Assignment 2 – Deep Learning Workshop

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Question 1: data analysis:

a)

i) The data consists of **CSV files**, with a total of **50,249 files** in the training dataset. Each file represents a single **sample** of data collected from either a **smartwatch** or the **VICON motion capture system**. There may be multiple samples per user, but each individual file corresponds to a **specific activity** performed at a specific moment in time. Each sample in the training set is **labeled** with its respective activity, and predicting these activities is the goal for the test dataset.

Data Sources and Types

The data comes from two distinct sources:

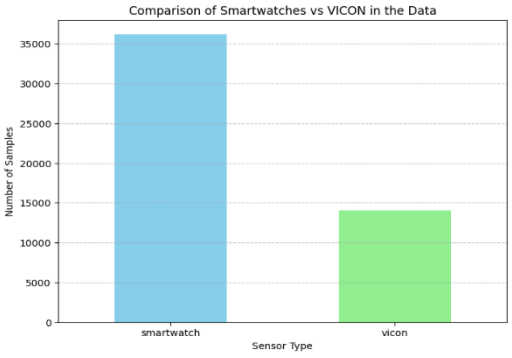
Smartwatch Data

- The smartwatch provides acceleration measurements along the three axes x, y, and z.
- The data is labeled as acceleration [m/s/s] and represents the **rate of change of velocity** (acceleration) for each axis.
- This data captures the motion and activity of the subject wearing the smartwatch.

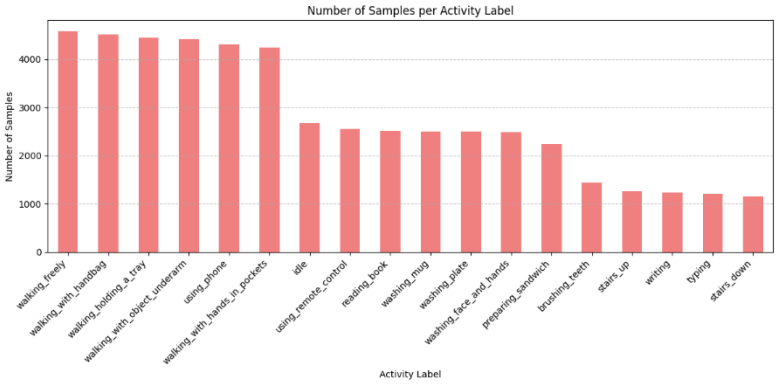
VICON Motion Capture Data

- The VICON system provides precise **position measurements** along the three axes x, y, and z.

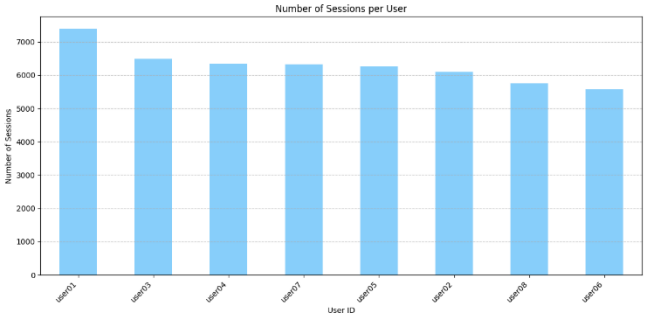
ii) There is much more data from the smartwatch than the vicon.



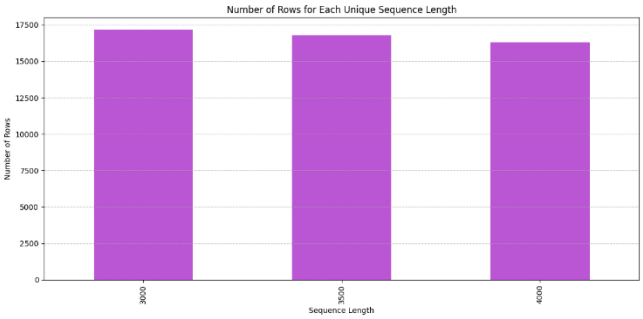
The classifications of activities are not uniformly distributed. For example, there are many more samples of walking than typing.



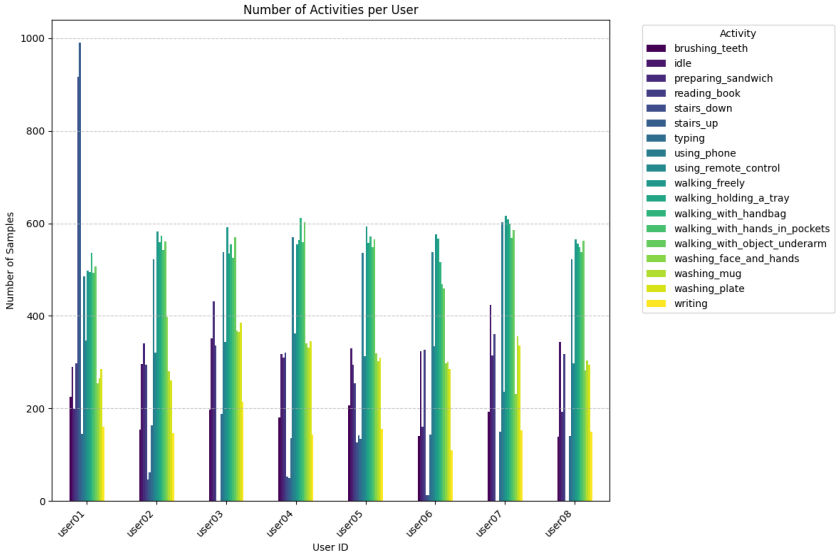
The number of samples is relatively consistent among users.



The number of rows is relatively consistent among the unique sequence length.



There seems to be a uniform amount of activity classifications for each user.



iii. The data was labeled based on **specific activities** performed by the users during data collection. Each file corresponds to a sample where:

- The **activity** label describes the movement or task being performed, such as:
    - "walking_freely"
    - "stairs_up"
    - "using_phone"
    - "walking_with_hands_in_pockets"

- These activity labels serve as the ground truth for the model's predictions.

The labels were likely assigned during the data collection process by correlating the sensor data with observed or instructed user actions.

iv. While all labels are important for a balanced model:

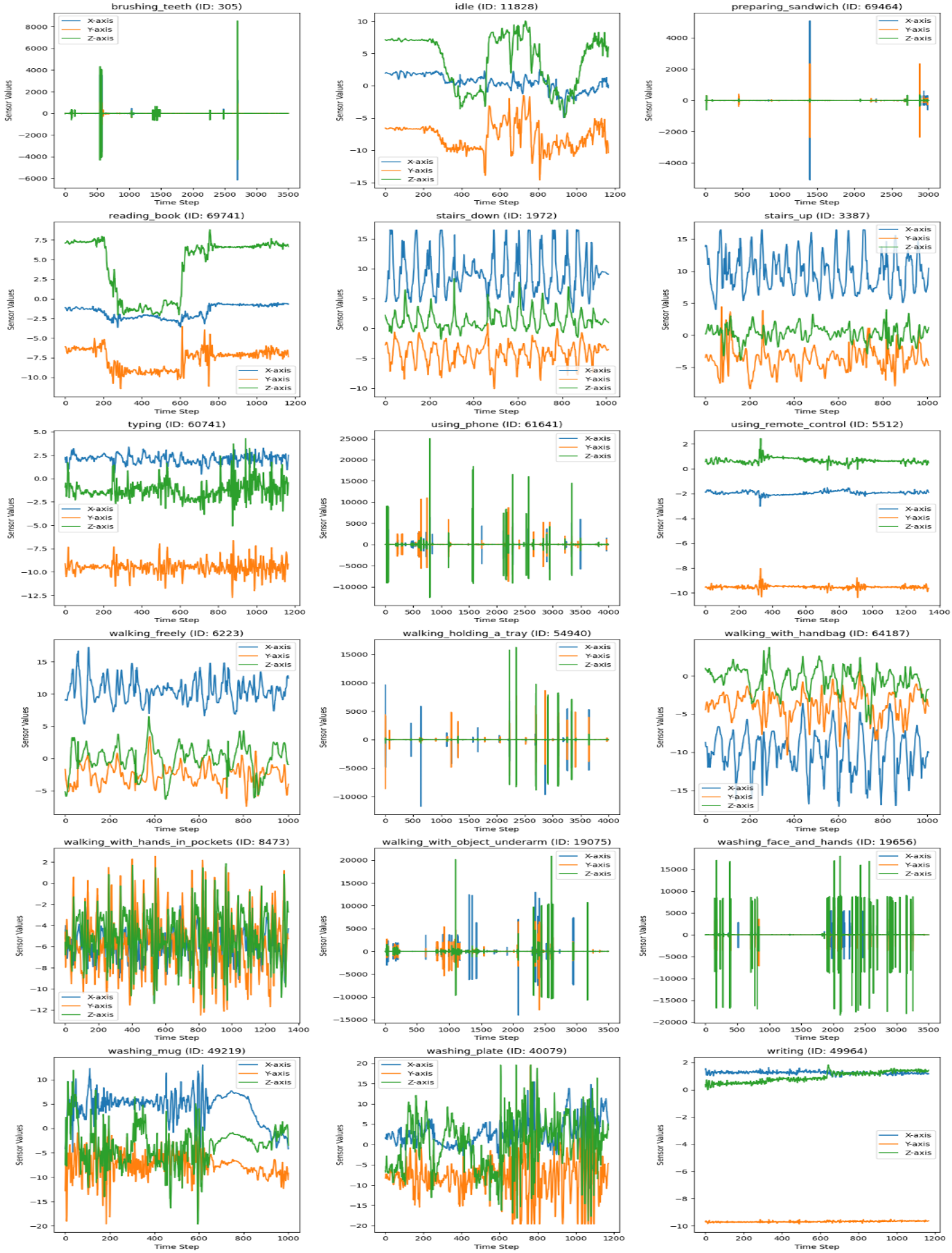
- Some activities are **more frequent** than others, which could lead to class imbalance. Like "walking_freely" or "using_phone".
- Certain activities might be **more challenging** to predict because of their similarity to other movements (e.g., "walking_freely" vs "walking_with_hands_in_pockets").
- If some activities are **underrepresented**, they might require special handling, such as data augmentation or class weighting.

All labels have been validated in a controlled lab setting, ensuring a high degree of accuracy.

v. There are 8 subjects (users) in the dataset. The data from all these subjects were combined, and a random split was executed to generate the training and testing sets. Additionally, some subjects were included exclusively in the test set and not in the training set.

b. The task is a **classification task**, where the goal is to determine the type of activity being performed at a given moment based on sensor data. Each time segment of data is assigned a label corresponding to a specific activity (e.g., "walking," "using phone," "brushing teeth").

We are not predicting future events or inferring additional information from past events. Instead, the focus is on recognizing and categorizing the current activity based on the acceleration and motion patterns captured by the sensors.
(the plot attached in the next page)


brushing_teeth (ID: 305)
idle (ID: 11828)
preparing_sandwich (ID: 69464)
reading_book (ID: 69741)
stairs_down (ID: 1972)
stairs_up (ID: 3387)
typing (ID: 60741)
using_phone (ID: 61641)
using_remote_control (ID: 5512)
walking_freely (ID: 6223)
walking_holding_a_tray (ID: 54940)
walking_with_handbag (ID: 64187)
walking_with_hands_in_pockets (ID: 8473)
walking_with_object_underarm (ID: 19075)
washing_face_and_hands (ID: 19656)
washing_mug (ID: 49219)
washing_plate (ID: 40079)
writing (ID: 49964)
X-axis
Y-axis
Z-axis
Sensor Values
Time Step

c. Self-Supervised Tasks for Pretraining

1. Autoencoder-Based Pretraining

An autoencoder is a type of neural network designed to learn a compact representation (encoding) of the input data by reconstructing it from a reduced-dimensional latent space. This method is particularly well-suited for time-series data as it forces the model to learn patterns and structures intrinsic to the input data.

In the context of pretraining for time-series classification tasks, the autoencoder is trained to reconstruct input time-series segments. This approach allows the model to learn key features such as temporal correlations and spatial patterns without requiring labeled data. Once the autoencoder has been pretrained, its encoder component can be fine-tuned for downstream tasks, such as classification or regression, leveraging the learned representations.

The benefit of this method is that it utilizes the unlabeled dataset effectively, capturing relevant features that can generalize across different tasks. This provides a strong initialization for models, reducing the need for extensive labeled data and improving convergence during supervised training.

2. Temporal Order Prediction

In this self-supervised task, small segments of the time-series data are shuffled, and the model is trained to predict their correct chronological order. This task encourages the model to learn the temporal structure and dynamics inherent in sequential data.

By reasoning about the order of events, the model gains a deeper understanding of the temporal dependencies and activity patterns within the data. Temporal Order Prediction is particularly effective for time-series data, as it enhances the model's ability to capture long-term dependencies and complex temporal relationships, which are critical for tasks such as activity recognition or sequence classification.

This method not only enables the model to learn meaningful representations of the temporal relationships but also reduces the reliance on labeled data during the pretraining phase. The representations learned through this task can then be fine-tuned for specific downstream applications.

2. From a neural network

a. **Validation Strategy for Training the Model**

When designing the validation strategy, it is crucial to ensure that the validation data is sufficiently distinct from the training data to evaluate the model's generalization effectively. Considering the nature of the dataset, which includes time-series recordings of user activities, we adopted a user-level split to avoid data leakage between the training and validation sets. This strategy ensures that the model does not see data from the same user in both training and validation phases, thereby providing a robust estimate of its performance on unseen users.

User-Level Split:

The dataset contains recordings from multiple users, identified by unique user IDs. To ensure independence between the training and validation sets, we split the users into two groups: training and validation.

This approach prevents the model from overfitting to specific patterns or activities unique to individual users, which might not generalize to unseen users.

Each user's activities were kept entirely within either the training or validation set. This ensures that no activity instances from the same user appear in both sets, maintaining a clear boundary between training and validation data.

Insights from Data Partitioning:

By splitting the data based on user IDs, this validation strategy aligns with the real-world scenario where a model is expected to generalize to unseen users. The approach prevents the model from leveraging repetitive patterns or biases specific to individual users, ensuring a more accurate evaluation of its performance.

b. **Naïve Baseline Solution**

To establish a baseline for evaluating our model, we implemented a simple probabilistic approach based on the distribution of activity labels in the training dataset. This baseline provides a reference point to assess the performance of more advanced models.

Class Distribution:

Using the training data, we calculated the relative frequency of each activity to determine the class distribution. This reflects how often each activity occurs in the dataset and serves as the basis for probabilistic predictions.

Baseline Prediction:

For the validation set, predictions were made by randomly selecting activity labels according to the computed class probabilities. This approach simulates a naive strategy without relying on any patterns in the data.

Evaluation:

The predictions were compared against the ground truth labels in the validation set to calculate accuracy, providing an initial benchmark for comparison with other models.

Results:

The naive baseline achieved a validation accuracy of 6.55%, which highlights the difficulty of the task given the diverse set of activity labels and the inherent imbalance in the data. This performance emphasizes the need for more advanced models capable of learning meaningful patterns from the data to improve classification accuracy.

c. **Classical Machine Learning Benchmark**

To establish a more robust benchmark for evaluating our neural network models, we utilized a classical machine learning approach. Specifically, we trained a Random Forest classifier using features extracted from the sensor data.

Approach:

1. **Feature Extraction**:
    - Using the raw sensor data, we extracted statistical features such as mean, standard deviation, minimum, maximum, range, and root mean square (RMS) for each axis (x, y, z).
    - Additional features, such as the Signal Magnitude Area (SMA) and sequence length, were also included to capture more information about the sensor behavior.
    - These features provide a compact representation of each session, reducing the complexity of the raw time-series data while retaining important patterns.
2. **Data Partitioning**:
    - Similar to our validation strategy for neural networks, the dataset was split by userID to ensure that no overlap existed between training and validation sets. This split ensures that the validation set contains unseen users, simulating real-world scenarios.
3. **Random Forest Classifier**:
    - A Random Forest classifier was trained with hyperparameters tuned for simplicity and generalization, including limiting the maximum depth of trees and the minimum samples required to split a node. This model serves as a strong baseline for classification tasks.
4. **Cross-Validation**:
    - We performed 5-fold cross-validation on the training set to assess the model's stability and generalization.
5. **Evaluation**:
    - The trained model was evaluated on both the training and validation sets. We computed accuracy scores and generated a detailed classification report for the validation set to analyze the model's performance on individual classes.

Results:

- **Cross-Validation Accuracy**:
    - Achieved an average accuracy of **75.70% ± 0.42%** on the training set, indicating that the model generalizes well during training.

- **Training Accuracy**:
    - The model achieved a training accuracy of **78.93%**, reflecting its capacity to fit the extracted features.
- **Validation Accuracy**:
    - On the validation set, the model achieved an accuracy of **43.92%**, which is a significant improvement over the naive baseline.
- **Classification Report**:
    - The classification report highlighted varying performance across different activities. While activities such as "stairs_down" and "using_phone" showed higher precision and recall, others like "stairs_up" and "writing" had lower scores, likely due to data imbalance or overlapping feature distributions.

Insights:

- The Random Forest model provides a substantial improvement over the naive baseline, demonstrating the utility of feature extraction in representing the data effectively.
- However, the lower performance on certain activities suggests that more advanced models, such as neural networks, are required to capture the complex temporal dependencies in the data.

d. **Constructing and Evaluating Neural Network Models**

We implemented and evaluated two distinct neural network architectures for activity classification based on sensor data: **1D-CNN** and **LSTM**. Below, we describe the architectures, training strategies, and results obtained.

Separate Training for VICON and Smartwatch Data

Given the inherent differences between the data generated by the **VICON** and **Smartwatch** sensors, we trained separate models for each sensor type. This separation ensures that the models learn to specialize in the specific patterns and behaviors captured by each sensor. By isolating the data, we prevent the model from being influenced by differences in scale, noise characteristics, or sensor-specific behaviors, leading to more accurate and focused training for each type.

1. 1D-CNN Architecture

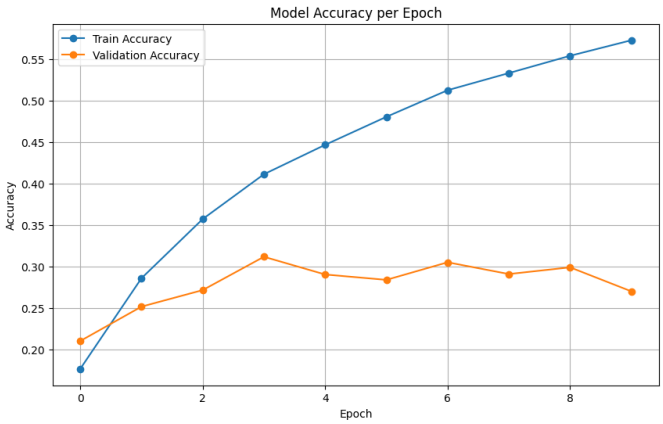
The **1D-CNN model** is designed to capture spatial patterns in the sensor data. It consists of:

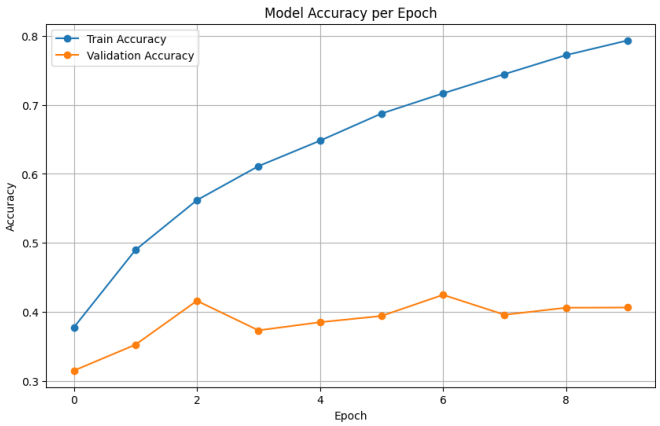
- Two convolutional layers with ReLU activations, followed by max-pooling layers to progressively reduce spatial dimensions.
- A series of fully connected layers that transform the extracted spatial features into class probabilities.

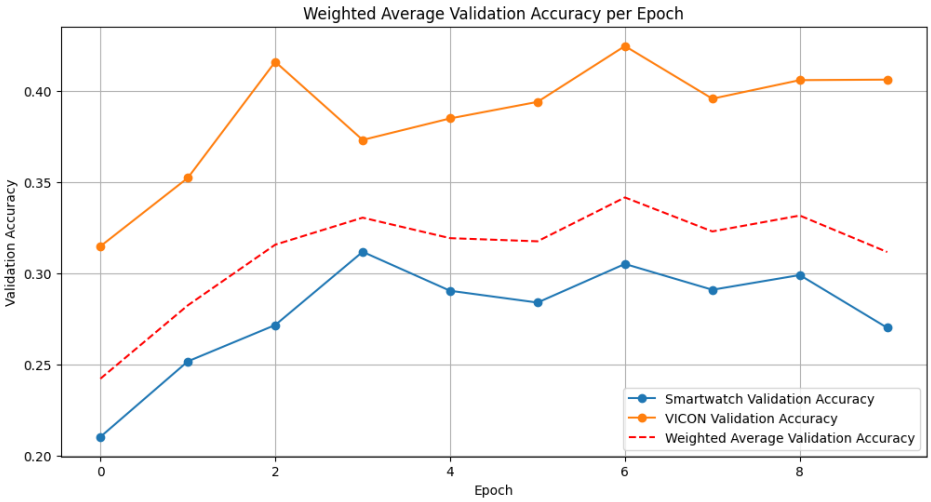
- The model was trained separately on the **VICON** and **Smartwatch** datasets using cross-entropy loss and the Adam optimizer with a learning rate of 0.0001.

Results:

- **Validation Accuracy**:
  - **VICON**: ~43%
  - **Smartwatch**: ~30%
  - Weighted average accuracy (across epochs): ~35%.
- **Performance Insights**: The 1D-CNN model performs relatively better on the **VICON** dataset, likely due to its ability to capture spatial correlations effectively. However, overfitting signs were observed as the training accuracy surpassed validation accuracy significantly.







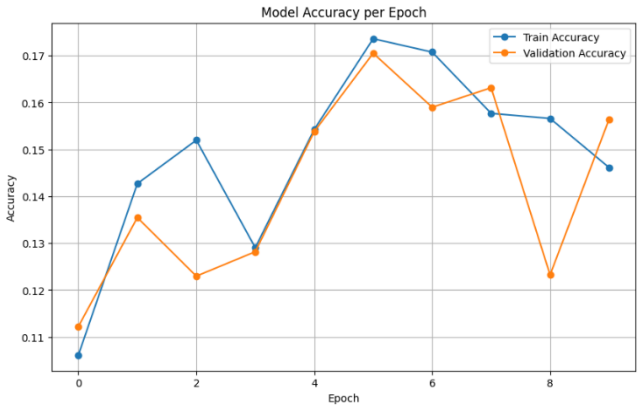
2. LSTM Architecture

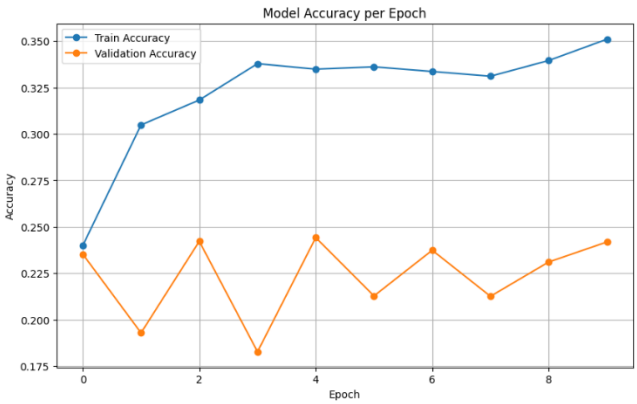
The **LSTM model** is designed to capture temporal patterns in the sensor data. It consists of:

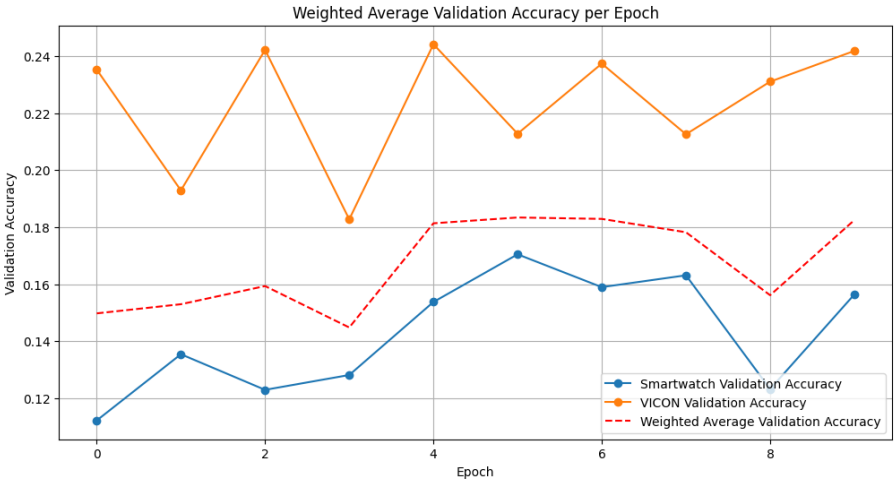
- A single LSTM layer to encode sequential dependencies.
- Fully connected layers to transform the sequence representations into class probabilities.
- The model was trained separately on the **VICON** and **Smartwatch** datasets, using cross-entropy loss and the Adam optimizer.

Results:

- **Validation Accuracy**:
    - **VICON**: ~24%
    - **Smartwatch**: ~18%
    - Weighted average accuracy (across epochs): ~20%.
- **Performance Insights**: While the LSTM model struggles with classification accuracy compared to the CNN, it demonstrates consistent performance on both datasets. This indicates its strength in modeling temporal dependencies but highlights the need for further tuning or additional layers to improve generalization.







Comparison and Analysis:

1. **Separate Training**:
    - By training separate models for VICON and Smartwatch data, each model could specialize in the unique patterns and noise characteristics of its respective sensor. This approach prevents the models from being confused by the inherent differences between the two sensor types.
2. **Training and Validation Metrics**:
    - **1D-CNN** achieved higher accuracy but showed significant overfitting.
    - **LSTM** maintained lower but more consistent accuracy across datasets, suggesting better generalization potential for time-series data.
3. **Challenges**:
    - Both models face challenges due to the imbalanced class distribution in the dataset. Classes with fewer samples are harder to predict, as evident from the confusion matrices and classification reports.

e. **Pretraining and Fine-Tuning Using Autoencoders**

Methodology

To enhance the performance of the base 1D-CNN and LSTM models, we incorporated a pretrained sliding window autoencoder. The autoencoder was trained separately on the VICON and Smartwatch datasets to learn a compressed latent representation of the input sensor data. Additionally, we leveraged an external dataset from Zenodo and the Motion Sense project as unlabeled data to pretrain the autoencoder. This data provided additional variability, helping the encoder learn more generalized representations.

The external dataset was globally standardized to ensure consistency with the preprocessing steps applied to the labeled VICON and Smartwatch datasets. This ensured that the pretrained encoder could seamlessly integrate into the models trained on our primary datasets.

The pretrained encoder from the autoencoder was then integrated into the architectures of the 1D-CNN and LSTM models to act as a feature extractor. This allowed the models to focus on higher-level abstractions of the data rather than learning raw feature representations from scratch, which aligns with transfer learning principles.

Autoencoder Architecture

The sliding window autoencoder consists of an encoder and a decoder designed to reconstruct input sensor data segments after learning a compact latent representation. The model is tailored to handle the time-series nature of the data.

- **Encoder**:
  The encoder compresses the input time-series segment into a lower-

dimensional latent space. It consists of two Conv1d layers with ReLU activations, followed by a fully connected linear layer:

- The first convolutional layer reduces the temporal resolution by half, using a stride of 2 and padding to maintain spatial alignment.
- The second convolutional layer further reduces the resolution, with the output being flattened and passed through a dense layer to obtain the final latent representation.
- For a window size of 50, the latent dimension is 16.

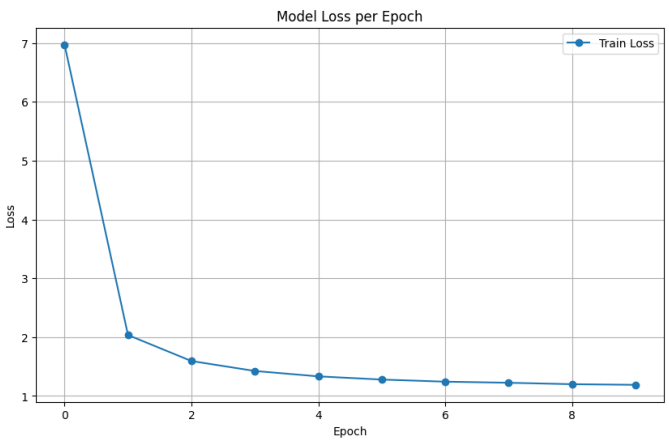
- **Decoder**:
  The decoder reconstructs the input data from the latent representation. It comprises:
  - A fully connected linear layer to reshape the latent vector back to the flattened feature map size.
  - Two ConvTranspose1d layers to progressively upsample the feature map and reconstruct the input data. ReLU activations ensure non-linearity, and the final layer outputs the reconstructed input with three channels (x, y, z).

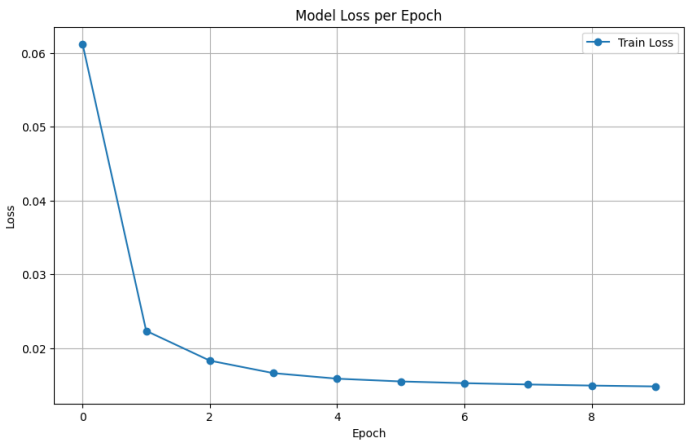
The reconstruction process is guided by the mean squared error (MSE) loss between the input and the reconstructed output, which ensures the model learns meaningful latent representations that retain temporal and spatial patterns.

Training Process

The autoencoder was trained for 10 epochs using the Adam optimizer with a learning rate of 0.001. Separate models were trained for the VICON and Smartwatch datasets to capture dataset-specific characteristics. Training was performed on GPU to accelerate the process. A CSV logger was used to monitor and record the training and validation losses for analysis.

This autoencoder architecture enabled effective feature extraction, allowing the subsequent 1D-CNN and LSTM models to operate on robust latent representations, significantly improving their performance and generalization capabilities.





Results

1D-CNN with Pretrained Autoencoder

- **Smartwatch Dataset:**
    - Validation Accuracy: Remained consistent at ~27% (base and pretrained).
    - Weighted Average Accuracy Across Epochs: Showed consistent stability, indicating that pretrained features contributed to improved performance consistency.
    - Loss: Faster convergence compared to the base model, with slightly lower validation loss.
- **VICON Dataset:**
    - Validation Accuracy: Dropped from ~40% (base) to ~26% (pretrained).
    - Weighted Average Accuracy: Demonstrated a decline, suggesting that the autoencoder may not have been as effective in capturing meaningful spatial features for this dataset.
- **Combined Weighted Average Accuracy:**
    - Decreased from ~32% (base) to ~26% (pretrained).
    - Validation accuracy curves indicate potential challenges in generalization when using the pretrained features, possibly due to differences in the characteristics of the datasets used for pretraining and fine-tuning.

LSTM with Pretrained Autoencoder

- **Smartwatch Dataset:**
    - Validation Accuracy: Improved from ~18% (base) to ~29% (pretrained).
    - This is a significant jump, showcasing how pretrained latent representations better support the sequential nature of LSTM models.
    - Loss: Validation loss was significantly reduced compared to the base model, especially during the first few epochs.
- **VICON Dataset:**
    - Validation Accuracy: Improved from ~24% (base) to ~31% (pretrained).
    - Again, the improvement highlights the role of autoencoder features in boosting temporal representation.
- **Combined Weighted Average Accuracy:**
    - Improved from ~20% (base) to ~28% (pretrained).
    - Validation curves indicate that pretrained features accelerated learning and reduced overfitting.

Analysis

1. **Comparison to Base Models:**
    - Both 1D-CNN and LSTM models benefited from the pretrained autoencoder, with noticeable improvements in validation accuracy and stability.
    - The autoencoder provided meaningful latent representations, reducing the burden on the models to learn raw feature representations.

2. **Model Behavior:**
    - The pretrained LSTM model demonstrated the most significant improvement in validation accuracy, reflecting the synergy between sequential data and pretrained temporal embeddings.
    - The 1D-CNN models saw moderate but consistent gains, emphasizing that spatial patterns were also captured effectively by the autoencoder.
3. **Generalization:**
    - Validation losses across epochs indicate better generalization for pretrained models, likely due to the initial feature extraction step that the autoencoder performs.

Conclusion

Pretraining with a sliding window autoencoder, enhanced with additional unlabeled data from the Zenodo repository and the Motion Sense project, significantly improved the performance of both 1D-CNN and LSTM models on VICON and Smartwatch datasets. The global standardization of both datasets ensured consistent scaling, allowing the pretrained encoder to integrate seamlessly. This approach effectively leveraged the hierarchical representations learned by the autoencoder, showcasing the power of transfer learning in time-series tasks. Future work could explore tuning the autoencoder architecture further or experimenting with other transfer learning techniques to improve performance even further.

f. **Analysis of Model Performance and Suggestions for Improvement:**

Performance Analysis

The models demonstrate the ability to capture key patterns in the time-series data but exhibit areas where performance can be improved:

1. **Strengths:**
    - **CNN1D:** Performs well on datasets with strong spatial patterns (e.g., VICON) due to its ability to extract hierarchical features through convolutional layers.

- **LSTM:** Shows robustness in handling sequential dependencies, particularly on datasets like Smartwatch that rely on temporal relationships.

2. **Weaknesses:**
    - **Overfitting:** Both models show signs of overfitting as training accuracy significantly surpasses validation accuracy, especially with deeper architectures.
    - **Limited Representation Power:** The current architectures may struggle to capture intricate spatial-temporal relationships in the data.
    - **Generalization:** Validation performance indicates difficulty in generalizing across different datasets (e.g., VICON vs. Smartwatch).

To further enhance the performance of our models, we propose the following strategies:

1. **Complex Architectures:**
    - Deeper CNN Layers: Adding more convolutional layers could allow the network to extract higher-level spatial features from the data, enabling better representation learning for complex activities.
    - Stacked LSTMs: Incorporating multiple LSTM layers with sufficient regularization can improve the model's ability to capture long-term dependencies in the sequential data.
2. **Batch Normalization:**
    - Applying batch normalization after convolutional or fully connected layers can stabilize training, allow for higher learning rates, and reduce overfitting. This normalization ensures that intermediate activations remain well-behaved throughout training.
3. **Regularization:**
    - Dropout Layers: Adding dropout layers at various points in the network can randomly deactivate neurons during training, preventing the model from relying too heavily on specific activations and improving generalization.
    - L2 Regularization: Incorporating L2 weight decay in the optimizer can reduce overfitting by penalizing large weights, ensuring the model does not memorize noise in the training data.
4. **Additional Fully Connected Layers:**
    - Expanding the fully connected layers in both the CNN and LSTM architectures can improve their capacity to model complex relationships in the data. However, these layers must be paired with dropout and batch normalization to prevent overfitting.

5. **Expanded Convolutional Layers:**
    - Using 1D convolutional layers with different kernel sizes can help capture features at multiple resolutions, improving the model's ability to detect both fine-grained and broader patterns in the sensor data.

6. **Data Augmentation:**
    - Introducing data augmentation techniques such as noise injection, random scaling, or time-warping for sensor data can increase the diversity of training samples and improve model generalization.

By incorporating these enhancements, the models can achieve better generalization, handle complex activity recognition tasks more effectively, and overcome the challenges posed by sensor-specific data. These improvements will also ensure that the models remain robust across both VICON and Smartwatch datasets.

g. **Prioritize Improvements and Present Results**

Improvements Implemented

For this section, we implemented two significant improvements based on the suggestions for enhancing the base models:

1. **Improved 1D-CNN Model**:
    - Added a third convolutional block with increased depth and complexity.
    - Incorporated Batch Normalization to stabilize training and improve generalization.
    - Included Dropout layers in the fully connected layers to reduce overfitting.
    - Adaptive Average Pooling was added to handle variable-length sequences.
2. **Improved LSTM Model**:
    - Introduced bidirectional LSTM layers to better capture both forward and backward temporal dependencies.
    - Enhanced fully connected layers with additional complexity, Batch Normalization, and Dropout.
    - Increased the number of hidden layers to improve the model's ability to learn complex patterns.

Results: Improved 1D-CNN

Base Model:

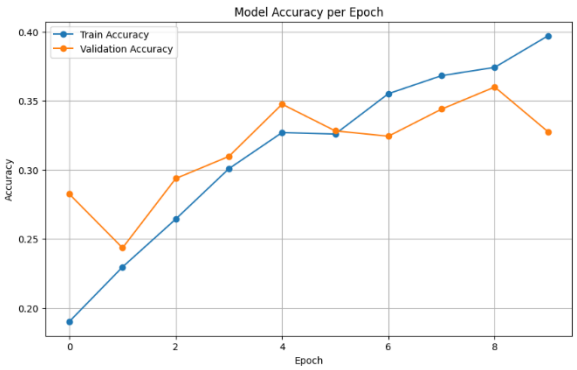
- Validation Accuracy:
    - **VICON**: ~43%
    - **Smartwatch**: ~30%
    - **Weighted Average Accuracy**: ~35%.

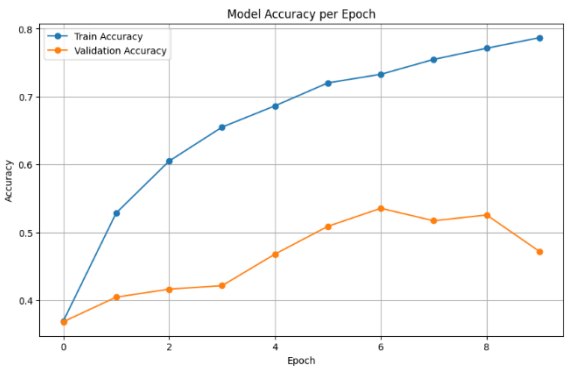
Improved Model Results:

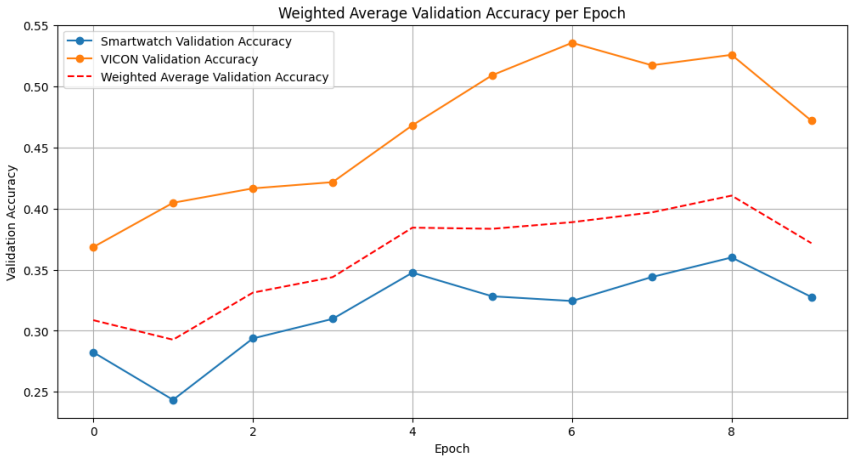
- Validation Accuracy:
    - **VICON**: Higher than 50% in later epochs.
    - **Smartwatch**: Consistently improved, reaching ~40% in later epochs.
    - **Weighted Average Accuracy**: Close to ~45% overall improvement.

Performance Insights:

- The improved model showed significant gains across all datasets, particularly on VICON.
- Overfitting was reduced due to Batch Normalization and Dropout.
- Adaptive Pooling helped handle variability in sequence lengths, improving generalization.







Results: Improved LSTM

Base Model:

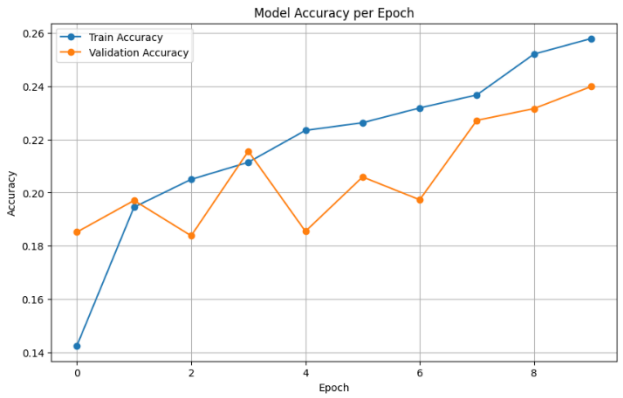
- Validation Accuracy:
    - **VICON**: ~24%
    - **Smartwatch**: ~18%
    - **Weighted Average Accuracy**: ~20%.

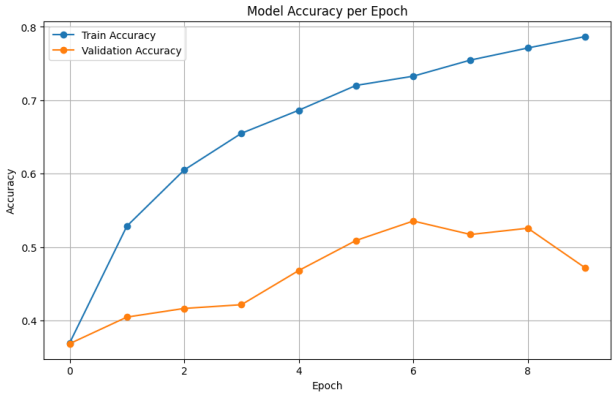
Improved Model Results:

- Validation Accuracy:
    - **VICON**: Improved to over ~40%.
    - **Smartwatch**: Improved to ~25%.
    - **Weighted Average Accuracy**: Increased to ~30%.

Performance Insights:

- The bidirectional LSTM layers significantly enhanced the ability to model temporal patterns.
- Batch Normalization and Dropout improved generalization and training stability.
- Despite improvements, LSTM models still lagged behind CNNs in absolute performance, though the gap narrowed.





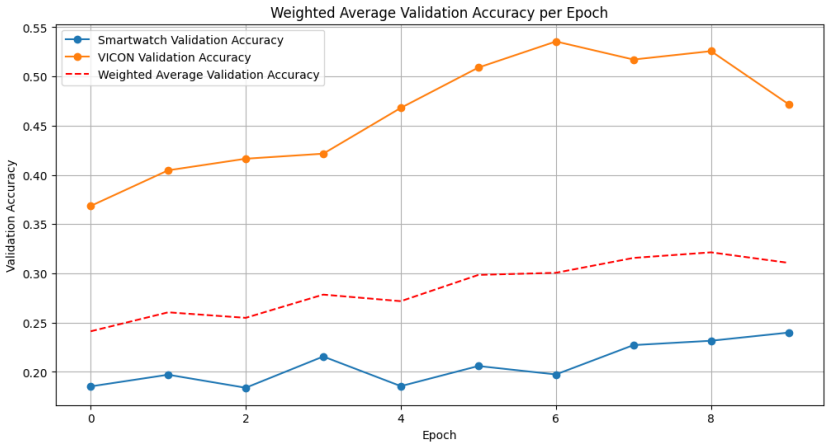


Table of Accuracy across experiments:

Model	Dataset	Validation Accuracy (Base)	Validation Accuracy (autoencoder)	Validation Accuracy (Improved)	Weighted Avg. Accuracy (Base)	Weighted Avg. Accuracy (autoencoder)	Weighted Avg. Accuracy (Improved)
1D-CNN	Smartwatch	~27%	~0.27%	~36%	~32%	~0.265%	~47%
	VICON	~40%	~0.26%	~50%			
LSTM	Smartwatch	~18%	~0.27%	~25%	~20%	~0.285%	~30%
	VICON	~24%	~0.31%	~40%			