Human Pose Estimation Using Wi-Fi Signals

Wireless Network Final Project

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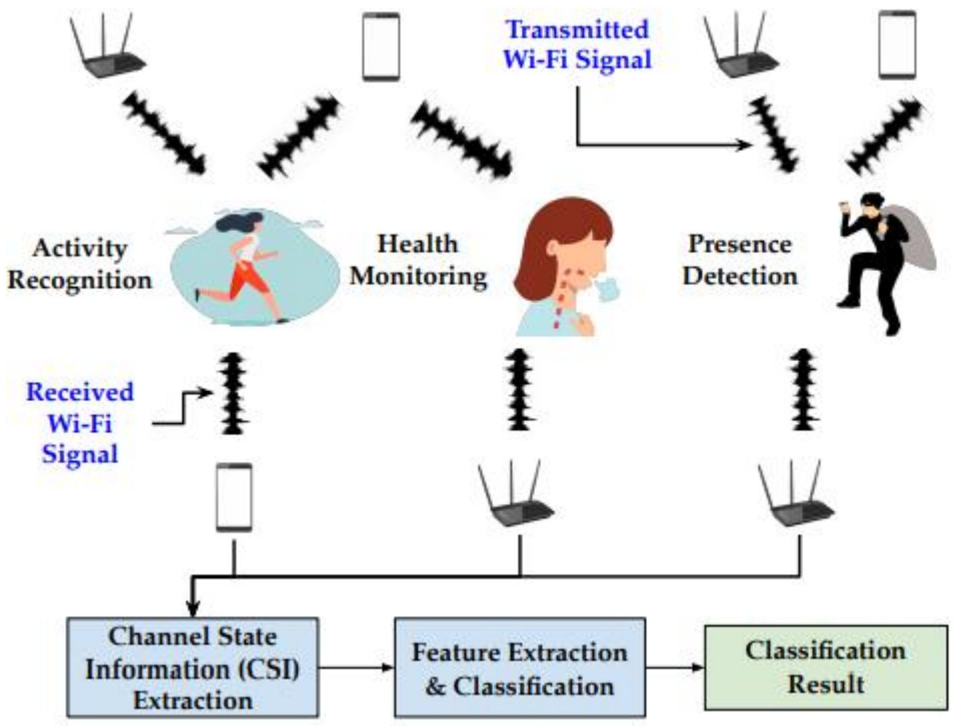
Motivation

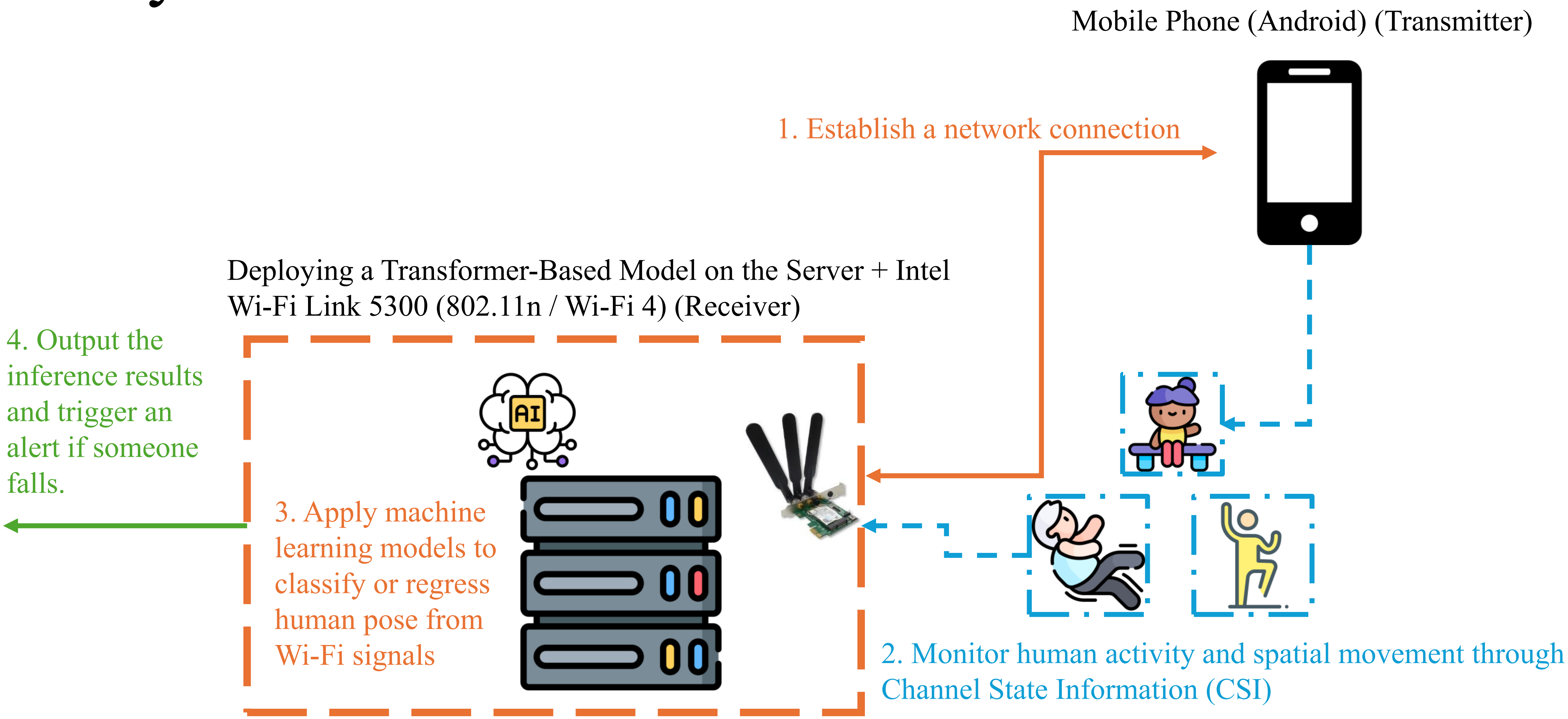
- **Human pose estimation** is essential for a wide range of applications, including healthcare monitoring, smart environments, and human-computer interaction. However, conventional approaches—such as camera-based systems and wearable sensors—pose challenges in terms of privacy, deployment complexity, and usability.
- **Wi-Fi sensing** has recently emerged as a promising alternative by leveraging Channel State Information (CSI) to infer human motion in a non-intrusive and privacy-friendly manner. This technology works even under poor lighting or visual occlusion. Motivated by these advantages, this project aims to experimentally investigate the feasibility and effectiveness of using Wi-Fi sensing for human pose estimation in indoor environments.



Objectives

- Integrate Wi-Fi sensing modules into human-centric indoor environments
- Monitor human activity and spatial movement through Channel State Information (CSI)
- Collect CSI data synchronized with pose labels for supervised learning
- Apply machine learning models to classify or regress human pose from Wi-Fi signals
- Analyze the separability of different poses in CSI feature space
- Demonstrate Wi-Fi sensing as a privacy-preserving alternative to vision-based pose estimation

System Architecture



Hardware Specification

- Intel Wi-Fi Link 5300 + 2x antenna (Rx)
  - Pros: Cheap. Well-established in the research community; widely adopted as the standard experimental platform in numerous studies on localization, sensing, and human activity recognition.

  - Cons: Only supports up to Wi-Fi 4. Requires custom driver installation and is limited to specific Linux kernel versions. Not suitable for high-performance transmission; primarily used as a receiver in CSI experiments. Uses Mini PCIe interface, which is mostly supported only by older laptops or desktop systems.

Hardware Specification

- Mobile Phone realme GT Neo2 5G (Tx)
  - Enable hotspot and cannot set a password.
  - The mobile phone typically acts as the **Wi-Fi transmitter (Tx)**, periodically sending packets that are received by the Intel 5300 for CSI collection.

  This allows the system to remain device-free on the user side, leveraging ambient Wi-Fi signals from commonly available devices.

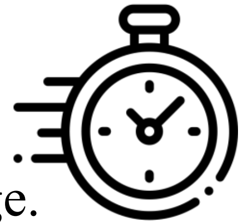
Hardware Specification

- Server (Just a normal, old PC)
  - Ubuntu 14.04.1 + kernel 3.14.04-24
  - Deploy Transformer-based model to classify or regress human pose from collected CSI data.

Challenges: System Setup for Intel 5300

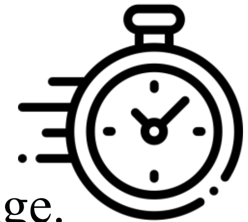
- Setting up the Intel 5300 Network Interface Card (NIC) for CSI extraction posed significant challenges. The process required downgrading the Linux kernel, compiling and installing modified drivers, and ensuring compatibility with the CSI Tool. Due to the outdated hardware and lack of official support, substantial time was spent troubleshooting driver issues, kernel mismatches, and dependency problems. This setup complexity highlighted the trade-off between using a mature CSI tool and the burden of legacy hardware integration.

Solved. We spent roughly 50 % of our time solving this challenge.



Challenges: Model Training and Data Collection

- After investing significant time in model training using publicly available CSI datasets (collected with 3-antenna configurations), we encountered a critical issue: the dataset format did not align with the data captured from our own hardware setup, which only supports 2 antennas. This mismatch in antenna dimensions and CSI matrix structure led to poor model inference performance and unreliable pose estimation. To address this, we had to design and execute our own data collection pipeline for both training and testing. This process was time-consuming, as it required synchronizing CSI recording with pose labeling, ensuring data quality, and capturing sufficient variation across poses and users to enable effective learning.



Unsolved (Data collection in progress). We spent roughly 40 % of our time solving this challenge.

Model Training & Inference

Trans CSI data to .npy format for model training and inference.

```python
file_path = "csi.dat"
output_npy = "test_csi.npy"
rx, tx = 0, 0
window = 100  # sliding window size

# 讀取資料
reader = get_reader(file_path)
csi_data = reader.read_file(file_path, scaled=True)
csi_matrix, total_frames, total_subcarriers = csitools.get_CSI(csi_data, metric="amplitude")

# 取指定 Rx/Tx 組合
csi_amp = csi_matrix[:, :, rx, tx]  # shape: (frames, subcarrier)

# sliding window 組成 sample
X = []
for i in range(len(csi_amp) - window + 1):
    X.append(csi_amp[i:i+window])  # shape: (window, subc)
X = np.array(X)  # shape: (N, window, subc)

# reshape for model: (N, 1, window, subc)
X = X[:, np.newaxis, :, :]  # e.g. (N, 1, 100, 30)

# 儲存
np.save(output_npy, X)
print(f"✅ Saved CSI data for model: shape = {X.shape} → {output_npy}")
```

Model Training & Inference

Pretrained model on open dataset then inference on our data.

```
[Epoch 30] Accuracy: 0.9803, Loss: 0.063770
[Epoch 31] Accuracy: 0.9844, Loss: 0.043479
[Epoch 32] Accuracy: 0.9869, Loss: 0.036912
[Epoch 33] Accuracy: 0.9874, Loss: 0.032232
[Epoch 34] Accuracy: 0.9753, Loss: 0.084749
[Epoch 35] Accuracy: 0.9889, Loss: 0.037285
[Epoch 36] Accuracy: 0.9839, Loss: 0.052290
[Epoch 37] Accuracy: 0.9856, Loss: 0.035581
[Epoch 38] Accuracy: 0.9914, Loss: 0.027260
[Epoch 39] Accuracy: 0.9922, Loss: 0.020241
[Epoch 40] Accuracy: 0.9904, Loss: 0.026504
```

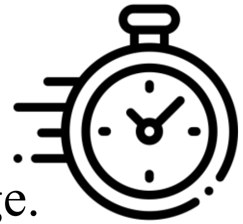
Inference Result:

```
[Frame 258] Predicted Label: 6
[Frame 259] Predicted Label: 6
[Frame 260] Predicted Label: 6
[Frame 261] Predicted Label: 6
[Frame 262] Predicted Label: 6
```

Challenges: Visualizing CSI

- Visualizing CSI data proved to be a non-trivial task due to its complex, high-dimensional, and noisy nature. Raw CSI matrices contain amplitude and phase information across multiple subcarriers and antenna pairs, often affected by noise, hardware imperfections, and environmental dynamics. To make the data interpretable, significant preprocessing was required. Selecting appropriate visualization techniques (e.g., heatmaps, temporal plots, or dimensionality reduction methods) also posed a challenge, especially when trying to link patterns in CSI to human motion in a meaningful way.

Solved. We spent roughly 10 % of our time solving this challenge.



Visualization Results

https://drive.google.com/file/d/1_4aJNXTiRjTQMFSXXXPvOBNLUoe6FdIQ/view?usp=sharing

Future Works

- The current experiment is still in progress, and several key components are planned for future development:

1. **Completion of high-quality CSI data collection** along with accurate pose label annotation to ensure reliable model training and evaluation.
2. **Model training and real-time inference demonstration**, showcasing the system's ability to estimate human poses based on live Wi-Fi signals.
3. **Development of a mobile or web-based application** that enables remote monitoring and real-time alerting in case of abnormal postures or dangerous events.

Thanks for Listening

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