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Smartwatch-Based Human Activity Recognition Using Random Forest, Kernel Support Vector Machine, and K-Nearest Neighbors: A Comparative Study of Sensor Data Classification Accuracy

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Abstract

This research presents a comparative analysis of machine learning algorithms for human activity recognition (HAR) based on smartwatches using accelerometer sensor data. The main objective of this research is to evaluate and optimise the classification performance of Kernel Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors(KNN) within an integrated experimental framework. Raw motion data is processed using Fast Fourier Transform (FFT) and statistical feature extraction such as Root Mean Square (RMS) and Signal Magnitude Area (SMA), followed by dimensionality reduction through Principal Component Analysis (PCA). Hyperparameter optimisation was performed using RandomizedSearchCV to ensure a fair comparison of models. The dataset from Kaggle, which includes six daily activities, was used for this test. The experimental results show that Kernel SVM achieved the highest accuracy of 98.69%, outperforming KNN (97.72%) and Random Forest (97.28%). These findings demonstrate that kernel-based methods are highly effective in capturing nonlinear relationships in motion signals, resulting in superior generalisation performance. This study highlights the critical role of feature engineering and hyperparameter tuning in enhancing model robustness. These results provide valuable insights for the development of lightweight and accurate smart sensor technology for health monitoring applications and smart home automation systems.

Keywords: *Accelerometer, Feature Extraction, Human Activity Recognition, Smartwatch, Wearable Computing*

INTRODUCTION

In recent years, the global population has in recent years, global lifestyle patterns have undergone significant transformations characterised by reduced physical activity and increased exposure duration to digital devices (Thakur & Biswas, 2022). This sedentary lifestyle has become a major risk factor for various chronic diseases such as obesity, heart disorders, and musculoskeletal problems (Ghate & Hemalatha C, 2023). Although physical activity has proven vital for physical and mental health through increased blood flow and mood stabilisation, many individuals still struggle to meet daily exercise targets (Joy Rakesh et al., 2021; Karayaneva et al., 2023). As a solution, wearable technology such as smartwatches is available to facilitate independent activity tracking through accelerometer and gyroscope sensors (Ghate & Hemalatha C, 2023). This device enables proactive health monitoring, ranging from medical rehabilitation to elderly care (Kurniawan et al., 2021). The integration of sensor data collection with artificial intelligence has opened new potential in Human Activity Recognition (HAR), which automatically classifies human movements (Fitra A. Bachtiar et al., 2021).

HAR systems play a crucial role in various modern domains, ranging from personalised medical patient monitoring, sports performance analysis, to the development of smart home ecosystems (Lina et al., 2024; Haider et al., 2024; Surya et al., 2024). However, the effectiveness of these applications heavily depends on the algorithm's ability to process complex and noisy sensor data into accurate information. If previously traditional rule-based HAR systems had limitations in flexibility and adaptation to variations in movement, the emergence of machine learning offers much higher precision (Nur et al., 2024). Algorithms such as Support Vector Machine (SVM), Random Forest (RF), and K-Nearest

Neighbors(KNN) consistently demonstrate superior performance in sensor based activity classification (Karayaneva et al., 2023). Each algorithm has unique characteristics, where SVM excels in non-linear modelling through kernel functions, Random Forest offers stability through ensemble methods, and KNN provides simplicity based on distance metrics (Wardana & Rahim, 2024; Arifien et al., 2022; Made Liandana et al., 2024).

Recent research has begun to explore the combination of these algorithms with various feature extraction methods such as RMS, SMA, FFT, and dimensionality reduction using PCA to enhance recognition effectiveness (Mashudi et al., 2024). Nevertheless, comprehensive comparative analyses involving kernel optimisation on SVM compared to ensemble based or distance-based algorithms within a uniform pre-processing framework are still very limited (Gondaliya et al., 2022). Many previous studies have only focused on general accuracy without making systematic parameter adjustments that actually significantly affect the final results.

Therefore, this study aims to evaluate and compare the effectiveness of Kernel SVM, Random Forest, and K-Nearest Neighborsclassification in the context of human activity recognition using accelerometer data. The main focus of the research is to identify the algorithm that provides an optimal balance between accuracy and efficiency after systematic parameter optimisation. The novelty of this study lies in the integration of FFT, RMS, SMA, and PCA-based feature extraction within a standardised experimental framework. The research results are expected to contribute to the development of more reliable smart health monitoring systems in wearable technology.

LITERATURE REVIEW

2.1 Human Activity Recognition and Wearable Technology

Human Activity Recognition (HAR) has become a primary pillar in digital health development, aimed at monitoring lifestyles and minimizing the risk of chronic diseases due to physical inactivity. According to Karayaneva et al. (2023), measurable physical activity is essential for mood stabilization and overall physical health. The use of wearable devices, particularly smartwatches, facilitates real-time movement data collection through accelerometer and gyroscope sensors. These devices serve not only as fitness trackers but also play a critical role in medical rehabilitation and elderly monitoring by transforming raw motion signals into meaningful activity information (Kurniawan et al., 2021).

2.2 Sensor Data and Feature Extraction

In the sensor data processing workflow, feature extraction plays a critical role in accurately representing human movement characteristics. The use of time-domain statistical features such as Root Mean Square (RMS) and Signal Magnitude Area (SMA) is effective for capturing the intensity and variability of movements (Mashudi et al., 2024). Meanwhile, frequency domain transformation using Fast Fourier Transform (FFT) enables the identification of periodic patterns in specific motions, such as distinguishing between rhythmic walking and static positions.

2.3 Dimensionality Reduction using Principal Component Analysis (PCA)

To address the complexity of high dimensional sensor data, Principal Component Analysis (PCA) is often integrated to reduce feature redundancy without losing essential information. This process transforms a large set of variables into a smaller one that still contains most of the information in the large set. In HAR systems, PCA is vital for making the classification process more computationally efficient, which is crucial for implementation on wearable devices with limited battery and processing power.

2.4 2.4 Machine Learning Algorithms and Optimization

The success of a HAR system heavily depends on the selection of appropriate classification algorithms. Support Vector Machine (SVM) is a leading algorithm capable of finding the optimal hyperplane through kernel functions like Radial Basis Function (RBF) to separate activity classes (Wardana & Rahim, 2024).

On the other hand, ensemble algorithms such as Random Forest (RF) offer advantages in stability and overfitting prevention by aggregating predictions from multiple decision trees. Additionally, K-Nearest Neighbors(KNN) remains a viable choice due to its simplicity in

classifying data based on proximity metrics. Systematic parameter optimization using methods like RandomizedSearchCV is crucial to ensure the objectivity and high accuracy of these comparative results (Gondaliya et al., 2022).

METHOD

This study compares the effectiveness of three supervised machine learning algorithms: Kernel Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors(KNN), in identifying and classifying human physical activities using sensor data from accelerometers and gyroscopes. The entire research process consists of five main steps: data collection, data cleaning, feature selection and labelling, model construction and refinement, and model testing.

3.1 Research Framework

The research began with the data collection phase, where the dataset was gathered and imported into the working environment. The next step involved data pre-processing, which eliminated duplicates and missing values to ensure the data was clean and reliable. In the third step, critical features from the dataset were identified and selected, and the target variables were labelled. Once the data was prepared, the training portion of the dataset was used to train three machine learning algorithms: Kernel SVM, Random Forest, and KNN.

Hyperparameter optimization was then utilized to fine-tune each algorithm to perform optimally for classification. Finally, the models were tested on previously unseen data (testing set), and their performance was measured using statistical tools such as accuracy, precision, recall, F1-score, and confusion matrices. This structured framework guarantees the validity and reproducibility of the research findings, facilitating a fair and objective comparison between the predictive capabilities of the algorithms under uniform experimental conditions.

3.2 Dataset Description

The Human Activity Recognition dataset, which is publicly available on Kaggle, was used in this study. This dataset contains sensor readings from a group of individuals performing different physical activities, such as walking, sitting, laying, standing, and running. Wearable sensors, primarily accelerometers and gyroscopes, were used to record the data. These sensors measure movement dynamics along multiple axes. The dataset was downloaded as a ZIP file containing several CSV files, which were then extracted and loaded into a Pandas Data Frame within the Google Collab environment. In this study, all numerical sensor readings were used as input features for the models, while the column indicating participants (i.e., Subject or Participant) was removed as it does not contribute to activity classification. The "Activity" column was used as the target label for classification. Subsequently, the dataset was split into two parts: a training set and a testing set. The training set utilized 70% of the data, while the testing set utilized 30%. This dataset is suitable for supervised classification problems because it clearly demonstrates how sensor measurements (as features) relate to activities (as labels).

3.3 Data Pre-processing

Before the data was used for training, it underwent several steps to ensure consistency, high quality, and suitability for model learning. To avoid redundancy that could affect the models, all duplicate entries were identified and removed first. Following that, missing values were checked, and since the dataset is well-structured, no imputation was necessary. After cleaning the data, all numerical sensor columns were selected as input features. These columns display various readings of movement and orientation captured by the sensors. We used label encoding to transform the "Activity" column into numerical values so they could be used with the machine learning algorithms. This study did not apply normalization or scaling to the feature set. While normalization is often used to improve model performance, especially for distance-based algorithms like KNN, it was intentionally omitted to maintain the original scale of the sensor readings. The research used equation (1) to split the data into training and testing sets:

$$X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 1) \quad (1)$$

3.4 Model Development and Optimization

The model development phase included the implementation and refinement of three

machine learning algorithms: Kernel SVM, Random Forest, and K-Nearest Neighbours. We used the scikit-learn library in Google Collab to build and train all models in Python 3.x. We used pandas and NumPy for data processing, as well as matplotlib and seaborn for visualizing the data and results.

3.4.1 Kernel SVM

The Support Vector Machine (SVM) algorithm finds the best hyperplane that separates data points from different classes in the feature space as much as possible. Since the dataset may not be separable by a line, a kernel function is used to move the data into a higher dimensional space where separation becomes possible. Equation (2) represents this distance calculation:

$$f(x) = sign(i = 1\sum n\alpha iyiK(xi, x) + b) \quad (2)$$

3.4.2 Random Forest

The Random Forest algorithm builds a group of decision trees and combines their predictions through majority voting. This helps reduce overfitting and improves generalization. The idea behind bagging is that each tree learns from a random sample of the data and features. Equation (3) represents the prediction calculation:

$$y\hat{} = mode(h1(x), h2(x), \ldots, hT(x)) \quad (3)$$

3.4.3 K-Nearest Neighbors(KNN)

The KNN algorithm classifies an unknown data point by examining the k nearest data points in the feature space. To determine the similarity between two instances, Euclidean distance is used. Equation (4) represents this distance calculation:

$$d(x, x_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{ij})^2} \quad (4)$$

3.4.4 Evaluation Metrics

Performance was measured using a Confusion Matrix as shown in equation (5):

$$ConfusionMatrix = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix} \quad (5)$$

Where True Positive, True Negative, False Positive, and False Negative represent the classification results across all classes. The following metrics are calculated:

a. Accuracy

Accuracy measures the proportion of correctly classified instances, as defined in equation (6).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

b. Precision

Precision measures the model's ability to avoid false positives, as defined in equation (7).

$$Precision = \frac{TP}{TP + FP} \quad (7)$$

c. Recall

Recall measures the model's ability to correctly detect positive instances, as defined in equation (8).

$$Recall = \frac{TP}{TP + FN} \quad (8)$$

d. F1-score

The F1-score provides the harmonic mean of precision and recall, as defined in equation (9).

$$F1\text{-}score = 2 \times \frac{Precision \times Recall}{Precision + \mathrm{Recall}} \quad (9)$$

The performance of each algorithm is analysed based on these metrics to determine the most effective model for human activity recognition. Furthermore, the results are visualized through confusion matrix heatmaps and classification reports to better understand the classification tendencies of each algorithm.

RESULT AND DISCUSSIONS

This section presents the research design, findings, and an in-depth discussion regarding the machine learning model

experiments. The discussion focuses on the interpretation of the findings, their implications, and their connection to relevant theories, definitions, and literature.

4.1 User Activity Distribution

This section illustrates the frequency of various user activities recorded in the dataset. Figure 1 shows the distribution of observations across different activity types.

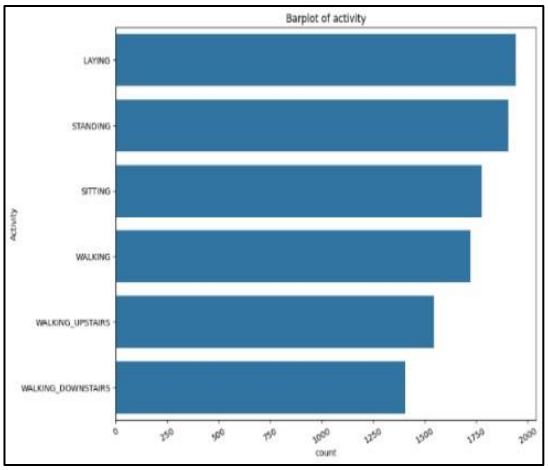


Figure 1. Distribution and Occurrence Count of Different Physical Activities.

The analysis reveals that "Laying" is the most frequent activity, occurring nearly 2,000 times, followed by "Standing" and "Sitting," which each account for over 1,750 observations. These static activities represent the majority of the dataset, potentially due to the nature of daily human behaviour or specific data collection protocols. Dynamic activities, such as "Walking," "Walking Upstairs," and "Walking Downstairs," show a lower frequency, with "Walking Downstairs" being the least common at approximately 1,250 instances. This imbalance highlights the importance of using robust evaluation metrics like F1-score and confusion matrices to ensure the models do not simply favour the majority classes.

4.2 Activity Feature Distribution

Analysis of the tBodyAccMag-mean feature across various activities reveals distinct patterns. Static activities exhibit high density peaks around -1.0, indicating minimal acceleration changes. In contrast, dynamic activities show broader, more dispersed distributions. The clear separation between static and dynamic activity distributions suggests that this feature is highly effective for activity recognition. Figure 2 demonstrates how this feature facilitates the distinction between static and dynamic states.

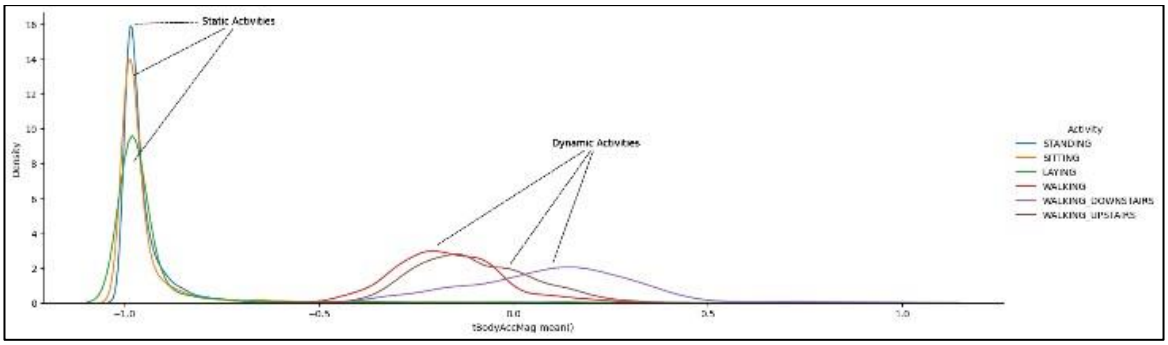


Figure 2. Distribution of tBodyAccMagmean() across Activities.

Static activities exhibit high-density peaks concentrated around -1.0. This narrow distribution confirms that body acceleration remains nearly constant during these periods. Conversely, dynamic activities show broader and more dispersed distributions with peaks shifted towards 0.0 or higher. The clear separation between these two clusters indicates that tBodyAccMag-mean is a critical feature for establishing the initial classification boundary between resting and active states.

4.3 Activity Feature Distribution

A more detailed examination of feature density profiles reveals subtle differences even within the same category. For static activities, although all peaks are centred near -1.0, their varying heights and widths suggest unique micro-movements inherent to each posture.

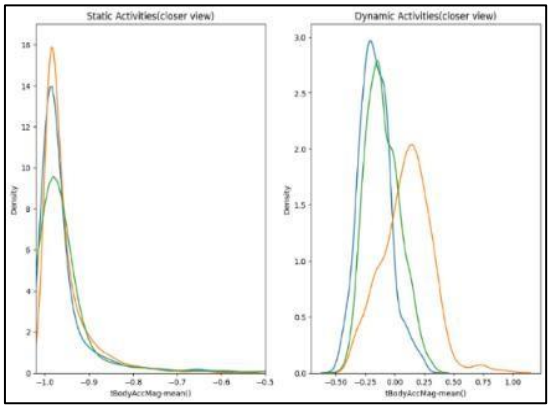


Figure 3. Detailed View of BodyAccMagmean Distribution for Static and Dynamic Activities.

In the dynamic category, as illustrated in Figure 3, "Walking" shows a peak slightly to the left of the stair-related activities. "Walking Upstairs" and "Walking Downstairs" present wider spreads, reflecting the increased complexity and intensity of vertical movement. This overlap in dynamic features underscores the necessity of high-dimensional mapping provided by algorithms like Kernel SVM to maintain high classification accuracy.

4.4 Kernel SVM Classification Performance Analysis

The Kernel Support Vector Machine (SVM) was evaluated using a Radial Basis Function (RBF) kernel, optimized with a regularization parameter (C) of 100. This configuration enables the model to effectively handle the non-linear nature of sensor data. Detailed performance metrics are summarized in Table 1.

Table 1. Kernel SVM Classification Report

Activity	Precision	Recall	F1-Score	Support
Laying	1.00	1.00	1.00	583
Sitting	0.98	0.96	0.97	533
Standing	0.97	0.98	0.97	572
Walking	1.00	1.00	1.00	517
Walking Downstairs	1.00	1.00	1.00	422
Walking Upstairs	1.00	1.00	1.00	463
Accuracy			**0.9869**	**3090**

The confusion matrix in Figure 4 indicates near-perfect classification for dynamic movements. The RBF kernel successfully identified the complex boundaries between various types of movement, resulting in an outstanding overall accuracy of 98.69%.

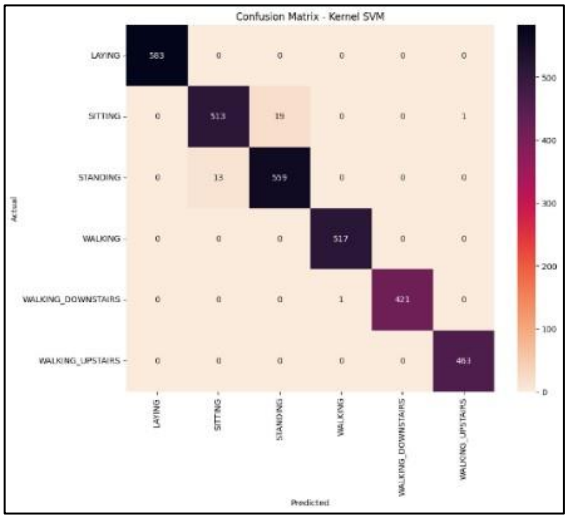


Figure. 4 Confusion Matrix of Kernel SVM Classifier Performance

4.5 Classification Performance Analysis: Random Forest

The Random Forest (RF) model was implemented utilizing 100 decision trees with a maximum depth of 14. This model achieved an overall accuracy of 0.9728 (97.3%). The comprehensive metrics for each class are presented in Table 2.

Table 2. Random Forest Classification Report

Activity	Precision	Recall	F1- Score	Support
Laying	1.00	1.00	1.00	583
Sitting	0.97	0.94	0.95	533
Standing	0.95	0.97	0.96	572
Walking	1.00	0.98	0.99	517
Walking Downstairs	0.98	0.98	0.98	422
Walking Upstairs	0.96	0.98	0.97	463
Accuracy			**0.9728**	**3090**

As shown in Figure 5, the confusion matrix indicates minor misclassifications between "Sitting" and "Standing." Despite these minor discrepancies, Random Forest demonstrated significant robustness against feature redundancy.

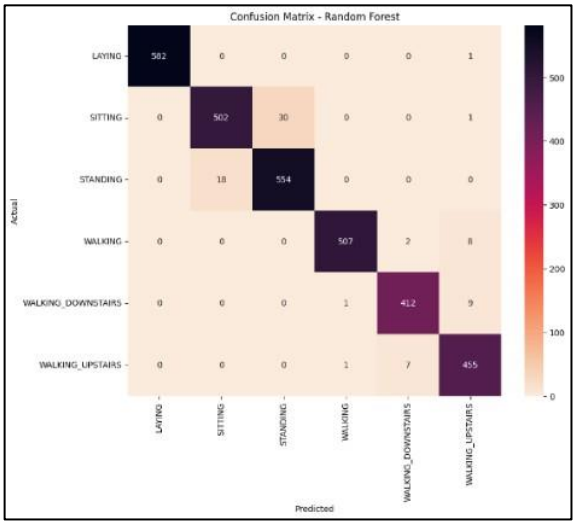


Figure. 4 Confusion Matrix of Random Forest Classifier Performance

4.6 Classification Performance Analysis: KNearest Neighbors(KNN)

The KNN algorithm was configured with *neighbours=4* and Manhattan distance weighting. The model achieved an accuracy of 0.9772 (97.7%), as detailed in Table 3.

Table 3. Classification Report for K-Nearest Neighbors (KNN)

Activity	Precision	Recall	F1- Score	Support
Laying	1.00	1.00	1.00	583
Sitting	0.96	0.94	0.95	533
Standing	0.96	0.96	0.96	572
Walking	1.00	1.00	1.00	517
Walking Downstairs	0.98	0.98	0.98	422
Walking Upstairs	0.97	0.98	0.97	463
Accuracy			**0.9772**	**3090**

The distribution of correct predictions for KNN is illustrated in Figure 6. KNN proves to be a highly efficient algorithm for real-time applications where computational simplicity is prioritized.

4. 7 Model Performance Comparison and Discussion

A comparative evaluation was performed to identify the most effective algorithm. Table 4 displays the optimized parameters and the best accuracy scores.

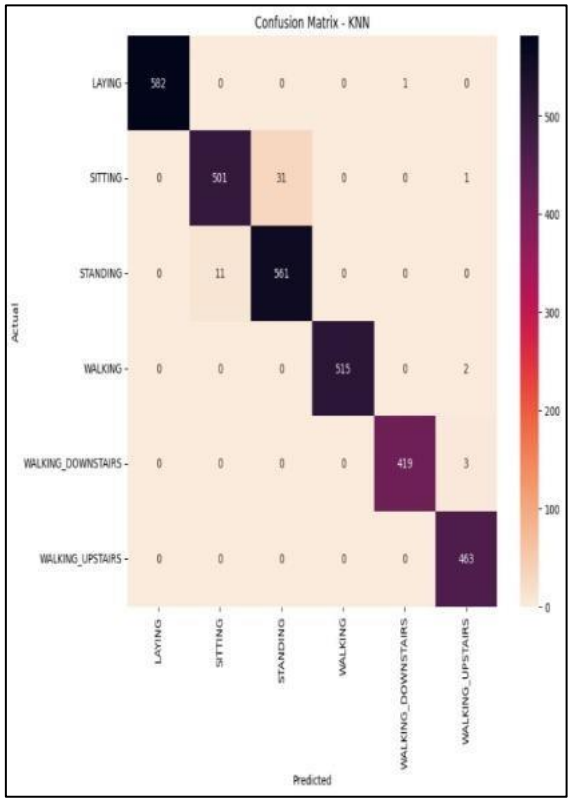


Figure 6. Confusion Matrix of KNN Classification Performance.

Table 4. Optimized Model Parameters and Comparative Accuracy

Model	Best Parameters	Best Score
Kernel SVM	{'kernel':'rbf','C':100}	0.9869
Random Forest	{'n_estimators': 100, 'max_depth': 14}	0.9728
KNN	{'weights': 'distance', 'n_neighbors':4, 'metric': 'manhattan'}	0.9772

As illustrated in Figure 7, Kernel SVM consistently outperformed the other algorithms due to its ability to capture non-linear interactions. All three models demonstrated accuracies exceeding 97%, indicating a high-quality pre-processing pipeline.

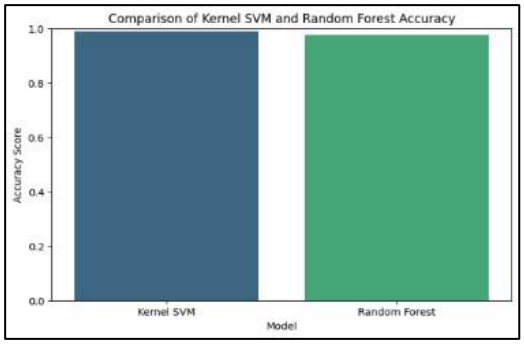


Figure 7. Model Accuracy Comparison.

CONCLUSIONS

This study conducted a comprehensive comparative analysis of three prominent supervised machine learning algorithms: Kernel Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN), for smartwatch-based Human Activity Recognition (HAR) using sensor data. Through rigorous experimentation and evaluation, each model demonstrated high classification accuracy, validating the feasibility of machine learning techniques for the precision identification of human activities from multisensory inputs. Kernel SVM achieved the highest accuracy of 98.69%, followed by KNN at 97.72% and Random Forest at 97.28%. These results indicate that Kernel SVM is superior in mapping complex and non-linear decision boundaries between different activity classes.

The findings confirm that Kernel SVM is highly effective for activity recognition tasks involving complex and overlapping signal patterns, thanks to its non-linear Radial Basis Function (RBF) kernel which efficiently transforms input features into a higher dimensional space. While SVM led in performance, the Random Forest model proved to be robust, interpretable, and resistant to noise, and the KNN model remained valuable due to its simplicity and accuracy for lightweight, real-time applications. This study highlights the critical importance of integrating algorithmic accuracy with wearable technology to enhance automated activity monitoring systems.

From a scientific perspective, this research enhances the understanding of model behavior in sensor-based classification tasks by offering a clear empirical comparison under uniform conditions. The insights gained from this comparative framework serve as a foundation for developing hybrid or ensemble methodologies that could further improve recognition precision and computational efficiency. Future research could investigate advanced feature extraction methodologies, scaling or normalization techniques, and deep learning architectures, such as CNN or LSTM, to uncover temporal dependencies in sequential motion data. Furthermore, real-time implementation on embedded devices could increase the relevance of this research in health monitoring, fitness tracking, and smart environments. Ultimately, this study underscores the role of machine learning as a fundamental component in intelligent human activity recognition and its potential to promote a healthier, data-driven lifestyle through pervasive computing systems.

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