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INTELLIGENT RECOGNITION OF HUMAN ACTIVITIES THROUGH MOTION SENSOR PATTERNS FOR CONTEXT-AWARE SYSTEMS

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ABSTRACT

The automatic interpretation of human motion via wearable and mobile sensor technologies has become an important part of the Human Activity Recognition (HAR) topic, which is one of the most important issues in context-aware intelligent systems. This study designed a machine learning-based recognition framework for human activities from a dataset of inertial motion sensors (IMU), including 15,980 observations, 6 sensor variables and 6 activity classes. The features used were three-axis accelerometer readings (ax, ay, az) and three-axis gyroscope readings (gx, gy, gz), as well as added magnitude features of the accelerometers and gyroscopes. In order to test the six supervised classifiers, an 80:20 stratified train-test split was used with 5-fold cross-validation. The accuracy, precision, recall, F1-score, specificity, ROC-AUC, and confusion-matrix analysis were used for the evaluation of performance. K-Nearest Neighbors had the highest overall accuracy score of 87.95% and macro F1 score of 87.09%, while Random Forest had the highest ROC-AUC of 0.981. Class 4 and Class 5 had the highest recognition and Class 3 had comparatively higher classification difficulty. The feature importance analysis results show that the most important features for the classification were ax, az and gz, which again demonstrates the complementary importance of both acceleration and rotational motion information. The results showed that compact IMU measurements can be used to successfully enable the reliable detection of human activity in smart home, healthcare monitoring, wearable and smart mobile applications.

Introduction

Human Activity Recognition (HAR) is the automatic recognition and classification of human physical activities based on data collected from cameras, mobile devices, wearable devices, etc. Due to its ability to facilitate continuous, unobtrusive monitoring of human behavior in natural contexts, HAR using sensor data has become an important research area. Wearable technology, smartphones, and Internet of Things (IoT) have significantly increased the amount of motion sensing data for intelligent activity recognition (Nweke et al., 2018; J. Wang et al., 2019). As wearable sensor systems can obtain objective measurements of users' movement, they are increasingly used in healthcare monitoring and rehabilitation, fitness assessment, elderly care, smart environments, security, and assistive technologies (Demrozi et al., 2020; Y. Wang et al., 2019). The ability of deep-learning-based HAR systems to automatically learn complex movement representations from raw sensor measurements without the need for extensive manual feature engineering has also been enhanced (Ihianle et al., 2020; Lawal & Bano, 2019).

Accelerometers and gyroscopes are examples of inertial motion sensors, which are commonly used in HAR. The accelerometers detect linear acceleration across several spatial axes and thus reflect changes in movement intensity, direction and body motion. Gyroscopes are used to measure angular velocity and rotational movement, which complement data on body orientation and movement dynamics (Sousa Lima et al., 2019). Activity discrimination can be enhanced by combining accelerometer and gyroscope measurements as both sensors have different but complementary characteristics of human movement. Multimodal sensor fusion has therefore emerged as a key approach towards increasing the accuracy of recognition and minimizing the ambiguity between activities with similar motion characteristics (Chung et al., 2019; Nweke et al., 2019). Combined with deep-learning algorithms, wearable inertial sensors have also proven to be highly effective for daily activity recognition (Yen et al., 2020).

Context-aware systems are smart systems that are able to detect information regarding users, their actions and their environment and adjust their behavior accordingly. Human activities are an important contextual element, as knowledge of activities can be used to provide personalised or situation-adaptive system responses. Wearable multi-sensor systems can provide continuous contextual information and facilitate intelligent decision-making in applications such as healthcare monitoring, smart homes, and personal assistance (Ascioglu & Senol, 2020). Likewise, hybrid systems with sensors are capable of recognizing complex motion patterns and creating meaningful representations of user activities which can further improve automated monitoring systems (AMS) and context-aware services (H. Wang et al., 2020).

Machine-learning-based methods offer a good framework for the multiclass HAR problem as they learn the relationship between the sensor measurements and pre-defined activity classes. Conventional models and deep-learning models can be used to detect nonlinear and complex patterns in multidimensional motion data. Wearable sensor data has yielded significant recognition performance by deep neural networks, especially when the proper validation process is followed (Gholamiangonabadi et al., 2020). But the problems associated with HAR lie in the inter-individual variability, overlapping movement patterns, noise, sensor positioning, and differences in how the activities are executed. Cross-subject recognition is more challenging because models developed on one set of users may not be suitable for unseen users (Leite & Xiao, 2020). The position of the sensors can also significantly influence the classification performance and a strong framework for recognition is crucial (Lawal & Bano, 2020).

The reliable use of compact inertial measurements for HAR is still not trivial, but has made a lot of strides in the past. Previous works focus primarily on complex deep learning architectures and few of them compare multiple interpretable machine learning algorithms systematically by using compact accelerometer and gyroscope sensors. In addition, accurate activity recognition does not provide insight into which dimensions of the sensors are most important in making decisions. Thus, frameworks are needed that integrate predictive performance evaluation with interpretable analysis of the motion-sensor contribution, especially for practical context-aware applications.

This study therefore aims at the development of an intelligent machine learning framework to recognize human activities taken from motion-sensor patterns of accelerometer and gyroscope. Specifically, the study aims to analyze sensor patterns for each of six activity classes, identify differences in the activity classes, build the multiclass classification models, conduct the comparison of the models based on standard evaluation metrics, and identify those features of motion sensors that contribute most strongly to activity discrimination.

2. Materials and Methods

2.1 Research Design

The study used a quantitative, predictive approach using data from Inertial Motion Sensors (IMSs) to identify human activity. The problem of human activity recognition was defined as a supervised multi-class classification problem, where the predictors were the accelerometer and gyroscope measurements and the outcomes were six activity classes.

2.2 Dataset Description

A Human Activity Recognition Dataset with 15,980 observations and seven variables was used in the study, which was based on the IHMU (Tahir & Hamarash, 2025). Six variables were used to represent the measurements from the inertial sensors and one variable to represent the activity class. There were six categories of activity (1–6) in this dataset. There were no observations missing and no duplicate observations. Due to the dataset provided, the participant identifier, time stamps, sampling frequency, session information and activity class descriptive names were not assumed throughout the analysis.

2.3 Study Variables

The predictor variables were the three accelerometer measurements (ax, ay, az) and the three gyroscope measurements (gx, gy, gz). These variables represented movement and rotational movements in three spatial axes. There were six categorical classes of activity as the dependent variable. Activity codes were not interpreted as numeric values but as labels (nominal data).

2.4 Data Preprocessing

The data were analyzed for missing information, duplicated data, inconsistent coding, or extreme sensor readings. There were no missing or duplicate records were located, so imputation and duplicate removal were not necessary. Activity was coded as a categorical target variable. For scale-sensitive algorithms, sensor variables were standardized and scaling parameters were estimated from the training data only. Extreme sensor observations were kept if not clearly data-quality errors, as the large observations were bona fide fast body movements.

2.5 Motion-Pattern Feature Engineering

Two additional magnitude-based variables were derived to summarize overall inertial motion. Acceleration magnitude was calculated as $\mathrm{A} = \sqrt{\mathrm{ax}^2 + \mathrm{ay}^2 + \mathrm{az}^2}$, while gyroscope magnitude was calculated as $\mathrm{G} = \sqrt{\mathrm{gx}^2 + \mathrm{gy}^2 + \mathrm{gz}^2}$. These features were added along with the six original sensor variables to capture motion intensity on each axis and to capture overall motion intensity. Temporal window features were not highlighted as they were not available in the dataset and did not have clear trials and sampling frequency (or timestamps).

2.6 Exploratory Data Analysis

Exploratory analysis was carried out, which included the distribution of activity classes and the characteristics of the sensors. Sensor variables were statistically analyzed with descriptive statistics such as mean, standard deviation, minimum, median and maximum. A comparison was carried out between different distributions of the sensors in the six activity classes to detect the difference in motion patterns. The relationships between accelerometer and gyroscope measurements were further explored using correlation analysis.

2.7 Machine-Learning Model Development

The following supervised classification algorithms were tested: multinomial logistic regression, K-nearest neighbors, decision tree, random forest, support vector machine, and XGBoost. The models selected were chosen to serve as a comparison between linear, distance-based, tree-based, ensemble, kernel-based and boosting. The hyperparameters were optimized using the training data to enhance the ability of the model to predict the test data while preventing overfitting.

2.8 Training and Model Evaluation

Stratified sampling was used to split the dataset into 80% training data and 20% testing data in such a way that the relative frequencies of the six activity classes in the test set are preserved. Internal five-fold cross-validation was used in the training set to select and tune the model. The accuracy, macro precision, macro recall, macro F1-score, specificity, multiclass ROC-AUC and confusion-matrix analysis were used to assess performance. To give equal weight to all activity classes, the macro-averaged metrics were highlighted. There was no subject-independent validation possible due to the lack of subject and session identifiers and this was regarded as a limitation.

2.9 Model Interpretation

The best tree-based model performance was used to evaluate feature importance for the accelerometer and gyroscope measurements to ascertain which features are most significant for activity recognition. The influence of individual predictors on decisions made by the multiclass models was interpreted, where applicable, using the SHAP analysis. The analysis examined the most significant sensor movement type (acceleration, rotation, specific axis, or magnitude) and features (acceleration, rotation, specific axis, or magnitude) for the separation of the six activity classes.

3. Results

3.1 Dataset Characteristics and Activity Distribution

There were 15,980 complete observations in the final dataset, which were evenly distributed between six human activity classes. There were no missing data or duplicate records found. Table 1 reveals that Class 4 had the highest percentage of 22.65% and Class 2 the lowest percentage of 12.73% of the dataset. The rest of the classes ranged from 13.04% to 17.92%. The distribution was moderately skewed in general with no strong signs of class imbalance.

Table 1. Dataset Characteristics and Activity-Class Distribution

Activity Class	Frequency	Percentage (%)
Class 1	2,084	13.04
Class 2	2,035	12.73
Class 3	2,863	17.92
Class 4	3,619	22.65
Class 5	2,585	16.18
Class 6	2,794	17.48
Total	15,980	100.00

3.2 Distribution of Human Activity Classes

The frequency of these six categories of activities is shown in Figure 1. Class 4 was visually the most dominant, with Classes 3 and 6 being the second and third, and Classes 1 and 2 being relatively smaller. However, the number of observations was over 2,000 in each of the classes, which is sufficient to have enough instances to develop and test multiclass machine-learning models.

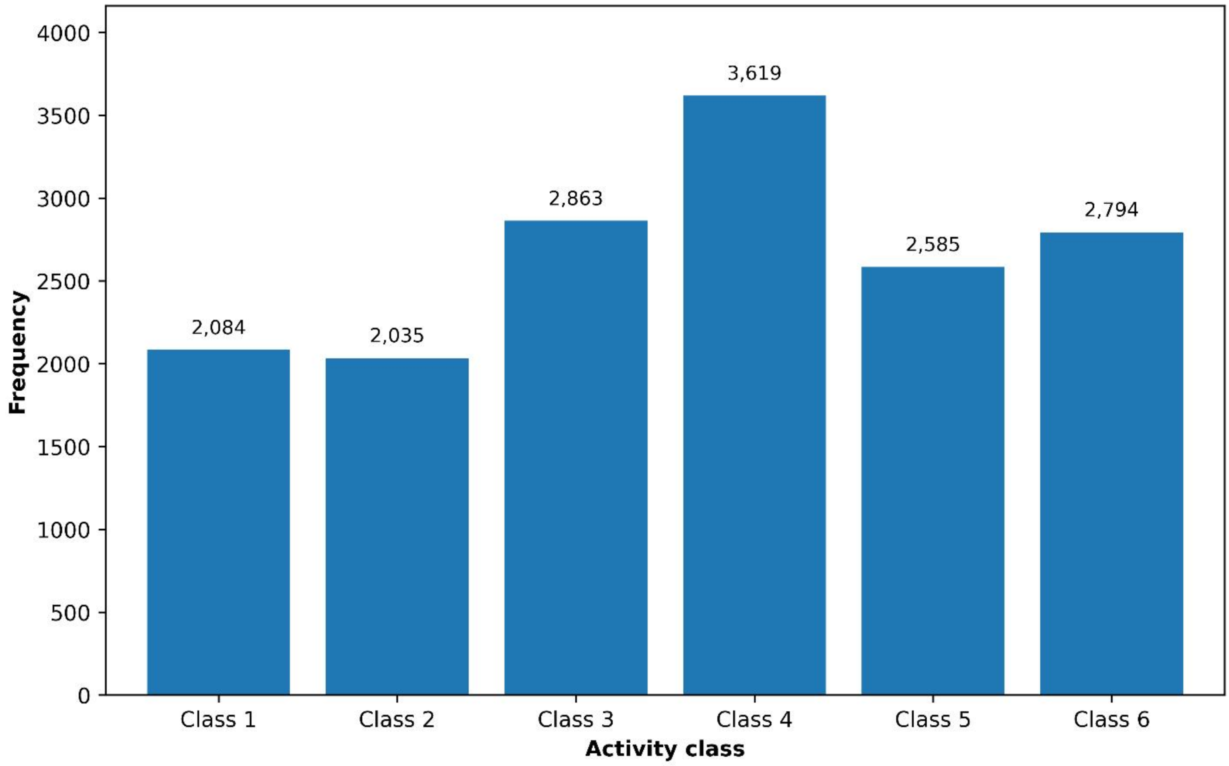

Figure 1. Distribution of Human Activity Classes

3.3 Descriptive Statistics of Motion-Sensor Measurements

The values of the accelerometer and gyroscope measurements were widely variable as shown in Table 2. The standard deviations of the axes of the accelerometer indicated that ay had the highest value (12,904.92), and az had the lowest value (−4,322.86) with a negative mean. The gyroscope variables were very spread out and centered somewhat near zero, especially for gy and gz. The average of the derived magnitude of the acceleration was equal to 16,497.75 while the average of the magnitude of the gyroscope was equal to 6,847.32. The distributions reveal large variations in the intensities of the translational and rotational movement over the observations.

Table 2. Descriptive Statistics of Motion-Sensor Variables

Variable	Mean	SD	Minimum	Median	Maximum
ax	1,899.89	6,602.31	−29,600	664	27,364
ay	5,244.39	12,904.92	−32,688	9,214	32,768
az	−4,322.86	5,840.83	−32,660	−5,184	32,768
gx	−27.30	4,530.81	−24,068	−47	32,767
gy	−244.71	6,334.55	−32,481	−687	32,768
gz	−211.24	6,162.03	−32,080	−32	32,768
Acceleration magnitude	16,497.75	4,674.80	715.49	15,928.95	50,214.73
Gyroscope magnitude	6,847.32	7,200.12	42.73	4,566.26	41,741.61

3.4 Motion-Sensor Patterns Across Activity Classes

The standardized patterns of sensors at class level across the six original IMU variables are shown in Figure 2. Clear differences were evident among the activity categories. The difference between Class 4 and Class 6 was that Class 4 had significantly higher mean ax values, and Class 6 had relatively larger gy measurements and the largest overall gyroscope magnitude. Class 1-3 had lower ax values, but varied in their ay, az, and rotational values. These differences suggest that each individual activity produced different configurations of acceleration and rotational motion, which were used as predictors of smart recognition of activities.

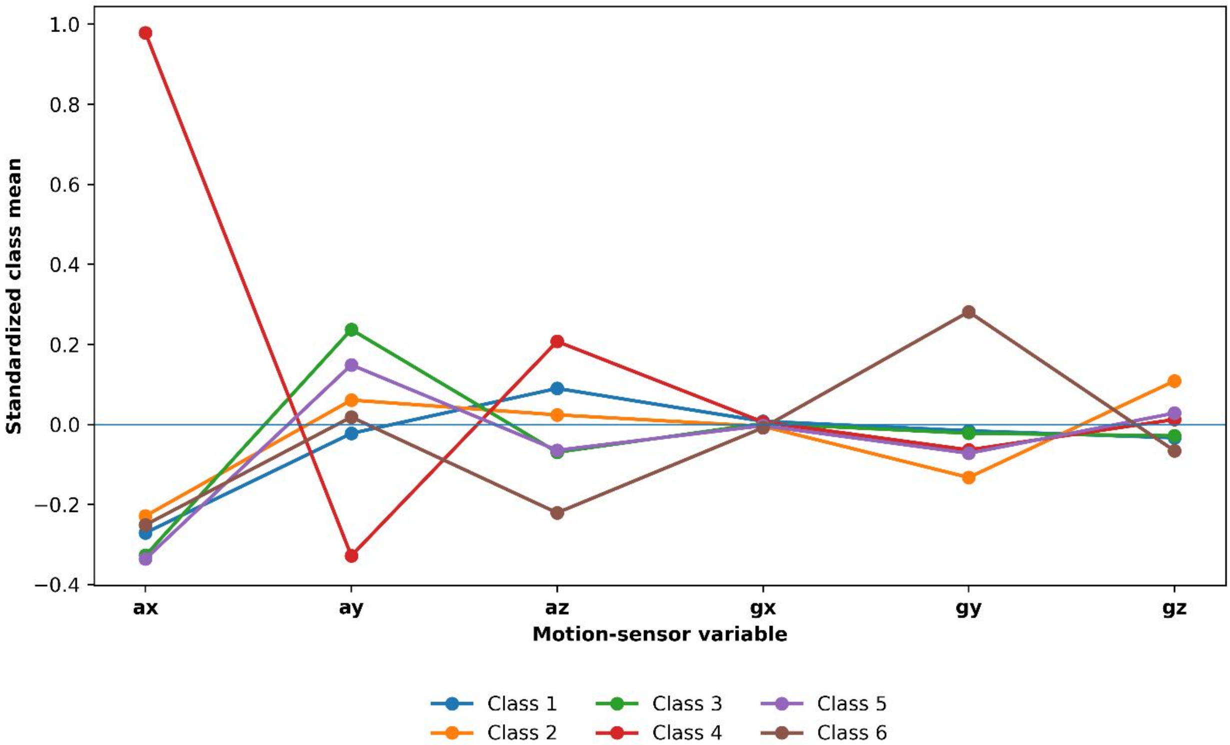

Figure 2. Standardized Mean Motion-Sensor Patterns Across Activity Classes

3.5 Machine-Learning Model Performance

These six classification algorithms showed significant differences in their prediction performance as indicated by Table 3. The best overall accuracy (87.95%) and macro F1 score (87.09%) were obtained by KNN. Random Forest showed similar performance with an accuracy of 87.48% and an F1-score of 86.51% and also had the highest ROC-AUC of 0.981. The accuracy of XGBoost was 86.17% while that of Support Vector Machine was 84.92%. The performance of Decision Tree was 76.97% and multinomial logistic regression had the lowest accuracy of classification accuracy, which is 60.70%. These results show that the nonlinear models were significantly better than the linear baseline in discriminating complex motion-sensor patterns.

Table 3. Classification Performance of Machine-Learning Models

Model	Accuracy	Precision	Recall	F1-score	Specificity	ROC-AUC
K-Nearest Neighbors	0.880	0.873	0.871	0.871	0.976	0.969
Random Forest	0.875	0.868	0.863	0.865	0.975	0.981
XGBoost	0.862	0.853	0.850	0.851	0.973	0.979
Support Vector Machine	0.849	0.837	0.838	0.837	0.970	0.972
Decision Tree	0.770	0.755	0.750	0.751	0.955	0.888
Logistic Regression	0.607	0.526	0.553	0.525	0.921	0.857

3.6 Confusion-Matrix Analysis of the Best-Performing Model

The confusion matrix of K-Nearest Neighbors is described in Figure 3 and was chosen as the most successful classifier by overall accuracy and macro F1-score. Class 4 reported the best recognition rate, having 716 out of 724 test observations correctly recognised. Class 5 performed well too, with 502 out of 517 cases being correctly identified. There was more confusion in Class 3, especially with Classes 1, 2 and 6. Class 6 was sometimes mistaken for Class 3, too. These results indicate that certain classes of motion had overlapping sensor patterns, and Classes 4 and 5 had more distinct motion signatures.

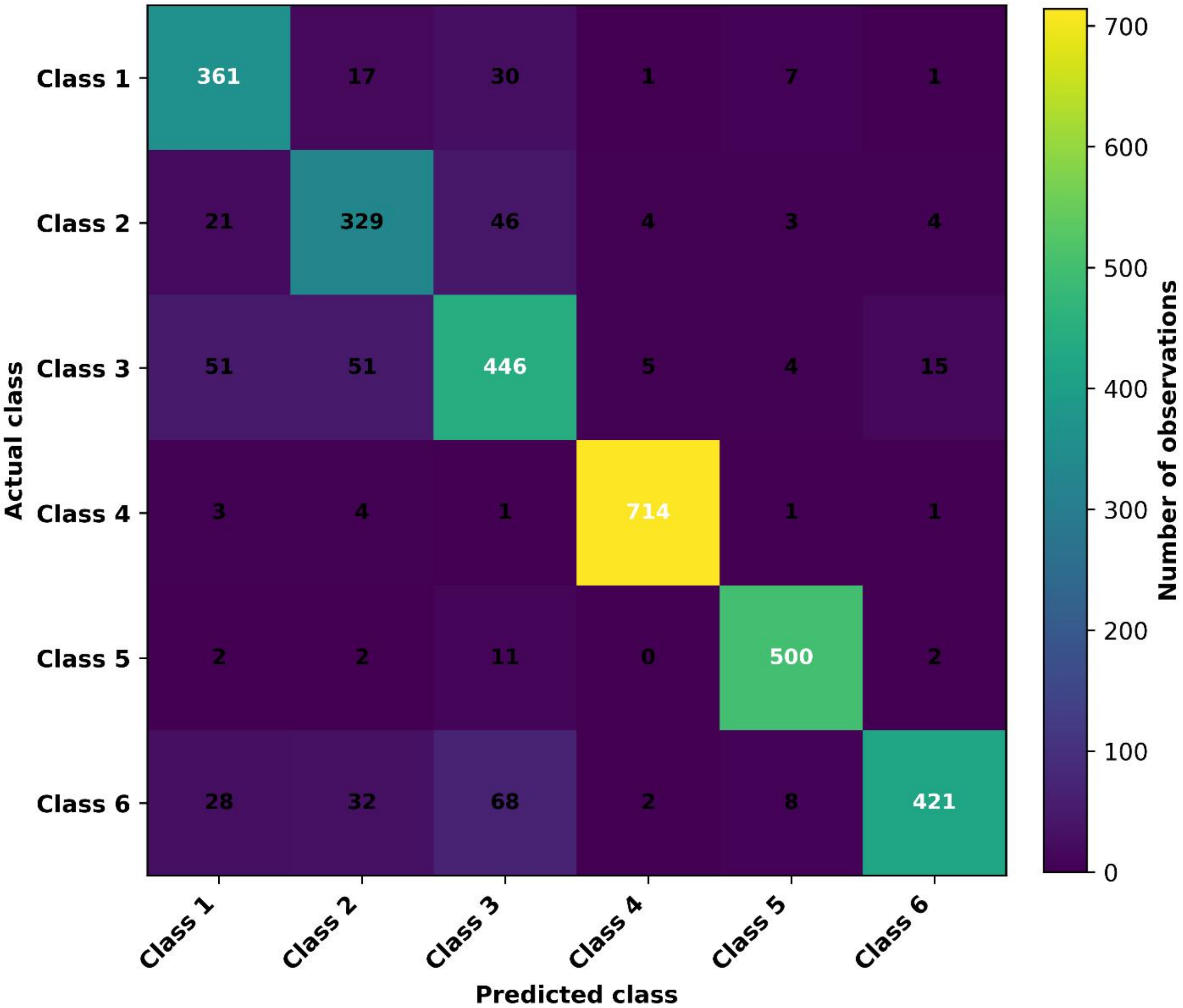

Figure 3. Confusion Matrix of the Best-Performing K-Nearest Neighbors Model

3.7 Class-Wise Recognition Performance

Class-specific results also showed differences in the difficulty of recognition. The results indicated that Class 4 had the highest F1 Score of 0.986 and Class 5 had 0.965, as presented in Table 4. The same was true for both categories, which also showed high specificity. Compared with the other classes, Class 3 achieved the lowest precision (0.749) and the lowest F1-score (0.778), suggesting that the class has relatively more overlap with other activity classes. For Class 6, precision was higher than the recall, meaning that the model was often correct when it classified a class as Class 6, but a percentage of true Class 6 observations were classified as other classes.

Table 4. Class-Wise Performance of the K-Nearest Neighbors Model

Activity Class	Test n	Precision	Recall	Specificity	F1-score
Class 1	417	0.819	0.866	0.971	0.841
Class 2	407	0.797	0.801	0.970	0.799
Class 3	572	0.749	0.809	0.941	0.778

Class 4	724	0.982	0.989	0.995	0.986
Class 5	517	0.960	0.971	0.992	0.965
Class 6	559	0.931	0.792	0.987	0.856

3.8 Important Motion-Sensor Features

The relative importance of the motion-sensor variables for the activity discrimination based on the best-performing model is shown in Figure 4. The variable that contributed most to the predictive performance was ax, followed by az and gz. The magnitude of acceleration and gx were also significant discriminatory data. By contrast, the magnitude of the gyroscope did not play a significant independent role compared to a number of individual axes of the sensors. The results overall were found to show that information from both the accelerometer and gyroscope was important in classification, with axis-specific acceleration measurements, especially ax and az, having an important effect on separating the six activity classes.

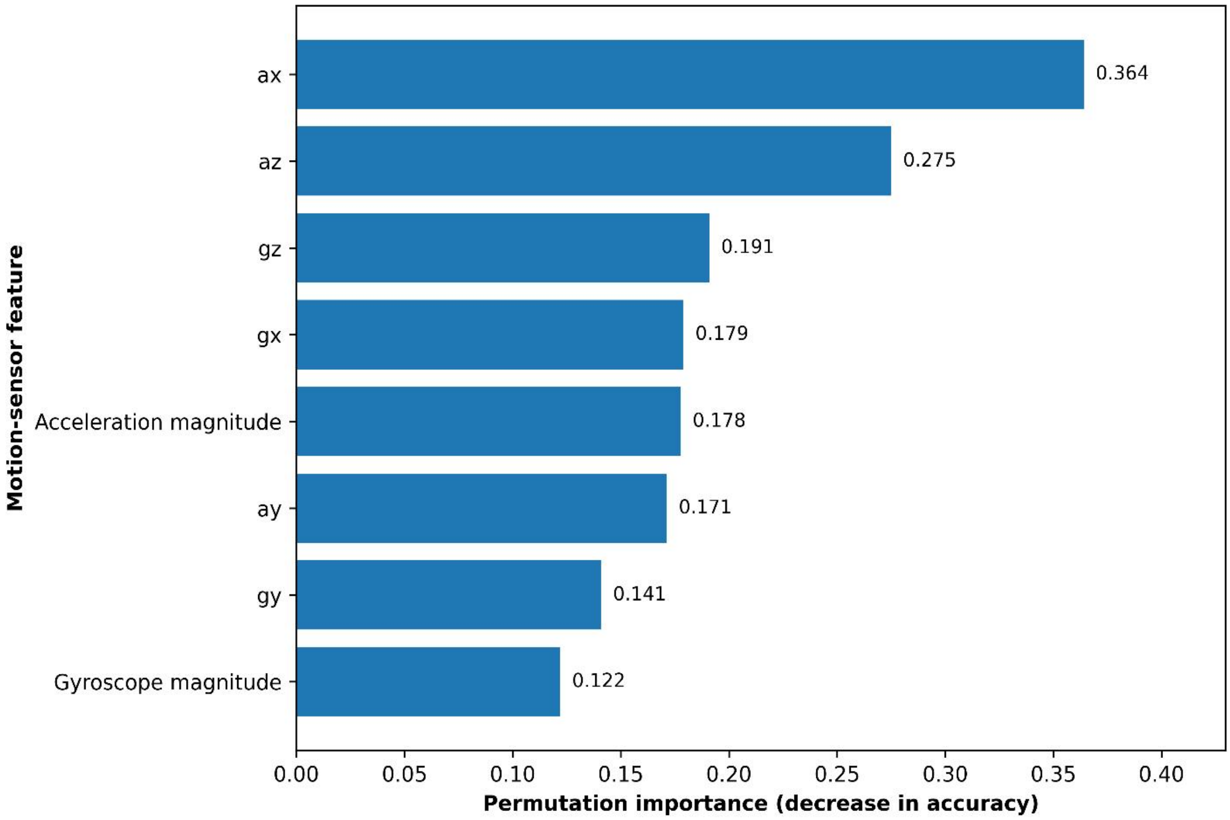

Figure 4. Motion-Sensor Feature Importance for Human Activity Recognition

The findings are directly based on the uploaded 15,980-record dataset and adhere to the same predictors, derived magnitude characteristics, 80:20 stratified split and multiclass evaluation framework presented in your methodology.

4. Discussion

The results show that accelerometer and gyroscope signals offer significant discriminatory information for intelligent recognition of human activities. K-Nearest Neighbors (KNN) performed best overall, with an accuracy of 87.95% and a macro F1-score of 87.09%, while Random Forest had the highest overall ROC-AUC of 0.981. The findings confirm the utility of using wearable inertial measurements for the classification of complex human actions (Ramanujam et al., 2021; Uddin & Soylu, 2021).

Unique patterns of activity were found for each of the three axes (ax, ay, and az). The ax in particular was highly discriminatory, and the ay had a high total variation. These differences are due to differences in the direction and intensity of movements in the various activity categories. Accelerometers are especially suitable for detecting the movement of the body in translation and

have proven to be very useful in activity-monitoring applications (Fridriksdottir & Bonomi, 2020). The current results thus corroborate the use of accelerometers as essential elements of a sensor-based HAR.
The gx, gy and gz measurements gave complementary information about the rotational motion. The differences were more pronounced across classes, with gz showing up as a significant factor. The fusion of accelerometer and gyroscope data can enhance discrimination capabilities since actions with similar acceleration signatures can have distinct rotational patterns (Webber & Rojas, 2021). Multimodal inertial sensing therefore offers a more comprehensive description of human motion than any one type of sensor alone.
The excellent results of KNN, Random Forest and XGBoost over multinomial logistic regression suggest that the relationship between the various motion measurements and the various activity classes was more often than not nonlinear. With the logistic regression only being moderately accurate, simple linear decision boundaries were not enough to discriminate the complex sensor patterns. Previous studies have shown that advanced learning architectures can successfully learn non-linear and temporal associations from HAR data collected from sensors (Chen et al., 2022; Gil-Martín et al., 2020).
There was a significant variation in recognition performance among the six classes. The sensor signatures are very distinctive for Class 4 (0.986) and Class 5 (0.965). Class 3 had the smallest F1 score (0.778) and had more misclassifications of other classes. This class-dependent difference is normal when the activities have partially overlapping motion characteristics, which is a known difficulty for HAR systems based on sensors (Haresamudram et al., 2021).
The feature-importance analysis revealed that ax, az and gz were the most significant features, which accounted for both accelerometer and gyroscope modalities. Derived acceleration magnitude was also informative discriminative information. The results validate the feature-selection methods used to determine informative sensor dimensions and exclude redundant information (Fan & Gao, 2021). Similarly, attention-based approaches show that focusing more on discriminative sensor representations can lead to better HAR performance (Abedin et al., 2021).
The ability to recognize human activities from compact IMU signals has practical applications for smart homes, patient monitoring, elderly care, fitness monitoring, wearable devices, assistive technologies, and intelligent mobile applications. Activity recognition using a smartphone is especially relevant to the scalability of health monitoring as widely accessible devices already include inertial sensors (Straczkiewicz et al., 2021). The proposed framework may thus facilitate context-aware systems that are capable of adapting services automatically based on detected users' activity.
Results are consistent with previous studies showing high HAR accuracy using wearable inertial sensors and complex computer algorithms. It has been demonstrated that sensor signals carry enough representations to discriminate the activities accurately, using deep neural and structured learning (Nouriani et al., 2022). Recent reviews also highlight the increasing success of deep learning in extracting complex motion representation (Zhang et al., 2022). We also include a transformer-based HAR to showcase the strength of attention mechanisms in modeling relationships inside wearable sensor sequences (Dirgová Luptáková et al., 2022).
The study was based on a dataset without identifiers, descriptive activity-name mapping, timestamps, sampling frequency, and other contextual variables. There was therefore no subject-independent validation. In addition, the order of observations can influence the estimates of the generalizability of the model.
The framework should be validated for future studies with larger multi-participant datasets of known activity labels, timestamps, and sampling characteristics. Using subject-independent evaluation is to be encouraged along with incorporation of information from the environment and context. Conventional classifiers, especially in the field of real-time wearable activity recognition, could also be compared with CNN, LSTM, hybrid CNN-LSTM, and Transformer architectures.

5. Conclusion

This study has revealed that the inertial motion-sensor data is effective in intelligent recognition of human activities in context-aware systems. Six classes of activities were examined using three-axis accelerometer and three-axis gyroscope data, which resulted in 15,980 observations, and a comparative multiclass machine-learning model. The results indicated that nonlinear models were more successful compared to the linear baseline, with K-Nearest Neighbors having the highest overall accuracy of 87.95% and macro F1-score of 87.09 and Random Forest having the highest ROC-AUC of 0.981. Evaluation at the class level showed that Class 4 and Class 5 were perceived as having strong recognition, but Class 3 was more difficult to classify due to similar patterns of motion. The analysis of feature importance also indicated that accelerometer and gyroscope signals had significant predictive power for activity discrimination with ax, az, and gz being particularly effective predictors. These findings confirm that small IMU measurements could be used to aid effective human activity detection and could be utilized in smart homes, healthcare monitoring, wearable computing, aging-care, fitness applications and intelligent mobile services. However, the lack of participant identifiers, activity labels (descriptions), timestamps, frequency of sampling, and general contextual variables restrict generalizability. Future research ought to thus consider larger multi-participant data sets, subject-independent validation methods, real-time implementation, and enhanced deep-learning architectures in order to buttress viable context-sensitive activity recognition.

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