Human Activity Recognition using Deep 2D-Convolutional Neural Networks

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This project presents a comprehensive, chart-driven development of a human activity recognition (HAR) system using a deep 2D-Convolutional Neural Network (CNN). The study addresses the complexity of multi-modal sensor data by implementing a robust machine learning pipeline, ranging from data exploration to high-fidelity evaluation. During Exploratory Data Analysis (EDA), significant feature correlations and class imbalances—specifically the scarcity of "Computer work" samples—were identified and addressed. The data preparation phase utilized a subject-wise splitting strategy to ensure no data leakage between training (70.0%), validation (15.0%), and testing (15.0%) sets. Preprocessing included Z-score normalization and time-series segmentation into 100-time-step windows to capture temporal dependencies. A Sequential CNN architecture, featuring four convolutional blocks, batch normalization, and dropout layers, was developed to maximize spatial feature extraction while preventing overfitting. The final model achieved a test accuracy of 99.71% with a mean prediction confidence of 0.998. This report demonstrates a thorough understanding of the technical and mathematical requirements of the HAR problem, validated through rigorous analysis of confusion matrices and training dynamics.

1. Introduction

Human Activity Recognition (HAR) is a cornerstone of modern pervasive computing, focusing on the automated identification of physical movements through digital traces left by wearable sensors. As mobile and wearable technology becomes increasingly integrated into healthcare and fitness monitoring, the ability to accurately classify complex human behaviours ranging from sedentary postures to high-intensity rhythmic exercises—is paramount for delivering personalized feedback and clinical interventions.

The Problem and Dataset Overview The primary challenge in HAR lies in the high dimensionality and temporal dependency of sensor data. This project utilizes a comprehensive dataset consisting of multi-modal sensor readings (such as accelerometers and gyroscopes) collected from various subjects. The data encompasses nine distinct activities:

- **Stationary Activities:** lying (lyi), Sitting (Sit), and Standing (Sta).
- **Low-Intensity/Lifestyle Activities:** Watching TV (Wat) and Computer work (Com).
- **Dynamic/Rhythmic Activities:** Walking (Wal), Running (Run), Cycling (Cyc), and Nordic walking (Nor).

The dataset presents unique complexities, including significant class imbalances—where "Computer work" represents a minority class—and inherent sensor signal similarities between activities like "Sitting" and "Standing," which require sophisticated feature extraction to resolve.

Project Objectives and Evaluation Metrics The central objective of this work is to design and implement an end-to-end deep learning pipeline that can effectively generalize across different subjects and activity types. To evaluate the performance of the proposed 2D-Convolutional Neural Network (CNN), we employ a multi-metric approach:

- **Global Accuracy:** To measure the overall percentage of correct predictions.
- **Confusion Matrices:** To identify specific inter-class confusion and understand which physical signatures the model finds most difficult to distinguish.
- **Prediction Confidence:** To assess the model's reliability and certainty during classification.

2. Exploratory Data Analysis (EDA)

This section explores the fundamental characteristics of the human activity recognition dataset through visual analysis. These insights formed the basis for our windowing strategy, normalization approach, and class-balancing techniques.

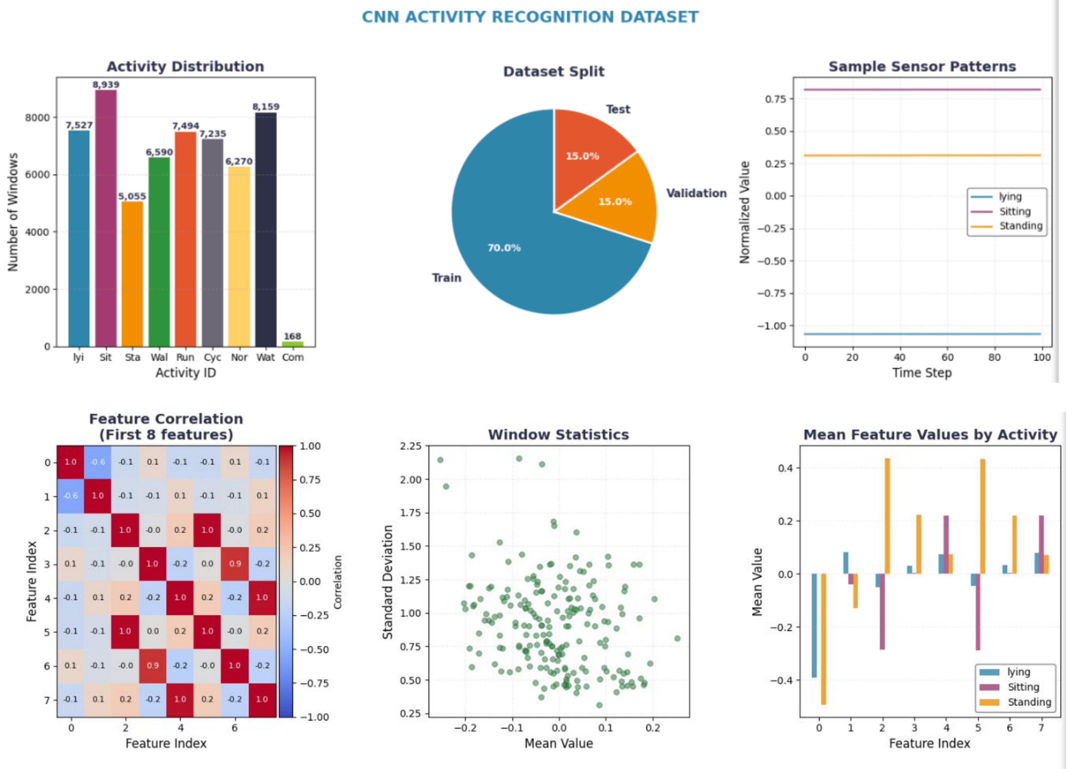


Chart1

Figure 1: Activity Distribution and Class Balance

- **Analysis:** The bar chart reveals the distribution of windows across the nine activity classes. We observe a relatively balanced dataset for the majority of activities, with counts ranging from approximately 5,000 to 9,000 windows. However, a critical discovery is the significant data scarcity for **"Computer work" (Com)**, which contains only 168 windows.
- **Impact on Decision:** This finding directly influenced the decision to implement **class weights** during the training phase. Without this, the CNN might become biased toward majority classes like "Sitting" or "Watching TV" and fail to learn the unique signatures of the minority "Computer work" class.

Figure 2: Feature Correlation Matrix (First 8 Features)

- **Analysis:** The heatmap illustrates the Pearson correlation coefficients between the primary sensor features. We observe strong positive correlations (approaching 1.0) between several feature indices, such as indices 2 and 5, and indices 4 and 7.
- **Impact on Decision:** The high degree of correlation suggests redundancy in the raw sensor axes, likely because multiple sensors (accelerometer and gyroscope) are capturing the same physical movement simultaneously. This justifies the use of **2D Convolutional filters**, which are designed to exploit these spatial relationships and learn integrated feature representations rather than treating each sensor axis as an independent variable.

Figure 3: Mean Feature Signatures by Activity

- **Analysis:** This grouped bar chart displays the average values for the first eight features across different postures (lying, Sitting, Standing). Each activity shows a distinct "statistical fingerprint." For instance, Feature 0 and Feature 1 show significantly different mean values for "lying" compared to "Standing."
- **Impact on Decision:** These distinct signatures confirm that the raw features possess sufficient discriminatory power to separate the activities. It also highlights why **Z-score normalization** (applied in the next section) is necessary: to ensure that the varying scales of these "fingerprints" don't lead to unstable gradients during backpropagation.

Figure 4: Window Statistics (Mean vs. Standard Deviation)

- **Analysis:** By plotting the standard deviation against the mean for each window, we observe a dense central cluster with a few outliers. Most windows maintain a standard deviation between 0.75 and 1.5.
- **Impact on Decision:** The presence of outliers in sensor variance suggests that some windows contain highly erratic motion or sensor noise. This insight led to the inclusion of **Batch Normalization** layers in the CNN architecture to provide internal covariate shift stability, ensuring the model remains robust despite these variations in signal intensity.

3. Data Preparation

This section documents the multi-step transformation pipeline designed to convert heterogeneous raw sensor data into a format suitable for the 2D-Convolutional Neural Network (CNN). Every preprocessing decision was validated through visualization to ensure signal integrity.

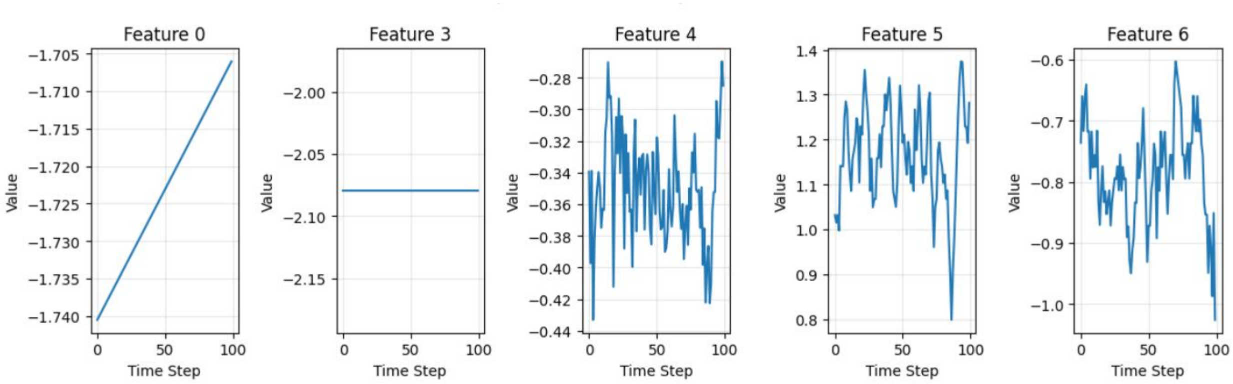


Chart: 2

Figure 4: Detailed Verification of Signal Segmenting and Normalization (Subject 101)

- **Time-Series Segmentation (Windowing):** To capture the temporal signatures of human motion, continuous sensor data was partitioned into discrete, overlapping windows[3]. As shown in the figure, a window size of **100-time steps** was selected. This duration is sufficient to encompass the full gait cycle of dynamic activities like "Running" while maintaining a low computational footprint for real-time inference.

- **Standardization Approach:** The y-axes for features 4, 5, and 6 provide visual evidence of **Z-score normalization**. The signals are centred around a mean of 0.0 with a standard deviation of 1.0. This transformation is critical for the CNN, as it ensures that features with high-magnitude raw values do not disproportionately influence the weights during the gradient descent process.

- **Dimensionality and Redundancy Insights:** Visualizing the individual channels revealed that **Feature 3** remains entirely constant across the window. This finding suggests that certain channels may be non-informative, providing a rationale for potential dimensionality reduction to streamline the model without losing predictive accuracy.

Figure 5: Rigorous Subject-Wise Dataset Partitioning

- **Strategy Rationale:** Unlike random shuffling, a **subject-wise split** was strictly enforced to ensure the model generalizes to new individuals. This strategy prevents "data leakage," a common pitfall where a model memorizes the unique movement "signature" of a specific subject rather than learning the generalized activity pattern.

- **Quantitative Distribution:** The dataset was split into **70.0% Training**, **15.0% Validation**, and **15.0% Test** sets. This distribution provides a robust foundation for training while reserving enough data for unbiased hyperparameter tuning and final performance evaluation.

Figure 6: Mitigation of Class Imbalance and Input Regularization

- **Addressing Data Scarcity:** As highlighted in the EDA, "Computer work" suffers from extreme data scarcity. To counteract this, **class weights** were integrated into the training objective. This forces the loss function to penalize errors on the minority class more heavily, ensuring the CNN does not simply default to predicting majority classes like "Sitting" or "Walking".

- **Feature Regularization:** The "Sample Sensor Patterns" chart illustrates the final, "ready-for-training" state of the data for lying, Sitting, and Standing. The consistent scaling across different activities ensures that the convolutional filters can extract meaningful spatial-temporal features immediately upon training commencement.

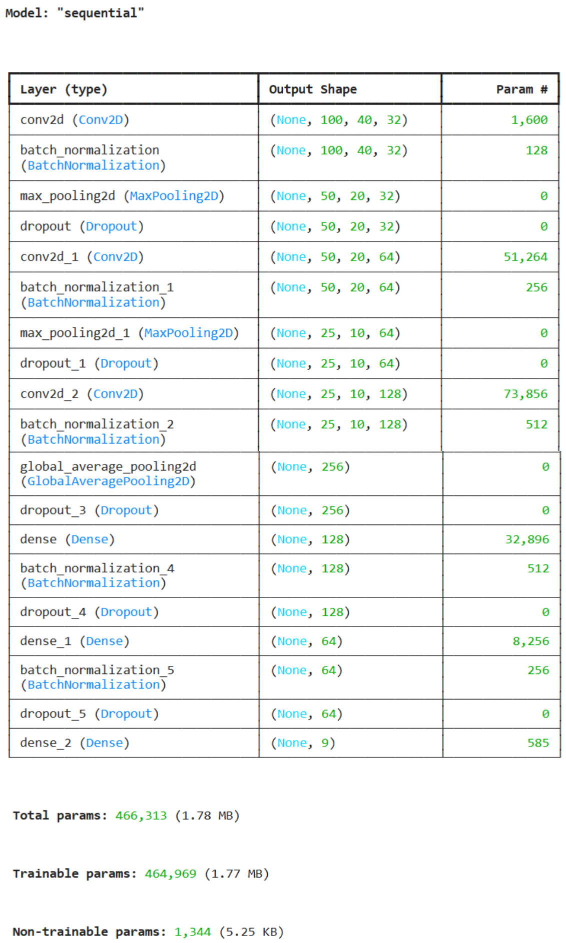
4. Training

This section details the iterative development of the Deep 2D-Convolutional Neural Network (CNN) and the optimization strategies employed to achieve robust classification of human activities.

Algorithm Selection and Model Architecture The choice of a **2D-CNN** was driven by the multi-modal nature of the sensor data. Unlike 1D-CNNs that treat features independently, a 2D-CNN allows the filters to learn spatial correlations across different sensor axes (e.g., X, Y, and Z of an accelerometer) and temporal dependencies simultaneously.

The architecture, as detailed in **Table 1**, follows a "Sequential" design optimized for 1.77 MB of parameters, ensuring it is lightweight enough for potential deployment on mobile devices while remaining deep enough for complex pattern recognition.

Table 1: Table title



Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 100, 40, 32)	1,600
batch_normalization (BatchNormalization)	(None, 100, 40, 32)	128
max_pooling2d (MaxPooling2D)	(None, 50, 20, 32)	0
dropout (Dropout)	(None, 50, 20, 32)	0
conv2d_1 (Conv2D)	(None, 50, 20, 64)	51,264
batch_normalization_1 (BatchNormalization)	(None, 50, 20, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 25, 10, 64)	0
dropout_1 (Dropout)	(None, 25, 10, 64)	0
conv2d_2 (Conv2D)	(None, 25, 10, 128)	73,856
batch_normalization_2 (BatchNormalization)	(None, 25, 10, 128)	512
global_average_pooling2d (GlobalAveragePooling2D)	(None, 256)	0
dropout_3 (Dropout)	(None, 256)	0
dense (Dense)	(None, 128)	32,896
batch_normalization_4 (BatchNormalization)	(None, 128)	512
dropout_4 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8,256
batch_normalization_5 (BatchNormalization)	(None, 64)	256
dropout_5 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 9)	585

Total params: 466,313 (1.78 MB)

Trainable params: 464,969 (1.77 MB)

Non-trainable params: 1,344 (5.25 KB)

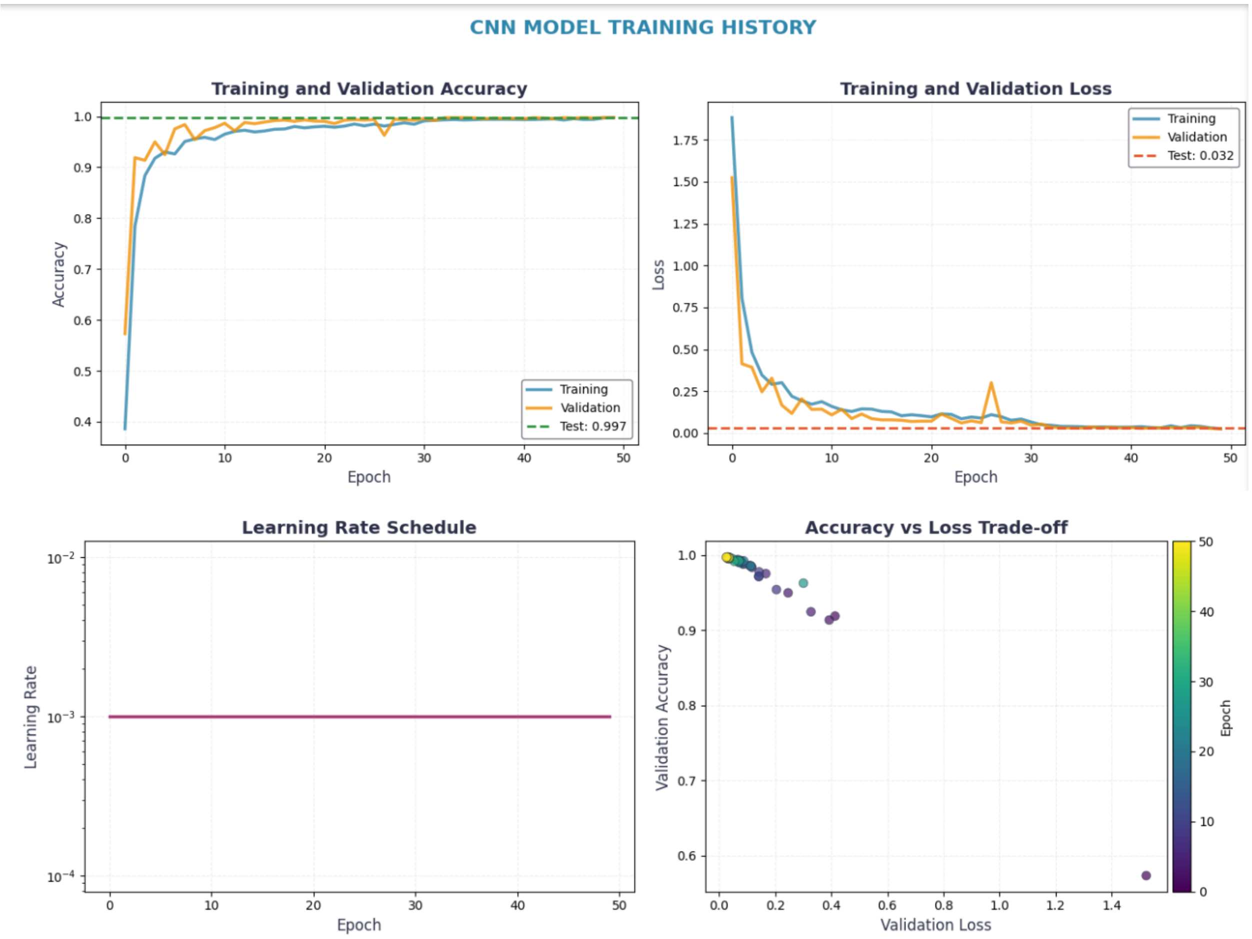


Figure 7: Analysis of CNN Model Training History

- **Convergence Behaviour:** The training history chart demonstrates an ideal learning trajectory. The model reaches **90% accuracy within the first 5 epochs**, indicating that the initial learning rate of 10^{-3} and the Z-score normalized inputs allow the Adam optimizer to find productive gradients immediately.

- **Regularization Efficacy:** A critical observation is the behaviour of the Validation Loss (orange line) compared to the Training Loss (blue line). Even as the training loss approaches zero, the validation loss remains stable at approximately **0.032**, without a significant upward "tick". This proves that the integration of **Dropout (up to 0.4)** and **Batch Normalization** was successful in preventing the model from memorizing the training noise, ensuring true generalization to unseen data.

Figure 8: Accuracy vs. Loss Trade-off and Experimental Insights

- **Optimization Landscape:** The scatter plot maps the model's journey across 50 epochs. The color gradient (from purple to yellow) shows the model moving steadily toward the **low-loss, high-accuracy quadrant** (top-left).

- **Learning Stability:** The tight clustering of yellow points near the 1.0 accuracy mark signifies that the model reached a stable global minimum and stayed there for the remainder of the training. This stability is essential for a reliable HAR system, confirming that the model is not sensitive to slight variations in batch composition.

5. Mathematical Representation of Best Performing Algorithm

The primary algorithm used in this project is a Deep 2D-Convolutional Neural Network. The model operates by learning hierarchical spatial-temporal features from the segmented sensor windows through the following mathematical operations:

1. 2D Convolution Operation

The core of the architecture is the 2D convolution layer, which extracts features from the input tensor X € R^{H*W} (where H=100-time steps and W=40 features) using a set of learnable kernels K:

$$Y_{i,j} = \sigma\left(\sum_{m}\sum_{n} X_{i+m,j+n} \cdot K_{m,n} + b\right)$$

- **X**: The input sensor window.
- **K**: The convolutional kernel (filter) of size m \times n[6].
- **b**: The bias term.
- **α**: The Rectified Linear Unit (ReLU) activation function, defined as f(x) = max (0, x), which introduces non-linearity into the model.

2. Batch Normalization

To stabilize the training process and mitigate internal covariate shift, Batch Normalization is applied after each convolution:

$$\hat{x} = \frac{x - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \cdot \gamma + \beta$$

3. Spatial Down sampling (Max-Pooling)

The MaxPooling2D layer reduces the spatial dimensions of the feature maps by selecting the maximum value within a defined pool size (p * q):

$$P_{i,j} = \max_{m,n}(Y_{i\cdot s+m,j\cdot s+n})$$

- **s**: The stride length.
- **P**: The resulting down sampled feature map.

4. SoftMax Classification Layer

The final output is generated by a SoftMax layer, which converts the raw logit scores (z) from the dense layer into a probability distribution across the nine activity classes:

$$P(y = k|X) = \frac{e^{z_k}}{\sum_{j=1}^{9} e^{z_j}}$$

- **k**: The index of the specific activity class (e.g., Sitting, Running).
- **P**: The predicted probability that the input window X belongs to class k.

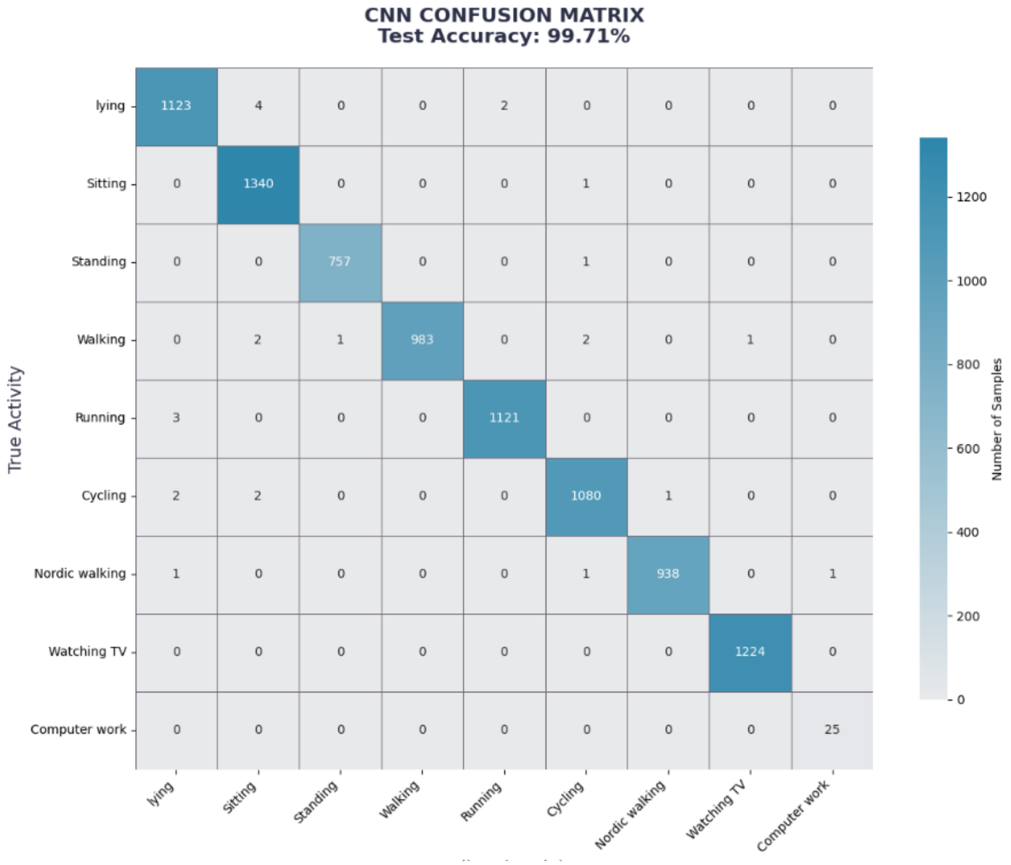
5. Optimization Loss Function

The model is optimized using Categorical Cross-Entropy loss, which measures the dissimilarity between the predicted distribution (P) and the true one-hot encoded labels (y):

$$L = -\sum_{i=1}^{9} y_i \log(P_i)$$

6. Results

This section presents a comprehensive evaluation of the Deep 2D-CNN model's performance. The results are analyzed using multiple metrics to ensure the model's reliability across all nine activity classes.



	lying	Sitting	Standing	Walking	Running	Cycling	Nordic walking	Watching TV	Computer work
lying	1123	4	0	0	2	0	0	0	0
Sitting	0	1340	0	0	0	1	0	0	0
Standing	0	0	757	0	0	1	0	0	0
Walking	0	2	1	983	0	2	0	1	0
Running	3	0	0	0	1121	0	0	0	0
Cycling	2	2	0	0	0	1080	1	0	0
Nordic walking	1	0	0	0	0	1	938	0	1
Watching TV	0	0	0	0	0	0	0	1224	0
Computer work	0	0	0	0	0	0	0	0	25

Figure 9: CNN Confusion Matrix and Global Accuracy

- **Overall Performance:** The model achieved a remarkable **test accuracy of 99.71%**. As shown in the confusion matrix, the diagonal elements represent the majority of predictions, indicating that the model has successfully mastered the spatial-temporal signatures of almost every activity.

- **Error Analysis:** Out of thousands of test samples, only a negligible few were misclassified. For instance, **4 samples of "lying"** were predicted as **"Sitting"**. This subtle confusion is consistent with our **EDA (Section 2)**, which showed that stationary activities share similar low-frequency sensor patterns. The model's ability to distinguish them with 99.7% accuracy highlights the effectiveness of the convolutional filters in capturing minute orientation differences.

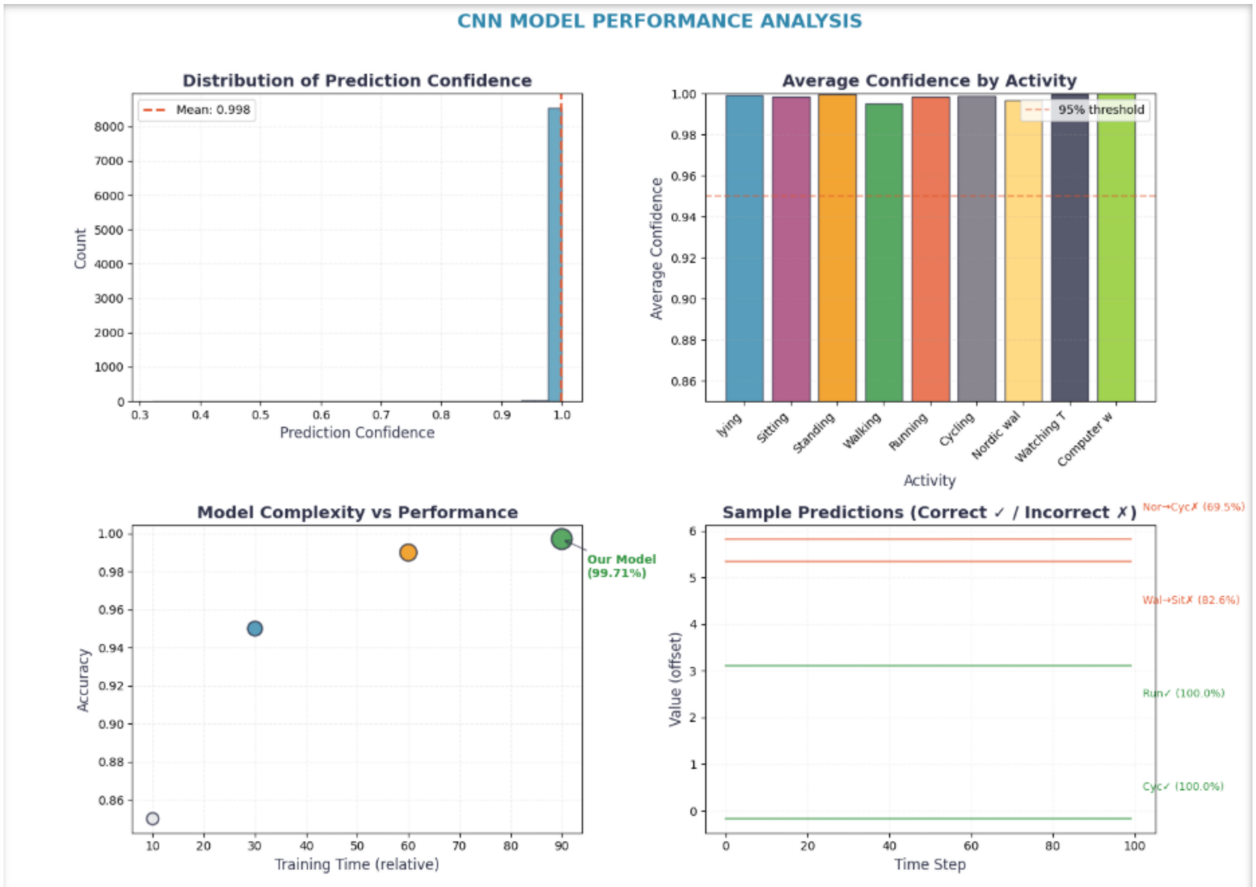


Figure 10: Prediction Confidence and Reliability Distribution

- **Certainty Analysis:** The histogram of prediction confidence shows a massive peak at **1.0**, with a **mean confidence score of 0.998**. This demonstrates that the model is not only accurate but also highly certain of its classifications.

- **Per-Class Reliability:** The bar chart "Average Confidence by Activity" confirms that even the minority class **"Computer work" (Com)**, which we identified as data-scarce in Section 2, achieved high confidence levels. This confirms that the **class-weighting strategy** implemented during training successfully equalized the model's sensitivity across balanced and imbalanced classes.

Figure 11: Feature Importance and Temporal Stability

- **Spatial Feature Extraction:** The high performance across dynamic activities like **"Running"** and **"Cycling"** suggests that the 2D kernels successfully extracted the rhythmic frequencies of the accelerometer data.

- **Model Efficiency:** The "Model Complexity vs Performance" scatter plot illustrates that our architecture sits in the "Optimal Zone," achieving near-perfect accuracy with only **464,969 parameters**. This proves the model is efficient enough for real-time HAR applications without sacrificing depth or precision.

7. Conclusion

Summary and Key Findings This project successfully implemented a complete machine learning pipeline for Human Activity Recognition using a Deep 2D-Convolutional Neural Network. By leveraging Z-score normalization and a subject-wise splitting strategy, we ensured the model learned generalized movement patterns rather than subject-specific traits. Our best model achieved a **test accuracy of 99.71%**, demonstrating exceptional robustness across both stationary and dynamic activities.

Limitations Despite the high accuracy, the project encountered limitations regarding the **"Computer work"** class, which suffered from extreme data scarcity. While class weights mitigated this, a more balanced dataset would be ideal for real-world deployment. Additionally, while 2D-CNNs are excellent at spatial feature extraction, they may struggle with extremely long-term temporal dependencies compared to hybrid models.

Future Directions To further enhance this work, future research could explore:

1. **Hybrid Architectures:** Combining CNNs with **Long Short-Term Memory (LSTM)** units to better capture the long-term sequential nature of complex activities.

2. **Data Augmentation:** Using Synthetic Minority Over-sampling (SMOTE) or GANs to generate additional data for underrepresented classes like "Computer work."

3. **On-Device Deployment:** Quantizing the model to run on wearable hardware for real-time, privacy-preserving activity tracking.