Report on UCI HAR Dataset Analysis(Task #1)

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1. Overview

This notebook focuses on building models to predict human activities using the UCI HAR dataset. The task involves two key approaches:

- **Deep Learning Models:** Implemented using LSTM and 1D CNN trained on raw accelerometer data.
- **Machine Learning Models:** Implemented using Random Forest, SVM, and Logistic Regression with features generated using the TSFEL library.
- A comparison is performed between models trained on the extracted features and those trained on the existing features provided by the dataset authors.

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2. Implementation Summary

2.1 Dataset Handling

- The dataset is extracted and preprocessed.
- The raw accelerometer data is used for Deep Learning models.
- Feature extraction is performed using the TSFEL library for Machine Learning models.
- Existing features from the dataset are also used for performance comparison.

2.2 Deep Learning Models

- Implemented LSTM and 1D CNN architectures using `tensorflow.keras`.
- Evaluated models using accuracy and confusion matrices.

2.3 Machine Learning Models

- Features extracted using `TSFEL` (time-domain, frequency-domain, and statistical features).
- Implemented models: **Random Forest, SVM, Logistic Regression**.
- Evaluated using precision, recall, F1-score, and accuracy.
- Models are trained on both extracted and existing features.

3. Results & Observations

3.1 Model Performance Comparison

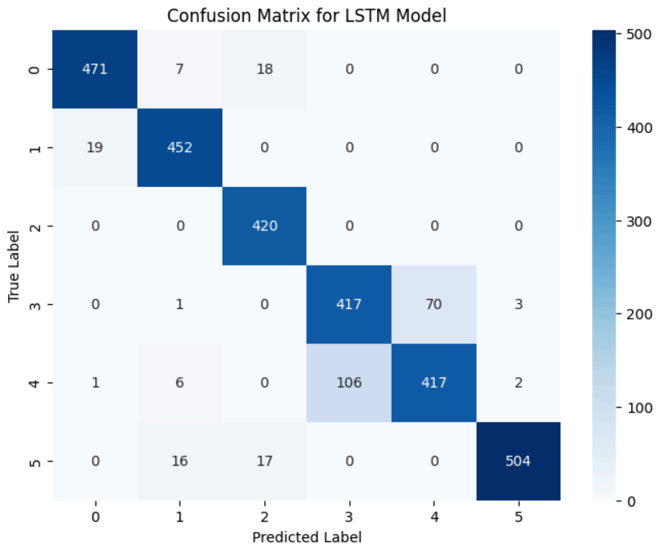
- **Deep Learning Models** (LSTM, CNN):
    - Performed well with raw sensor data.
    - The 3 layered LSTM achieved accuracy of 90.97% trained and tested on the raw features.
    - The 3 layered CNN achieved accuracy of 90.87% trained and tested on the raw features.
    - The combined model (LSTM+CNN) achieved accuracy of 90.93%.

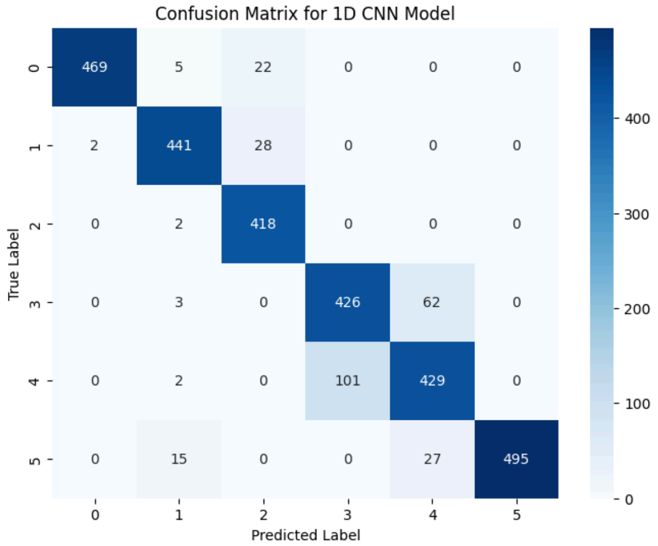
- **Machine Learning Models** (Random Forest, SVM, Logistic Regression):
    - The ML models performed somewhat worse and achieved less accuracy than the deep learning models.
    - Among the ML models, the SVM was the best achieving accuracy of ~90%.

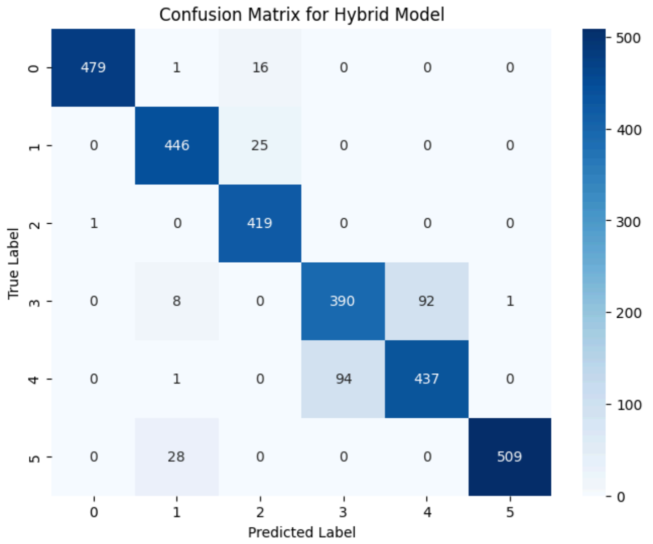
- **Comparison of Pre-Existing and TSFEL Extracted features:**
    - The ML models achieved better accuracy when trained and tested on the features provided by the Authors(accuracy ~ 92%) performed better than on raw features(accuracy ~ 90%) and the extracted features(accuracy ~70%).
    - I also tried the selection of most important features by removing some of the features but that also did not improve the accuracy much.

3.2 Visualizations & Evaluation

- Confusion matrices were generated for model evaluation.
- Performance metrics like accuracy, precision, recall, and F1-score were analyzed.
- A summary table comparing Deep Learning and Machine Learning model performance was included.


Confusion Matrix for LSTM Model
True Label
Predicted Label
0 1 2 3 4 5
0: 471 7 18 0 0 0
1: 19 452 0 0 0 0
2: 0 0 420 0 0 0
3: 0 1 0 417 70 3
4: 1 6 0 106 417 2
5: 0 16 17 0 0 504
500
400
300
200
100
0


Confusion Matrix for 1D CNN Model
True Label
Predicted Label
0 1 2 3 4 5
0: 469 5 22 0 0 0
1: 2 441 28 0 0 0
2: 0 2 418 0 0 0
3: 0 3 0 426 62 0
4: 0 2 0 101 429 0
5: 0 15 0 0 27 495
400
300
200
100
0


Confusion Matrix for Hybrid Model
True Label
Predicted Label
0 1 2 3 4 5
0: 479 1 16 0 0 0
1: 0 446 25 0 0 0
2: 1 0 419 0 0 0
3: 0 8 0 390 92 1
4: 0 1 0 94 437 0
5: 0 28 0 0 0 509
500
400
300
200
100
0

4. Areas for Improvement

4.1 Feature Engineering

- A deeper analysis of which TSFEL features contribute most to classification performance.
- Consider feature selection techniques to remove redundant features.

4.2 Hyperparameter Tuning

- Fine-tune hyperparameters for SVM, Random Forest, and Logistic Regression using GridSearchCV.
- Experiment with different architectures for LSTM and CNN models.

4.3 Additional Metrics

- Evaluate latency and computational efficiency of models.
- Include ROC curves for better class separation analysis.

5. Conclusion

- Deep Learning models (LSTM, CNN) effectively learn activity patterns from raw sensor data.
- Training on extracted features **did not provide** as good performance as using pre-existing dataset features.
- Further improvements can be achieved through feature selection, hyperparameter tuning, and additional evaluation metrics.

6. Future Work

- Implement hybrid models combining Deep Learning with feature-engineered Machine Learning.
- Explore Transformer-based models for time-series classification.
- Conduct real-time testing on embedded devices or mobile platforms.

End of Report