Leveraging Ensemble Learning Models for Human Activity Recognition

M.Janaki[1,*], Sarojini Balakrishnan[1]

[1]Department of Computer Science, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, India.
[*]Department of BCA, New Horizon College, Marathahalli Bengaluru

Article Info

Article history:

Received Dec 16, 2024
Revised Mar 2, 2025
Accepted Mar 23, 2025

Keywords:

Classification Metrics
Ensemble Learning
Human Activity Classification
Hyperparameter optimization
Kaggle Datasets
Majority Voting

ABSTRACT

This paper presents a novel method for categorizing human activities by processing sensor data obtained from IoT devices, focusing on improving accuracy. The proposed approach leverages an ensemble learning framework with majority voting, integrating hyperparameter-optimized classifiers to enhance predictive performance.The ensemble approach minimizes individual biases and errors, effectively handling the variability inherent in sensor data. Adequate preprocessing techniques refine data quality before feeding it into the model. A diverse set of base classifiers, such as KNN, Decision Tree, and Random Forests, are considered for classification. Hyperparameter-optimized KNN Grid Search, Gradient-Boosted Decision Trees, and Random Forests with Optimal Trees are ensembled. Extensive experiments were conducted on Human Activity Recognition datasets, WISDM, HAPT, HAR, and KU-HAR.The model performance was rigorously evaluated using classification metrics such as accuracy, precision, recall, and F1-score. Empirical results demonstrate that the proposed ensemble method significantly enhances classification accuracy. Future research will investigate applying deep learning techniques to capture complex feature interactions within sensor data better.

Corresponding Author:

M.Janaki
Department of Computer Science
Avinashilingam Institute for Home Science and Higher Education for Women
Coimbatore, India.

1. INTRODUCTION

Human Activity Recognition focuses on identifying and understanding various human activities by analyzing data acquired from IoT-based sensors[1]. Artificial intelligence (AI) plays a significant role in assessing and identifying human activities.Accurate and robust classification methods are essential for effectively interpreting sensor data and improving activity recognition performance[2]. However, variations in movement patterns, sensor placements, and environmental factors make recognition challenging[3].

This work uses ensemble learning techniques to increase the accuracy of human activity recognition. Wearable sensor readings from Kaggle repositories , including "WISDM, HAPT, HAR, and KU-HAR", are utilized for this empirical study. Even though human activity classification utilising sensor datasets and ensemble learning approaches has advanced significantly, there are still certain research gaps that need to be filled. One limitation is the lack of comprehensive comparison and evaluation of different ensemble methods for human activity classification[4]. While previous studies have employed ensemble learning[5], there is a need to systematically compare the performance of various ensemble combinations. Using Gradient Boosted Decision Trees (GBDT), Random Forests with Optimal Trees (RFOT), and KNN Classifier with Grid Search (KNN-GS), this study determines the optimal ensemble combination.

In the proposed study, two ensemble models are compared. The classification algorithms K-Nearest Neighbours (KNN), Decision Trees, and Random Forest are combined in the first ensemble technique.The second ensemble model integrates hyperparameter-tuned versions of “KNN (with Grid Search optimization), Gradient-Boosted Decision Trees (GBDT), and Random Forests with Optimal Trees (RFOT)”, utilizing majority voting to make predictions.Each model is trained separately, and their predictions are combined using a majority voting strategy**,** leveraging the strengths of each classifier to achieve higher accuracy than any single model alone[6]. The classification measures precision, recall, and F1-scores are used to assess the models' performance. Next, the individual classifiers' performance is contrasted with that of the ensemble models.Empirical results demonstrate that the proposed ensembled tuned hyperparameter classifiers significantly enhance theaccuracy compared to the ensemble model with untuned and individual classifiers.

The structure of this paper is as follows: Section 2 presents related works in the HAR classification, Section 3 provides a detailed description of the proposed methodology, and Section 4 presents the empirical results and discussion. Finally, Section 5 summarizes the findings, concludes the study, and suggests areas for further research in the future.

2. LITERATURE REVIEW

Recently, there has been a burgeoning interest in utilizing sensor data for human activity classification. This surge is attributed to the ubiquitous presence of IoT devices and the continuous advancements in machine-learning techniques.This literature review examines recent research works in this field, focusing on the contributions and limitations of existing approaches.

In the framework of Human Activity Recognition (HAR), Thakur and Biswas investigated the usage of Support Vector Machine (SVM) for classification and Guided Regularised Random Forest (GRRF) for feature selection. Their approach demonstrated high accuracy, exceeding 90%, on both UCI and self-collected datasets. However, the study did not thoroughly address concerns related to computational complexity or the generalizability of the method to diverse environmental conditions [7].

The KNN method is a commonly used algorithm for activity prediction. Recent studies have explored its application in human activity classification. For instance, S. Mohsen et al. employed KNN to classify daily activities using accelerometer data, achieving satisfactory results. However, the limitations of KNN in handling large-scale datasets and optimizing hyperparameters have prompted researchers to explore alternative approaches [8].In the last few years, exhaustive research has been carried out on activity classification using Decision Trees. Many proposed methods have been based on decision trees for classifying activities from sensor data.On the other hand, Naïve Bayes (NB) and Decision Tree (DT) classifications were applied by Maswadi, K. to classify human activities sitting, standing, walking, sitting down and standing up using 89.5% and 99.9% accuracies, respectively [9].

Li et al., developed a model that consists of Residual Blocks for spatial feature extraction and BiLSTM for temporal dependencies, which performed better than previous models, with 97.32% accuracy on WISDM and 97.15% on PAMAP2 (Physical Activity Monitoring with Pervasive 2)[10]. The research work presented a human action recognition method using “Linear Discriminant Analysis (LDA) and Artificial Neural Networks (ANN)” for precise detection. It extracts multidimensional features from different body parts and achieves reliable recognition on KTH and Weizmann datasets[11].Ensemble learning techniques have recently gained significant attention to improve classification performance. Random Forests, an ensemble method, have been extensively explored in this context. For instance, to classify activities using sensor data, achieving superior accuracy compared to individual classifiers. However, determining the optimal number of trees in the forest remains an ongoing research challenge [12, 13] demonstrated this technique for activity identification with wearable sensors and achieved better performance than individual decision trees. However, gradient boosting can be computationally intensive and requires proper tuning of learning rate parameters.

Ramyaet al. [14] suggested HAR methods on silhouette images, distance transform, and entropy features. The technique gives 92.5% on Weizmann, 91.4% on KTH and 80% on UCF50, which shows the strongest performance. Sánchez-Caballero et al. [15] generated a 3D fully convolutional neural network named 3DFCNN for HAR to protect people’s privacy.This review explores the significance of hyperparameter tuning in optimizing ML model performance. It discusses key factors like data quality, algorithm selection, and model complexity. Several tuning techniques, such as Bayesian optimisation, random search, and grid

search, are investigated. The impact of learning rate optimization in deep learning is highlighted. Challenges, trade-offs, and future directions in hyperparameter tuning are also addressed[16].
LSTM-based deep learning model was proposed with batch normalization and Bayesian Optimization for Human Activity Recognition (HAR) using wearable sensors. The model is trained and evaluated on the PAMAP2 dataset, achieving 97.71% accuracy with high F1-score, precision, and recall[17].

Table 1 shows the existing work on human activity recognition.

Table 1. Literature Review

Author & Year	ML Algorithms	Dataset Names	Accuracy (%)
Rahayu et al. (2022)[18]	Convolution Neural Networks (CNN)	3D Action-Net	94.08%
Park et al. (2021)[19]	Deep Learning (LSTM)	MHEALTH	87%
Sarah et al.(2022)[20]	ResIncConvLSTM	KTH	94.08%
N. Zehra, S. H. Azeem and M. Farhan(2021)[21]	Convolution Neural Networks (CNN)	WISDM	94%
Kim et al. (2022)[22]	CNN	3D Action-Net	95%
Rahman et al. (2021)[23]	ELM	Wrist Sense	88%

3. PROPOSED METHODOLOGY

Figure 1 illustrates the overall framework of the proposed methodology, detailing the sequential steps involved in the Human Activity Recognition process.

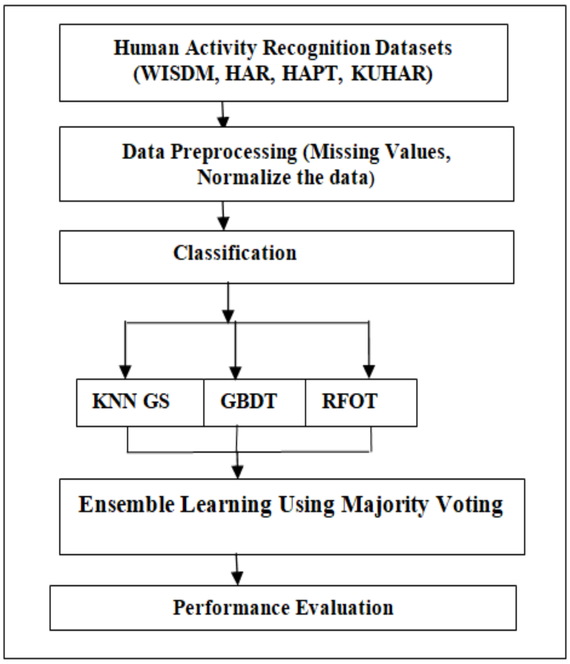

Figure 1 Framework of the proposed methodology.

In this research, the majority voting ensemble technique combines the predictions of multiple classification models, enhancing the overall accuracy and robustness of the final predictions. Majority voting works by aggregating the outputs of several classifiers, where each model independently makes a prediction. The class that receives the most votes across all models is the final prediction. This approach helps leverage the strengths of individual classifiers while minimizing their weaknesses, ultimately leading to improved generalization and reduced overfitting. The Majority Voting ensemble technique formed by combining different models such as “K-Nearest Neighbor (KNN), Decision tree (DT),and Random Forest(RF)”, EKDR, ensures a more reliable and stable prediction, making it particularly effective in human activity classification tasks. This ensemble strategy enhances performance by reducing the risk of model-specific biases and uncertainties [24]. Another Ensemble model, EKGRFOT, is derived by tuning the hyperparameters of the classification algorithms DT, KNN, and RF and combining the models KNN-GS, RFOT, and GBDT. The empirical results of the models are compared using the classification metrics.

3.1 Dataset Description

In this study, “WISDM, HAPT, HAR, and KU-HAR” datasets are collected from smartphone sensors like accelerometers and gyroscopes.

3.1.1 WISDM

The WISDM dataset consists of accelerometer and gyroscope sensor data from 51 test individuals, acquired at 20Hz from smartphones and smartwatches.

Table2. WISDM dataset description

Activity Types	No. of training instances	No. of testing instances
Laying	1125	282
Standing	1099	275
Sitting	1028	258
Walking	981	245
Walking_upstairs	859	214
Walking_downstairs	789	197

Table 2 presents the sample numbers for the six activities in the WISDM dataset, showing the distribution of instances across each activity. It provides an overview of the training and testing instances for these activities. The dataset comprises a total of 7,352 instances, encompassing all recorded samples.

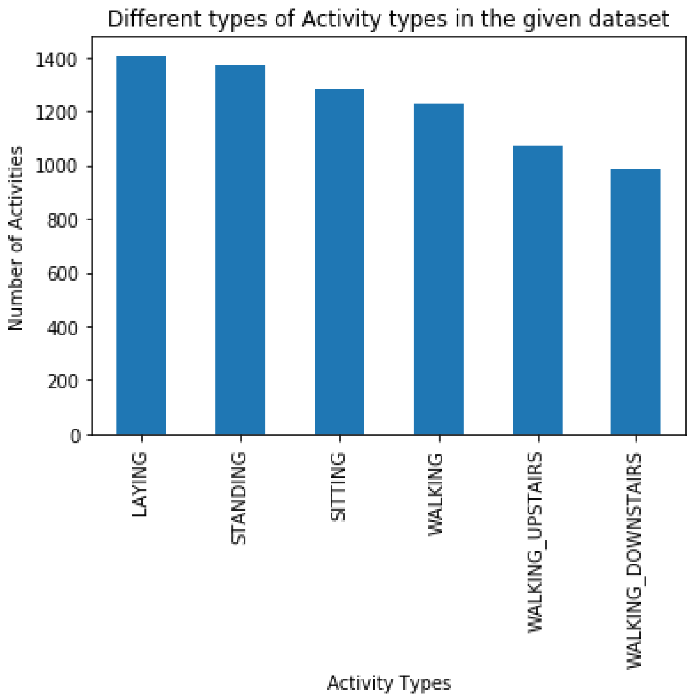

Figure 2. Types of activities in the WISDM dataset

Figure 2 illustrates the distribution of activity types in the WISDM dataset, visually representing their occurrence frequencies. It offers insights into the relative proportions of different activities, enabling a better understanding of the dataset's composition.

3.1.2 HAPT

The HAPT dataset, a study involving 30 individuals, expands the WISDM dataset by including six postural changes. It uses unprocessed tri-axial signals from a Samsung Galaxy II mobile device, covering six primary activities and six transitional movements.Accelerometersand gyroscopes are commonly used together for Human Activity Recognition (HAR) as they complement each other. Their combined data improves accuracy by capturing both movement and orientation.

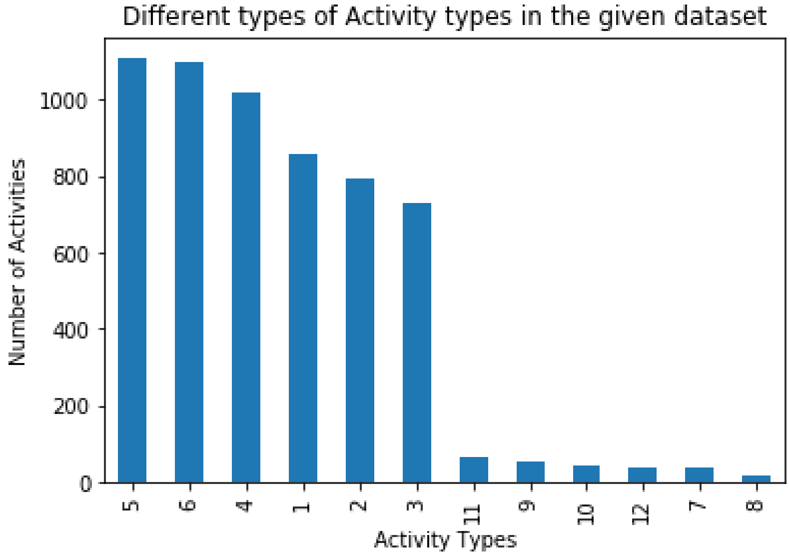

Figure 3. Types of activity in the HAPT dataset

Figure 3 presents a concise overview of the instances within the HAPT dataset, presenting the distribution of activities and postural transitions.Table3 gives the HAPT dataset.

Table 3 HAPT DATASET

Activity Types	No. of training instances	No. of testing instances
Standing	887	222
Laying	878	220
Sitting	814	203
Walking	685	171
Walking_Upstairs	634	159
Walking_Downstairs	584	146
Stand_To_Lie	52	13
Sit_To_Lie	44	11
Lie_To_Sit	36	9
Lie_To_Stand	32	8
Stand_To_Sit	29	7
Sit_To_Stand	15	4

3.1.3 HAR

30 volunteers created a 165,633-point Human Activity Recognition dataset, recording their movements using a Samsung Galaxy S II Smartphone while engaging in five activities..Table 4 gives the details of the Human activity dataset split up of sizes and activity types in the HAR dataset, which are shown in Figure 4.

Table 4. HAR DATASET

Activity Types	No. of training instances	No. of testing instances
Sitting	40,505	10,126
Standing	37,896	9,474
Walking	34,712	8,678
Standing Up	9,932	2,483
Sitting Down	9,461	2,366

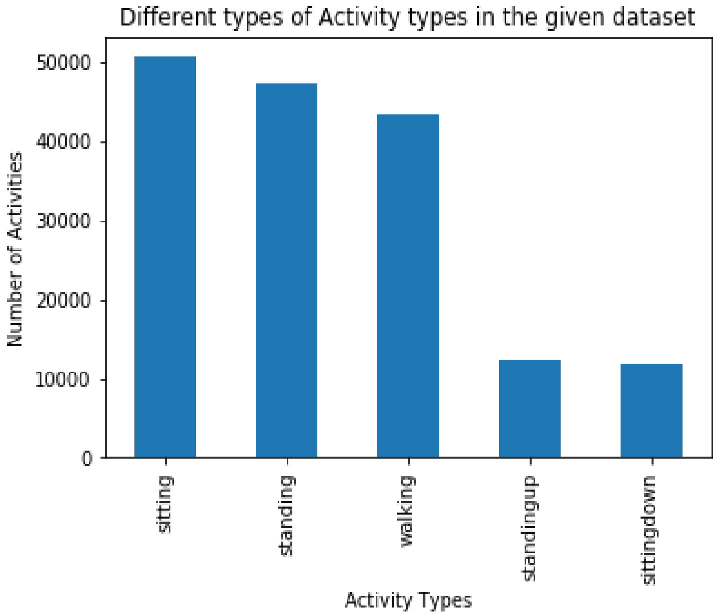

Figure 4. Types of activities in the HAR dataset

3.1.4 KU-HAR

The KU-HAR dataset, capturing data from 90 participants using Smartphone sensors, focuses on machine perception of human actions. It includes 1,945 original activity samples and 20,750 subsamples, covering 18 activities. This dataset is valuable for studying and developing machine learning algorithms for analyzing human behaviour and identifying activities. Activity types in theKU- HAR dataset are shown in Figure 5 and table 5 gives the dataset of KUHAR

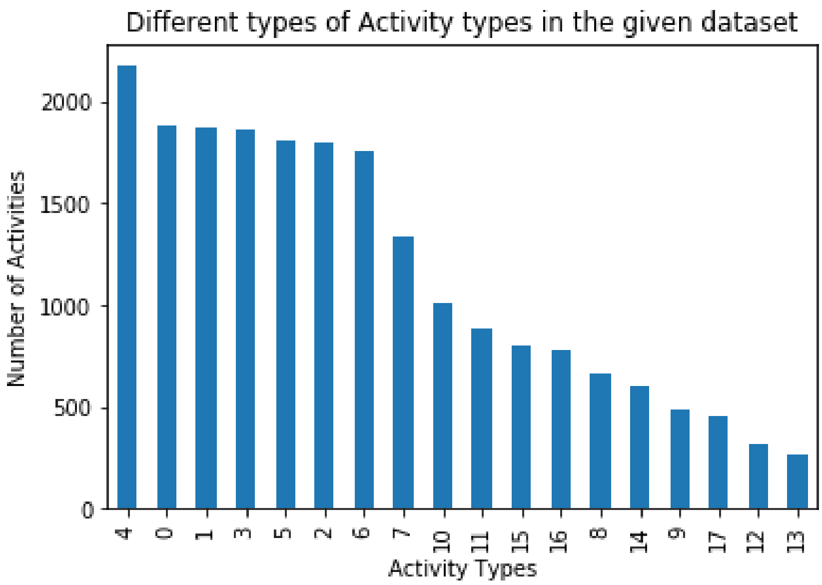

Figure 5. Types of activity in the KU-HAR dataset

Table5. KU-HAR DATASET

Activity Types	No. of training instances	No. of testing instances
Stand-sit	1742	436
Stand	1508	378
Sit	1499	375
Talk-stand	1493	373
Lay	1449	364
Talk-sit	1437	360

Activity Types	No. of training instances	No. of testing instances
Lay-stand	1409	353
Pick	1066	267
Sit-up	804	201
Walk	705	177
Stair-up	638	160
Stair-down	625	156
Jump	533	133
Run	476	119
Push-up	384	96
Table-tennis	366	92
Walk-backward	253	64
Walk-circle	207	52

3.2 Data Pre-processing
Missing values are handled using interpolation techniques to estimate and fill gaps. Sensor readings are normalized using Min-Max Scaling, which scales values between 0 and 1 for consistency and noises and eliminates special characters [25]. Effective pre-processing enhances model accuracy, reduces errors, and improves the overall efficiency of human activity recognition tasks.

3.3 MODEL BUILDING
80% of the dataset is used for training, while 20% is used for testing. Three categorization algorithms , K-nearest neighbours (KNN), Random Forest, and Decision Tree are used to predict human actions.

3.3.1 KNN Classifier with Grid Search (KNN-GS) Model
The KNN Classifier with Grid Search is a powerful algorithm for classifying human activities. It utilizes the K-Nearest Neighbors (KNN) approach to determine the label of a given activity based on its closest neighbors in the training dataset [26].KNN classification model is enhanced using Grid Search.The K-Nearest Neighbors (KNN) classifier is enhanced using Grid Search for hyperparameter tuning, resulting in the KNN-GS model. In this approach, Grid Search is applied to find the optimal values for hyperparameters, such as the number of neighbors (k), distance metrics, and weights. Grid Search aims to improve the model's performance and accuracy by evaluating various combinations of these parameters.

3.3.2 Gradient Boosted Decision Trees (GBDT) Model
Gradient Boosting Decision Trees (GBDT) combines the principles of decision trees with boosting techniques to form a robust ensemble model. The core mechanism of GBDT involves the iterative addition of decision trees to the ensemble, each designed to minimize a loss function. Through this process, GBDT focuses on correcting errors made by previous trees, progressively improving its predictive accuracy. The learning rate parameter plays a key role by controlling the contribution of each new tree to the final prediction, which helps to reduce overfitting and improves the model's ability to generalize. By continuously refining the model in this manner, GBDT enhances its capability to predict the target labels accurately, based on the given features [27].

3.3.3 Random Forests with Optimal Trees (RFOT)Model
The RFOT model combines Random Forests with optimal tree selection to enhance human activity classification. It involves training multiple decision trees on varied subsets of data and features. During the prediction phase, each tree independently classifies the input data, and the final prediction is made through a majority voting mechanism. By selecting the most informative trees, the model improves accuracy while reducing computational complexity [28].

3.3.4 Ensemble KNN-GS, GBDT, and RFOT Model
To further improve classification accuracy, the ensemble model integrates K-Nearest Neighbors (KNN) with GridSearch (GS), Gradient Boosted Decision Trees (GBDT), and Random Forests with Optimal Trees (RFOT). GridSearch is employed for hyperparameter tuning, optimizing each classifier’s performance[29]. GBDT enhances predictive accuracy by sequentially correcting errors, while RFOT constructs optimal decision trees, improving model robustness. This ensemble strategy leverages hyperparameter tuning, boosting techniques, and optimized tree structures, leading to superior generalization and minimized overfitting. By integrating these models, the ensemble effectively captures complex activity patterns,

ensuring higher accuracy and stability in HAR applications. This confirms that the best performance is given by the full EKGRFOT ensemble and that every component is necessary for optimal performance.

4. PERFORMANCE ASSESSMENT :

The proposed classification model's effectiveness is evaluated using performance metrics like Accuracy, Precision, Recall (Sensitivity), and F1-Score to evaluate its predictive capabilities and robustness[30].

Accuracy provides an overall performance evaluation by calculating the percentage of correctly identified occurrences out of all instances.The accuracy is determined via Eq. (1).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Precision quantifies the proportion of correctly predicted positive instances among all predicted positives.It is calculated via Eq. (2)

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

Recall (Sensitivity) : Gives the number of positive estimates that are correctly classified.Recall can be determined from Eq. (3).

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

F1-Score is the harmonic mean of Precision and Recall, offering a balanced measure when there is an imbalance between positive and negative samples. It is calculated from Eq(4)

$$\text{F1 score} = 2 \text{ x} \frac{PrecisionXRecall}{Precision+Recall} \quad (4)$$

4.1 Results and Discussions:

To make results generalizable, the study used multiple sensor-based datasets with different activity patterns that were publicly available. The model was evaluated on unseen data, with the dataset divided into 80:20 subsets. Ensemble approaches are used to improve the robustness of the model, thereby weakening the bias of individual classifiers.

Class imbalance, demographic constraints and variations in sensor placements create potential biases in the datasets used in HAR. The existence of these biases might, in turn, limit a model’s generalizability to the real-world setting, resulting in poor performance. The study deals with this by using multiple benchmark datasets like WISDM, HAPT, HAR, and KU-HAR to provide variability in the activity pattern and user demographics. Also, data preprocessing techniques are applied to minimize the influence of dataset-specific biases. Together, these measures assure that the proposed ensemble classification approach will continue to be effective and reliable for any population and real-world application.

Table 6 presents the performance metricsAccuracy, Precision, Recall and F1-Score of ensemble machine learning algorithms applied to the WISDM, HAR, HAPT, and KUHAR datasets in tabulation form.

Table 6. Performance Metrics of Ensemble Machine Learning Algorithms on Four Datasets

Dataset	Model	Accuracy(%)	Recall(%)	Precision(%)	F1-Score(%)
WISDM	KNN	96.41	95.21	93.31	92.51
	DT	89.98	86.98	87.98	85.98
	RF	97.28	94.18	95.38	96.28
	KNN-GS	96.53	92.33	93.23	94.43
	GBDT	98.77	92.17	93.37	95.27
	RFOT	97.55	91.35	93.45	95.55
	EKDR	97.68	92.18	94.28	95.38
	EKGRFOT	98.95	94.50	92.80	96.00

Dataset	Model	Accuracy(%)	Recall(%)	Precision(%)	F1-Score(%)
HAPT	KNN	94.54	90.24	92.34	91.04
	DT	88.86	82.16	83.36	82.76
	RF	96.59	91.19	90.39	92.39
	KNN-GS	95.45	89.45	90.15	92.35
	GBDT	96.98	90.18	91.38	92.37
	RFOT	96.84	96.84	96.84	96.84
	EKDR	97.90	91.30	93.40	95.10
	EKGRFOT	98.00	98.05	98.03	92.00
HAR	KNN	90.87	89.07	88.17	86.67
	DT	84.22	81.12	82.22	80.11
	RF	86.32	81.12	83.32	84.11
	KNN-GS	91.83	89.13	88.43	86.33
	GBDT	94.83	90.11	89.83	91.23
	RFOT	95.14	85.44	89.34	91.64
	EKDR	96.23	89.23	90.33	91.23
	EKGRFOT	98.43	98.43	98.51	98.44
KU-HAR	KNN	84.65	79.65	78.22	80.33
	DT	78.54	72.55	73.64	75.94
	RF	78.43	73.23	75.33	76.43
	KNN-GS	83.16	80.11	83.56	85.26
	GBDT	82.45	77.15	78.45	79.45
	RFOT	79.06	72.36	74.53	75.26
	EKDR	85.30	81.31	80.20	83.43
	EKGRFOT	90.60	90.60	95.23	92.07

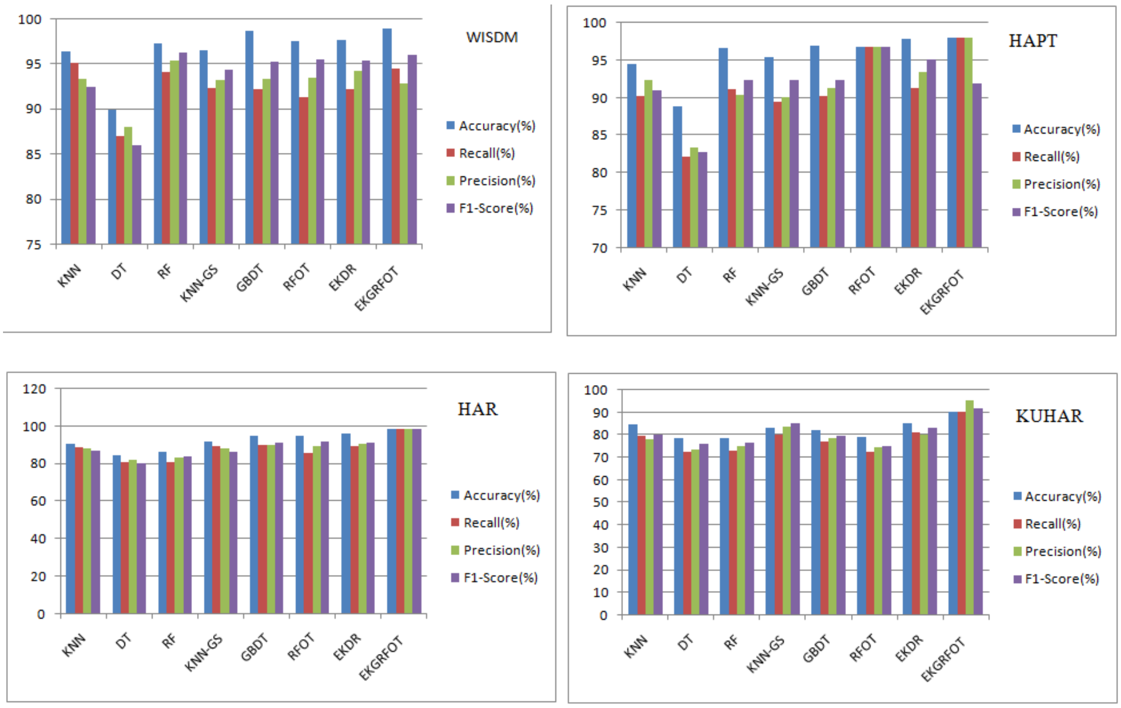

Figure 6. Performance metrics on four datasets

Figure 6 shows the effectiveness metrics of ensemble machine learning models across four datasets,the performance comparison across "WISDM, HAPT, HAR, and KU-HAR" datasets highlights the superiority of the EKGRFOT model, especially when contrasted with the EKDR model, which lacks hyperparameter tuning. EKGRFOT achieved the highest accuracy across all datasets, with 98.95% for WISDM, 98. % for HAPT, 98.43% for HAR, and 90.60% for KU-HAR. This performance is attributed to meticulous hyperparameter tuning, optimizing parameters such as the number of estimators, maximum depth, and learning rate, thereby balancing model complexity and generalization. In contrast, EKDR, without hyperparameter tuning, showed slightly lower accuracies: 97.68% for WISDM, 97.90% for HAPT, 96.23% for HAR, and 85.30% for KU-HAR. Precision, Recall, and F1-Scoresfollowed a similar trend, with EKGRFOT consistently outperforming EKDR. This comparison underscores the impact of hyperparameter tuning in enhancing model performance, positioning EKGRFOT as a more effective solution for human activity recognition tasks.

4.2 Comparison

Below Table 7, the result demonstrates that applying hyperparameter tuning significantly improves performance compared to the traditional ensemble classifier. The EKGRFOT model, with hyperparameter tuning, achieves higher accuracy across all datasetsWISDM, HAPT, and HAR, and outperforms the EKDR model without tuning. This highlights the effectiveness of hyperparameter optimization in enhancing classification accuracy for human activity recognition.

Table 7. Comparison of EKDR and EKGRFOT Model

Model	Dataset	Accuracy(%)
EKDR (Without Hyperparameter tuning)	WISDM	97.68
	HAPT	97.90
	HAR	96.23
	KU-HAR	85.30
EKGRFOT (With Hyperparameter tuning)	WISDM	98.03
	HAPT	98.25
	HAR	97.42
	KU-HAR	88.83

Future work will explore deep learning for capturing complex temporal dependencies in sensor data. Advanced optimization techniques will also be investigated to improve real-time HAR classification in IoT-driven environment.

5. CONCLUSION

In conclusion, the suggested ensemble learning method uses sensor data from Internet of Things devices to improve human activity recognition. By integrating multiple machine learning classifiers and employing hyperparameter tuning, the method achieves superior accuracy and robustness compared to traditional approaches. Experimental evaluations on benchmark datasets, demonstrate significant improvements inperformance, with the ensemble learning using majority votingcomplemented by hyperparameter tuning to achieve better prediction results.These results highlight the potential of ensemble learning for accurate activity classification, particularly in healthcare and elder care applications. Future work will focus on leveraging deep learning techniques to capture complex feature interactions for further performance enhancement.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

REFERENCES:

[1] S. Wan, L. Qi, X. Xu, C. Tong, and Z. Gu, "Deep learning models for real-time human activity recognition with smartphones," *Mobile Networks and Applications*, vol. 25, no. 2, pp. 743–755, 2020, doi: 10.1007/s11036-019-01445-x.

[2] N. Gupta, S. K. Gupta, and R. K. Pathak, "Human activity recognition in artificial intelligence framework: A narrative review," *Artificial Intelligence Review*, vol. 55, pp. 4755–4808, 2022, doi: 10.1007/s10462-021-10116-x.

[3] N. Zurbuchen, A. Wilde, and P. Bruegger, "A machine learning multi-class approach for fall detection systems based on wearable sensors with a study on sampling rates selection," *Sensors*, vol. 21, p. 938, 2021, doi: 10.3390/s21030938.

[4] U. Sarmah, P. Borah, and D. K. Bhattacharyya, "Ensemble learning methods: An empirical study," *SN Computer Science*, vol. 5, p. 924, 2024, doi: 10.1007/s42979-024-03252-y.

[5] T.-H. Tan, J.-Y. Wu, S.-H. Liu, and M. Gochoo, "Human activity recognition using an ensemble learning algorithm with smartphone sensor data," *Electronics*, vol. 11, no. 3, p. 322, 2022, doi: 10.3390/electronics11030322.

[6] D. Sharma, A. Roy, S. P. Bag, P. K. Singh, and Y. Badr, "A hybrid deep learning-based approach for human activity recognition using wearable sensors," in *Studies in Big Data*, vol. 134, pp. 231–259, Springer, 2023, doi: 10.1007/978-3-031-40688-1_11.

[7] D. Thakur and S. Biswas, "Guided regularized random forest feature selection for smartphone-based human activity recognition," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, pp. 9767–9779, 2023, doi: 10.1007/s12652-022-03862-5.

[8] S. Mohsen and A. Elkaseer, "Human activity recognition using k-nearest neighbor machine learning algorithm," in *Proceedings of the International Conference on Advances in Intelligent Systems and Computing*, Springer, pp. 309–320, 2021, doi: 10.1007/978-981-16-6128-0_29.

[9] K. Maswadi, N. A. Ghani, S. Hamid, and M. B. Rasheed, "Human activity classification using Decision Tree and Naïve Bayes classifiers," *Multimedia Tools and Applications*, vol. 80, no. 14, pp. 21709–21726, 2021.

[10] Y. Li and L. Wang, "Human activity recognition based on residual network and BiLSTM," *Sensors (Basel)*, vol. 22, no. 2, p. 635, 2022.

[11] A. Nadeem, A. Jalal, and K. Kim, "Human actions tracking and recognition based on body parts detection via artificial neural network," in *Proc. 2020 3rd Int. Conf. Advancements in Computational Sciences (ICACS)*, 2020.

[12] Z. Sun, "An improved random forest based on the classification accuracy and correlation measurement of decision trees," *Expert Systems with Applications*, vol. 237, p. 121549, 2023, doi: 10.1016/j.eswa.2023.121549.

[13] R. K. Priyadarshini, "Gradient boosted decision tree-based classification for recognizing human behavior," in *Proc. IEEE Int. Conf. Advances in Communication, Computing and Electronics (ICACCE)*, 2019, doi: 10.1109/ICACCE46606.2019.9080014.

[14] P. Ramya and R. Rajeswari, "Human action recognition using distance transform and entropy-based features," *Multimedia Tools and Applications*, vol. 80, no. 6, pp. 8147–8173, 2021.

[15] A. Sánchez-Caballero et al., "3DFCNN: real-time action recognition using 3D deep neural networks with raw depth information," *Multimedia Tools and Applications*, vol. 81, no. 17, pp. 24119–24143, 2022.

[16] Ilemobayo et al., "Hyperparameter tuning in machine learning: A comprehensive review," *Journal of Engineering Research and Reports*, vol. 26, no. 6, pp. 388–395, 2024, doi: 10.9734/jerr/2024/v26i61188.

[17] M. E. Ghazi et al., "Optimizing Deep LSTM model through hyperparameter tuning for sensor-based human activity recognition in smart home," *Informatica*, vol. 47, pp. 109–122, 2023, doi: 10.31449/inf.v47i10.5268.

[18] E. S. Rahayu, E. M. Yuniarno, I. K. E. Purnama, and M. H. Purnomo, "Human activity classification using deep learning based on 3D motion feature," *Machine Learning with Applications*, vol. 12, p. 100461, 2023.

[19] S. Park, Y. Kim, and S. Lee, "Deep learning approaches for human activity recognition on mobile health data," *IEEE Access*, vol. 9, pp. 107836–107847, 2021, doi: 10.1109/ACCESS.2021.3100238.

[20] S. Khater, M. Hadhoud, and M. B. Fayek, "A novel human activity recognition architecture: using residual inception ConvLSTM layer," *Journal of Engineering and Applied Science*, vol. 69, no. 1, 2022, doi: 10.1186/s44147-022-00098-0.

[21] N. Zehra, S. H. Azeem, and M. Farhan, "Human activity recognition through ensemble learning of multiple convolutional neural networks," in *Proc. 55th Annu. Conf. Information Science and Systems (CISS)*, Baltimore, MD, USA, pp. 1–5, 2021.

[22] D. Kim, S. Kim, and C. Kim, "Convolutional neural networks for human activity recognition on 3D Action-Net dataset," *Sensors*, vol. 22, no. 2, p. 464, 2022, doi: 10.3390/s22020464.

[23] M. S. Rahman, M. M. Hassan, and A. Almogren, "Extreme learning machines for activity recognition using WristSense dataset," *IEEE Transactions on Industrial Informatics*, vol. 17, pp. 1–1, 2021, doi: 10.1109/TII.2021.3090991.

[24] V. Sheth et al., "A comparative analysis of machine learning algorithms for classification purpose," *Procedia Computer Science*, vol. 215, pp. 422–431, 2022, doi: 10.1016/j.procs.2022.12.044.

[25] M. Janaki et al., "Human activity recognition using chaotic logistic map guided grey wolf optimization with decision tree," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 12, no. 1, pp. 142–150, Jan. 2025, doi: 10.14445/23488379/IJEEE-V12I1P113.

[26] H. Saadatfar, S. Khosravi, J. H. Joloudari, A. Mosavi, and S. Shamshirband, "A new K-nearest neighbors classifier for big data based on efficient data pruning," *Mathematics*, vol. 8, p. 286, 2020, doi: 10.3390/math8020286.

[27] N. Gunasekara and B. Pfahringer, "Gradient boosted trees for evolving data streams," *Machine Learning*, vol. 113, pp. 3325–3352, 2024, doi: 10.1007/s10994-024-06517-y.

[28] N. Jalal, A. Mehmood, G. S. Choi et al., "A novel improved random forest for text classification using feature ranking and optimal number of trees," *Journal of King Saud University – Computer and Information Sciences*, vol. 34, pp. 2733–2742, 2022, doi: 10.1016/j.jksuci.2022.03.012.

[29] S. M. Ganie, "An investigation of ensemble learning techniques for obesity risk prediction using lifestyle data," *Decision Analytics Journal*, vol. 12, 2025, doi: 10.1016/j.dajour.2024.100539.

[30] I. Priyadarshini, "Human activity recognition in cyber-physical systems using optimized machine learning techniques," *Cluster Computing*, 2022, doi: 10.1007/s10586-022-03662-8.

BIOGRAPHIES OF AUTHORS

Ms. M. Janaki is a Senior Assistant Professor in the Department of Computer Science at New Horizon College, Marathahalli, Bangalore, with 12 years of teaching experience. She completed her MCA and M.Phil. in Computer Science and is currently pursuing a Ph.D. in Computer Science at Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore. She has published research papers in Scopus Index Journal and presented papers in National Conferences, and her research interests include Data Analytics, Machine Learning, and Deep Learning. She also cleared the UGC NET and SLET exams in 2016. ORCID id: 0000-0001-9400-1626.ResearcherId:HMU-9503-2023,Email id:19phcsp08@avinuty.ac.in, Google scholar Id:Vjegs68AAAAJ

Dr. Sarojini Balakrishnan is working as Assistant Professor (SG) in the Department of Computer Science at Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore. She has more than 25 years of teaching and research experience. She completed her Ph.D. and M.Phil in Computer Science from Mother Teresa Women's University, Kodaikanal and MCA from Alagappa University, Karaikudi. Her areas of interest are Medical Informatics, Machine Learning, and Network Security. To her credit, she has completed a UGC-funded research project and has published more than 30 quality research articles in indexed journals. Under her guidance, two candidates have completed their doctoral degrees, and three are pursuing. She is a lifetime member of professional forums, CSI, ISTE and IAENG.Email-id: sarojini_cs@avinuty.ac.in, Orcid-id: 0000-0002-7740-7058, Scopus-id: 172121