A Human Activity Recognition Model for Aging People Using Machine Learning

Shashank Reddy Kandimalla
Machine Learning Technologies
Department of Data Analytics
SID Last digit
Email:

Sujata Mahajan
Machine Learning Technologies
Department of Data Analytics
SID Last digit
Email:

Sowmya Manchikanti
Machine Learning Technologies
Department of Data Analytics
SID Last digit: 4882
Email: sowmya.manchikanti2sjsu.edu

Anjali Himanshu Ojha
Machine Learning Technologies
Department of Data Analytics
SID Last digit
Email:

Akanksha Tyagi
Machine Learning Technologies
Department of Data Analytics
SID Last digit
Email:

Abstract—In the field of machine learning and artificial intelligence, Human Activity Recognition (HAR) represents a critical problem. The use of gadgets with sensors and the urgent need for automated systems that can understand human behavior have brought HAR to the forefront of the study. HAR involves using sensors and data processing to identify and classify different activities performed by humans, such as walking, running, sitting, etc. The main goal of this project is to address the complex problems posed by HAR. We recognize the complexity arising from the diversity of humans, and the existence of noise in sensor data. We aim to build a reliable and accurate HAR system by utilizing cutting-edge machine-learning approaches, and ensemble methods. To exploit these data, various algorithms will be used like Random Tree, SVM, KNN, and ensemble methods like Random Forests and XGBoost. The model training phase will follow rigorous protocols, with the dataset divided into training, validation, and testing subsets. Cross-validation methodologies will be employed to fine-tune model hyperparameters and enhance generalization. In conclusion, this project proposal sets forth a comprehensive roadmap for advancing the state of HAR in machine learning. Our goal in conducting this research is to provide profound insights and useful solutions that improve our ability to effectively perceive and interpret human activity.

Keywords— Human Activity Recognition, Support Vector Machine, K-nearest neighbor.

I. INTRODUCTION

As per the World Health Organization (2022), every country in the world is experiencing growth in the proportion of older persons in the population. As the world experiences a demographic shift towards an aging population, there is an increasing demand for technologies and solutions that can support the well-being, health, and independence of older adults.

Human Activity Recognition (HAR) for the aging population addresses a critical need in today's society. The primary motivation is to improve the overall quality of life for older adults. HAR can enable technologies that assist them in daily activities, promoting independence and a higher level of comfort. HAR-based systems can provide real-time monitoring and immediate response in the event of a fall, potentially saving lives and reducing healthcare costs. HAR technology allows for remote monitoring, providing peace of mind for both seniors and their caregivers. HAR can help identify early signs of conditions like cognitive decline, mobility issues, or other health concerns.

The major goal of this research is to investigate the feasibility of using a publicly accessible dataset that is gathered to create a robust and generalized Human Activity Recognition model. The dataset this paper uses is a professionally annotated dataset containing 22 subjects wearing two 3-axial accelerometers for around 2 hours in a free-living setting. The sensors were attached to the right thigh and lower back. The professional recordings and annotations provide a promising benchmark dataset for researchers to develop innovative machine-learning approaches for precise HAR in free living.

II. LITERATURE SURVEY

Human activities reveal important details about a person's self, personality, appearance, and mental health and are essential to people's lives. For any average person, the ability to distinguish activities is simple and intuitive, but for a computer, it requires intricate operations for sensing, learning, and inference. It is a major challenge to implement the essential capabilities for detecting the environment, learning from the past, and applying knowledge for activity inference.

Human Activity Recognition (HAR) as named automatically recognizes and categorizes the activities or actions carried out by humans using sensor data. It's an important field with many potential benefits for improving human well-being and enhancing the capabilities of technology. The purpose of HAR is to understand and interpret people's actions or motions using data from sensors, such as accelerometers, gyroscopes, and other wearable or embedded devices [2]. HAR systems recognize activities like walking, running, sitting, standing, cycling, and driving, as well as a number of certain gestures or motions.

People are more prone to issues including cognitive decline, memory loss, chronic disease, visual and hearing impairment, as well as many other disorders, as they age [1]. They might also struggle to communicate with others. All of these challenges make it difficult for the patients to carry out their daily tasks, lower their quality of life, and compel them to ask for assistance. As a result, patients needed a support system to enable them to carry out their everyday tasks on their own. Here comes HAR, a system that helps patients do their daily chores correctly by setting up an alert system that can correct them if they commit a mistake, such as forgetting to complete an activity or taking too long to complete it.

Not only in healthcare (for monitoring), HAR has a wide range of other real-world applications like sports science, assistive technology, smart homes, and more [4]. In recent years, human activity recognition (HAR) has been a hot topic in a number of areas, including intelligent environments, security, and surveillance. In addition, HAR is a critical component in the development of Autonomous Vehicles where the main objective is to travel safely and effectively without human intervention [5]; therefore, it is crucial to comprehend and anticipate human activity around the car in order to ensure safety and improve the car's interaction with pedestrians and other road users.

HAR models are built on machine learning techniques [6]. The quantity and quality of data utilized for model training substantially influence the success of machine-learning approaches. As a result, a number of studies concentrate on the process of data collecting and sharing for use by other scientists in analysis, model construction, and comparison. Smartphones and wearable technology are the primary devices utilized for data collection. The outcomes of machine learning models can be impacted by the number of users, instances, or activities.

III. METHODOLOGY

A. Experiment Design and Dataset

Human Activity Recognition (HAR) datasets are created by utilizing the following three core domain-specific knowledge bases. Data on the sensor device (i) data of the subject or actor (ii) and data about the sensing background (iii)Data related to the sensing background[7].

We're using the Human Activity Recognition Trondheim (HARTH) dataset hosted at the UCI machine learning repository. The dataset was collected by 22 subjects who wore two 3-axial accelerometers for 2 hours. The data was collected in a free-living setting. Each accelerometer provides acceleration data along the x, y, and z axes, which constitute six features per sample.

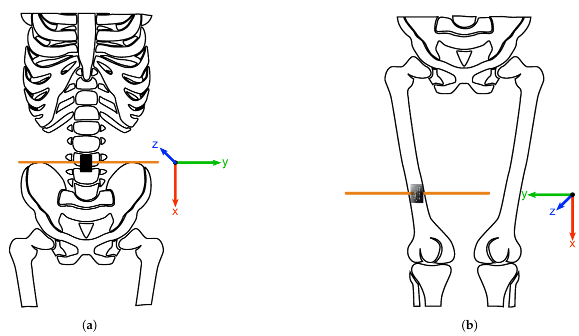


Figure 1

Figure 1 shows the two sensor positions (highlighted with orange lines) used for our dataset. (a) The lower back sensor is positioned at approximately the 3rd lumbar vertebra. The z-axis of the coordinate system points forward. (b) The thigh sensor is positioned approximately 10 cm above the upper kneecap. The z-axis points backward [2].

1) Data Preprocessing: This stage involves cleaning the data by handling missing values and outliers. Normalization techniques may also be applied to standardize the sensor readings. Filtering methods could smooth transient errors present in real-world data.

2) Feature Engineering: It will focus on deriving supplementary insights from the raw accelerometer readings to better represent movement patterns. Additional statistics like the mean, median, and standard deviation will be computed to capture the central tendency and variability present in the sensor data. This provides a more descriptive overview of motions.

Features may also be constructed to quantify the recurrence of certain movement motifs. Counting specific gesture repeats could help discriminate between activities such as walking, sitting, or falling. Such synthesized attributes aim to strengthen the ability of models to differentiate between human behaviors based on enhanced predictive relevance. In summary, further information extraction and aggregating recurrent motion properties during feature engineering seek to transform the sensor sequences into a more instructive format for robust activity classification.

3) Data Splitting: The dataset will be divided into training, and test sets proportionally at 80% and 20%. Distinct subsets are dedicated to training, tuning, and evaluating model performance to avoid overfitting any single portion of the data.

4) Clustering

We'll use PCA to reduce the number of dimensions to two, to be able to visualize the data in 2D. We can find out the importance of dimensions using the Sklearn plot and pick the two most important ones. The two-dimensional data can be plotted to analyze how each feature is distributed. We can cluster the data using K-means clustering and plot it in two dimensions.

B. Algorithms

We considered 5 different machine learning algorithms for developing a model for HAR.

- K-Nearest Neighbors (KNN) is relatively easy to understand and implement. It doesn't make any assumptions about the underlying data distribution. It stores the entire dataset in memory and uses it directly during classification. KNN naturally handles multi-class classification tasks. In HAR, where activities can often fall into multiple classes (e.g.Walking can be classified as "Walking" and "Moving" simultaneously), KNN can be effective. One drawback of KNN is that it uses a lot of memory to save the data for searching.

- Support vector machine (SVM) constructs a hyperplane to separate two classes. The hyperplane is constructed such that it maximizes the margin between the plane and the closest samples from the training data. For linearly separable data, this results in a perfect classification of the training data. If the data is not linearly separable, SVMs employ kernels like Radial

Basis Function (RBF). Since our data is multiclass, we'll employ multiclass SVMs. They are implemented using one-vs-one and one-vs-rest strategies.

- Random Forest (RF) is a collection of Decision Trees. It provides a measure of feature importance, which can help in identifying which sensor readings are most relevant for classifying activities. Random Forest can handle datasets with a large number of features, making it suitable for HAR tasks where the data might be represented by many sensor readings.

- eXtreme Gradient Boost (XGBoost) provides a measure of feature importance, helping to identify which sensor readings are most relevant for classifying activities. XGBoost is optimized for training and prediction speed, making it practical for real-world applications like HAR.

- Logistic Regression assumes that the data is linearly separable. It is used for binary classification. For multi-class classification, we can again employ one-vs-one and one-vs-rest strategies. It provides interpretable coefficients for each feature, which can help in understanding the contribution of each sensor reading to the prediction.

C. Evaluation Methods

Several metrics will assess model performance: Accuracy gives basic understanding, confusion matrices evaluate correct/incorrect predictions, and precision/recall/F1 scores examine false positives/negatives. Receiver operating characteristic curves and area under the curve values allow threshold selection and comparisons using probability outputs. K-fold cross-validation ensures generalizability beyond specific data splits.

D. Technical Difficulties

Identifying an activity based on body movement is a challenging task. It's a classification problem with data coming from multiple sources. Data is gathered from sensors like accelerometers, gyroscopes, LED lights, etc, so collecting good quality signals from these sensors in a changing environment needs a lot more information. The accuracy of the model will be directly impacted by the quality of the samples collected. So identifying a good predictor (set of features) for a given activity will also need medical domain information or the use of various feature importance algorithms like PCA. This is a multiclass classification problem, so we have to experiment with multiple models and evaluate their performance. To avoid overfitting, we have to use the k-fold cross-validation methods.

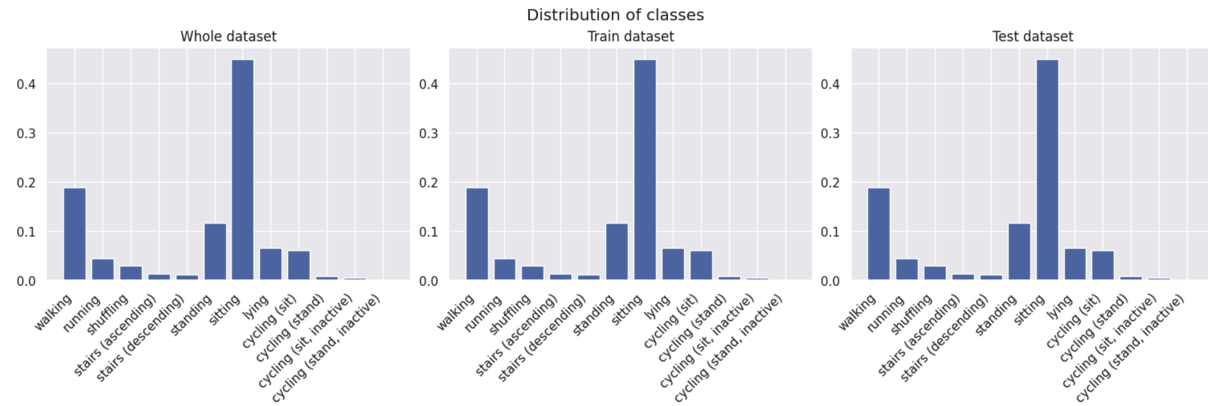
IV. IMPLEMENTATION

A. Data Preparation

Before training machine learning models, we have preprocessed the HAR dataset. The dataset consists of time and frequency domain features of 12 activities 'walking', 'running', 'shuffling', 'stairs (ascending)', 'stairs (descending)', 'standing', 'sitting', 'lying', 'cycling (sit)', 'cycling (stand)', cycling (sit, inactive)', 'cycling (stand, inactive) which is captured using two body-worn three-axis accelometers located on 22 participants thigh and lower back. These sensor readings are captured from human body activities which are usually below 20 Hz frequency.

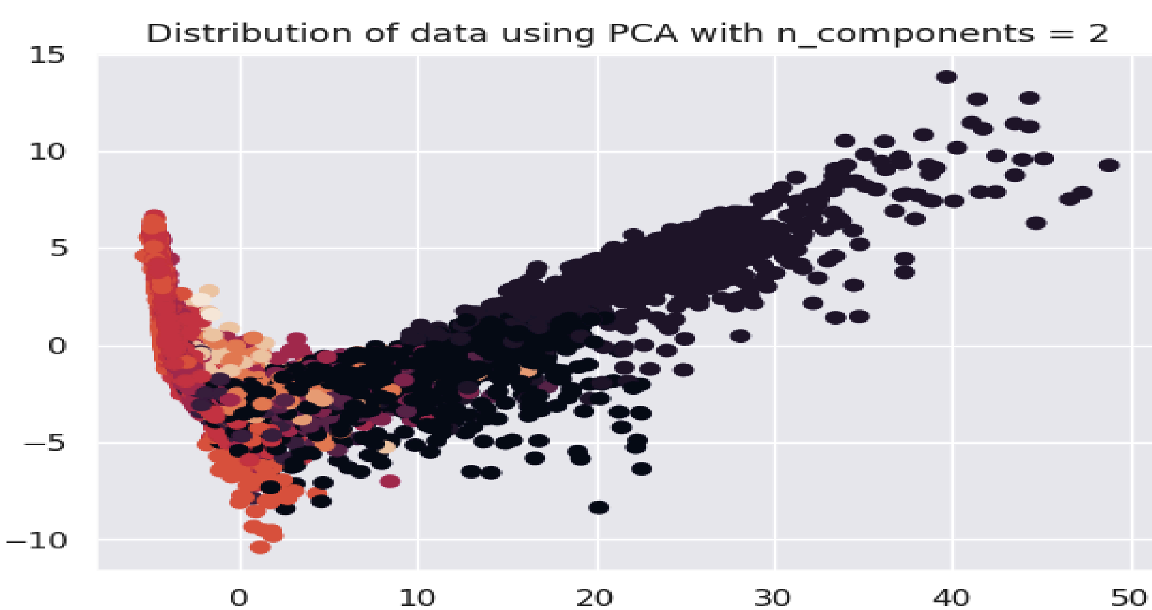
At first, a new Python data frame is prepared with acceleration readings of the back as 'back_x', 'back_y', 'back_z' and, acceleration readings of the thigh as, 'thigh_x', 'thigh_y', 'thigh_z'. The last column represents the class of physical activity as another data frame. The first data frame is iterated to create a window of 250 consecutive data points and computes the norm of back and thigh accelerations. As these are recordings of human activities and contain high-frequency noise, a linear filter called a low-pass Butterworth filter which is mostly used in signal processing is applied to filter out the gravitational component. Then the features are extracted by calculating statistical measures like mean, standard deviation (higher values of this indicate more dynamic movements), coefficient of variation means the ratio of standard deviation to mean, and total energy which is calculated as the sum of squares of data points, means of the original signal obtained after removing noise, the standard deviation of signal. Other measures like Fourier transform which converts the time domain to the frequency domain, total frequency power as the sum of squares of Fourier transform components (fft), fft magnitude mean, fft magnitude standard deviation, fft maximum, and frequency at which fft is maximum. The features extracted and their labels representing the physical activity performed are saved as new preprocessing files.

These features are used as input to train the models. This extracted dataset is clean with no missing values in it. This cleaned dataset is divided into training and testing samples by dividing in 80:20 proportions respectively to use training samples as input to models and predict the values which are compared with test data available. The following figures depict the class distributions of datasets before and after division.

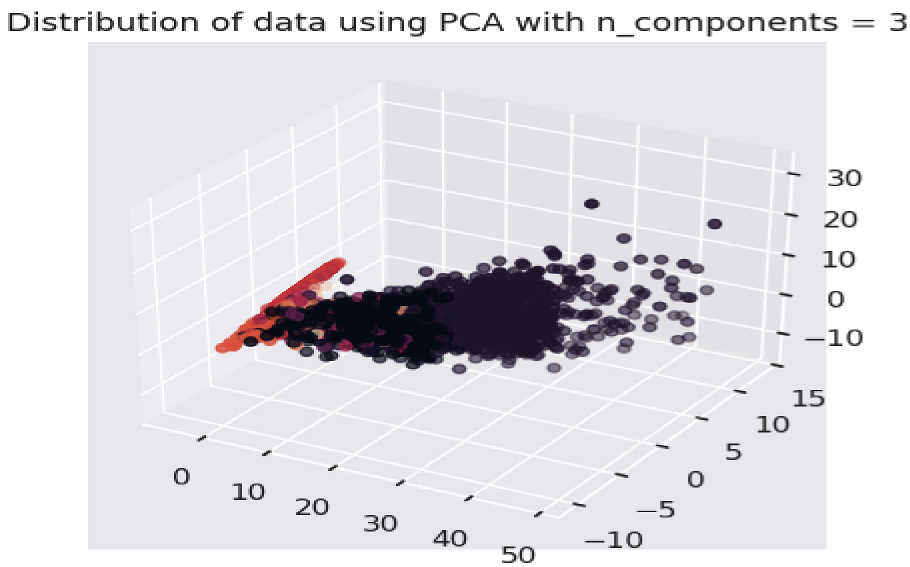


From the above graphs, it can be seen that the distribution of classes is uniform in all datasets obtained before and after dividing the original dataset into training and testing samples, which also infers that data is balanced in each subset of it.

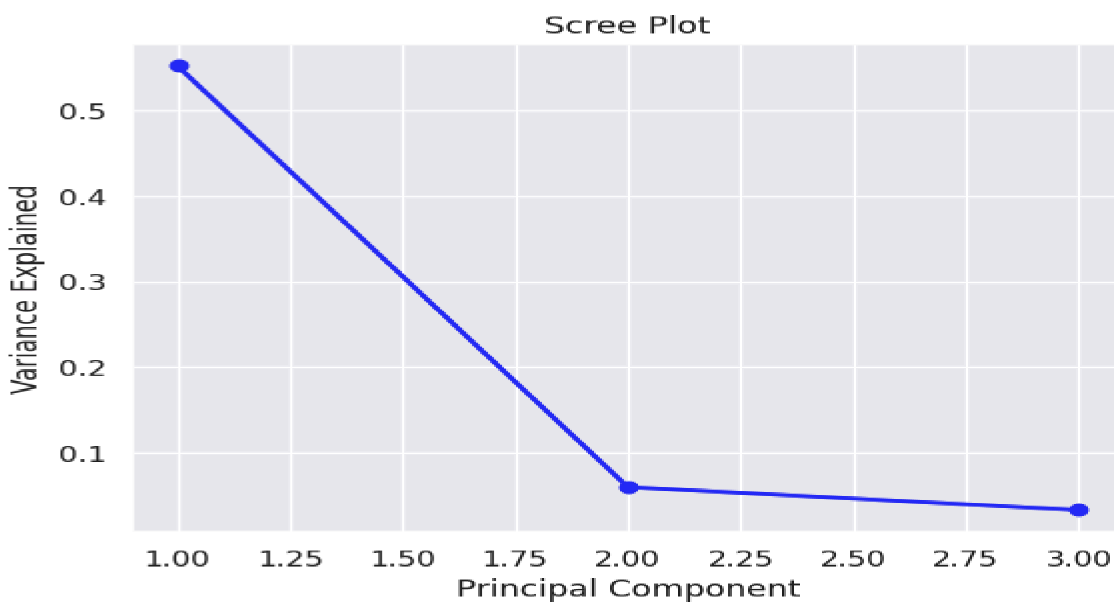
The distribution of the dataset as a whole which consists of 12 features can be visualized in reduced dimensions using Principal Component Analysis (PCA). Standardization is a common technique used to scale the features of the dataset before proceeding with PCA to ensure all the features are on the same scale. Therefore, the training and testing subsets of the HARTH dataset are standardized. The distribution of these standardized datasets using PCA is shown below.



The red color in the above graph visualizes the distribution of the target label in two dimensions.



The red color in the above graph visualizes the distribution of the target label in three dimensions.



The above graph is a Scree plot to understand the contribution of each principal component to the total variance in the dataset. Each X-axis point represents a principal component and the y-axis represents the amount of variance of each point. The elbow point in the above Scree plot clearly shows that beyond 2 components, the explained variance decreases at a slower rate. This indicates that retaining 2 components will suffice to capture most of the variability in the data.

B. Models

1) K-Nearest Neighbors (KNN): K-Nearest Neighbors is a simple, instance-based learning algorithm used for classification and regression. It classifies a data point based on the majority class of its k nearest neighbors in the feature space. The choice of the parameter k influences the model's performance. The scikit-learn's GridSearchCV is used to perform a grid search for hyperparameter tuning on a k-nearest neighbors classifier. Our aim is to enhance the KNN model's accuracy by systematically exploring different hyperparameter combinations. The key hyperparameter under consideration is the number of neighbors (n_neighbors). The grid search employs 5-fold cross-validation to evaluate the performance of each combination of hyperparameters. The chosen performance metric is accuracy. A new KNeighborsClassifier is initialized with the optimal value of n_neighbors determined during the grid search. The model is then trained on the normalized training data. Finally, the effectiveness of the trained KNN classifier is assessed on the test data. The goal was to identify the best configuration of hyperparameters that enhances the generalization performance of the KNN model on unseen data. The final KNN model is then built based on the identified optimal hyperparameters with an accuracy of 92%.

2) Support vector machine (SVM)

3) Random Forest (RF): Random Forest is a versatile ensemble learning technique used for classification and regression tasks. It functions by constructing multiple decision trees independently during training and then combining their predictions to make accurate and robust predictions. This ensemble approach mitigates overfitting and improves generalization to new data. The model employs bagging (Bootstrap Aggregating) to create multiple bootstrap samples of the data, training a decision tree on each. In our specific Random Forest model, hyperparameter tuning using GridSearchCV was conducted, resulting in the identification of optimal hyperparameters: a max_depth of 20, max_features set to 'sqrt', min_samples_leaf at 1, min_samples_split at 2, and n_estimators set to 100. These settings yielded a top training accuracy of approximately 92.16% in a 5-fold cross-validation setup. The model demonstrated strong classification

performance across various activities, achieving an overall accuracy of 94.80%.

4) eXtreme Gradient Boost (XGBoost)
Gradient Boosting is an ensemble technique where predictions from multiple weak learners are combined. The weak learners are built in a sequential manner. At every iteration, the misclassified samples get a higher weight and the new decision trees minimize the errors from the previous trees. If we use decision trees as weak learners, it's called Gradient-Boosted Trees (GBTs). GBTs combine the power of decision trees and boosting. We use XGBoost, which stands for Extreme Gradient Boosting, for training GBTs. XGBoost is a highly optimized library that provides efficient implementation of GBTs. We combine XGBoost with sci-kit-learn to perform a grid search to find the best hyperparameters. We perform 5-fold cross-validation for each hyperparameter.

5) Logistic Regression:
The model was built using the LogisticRegression method of the Sklearn linear model. The performance of the model is improved by the hyperparameter tuning method GridSearchCV. 5-fold cross-validation is used to evaluate the performance of each combination of hyperparameters. The performance of this model is evaluated using Accuracy. The combinations of different hyperparameters are used during grid search like penalty which is a regularization term to prevent overfitting, multi-class parameter to define the strategy to handle multiple classes, solver is the algorithm used for optimization. Logistic Regression model built for HARTH dataset using two sets of parameters. One with penalty ‘l2’ which denotes L2 Regularization or Ridge Regularization that adds a squared magnitude of coefficients as a penalty term to the loss function, multinomial strategy as the dataset involves 12 classes, and ‘lbfgs’ (Limited-memory Broyden–Fletcher–Goldfarb–Shanno) optimization algorithm. The other is with the same L2 penalty, ‘One-vs-Rest’ strategy, and ‘liblinear’ coordinate descent algorithm. These combinations are used for building a Logistic Regression model. By analyzing the best hyperparameter using accuracy scores, the final Logistic Regression is built. The hyperparameter with ‘lbfgs’ gives the best training accuracy with a 5-fold validation of 93%.

C. Evaluation Metrics

To evaluate the performance of models, we used confusion matrix metrics like Accuracy, Precision, Recall, and F1-score.

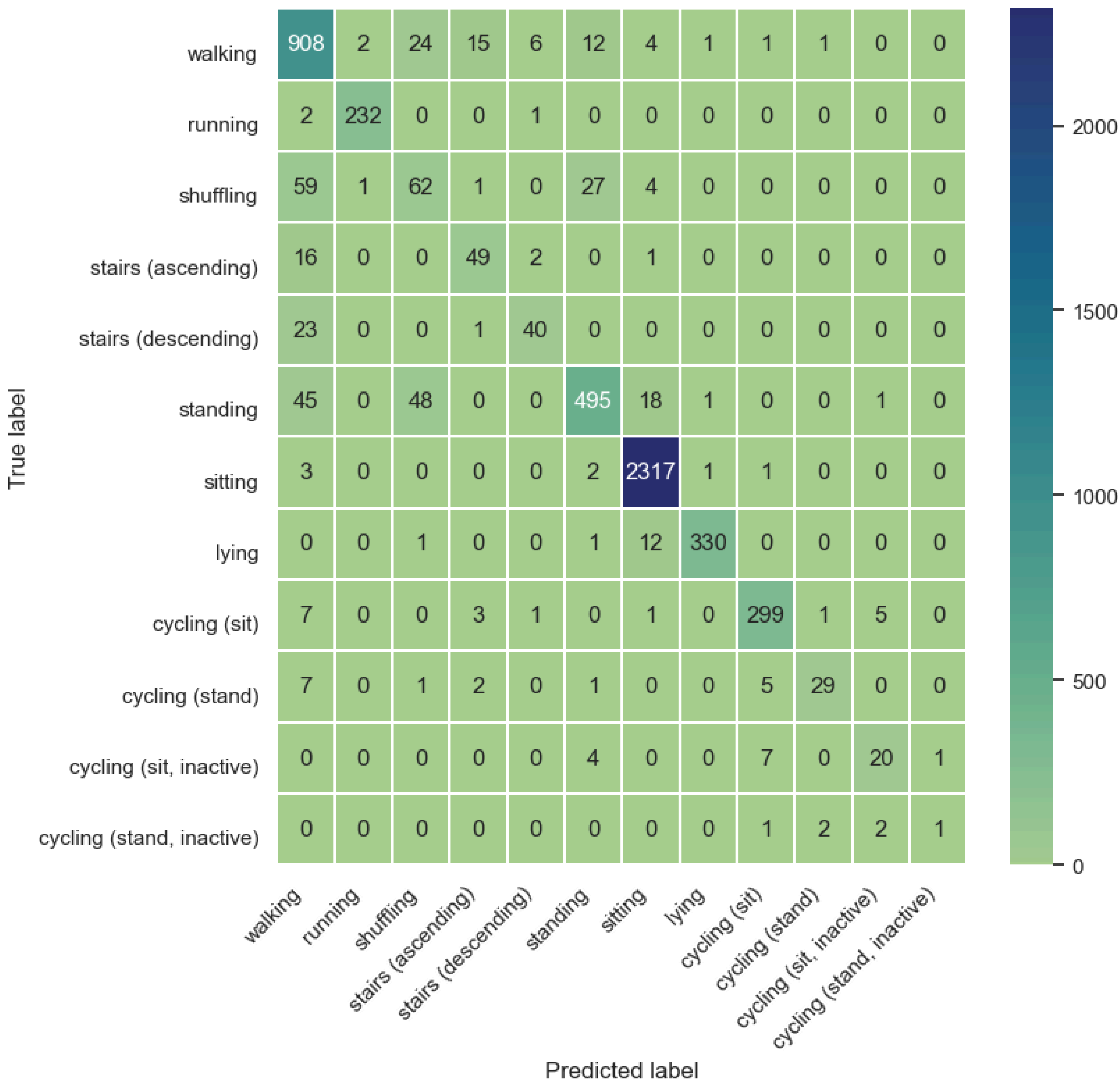
1) K-Nearest Neighbors (KNN)
The performance of the K-Nearest Neighbors model result is 92% accuracy.The summary of the performance of the model is given below as a classification report.

	precision	recall	f1-score	support
walking	0.8486	0.9322	0.8885	974
running	0.9872	0.9872	0.9872	235
shuffling	0.4559	0.4026	0.4276	154
stairs (ascending)	0.6901	0.7206	0.7050	68
stairs (descending)	0.8000	0.6250	0.7018	64
standing	0.9133	0.8141	0.8609	608
sitting	0.9830	0.9970	0.9900	2324
lying	0.9910	0.9593	0.9749	344
cycling (sit)	0.9522	0.9432	0.9477	317
cycling (stand)	0.8788	0.6444	0.7436	45
cycling (sit, inactive)	0.7143	0.6250	0.6667	32
cycling (stand, inactive)	0.5000	0.1667	0.2500	6
accuracy			0.9248	5171
macro avg	0.8095	0.7348	0.7620	5171
weighted avg	0.9234	0.9248	0.9229	5171

```
Accuracy: 0.9248
Micro Precision: 0.9248
Micro Recall/TPR: 0.9248
Micro f1-score: 0.9248
```

From the above figure, the precision, accuracy, recall, and f1-score metrics of sitting are high at 92%.

The confusion matrix for KNN :



2) SVM
   Support Vector Machines are popular Machine Learning algorithms for classification problems. It constructs a hyperplane between classes that works as a decision boundary and predicts the output labels using this decision boundary. It creates a hyperplane by using the training data features and finding the decision boundary with the largest margin. As a simple out-of-the-box, SVM may not work well for all problems, so we have to tune it with the help of various hyper-parameters. We used the Grid-Serarch technique to try various hyper-parameters, we tried combinations of

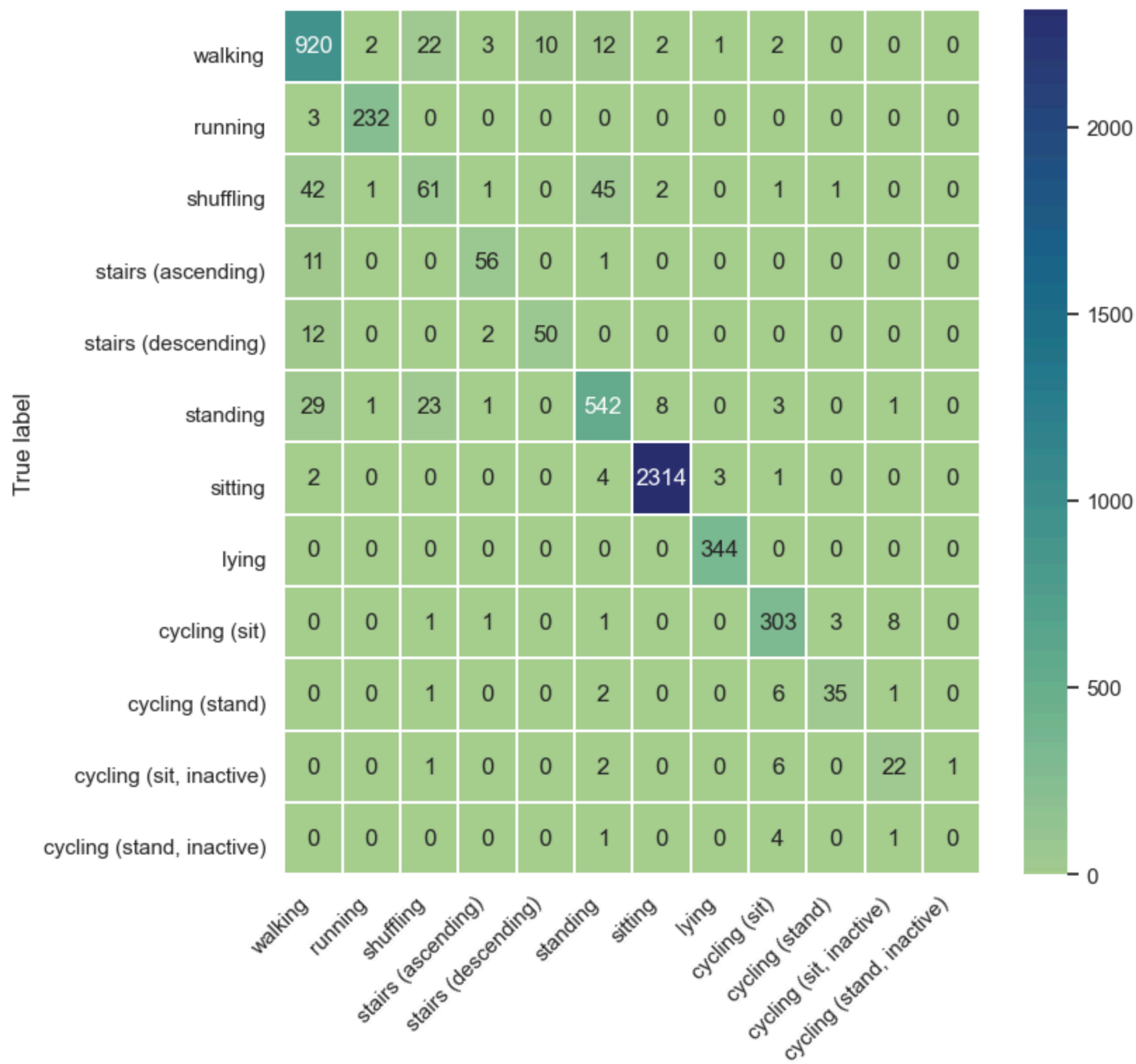
hyper-parameters like *kernel: linear & rbf, gamma: .01, .001, .0001, and C: 1, 100, 1000.* Overall we get the best accuracy with the hyper-parameters combination {'C': 100, 'gamma': 0.001, 'kernel': 'rbf'}, and we get an overall accuracy of 94.35 %. We also used the 5-fold cross-validation to avoid overfitting.

Here are the precision, recall, and f1-score metrics for all the output classes.

Predicted label

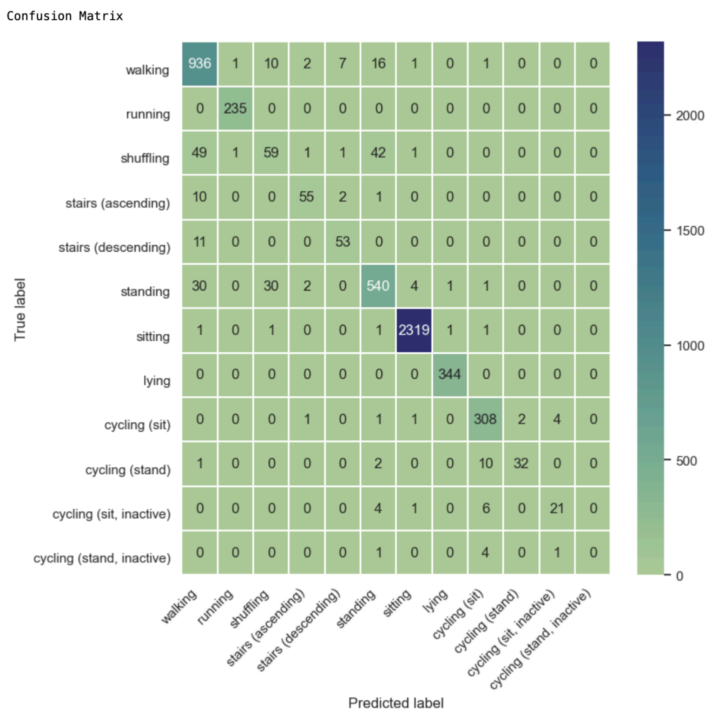
	precision	recall	f1-score	support
walking	0.9028	0.9446	0.9232	974
running	0.9831	0.9872	0.9851	235
shuffling	0.5596	0.3961	0.4639	154
stairs (ascending)	0.8750	0.8235	0.8485	68
stairs (descending)	0.8333	0.7812	0.8065	64
standing	0.8885	0.8914	0.8900	608
sitting	0.9948	0.9957	0.9953	2324
lying	0.9885	1.0000	0.9942	344
cycling (sit)	0.9294	0.9558	0.9425	317
cycling (stand)	0.8974	0.7778	0.8333	45
cycling (sit, inactive)	0.6667	0.6875	0.6769	32
cycling (stand, inactive)	0.0000	0.0000	0.0000	6
accuracy			0.9435	5171
macro avg	0.7933	0.7701	0.7799	5171
weighted avg	0.9395	0.9435	0.9409	5171

The confusion matrix for the SVM classifiers.



3) Random forest: The Random Forest model, optimized with parameters including a maximum depth of 20 and 100 estimators, exhibits an impressive overall accuracy of 94.8%. It demonstrates exceptional performance in identifying activities like running (99.16% precision, 100% recall), sitting (99.66% precision, 99.78% recall), and lying (99.42% precision, 100% recall), almost reaching perfection in these categories. However, it faces challenges in accurately classifying activities like shuffling (59% precision, 38.31% recall) and cycling in the standing position, particularly the inactive variations where it shows a notable decline. While activities such as walking (90.17% precision, 96.1% recall) and ascending or descending stairs are identified with good precision and recall, the model struggles significantly with cycling (stand, inactive) at 0% for both precision and recall, indicating

a critical area for improvement. Despite these specific challenges, the high overall accuracy, coupled with balanced micro precision, recall, and f1-score, all at 94.8%, highlights the model's robustness and effectiveness in handling a diverse range of activity classifications.



Predicted label

	precision	recall	f1-score	support
walking	0.8964	0.9415	0.9184	974
running	0.9831	0.9872	0.9851	235
shuffling	0.5604	0.3312	0.4163	154
stairs (ascending)	0.7656	0.7206	0.7424	68
stairs (descending)	0.8136	0.7500	0.7805	64
standing	0.8754	0.9013	0.8882	608
sitting	0.9940	0.9970	0.9955	2324
lying	0.9914	1.0000	0.9957	344
cycling (sit)	0.8949	0.9401	0.9169	317
cycling (stand)	0.7895	0.6667	0.7229	45
cycling (sit, inactive)	0.5238	0.3438	0.4151	32
cycling (stand, inactive)	0.5000	0.1667	0.2500	6
accuracy			0.9371	5171
macro avg	0.7990	0.7288	0.7522	5171
weighted avg	0.9315	0.9371	0.9330	5171

```
Accuracy: 0.9371
Micro Precision: 0.9371
Micro Recall/TPR: 0.9371
Micro f1-score: 0.9371
```

4) XGBoost
5) Logistic Regression: The performance of the Logistic Regression Model results in 93% accuracy. The summary of the performance of the model is given below as a classification report.

Predicted label

	precision	recall	f1-score	support
walking	0.8964	0.9415	0.9184	974
running	0.9831	0.9872	0.9851	235
shuffling	0.5604	0.3312	0.4163	154
stairs (ascending)	0.7656	0.7206	0.7424	68
stairs (descending)	0.8136	0.7500	0.7805	64
standing	0.8754	0.9013	0.8882	608
sitting	0.9940	0.9970	0.9955	2324
lying	0.9914	1.0000	0.9957	344
cycling (sit)	0.8949	0.9401	0.9169	317
cycling (stand)	0.7895	0.6667	0.7229	45
cycling (sit, inactive)	0.5238	0.3438	0.4151	32
cycling (stand, inactive)	0.5000	0.1667	0.2500	6
accuracy			0.9371	5171
macro avg	0.7990	0.7288	0.7522	5171
weighted avg	0.9315	0.9371	0.9330	5171

```
Accuracy: 0.9371
Micro Precision: 0.9371
Micro Recall/TPR: 0.9371
Micro f1-score: 0.9371
```

From the above figure, the precision, recall, and f1-score metrics of sitting are high at 99% when compared with those of other features. The lowest is observed in cycling. Support indicates the number of true occurrences of each label.

V. RESULTS

Compare Models

KEY LEARNINGS

- Logistic Regression can also be used for solving multi-classification problems by specifying the parameters to perform using multinomial regression or one-vs-rest strategy.
- Logistic Regression performed best with the ‘lbfgs’ solver to handle the multinomial loss.

- The use of a grid search (GridSearchCV) to find the optimal hyperparameters for the KNN classifier. Our model's number of neighbors (n_neighbors) is tuned over a predefined range (2, 5, 7).
- Hyperparameter tuning is crucial for improving model performance by selecting the most suitable configuration for the given data.
- Variability of the data can be captured using a Scree plot when PCA is performed. The elbow of the plot helps in deciding the number of components required to proceed with further process and the contribution of each component.
- Data Standardization plays an important role in preprocessing the data to scale the features.
- Computing features from signal data requires domain knowledge like the impact of gravity on data captured for different activities.
- Usage of Fourier transform (FFT) in converting signal data like time to frequency domain, the concept of magnitude spectrum that is calculated to normalize the FFT conversion are new learnings.
- Addressing issues like extreme skewness in features through transformations (like log transformation) can improve model performance. In cases of class imbalance, techniques like SMOTE (Synthetic Minority Over-sampling Technique) are employed to balance the classes, although this does not always guarantee a significant increase in model accuracy.
- Applying a logarithmic transformation to features with extreme skewness (such as a skewness of 70) can significantly improve the model's performance by normalizing the distribution of these features especially for logistic regression
- Random Forest is generally resistant to outliers and noise, making it suitable for real-world data that might not be perfectly clean.
- Feature engineering techniques for activity classification, including the calculation of norm magnitudes, gravity subtraction using a low-pass filter, and Fourier transform for frequency analysis. These methods enhance the model's ability to capture and distinguish between complex patterns in human activities, making it more effective in classifying varied motions such as walking, running, and different types of cycling.
- The implementation of a windowed approach, where features and labels are extracted from fixed-size segments of the time-series data, is a key strategy. This method allows the model to capture temporal patterns within each window, crucial for accurately classifying activities that have distinct movements over time, thereby improving the model's ability to recognize and differentiate between various activities based on temporal characteristics.

- Random Forest model excels in classifying activities with distinct patterns, like 'running' and 'sitting', showing its strength in handling complex, non-linear relationships in high-dimensional data.

SUSTAINABILITY

SDG3 | | Good Health and Well-being
Ensure healthy lives and promote well-being for all at all ages
We cover Sustainable Development Goal (SDG) 3, which focuses on "Good Health and Well-being."
These objectives cover cognitive, socio-emotional, and behavioral domains to ensure a comprehensive understanding and practical application of knowledge related to health and well-being.
Within the realm of machine learning and artificial intelligence, the identification and understanding of Human Activity Recognition (HAR) pose a significant challenge. The proliferation of sensor-equipped devices and the pressing demand for automated systems capable of comprehending human behavior have propelled HAR to the forefront of research. HAR entails the utilization of sensors and data processing to discern and categorize various activities undertaken by humans, encompassing actions like walking, running, sitting, and more. Our emphasis is on highlighting the influence of these activities in daily life, with a specific focus on promoting good health and well-being, especially for individuals within a certain age group. This emphasis is driven by the insights gleaned through the development of machine learning models. We can contribute to the establishment of policies that advocate for health and well-being. Additionally, we can suggest suitable prevention strategies to enhance positive physical and mental health. Research on Human Activity Recognition (HAR) for the aging population can have a significant and positive impact on various aspects of healthcare, well-being, and independent living for older adults. HAR technology can enhance the quality of life for older adults by providing them with tools and systems that support their daily activities.

VI. CONCLUSION AND RECOMMENDATIONS

A. Summary and Conclusions

By comparing all the models, ______ results as the best model. All the models have similar performance. All trained algorithms perform well, indicating that the hyperparameter assignments were well-chosen.

For physical-activity-behavior-based public health research, an accelerometer-based HAR dataset must have two prerequisites. First, fixed sensor placements, durability against noise, and professionally annotated physical activities are needed for accurate acceleration readings. Secondly, the information must be collected in a free-living environment. We trained the model using the most commonly used machine learning algorithms without any involvement of deep learning methods which are usually used for the HARTH dataset. Most of the existing work identified the imbalanced nature of the class of the HARTH dataset as a challenging task but we have overcome that by scaling data and principal component analysis. Our findings indicate that additional work needs to be done to create cutting-edge machine-learning techniques that would enable more accurate human activity recognition in free-living environments.

B. Recommendations for Future Works

REFERENCES

[1] Murman D. L. (2015). The Impact of Age on Cognition. *Seminars in hearing*, *36*(3), 111–121. https://doi.org/10.1055/s-0035-1555115

[2] A. Logacjov, K. Bach, A. Kongsvold, H. B. Bårdstu, and P. J. Mork, “HARTH: A Human Activity Recognition Dataset for Machine Learning,” Sensors, vol. 21, no. 23, Art. no. 23, Jan. 2021, doi: 10.3390/s21237853.

[3] K. Bach et al., “A Machine Learning Classifier for Detection of Physical Activity Types and Postures During Free-Living,” Journal for the Measurement of Physical Behaviour, vol. 1, no. aop, pp. 1–8, Dec. 2021, doi: 10.1123/jmpb.2021-0015.

[4] Oyibo, K., Wang, K., & Morita, P. P. (2023). Using Smart Home Technologies to Promote Physical Activity Among the General and Aging Populations: Scoping Review. Journal of medical Internet research, 25, e41942. https://doi.org/10.2196/41942

[5] Human activity recognition in car workshop - thesai.org. (n.d.). https://thesai.org/Downloads/Volume13No4/Paper_95-Human_Activity_Recognition_in_Car_Workshop.pdf.

[6] Binh Nguyen, Yves Coelho, Teodiano Bastos, Sridhar Krishnan, Trends in human activity recognition with focus on machine learning and power requirements, Machine Learning with Applications, Volume 5, 2021, 100072, ISSN 2666-8270, https://doi.org/10.1016/j.mlwa.2021.100072.

[7] Author links open overlay panelAbhisek Ray et al., “Transfer learning enhanced vision-based human activity recognition: A Decade-long analysis,” International Journal of Information Management Data Insights, https://doi.org/10.1016/j.jjimei.2022.100142 (accessed Nov. 2, 2023).

[8]https://unesdoc.unesco.org/in/documentViewer.xhtml?v=2.1.196&id=p::usmarcdef_0000247444&file=/in/rest/annotationSVC/DownloadWatermarkedAttachment/attach_import_82603519-4d73-431c-9324-8e0dcc1b6b1e%3F_%3D247444eng.pdf&locale=en&multi=true&ark=/ark:/48223/pf0000247444/PDF/247444eng.pdf#815_18_Learning%20Objectives_int_En.indd%3A.121521%3A380

Name	Role and Responsibilities
Anjali Himanshu Ojha	Data Collection and Preprocessing, Support Vector Machine (SVM) Model Development, Model Testing, Model Evaluation and Performance Metrics, Documentation of Development Process.
Sowmya Manchikanti	Data Analysis and Visualization, Logistic Regression Model Development and Testing, Hyperparameter Tuning for Logistic Regression, Model Evaluation and Performance Metrics, Report Preparation. Setup and monitor Trello.
Akanksha Tyagi	Feature Engineering and Data Transformation, xGBoost Model Development and Testing, Ensemble Strategy Design and Testing, Model Evaluation and Performance Metrics, Preparing Interim Report of Findings, Github collaboration.
Shashank Reddy Kandimalla	Random Forest Model Development and Testing, Hyperparameter Tuning, Model Evaluation and Performance Metrics. Preparing a presentation.
Sujata Mahajan	K-Nearest Neighbors (KNN) Model Development, Hyperparameter Tuning for KNN, Model Evaluation and Performance Metrics, Preparing Presentation.