The Original

Enhancing Elderly People's Quality of Life by Identifying Their Actions using an Effective Machine Learning Model

Anthonisamy S[1] , P. Prabhu[2]

[1]Research Scholar (Part-Time), Department of Computer Applications, Alagappa University, Karaikudi-630003,Tamil Nadu, India. Email:antony2006reegan@gmail.com. Orchid id - https://orcid.org/0000-0003-3516-1747
[2]Associate Professor in Information Technology, Centre for Distance and Online Education, Alagappa University, Karaikudi.630003, Tamil Nadu, India. Email:prabhup@alagappauniversity.ac.in Orchid - https://orcid.org/0000-0002-5960-4103
*Corresponding Author: prabhup@alagappauniversity.ac.in

Abstract: Globally, millions of people are above 65 years of age which affects both their physical and emotional well-being. They are likely to face incidents like falls resulting in potentially severe repercussions including hospitalizations. Human Action Recognitions (HARs) are techniques that recognize and categorize human behaviours from sensor data using machine learning (ML) algorithms. These are essential for human behavior analyses in applications including diagnosis of severe illnesses, patient rehabilitations, and healthy lifestyles. One increasingly effective use of ML methods are predictions of human behaviours, whereby computers monitor routines and intervene in crisis, which may be quite beneficial for the elderly. Moreover, there aren't many studies on HARs for the elderly making it imperative to study human gestures. This work introduces a Logistic Regression Based Identification of Human actions (LRBIHA) schema based on ML that can identify human actions with accuracies of over 90%. Solutions based on LRBIHA HARs can enable the appropriate use of supported living applications for humans including home based monitoring. The schema cam also be useful to clinicians, potential therapeutics and research.

Keywords: Falls and Injuries, human activities; machine learning, deep learning, elderly population.

INTRODUCTION: Globally, the percentage of humans who are 65+ years of age and living alone has been on the rise. Japan is the only country with a population of more than 124 million (as of 2025), with approximately 1/3rd being 65+. In contrast, much of Southern and Western Europe has at least one in every five individuals aged 65 and older. In 2025, more than 23% of Germany, Italy, Portugal, Greece, and Finland's populations will be senior citizens. By 2050, there will be more than 2.1 billion elderly citizens where 2/3rd of global population reside in developing countries and rising more quickly there than in industrialized countries. The world's aging population is depicted in Figure 1.

Fig. 1 – Global ageing population (Highest Number of Seniors (65+)

World Health Organization (WHO) studies have found insufficiency of facilities for these elderly [1]. There is a need to keep an eye the actions of the elderly and avoid avoiding falls, the most common cause of mortalities in the elderly. Anxiety and a fear of falling are two psychological repercussions of falls. It is essential to set up reliable and secret healthcare-related internal security mechanisms that allow medical professionals to be contacted in an emergency. Elderly adults require constant supervision and protection to avoid accidents, harm, or danger [2]. With direct medical expenses for non-fatal injuries reaching $1 billion yearly and expected to increase, falls among the elderly cause substantial financial difficulties. Hospitalizations are the main source of costs; fractures are the most costly and frequently need long-term care. Osteoporosis, adverse drug reactions, and environmental risks are important risk factors. Over $1 billion was spent on direct medical care for non-fatal fall injuries in 2015; the entire cost, including fatal injuries, was significantly greater. This expense is projected to reach billions by 2030 making them costly. Sixty five percentage of all expenses are related to inpatient hospital stays, fractures account for more than 60% of non-fatal expenses,. In the early 2000s, the average cost per person who fell was higher. Despite making up just 6% of the population, women pay 33% of all medical expenses, which are two to three times more than those of males. Figure 2 depicts medical expenses arising from non-fatal falls.

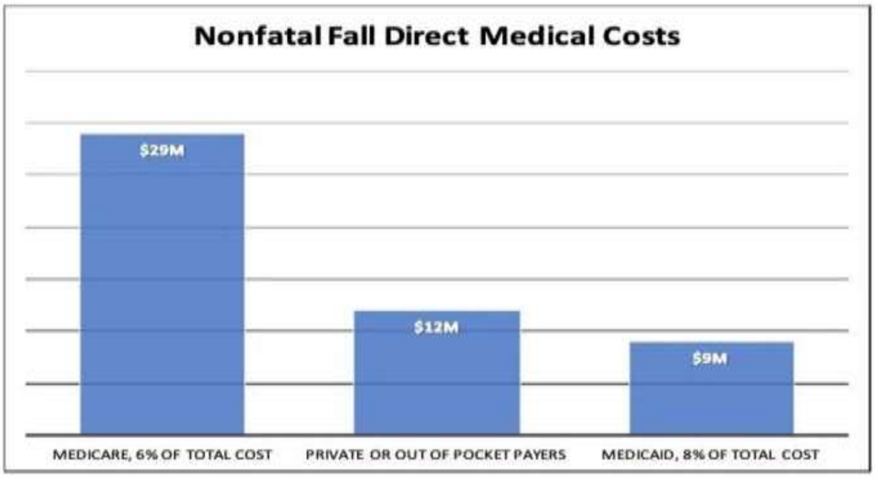


Fig. 2 - Medical expenses arising from non-fatal falls

The most common injuries are fractures (particularly hip fractures), contusions, and head traumas. Implementing evidence-based solutions can considerably lower the expenses. People's behaviours have been frequently observed using mobile phones [3]. Wearable sensor applications in medicine are becoming increasingly important in today's environment [4]. Wearable sensors can be used for surveillance, physical treatment, keeping an eye on the elderly, documenting sporting and recreational activities, and monitoring social interactions. Their costs have reduced [5] and are also secure as IoT based equipment do not t need any human involvement [6]. Certain characteristics of wearable like heart rate monitors distinguish them from pharmaceutical-grade surveillances [7]. Patient information generated by sensors can be shared with clinicians and hospitals using the internet [8]. Human behavior cannot be broadly categorized or described where sensor placements play a major role in tracking diverse human actions [9]. HARs offer a plethora of opportunities for system development and implementation .HARs can assess physiological activities by analysing sensor or camera data and anticipate dangerous circumstances by revealing usage patterns. Developments in AI have resulted in numerous studies for HARs which use accelerometers, gyroscopes and sensors for evaluating movements or actions of humans[10]. Sensors can record angular or gravity accelerations generated by the human body which are proliferated by ML/DL models of HARs for classifications based on their self-learning capabilities [11]. Studies focussing on creating frameworks of HARs for the elderly are limited [12]. The work in [13] gave a summary of opportunities and challenges for DL algorithms in HARs. Multimodal features need to be processed efficiently to optimize system performances because of the variety of sensor data that is gathered [14]. Algorithmic HARs require improved accuracy for monitoring human activities in the elderly. Studies have identified human actions [15] from data sets [16] where predictions imply future or possible actions [17]. ML methods including Naive Bayes (NBs), Random Forests (RFs), KNNs (K-Nearest Neighbors), Neural Networks (NNs) and Support Vector Machines (SVMs) have categorized complex features [18]. Attention based approaches [19] with agents emphasized relevant and identifiable modalities for HARs, but were not validated on older datasets. These studies indicate the existence of gaps in HARs and hence, this work attempts at a framework for assessing HARs in the elderly. Following this introductory section, section two is definition of the problem followed by review of related literature in section three. The suggested schema LRBIHA is detailed in section four followed by its implementation results and discussions in section five. This work concludes in subsequent section with future scope.

Definition of the Problem:

Falls among senior citizens are a prevalent, dangerous, and quickly expanding public health issue. In all age groups, falls are the most common cause of trauma-related deaths. Falls account for a significant portion of healthcare costs for persons 65 and older due to the rising fall rate. If more effective fall prevention measures are not put in place, the financial cost of falls is expected to rise significantly in the upcoming years. The cost of treating falls is expected to almost double if the fall rate keeps rising at the current rate. The most common injuries are head injuries, contusions, and fractures (particularly hip fractures). Implementing evidence-based solutions can significantly reduce these costs. Monitoring the elderly lowers medical expenses and hospital admissions where Wi-Fi equipments using channel states can identify human activities. These structures are more reliable, less costly than radars and are made possible by the widespread presence of Wi-Fi hotspots [20]. Many studies have employed these devices for motion tracking or detections [21]. Providers must give objective, accurate screening for all older persons first priority in order to combat the growing fall rate and fall treatment costs associated with an aging population. This should be combined with straightforward, useful techniques that the physician may suggest or prescribe from the community, such as physical therapy. Regular follow-up measures should be a part of standard treatment, and for some demographic groups, they should be integrated into remote patient monitoring. Falls of the elderly increase the complexity and costs of treatments. A monitoring system for the elderly can help save time and money by identifying possible dangers. Monitoring actions of the elderly can enhance their general quality of life where they experience greater peace and comfort. Effective fall prevention strategies can effectively address the impending falls pandemic where doctors need reliable technologies that operate with their existing processes. Thus, this work focuses on decoding human actions based on sensor data for assisting the elderly in times of need and help early interventions in cases of possible falls.

Literature Review: HARs have been the subject of extensive investigation in recent years because of their usefulness and durability where smartphones are excellent instruments for activity recognitions. Accelerometer data from Android-based HARs have been used for online classifications [22]. Clustered k-NN approach enhanced classification performances with better execution times despite limited resources of Android platforms. Online HARs based on smartphone inertial sensors were also proposed by the study in [23] where the system's performances on sets of twenty-three activities were evaluated using six incremental learning approaches. The outcomes were then contrasted with the most advanced HAR methods, including Decision Trees (DTs) and AdaBoost where accuracy of 95% was attained using incremental k-NNs and NBs. The work in [24] developed a novel tracking system for the elderly with k=5 in a k-NN model, achieving an accuracy of 96.40% on action detections. The users could message in emergency situations. An energy efficient model for HARs of [25] based on smartphones used fixed point arithmetic with enhanced SVMs. The schema produced results equivalent to other commonly used classification methods. Their activity detections were based on long short-term memory (LSTM) in a variety of environments including homes and clinics [26]. Human action features were grouped by Kernel based Discriminant Analysis (KDA) which maximized data distributions between classes while minimizing variations within classes. The study obtained a recall value of 99% when compared to Convolutional Neural Networks (CNNs), and Deep Belief Networks (DBNs). Similarly, the work in [27] demonstrated deep LSTM based differentiation on six distinct human activities using smartphone data. The work achieved 96.70% accuracy on the UCI-HAD dataset. CNNs identified human actions in [28] where nine distinct actions were detected with 98% accuracy using data from smartphone accelerometers, magnetometers, gyroscopes, and barometers. LSTM and CNNs tn [29], with an accuracy of 81.1%, performed better than most other methods in their predictions of actions in the elderly. Activity images from accelerometers and gyroscopes were trained on Deep CNNs (DCNNs) in [30] for detecting classifiable human activities, outperforming other methods. CNNs in [31] effectively identified human activity highlights without training, despite prior research showing that some recurring patterns are good at detecting one movement but bad at identifying others (e.g., walking, running, walking, etc.). They demonstrated how CNNs use feature extraction to effectively gather spectrum variations and local signals for activities. After testing their approach on three datasets, the researchers achieved the highest accuracy of 96.88%. CNNs were used in [32] to execute HARs on single altimeter inputs supplied by angular velocities from mobile devices. Using tri-axial accelerometer data from Android applications, their approach obtained 93.8% accuracy. To ensure data diversity, the experiments were repeated using devices implanted in three distinct body areas. CNNs outperformed other popular classifiers that used SVMs to manually create input features for the Discrete Cosine Transform (DCT) and Fast Fourier Transform (FFT) on the same dataset. A revolutionary Human-Robot Collaboration (HRC) approach was put out in [33] to manage assembly tasks completed by a group, either alone or with people and robots. DL was utilized in HRC design to predict HARs from RGB camera data [34]. The features of more than 65 patients were collected for study without the use of automated data collecting methods or feature fusions, which accurately recognized activities. The work in [35] installed non-wearable radars on mobile robots, collected data at a predefined distance for HARs. The primary issue was that accuracy was not guaranteed when patients passed specified ranges. It also sometimes overlooked hazardous fall situation. Convolutional sensing by sensors using Wi-sense technology were used to monitor HARs through image and video captures. A hybrid DL retrieved and evaluated images obtained by opportunistic scheduling which used available resources (such as relay nodes or bandwidth) to determine when data should be sent [36]. The Model's Predictive Control, enhanced general security and robustness where interferences or mutual contacts between adjacent antenna elements were examined and reduced during optimizations. Studies on HARs for the elderly are limited, making it imperative to assess their daily movements and warn in times of difficulties. Hence, this work focuses on determining activities amongst the elderly and assessing the models' performance intricately. Acknowledging the possible medical or scientific usages of HARs, the suggested LRBIHA schema can facilitate human centric applications like home monitors and supportive living for the elderly to prevent falls and enhance researches on HARs.

The suggested LRBIHA Schema: Although it may be prevented, falling is believed to be an inevitable part of aging. Research indicates that patient-specific treatments, multimodal therapy, and screening can all help avoid falls. Nevertheless, healthcare settings have not made extensive use of fall risk assessment. This might be because current practices are inconsistent or because sophisticated methods that rely on patient self-reporting, medical expertise, or time are used. Walking, sitting, standing, and lying are human positions that may be very helpful in monitoring the elderly. This study aimed to classify these behaviours. The study is informed by data visualizations where errors in activity labels that are different from each other are examined. Before classifying data samples according to label similarities, the methodology employed in this study cleans and sorts inputs by identifying null values, irregularities (missing values), and duplicates. Test and training data sets are used to extract independent variables, sometimes referred to as features. The data is then scaled and normalized using Min-Max Scaling. The next step is to choose features based on correlations for reducing data's complexity while enhancing prediction accuracy. The data is fed to LRBIHA model following reduction of dimensionality and encoding of labels which convert categorical inputs into numerical values. Figure 3 illustrates the main components of the proposed LRBIHA schema that might be used to HARs.

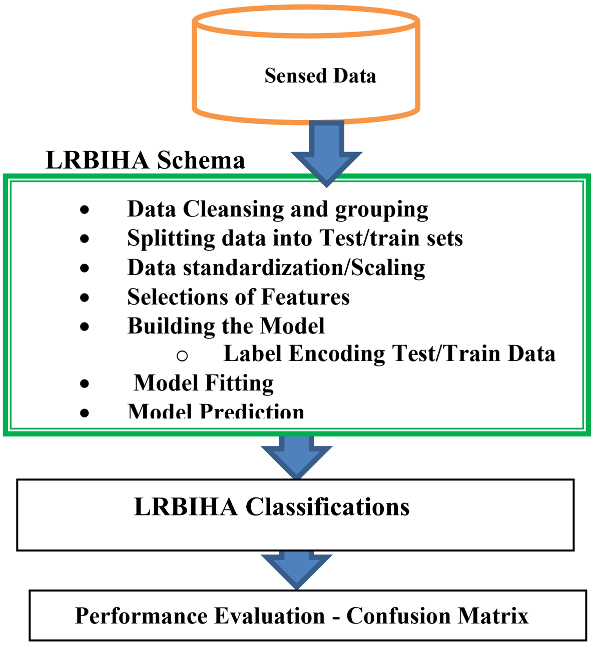


Fig. 3 – LRBIHA's schematic Diagram

Results with Discussions: This section displays the experimental outcomes of categorized activities like WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, and

LAYING on the Smart Phone Data Set obtained from Kaggle. Python 3.7.5 on an AMD Athelon CPU with 4 GB of RAM was used to implement the suggested schema. The dataset includes triaxial angular velocities from gyroscopes, triaxial accelerations from accelerometers (total acceleration), and anticipated body accelerations of participants up to seventy years of age. The dataset encompasses more than 500 feature vectors, including means, standard deviations, max/min values of arrays as time and frequency activity labels, median absolutes, signal-inferred variables, Interquartile ranges, vector angles, areas and energies of signal magnitudes (sums of squares divided by value counts), weighed averages of frequencies, signal entropies, greatest magnitude frequency indices, skewness, kurtosis, energies, and auto-regression coefficients with Burg order equal to 4. Signals were averaged to provide additional vectors, such as the gravity mean. Before beginning statistical applications, LRBIHA arranges and cleans the data. The statistical information of the dataset. Figure 4 displays the data's statistical information.

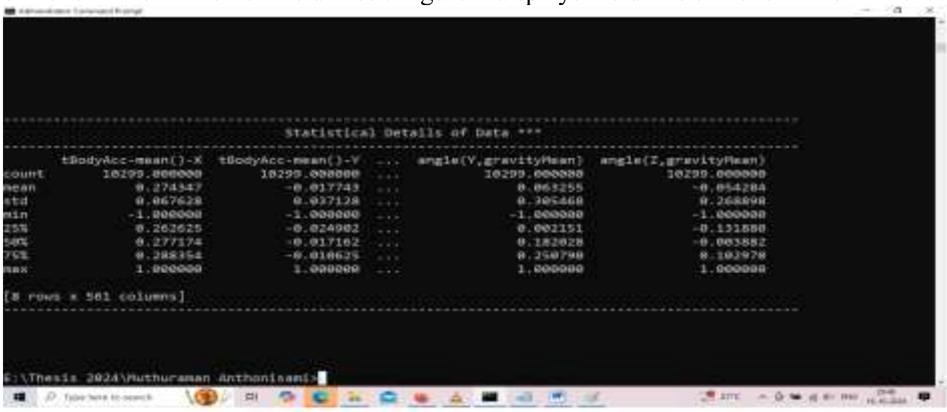


Fig. 4 – Statistical overview of the Data

Subsequent to data cleaning or data cleansing or data wrangling which includes eliminating errors, finding duplications or missing data from dataset inputs, an essential initial phase in the data analytics, LRBIHA uses labels to categorize related data after examining null, missing, or duplicate values. Figure 5 depicts activity distribution as a pie chart.

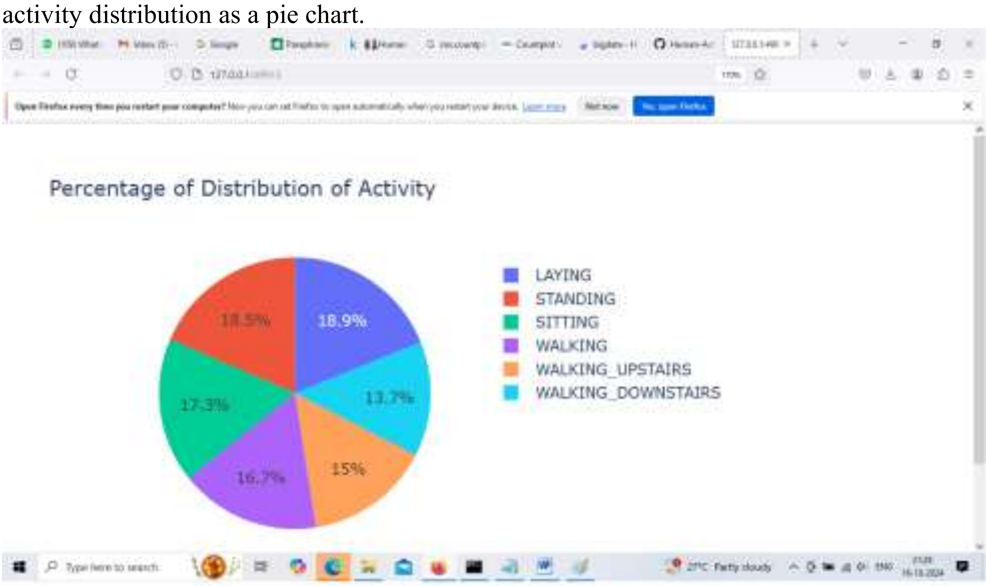
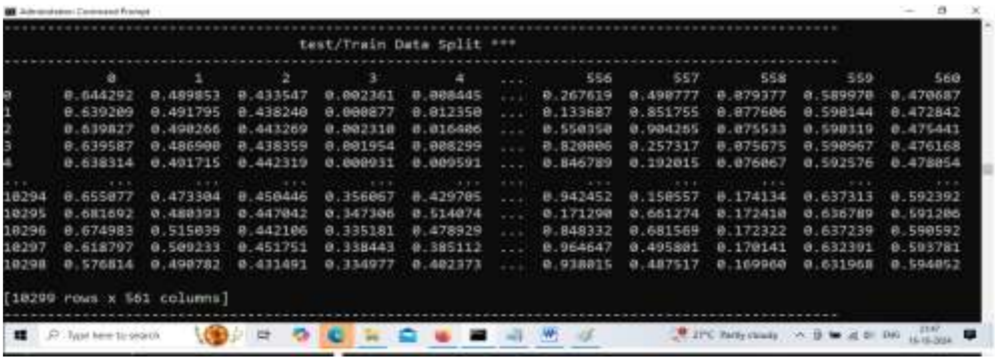


Fig. 5 - Distribution of the data

LRBIHA splits inputs in test/train sets. The train-test split method evaluates ML algorithm's predictive modelling outcomes with non-training data. Though an easily comprehensible method, they cannot be used on small or imbalanced and additional preparations are required for categorizations. LRBIHA handles these issues by eliminating unnecessary columns and differentiating features (independent variables) and labels for improved performances. Figure 6 depicts . LRBIHA's splits of data into test/train sets.



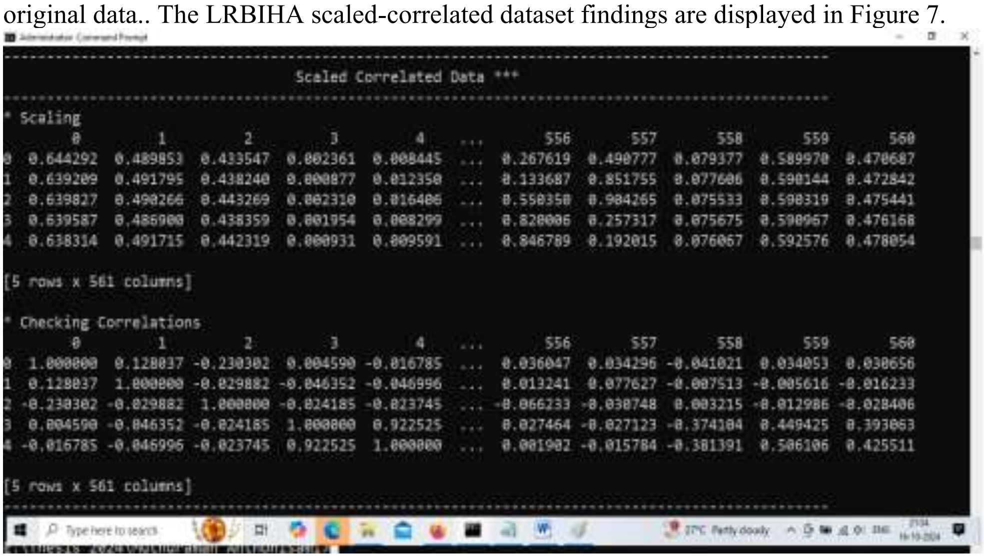
test/Train Data Split ***

	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]

Fig. 6 - Test/Train Split of the Dataset

LRBIHA uses Min-Max scaling to standardize data inputs. Normalizations and min-max scaling are commonly used in data preparations. Numerical properties are converted into similar ranges (between 0 and 1) . Normalizing input characteristics improves performances of ML methods. Scaling the features to predefined ranges reduce dominances from specific features during the learning process. LRBIHA also searches inputs for correlations during scaling and considers only variables with correlations greater than 90% resulting in successful reduction of data's dimensionality. This technique builds models with fewer variables and representing datasets with fewer characteristics while maintaining important aspects of original data.. The LRBIHA scaled-correlated dataset findings are displayed in Figure 7.



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]

Fig. 7 – LRBIHA's scaled-correlated Output

LRBIHA additionally uses label encoding, which converts all category variables into number values. Logistic regressions (LRs) are methods of data analysis that use arithmetic to find connections between data items. The values of components that rely on one another are then predicted using these connections. This forms the basis of the prediction model. Forecasts are frequently restricted to the quantity of affirmative or negative responses. LRBIHA schema, using LRs in training, predicts events in test sets as yes or no based on learnt relationships between data points. The aforementioned variables were statistically processed to provide dependent measures including precision, recall, accuracy, and F1-score in order to assess the study's conclusions. False positive (fp), false negative (fn), true positive (tp), and true negative (tn) are other crucial characteristics [48]. In this case, TP stands for the quantity of accurate right-activity forecasts, TN for accurate wrong-activity forecasts, FP for inaccurate wrong-activity forecasts, and FN for incorrect wrong-activity forecasts. The following formulas were used to determine the precision, recall, accuracy, and F1-score values: precision = (TP)/(TP+FP), recall = (TP)/(TP+FN), accuracy = (TP+TN)/(TP+TN+FP+FN), and F1-score = (2TP)/(2TP+FP+FN). The modelling and accuracy results of LRBIHA are shown in Figure 8.

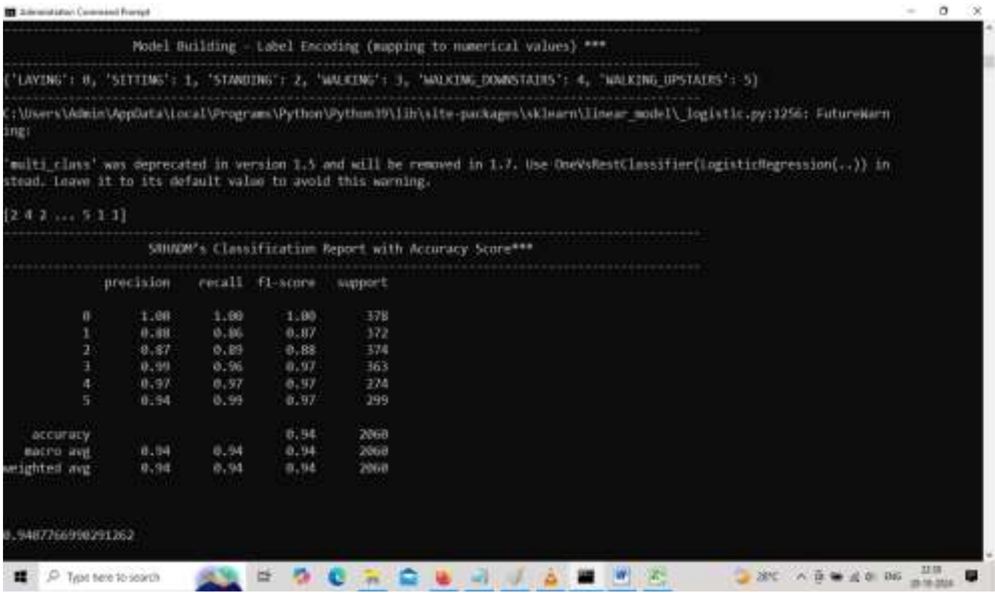


Fig.8 - Modelling and accuracy outputs of LRBIHA

The proposed LRBIHA schema has a high accuracy score of 94.08 (rounded off to the nearest decimal) This design was also assessed using test data and a confusion matrix, which is a numerical matrix that shows where a model becomes confused. These are class-wise distributions of the expected performance of the LRBIHA model, which are methodical ways of allocating predictions to the initial data classes. Confusion matrices help with model evaluation metrics and classifier accuracy calculations, however they are only used when output distributions are known. The LRBIHA Confusion Matrix is shown in Table 2.

Table 2 - Confusion Matrix values of LRBIHA Predictions

WALKING	**376**	**0**	**0**	**0**	**1**	**0**
WALKING_ UPSTAIRS	**1**	**321**	**50**	**0**	**0**	**1**
WALKING_ DOWNSTAI RS	**0**	**41**	**330**	**0**	**0**	**1**
SITTING	**0**	**0**	**0**	**348**	**5**	**11**
STANDING	**0**	**0**	**0**	**3**	**265**	**5**
LAYING	**0**	**0**	**0**	**0**	**2**	**298**
	WALKIN G	**WALKING_ UPSTAIRS**	**WALKING_ DOWNSTAI RS**	**SITTIN G**	**STANDI NG**	**LAYIN G**

The performance of LRBIHA algorithm is described by confusion matrix values of table 2 where rows denote anticipated class instances and columns denote actual class occurrences. The diagonal elements namely WALKING 376, WALKING_UPSTAIRS 321, WALKING_DOWNSTAIRS 330, SITTING 348, STANDING 265, and LAYING 298 represent properly predicted samples, showing higher performance of LRBIHA schema.

Discussions

HARs make an effort to infer human actions from sensors. The sensed data needs to be formalized by removing duplicates and inappropriate numbers, ensuring balanced distributions of activity data. Correlations can be used to construct lower-dimensional subspaces of features that retain most important properties of original feature sets and reducing data dimensionalities. Data collections are combined linearly to form primary components of inputs for models. However, modeling on parameters generated from correlations of non-linear high dimensional data may result in less accurate results where LRs are important techniques to overcome this hurdle. ML models based on LRs can employ predictive analytics and get valuable insights from their business data to identify business trends. They can assist in boosting productivity, reducing operative expenses, and spur expansions. The benefits of using LRs for predictions are detailed below:

- Simple: Models of LRs are simpler than other ML approaches. Hence, substantial knowledge of ML may be employed.
- Efficacy: Models based on LRs can handle large amounts of data quickly due to their efficient use of resources like memory and computing. This is ideal for firms seeking quick results from ML .
- Flexibility: LRs are good approaches when faced with problems that have two or more limited outcomes. Data preparation is another application of LRs which for instance, may be used to reduce a wide range of values to a more manageable, narrower ranges (Stock Trading Transactions). To create a more accurate assessment, this condensed data set might subsequently be assessed using further machine learning methods.

- Visibility: Analyses by LRs are more visible than other approaches for data analyses and ensure developers have better grasp of internal program functions as their computations are simpler and troubleshooting and error correction are also easier..

Conclusion:

Although past fall history is the strongest predictor of falls, more than half of patients do not report it to their doctors. These measures have not proven useful in predicting falls; current therapeutic approaches fail to detect 69-85% of individuals at risk of falling. Fall prediction can be simplified by approaching the subject from a different perspective. Falling is fundamentally a gravitational problem. One should objectively measure the patient's postural stability, or capacity to endure the force of gravity. Then, focus on a streamlined set of concrete techniques for intervention and patient empowerment, and retest/monitor on a frequent basis to adjust course as needed. These simple actions with regular measurements may be integrated into and improve other chronic illness care, whether in a clinic or via remote patient monitoring. The accompanying software walks the doctor through simplified practical methods tailored to each patient, and a patient-facing app and educational resources may be utilized to empower individuals. The scale may also be used securely at home as a remote patient monitoring system to track balance and encourage healthy habits. Regular self-testing by older persons in an independent living facility resulted in a 74% reduction in falls, with an average duration to transition from high risk to moderate risk of 34 days, demonstrating that the reduction in falls was due to observable improvements in postural stability. The present healthcare system is primarily based on HAR research. Academics are becoming increasingly interested in the evaluation of time series data for HARs which focuses largely on selecting meaningful qualities from time series data. An accurate method for categorizing tasks of HARs is also required. Gadgets can records data on a range of behaviours using DL Methods and Wi-Fi wearable sensors, allowing for identification of anomalous patterns. This work’s suggested LRBIHA schema suggests a unique method for gathering data that is simple to incorporate into people's daily routines and permits the completion of many activities in any sequence within predetermined time frames. Since most elderly people may have difficulties, this research attempts to monitor their habits for indicating their health status. Appropriate action may be taken when unexpected changes in routine tasks occur. Elderly individuals can be live freely in their own houses due to this automated activity recognitions. The proposed study detects older people's actions using a range of conventional ML and DL techniques. The LRBIHA technique is aimed at creating an automated activity monitoring system that identifies activities of senior citizens with 945% accuracy. This is crucial since developing an efficient HAR system is difficult due to the large range of Action kinds, some of which are somewhat similar to one another. However, further work and validation with larger datasets are required to make the models offered better. Other businesses that require continuous activity monitoring might apply the models developed in this study. In addition to Wi-Fi and LRBIHA system-based interior activity monitoring for the elderly, video conferencing technology must be utilized to promptly detect originality of action in future senior monitoring. The precision of monitoring may be increased by integrating an IoT-based infrastructure.

References

[1] Du, Y.; Lim, Y.; Tan, Y. A Novel Human Activity Recognition and Prediction in Smart Home Based on Interaction. Sensors 2019, 19, 4474.

[2] Chernbumroong, S.; Cang, S.; Atkins, A.; Yu, H. Elderly Actions recognition and classification for applications in assisted living, Expert Systems with Applications. Expert Syst. Appl. 2013, 40, 1662–1674. [CrossRef]

[3] Bulbul, E.; Cetin, A.; Dogru, I.A. Human Activity Recognition Using Smartphones. In Proceedings of the 2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), Ankara, Turkey, 19–21 October 2018; pp. 1–6.

[4] Nweke, H. F., Teh, Y. W., Mujtaba, G. & Al-garadi, M. A. Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions. Inf. Fus. 46, 147–170 (2019)
[5] Zhang, R., et al. Differential Feature Awareness Network within Antagonistic Learning for Infrared-Visible Object Detection. In IEEE Transactions on Circuits and Systems for Video Technology, (2023).
[6] Gravina, R., Alinia, P., Ghasemzadeh, H. & Fortino, G. Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges. Inf. Fus. 35, 68–80 (2017).
[7] Roy, N., Misra, A. & Cook, D. Ambient and smartphone sensor assisted ADL recognition in multi-inhabitant smart environments. J. Ambient Intell. Hum. Comput. 7(1), 1–19 (2016).
[8] Lara, O. D. & Labrador, M. A. A survey on human activity recognition using wearable sensors. IEEE Commun. Surveys Tutor. 15(3), 1192–1209. https://doi.org/10.1109/SURV.2012.110112.00192 (2013)
[9] Bulling, A., Blanke, U. & Schiele, B. A tutorial on human activity recognition using body-worn inertial sensors. ACM Comput.Surveys (CSUR) 46, 1–33. https://doi.org/10.1145/2499621135-145 (2014)
[10] Paul, P.; George, T. An Effective Approach for Human Activity Recognition on Smartphone. In Proceedings of the 2015 IEEE International Conference on Engineering and Technology (ICETECH), Coimbatore, India, 20–20 March 2015; pp. 1–3.
[11] Nguyen, T.H.C.; Nebel, J.C.; Florez-Revuelta, F. Recognition of Actions of living with egocentric vision: A review. Sensors 2016, 16, 72.
[12] Dhiman, C.; Vishwakarma, D.K. Review of state-of-the-art techniques for abnormal human activity recognition. Eng. Appl. Artif. Intell. 2019, 77, 21–45.
[13] Chen, K.; Zhang, D.; Yao, L.; Guo, B.; Yu, Z.; Liu, Y. Deep Learning for Sensor-based Human Activity Recognition: Overview, Challenges, and Opportunities. ACM Comput. Surv. 2021, 54, 77.
[14] Chen, K.; Yao, L.; Zhang, D.; Wang, X.; Chang, X.; Nie, F. A semisupervised recurrent convolutional attention model for human activity recognition. IEEE Trans. Neural Netw. Learn. Syst. 2019, 31, 1747–1756.
[15] Bustoni, I.A.; Hidayatulloh, I.; Ningtyas, A.M.; Purwaningsih, A.; Azhari, S.N. Classification methods performance on human activity recognition. J. Phys. Conf. Ser. ICTVT 2019, 1456, 012027.
[16] Xia, K.; Huang, J.; Wang, H. LSTM-CNNs Architecture for Human Activity Recognition. IEEE Access 2020, 8, 56855–56866.
[17] Zhang, S.; Wei, Z.; Nie, J.; Huang, L.; Wang, S.; Li, Z. A review on human activity recognition using vision-based method. J. Healthc. Eng. 2017. Available online: https://www.hindawi.com/journals/jhe/2017/3090343/ (accessed on 10 July 2019).
[18] Uddin, T.; Billah, M.; Hossain, F. Random forests based recognition of human Actions and postural transitions on smartphone. In Proceedings of the 2016 5th International Conference on Informatics, Electronics and Vision (ICIEV), Dhaka, Bangladesh, 13–14 May 2016; pp. 250–255. [CrossRef]
[19] Chen, K.; Yao, L.; Zhang, D.; Guo, B.; Yu, Z. Multi-agent Attentional Activity Recognition. In Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI, Macao, China, 10–16 August 2019; pp. 1344–1350.
[20] Halperin, D., Hu, W., Sheth, A. & Wetherall, D. Tool release: Gathering 802.11N traces with channel state information. ACM SIGCOMM Comput. Commun. Rev. 41(1), 53–53 (2011).
[21] Chowdhury, T.Z. Using Wi-Fi channel state information (CSI) for human activity recognition and fall detection, Ph.D. dissertation, (University of British Columbia, Vancouver, 2018)., indoor geolocation-\13.\ Chang, R. Y., Liu, S., & Cheng, Y. Device- free indoor localization using Wi-Fi channel state information for Internet of things. In IEEE Global Communications Conference (GLOBECOM), 1–7 (2018).

[22] Usharani, J.; Saktivel, U. Human Activity Recognition using Android Smartphone. In Proceedings of the International Conference on Innovations in Computing & Networking ICICN16, Bengaluru, Karnataka, 12–13 May 2016.
[23] Vakili, M.; Rezaei, M. Incremental Learning Techniques for Online Human Activity Recognition. arXiv 2021, arXiv:2109.09435.
[24] Muangprathub, J.; Sriwichian, A.; Wanichsombat, A.; Kajornkasirat, S.; Nillaor, P.; Boonjing, V. A Novel Elderly Tracking System Using to Classify Signals from Mobile and Wearable Sensors. Int. J. Environ. Res. Public Health 2021, 18, 12652. [CrossRef] [PubMed]
[25] Anguita, D.; Ghio, A.; Oneto, L.; Parra-Llanas, X.; Reyes-Ortiz, J. Energy Efficient Smartphone-Based Activity Recognition using Fixed-Point Arithmetic. J. Univers. Comput. Sci. 2013, 19, 1295–1314.
[26] Uddin, Z.; Soylu, A. Human activity recognition using wearable sensors, discriminant analysis, and long short-term memory-based neural structured learning. Sci. Rep. 2021, 11, 16455. [CrossRef]
[27] Murad, A.; Pyun, J.-Y. Deep Recurrent Neural Networks for Human Activity Recognition. Sensors 2017, 17, 2556. [CrossRef]
[28] Zhou, B.; Yang, J.; Li, Q. Smartphone-Based Activity Recognition for Indoor Localization Using a Convolutional Neural Network. Sensors 2019, 19, 621. [CrossRef]
[29] Nan, Y.; Lovell, N.H.; Redmond, S.J.; Wang, K.; Delbaere, K.; van Schooten, K.S. Deep Learning for Activity Recognition in Older People Using a Pocket-Worn Smartphone. Sensors 2020, 20, 7195. [CrossRef]
[30] Jiang, W., & Yin, Z. Human activity recognition using wearable sensors by deep convolutional neural networks. In MM 2015— Proceedings of the 2015 ACM Multimedia Conference 1307–1310 (2015)
[31] Zeng, M. et al. Convolutional neural networks for human activity recognition using mobile sensors. In Proceedings of the 2014 6th International Conference on Mobile Computing, Applications and Services, MobiCASE 2014, 197–205 (2015)
[32] Chen, Y., & Xue, Y. A deep learning approach to human activity recognition based on single accelerometer. In Proceedings—2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015, 1488–1492 (2016)
[33] Garcia, P. P., Santos, T. G., Machado, M. A. & Mendes, N. Deep learning framework for controlling work sequence in collaborative human-robot assembly processes. Sensors 23(1), 553 (2023)
[34] Yang, W., Zhang, J., Cai, J. & Zhiyong, Xu. HybridNet: integrating GCN and CNNs for skeleton-based action recognition. Appl. . The article-\29.\ Noori, F. M., Uddin, M. Z. & Torresen, J. Ultra-wideband radar-based activity recognition using deep learning. IEEE Access 9, 138132–138143 (2021)
[35] Liang, X., Huang, Z., Yang, S. & Qiu, L. Device-free motion & trajectory detection via RFID. ACM Trans. Embed. Comput. Syst.17(4), 78 (2018).
[36] Zhao, Z., Xu, G., Zhang, N. & Zhang, Q. Performance analysis of the hybrid satellite-terrestrial relay network with opportunistic scheduling over generalized fading channels. IEEE Trans. Vehic. Technol. 71(3), 2914–2924 (2022).
[37] Hu, Z. et al. Energy flow and functional behavior of individual muscles at different speeds during human walking. IEEE Trans.Neural Syst. Rehabil. Eng. 31, 294–303 (2023).