Comparative Analysis of Machine Learning Approaches for Human Activity Recognition

Machine Learning I - Final Project Report

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Abstract

This report presents a comparative study of four different machine learning pipelines for Human Activity Recognition (HAR) using the UCI Smartphone dataset. We investigate the effectiveness of dimensionality reduction techniques, including Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), against traditional baseline models. Our experimental results demonstrate that the PCA-based Ensemble approach achieves a test accuracy of 93.32%, offering an optimal balance between computational efficiency and performance.

Keywords

Human Activity Recognition, PCA, Ensemble Learning, LDA, Machine Learning

1 Introduction

2 Methodology

In this study, each team member explored a different pipeline to solve the classification problem.

2.1 Approach 1: [Racim's Method]

2.2 Approach 2: PCA & Ensemble Learning

In this approach, we investigated the trade-off between dimensionality reduction and classification accuracy. The primary objective was to design a computationally efficient pipeline suitable for embedded devices by compressing the feature space while maintaining high predictive performance.

2.2.1 Data Preprocessing and PCA. Principal Component Analysis (PCA) is inherently sensitive to the scale of input features. Since the UCI HAR dataset contains features with varying ranges, we first applied Z-Score normalization to standardize all 561 features to zero mean and unit variance:

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

Following normalization, PCA was applied with a cumulative variance threshold of **95%**. This process reduced the original 561 dimensions to **102 principal components**, achieving an **81.8% compression rate**. This significant reduction drastically lowers the computational cost for subsequent training steps.

2.2.2 Model Optimization. We trained four distinct classifiers on the reduced feature space using 10-Fold Stratified Cross-Validation (CV) to ensure robustness. The hyperparameter tuning yielded the following optimal configurations:

- **Artificial Neural Network (ANN):** A multi-layer perceptron with two hidden layers ([200, 100] neurons) achieved the highest individual CV accuracy (97.31%).
- **Support Vector Machine (SVM):** Optimized with a *Linear Kernel* and $C = 1.0$, demonstrating that the PCA-transformed space is linearly separable (CV: 97.23%).
- **k-Nearest Neighbors (kNN):** The best performance was observed at $k = 1$ (CV: 96.54%), though this suggests potential susceptibility to noise (overfitting).
- **Decision Tree (DT):** Achieved only 84.47% CV accuracy. The poor performance is attributed to PCA's feature rotation, which disrupts the axis-aligned splits required by decision trees.

2.2.3 Ensemble Strategy. To mitigate individual model biases—specifically the overfitting of kNN and the decision boundaries of SVM—we constructed a **Voting Ensemble** comprising the top three models (ANN, SVM, and kNN). The ensemble aggregates predictions using majority voting to improve generalization on unseen subjects.

2.2.4 Performance Analysis. The models were evaluated on the strictly separated Test Set. To visualize the comparative performance, we computed accuracy metrics across all models, as illustrated in Figure 1. The quantitative results are detailed in Table 1, which compares the cross-validation (CV) and testing phases.

While the individual kNN model suffered a significant drop in testing (indicating overfitting due to $k = 1$), the **Ensemble model** successfully compensated for this, achieving the highest overall accuracy of **93.32%**.

To analyze the specific error patterns, we examined the Confusion Matrix shown in Figure 2. The matrix reveals that the model is highly robust, yet slight confusions exist between static activities.

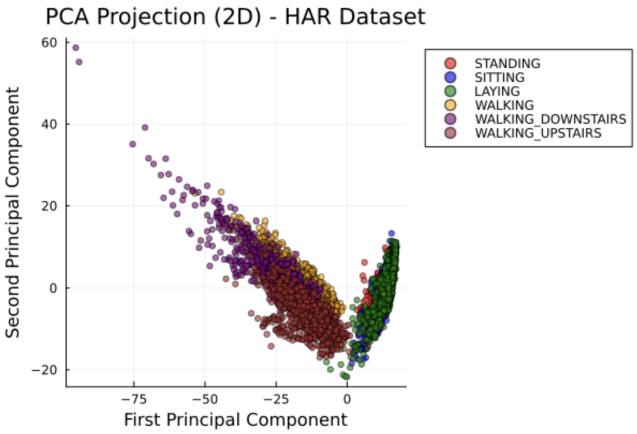

Figure 1: Test Accuracy Comparison. The Ensemble model outperforms individual classifiers.

Table 1: Performance Comparison (PCA Approach)

Model	CV Accuracy	Test Accuracy	F1-Score
Ensemble	-	**93.32%**	**0.9329**
ANN	97.31%	93.04%	0.9302
SVM	97.23%	92.20%	0.9216
kNN ($k = 1$)	96.54%	84.39%	0.8437
Decision Tree	84.47%	78.38%	0.7836

To further validate this, Table 2 presents the detailed precision and recall values for each class.

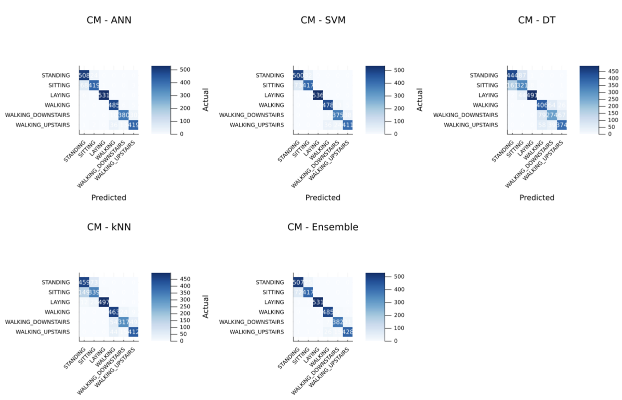

Figure 2: Confusion Matrix of the Ensemble Model. Note the slight confusion between Sitting and Standing.

2.2.5 Limitations and Future Work. As confirmed by the confusion matrix, misclassifications primarily occurred between *Sitting* and *Standing*. Since PCA transforms the feature space, the explicit vertical orientation signal (gravity-z) may have been diluted. Future improvements include:

Table 2: Per-Class Performance of the Best Model (Ensemble)

Activity	Precision	Recall	F1-Score	Support
Standing	0.8696	0.9530	0.9094	532
Sitting	0.9350	0.8493	0.8901	491
Laying	0.9981	0.9888	0.9935	537
Walking	0.9363	0.9778	0.9566	496
Walk Down	0.9409	0.9095	0.9249	420
Walk Up	0.9264	0.9087	0.9175	471
Weighted Avg			**93.32%**	**2947**

(1) **Explicit Gravity Injection:** Concatenating the raw ‘tGravityAcc-mean()-Z‘ feature with PCA components to restore orientation data.
(2) **k-Value Optimization:** Increasing k (e.g., to 7) in kNN to improve generalization on unseen subjects.

2.3 Approach 3: [Erik's Method]

2.4 Approach 4: [Roi's Method]

3 Experimental Results

4 Conclusion

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