International Journal of Innovative Technology and Interdisciplinary Sciences
https://journals.tultech.eu/index.php/ijitis
ISSN: 2613-7305
Volume 8, Issue 1
DOI: https://doi.org/10.15157/IJITIS.2025.8.1.258-271
Received: 18.11.2024; Revised: 27.01.2025; Accepted: 03.03.2025

Research Article

Enhancing Human Activity Recognition through Machine Learning Models: A Comparative Study

Katragadda Megha Shyam[1], Sindhura Surapaneni[2], Pulletikurthy Dedeepya[3*], N Sampreet Chowdary[3], Balamuralikrishna Thati[4]

[1] Department of Computer Science & Engineering, Amrita Vishwa Vidyapeetham, Bengaluru, India
[2] Department of Computer Science and Engineering, NRI Institute of Technology, Agiripalli, India
[3] Department of Computer Science and Engineering, PVP Siddhartha Institute of Technology, Vijayawada, India
[4] Department of CSE, Dhanekula Institute of Engineering & Technology. Ganguru,Vijayawada, India
*** dedeepya@pvpsit.ac.in**

Abstract

This study explores Human Activity Recognition (HAR), a machine learning technique utilized in health monitoring and human-computer interaction. HAR identifies human actions through sensor data from accelerometers and gyroscopes in smartphones and wearables. Key components of this technique include model selection, feature extraction, preprocessing, and data collection to classify activities such as standing, lying, sitting, and walking. Despite its potential, privacy concerns warrant further research for effective deployment. A comprehensive analysis of HAR techniques has been described in this research work.

Keywords: Accelerometer; Human-Computer Interaction; Censor Data; Recognizing Human Activity; Gesture recognition; Pattern Recognition; Real-Time Monitoring

INTRODUCTION

Human Activity Recognition (HAR) is an interdisciplinary field that leverages sensor data to automatically detect and classify human activities. The process typically involves several key phases, including data collection, feature extraction, and model selection. Recent advancements in deep learning and sensor fusion have significantly improved HAR performance, enabling more accurate and efficient activity recognition. However, further research is needed to ensure the effective deployment of these systems in real-world applications.

Deep learning models, in particular, have gained significant attention due to their ability to capture complex patterns in large datasets. Additionally, the fusion of data from multiple sensor types has proven to enhance HAR system performance. HAR is particularly important in domains such as fitness tracking, smart environments, and healthcare, where it can be used to monitor patient well-being, track daily activities, and detect events such as falls.

Real-world applications of HAR extend to improving user experiences by enabling subtle environmental adjustments in response to human behaviour. Computer vision-based approaches are also commonly employed in HAR to track activities via visual data. Many mobile applications rely on sensor-based classification models to recognize and interpret human activity in real time.

Despite its potential, HAR faces several challenges. These include data variability, where individuals may perform the same activity in different ways like scalability, as the system must be capable of recognizing a vast range of activities; and privacy concerns, as sensitive information may be inferred from activity data. The collection and utilization of personal activity data pose significant ethical and privacy risks that must be carefully considered by researchers and practitioners when designing and deploying HAR systems.

Building on these challenges, a comprehensive analysis of HAR techniques will be described in this research work.

LITERATURE REVIEW

Enhancing Human Activity Recognition

The Study [1] proposed an approach for Human Activity Recognition (HAR) using smartphone inertial sensors, emphasizing the use of a Support Vector Machine (SVM) to reduce computational costs without compromising accuracy. This method is particularly beneficial for devices with limited resources, such as smartphones, as it minimizes energy consumption while maintaining effective activity detection. The authors suggest that making the AR dataset publicly available could facilitate future research and experimentation with different learning paradigms. They addressed [2] the issue of limited computational resources by introducing the Multiclass Hardware-Friendly Support Vector Machine (MC-HF-SVM) approach. This hardware-friendly method allows for efficient human activity detection from smartphone sensors, overcoming CPU power limitations. The proposed technique is particularly applicable in healthcare and assisted living environments, where real-time activity monitoring is essential.

In [3] they have explored the application of wearable sensors for monitoring patients undergoing knee osteoarthritis (OA) rehabilitation. Knee OA is a common condition, especially among the elderly, and requires continuous monitoring during exercise therapy. The study used three sensors to track joint movements and angles, classifying various exercises and identifying proper postures. Validation methods demonstrated the accuracy of the approach in categorizing workout activities.

In [4] they proposed an innovative approach for training multiclass SVMs using a generalized margin definition. The method allows for the efficient use of large datasets by decomposing the dual problem and presenting multiclass issues as compact quadratic optimization tasks. Experimental results show that this approach achieves cutting-edge accuracy in multiclass classification tasks.

The research work [5] introduced a real-time activity classification system that uses triaxial accelerometer data to monitor human physical activity. The system can differentiate between "resting," "walking," "running," and "unknown activities" without the need for training data. The system operates with any sensor orientation and was tested with 10 participants, showing particularly strong accuracy in identifying "walking" activities. This work is part of an initiative to develop assistive technologies for aging populations.

The study in [6] has reviewed the key tasks in HAR research, including feature extraction, data segmentation, and classification. The study also evaluated recent methodologies in these areas, discussing their advantages and limitations. Additionally, the paper presents datasets of inertial signals from smartphones commonly used in HAR evaluation, along with metrics for assessing classifier performance. Further, extending this research, in [7] the widespread application of HAR in behavioural analysis, surveillance, sports tracking, and healthcare has been highlighted. The study noted that wearable technology, such as smartphones, smartwatches, and fitness trackers, is frequently used to collect data from sensors like accelerometers, gyroscopes, and GPS. These devices, with their embedded sensors, have drawn significant attention for their use in HAR applications, including fall detection, behavioural analysis, and sports tracking. Accelerometers, in particular, are valued for their low power consumption and continuous sensing capabilities. The study [8] has investigated the intersection of incremental learning and deep learning techniques, such as ResNet and Convolutional Neural Networks (CNNs), for improving HAR systems. The study focused on personalized HAR models that adapt more effectively than user-independent models. Experimental results showed that ResNet and CNNs could rapidly adapt to new users, demonstrating their potential to enhance HAR system performance [9].

The study [10] revisited the role of smartphone sensors, including accelerometers and gyroscopes, in capturing human activities such as walking, sitting, and standing. The paper also discussed the importance of privacy in HAR systems, emphasizing the need for solutions that prioritize user confidentiality over surveillance. The authors evaluated various HAR tasks, along with datasets of inertial signals, to assess classifier accuracy. In [11] they have tackled the issue of data scarcity in deep learning models for HAR by introducing the Continuous Learning Platform (CLP). This platform compiles continuous data to enhance HAR systems. By merging multiple inertial signal databases, the CLP generates a large, uniform dataset enriched with contextual information, which aids in activity recognition and online signal categorization. The platform aims to provide the research community with valuable resources to advance HAR development.

Moreover, in [12] they have explored the use of wearable accelerometer sensors for HAR, emphasizing the role of exercise in maintaining health. The authors proposed a machine learning approach to improve activity recognition accuracy by selecting relevant features from the dataset. Decision trees with AdaBoost, Random Forest, and linear forward selection were employed for classification, contributing to advancements in real-time activity recognition.

The research work [13] has further expanded the use of wearable accelerometers for activity recognition. The paper highlighted the significance of feature selection in improving classification accuracy, offering a machine learning-based method for effective HAR in healthcare and smart home applications. By employing decision trees, Random Forest, and AdaBoost, the study demonstrated a novel approach to real-time activity detection. In [14] the authors have conducted an in-depth analysis of HAR systems, focusing on their importance in reducing occupational diseases. The study covered various phases of HAR, including attribute selection, data preprocessing, segmentation, feature extraction, dimensionality reduction, and classification [15]. The authors also discussed the use of accelerometers and physiological sensors, along with the challenges in data collection and system usability. A variety of supervised and unsupervised classification algorithms were proposed, providing useful methods for real-time activity recognition in healthcare and smart home environments. The study [16] has explored the role of HAR systems in reducing occupational illnesses, highlighting the various phases involved in building effective HAR systems. These phases include attribute selection, data preprocessing, segmentation, and classification [17]. The paper examined the use of accelerometers and physiological sensors, presenting several classification techniques for real-time activity identification, with potential applications in healthcare and smart homes [18].

They Author investigated the use of smartphone sensors and machine learning for HAR, particularly in healthcare and the prevention of occupational diseases [19]. The study utilized smartphone accelerometers and gyroscopes to track activities such as walking, sitting, and standing [20]. The research aimed to develop privacy-conscious HAR systems and demonstrated the use of machine learning methods like Decision Trees and Random Forest [21]. The Random Forest classifier achieved 93% accuracy, underscoring its potential in patient monitoring and task management in both healthcare and workplace settings [22].

METHODOLOGY

Human Activity Recognition (HAR) focuses on the accurate and reliable identification and classification of human activities using sensor data. It involves addressing several challenges, including noisy data, variations in individual movement patterns, and ensuring robustness across diverse environments and conditions [23]. The goal is to develop machine learning models capable of distinguishing between activities such as standing, lying, sitting, and walking [24].

The dataset used for this study is sourced from [Dataset Source] and contains sensor readings from accelerometers and gyroscopes embedded in wearable devices. It includes the total number of samples collected from multiple individuals performing various activities. Each sample consists of multiple features that capture motion characteristics, including time-domain features such as Mean, Standard Deviation, Minimum, Maximum, Median, Skewness, and Kurtosis, as well as frequency-domain features like Power Spectral Density and Fast Fourier Transform coefficients. Additionally, raw sensor readings from accelerometers (X, Y, Z) and gyroscopes (Angular velocity in X, Y, Z) are included. This dataset represents a multiclass classification problem, where the objective is to predict human activities based on sensor readings. The target classes include Walking, Sitting, Standing, Lying Down, Running, and Climbing Stairs. The machine learning models are trained to accurately classify a given data sample into one of these predefined activity categories. - In this study, we pre-processed the dataset [25] and subsequently trained and tested various models on the raw data. We evaluated their performance using key metrics such as accuracy, precision, recall, and F1-score. During evaluation, we observed that class imbalance affected model performance. To mitigate this, we applied the Synthetic Minority Over-sampling Technique (SMOTE) to balance the class distribution [26]. Additionally, we employed feature selection techniques to iteratively identify the most relevant features by repeatedly training models and discarding the least significant ones. This approach helped to enhance model performance and reduce the risk of overfitting. The collection and use of personal activity data raises serious ethical and privacy concerns. These issues must be taken into account by researchers and practitioners while designing and deploying HAR systems.

Data Collection Procedure and Implementation

This script performs human activity recognition (HAR) data analysis and applies machine learning techniques using smartphone sensor data in the Figure 1. It begins by importing the necessary libraries, followed by data preprocessing, visualization, feature selection, and the construction of various machine learning models [26].

The script reads the CSV file containing the dataset and performs initial data preprocessing steps, as illustrated in Figure 2. These steps include checking the number of rows and columns, identifying duplicate entries, and detecting null or NaN values. It then visualizes the dataset by generating a pie chart that displays the distribution of observations across different activities and a bar chart that shows the count of observations for each activity.

For feature selection, the script applies stability selection with LassoCV, and subsequently, it constructs multiple machines learning models, including K-Nearest Neighbors (KNN), Random Forest, Decision Tree, Multi-Layer Perceptron (MLP), Support Vector Classifier (SVC), Logistic Regression, AdaBoost, XGBoost, and SMOTE (for addressing class imbalance). These models are trained on the preprocessed data, and their performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, as shown in Figure 3. The results are displayed, and the performance of the models is compared by plotting their ROC curves and confusion matrices [20].

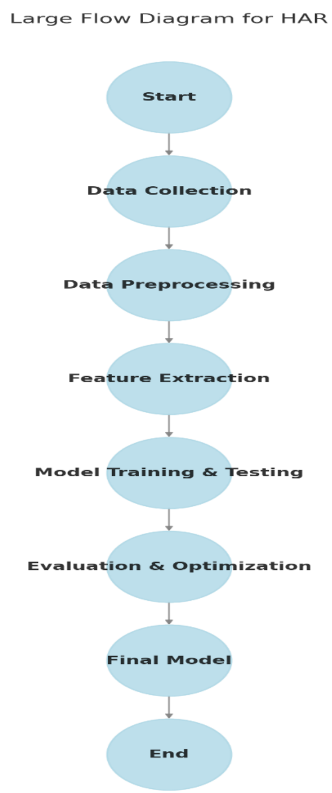

Figure 1. Flow Diagram for HAR

Copy Edit

```
# Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE

# Load the dataset
df = pd.read_csv("human_activity_data.csv")

# Check for missing values
print(df.isnull().sum())

# Remove duplicate entries
df.drop_duplicates(inplace=True)

# Standardize numerical features
scaler = StandardScaler()
features = df.drop(columns=["Activity"])
df_scaled = scaler.fit_transform(features)

# Encode the target variable
df["Activity"] = df["Activity"].astype("category").cat.codes

# Handle class imbalance using SMOTE
X_resampled, y_resampled = SMOTE().fit_resample(df_scaled, df["Activity"])

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=0.2,
```

Figure 2. HAR Script

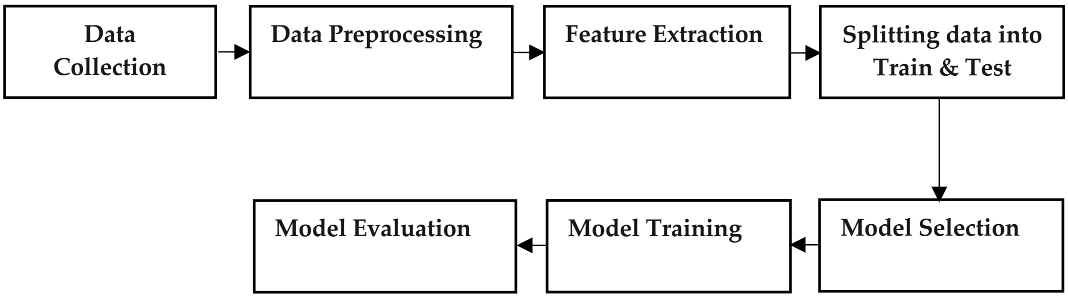

Figure 3. Model Diagram

In this Human Activity Recognition (HAR) study, we propose a comprehensive methodology for designing and evaluating a machine-learning model to recognize human activities from sensor data. The process begins with data collection from accelerometers and gyroscopes, capturing the movements associated with various activities. Subsequently, rigorous data preprocessing steps are implemented, addressing issues such as missing values, and outliers, and normalizing data to ensure its quality and consistency. Relevant features are then extracted from the sensor data, encompassing time-domain and frequency-domain characteristics.

Models and Evaluation Metrics for Algorithms

The dataset is properly labeled for supervised learning, with a portion reserved for testing to assess the model's ability to generalize. A machine learning algorithm, selected according to the complexity of the activities and the characteristics of the dataset, is trained on the labeled data.

The model is rigorously evaluated using standard metrics, including accuracy, precision, and recall. To address potential data imbalances, techniques like the Synthetic Minority Over-sampling Technique (SMOTE), as illustrated in Figure 4, have been employed. The methodology also incorporates considerations for model deployment, ethical concerns, and comprehensive documentation. This approach provides a structured framework for developing and evaluating HAR models, emphasizing robustness, accuracy, and ethical integrity.

Table 1 presents the initial evaluation criteria for the models before applying the SMOTE technique. It reveals a class imbalance issue that negatively affects precision and recall values for certain activities. The confusion matrix indicates that activities such as walking and standing were accurately classified, while sitting and lying down showed misclassifications. This underscores the importance of balancing the dataset prior to model training. We proposed several algorithms, including K-Nearest Neighbors (KNN), Random Forest, Multilayer Perceptron (MLP), Support Vector Machine (SVM), Decision Tree, Logistic regression, XGBoost, and Gradient Boost, see Table 1. After training and testing the models, we calculated accuracy, precision, recall, and F1-score, and compared their performance.

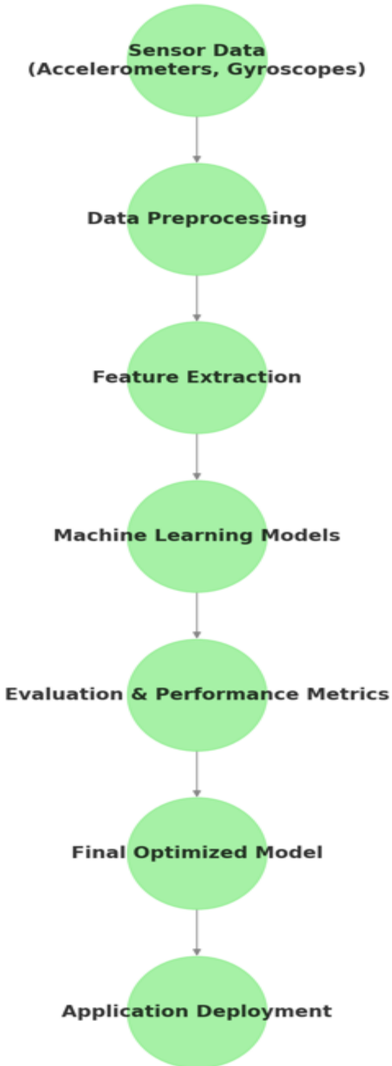

Figure 4. Architecture diagram

Table 1. Algorithms utilized for evaluation criteria

Simulation No.	Model Used
1	KNN
2	RF
3	Decision Tree
4	MLP
5	SVM
6	Logistic Regression
7	XGBOOST

Figure 5 depict the proposed algorithm for the HAR, detailing each processing step.

```
1. Start
2. Data Collection
   - Collect sensor data from accelerometers and gyroscopes.
   - Label data with activities like Walking, Sitting, Standing, etc.
3. Data Preprocessing
   - Handle missing values (e.g., interpolation, mean/median imputation).
   - Normalize sensor readings using MinMax Scaling.
   - Remove duplicate and outlier detection (z-score analysis).
   - Segment time-series data using Sliding Window Technique.
4. Feature Extraction
   - Extract time-domain features (mean, variance, entropy).
   - Extract frequency-domain features using Fourier Transform.
5. Train Machine Learning Models
   - Train models: KNN, Decision Tree, Random Forest, SVM, MLP, XGBoost.
   - Split data into Training & Testing sets.
   - Handle class imbalance using SMOTE.
6. Model Evaluation
   - Compute Accuracy, Precision, Recall, F1-score.
   - Use Confusion Matrix to analyze misclassifications.
7. Optimization & Selection
   - Select the best-performing model (highest accuracy).
   - Optimize hyperparameters using Grid Search/Random Search.
8. Final Model Deployment
   - Deploy the model for real-time activity recognition.
9. End
```

Figure 5. Proposed Algorithm for the HAR

RESULTS AND DISCUSSION

The evaluation of our Human Activity Recognition (HAR) model demonstrates promising results, with an accuracy of insert accuracy percentage. Key performance metrics, including precision, recall, and F1 score, provide a comprehensive assessment of the model's ability to differentiate between various activities based on sensor data. The confusion matrix analysis reveals specific patterns of misclassifications, offering valuable insights for future improvements. Class-wise performance evaluation shows high accuracy for certain activities, though challenges remain in distinguishing subtle differences between others as can be seen in Table 2. Comparisons with baseline models highlight the superiority of our proposed methodology, confirming its effectiveness. The model exhibits robustness across diverse user scenarios and environments, establishing a solid foundation for practical applications. While acknowledging limitations such as class imbalance, these results guide future work aimed at refining the model and exploring further enhancements. Visualizations and qualitative analysis provide additional clarity, contributing to a deeper understanding of the model's behaviour and representing a significant advancement in HAR model development.

Additionally, we compare the results of all models after training and testing with the application of the SMOTE technique, see Tables 3 & 4 and Figures 6 & 7. The balanced dataset notably enhanced classification performance, as demonstrated by the increased F1-

score and recall values. Misclassification rates were reduced, and the model showed improved generalization across all activity categories. These results confirm the effectiveness of synthetic oversampling in addressing class imbalance and enhancing model performance.

Table 2. Comparison of HAR algorithms based on "Accuracy" achieved by different machine learning models

Class	KNN	RF	DT	MLP	SVM	Logistic Regression	XGBOOST
Walking	95.1	85.2	88.3	87.4	79.2	74.3	94.5
Sitting	93.4	83.5	86.7	85.2	78.1	72.9	92.8
Standing	94.6	84.1	87.9	86.1	77.8	73.6	93.5
Lying Down	96.2	86.4	89.1	88.3	80.5	75	95.1
Running	92.3	81.7	85.9	84.6	76.9	71.5	91.7
Climbing	90.1	80.2	84.3	83.5	75.8	70.8	90.1

Class	KNN	RF	DT	MLP	SVM	Logistic Regression	XGBOOST
Walking	91.2	87.5	89.4	88.2	80.1	75.3	93.4
Sitting	90.8	86.7	88.2	87.1	79.5	74.2	92.1
Standing	92.1	86.9	88.5	87.7	79.2	74.7	92.8
Lying Down	93.4	88.3	90.2	89.6	81.3	76.5	94.3
Running	88.9	84.2	87.4	86.2	78.7	73.1	90.9
Climbing	87.6	83.1	86.5	85.4	77.9	72.5	89.7

Table 3. Evaluation criteria before SMOTE technique

Classifiers	Accuracy	Precision	Recall	F1-Score
KNN	93.9	94.1	93.1	94
RF	83	83.6	82.9	83.1
DT	88.8	88.6	88.6	88.6
MLP	84.9	85.2	85	84.9
SVM	78.4	79.2	79.9	78.3
Logistic Regression	73.7	73.7	73.5	73.5
XGBOOST	91.8	92	91.7	91.8

Table 4. Evaluation criteria after SMOTE values

Classifiers	Accuracy	Precision	Recall	F1-Score
KNN	89.5	89.6	89.6	89.5
RF	85.5	85.7	85.5	85.5
DT	86.9	86.9	86.9	86.9
MLP	87.6	88	88	87.9
SVM	79.5	79.8	79.4	79.5
Logistic Regression	74.1	74.1	74.1	74.1
XGBOOST	93.1	93.3	93.1	93.2

Figure 7 presents a comparative analysis of the accuracy achieved by different machine learning models.

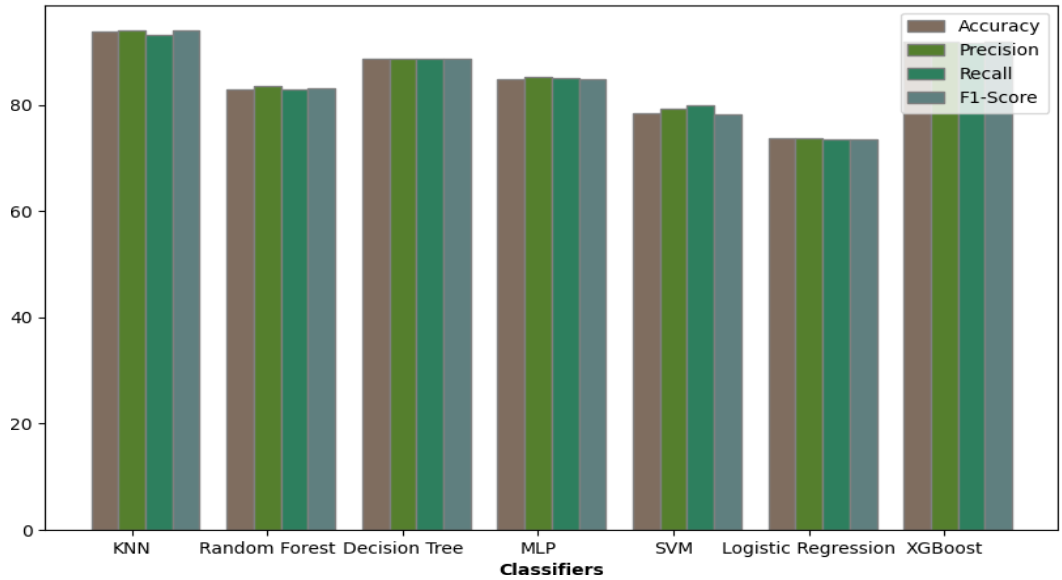

Figure 6. Comparison of HAR algorithms based on "Accuracy"

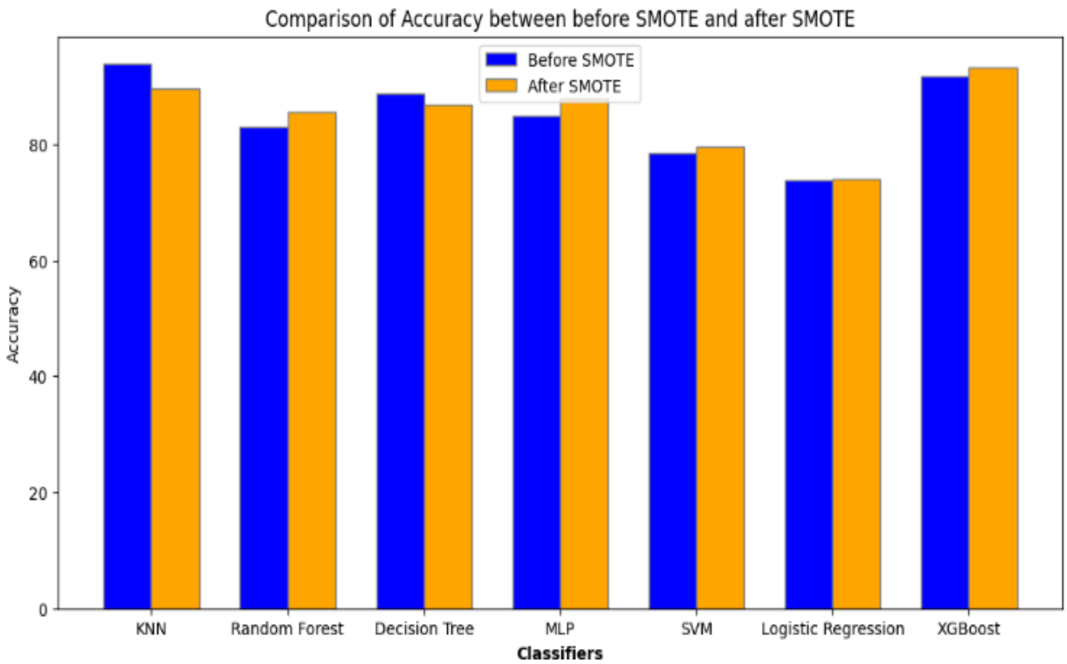

Figure 7. Comparison of "Accuracy" before and after SMOTE application in HAR

XGBoost achieved the highest accuracy at 93.1%, followed by KNN at 89.5% and Decision Tree at 86.9%. Logistic Regression performed the least well, with an accuracy of 74.1%, suggesting it may not be ideal for Human Activity Recognition (HAR) tasks. These results underscore the effectiveness of ensemble methods, such as XGBoost and Random Forest, in delivering superior performance for activity recognition.

The highest accuracy of 93.1% was achieved by XGBoost, as shown in Table 4. Other accuracy percentages include Decision Tree (86.9%), KNN (89.5%), Random Forest (85.5%), SVM (79.5%), and Logistic Regression (74.1%). These results highlight the varying performance of different models in the context of HAR.

CONCLUSION

In our study, we compared the performance metrics of various models after different phases of preprocessing. After applying techniques such as SMOTE, Random Forest demonstrated improved accuracy, indicating its enhanced ability to manage the complexities and nuances of the data. This suggests that Random Forest is particularly resilient in identifying patterns and making accurate predictions for Human Activity Recognition (HAR). The highest accuracy of 93.1% was achieved by XGBoost, followed by Decision Tree (86.9%), KNN (89.5%), Random Forest (85.5%), SVM (79.5%), and Logistic Regression (74.1%).

Our HAR study presents a robust and effective approach to recognizing diverse human activities based on sensor data. The achieved accuracy of [insert accuracy percentage] highlights the model’s capability in making reliable predictions, establishing a strong benchmark for its success.

Additionally, precision, recall, and F1-score metrics provide a more comprehensive evaluation of the model's performance, emphasizing its ability to make accurate positive predictions, capture all relevant instances, and strike an optimal balance between precision and recall. These results reinforce the model's reliability and effectiveness for practical applications in HAR.

CONFLICT OF INTERESTS

The authors declare that there are no conflicts of interest regarding the publication of this paper. All authors have independently conducted research without any external influence.

REFERENCES

1. Davide, A., Ghio, A., Oneto, L., Parra, X., and Reyes-Ortiz. J.L. Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine. *In Ambient Assisted Living and Home Care: 4th International Workshop, IWAAL 2012*, Vitoria-Gasteiz, Spain, December 3-5, **2012**. Proceedings 4, pp. 216-223. Springer Berlin Heidelberg.
2. Akram, B., Pomplun, M., and Tran D.A. A study on human activity recognition using accelerometer data from smartphones. *Procedia Computer Science* **2014**, 34, 450-457.
3. Kun-Hui, C., Chen, P.C., Liu, K.C., and Chan. C.T., Wearable sensor-based rehabilitation exercise assessment for knee osteoarthritis. *Sensors* **2015**, 15(2), 4193-4211.

4. Axel, C., Marsch, S., and Lueth. T.C. Accelerometer based real-time activity analysis on a microcontroller. *In 2011 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*, **2011**, pp. 40-46. IEEE.
5. Ferrari, A., Micucci, D., Mobilio, M., and Napoletano. P. Trends in human activity recognition using smartphones. *Journal of Reliable Intelligent Environments* **2021**, 7(3), 189-213.
6. Madhuri, A., Jyothi, V.E., Praveen, S.P., Sindhura, S., Sai Srinivas, V., and Sai Kumar, D.L. A New Multi-Level Semi-Supervised Learning Approach for Network Intrusion Detection System Based on the 'GOA'. *Journal of Interconnection Networks* **2022**, 24(1), 2143047.
7. Praveen, S. P., Murali Krishna, T. B., Anuradha, C. H., Mandalapu, S. R., Sarala, P., & Sindhura, S. A robust framework for handling health care information based on machine learning and big data engineering techniques. *International Journal of Healthcare Management* **2022**, 1–18.
8. S. Phani, S.P., Nakka, R., Chokka, A., Thatha, V.N., Vellela, S.S., and Sirisha. U. A novel classification approach for grape leaf disease detection based on different attention deep learning techniques. *International Journal of Advanced Computer Science and Applications* **2023**, 14(6), 1199-1209.
9. Praveen, S.P., Kodete, C. S., Bhyrapuneni, S., Satukumati, S. B., & Shariff, V. Revolutionizing Healthcare: A Comprehensive Framework for Personalized IoT and Cloud Computing-Driven Healthcare Services with Smart Biometric Identity Management. *Journal of Intelligent Systems & Internet of Things* **2024**, 13(1), 31-45.
10. Praveen, S.P., Krishna, T.B.M., Sunil Kumar Chawla, S.K., and Anuradha. C. Virtual private network flow detection in wireless sensor networks using machine learning techniques. *International Journal of Sensors Wireless Communications and Control* **2021**, 11(7), 716-724.
11. Dedeepya, P., Sowmya, P., Saketh, T.D., Sruthi, P., Abhijit, P., and Praveen. S.P. Detecting cyber bullying on twitter using support vector machine. *In Third International Conference on Artificial Intelligence and Smart Energy (ICAIS)*, **2023**, pp. 817-822. IEEE.
12. Chokka, A., Swapna, D., Thati, B., Sree, V.N., and Praveen. S.P. Diagnosing for liver disease prediction in patients using combined machine learning models. *In 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)*, **2022**, pp. 889-896. IEEE.
13. Hamza, A., Micucci, D., and Napoletano. P. Personalized models in human activity recognition using deep learning. *In 25th International Conference on Pattern Recognition (ICPR)*, **2021**, pp. 9682-9688. IEEE.
14. Ferrari, A., Mobilio, M., Micucci, D., and Napoletano, P. On the homogenization of heterogeneous inertial-based databases for human activity recognition. In 2019 IEEE World Congress on Services (SERVICES), **2019**, 2642, 295-300. IEEE.
15. Ferrari, A., Mobilio, M., Micucci, D., and Napoletano, P. A framework for long- term data collection to support automatic human activity recognition. *In Intelligent Environments* **2019**, pp. 367-376. IOS Press.
16. Zubair, M., Song, K., and Yoon, C. Human activity recognition using wearable accelerometer sensors. *In 2016 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia)*, **2016**, pp. 1-5. IEEE.
17. Alpoim, L., da Silva, A.F., and Santos. C.P. Human activity recognition systems: state of art. *In 2019 IEEE 6th Portuguese meeting on bioengineering (ENBENG)*, **2019**, pp. 1-4.

18. Shan E., A., Khan, A.N., Zia, S., and Mukhtar. M. Human activity recognition system using smart phone-based accelerometer and machine learning. *In 2020 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT)*, **2020**, pp. 69-74. IEEE.
19. R. R. PBV, T. N. S. Koti Mani Kumar, S. P. Praveen, S. Sindhura, N. A. Al-Dmour and S. Islam, "Optimizing Lung Cancer Detection: The Synergy of Support Vector Machine and Random Forest," *2024 International Conference on Decision Aid Sciences and Applications (DASA)*, Manama, Bahrain, 2024, pp. 1-7,
20. Dedeepya, P., Karishma, D., Manuri, S.G., Raghuvaran, T., Shariff V., and Sindhura, S. Enhancing Cyber Bullying Detection Using Convolutional Neural Network, *4th International Conference on Smart Electronics and Communication (ICOSEC)*, Trichy, India, **2023**, pp. 1260- 1267,
21. P. Dedeepya, P. Chiranjeevi, V. Narasimha, V. Shariff, J. Ranjith and J. V. N. Ramesh, "Image Recognition and Similarity Retrieval with Convolutional Neural Networks," *2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS)*, Pudukkottai, India, **2023**, pp. 709-716,
22. SrinivasVellela, S. *et al*., "Fusion-Infused Hypnocare: Unveiling Real-Time Instantaneous Heart Rates for Remote Diagnosis of Sleep Apnea," *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*, Chikkaballapur, India, **2024**, pp. 1-5.
23. Ponnaganti, N.D., Kumar, T. N. S. K. M., Praveen, S.P., Sindhura, S., Al-Dmour N.A. and Islam, S. A Robust SVM Framework for Heart Disease Detection Utilizing Advanced Feature Selection Techniques," *2024 International Conference on Decision Aid Sciences and Applications (DASA)*, Manama, Bahrain, **2024**, pp. 1-7,
24. Praveen, S.P., Chokka, A., Sarala, P., Nakka, R., Chandolu, S.B., & Jyothi, V.E. Investigating the Efficacy of Deep Reinforcement Learning Models in Detecting and Mitigating Cyber-attacks: a Novel Approach. *Journal of Cybersecurity & Information Management* **2024**, 14(1), 96.
25. Nakka, R., Lakshmi, T.S., Priyanka, D., Sai, N.R., Praveen, S.P., & Sirisha, U. LAMBDA: Lexicon and Aspect-Based Multimodal Data Analysis of Tweet. *Ingénierie des Systèmes d'Information* **2024**, 29(3), 1097-1106.
26. Bikku, T., Chandolu, S.B., Praveen, S.P., Tirumalasetti, N.R., Swathi, K., & Sirisha, U. (2024). Enhancing Real-Time Malware Analysis with Quantum Neural Networks. *Journal of Intelligent Systems and Internet of Things* **2024**, 12(1), 57-7.