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A Time-Series Deep Learning Model for Smartphone-Based Human Activity Recognition Using LSTM Networks

In Partial Fulfillment of the Requirements for
CCS 248 - Artificial Neural Networks

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1. Project Overview and Justification

1.1. Problem Definition

Wearable devices and smartphones can track physical activity for health monitoring, fitness apps, or elderly care. This project focuses on addressing the challenge of **Human Activity Recognition (HAR)** using raw sensor data collected from smartphones. The system aims to classify six daily human activities—walking, walking upstairs, walking downstairs, sitting, standing, and lying—using tri-axial accelerometer and gyroscope readings.

Problem Relevance:

- **Real-world Applications:** HAR systems are crucial in healthcare (elderly monitoring), fitness tracking, smart home automation, and human-computer interaction.
- **Research Significance:** Activity recognition from sensor data is an active research area in mobile computing and machine learning.
- **Technical Challenge:** Requires processing high-dimensional temporal sensor data to distinguish between similar activities (e.g., sitting vs. standing).

1.2. Project Justification

This project was chosen due to the combination of strong academic value and practical usefulness:

1. **Well-defined Problem:** Activity classification is a clear, measurable problem with established benchmarks.
2. **High-quality Dataset:** UCI HAR Dataset is widely recognized, well-documented, and provides reproducible results.
3. **Temporal Nature:** Sensor data has inherent sequential patterns, making it ideal for LSTM networks.
4. **Appropriate Complexity:** Challenging enough to require deep learning but manageable within project constraints.

2. Dataset Selection and Validation

2.1. Dataset Details

Dataset: UCI Human Activity Recognition Using Smartphones Dataset
URL: https://archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones

The **UCI Human Activity Recognition Using Smartphones Dataset** was selected due to its reputable use in academic research and its suitability for deep learning mode.

Dataset Validation:

1. **Academic Approval:** UCI dataset is widely used in published research papers.
2. **Quality Assurance:** Data collected under controlled experimental conditions.
3. **No Privacy Concerns:** Dataset contains only sensor readings, no personal identifiers.
4. **No Bias:** Balanced representation of activities across subjects.
5. **Documentation:** Complete documentation of data collection methodology.

2.2. Dataset Characteristics

The dataset offers rich time-series data with 561 engineered features derived from accelerometer and gyroscope signals. The smartphone was worn securely at the waist, ensuring consistent motion capture. The large number of samples (over 10K) supports stable model training and testing.

Metric	**Value**
Total Samples	10,299 (7,352 train + 2,947 test)
Features per Sample	561 sensor-derived features

Metric	**Value**
Activity Classes	6
Subjects	30 volunteers
Sensor Sampling Rate	50Hz
Data Collection	Smartphone (Samsung Galaxy S II) waist-mounted

3. Model Architecture Selection and Design

3.1. Neural Network Used

The project uses **Long Short-Term Memory (LSTM) Networks**, a specialized type of **Recurrent Neural Network (RNN)**. **LSTMs** are ideal for **HAR** because they can retain long-term dependencies within sensor sequences.

LSTM Key Features:

1. **Temporal Dependencies:** Sensor data represents time-series sequences with important temporal patterns.
2. **Vanishing Gradient Solution:** LSTMs handle long-range dependencies better than standard RNNs.
3. **Sequence Learning:** LSTMs excel at learning from sequential data where order matters.
4. **Proven Success:** LSTMs have demonstrated state-of-the-art performance in HAR tasks.

3.2. Network Structure

The base architecture includes:

Input Layer: (128 timesteps × 4 features)

LSTM Layer: 64 units, return_sequences=False

Dropout Layer: 0.3 (regularization)

Dense Layer: 32 units, ReLU activation

Output Layer: 6 units, Softmax activation

Explored variations included Bidirectional LSTMs, stacked architectures, different dropout values, and increased LSTM units. These experiments helped determine the model configuration that offered the best balance between accuracy and efficiency.

Variations Explored:

1. **Bidirectional LSTM:** Processes sequences in both forward and backward directions
2. **Stacked LSTM:** Multiple LSTM layers for hierarchical feature learning
3. **Different Unit Sizes:** 64 vs. 128 LSTM units
4. **Regularization Techniques:** Dropout (0.3-0.4) and L2 regularization

4. Model Training and Hyperparameter Tuning

4.1. Optimizer Selection

The **Adam optimizer** was chosen due to its adaptive learning rate mechanism and excellent convergence behavior for deep models. It performs well even with noisy gradients and varying data scales—typical in sensor data.

Adam Key Features:

1. **Adaptive Learning Rates**: Per-parameter learning rates for faster convergence
2. **Momentum:** Helps navigate through saddle points and local minima
3. **Proven Performance:** Widely successful in deep learning applications
4. **Robustness:** Less sensitive to hyperparameter choices than SGD

Alternative Optimizer Tested: **RMSprop** (Experiment 5)

4.2. Hyperparameter Tuning Process

A structured experimental approach was used to evaluate how adjustments in LSTM units, optimizers, batch sizes, and regularization affected performance. Results revealed that:

Experiment	**Variable Tested**	**Values Tested**	**Outcome**
Exp1	Baseline	Default parameters	Reference performance
Exp2	LSTM Units	64 → 128	No improvement
Exp3	Bidirectional	False → True	Best performance
Exp4	Stacked Layers	1 → 2	Marginal improvement
Exp5	Optimizer	Adam → RMSprop	Similar performance
Exp6	Learning Rate	0.001 → 0.0005	Worse performance

Exp7	Batch Size	64 → 128	Similar performance
Exp8	Regularization	None → L2 (0.001)	Slight improvement

4.3. Training Configuration Details

All experiments were conducted using 50 epochs with early stopping and learning rate reduction techniques enabled. TensorFlow/Keras served as the development framework, ensuring stable implementation of deep learning workflows.

Common Parameters Across All Experiments:

- **Loss Function:** Categorical Cross-entropy
- **Metrics**: Accuracy
- **Epochs**: 50 (with early stopping monitoring validation loss)
- **Validation Split:** 20% of training data
- **Callbacks**: EarlyStopping, ReduceLROnPlateau, ModelCheckpoint

Hardware/Software Configuration:

- **Framework:** TensorFlow/Keras
- **Programming Language**: Python 3.13.5
- **Libraries:** NumPy, Pandas, Scikit-learn, Matplotlib
- **Environment**: Jupyter Notebook for experimentation

5. Results, Evaluation and Analysis

5.1. Experiments Results

All models significantly exceeded the 50-60% minimum accuracy requirement:

Experiment	Test Accuracy	Test Loss	Validation Accuracy	Training Accuracy
Exp3_Bidirectional_LSTM	93.79%	0.1927	97.76%	98.79%
Exp1_Baseline_LSTM	92.57%	0.2265	95.92%	97.25%
Exp5_RMSprop_Optimizer	92.50%	0.2010	95.11%	95.37%
Exp7_Larger_Batch	92.23%	0.2051	95.85%	94.92%
Exp8_L2_Regularization	92.20%	0.2431	95.72%	96.02%
Exp4_Stacked_LSTM	92.13%	0.2507	96.33%	96.38%
Exp2_Larger_LSTM	91.35%	0.2532	95.58%	97.55%
Exp6_Lower_LR	91.04%	0.2263	93.75%	93.40%

Across all experiments, the models achieved accuracy above 90%, surpassing typical benchmark expectations. The **Bidirectional LSTM** model achieved the highest accuracy of **93.79%**, demonstrating that processing sequences from both forward and backward directions significantly improves recognition capability.

5.2. Training Results

Key Findings:

1. **Bidirectional LSTMs** achieved **highest accuracy (93.79%)**, confirming the importance of bidirectional context in activity recognition.
2. **Overfitting Management:** Dropout (0.3) and early stopping effectively prevented overfitting despite high training accuracy.
3. **Hyperparameter Sensitivity:** Learning rate showed the most sensitivity - lower rate (0.0005) degraded performance.
4. **Model Size vs Performance**: Larger LSTM (128 units) did not improve test accuracy, suggesting 64 units is sufficient for this problem.

6. Conclusion

This project successfully demonstrated the effectiveness of **LSTM-based deep learning models** for smartphone-based Human Activity Recognition. By leveraging the UCI HAR dataset and systematically evaluating different model variations, the project confirmed that **Bidirectional LSTMs achieve superior performance**, reaching a test accuracy of 93.79%.

The results highlight several important conclusions:

- **Temporal modeling is essential** for accurately detecting human activities.
- **Balanced datasets and proper regularization** ensure strong generalization to unseen users and movements.
- **Model simplicity can outperform overly complex architectures**, emphasizing the importance of thoughtful design over size alone.

Overall, this project validates that deep learning, particularly LSTM architectures, offers a robust approach for real-world HAR applications such as healthcare monitoring, fitness tracking, and smart IoT environments. Future work may explore CNN-LSTM hybrids, Transformer models, or real-time deployment on mobile devices.