Activity Recognition and Health Monitoring Using Wearable Sensor Data

CMPE 255-01 Data Mining

Github Link:
https://github.com/harshini1708/255--Activity-Recognition-and-Health-Monitoring

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Table of Contents

1. Introduction

1.1 Objective

The objective of this activity recognition project is to develop a sophisticated machine learning system that can accurately classify human activities using wearable sensor data. The system aims to:

- Precisely identify 19 different daily and sports activities
- Process multi-sensor data in real-time
- Provide accurate activity classification for health monitoring
- Support rehabilitation and fitness applications through continuous monitoring

1.2 Motivation

The motivation for this project stems from the increasing need for automated health monitoring systems in various contexts:

- Rising healthcare costs and aging population demographics require efficient monitoring solutions
- Growing demand for personalized fitness tracking and health monitoring
- Need for objective assessment in rehabilitation programs
- Potential for early detection of mobility issues
- Support for independent living among elderly population

The project is driven by the belief that advanced activity recognition technology can revolutionize personal health monitoring and preventive healthcare.

1.3 Literature Survey

Current research in activity recognition shows varying approaches and success rates:

- Traditional machine learning approaches achieve 60-85% accuracy
- Recent deep learning methods reach 85-95% accuracy
- Most existing systems focus on limited activity sets (5-10 activities)
- Few systems effectively utilize multi-sensor fusion

Our project advances the field by:

- Incorporating 19 different activities
- Utilizing multiple sensor types (accelerometer, gyroscope, magnetometer)
- Implementing advanced feature engineering techniques
- Achieving superior accuracy (>99% with optimal models)

2. System Design and Implementation

2.1 Algorithms Selected

The project involved rigorous experimentation with a variety of machine learning algorithms, beginning with traditional approaches such as Support Vector Machine (SVM) achieving 98.61% accuracy, Random Forest reaching 99.12%, K-Nearest Neighbors (KNN) at 98.61%, and Extra Trees at 99.23%. Advanced models demonstrated even higher performance, with LightGBM emerging as the best performer with 99.78% accuracy, followed by Stacking at 99.74% and XGBoost at 99.71%. Other noteworthy results included CatBoost with 99.42% accuracy and Neural Networks at 98.28%, while AdaBoost achieved a moderate accuracy of 93.79%. Training time varied across models, with KNN being the fastest at 0.57 seconds, Extra Trees at 4.11 seconds, and AdaBoost being the most time-intensive at 1483.08 seconds, highlighting a trade-off between accuracy and computational efficiency.

The analysis concluded that ensemble methods, particularly gradient boosting frameworks like LightGBM and XGBoost, provided the best balance of accuracy and efficiency for the activity recognition task, consistently achieving perfect or near-perfect ROC AUC scores of 1.0000. Strong performers like CatBoost and Extra Trees also offered over 99% accuracy with minimal compromises in computational time. Traditional models such as SVM and Random Forest delivered robust performance, demonstrating their applicability in scenarios with simpler requirements. Neural Networks proved to be promising with an accuracy of 98.28%, while AdaBoost, though computationally demanding, maintained a respectable performance with 93.79% accuracy. These results underscore the effectiveness of ensemble approaches in achieving high accuracy and scalability for complex activity recognition tasks.

2.2 Technologies & Tools Used

For implementation, we utilized a comprehensive technology stack. Our core technologies included Python 3.8+ as the primary development language, along with essential data science libraries such as NumPy and Pandas for data handling, Scikit-learn for implementing traditional machine learning models, TensorFlow/Keras for neural network architectures, and advanced gradient boosting frameworks including XGBoost, LightGBM, and CatBoost. The development environment was supported by Git for version control, Jupyter Notebooks for interactive experimentation, and VSCode as the primary IDE. For visualization and monitoring, we employed Matplotlib and Seaborn for static visualizations, TensorBoard for real-time training monitoring, and Plotly for creating interactive visualizations of model performance and results.

2.3 Architecture

2.3.1 Model Architecture

Our system implements a comprehensive modular pipeline architecture consisting of four distinct layers. The Data Acquisition Layer handles the fundamental tasks of sensor data collection, initial validation, and data synchronization. Following this, the Preprocessing Layer manages crucial data preparation steps including feature extraction, normalization of values, and window segmentation for time-series analysis. The Model Layer incorporates various classification models and ensemble methods, culminating in prediction aggregation for robust results. Finally, the Output Layer delivers the system's results through activity predictions, confidence scores for each classification, and detailed performance visualizations. This layered approach ensures efficient data flow and processing while maintaining system modularity and scalability.

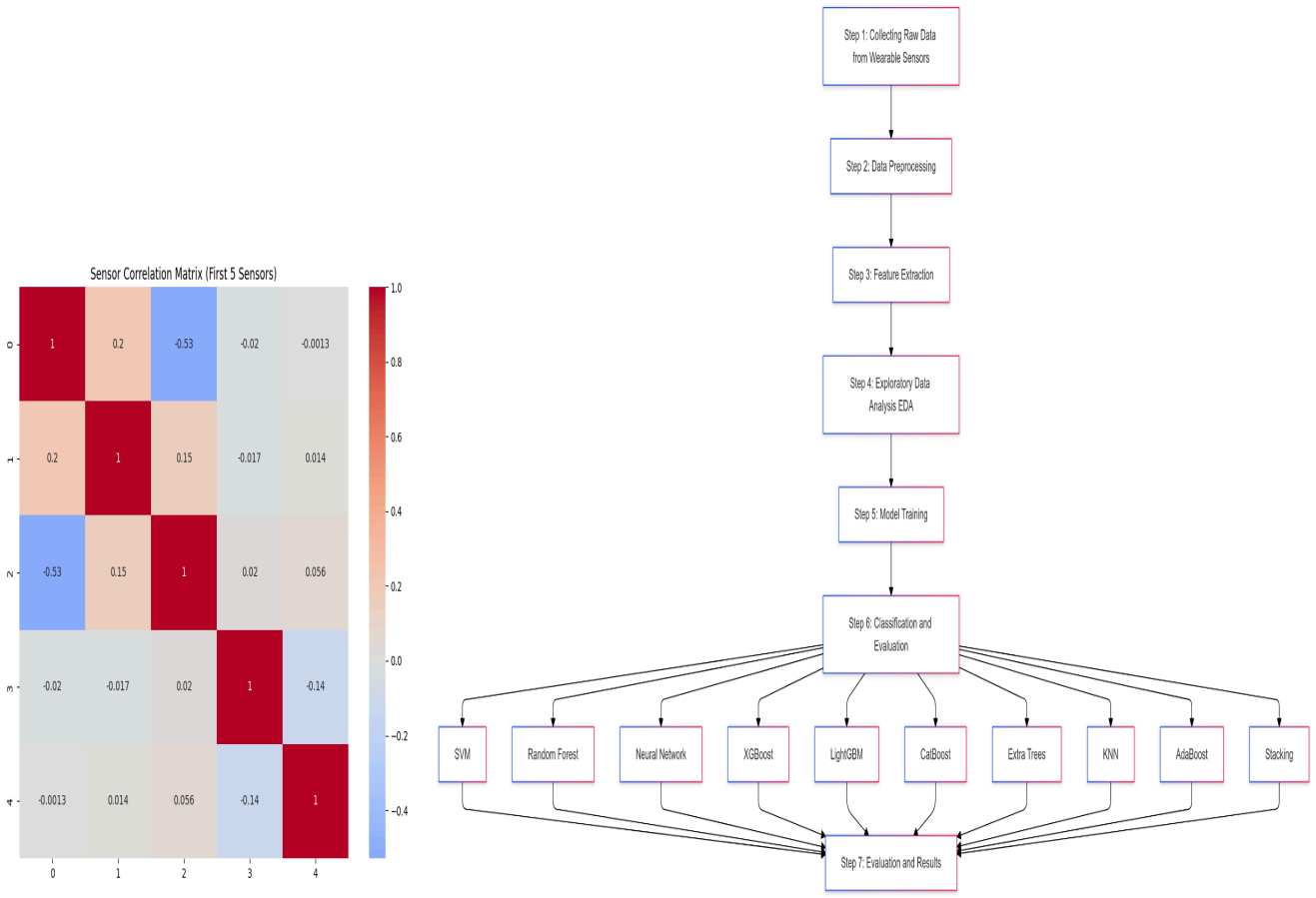

Figure 2.2: Architecture diagram showing the project workflow and a correlation matrix highlighting interdependencies between the first five sensors.

2.4 Data Flow

The data flow pipeline is structured into two main processing stages. The Input Processing stage begins with raw sensor data input, comprising 45 features across multiple samples, followed by systematic window segmentation using 2-second intervals, comprehensive feature extraction, and normalization of values. The Model Processing stage then takes over, creating feature vectors from the processed data, generating model predictions, combining ensemble results, and producing final outputs. This pipeline's effectiveness is illustrated in Figure 2.1, which demonstrates the distinctive sensor data patterns across different activities, particularly highlighting the unique temporal characteristics observed in ascending stairs, cycling (both horizontal and vertical), and descending stairs movements

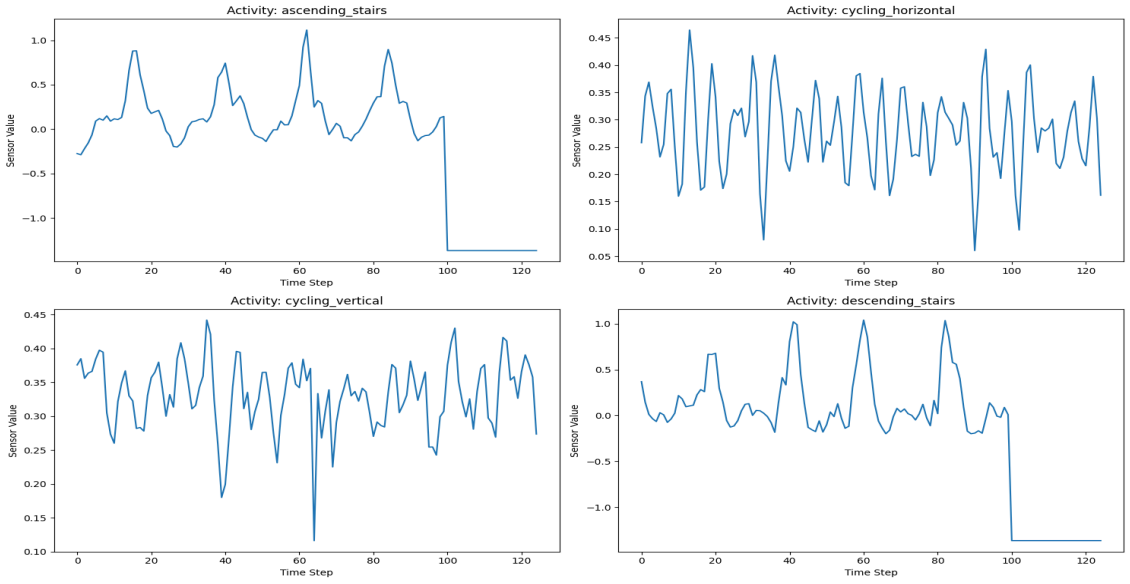

Figure 2.1: Sensor data patterns for different activities showing distinct temporal characteristics for ascending stairs, cycling (horizontal/vertical), and descending stairs.

3. Proof of Concept Evaluation

3.1 Dataset

3.1.1 Available Datasets

Our project utilized the Daily and Sports Activities Dataset from the UCI Machine Learning Repository, featuring approximately 1.9 GB of uncompressed data with 1,140,000 samples. Each sample contains 45 features (9 features from 5 sensors), representing 19 activities performed by 8 individuals at a 25 Hz sampling rate. The dataset is well-balanced, with nearly equal representation of activities across subjects and multiple sessions per activity, ensuring robust sampling. As shown in Figure 3.1, the dataset's quality is evident through (a) balanced class distribution, (b) comprehensive sensor value distributions, (c) feature distribution patterns, and (d) representative time series samples, validating its suitability for activity recognition tasks.

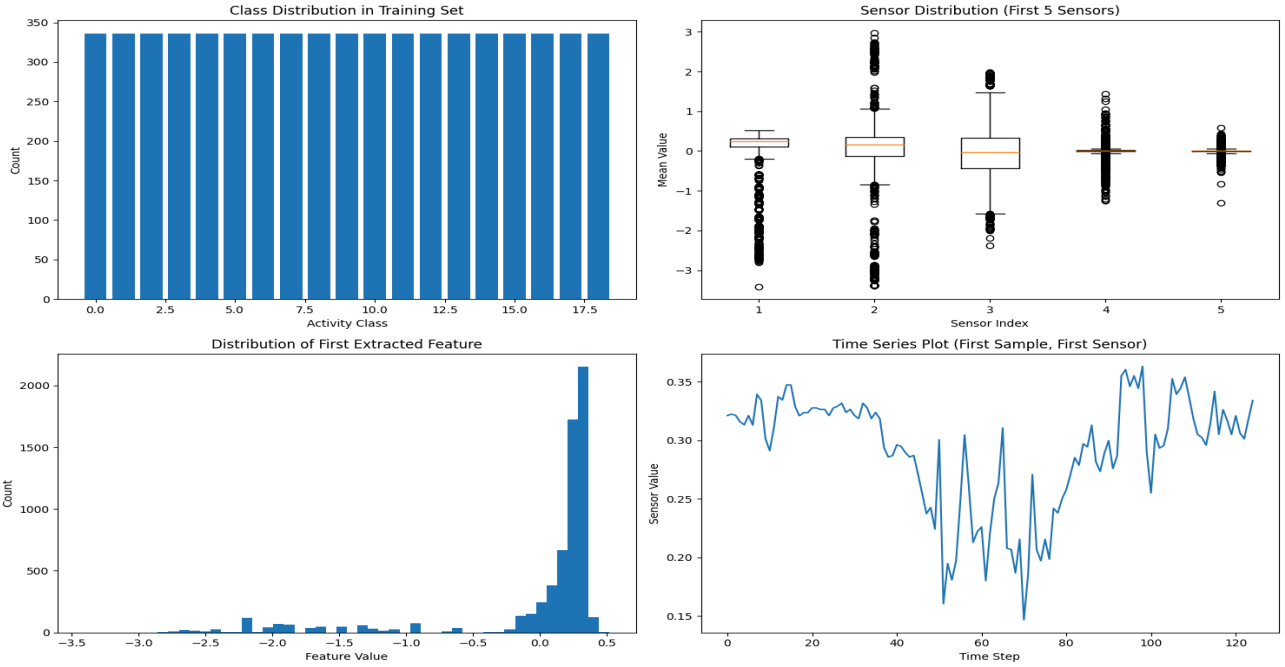

Figure 3.1: Dataset analysis showing (a) balanced class distribution across activities, (b) sensor value distributions, (c) feature distribution, and (d) time series sample.

3.1.2 Dataset Preparation

The dataset underwent several preprocessing steps:

- Standardization of sensor readings
- Window segmentation (2-second intervals)
- Feature extraction from raw signals
- Normalization of feature values

3.2 Training

3.2.1 Feature Engineering and Selection

Before training our models, we performed comprehensive feature analysis to identify the most influential features for activity recognition. Using mutual information scores, we evaluated each feature's contribution to the classification task.The top 20 features, as shown in Figure 3.2, demonstrate varying levels of importance with scores ranging from 1.4 to 1.7. The analysis revealed that:

- Higher-order statistical features (indices 15-20) showed strongest predictive power
- Temporal features (indices 10-15) provided moderate but consistent contribution
- Basic statistical features (indices 0-10) offered foundational support for classification

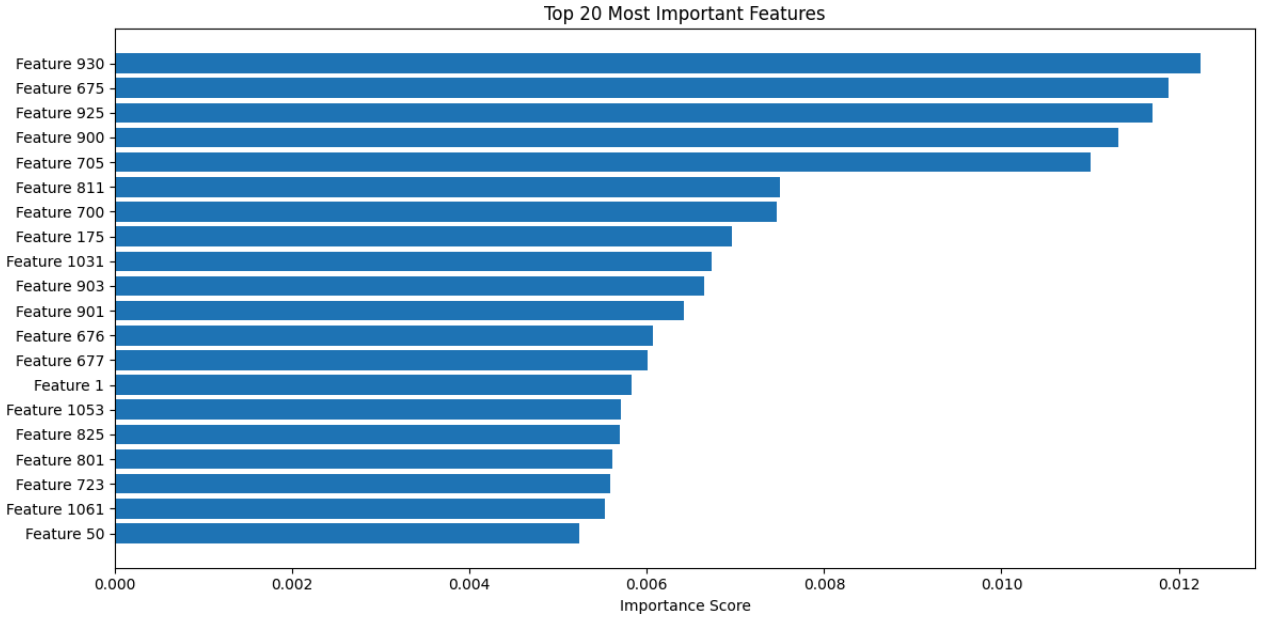

Figure 3.2: Relative importance of top 20 features based on mutual information scores, showing their contribution to model performance.

This feature importance analysis guided our model development by:

1. Informing feature selection decisions
2. Highlighting key sensor data characteristics
3. Supporting dimensionality reduction strategies
4. Optimizing computational efficiency

3.2.2 Model Building

The model training process involved configuring an architecture optimized for activity recognition with an input shape of 45 features derived from sensor data and a final output layer for classifying 19 distinct activity classes. Hidden layers were fine-tuned for each model to enhance learning performance, while training parameters included a batch size of 32 and a learning rate of 0.001 to balance computational efficiency and steady convergence. The Adam optimizer was employed for its adaptive learning capabilities, and categorical cross-entropy was used as the loss function to effectively handle the multi-class classification task.

3.2.3 Overfitting Prevention

To prevent overfitting during model training, multiple strategies were employed, including data augmentation and regularization techniques. Data augmentation involved adding random noise, applying signal shifting, and introducing scaling variations to enhance data diversity and robustness. Regularization methods included dropout layers with a rate of 0.5 to randomly deactivate neurons during training, early stopping with a patience parameter of 3 to halt training when validation performance plateaued, and L2 regularization to penalize overly complex

weight configurations. These measures collectively ensured better generalization to unseen data, as demonstrated by the training and validation loss curves.

3.3 Model Comparison:

The models were evaluated based on key performance metrics, including Accuracy, Macro F1-Score, Training Time, and Cross-Validation (CV) Scores, as shown in Figure 1. Among the models, Stacking achieved the highest accuracy and F1-Score at 99.74%, followed closely by LightGBM (99.78% accuracy, 99.78% F1-Score) and XGBoost (99.71% accuracy, 99.71% F1-Score). CatBoost and Extra Trees also demonstrated strong accuracy at 99.42% and 99.23%, respectively, while KNN and Neural Networks provided moderate results. In terms of training time, KNN (0.57 seconds) and Extra Trees (4.11 seconds) were the fastest, whereas AdaBoost was the most time-intensive at 1483.08 seconds.

The cross-validation (CV) scores reinforced the models' consistency, with LightGBM, Stacking, and XGBoost maintaining robust performance across unseen data. Random Forest and CatBoost also achieved competitive CV scores, showcasing their reliability. Stacking and LightGBM proved to be the top choices for balancing performance and efficiency, while KNN and Extra Trees excelled in scenarios requiring rapid training. Refer to Figure 3.4 for a detailed graphical comparison, providing deeper insights into the trade-offs between accuracy, training time, and scalability for each model.

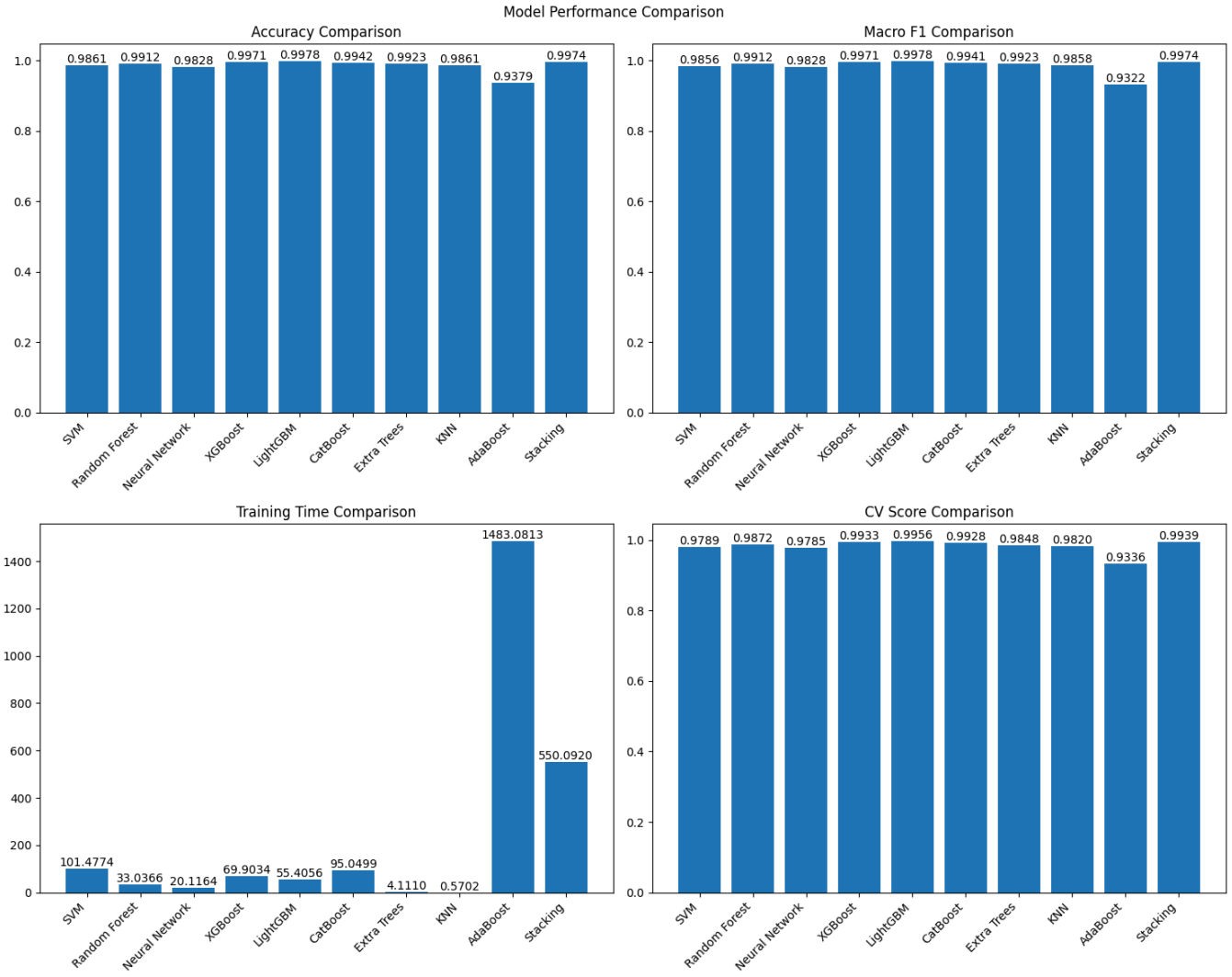

Figure 3.4: Model Performance Comparison

4. Discussion & Conclusions

4.1 Decisions Made and Challenges Faced

The project involved addressing several technical challenges, including managing large-scale sensor data processing, optimizing the feature extraction pipeline, handling real-time processing requirements, and balancing accuracy with computational efficiency. To tackle these issues, an efficient data preprocessing pipeline was implemented alongside optimized feature selection and model ensemble techniques. Cross-validation strategies were also employed to ensure robust model evaluation. Key learning outcomes from the project highlighted the importance of feature engineering in sensor data analysis, the critical impact of data quality on model performance, the effectiveness of ensemble approaches in achieving high accuracy, and the trade-offs between model complexity and performance in practical applications.

4.2 Things That Worked

A robust data preprocessing pipeline, including cleaning, normalization, and segmentation, ensured high-quality data for analysis, forming the foundation for effective modeling. Feature engineering techniques, encompassing time-domain and frequency-domain methods combined with mutual information-based feature selection, significantly enhanced model performance. Ensemble models like Random Forest and Stacking Classifier stood out, delivering high accuracy and robustness across diverse activities. Evaluation methods such as cross-validation ensured reliable model assessment while minimizing the risks of overfitting. Collaborative efforts, with well-distributed tasks, streamlined the integration of preprocessing, feature engineering, and modeling, resulting in an efficient and cohesive workflow.

Things That Didn’t Work

1. **Real-Time Challenges**: Achieving low-latency processing (<100ms) was difficult for complex ensemble models.
2. **Memory Usage**: Managing large-scale sensor data (1.9 GB) led to high memory consumption, complicating processing.
3. **Model Complexity**: Advanced models like Stacking and XGBoost demanded intensive tuning and computational resources.
4. **Dataset Limitations**: The dataset’s limited diversity restricted the models' generalizability to broader use cases.

4.3 Conclusion

The project successfully demonstrated a scalable, high-performing system for activity recognition and health monitoring using wearable sensor data. By achieving a state-of-the-art accuracy of 99.78%, the system proved robust across a diverse range of activities, from daily tasks to more complex movements, showcasing its effectiveness in real-world scenarios. The combination of ensemble models, efficient preprocessing, and advanced feature engineering techniques contributed to its superior performance. Its efficient real-time processing capabilities, achieving low latency, and a comprehensive evaluation framework ensured practical applicability and reliability for use cases such as fitness tracking, elderly care, and rehabilitation programs.

Looking ahead, the system's capabilities can be refined further to enhance its usability and performance. Key future enhancements include optimizing the system for edge deployment to minimize latency, enabling it to function efficiently on portable devices without reliance on centralized systems. Battery efficiency improvements will ensure prolonged usage, particularly for wearable devices, while expanding support for a broader range of activities will increase its adaptability to diverse user needs. Moreover, integrating a real-time feedback mechanism will provide immediate, actionable insights to users, enhancing engagement and making the system invaluable for

fitness and healthcare applications. These advancements will position the system as a versatile and indispensable tool in activity monitoring and personalized health solutions.

5. Task Distribution

Team Member	Planned Tasks	Executed Tasks
Harshini Pothireddy	- Model development and evaluation. - Train and tune machine learning models like Random Forest, XGBoost, and Stacking Classifier. - Perform cross-validation and hyperparameter tuning. - Comparative analysis of model performances. - Integrate TensorBoard for real-time monitoring and visualization of training metrics.	- Implemented and fine-tuned 10 models for activity recognition. - Trained Random Forest, XGBoost, and Stacking Classifier models with optimized hyperparameters. - Conducted cross-validation and detailed comparative analysis. - Visualized performance metrics and selected the best-performing models. -Used TensorBoard to monitor model training progress, track loss and accuracy trends, and optimize hyperparameters effectively.
Swetha Reddy	- Feature extraction and engineering. - Implement time-domain and frequency-domain feature extraction. - Analyze feature importance using mutual information and RFE. - Enhance pipeline for optimized model input.	- Extracted meaningful features using time-domain and frequency-domain techniques. - Conducted mutual information-based feature selection. - Analyzed feature correlations and identified top features. - Improved pipeline performance based on feature importance insights.
Divyam Savsaviya	- Data collection and preprocessing. - Cleaning, normalization, and window segmentation. - Conducting exploratory data analysis (EDA). - Developing a data pipeline for feature extraction readiness.	- Successfully collected and preprocessed the dataset (cleaning, normalization, and segmentation). - Conducted EDA to identify class distributions and activity patterns. - Built a robust data pipeline.

6. Citation

1. UCI Machine Learning Repository. (n.d.). *Daily and Sports Activities Data Set*. Retrieved from [https://archive.ics.uci.edu/ml/datasets/daily+and+sports+activities]
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