

HUMAN ACTIVITY RECOGNITION USING **FEDERATED LEARNING**

GUIDE: PROF. RAJA S. P.

TEAM MEMBERS

GOKULESHWARAN N [20BCI0031]

SOLOMON ABHILASH MARTIN [20BCE0638]

PRADYUMN TENDULKAR [20BCE0762]





TABLE OF CONTENTS

- | | |
|-----------------------|----|
| • Introduction | 01 |
| • Applications | 02 |
| • About the Dataset | 03 |
| • FL Architecture | 04 |
| • System Architecture | 05 |
| • Model Architecture | 06 |



INTRODUCTION

UNLOCKING THE POTENTIAL OF SMARTPHONES, THIS PROJECT FOCUSES ON HUMAN ACTIVITY RECOGNITION-A VITAL TECHNOLOGY FOR HEALTH MONITORING AND ELDER CARE SUPPORT. BY LEVERAGING SMARTPHONE SENSORS, THE SYSTEM AUTOMATES TASKS LIKE REHABILITATION ASSISTANCE. INNOVATIVE METHODS LIKE ACTIVE LEARNING STREAMLINE TRAINING, ENHANCING ACCURACY WITH MINIMAL USER INPUT.



APPLICATIONS

Healthcare

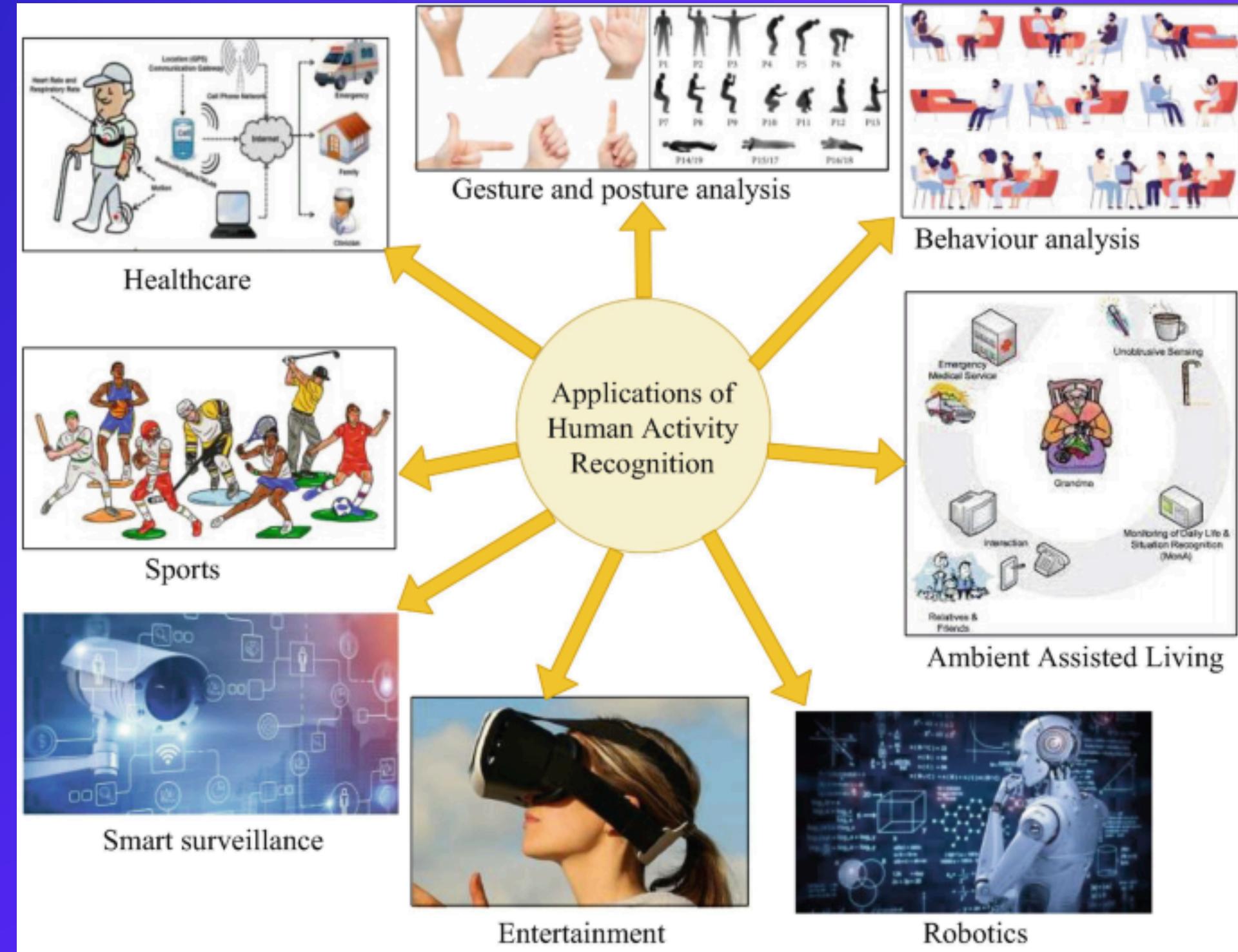
Sports

Surveillance

Behaviour Analysis

Ambient Assisted Living

Robotics



ABOUT THE DATASET

THIS CHOSEN DATASET CONTAINS SMARTPHONE SENSORS DATA FOR SIX PHYSICAL ACTIVITIES. THE DATASET INCLUDES SIX ACTIVITIES: WALKING, RUNNING, SITTING, STANDING, JOGGING, BIKING, WALKING_UPSTAIRS, AND WALKING_DOWNSTAIRS. DATA WAS COLLECTED FOR THREE SMARTPHONE SENSORS (AN ACCELEROMETER, A GYROSCOPE, A MAGNETOMETER) AT 50 SAMPLES PER SECOND.

	Ax	Ay	Az	Lx	Ly	Lz	Gx	Gy	Gz	Mx	My	Mz	MA	ML	MG
0	-1.81150	-14.873	-1.34840	-1.26910	-5.1057	-0.66445	-0.53206	-3.18690	0.23976	12.72	40.74	-6.00	15.043465	5.302856	3.239893
1	0.24517	-14.070	-0.84446	0.70147	-4.2969	-0.17199	-0.25229	-1.79660	0.40745	12.54	40.74	-6.78	14.097451	4.357177	1.859419
2	-0.57205	-14.628	-1.75700	-0.21760	-4.8531	-1.05650	-1.04920	0.29138	0.29230	12.42	40.68	-8.10	14.744242	4.971531	1.127458
3	-0.69464	-12.939	-3.09180	-0.32273	-3.1786	-2.21970	-2.37200	1.00820	0.34972	12.30	40.74	-8.52	13.321392	3.890337	2.600991
4	0.87170	-12.000	-1.56630	1.13740	-2.2390	-0.65476	-2.79010	0.65485	0.22724	12.24	40.80	-8.88	12.133143	2.595286	2.874913

WORK FLOW

Loading the Data

Preprocessing the
Loaded Data

Definition of Model

Compiling the Model

Fit the Specified Model

Evaluate the Model

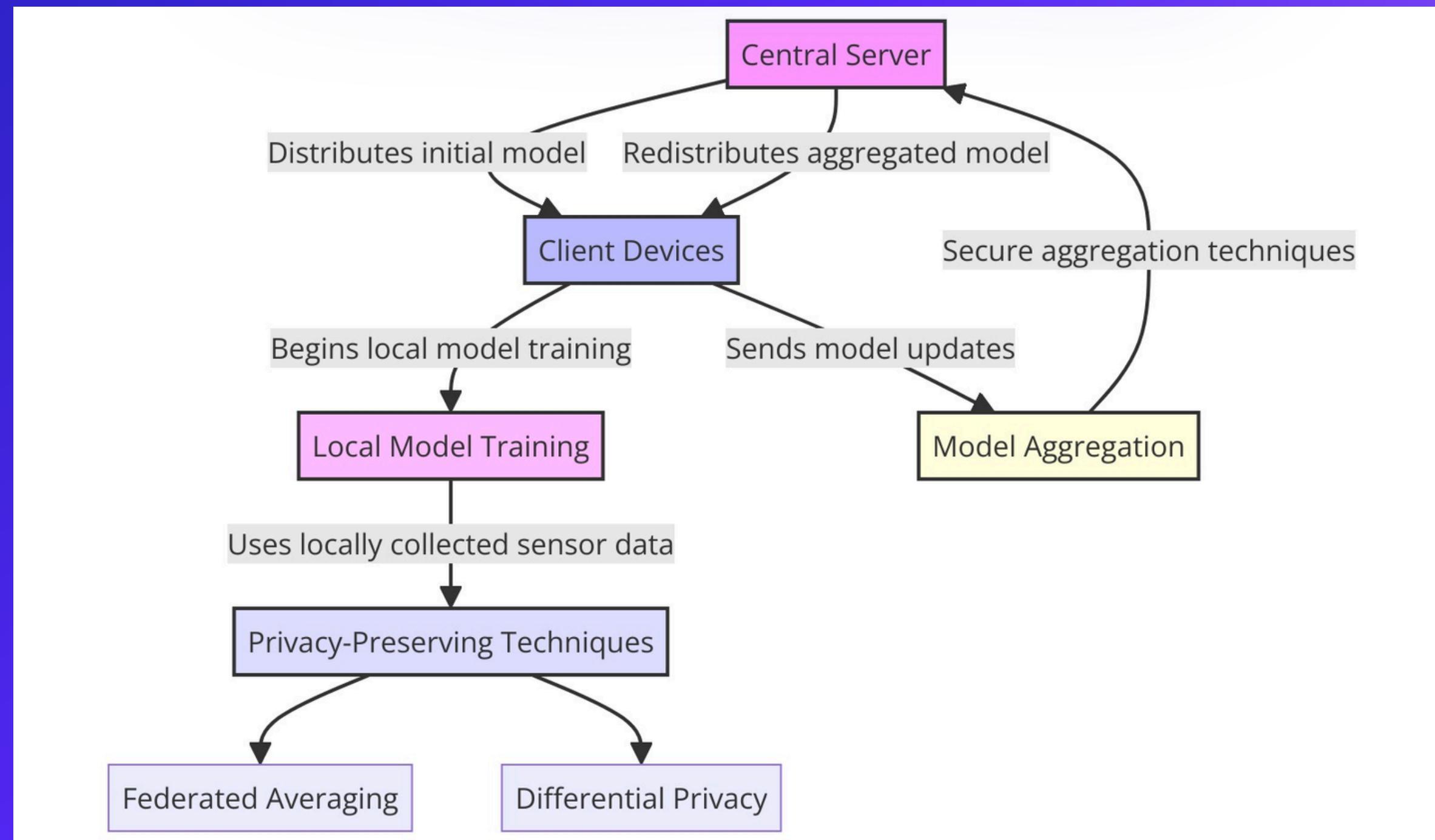
Export the Model

Create the Android
App

Import the Saved
Model

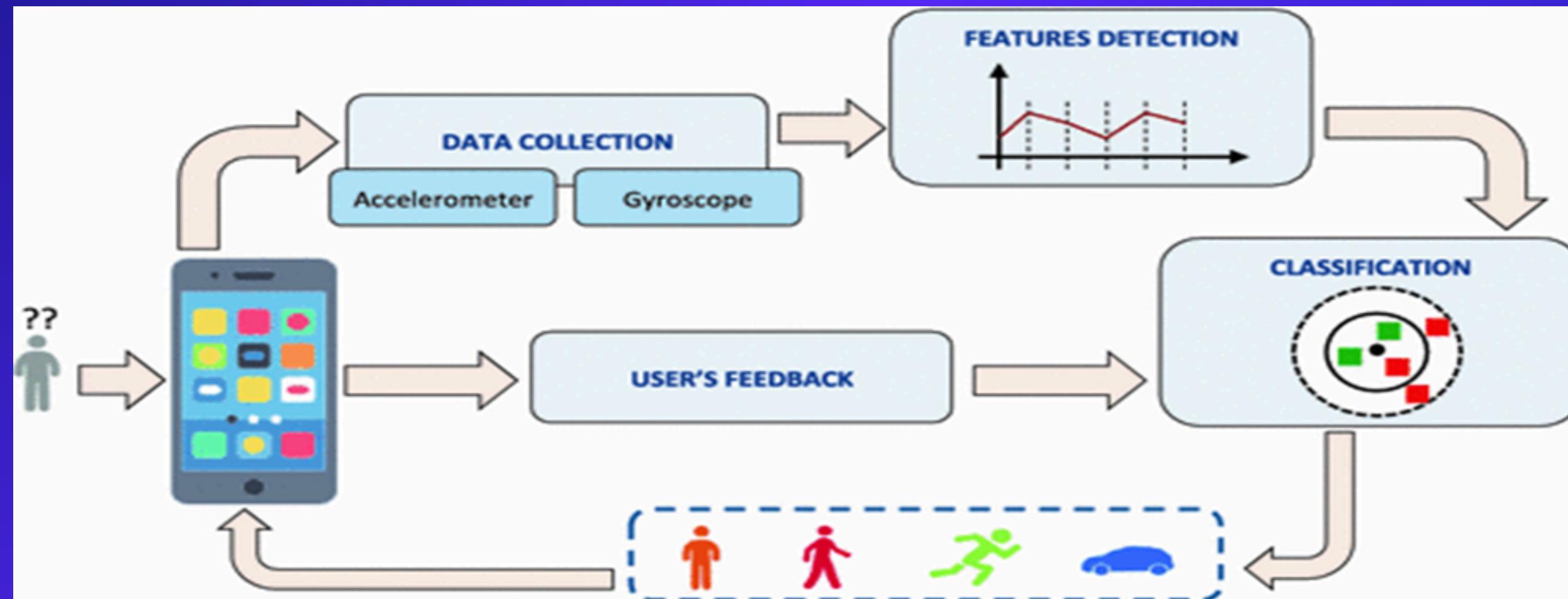
Testing

FL ARCHITECTURE



SYSTEM ARCHITECTURE

- **Data Collection:** Sensor data, including accelerometer and gyroscope readings, are collected from smartphones worn by individuals during various activities.
- **Preprocessing:** The collected data undergo preprocessing steps, including noise filtering and windowing, to extract relevant features for model training.
- **Federated Learning Setup:** The dataset is divided into multiple parts, with a portion used for training local models on individual devices and another portion designated as the public dataset for testing the global model's accuracy.
- **Model Architecture:** The model architecture consists of multiple layers, including dense layers with ReLU activation and dropout layers to prevent overfitting.



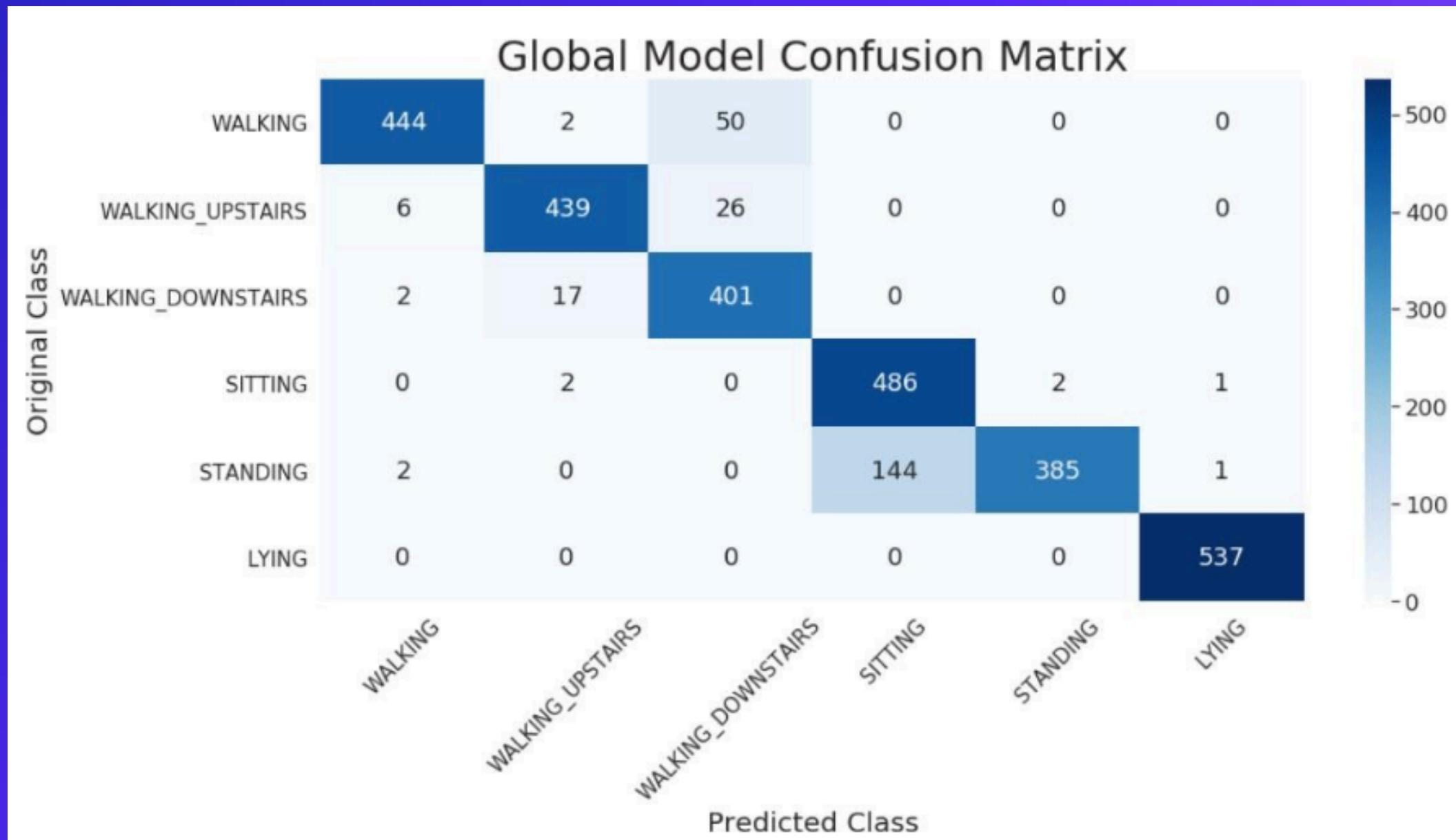
MODEL ARCHITECTURE

Layer Type	Specifics
Input Layer	Number of units dependent on size of training set
Dense Layer	256 units, ReLU activation
Dropout	probability 0.2
Dense Layer	128 units, ReLU activation
Dropout	probability 0.2
Dense Layer	64 units, ReLU activation
Dropout	probability 0.2
Dense Layer	32 units, ReLU activation
Output Layer	6 units(Number of classes), Softmax activation

MODEL ARCHITECTURE

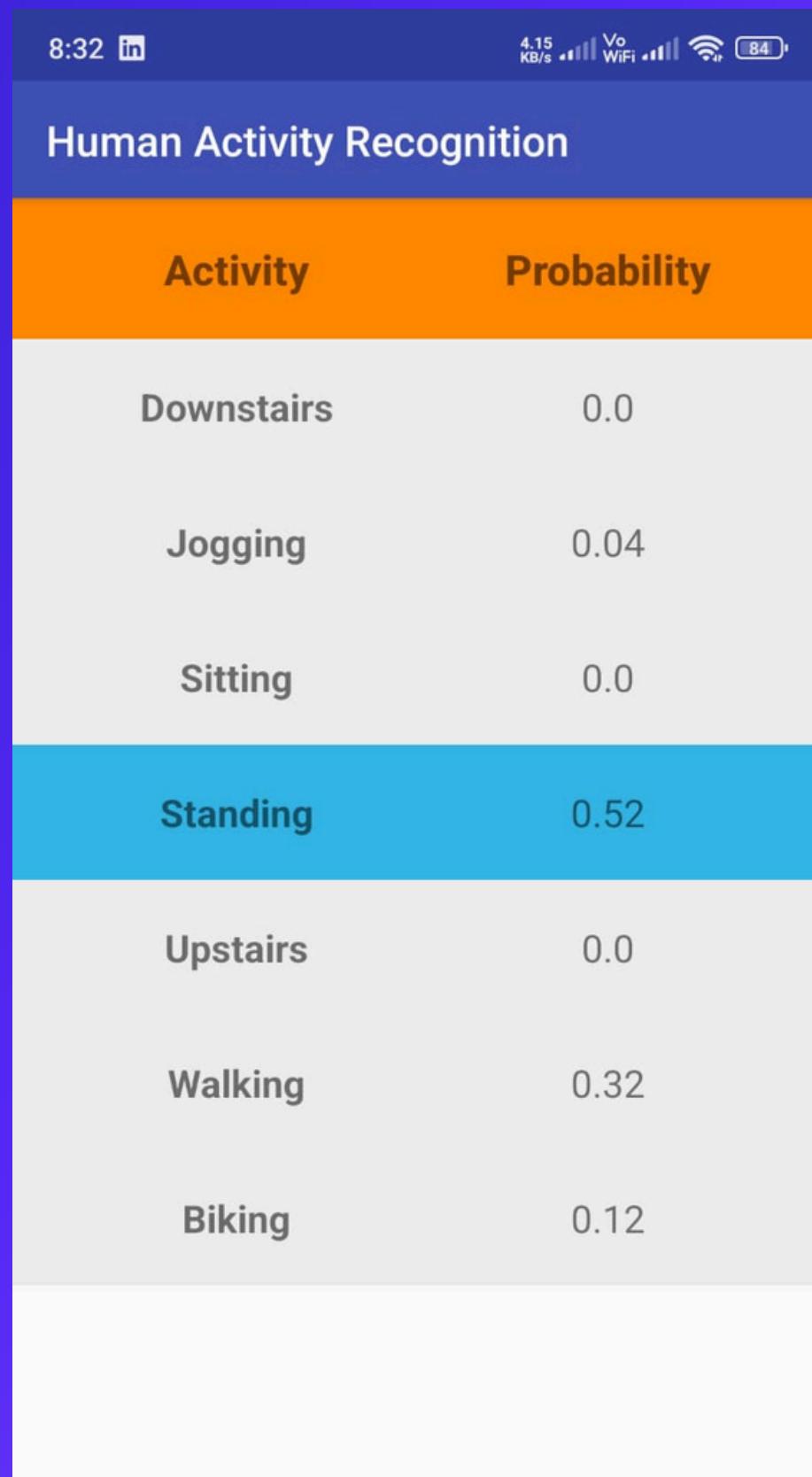
- Input Layer: Adjusts units based on training set size for initial data input.
- Dense and Dropout Layers: Sequentially arranged with 256, 128, 64, and 32 units respectively, each followed by a dropout of 0.2 to prevent overfitting. ReLU activation is used for non-linearity.
- Output Layer: 6 units with Softmax activation for classifying into six categories.

Result: Confusion Matrix



Accuracy: 88.67

Final Outcome: Mobile Application for Human Activity Recognition



A screenshot of a mobile application interface titled "Human Activity Recognition". The screen shows a table with two columns: "Activity" and "Probability". The activities listed are Downstairs, Jogging, Sitting, Standing, Upstairs, Walking, and Biking. The probability values are 0.0, 0.04, 0.0, 0.52, 0.0, 0.32, and 0.12 respectively. The "Standing" row is highlighted with a blue background.

Activity	Probability
Downstairs	0.0
Jogging	0.04
Sitting	0.0
Standing	0.52
Upstairs	0.0
Walking	0.32
Biking	0.12

CONCLUSION

IN CONCLUSION, OUR PROPOSED FEDERATED MACHINE LEARNING ARCHITECTURE FOR HUMAN ACTIVITY RECOGNITION (HAR) PRESENTS A COMPREHENSIVE SOLUTION TO THE CHALLENGES INHERENT IN TRADITIONAL HAR SYSTEMS. BY DECENTRALIZING DATA PROCESSING TO CLIENT DEVICES WHILE MAINTAINING ROBUST PRIVACY AND SECURITY MEASURES, OUR SYSTEM NOT ONLY PRESERVES USER PRIVACY BUT ALSO ENHANCES SCALABILITY AND EFFICIENCY. THROUGH THE ORCHESTRATION OF MODEL TRAINING AND AGGREGATION BY A CENTRAL SERVER, OUR ARCHITECTURE ENSURES SEAMLESS COLLABORATION BETWEEN CLIENT DEVICES WHILE MINIMIZING COMMUNICATION OVERHEAD. WITH THE SUCCESSFUL IMPLEMENTATION OF OUR SYSTEM WORKFLOW, WE DEMONSTRATE THE VIABILITY AND EFFECTIVENESS OF FEDERATED LEARNING IN HAR, PAVING THE WAY FOR INNOVATIVE SOLUTIONS IN ACTIVITY RECOGNITION WHILE SAFEGUARDING USER DATA PRIVACY.

FUTURE WORK

1. CROSS-MODAL DATA INTEGRATION:

- DEVELOP CAPABILITIES TO INTEGRATE AND ANALYZE DATA FROM MULTIPLE SENSORY INPUTS (LIKE VISUAL, AUDITORY, AND TACTILE SENSORS) TO CREATE A MORE COMPREHENSIVE AND ACCURATE HUMAN ACTIVITY RECOGNITION SYSTEM. THIS MULTIDIMENSIONAL APPROACH CAN ENHANCE CONTEXTUAL UNDERSTANDING AND APPLICATION IN DIVERSE ENVIRONMENTS.

2. PREDICTIVE BEHAVIOR MODELING:

- SHIFT FOCUS FROM REAL-TIME ACTIVITY RECOGNITION TO PREDICTIVE MODELING, WHERE THE SYSTEM ANTICIPATES USER ACTIONS BASED ON HISTORICAL DATA AND CURRENT CONTEXT. THIS COULD BE PARTICULARLY VALUABLE IN ASSISTIVE TECHNOLOGIES, SMART HOMES, AND PROACTIVE HEALTH MANAGEMENT SYSTEMS.

THANK YOU!

