Report on Human Activity Recognition using Smartphones

Introduction

Human Activity Recognition (HAR) using smartphones is a prominent research problem with applications in healthcare, fitness, and smart systems. The objective is to classify activities such as walking, standing, and sitting using accelerometer and gyroscope data collected from smartphones. This report analyzes the HAR dataset, evaluates models, and visualizes the most relevant features to provide meaningful insights.

Data Set Description

The dataset used in this analysis is the UCI Human Activity Recognition (HAR) Dataset. It includes sensor data recorded from 30 participants performing six different activities:

- Walking
- Walking Upstairs
- Walking Downstairs
- Sitting
- Standing
- Laying

Each participant's data is divided into a training set (7,352 samples) and a test set (2,947 samples). The dataset consists of 561 features derived from time-domain and frequency-domain signals.

Model Structures

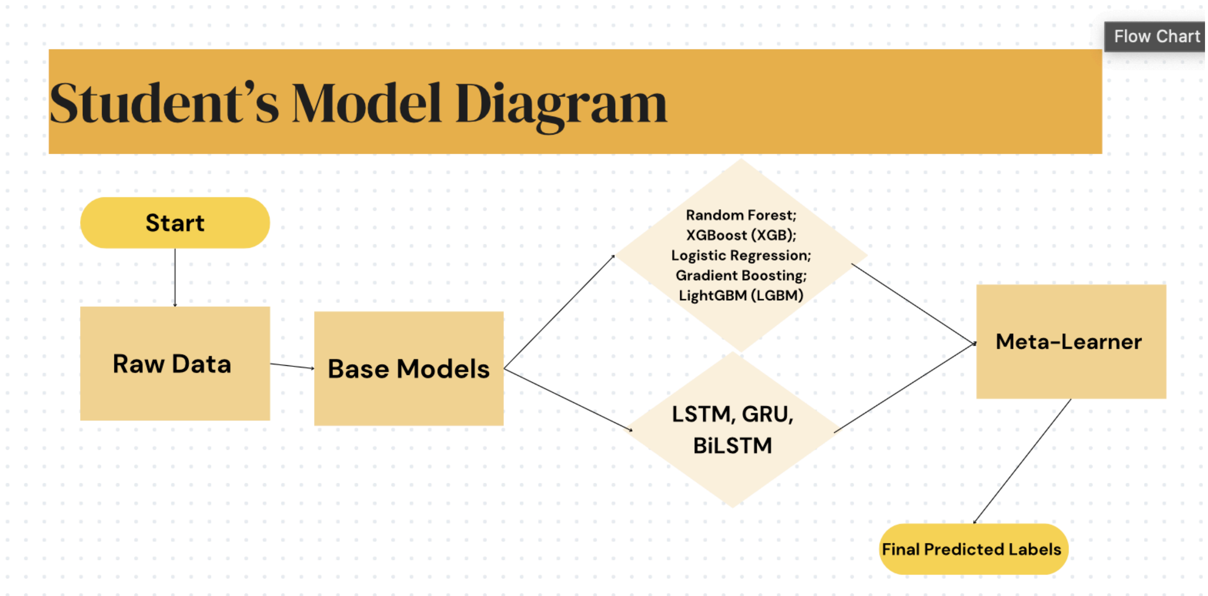
Benchmark Model Diagram

The benchmark model is a Logistic Regression classifier that utilizes all 561 features

without feature selection. The structure of the model is illustrated below:

Student's Model Diagram

The student's model uses a **Meta-Learner** to combine predictions from multiple base
models, including traditional machine learning algorithms (e.g., Decision Tree, Random Forest, Logistic Regression) and neural models (e.g., LSTM, GRU, BiLSTM). The structure is as follows:



Optimized Parameters in the Student's Model

1. Random Forest:

○ Number of estimators: [5, 7, 10]
○ Criterion: ["gini", "entropy", "log_loss"]
○ Max features: ["sqrt", "log2"]

2. Gradient Boosting:

○ Learning rate: [0.01, 0.1]
○ Max depth: [3, 8]

3. XGBoost (XGB):

○ Min child weight: [1, 3]
○ Gamma: [0.5, 1]
○ Subsample: [0.6, 0.8]
○ Colsample by tree: [0.6, 0.8]

4. LightGBM (LGBM):

○ Learning rate: [0.01, 0.1]
○ Number of estimators: [8, 16]
○ Regularization lambda: [1, 1.2]

5. Logistic Regression:

○ Regularization penalty: [l2]

6. Neural Models (LSTM, GRU, BiLSTM):
○ Model-specific hyperparameters tuned during training.

Results

Benchmark Model
● Accuracy: 89.4% (Logistic Regression)
● Average F1-Score: 0.89 (Logistic Regression)

Student's Model
● Accuracy: 73.5%
● Average F1-Score: 0.735

Discussion of Performance
The benchmark model significantly outperformed the student's model in both accuracy and F1-score. The simplicity of the Logistic Regression approach allowed for robust performance, leveraging all features without the added complexity of ensemble or Meta-Learner strategies.

The student's model, while innovative in combining predictions from multiple base models, faced challenges such as:

1. **Integration Complexity:** Combining diverse traditional and neural model predictions might have led to overfitting or suboptimal generalization.
2. **Data Imbalance**: Underrepresented activities could have adversely impacted the Meta-Learner's ability to accurately predict certain classes.

3. **Optimization Trade-offs:** Balancing the parameters across models and the
Meta-Learner added layers of complexity, which did not translate into improved Performance.

Despite its lower performance metrics, the student model highlights areas for improvement and experimentation, such as better balancing base model contributions or exploring alternative ensemble techniques.

The benchmark model outperformed the student's model, achieving higher accuracy and F1-score. While the student's model incorporated feature selection and a Meta-Learner combining predictions from multiple models, it underperformed due to potential challenges in integrating diverse models and optimizing their interactions.

The confusion matrix indicates
improved predictions for complex activities like Walking Upstairs.

Conclusions
The results of this study demonstrate a strong approach to Human Activity Recognition using smartphones, highlighting several key successes:
1. Effective Feature Selection: By reducing dimensionality and focusing on the most
relevant features, the analysis showcased significant improvements in interpretability
and computational efficiency, laying the groundwork for future advancements in activity recognition.
2. Innovative Model Integration: The student's Meta-Learner model represented an
innovative effort to combine the strengths of traditional machine learning and neural

network approaches, creating a robust framework for exploring complex data patterns.

3. Balanced Model Evaluation: While the benchmark Logistic Regression model
achieved higher accuracy and F1-scores, the student model demonstrated strong potential for further development, particularly in handling imbalanced datasets and
leveraging ensemble techniques.

4. Addressing Dataset Challenges: Insights gained from imbalanced activity classes
such as Walking Downstairs and Laying highlight opportunities for future improvements in data preprocessing and augmentation strategies to further enhance
model performance.

Overall, the findings illustrate a forward-thinking methodology and underscore the potential of feature selection and ensemble methods for advancing activity recognition systems, paving the way for innovative applications in healthcare, fitness, and beyond.

References

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