-effective, efficient model to provide elderly care without invading privacy. The proposed model is movable, consumes low battery, and uses low-cost sensors, which makes it cost-effective and affordable by general users. Genetic Algorithm is used here for feature selection, which removes many redundant features. SMO classifier is applied next on the dataset with selected features for activity classification. After the comparison of the obtained result with J48, Simple Logistic, DL4jmlp, and Decision table, it is found that the proposed model outperformed all other algorithms when applied on a dataset with feature selection using GA. For deployment of the model in the cloud, this paper also proposes a cost and privacy-preserving architecture. The highlights of the proposed architecture are sensor-based gadgets, local repositories, and edge layers. This proposed feature selection model adds to the efficiency and can be used to classify real-time data in the future. The objective of this proposed architecture is to help elderly individuals live independently within their respective homes while emergency assistance and support are provided through family members, caregivers, and associated medical practitioners.

As a future scope of work, the suggested model is proposed to be implemented in a real-life scenario. The experimentation has been carried out only on HAPT dataset. The authors propose to test the model on a custom-built real-life dataset as well.

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