Wi-Fi Based Gesture Recognition: Leveraging RSSI Data for Privacy-Preserving Interaction

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ABSTRACT

- **Problem**:
  - Traditional gesture recognition systems rely on specialized sensors or cameras, which can be costly, intrusive, and pose privacy concerns.
  - There is a need for a non-intrusive, privacy-preserving, and cost-effective gesture recognition system.
- **Approach**:
  - Leverage Wi-Fi Received Signal Strength Indicator (RSSI) data, collected using standard Wi-Fi hardware, to detect and classify human gestures.
  - Train NN models on RSSI data, incorporating environmental variables like distance, walls, and connected devices for robust performance.
- **Key Contributions**:
  - Demonstrated the feasibility of gesture recognition using RSSI data without the need for cameras or specialized hardware.
  - Achieved promising accuracy in identifying gestures such as **swipes, waves, push and claps** under diverse environmental conditions.
  - Highlighted potential applications in smart homes, healthcare monitoring, and human-computer interaction.

INTRODUCTION

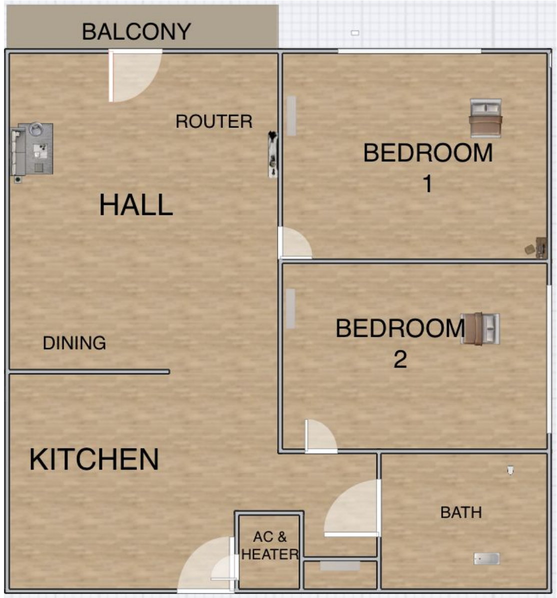
Gesture recognition is a growing field in human-computer interaction, yet traditional methods rely on costly and intrusive sensors. This research introduces a novel approach using Wi-Fi Received Signal Strength Indicator (RSSI) data to recognize gestures. The system leverages existing Wi-Fi infrastructure, providing a cost-effective and privacy-preserving solution.

OBJECTIVE

- **Primary Goal**: To develop a privacy-preserving gesture recognition system leveraging Wi-Fi Received Signal Strength Indicator (RSSI) data.
- **Key Features**:
  - Non-intrusive recognition using standard Wi-Fi hardware.
  - Elimination of specialized sensors or cameras for gesture detection.
- **Challenges Addressed**:
  - Environmental variability: accounting for distance, obstructions, and connected devices.
  - Real-time gesture classification using machine learning techniques.
- **Applications**:
  - Smart homes and healthcare monitoring.
  - Human-computer interaction in private and obstructed spaces.

Setup

- The gesture recognition system was tested in a residential flat to simulate real-world conditions.
- The flat included two bedrooms, a kitchen, a bathroom, a hall, and a connected balcony.
- The Wi-Fi router was centrally placed in the hall for optimal signal coverage.
- Gestures were performed in three zones: close proximity (1–2 meters, direct line of sight), intermediate zones (up to 10 meters with walls obstructing the signal), and the balcony (partial signal due to open environment).
- This setup allowed testing under various distances and obstructions, providing a robust performance assessment.



DATASET OVERVIEW

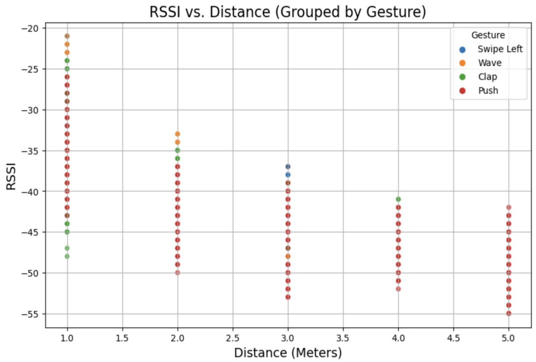
Key Details:

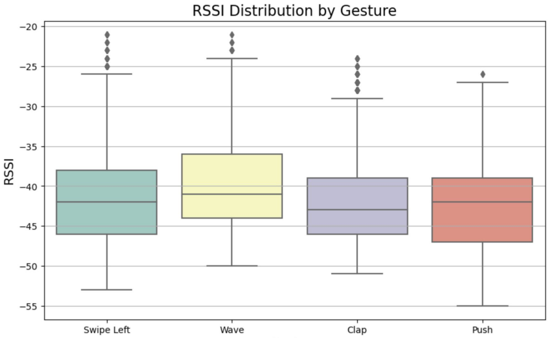
- **Purpose**: To analyze variations in Received Signal Strength Indicator (RSSI) data caused by human gestures and environmental factors (e.g., distance, obstructions, and connected devices). This analysis aims to extract meaningful patterns for developing a gesture recognition system that is both privacy-preserving and cost-effective.
- **Dataset Attributes**:
  - **RSSI**: Measures signal strength; key for detecting gesture-induced variations.
  - **Gesture**: Represents the action performed (e.g., "Swipe Left"); target for classification.
  - **Distance**: Physical separation between source and receiver; impacts signal strength.
  - **Walls**: Number of obstructions; affects signal attenuation.
  - **Connected Devices**: Influences signal variability and noise.
  - **Timestamp**: Organizes data trends over time.

Attribute	Type	Example Value
Timestamp	Datetime	2024-12-11 10:00
RSSI	Float	-45.7
Gesture	Categorical	Swipe Left
Distance (meters)	Float	3.0
Walls (#)	Integer	2

EXPLORATORY DATA ANALYSIS(EDA)ON RSSI DATA

- **No Missing Values**:
  - The dataset has no missing values, ensuring data consistency for analysis.
- **Key Trends**:
  - **RSSI Distribution**: Stable and concentrated around typical ranges, indicating robust signal quality.
  - **Gesture Patterns**: Significant RSSI variation across gestures; distinct patterns for gestures like "Swipe Left" and "Clap" (highlight boxplot insights).
  - **Environmental Impact**:
    - Clear negative correlation between distance and RSSI.
    - Obstructions (walls) and higher connected devices lead to weaker signals.





EXPLORATORY DATA ANALYSIS(EDA)ON RSSI DATA

- **Insights**:
  - RSSI values weaken with increasing distance, obstructions, and connected devices.
  - Gesture-specific RSSI patterns support reliable gesture classification.
  - Over-representation of the **"Swipe Left"** gesture in the dataset.
- **Implications for Modeling**:
  - Balancing the dataset for fair predictive performance.
  - Addressing outliers and anomalies to enhance robustness.
  - Refining preprocessing steps to leverage RSSI insights effectively.

METHODOLOGY

- The system collects RSSI data using a MacBook's Wifi interface in three gesture zones (proximity, intermediate, and balcony).
- A Gesture GRU(RNN) model, designed with 4 fully connected layers, processes the data.
- Hyperparameter tuning like “Early stopping”.
- Findings: why GRU is Better than CNN

ARCHITECTURE

Input Data

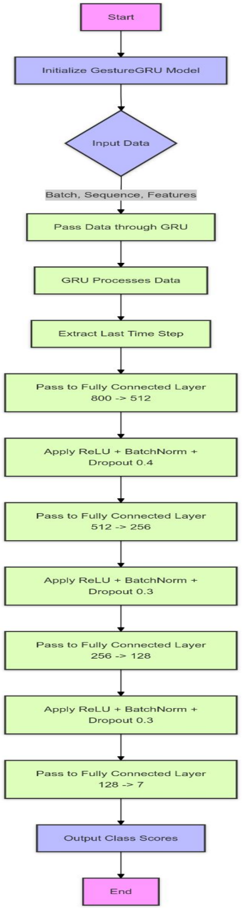
- The input to the model consists of features like:
    - **RSSI**, **connected devices**, **distance in meters**, and **number of walls**.
- The input is preprocessed into batches and sequences of features for sequential processing.

GRU Layer

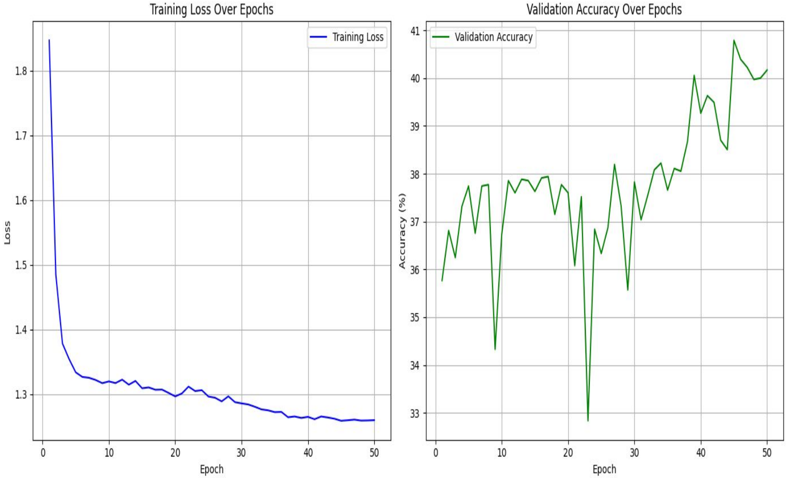
- The sequential data is passed through a **bidirectional GRU layer**:
    - **Hidden Size**: 400 neurons.
    - **Layers**: 5 stacked GRU layers for deep sequential feature extraction.
    - **Bidirectional**: Captures both forward and backward temporal dependencies.

Fully Connected Layers

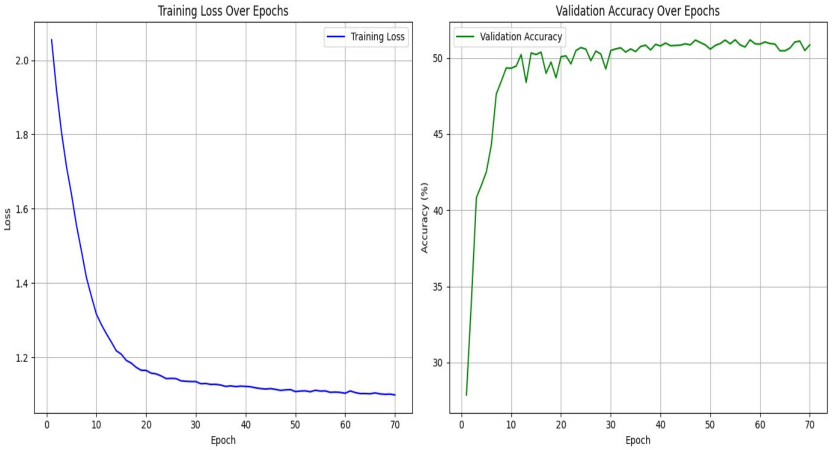
1. **Layer 1 (800 → 512)**
2. **Layer 2 (512 → 256)**
3. **Layer 3 (256 → 128)**
4. **Layer 4 (128 → 7)**



RESULTS



CNN



Gesture GRU(GATED RECURRENT UNIT)

RESULTS

Results Analysis

- **Gesture_CNN Performance**:
  - Achieved **43.42% training accuracy** and **43.42% validation accuracy**.
  - Indicates minimal overfitting but limited learning capacity for the task.
- **Gesture_GRU Performance**:
  - Achieved **49.45% training accuracy** and **51.24% validation accuracy**.
  - Demonstrates better learning capability and generalization compared to CNN.

MODELS	TRAINING ACCURACY	VALIDATION ACCURACY	Epoch
GESTURE_CNN	43.42	43.42	40
GESTURE_GRU	49.45	51.24	600

DEMO

[DEMO1]

[DEMO2]

FUTURE WORK

- More interactive Web application
- Work on better accuracy and performance

THANK YOU