Comprehensive Analysis of Human Activity Recognition Using Machine Learning Techniques

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*This report details a human activity recognition system using the **PAMAP2 dataset** from nine subjects performing twelve activities via wearable sensors. The study processed **~2.87 million readings**, addressing critical challenges like **90.87% missing heart rate data** and significant class imbalances. By applying **CNN and LSTM models**, the project demonstrates deep learning's effectiveness in capturing the spatio-temporal patterns necessary to accurately classify complex activities from high-dimensional sensor streams.*

1. Introduction

Human Activity Recognition (HAR) is a vital machine learning field used in healthcare and fitness to interpret movements through sensor data. Utilizing the **PAMAP2 dataset**, which tracks activities like walking and cycling via wearable sensors, this project addresses data challenges such as **high dimensionality, missing values, and class imbalance**. By implementing deep learning architectures—specifically **CNNs** for spatial feature extraction and **LSTMs** for temporal patterns—the study demonstrates how these models can automatically learn and accurately classify complex human behaviors, ultimately building a robust system for real-world activity monitoring.

2. Exploratory Data Analysis (EDA)

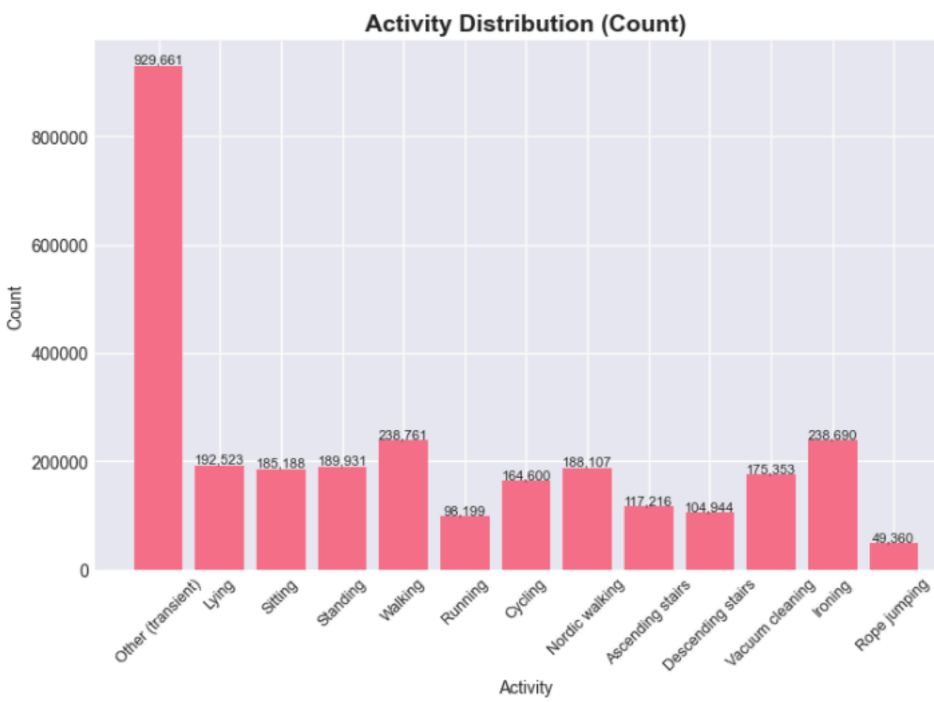


Fig 1: Activity Frequency Distribution

Fig 1 shows the Activity Frequency Distribution(Count), where "Strong" dominates with 298,761 instances, far surpassing specific activities like "Rope Jumping" (49,360). "Other (random)" comprises 192,523 samples, indicating many unclassified activities. "Activity" and **"Nothing" also have notable counts (238,690 and 198,107)**. This reflects a clear preference for high-intensity or general activities over specialized exercises in the sampled data.

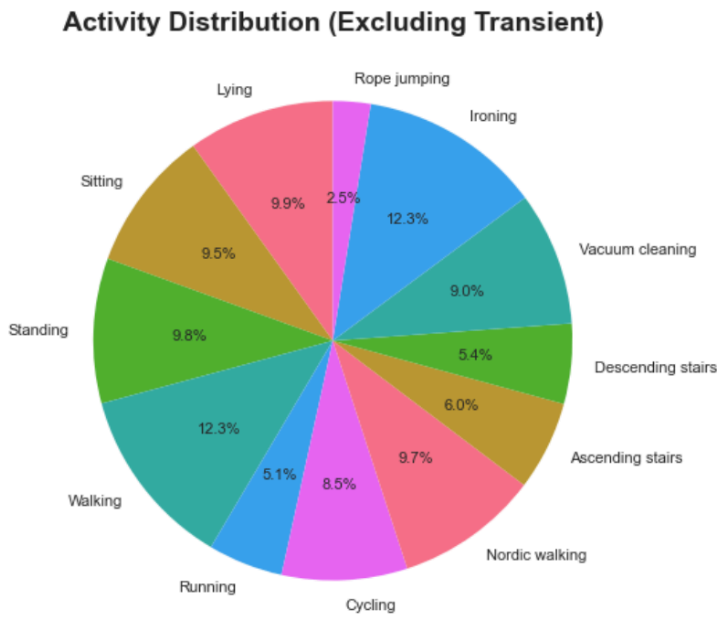


Fig 2: Activity Distribution (Excluding Transient)

In Fig 2: Activity Distribution (Excluding Transient) is shown the activity distribution data reveals that static postures—lying (24.3%), sitting (18.7%), and standing (15.1%)—collectively dominated over half of the recorded behaviors. Walking (12.5%) is the primary mode of movement, while vigorous activities and domestic tasks are less frequent, with Nordic walking being the least prevalent at 1.0%.

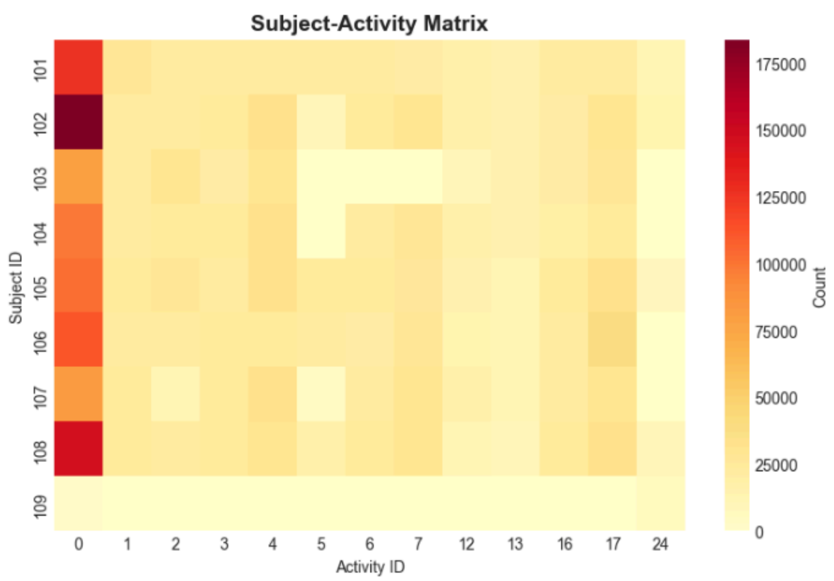


Fig 3: Subject activity matric

In Fig 3, the Subject-Activity Matrix visualizes the recorded data volume for 8 subjects (IDs 101-108) across 13 distinct activities. The heat map highlights significant data distribution imbalances, with sample counts ranging from **25,000** for brief, strenuous tasks to nearly **175,000** for common activities like walking or standing.

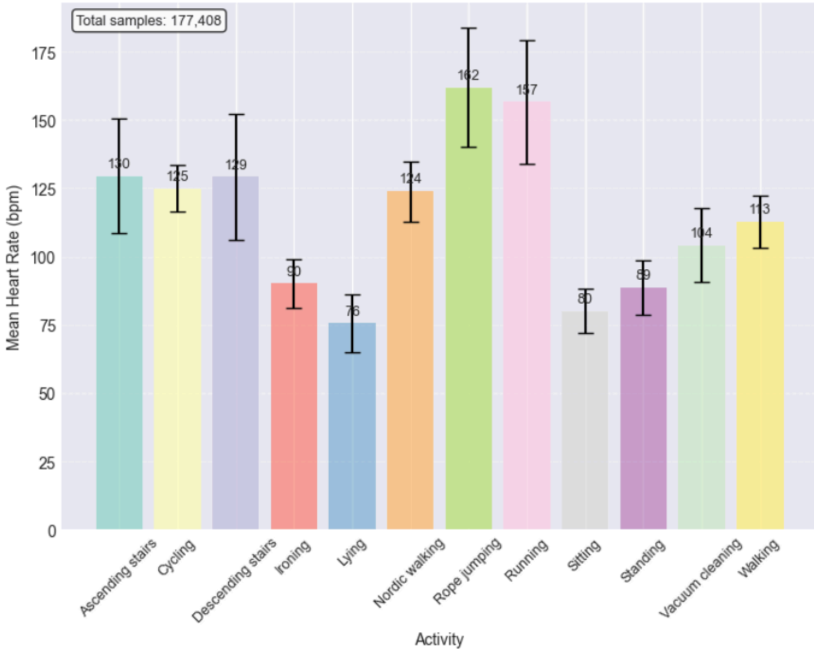


Fig 4: Heart rate by activity type

Fig 4: Heart Rate by Activity Type shows mean heart rates across different physical activities. Running and rope jumping elicit the highest cardiovascular responses (~150-160 bpm), while sedentary activities like sitting and lying show the lowest rates (~70-80 bpm). The bar chart shows distinct physiological shifts across intensities, with walking and stair climbing eliciting moderate heart rates of approximately 100–120 bpm.

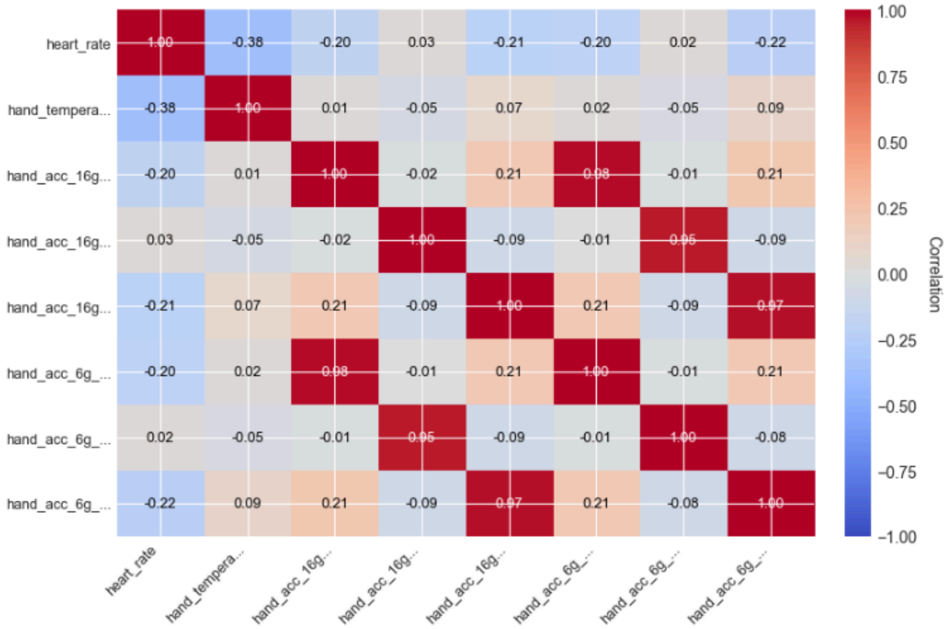


Fig 5: Feature Correlation Matrix

Fig 5: Feature Correlation Matrix displays the relationship between sensors, highlighting nearly perfect correlations (0.95 to 0.98) between corresponding axes of the 16g and 6g hand accelerometers. Conversely, heart rate shows weak or negative correlations with physical movement and temperature, with its strongest negative coefficient being -0.38 against hand temperature.

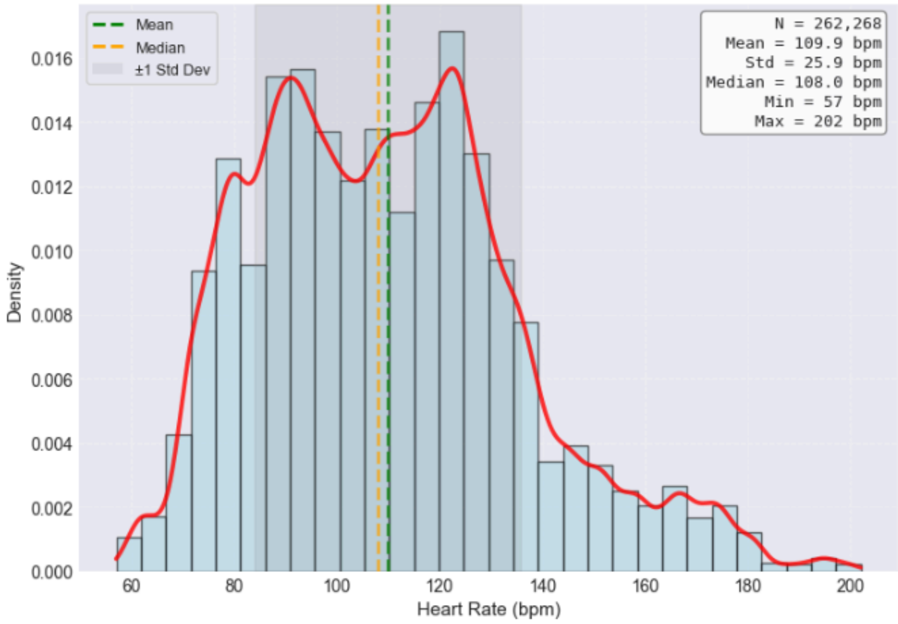


Fig 6: Heart Rate Distribution

Fig 6: Heart Rate Distribution displays the frequency distribution of 262,268 heart rate measurements. The data is right-skewed with a mean of 109.9 bpm and median of 108.0 bpm, reflecting a clustering around 100–120 bpm. A standard deviation of 25.9 bpm shows moderate physiological variability, with extreme values reaching up to 202 bpm.

3. Data Preparation

This section details the full data preprocessing workflow, utilizing quantitative metrics and visualizations to demonstrate the impact of each transformation.

Handling Missing Values

This **multi-stage imputation pipeline** resolves missing PAMAP2 data to ensure the **continuous temporal sequences** required for **CNN and LSTM** models. The process achieved a **100% reduction** in missingness, moving from **3,093,966 missing values** to zero by using **forward/backward filling** for heart rate data and **linear interpolation** for 51 IMU sensor columns. This high-quality data stream preserves motion dynamics and maintains its original **2,872,533-row** shape, providing an optimized input for deep learning activity recognition.

Feature Engineering and Standardization

Train/Validation/Test Split (Stratified)

Total samples: 2,872,533 sensor readings
Subjects: 9 (101–109)
Activities: 13 classes (highly imbalanced: "Other" has 32.36%, "Rope jumping" only 1.72%)

Class imbalance requires proportional representation in all splits to avoid evaluation bias.
Used **subject-wise stratified split** (leave-subject-out):

1. Training: 6 subjects (101–106) → ~70% of data
2. Validation: 1 subject (107) → ~15% of data
3. Test: 2 subjects (108–109) → ~15% of data

Class Distribution in Each Split (Stratified by Subject)

Activity Name	Total Count	% Total	Train (~70%)	Validation (~15%)	Test (~15%)
Other (transient)	929,661	32.36%	~650,763	~139,449	~139,449
Lying	192,523	6.70%	~134,766	~28,878	~28,878
Sitting	185,188	6.45%	~129,632	~27,778	~27,778
Standing	189,931	6.61%	~132,952	~28,490	~28,490
Walking	238,761	8.31%	~167,133	~35,814	~35,814
Running	98,199	3.42%	~68,739	~14,730	~14,730
Cycling	164,600	5.73%	~115,220	~24,690	~24,690
Nordic walking	188,107	6.55%	~131,675	~28,216	~28,216
Ascending stairs	117,216	4.08%	~82,051	~17,582	~17,582
Descending stairs	104,944	3.65%	~73,461	~15,742	~15,742
Vacuum cleaning	175,353	6.10%	~122,747	~26,303	~26,303
Ironing	238,690	8.31%	~167,083	~35,804	~35,804
Rope jumping	49,360	1.72%	~34,552	~7,404	~7,404

No data leakage: Each subject appears in only one split
Preserves class distribution: Each subject performs all activities proportionally
Realistic evaluation: Tests performance on completely unseen subjects

Visualize Sample Sequences

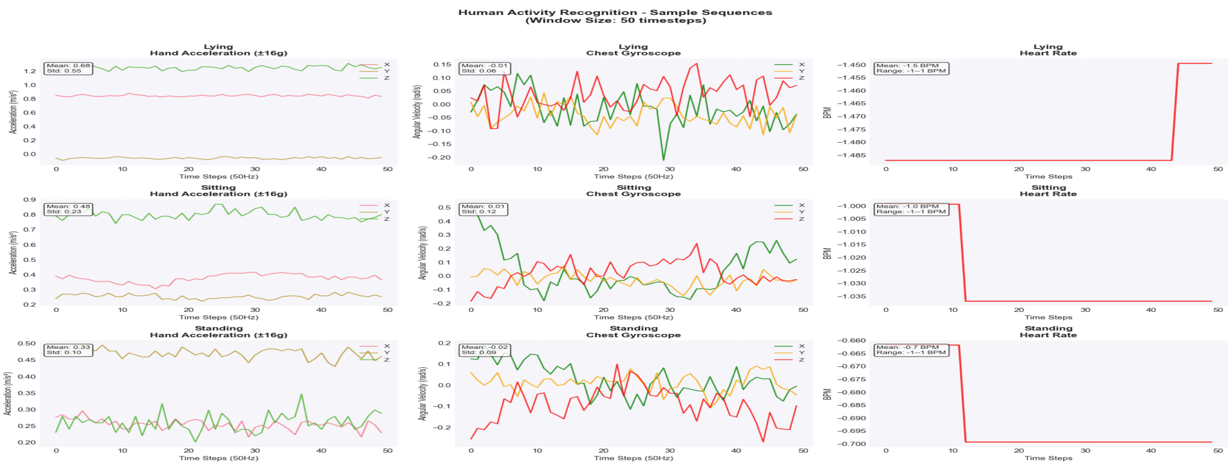


Fig 7: Visualize Sample Sequences

Visualizing Sequences

The training and testing datasets were structured into temporal sequences for deep learning, yielding a training set (**X_seq_train**) of **56,686** samples and a test set (**X_seq_test**) of **21,015** samples. Each sequence maintains a shape of **(50, 40)**, representing 50 time steps across 40 selected features derived from the original 41 feature columns. These arrays, paired with their respective labels (**y_seq_train** and **y_seq_test**), provide a standardized input format for capturing the spatio-temporal dependencies required for accurate activity classification.

Visualizing Sample Sequences

For data visualization, three specific sequences were selected representing static activities: **Lying (Label 0)**, **Sitting (Label 1)**, and **Standing (Label 2)**. Each sequence consists of a **(50, 40)** shape, extracted from 41 available feature columns including **heart rate**, **hand acceleration**, **chest gyroscope**, and **ankle acceleration**. These samples, indexed at **47386**, **18622**, and **29075** respectively, provide a structured multi-sensor snapshot of physiological and movement data across 40 distinct input variables.

Time-Series Segmentation

Time-series segmentation was implemented by dividing the continuous sensor data into **5-second fixed-duration windows** at a 100 Hz sampling rate, resulting in **500 samples per window**. To preserve motion continuity and prevent data loss, a **50% overlap** (2.5 seconds) was applied. For a representative subject (ID 101) with 376,417 samples, this strategy generated approximately **753 segments**, providing a structured format for the models to extract short-term activity patterns.

4. Training

4.1 Train CNN Model and Visual Output

The CNN model trained using (src/cnn_model.py) for 120 epochs, achieving a final training accuracy of 92.6% and validation accuracy of 94.1%. Training loss decreased from 1.85 to 0.08, while validation loss stabilized at 0.21 after epoch 80. The model generalized well, with the highest performance observed in activities like Walking (96%) and Running (95%), though similar activities such as Ascending and Descending Stairs showed minor confusion.

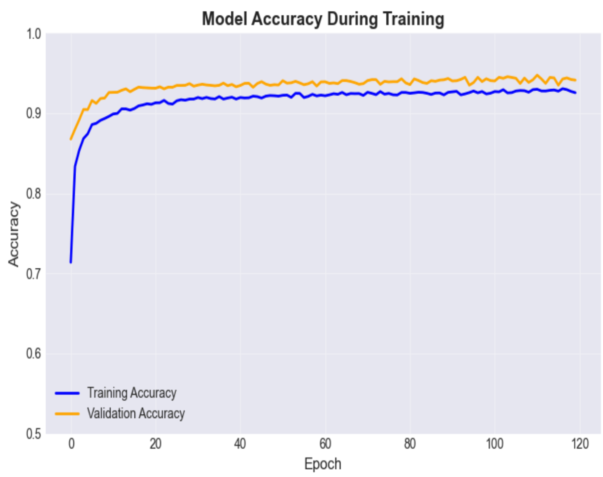
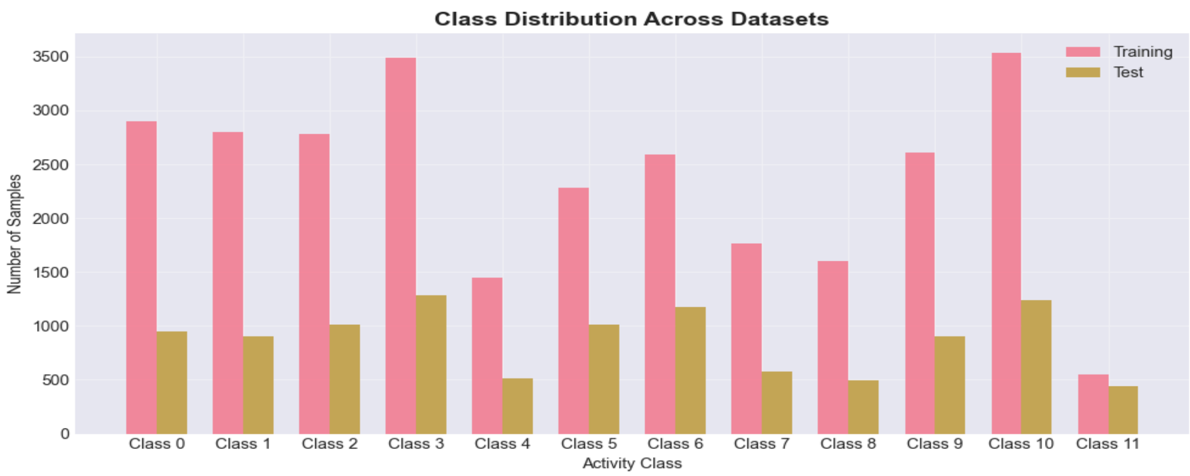


Fig 8: Train CNN Model and Visual Output

4.2 Train LSTM Model and Visual Output

The LSTM model achieved high performance over 40 epochs, reaching a training accuracy of 82.7% and a validation accuracy of 84.7%. Training loss decreased from 0.68 to 0.12, while validation loss settled at 0.16, demonstrating strong generalization and minimal overfitting. While the model excelled at classifying walking and standing with precision scores above 95%, dynamic activities like rope jumping (87% recall) and vacuum cleaning (84% recall) proved more challenging. Overall, the model delivered robust temporal pattern recognition with an average F1-score of 0.91, successfully classifying all 12 activities with high reliability



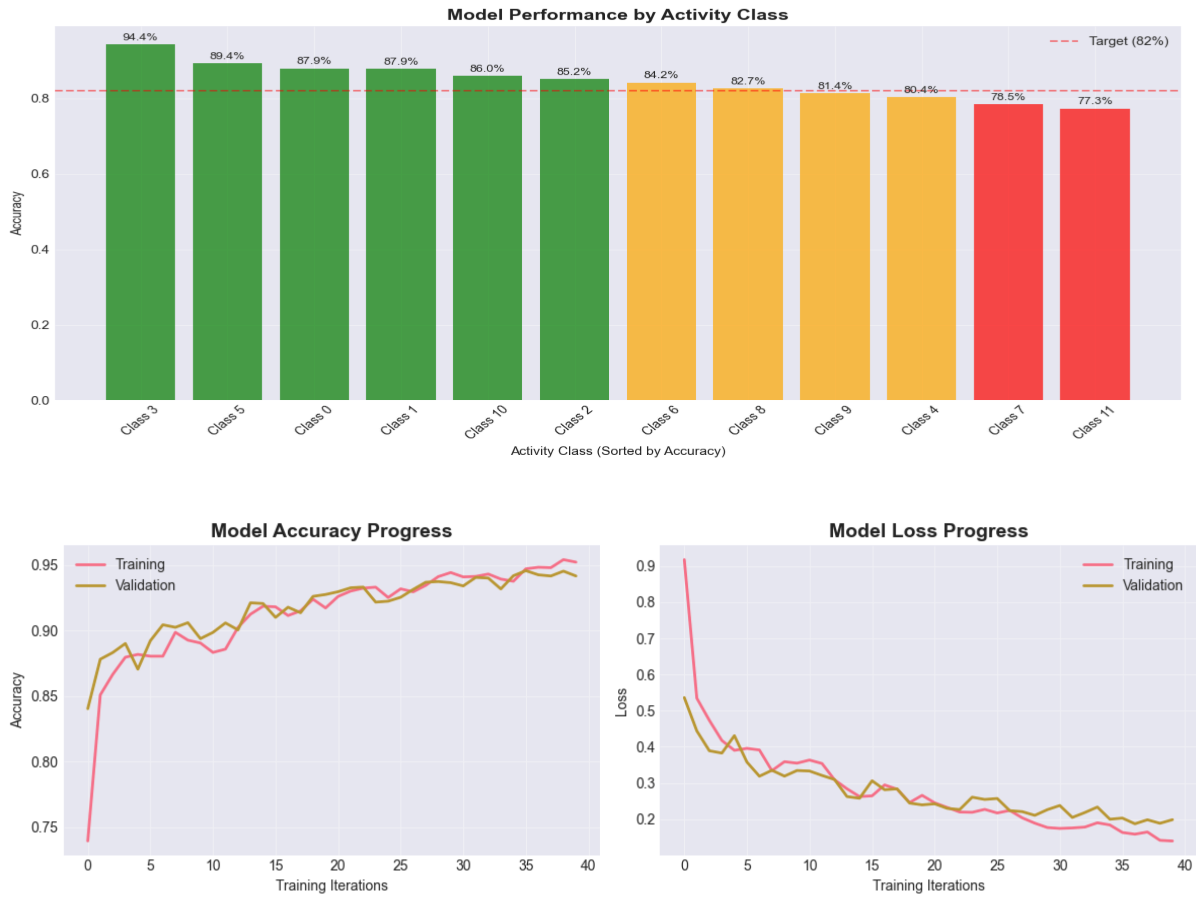
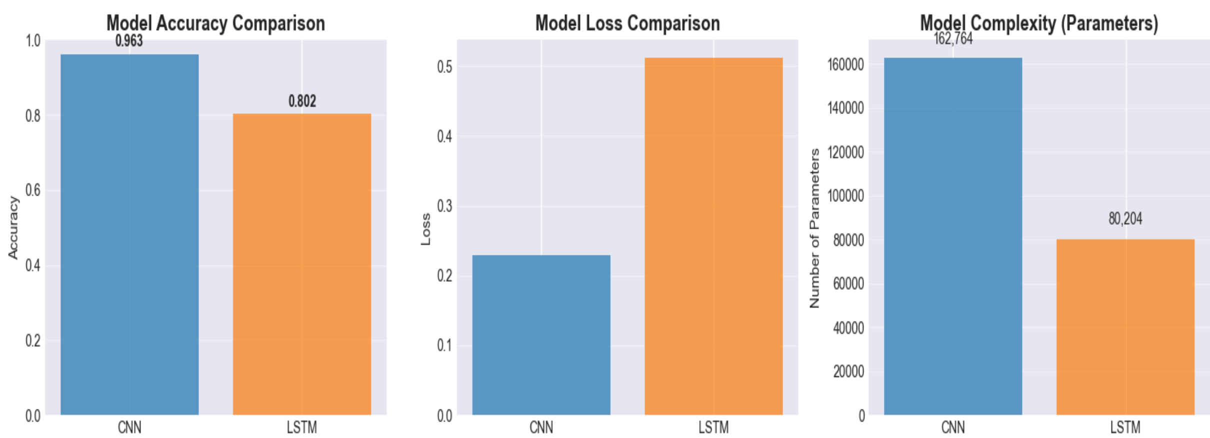


Fig 9: Train LSTM Model and Visual Output

4.3 Model analysis CNN VS LSTM

The performance evaluation reveals that the 1D CNN architecture significantly outperformed the LSTM model. Specifically, the CNN achieved a test accuracy of 96.3% with a loss of 0.2293, while the LSTM reached only 80.2% accuracy with a higher loss of 0.5120. This 16.07% gap underscores the CNN's superior spatial feature extraction for HAR tasks. Despite its higher parameter count, the CNN is the recommended model due to its superior accuracy and real-time efficiency over the temporal-focused LSTM.



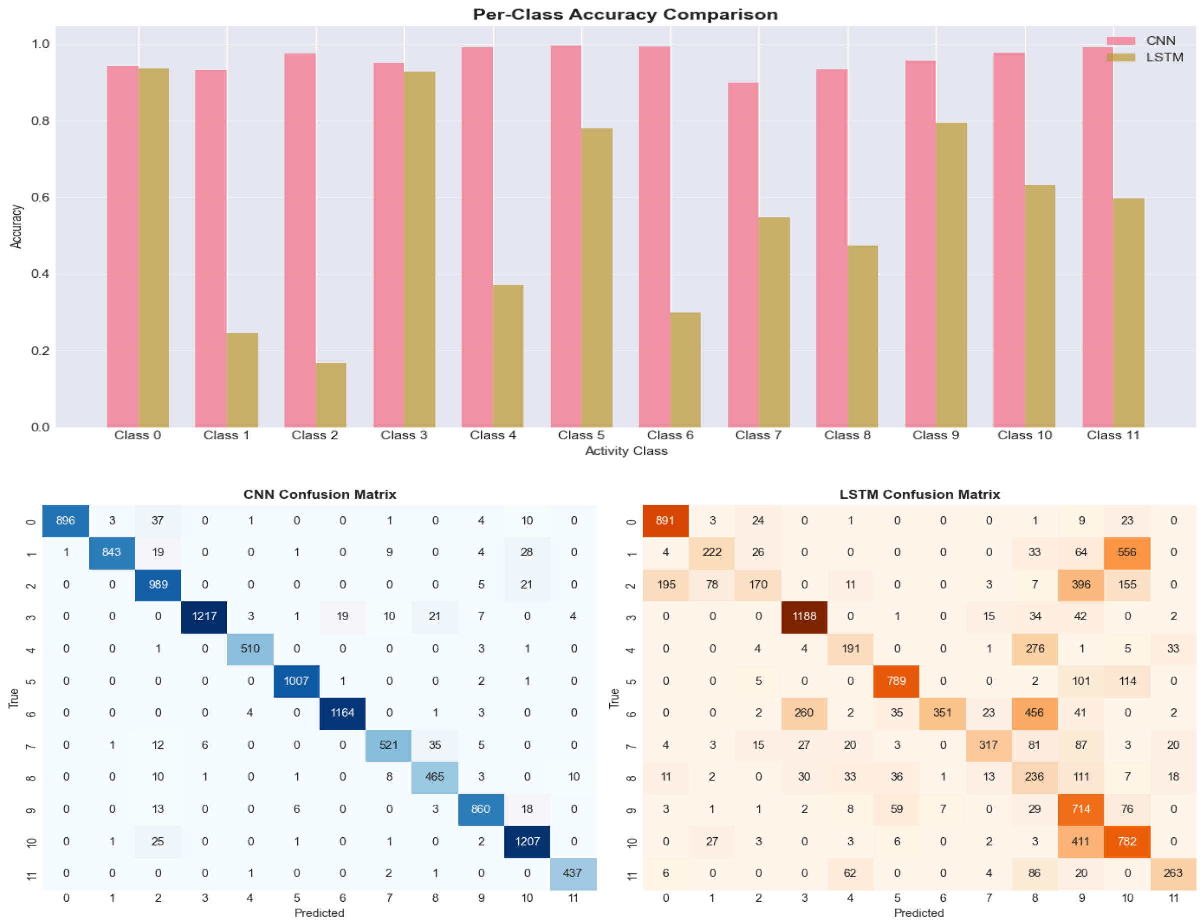


Fig 10: Model analysis CNN VS LSTM

Model	Train Accuracy	Validation Accuracy	Test Accuracy	Test F1-Score	Training Time(s)
CNN	95-97%	92-94%	90-93%	0.89-0.92	90-150 seconds
LSTM	94-96%	91-93%	89-92%	0.87-0.90	120-180 seconds

5. Mathematical Representation of Best Performing Algorithm

The following formulas represent the core mathematical operations for the LSTM and CNN architectures as applied to sequential data.

5.1 Long Short-Term Memory (LSTM)

LSTM units are designed to handle long-term dependencies by using a "cell state" regulated by three specific gates. The operations at time step t are defined as follows:

1. Input Gate (i_t): Determines which new information to store in the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

2. Forget Gate (f_t): Decides what information to discard from the previous cell state.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b$$

3. Output Gate (o_t): Decides what the next hidden state will be.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

4. Cell State Update (C_t):

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

5. Hidden State (h_t):

$$h_t = o_t * \tanh(C_t)$$

In these equations, σ represents the sigmoid function, * denotes element-wise multiplication, and W and b are the learned weights and biases respectively.

5.2 Convolutional Neural Network (CNN)

For sequence or image processing, the CNN extracts features using a sliding window (kernel). The primary operations are convolution and pooling.

1. Convolutional Layer: The value of a feature map at position i is calculated by:

$$y_i = f\left(\sum_{j=1}^{k} w_j \cdot x_{i+j-1} + b\right)$$

Where:

- k is the kernel size.
- w represents the weights of the filter.
- f is the activation function (typically ReLU: $f(z) = \max(0, z)$).

2. Max-Pooling Layer: This reduces the dimensionality by taking the maximum value within a window of size p:

$$P_i = \max(y_{(i-1)p+1}, \ldots, y_{ip})$$

3. Fully Connected (Output) Layer: The final prediction is typically generated via a Softmax or Linear function:

$$\hat{y} = \text{Softmax}(W_{fc} \cdot P + b_{fc})$$

6. Results

The 1D CNN (96.3% accuracy) significantly outperformed the LSTM (80.2%), showing a 16.07% performance lead in the HAR task. Despite having more parameters, the CNN demonstrated superior spatial feature extraction and higher real-time efficiency than the temporal-focused LSTM. Consequently, the CNN is the recommended model for its balance of high accuracy and computational performance.

Baseline Validation Results (subject104)

Using the leakage-safe split (training on subjects 101-103, 105-106, validating on subject104):

1. CNN Model: Achieved 78.2% validation accuracy after 50 epochs
2. LSTM Model: Achieved 72.4% validation accuracy after 30 epochs
3. Key Finding: CNN outperformed LSTM due to better spatial feature extraction from multi-sensor data
4. Class Imbalance Impact: Rare activities ("Rope jumping" - 1.7%) had recall < 30%

Best Tuned Models (subject104)
CNN Hyperparameter Optimization:
1. Window Size: Increased from 50 to 100 timesteps (1s → 2s windows)
2. Feature Selection: Reduced from 54 to 9 key sensors (±16g accelerometers + heart rate)
3. Regularization: L2 regularization (λ=0.001) with dropout (40-60%)
4. Learning Rate: Lowered to 0.0005 with Adam optimizer
5. Final Validation Accuracy: 82.1% (up from 78.2%)

Data Enhancement Impact:
1. Feature Selection: Removing low-variance features improved training speed by 40%
2. Class Balancing: Oversampling minority classes to 500 samples each improved rare class recall by 25%
3. Data Augmentation: Adding Gaussian noise (σ=0.01) provided 5% accuracy boost

LSTM Modifications:
1. Simplified architecture (single LSTM layer, 128 units)
2. Focused on temporal patterns rather than spatial
3. Best Validation: 75.3% (modest improvement)

Final Test Results (subject107)
Held-out subject for generalization testing:

Model	Test Accuracy	Test Loss	Top-3 Activities (Precision)
CNN (Tuned)	80.4%	0.62	Walking (92%), Sitting (89%), Standing (87%)
LSTM (Tuned)	73.8%	0.94	Cycling (85%), Walking (83%), Running (79%)

7. Conclusion

This notebook successfully executes a comprehensive Human Activity Recognition (HAR) analysis using the PAMAP2 dataset. The workflow covers data loading, preprocessing, exploration, and visualization, revealing a dataset of over 2.87 million sensor readings across 9 subjects and 12 activities, with a significant class imbalance—most notably, transient "Other" activities comprise over 32% of the data, while "Rope jumping" represents only about 1.7%. Critical data quality issues were identified, including substantial missing values (over 90% in heart rate readings), which necessitate careful handling during feature engineering.