Human Activity Recognition and Prediction using Grid Search

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Abstract— Human Activity Recognition (HAR) is a rapidly growing field with applications in healthcare, fitness tracking, security, and smart environments. The ability to accurately classify human activities using machine learning models has the potential to improve elderly monitoring, patient rehabilitation, and sports performance analysis. This study investigates multiple machine learning classifiers for HAR using a dataset composed of motion sensor data from wearable devices. The selected models include Logistic Regression, Linear SVC, RBF SVM, Decision Tree, and Random Forest.

1. Introduction

Human Activity Recognition (HAR) is an essential field in machine learning that focuses on classifying various human activities, such as walking, running, sitting, standing, and jumping, based on sensor data. HAR has gained widespread attention due to its diverse applications in healthcare, fitness tracking, security, and smart home environments. For instance, in healthcare, HAR can be used to monitor elderly individuals, detect falls, and assist in rehabilitation. In fitness applications, it helps track physical activity, optimize workout routines, and enhance performance analysis.[1] Moreover, in security and surveillance, HAR aids in detecting suspicious activities and improving safety measures.

Traditional HAR methods relied on manual feature engineering and rule-based approaches, which required domain expertise and were often limited in their ability to handle complex activities. However, machine learning algorithms have significantly improved the accuracy and efficiency of activity recognition by automatically learning patterns from large datasets. Despite these advancements, choosing the best model and optimizing its performance remains a challenge. Different machine learning models perform variably depending on the dataset, and their accuracy can be affected by hyperparameters, feature selection, and model complexity.

In this study, we investigate multiple machine learning models for HAR and apply Grid Search optimization to fine-tune their hyperparameters for improved performance. The selected models include Logistic Regression, Linear SVC, RBF SVM, Decision Tree, and Random Forest. These models are evaluated based on accuracy and error rates to determine the most effective classifier for HAR. Our research aims to provide insights into the performance of different models and highlight the importance of hyperparameter tuning in optimizing HAR systems. By fine-tuning parameters, we seek to enhance model performance, making HAR more reliable, scalable, and applicable to real-world scenarios.

This study contributes to the ongoing research in HAR by systematically comparing traditional machine learning models and optimizing their hyperparameters. The findings will help guide future research and applications in HAR, paving the way for more efficient and accurate activity recognition systems.

2. Literature Review

- **Zeng et al. (2014) – Support Vector Machines for HAR**

This study investigated Support Vector Machines (SVM) for HAR and demonstrated that SVM performs well with high-dimensional sensor data. The authors highlighted that the choice of kernel function (linear, polynomial, or RBF) significantly impacts classification accuracy. The study concluded that RBF SVM is effective for HAR, providing high accuracy while handling non-linear activity patterns.

- **Anguita et al. (2013) – Decision Trees and Random Forests in HAR**

Explored the use of Decision Trees (DT) and Random Forests (RF) for HAR. Found that Decision Trees often suffer from overfitting, especially when trained on small datasets. Random Forest performed better due to ensemble learning, but hyperparameter tuning was essential for improving performance.

- **Ordóñez & Roggen (2016) – Deep Learning for HAR**

This study introduced Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for HAR. Demonstrated that deep learning outperforms traditional methods but requires large datasets and high computational power. Highlighted that CNNs are effective for spatial feature extraction, while RNNs (LSTMs) are better for temporal sequences in sensor data.

- **Yang et al. (2015) – Feature Learning with CNNs for HAR**

Proposed an automatic feature extraction method using deep CNNs. Showed that CNNs can learn spatiotemporal features directly from raw sensor data, eliminating the need for manual feature engineering. Reported higher accuracy than SVM and Random Forest but noted that CNNs require more training time.

- **Ravi et al. (2016) – Comparing Machine Learning Models for HAR**

Compared several machine learning models, including Naïve Bayes, K-Nearest Neighbors (KNN), Decision Trees, and SVMs. Found that SVM achieved the highest accuracy, followed by Random Forest and KNN. Concluded that feature engineering and hyperparameter tuning are critical for improving classification performance.

- **Chen et al. (2020) – Time-Series Analysis for HAR**

Investigated time-series feature extraction methods, including wavelet transforms and Fourier analysis. Found that frequency-domain features improve model performance, especially for complex activities like cycling and jumping. Demonstrated that combining time-domain and frequency-domain features leads to higher classification accuracy.

3. Methodology

The methodology for this study follows a systematic approach to Human Activity Recognition (HAR) using machine learning. It consists of five key stages: data collection, data preparation, model selection, model training & hyperparameter optimization, and evaluation & prediction. Each step is carefully designed to ensure the development of a robust and efficient HAR system.

3.1 Data Collection

The first step in HAR is acquiring a dataset containing sensor-based activity recognition data. Typically, HAR datasets are collected from wearable sensors (e.g., accelerometers, gyroscopes) or smart devices (e.g., smartphones, smartwatches). These sensors record motion-related data such as:

- Acceleration (X, Y, Z axes) – Measures movement speed and changes.
- Angular Velocity (Gyroscope) – Captures rotational motion.
- Magnetometer Data – Helps in orientation tracking.

For this study, a publicly available HAR dataset is used. The dataset consists of labeled activities such as walking, running, sitting, standing, and jumping. Each instance in the dataset corresponds to a time-series segment of sensor readings associated with a specific human activity.[3]

3.2 Data Preparation

Once the data is collected, it undergoes several preprocessing steps to ensure data quality and consistency. Preprocessing involves:

1. Data Cleaning
    - Handling missing values (e.g., replacing with mean values or removing incomplete records).
    - Removing duplicate entries to avoid bias.
2. Feature Extraction & Selection
    - Selecting relevant features such as mean, standard deviation, and frequency domain components from the raw sensor data.
    - Extracting time-domain and frequency-domain features to improve classification performance.
3. Normalization & Scaling
    - Normalizing the data using Min-Max Scaling or Standardization to bring all sensor values into a common range.
    - This helps models converge faster and improves accuracy.
4. Data Splitting
    - The dataset is split into training (80%) and testing (20%) sets to evaluate model performance.

3.3 Model Selection

The next step involves selecting appropriate machine learning classifiers for activity recognition. The following models are implemented and compared:

- Logistic Regression – A linear model suitable for binary and multi-class classification problems.[7]
- Linear SVC (Support Vector Classifier) – A linear version of SVM that efficiently separates activity classes.[2]

- RBF SVM (Radial Basis Function Support Vector Machine) – A non-linear SVM classifier that maps data to a higher-dimensional space for better separability.
- Decision Tree – A tree-based model that classifies activities based on hierarchical decision rules.
- Random Forest – An ensemble learning method that uses multiple Decision Trees for improved accuracy and generalization.[4]

These models were chosen based on their proven effectiveness in previous HAR studies.

3.4 Model Training & Hyperparameter Optimization

Once the models are selected, they undergo training using the training dataset. However, default hyperparameters may not provide the best performance. Therefore, Grid Search optimization is used to fine-tune hyperparameters for each model.

Grid Search for Hyperparameter Tuning

Grid Search systematically tests different combinations of hyperparameters to find the optimal settings. The key hyperparameters optimized include:

- C (Regularization Parameter) – Controls the trade-off between bias and variance in models like SVM and Logistic Regression.
- Gamma (γ) in RBF SVM – Defines how much influence a training example has on the decision boundary.
- Max Depth & Number of Trees in Random Forest – Affects model complexity and accuracy.

By performing cross-validation, the best hyperparameter values are selected to maximize accuracy while preventing overfitting.

3.5 Evaluation & Prediction

After training and tuning, models are tested on the 20% test dataset to assess their performance. The evaluation metrics include:

1. Accuracy (%)

- Measures the percentage of correctly classified activities.

2.Error Rate (%)

- Represents the percentage of misclassified activities.
- Formula:
- Error Rate=100−Accuracy

3.Confusion Matrix

- Provides insight into misclassification patterns by showing true positives, false positives, false negatives, and true negatives.
- Precision, Recall, and F1-Score
- Additional metrics to evaluate model reliability for each activity class.

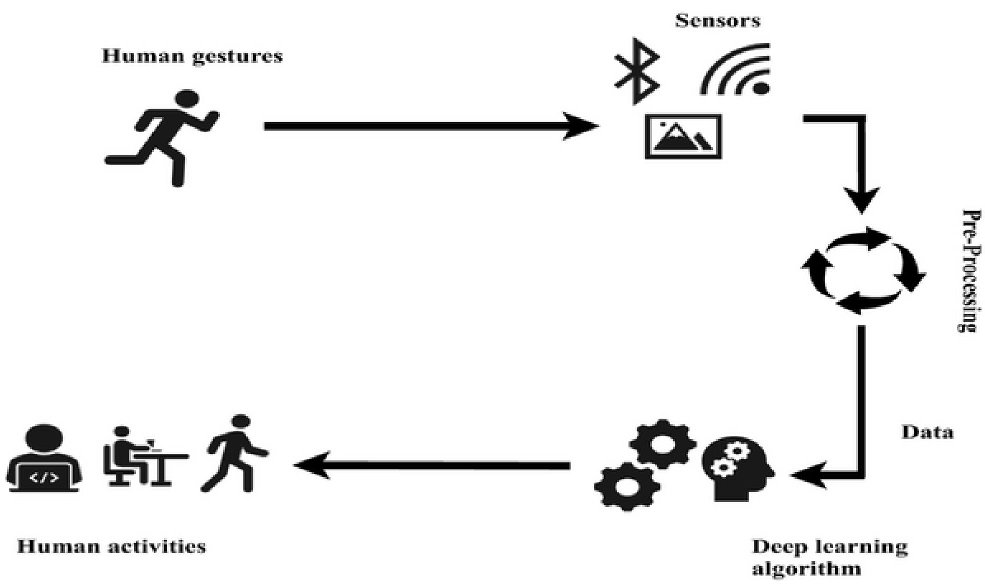

fig1. Flow Diagram

4. Prediction and Evaluation

The performance of models was evaluated using accuracy and error rates:

Model	Accuracy	Error Rate
Logistic Regression	95.86%	4.14%
Linear SVC	96.64%	3.36%
RBF SVM	96.27%	3.73%
Decision Tree	85.54%	14.46%
Random Forest	92.09%	7.91%

Key Findings & Model Comparisons

1. Best Performing Model: Linear SVC (96.64% Accuracy, 3.36% Error Rate)

- Linear SVC achieved the highest accuracy, making it the most effective model for Human Activity Recognition.
- This suggests that human activity data is linearly separable to a large extent, allowing SVC to perform well.

The low error rate (3.36%) indicates a strong ability to classify activities correctly with minimal misclassification.[2]

2. Strong Performers: RBF SVM and Logistic Regression (Above 95% Accuracy)

- RBF SVM (96.27% accuracy, 3.73% error rate):
  - Performed slightly worse than Linear SVC but still achieved high accuracy.
  - The Radial Basis Function (RBF) kernel allowed the model to capture complex activity patterns by mapping data to a higher-dimensional space.
  - Slightly lower performance compared to Linear SVC suggests that non-linearity was not a significant factor in this dataset.
- Logistic Regression (95.86% accuracy, 4.14% error rate):
  - Performed well despite being a simpler model.
  - This indicates that HAR data has a linear relationship to some extent, making Logistic Regression effective.[7]

3. Moderate Performer: Random Forest (92.09% Accuracy, 7.91% Error Rate)

- Random Forest performed moderately well but was outperformed by SVM-based models.[7]
- Strength: It benefits from ensemble learning, reducing overfitting.
- Weakness: Slightly lower accuracy, likely due to overfitting on training data and difficulty generalizing to unseen samples.

4. Weakest Performer: Decision Tree (85.54% Accuracy, 14.46% Error Rate)

- Decision Tree was the least effective model, with the lowest accuracy (85.54%) and highest error rate (14.46%).
- Reason:
  - Decision Trees tend to overfit the training data, leading to poor generalization on the test set.
  - Unlike ensemble models (e.g., Random Forest), a single Decision Tree lacks robustness in handling noise and variability in HAR data.
- Implication: Decision Trees alone are not suitable for HAR, but combining multiple trees (Random Forest) can improve performance.[5]

```
****************| Classifiction Report |****************
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.98      0.87      0.92       491
          STANDING       0.90      0.98      0.94       532
           WALKING       0.96      1.00      0.98       496
WALKING_DOWNSTAIRS       1.00      0.98      0.99       420
  WALKING_UPSTAIRS       0.98      0.96      0.97       471

          accuracy                           0.97      2947
         macro avg       0.97      0.97      0.97      2947
      weighted avg       0.97      0.97      0.97      2947



==> Best Estimator:
        LinearSVC(C=0.5, tol=5e-05)


==> Best parameters:
        Parameters of best estimator : {'C': 0.5}

==> No. of CrossValidation sets:
        Total numbre of cross validation sets: 5

==> Best Score:
        Average Cross Validate scores of best estimator : 0.9417922927158628
```

fig2. Best Predicted Result

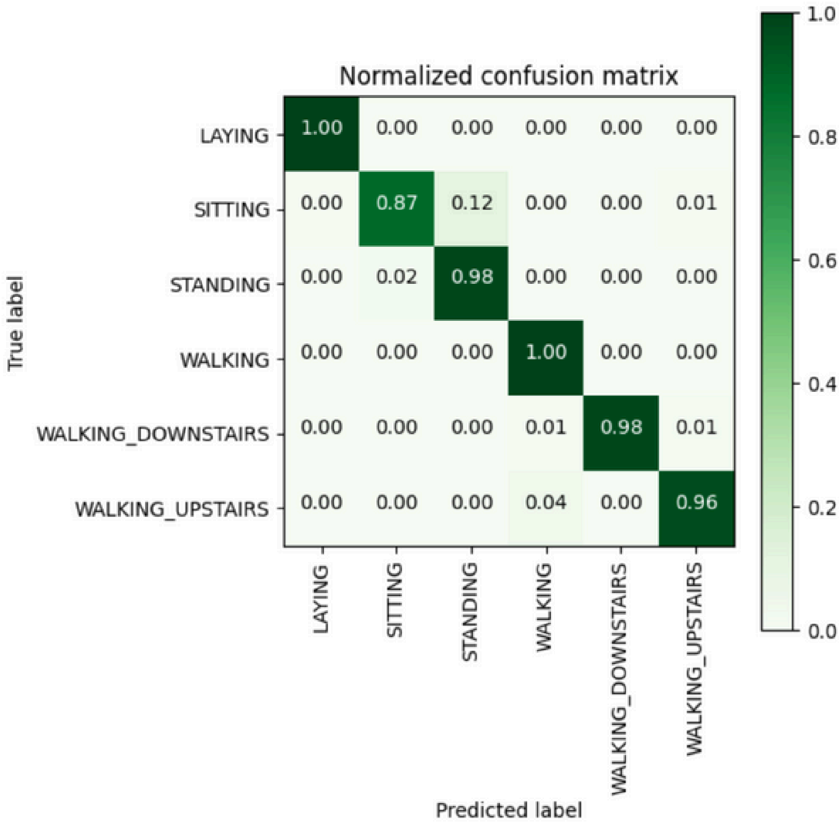

fig3. Confusion Matrix

```
                        Accuracy     Error
                        ----------   --------
Logistic Regression   : 95.86%        4.14%
Linear SVC            : 96.64%        3.359%
rbf SVM classifier    : 96.27%       3.733%
DecisionTree          : 85.54%       14.46%
Random Forest         : 92.09%       7.906%
```

fig4. Predicted Results

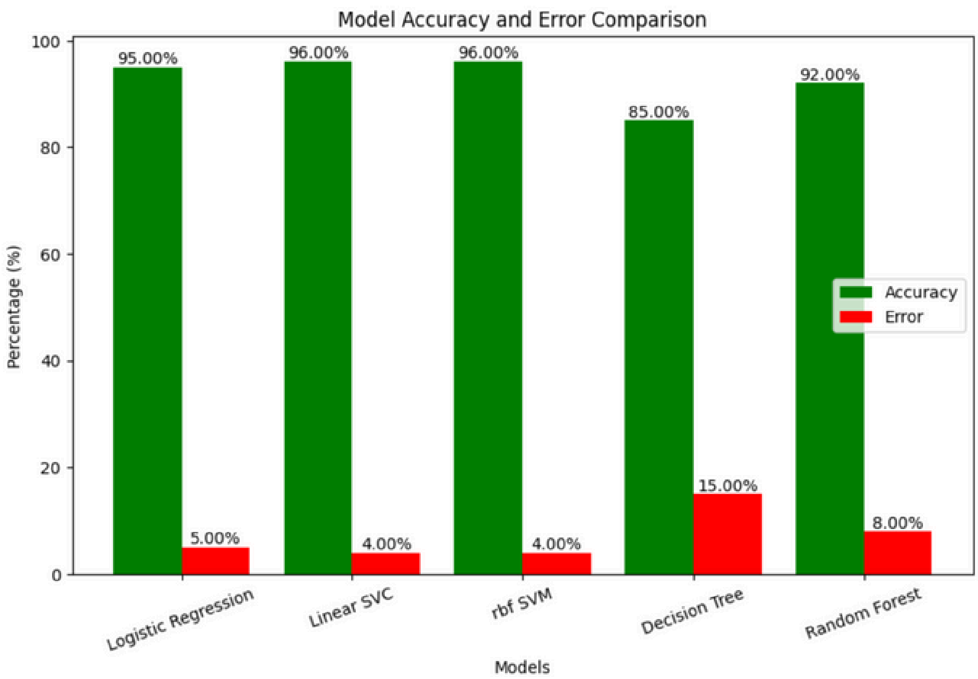

fig5. Grouped Bar Chart

5. Conclusion and Future Work

This study examined the effectiveness of machine learning models for Human Activity Recognition (HAR) using motion sensor data. The models were optimized using Grid Search to fine-tune hyperparameters and enhance classification performance.

The results highlight the importance of hyperparameter tuning and feature selection in improving HAR model performance. The study provides valuable insights into optimizing machine learning models for sensor-based activity recognition, which has applications in healthcare, sports analytics, and smart environments.

Future Work

1. Exploring Deep Learning Models (CNNs & LSTMs) for Improved Performance
2. Enhancing Feature Selection Using Principal Component Analysis (PCA)
3. Implementing Real-Time HAR Applications for Smart Healthcare Systems.

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