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Enhanced Modelling for Detection of Daily Activities of Aged People for Health Care

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Abstract

Millions of individuals around the world are sixty years of age or older. Global concerns about aging populations have been impacting social welfare and healthcare systems. As people get older, people find it more difficult to carry out their daily tasks, which affects their mental and physical health. Additionally, there are increasing events affecting the elderly, especially in and around their homes, with serious consequences including hospitalization. The most prevalent cause of injuries among the elderly is falls. Human Activity Recognitions (HARs) are techniques that use (ML) algorithms to identify human activities from sensor data and categorize human behaviors such as standing, walking, and running. HARs are crucial for human behavior analysis and human-computer interaction in applications related to serious illness identification, patient rehabilitation, and healthy lifestyles. A growingly useful use of MLis the prediction of human behavior, where computers that keep an eye on routines and step in when there is a crisis or a shift in behavior may be very helpful to the elderly. Despite the fact that many academics use ML approaches, only few studies about HARs of elderly people exist. By concentrating on tracking human motions utilizing perceived accelerometer and gyroscope data, this effort aims to close the aforementioned gap. According on the results of experiments, this paper proposes the Scaled Regressive Human Activity Detection Model (SRHADM), an ML -based schema that can accurately identify human activities 90% of the time. Human centered applications such as actively supported living and home monitors can be properly utilized with the help of SRHADM implementations. Since it could shed light on the possible therapeutic or research uses of HARs, this knowledge might be important for clinical applications.
Keywords: Human activity recognition (HARs); (ML) classification; feature selections, elderly people, injuries

Introduction

Over eight out of are elderly in developing nations by 2050. Among the 143 nations or territories with accessible data, the percentage of persons who are 60 and living alone with maximum in Netherlands (93.4%). It is predicted that there will be over 2.1 billion senior people by 2050, more than double the current population. Developing nations are home to 2/3 of the world's senior population, and their numbers are growing faster there than in developed nations. Figure 1 displays the ageing population around the globe.

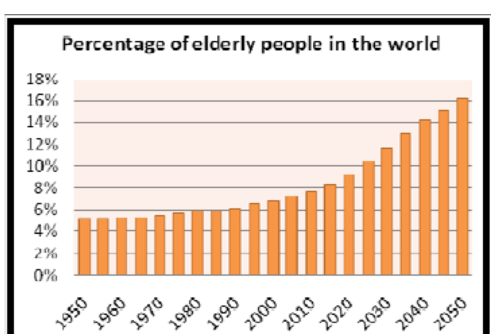


Fig. 1 – Global ageing population

However, aWorld Health Organization (WHO) study found that over 650 million people of working age do not reach their full potential due to inadequate facilities due to disabilities [1].One of these is the need for a partner to supervise their activities. Every year, fall-related injuries send around a million senior citizens to the hospital. For those over 65, falls are the primary cause of mortality. Injuries from falls can limit one's activities for at least a day. Psychological effects including anxiety and a fear of falling might result from falls. 962 million individuals worldwide were 60 years of age or older in 2017, twice of 382 millions in 1980. Table 1 is and indicative list of treatment costs for falls or injuries.

Table 1 – Treatment Costs for Falls or Injuries with tentative percentages of affected people

SNO	Percentage of People Falling	Cost of Treatment for Injuries
1	18	Greater than Rs. 10000
2	57	Between Rs. 5000 to Rs. 10000
3	25	Less than 500

Hence, it is essential to design dependable and discrete in-house security systems linked to healthcare which enables contact of medical providers in emergencies. Elderly people must be watched after and safeguarded around-the-clock to prevent accidents, harm, or danger [2]. People's actions have been regularly monitored via mobile phones [3]. The application of wearable sensors in medicine is growing in importance in the modern world [4]. Wearable sensors are ideal for surveillance, physiotherapy, monitoring senior adults, tracking physical and recreational events, and interpersonal behavior in order to enhance ambient living. Both their size and price have decreased recently [5]. However, It would be a significant improvement in terms of security because it is based on IoT and does not require human measures [6]. Wearable digital energy, activity, weight, and pulse rate monitors have generated a lot of attention, but few of these features recognize the distinction between pharmaceutical-grade surveillance and efficient information collection [7]. Application developers will have access to a variety of health sensing methods. They employ wireless and networked sensors to gather data. Users can view their encrypted medical information online and share them with family members, clinics, and physicians as necessary [8]. HARs analyze sensor and camera data in order to identify physiological activity. By exposing usage habits, it may thus anticipate and avert dangerous circumstances. There are several options for system deployment and building with HARs. Human activity cannot be broadly defined or categorized. Secondly, human activities are many. Therefore, the placement and choice of sensors are essential for differentiating particular behaviors [9]. Therefore, choosing sensor measures and gathering data under practical circumstances are two crucial issues. Because user behaviors and sensor data vary, the HAR problem cannot be resolved deterministically. HAR systems are increasingly using ML to detect human behaviors from sensor data. In recent years, HARs have become one of the most appealing study topics. Applications for identifying, detecting, and categorizing human behaviors use monitoring, and a variety of methods have been presented by researchers in this area. This is because accelerometers and sensors are widely available, they are inexpensive and energy-efficient, and advances in artificial intelligence, computer vision, ML, and the Internet of Things have all contributed to this. HARs, which may be performed with ML, are essential tools for monitoring the elderly. These methods make advantage of information from numerous sensors, including gyroscope and accelerometer sensors. to automatically identify and analyze human activities [10].where one may utilize data on body accelerations, body angular speeds, body angular accelerations, and gravity accelerations, among many other factors. Due to its powerful categorization models and self-learning nature, artificial intelligence (AI) is becoming more and more popular for HAR [11]. Although HAR has lately been the subject of several studies employing ML and deep learning (DL) techniques, relatively few have focused on creating a framework for the Few research have focused on creating a framework for the HAR system for senior adults, despite the fact that several have recently been conducted for HAR employing ML and DL [12]. In their paper, Kaixuan Chen et al. [13] provided an overview of the prospects and difficulties in the field of DL algorithms for human activity detection. Multimodal characteristics are necessary to maximize the system's performance due to the diversity of sensor data collected [14]. For this senior citizen human activity monitoring application, high HAR algorithm classification accuracy, precision, and recall are necessary. Additionally, several past studies have suggested ML techniques for classifying human activity [15]. ML approach called classification or supervised learning is used to determine which category a given collection of data belongs to [16].

Classification and prediction may be used to analyze data; this helps to separate the data into classifications that facilitate the prediction of future trends. Prediction aids in identifying the data value, whereas grouping aids in assigning labels to the data [17]. Several characterisation algorithms have been used for HAR; the most well-known methods that have been studied include Naive Bayes (NB), Random Forests (RFs), KNNs (K-Nearest Neighbours), Neural Networks (NNs), Support vector Machines (SVMs), and ML techniques which provided higher accuracy in data mining, specifically for complex feature classifications [18]. Regretfully, it is difficult to compare the performance of all of these cutting-edge algorithms in terms of computing speed, precision, accuracy, and F1-score. To improve comprehension, all of the algorithms in this work are assessed using the aforementioned standards. The most significant and distinguishable modalities may be highlighted in HAR using the attention-based approach [19], which employed numerous agents to concentrate on modalities associated with sub-motions. Despite outperforming all state-of-the-art techniques, they have yet to be verified on an older dataset. Hence, the primary goal of this study is to determine the best method for creating the HAR framework for senior citizens. This introductory section is followed by definition of the problem and literature review. Subsequently the suggested schema's methodology is explained with results and discussion followed by conclusion and future scope.

Definition of the Problem

Keeping an eye on the elderly helps lower hospital admissions and healthcare expenses. It will allow people to age in place, which is frequently less expensive than receiving care in a facility. Channel state information (CSI) of commercial Wi-Fi equipment identify human actions. These structures are cost effective and reliable when compared to radars. Moreover abundance of Wi-Fi hotspots allows easier implementations of CSI at very reasonable costs [20]. This device has been utilized in more than 400 research for a variety of tasks, such as motion tracking, detection, and tracking [21]. Home security systems that may need to analyze sensor data are built on top of HARs. Sensor gathered is often cleansed. Using a learning technique, the classification module classifies the activities. An aging monitoring system is very necessary as it helps individuals save time and money by identifying dangers in their environment early. Even when we are outside, the technology has been updated to keep an eye on what is happening at home. For the elderly and the blind, safety is the top priority. Because of their limited movement and eyesight impairment, these people are frequently more vulnerable to accidents, falls, and other risks. Keeping an eye on their activities might help avoid mishaps and offer prompt support when required. It makes it possible to identify health problems, behavioral changes, or indications of distress early on, which enables timely medical intervention or care plan modifications. Monitoring activities enhances general quality of life in the elderly in terms of everyday tasks and resolving any safety issues. It enables them to experience greater comfort and tranquility.

Literature Review

Many researches on HARs have been undertaken in recent years. Given their longevity and ease of use, cellphones are a great tool for activity recognition. For online training and classification, accelerometer data from Android-based HARs was proposed In [22],. The clustered k-NN technique improved the k-NN classifier's performance, accuracy, and execution time on the Android platform in spite of its constrained resources. The study found that categorization times varied depending on the device's type and capabilities. Online HARs based on smartphone inertial sensors was also proposed in the work in [23]. The system's performance on a selection of twenty-three activities was assessed using six incremental learning techniques. Then, each of them was compared to the most sophisticated HAR techniques, such as AdaBoost and Decision Trees (DTs). The highest 95% accuracy has been achieved by incremental k-NN and incremental NBs. Using a MLtechnique, the work in [24] presented a revolutionary elderly person tracking system. With a k value of 5, the k-NN model used in this study produced the best results, detecting the real-time activities of older individuals with an accuracy of 96.40%. They also created a system that enabled elderly persons to use messaging devices for assistance in emergencies. The work in [25] produced an energy-efficient model for categorization of HSRs using a smartphone where their improvised SVMs used fixed point arithmetic and for saving energy and maintaining results that were comparable to other widely used categorization approaches, they used the novel technology for a variety of intelligence applications and smart settings. A body-sensor-based activity detection system using deep neural stretchered learning based on long short-term memory (LSTM) was created in order to understand people's behavior in a variety of contexts, such as homes, clinics, etc. [26].

The grouping of features from all the activities was improved by using Kernel-based Discriminant Analysis (KDA), which maximizes inter-class scattering and decreases intra-class scattering of the data. When compared to various DL models, including the RNN, Convolutional Neural Networks (CNNs), and Deep Belief Network (DBN), the suggested model obtained a recall of 99%. The suggested method's recall rate would be too high for any of the DL models currently in use. Similarly, using data from smartphones, A deep LSTM network was proposed by the study in [27] to recognize six different activities. With the help of the UCI-HAD dataset, the network's accuracy was 96.70%. CNNs were suggested by [28] to identify any human activity within. Nine different activities were found using cellphone accelerometers, magnetometers, gyroscopes, and barometers. It is excellent that the recommended strategy has an accuracy rate of 98%. In [29], CNNs and LSTM were integrated to determine the actions of elderly individuals, A multichannel CNNs-LSTM model with an accuracy of 81.1% outperformed all the other combinations. The work in [30] used activity images created from accelerometers and gyroscope signals which were learnt by Deep CNNs (DCNNs) to discriminate classifiable activity features. Their experimental outcomes showed better performances than most other approaches. Even if earlier studies have demonstrated that some iterative features may be good at identifying one movement but bad at identifying others (e.g., walking, running, walking, etc.) CNNs in [31] competently performed the HARs, extracting human activity highlights all without any technical experience. They show how feature extraction may be used by CNNs to efficiently collect local signals and spectrum fluctuations of the same activity. The greatest accuracy of 96.88% was attained by the researchers when they evaluated their method on three datasets that were made available to the general public. CNNs employed in [32] single altimeter inputs for HARs generating angular velocities of HAR from mobiles. Their schema achieved accuracies of 93.8% on tri-axial accelerometer data collected by Android apps. The experiments were conducted again with the device implanted in three different body regions to maintain data variety. When compared to other well-known classifiers on the same dataset, including SVMs, CNNs appeared to have retrieved more significant features than the manually computed input features of the Fast Fourier Transform (FFT) and Discrete Cosine Transform (DCT), which are used by SVMs.. An HRC framework for managing assembly tasks performed by a group either alone or in conjunction with humans and robots was a novel HRC concept introduced in [33]. Just o ne piece of RGB camera data is needed for HRC design that uses DL or setup and HARS predictions in [34]. Features for individuals 60 years of age and older were manually collected for analysis. The activity is correctly recognized by the feature fusion technique in use. No automatic data collection methods are used in this instance. Radar-based data collection for HARs was carried out in [35]. This non-wearable radar fixes radar in mobile robots at a predetermined distance to sense activities. The main problem is that the data's accuracy isn't guaranteed if the subject moves beyond a certain reach. Additionally, it occasionally fails to recognize a serious fall scenario. The article uses sensors to identify human activity throughout time. This sensor senses by using a convolution technique. Solid real-time monitoring is not guaranteed, though. This research employs Wi-sense technology to monitor HAR utilizing picture and video capture methods in order to get around the sensing problem. Moreover, the photos are accessed and processed using a hybrid DL model. Additionally, a hybrid DL model is used for both accessing and processing the photographs. In communication networks, opportunistic scheduling is a mechanism that chooses the best time to send data based on available resources (such as bandwidth or relay nodes) [36]. In order to improve the overall security and resilience of networked systems against cyberthreats, it uses Model Predictive Control In the process of optimizing, possible interference or mutual coupling effects between neighboring antenna elements are taken into account and mitigated. In summary, the majority of studies aimed at identifying general human activities do not specifically address the needs of the aged, nor are they assessed using comprehensive assessment criteria. The total activity identification of older adults was the main emphasis of this study, and the models' performance was checked using more intricate assessment parameters. Hence this work's suggested SRHADM solutions enable effective use of human-centered applications, including actively supported living and home monitoring. Understanding the potential therapeutic or scientific uses of HARs might be crucial for clinical applications. SRHADM solutions enable the correct use of human-centered applications such as actively supported living and home monitoring. This knowledge may be useful in clinical applications since it sheds light on the potential therapeutic or research uses of HARs.

SRHADM

This study attempts to categorize human actions of walking, walking_upstairs, walking_downstairs, sitting, standing, and lying A data visualization informs the analysis. We examine how the mistake rates for various m activity labels differ from one another.

Before grouping the data samples based on label similarities, the schema proposed in this study first cleans and groups the input data by checking them for null values, irregularities, such as missing values, and duplicates. After that, features—which are the independent variables—are separated from labels to provide test and training data. After then, Min-Max Scaling is used to standardize and scale this data. The following step involves choosing features based on correlations, mostly to lower the dimensionality of the data and increase prediction accuracy. In order to construct the SRHADM model based on logistic regression, the dimensionality-reduced data is subsequently subjected to label encoding, which transforms categorical data into numerical values. After that, the data is fitted to the proposed prediction schema. The confusion matrix is used to assess the performance of the SRHADM schema. The fundamental components of the proposed SRHADM schema, which may be applied to HARs, are depicted in Figure 3. The recommended SRHADM Schema is shown in Figure 3

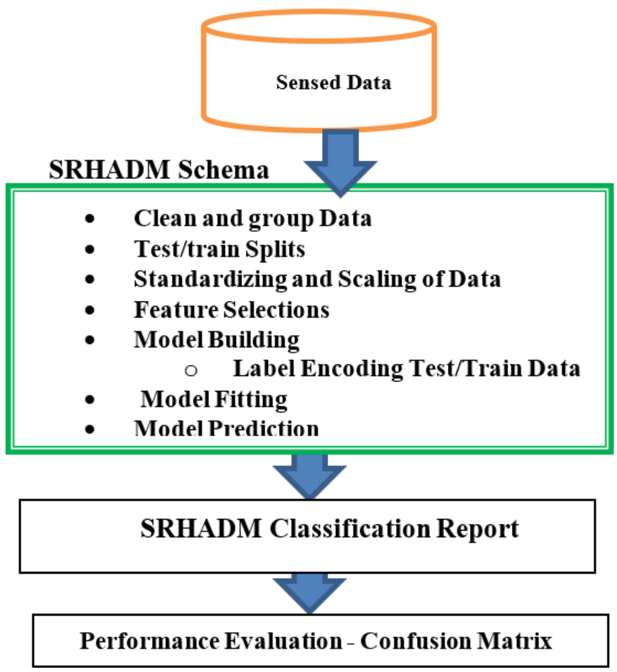


Fig. 3 – SRHADM's schematic Diagram

Results with Discussions

The experimental results of the suggested plan, carried out using Python 3.9 on an AMD Athelon CPU with 4 GB of RAM, are shown in this section step-by-step. Implementations were conducted using Python 3.7.5. In order to categorize activities into WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, and LAYING, the experiments were coded using a Smart Phone Data Set that was acquired from Kaggle for HARs. The experiments were conducted with a group of volunteers who were between the ages of 50 and 70. The dataset records include estimated body accelerations, triaxial angular velocities from gyroscopes, and triaxial accelerations from accelerometers (total accelerations). In the domains of times and frequencies, activity labels, and variables inferred from signals, the dataset in question had 561 feature vectors, including mean values, standard deviations, median absolute deviations, and largest/smallest values in arrays. Areas and energies of the signal magnitude (sums of squares divided by the number of values) interquartile ranges, signal entropies, Autorregresion coefficients with Burg order equal to 4, signal correlation coefficients, greatest magnitude frequency indices, weighted averages of frequencies, their skewness/kurtosis/energies, and vector angles. Averaging signals yielded additional vectors, such as gravity means. SRHADM first organizes and cleans the data before looking at its statistical applications. statistical information on the dataset. The data's statistical details are shown in Figure 4.

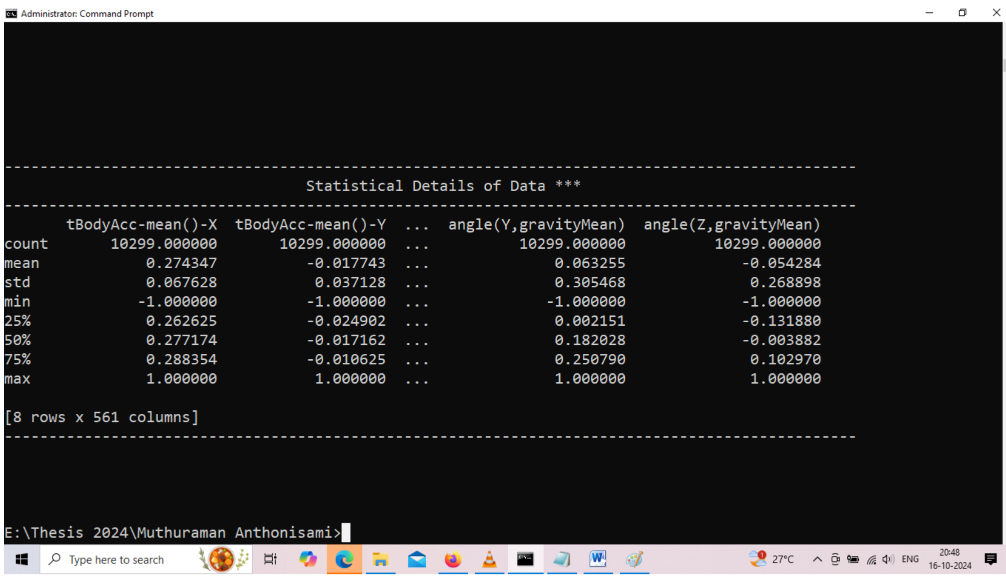


Fig. 4 – Statistical overview of the Data

After cleaning, SRHADM looks for null, missing, or duplicate values before classifying related data according to labels. The act of correcting or eliminating inaccurate, redundant, or incomplete data from a dataset is called data cleaning, often referred to as data cleansing or data wrangling. It often occurs before to the core analysis and is a crucial initial stage in the data analytics process. A pie chart illustrating the data distribution is shown in Figure 5.

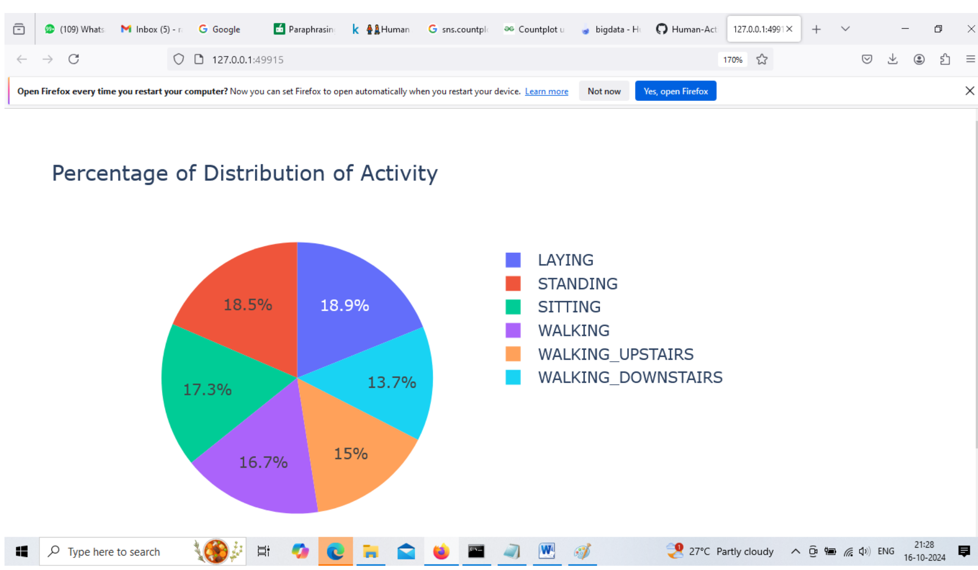
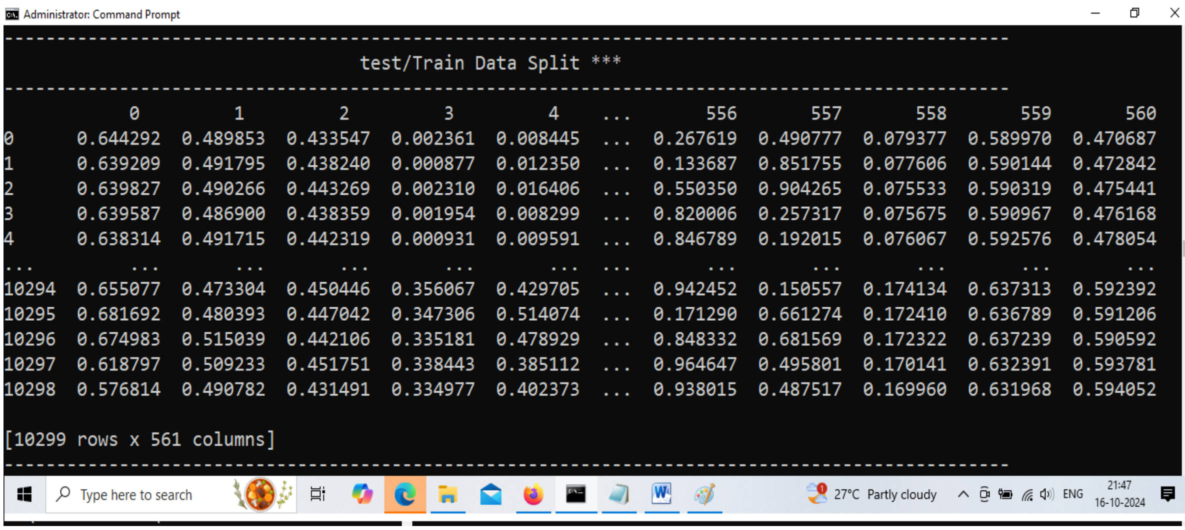


Fig. 5 - Distribution of the data

SRHADM then divides the data into test and train datasets. ML algorithms' performance is estimated using the train-test split technique when they are used to make predictions on non-training data. You can compare how well MLalgorithms perform for your predictive modelling task using the results of this quick and easy method. Even if the technique is simple to apply and comprehend, there are some situations in which it shouldn't be applied, including in cases where the dataset is small or further preparation is required, like in cases where the dataset is unbalanced and being used for classification. When distinguishing between features (independent variables) and labels, SRHADM eliminates irrelevant columns. Figure 6 displays the Test/Train Data details.



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                        test/Train Data Split ***
-------------------------------------------------------------------------------------------
            0         1         2         3         4  ...       556       557       558       559       560
0      0.644292  0.489853  0.433547  0.002361  0.008445  ...  0.267619  0.490777  0.079377  0.589970  0.470687
1      0.639209  0.491795  0.438240  0.000877  0.012350  ...  0.133687  0.851755  0.077606  0.590144  0.472842
2      0.639827  0.490266  0.443269  0.002310  0.016406  ...  0.550350  0.904265  0.075533  0.590319  0.475441
3      0.639587  0.486900  0.438359  0.001954  0.008299  ...  0.820006  0.257317  0.075675  0.590967  0.476168
4      0.638314  0.491715  0.442319  0.000931  0.009591  ...  0.846789  0.192015  0.076067  0.592576  0.478054
...         ...       ...       ...       ...       ...  ...       ...       ...       ...       ...       ...
10294  0.655077  0.473304  0.450446  0.356067  0.429705  ...  0.942452  0.150557  0.174134  0.637313  0.592392
10295  0.681692  0.480393  0.447042  0.347306  0.514074  ...  0.171290  0.661274  0.172410  0.636789  0.591206
10296  0.674983  0.515039  0.442106  0.335181  0.478929  ...  0.848332  0.681569  0.172322  0.637239  0.590592
10297  0.618797  0.509233  0.451751  0.338443  0.385112  ...  0.964647  0.495801  0.170141  0.632391  0.593781
10298  0.576814  0.490782  0.431491  0.334977  0.402373  ...  0.938015  0.487517  0.169960  0.631968  0.594052

[10299 rows x 561 columns]
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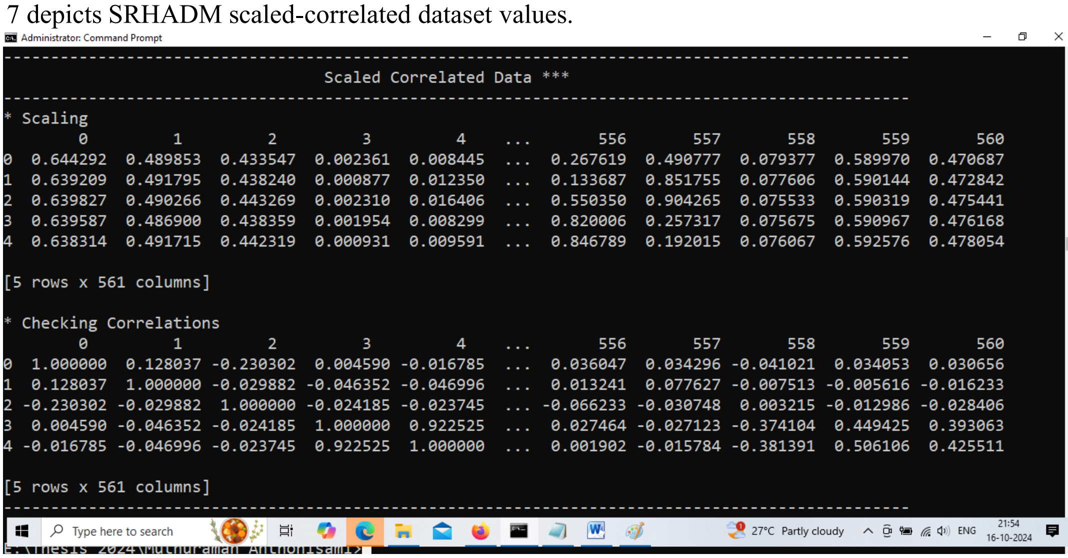
Fig. 6 - Test/Train Split of the Dataset

SRHADM subsequently standardizes the data inputs using Min-Max scaling. Normalizations or min-max scaling are frequently employed in data preparations. It is employed to convert numerical characteristics into a predetermined range, usually 0–1. For MLprocedures, min-max scaling may be helpful. Normalizing the input characteristics improves the performance of several MLmethods. Specific feature dominances throughout the learning process can be removed by scaling the features to a predetermined range. When scaling, SRHADM also finds correlations in the data, taking into account only variables with correlations greater than 90%. Thus, SRHADM effectively reduces data's dimensionalities. Data dimensionality reduction is a technique that uses fewer features to represent a dataset where the goal is to create a models with fewer variables while still capturing the original data's important properties. Figure 7 depicts SRHADM scaled-correlated dataset values.



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Administrator: Command Prompt
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                        Scaled Correlated Data ***
-------------------------------------------------------------------------------------------
* Scaling
          0         1         2         3         4  ...       556       557       558       559       560
0  0.644292  0.489853  0.433547  0.002361  0.008445  ...  0.267619  0.490777  0.079377  0.589970  0.470687
1  0.639209  0.491795  0.438240  0.000877  0.012350  ...  0.133687  0.851755  0.077606  0.590144  0.472842
2  0.639827  0.490266  0.443269  0.002310  0.016406  ...  0.550350  0.904265  0.075533  0.590319  0.475441
3  0.639587  0.486900  0.438359  0.001954  0.008299  ...  0.820006  0.257317  0.075675  0.590967  0.476168
4  0.638314  0.491715  0.442319  0.000931  0.009591  ...  0.846789  0.192015  0.076067  0.592576  0.478054

[5 rows x 561 columns]

* Checking Correlations
          0         1         2         3         4  ...       556       557       558       559       560
0  1.000000  0.128037 -0.230302  0.004590 -0.016785  ...  0.036047  0.034296 -0.041021  0.034053  0.030656
1  0.128037  1.000000 -0.029882 -0.046352 -0.046996  ...  0.013241  0.077627 -0.007513 -0.005616 -0.016233
2 -0.230302 -0.029882  1.000000 -0.024185 -0.023745  ... -0.066233 -0.030748  0.003215 -0.012986 -0.028406
3  0.004590 -0.046352 -0.024185  1.000000  0.922525  ...  0.027464 -0.027123 -0.374104  0.449425  0.393063
4 -0.016785 -0.046996 -0.023745  0.922525  1.000000  ...  0.001902 -0.015784 -0.381391  0.506106  0.425511

[5 rows x 561 columns]
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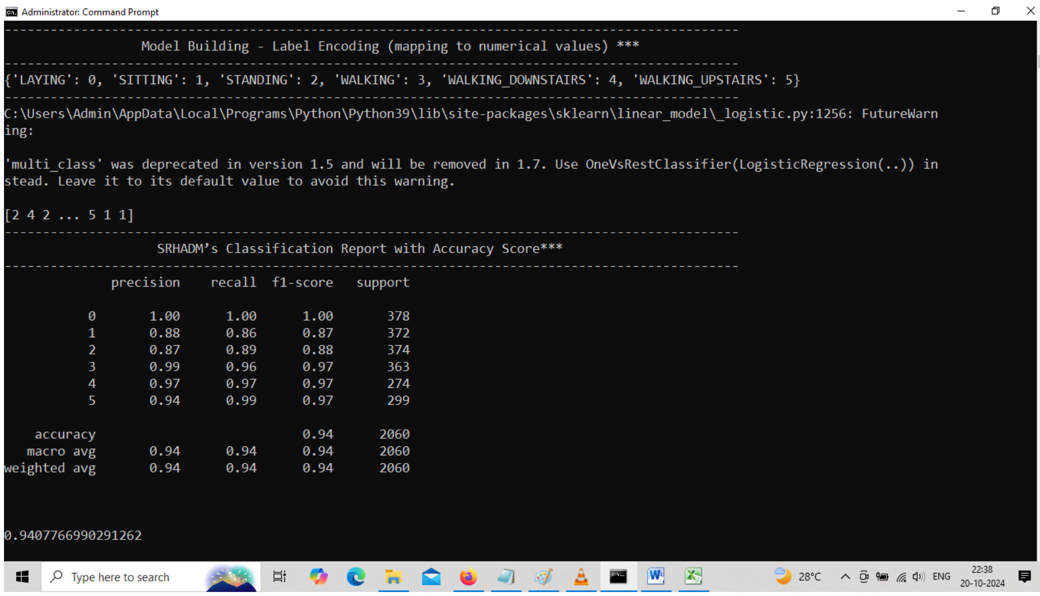
Fig. 7 – SRHADM's scaled-correlated Output

SRHADM also follows label encoding where all categorical values are converted to their numerical equivalents. Logistic Regressions (LRs) are data analysis techniques that employ mathematics to uncover links between data elements. These relationships are then used to forecast values of factors depending on other factors. This is the foundation upon which the prediction model is built. Typically, the forecasts are limited counts of yes/no answers. SRHADM uses LRs for its training and predicts the instances on the test set. LRs predict values with finite outcomes, usually yes or no, by using the connections they have learned between data elements. In this study, dependent parameters like precision, recall, accuracy, and F1-score were obtained by mathematically processing the aforementioned parameters for the result evaluations, in addition to the fundamental parameters: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) [37]. Here, TP stands for the number of rightactivity predictions that were accurate, TN for the number of wrong-activity predictions that were accurate, FP for the number of wrong-activity predictions that were incorrect, and FN for the number of wrong-activity predictions that were incorrect. The values of precisions, recalls, accuracies, and F1-scores were computed using: Precision = (TP)/(TP+FP), Recall = (TP)/(TP+FN), Accuracy = (TP+TN)/(TP+TN+FP+FN) and F1-Score = (2TP)//(2TP+FP+FN). Figure 8 depicts the Modelling and accuracy outputs of SRHADM.



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Administrator: Command Prompt
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                  Model Building - Label Encoding (mapping to numerical values) ***
------------------------------------------------------------------------------------------------
{'LAYING': 0, 'SITTING': 1, 'STANDING': 2, 'WALKING': 3, 'WALKING_DOWNSTAIRS': 4, 'WALKING_UPSTAIRS': 5}
------------------------------------------------------------------------------------------------
C:\Users\Admin\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn\linear_model\_logistic.py:1256: FutureWarn
ing:

'multi_class' was deprecated in version 1.5 and will be removed in 1.7. Use OneVsRestClassifier(LogisticRegression(..)) in
stead. Leave it to its default value to avoid this warning.

[2 4 2 ... 5 1 1]
------------------------------------------------------------------------------------------------
                    SRHADM's Classification Report with Accuracy Score***
------------------------------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       378
           1       0.88      0.86      0.87       372
           2       0.87      0.89      0.88       374
           3       0.99      0.96      0.97       363
           4       0.97      0.97      0.97       274
           5       0.94      0.99      0.97       299

    accuracy                           0.94      2060
   macro avg       0.94      0.94      0.94      2060
weighted avg       0.94      0.94      0.94      2060


0.9407766990291262
```


Fig.8 - Modelling and accuracy outputs of SRHADM

The suggested SRHADM schema achieves an accuracy score of 94.07766990291262 which is high. Additionally, this schema was assessed using test data and a confusion matrix, which is a numerical matrix that indicates areas in which a model becomes confused. These are systematic methods of assigning predictions to the original data classes: class-wise distributions of the SRHADM model's predictive performances. Only in cases where output distributions are known are confusion matrices employed and assist in significant assessment metrics of models along with classifiers' accuracy (global/class-wise accuracy) computations. Confusion Matrix of SRHADM is displayed as Table 2.

Table 2 - Confusion Matrix of SRHADM

WALKING	**377**	**0**	**0**	**0**	**1**	**0**
WALKING_UPSTAIRS	**1**	**320**	**50**	**0**	**0**	**1**
WALKING_DOWNSTAIRS	**0**	**42**	**331**	**0**	**0**	**1**
SITTING	**0**	**0**	**0**	**347**	**4**	**12**
STANDING	**0**	**0**	**0**	**3**	**266**	**5**
LAYING	**0**	**0**	**0**	**0**	**2**	**297**
	WALKING	**WALKING_UPSTAIRS**	**WALKING_DOWNSTAIRS**	**SITTING**	**STANDING**	**LAYING**

Performances of classification algorithms are represented by table values which also display standardized confusion matrix of the suggested schema where rows represent instances of predicted classes while columns represent actual class instances. The accurately predicted samples in the above table's total dimensionally reduced 292 samples are the diagonal elements shown in red: WALKING 377, WALKING_UPSTAIRS 320, WALKING_DOWNSTAIRS 331, SITTING 347, STANDING 266 and LAYING 297. When compared to the real numbers, it is possible to conclude that SRHADM produced the best results by looking at the entire confusion matrix.

Discussions

HARs try to ascertain human behaviors from collections of observations about them and their surroundings. Combining data from many sources, including ambient or body-worn sensors, can help with recognition. An equitable distribution of data for each activity has been confirmed, and duplicate data and incorrect values have been removed from the dataset. Well-known methods, such as selecting the most useful attributes from the data, were employed to cut down on the amount of data. The dimensionality of the original features can be reduced by using correlations to create a lower-dimensional subspace of features while retaining the important aspects of the original feature set. Primary components are created by linearly combining the features that are already present in the data set. The original data collection is then described using these elements. However, if the data has to be modeled using a non-linear high-dimensional feature dataset, modeling it with parameters derived from performing correlations on the data set will result in a very poor model and less accurate recognition results. One important method in the fields of AI and ML is logistic regression. ML models are computer algorithms that can be trained to comprehend complex data without the need for human interaction. Organizations may utilize ML models based on LRs to get useful insights from their business data. They may increase efficiency, reduce operational costs, and accelerate expansion by applying predictive analysis to these data like finding business trends or enhancing staff retentions, resulting in more lucrative product designs. The advantages of using logistic regression over other ML methods are detailed below.

- Simplicity: Compared to other ML techniques, logistic regression models have a lower mathematical complexity. Hence, extensive knowledge of M can be applied.
- Speed: Because logistic regression models reduce the usages of resources including memory and processing capacities, they can manage voluminous data quickly. For businesses looking to get some rapid wins from their ML efforts, this makes them perfect.
- Flexibility: Logistic regression is a useful tool for answering questions with two or more limited outcomes. It may be used for preparing data as well. For example, logistic regression may be used to categorize data with a large range of values, such as bank transactions, into a smaller, easier-to-manage range of values. Then, for a more precise examination, this reduced data set can be processed using further ML algorithms.

Visibility: Compared to other data analysis methods, logistic regression analysis provides developers with a better understanding of internal software operations. Because the calculations are simpler, troubleshooting and error repair are also simpler.

Conclusion

The current healthcare system depends heavily on HAR research. The increasing need to analyze time series data in order to HAR has piqued researchers' interest in this field. Selecting relevant features from time series data is crucial for HAR. While there are many challenges in this industry, a precise classification technique for actions is also necessary. We describe in this work a revolutionary IoT solution for personal, ongoing monitoring of household chores. With the use of Deep Learning Methods and a Wi-Fi wearable sensor, the device generates data on a variety of acts from which abnormal patterns can be deduced. The suggested approach is meant to be expanded to offer personalized data from an abundance of wearable sensors (as in a multi-occupant home). This work introduced a novel approach to data collection that can be easily integrated into people's daily routines and allows for the completion of many activities in any order within a set amount of time. Other researchers are welcome to use the dataset and the data collection techniques at no cost. Since senior individuals typically lead monotonous lives, this research aims to track the daily activities of elderly persons in order to protect their health. Thus, appropriate action can be done if a sudden shift is noticed in routine tasks. In an aging society, automatic activity recognition could let senior citizens live independently in their own houses. The suggested study included a variety of traditional ML and DL techniques to identify the activities of senior citizens. The proposed work's objective was to develop an automated activity monitoring system that would use the recommended SRHADM approach to detect older people's activities with a 94.5% accuracy rate. This is important since there are many different types of activities, some of which are quite similar to one another, making it challenging to develop an accurate HAR system. However, the proposed models still require improvement through validation with larger datasets and more tasks. The models developed in this work can also be applied in other domains where ongoing activity supervision is necessary. Wi-Fi and SRHADM system-based indoor activity monitoring for the elderly and Future senior monitoring needs to be improved using video conferencing technology in order to identify uniqueness of action easily. Integration of IoT-based architecture can increase monitoring accuracy.

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