אוניברסיטת בן-גוריון בנגב
Ben-Gurion University of the Negev

HUMAN ACTIVITY RECOGNITION

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MOTIVATION

HEALTH & SAFETY

- Detect falls
- Chronic-disease early warnings
- alerts to keep patients safe

MOVEMENT REMINDERS

Track sitting time and send movement alerts

DYNAMIC UI ADAPTATION

Adjust the interface according to movement (e.g, pause music)

FITNESS & COACHING

- Record workouts
- offer simple form tips

DATA

PARTICIPANTS

30 volunteers (age 19–48) wearing a Samsung Galaxy S II on the waist

FEATURES

561 columns containing time and frequency (normalized to [–1, 1])

ACTIVITIES LABELS:

Walking, Walking Upstairs, Walking Downstairs, Sitting, Standing, Laying

Challenges

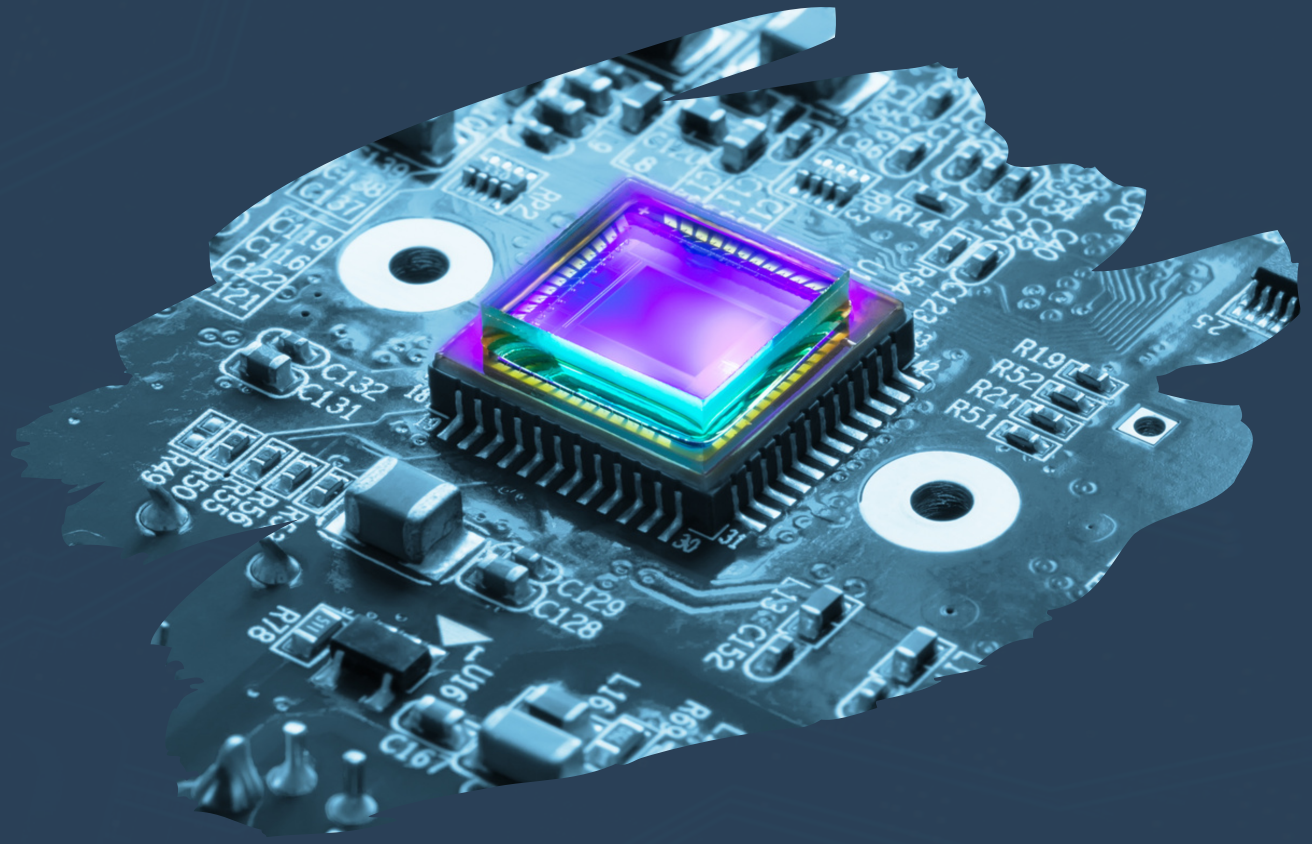
PRE-PROCESSED DATASET

First decode its structure, then adapt it to our goals

561 FEATURES

High dimensionality demands smart reduction

Preprocessing of Sensor Signals



Noise filtering

Apply noise filters to accelerometer and gyroscope readings to remove glitches.

Sliding-window segmentation

Split the continuous signal into overlapping 2.56-(50%) second windows.

Gravity vs. body-acceleration separation

Apply a 0.3 Hz filter to capture gravity, then subtract it to isolate body motion.

Feature extraction (time & frequency domains)

From each window compute summary stats and spectral measures or model input

Column Explanation

SubjectID
Volunteer identifier (1–30)

ActivityLabel
Type of movement (6 classes)

FeatureVector (561 numbers)
Summary of each 2.56 s window of sensor data, combining:

Time-domain metrics
(e.g. average, variability, peaks)

Describe how acceleration and rotation change over time

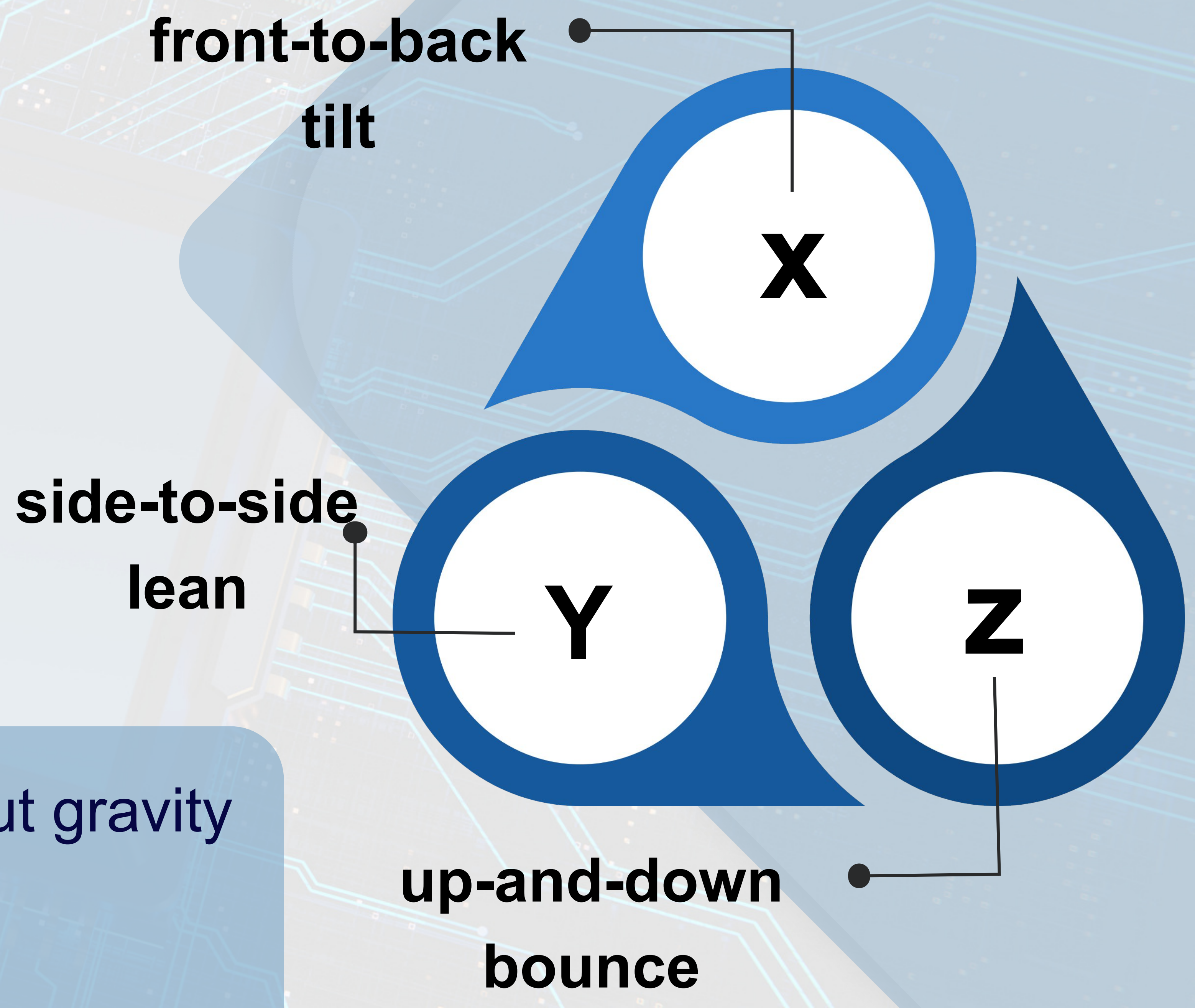
Frequency-domain metrics
Capture repeating patterns in the motion data

What’s Inside Our Data?

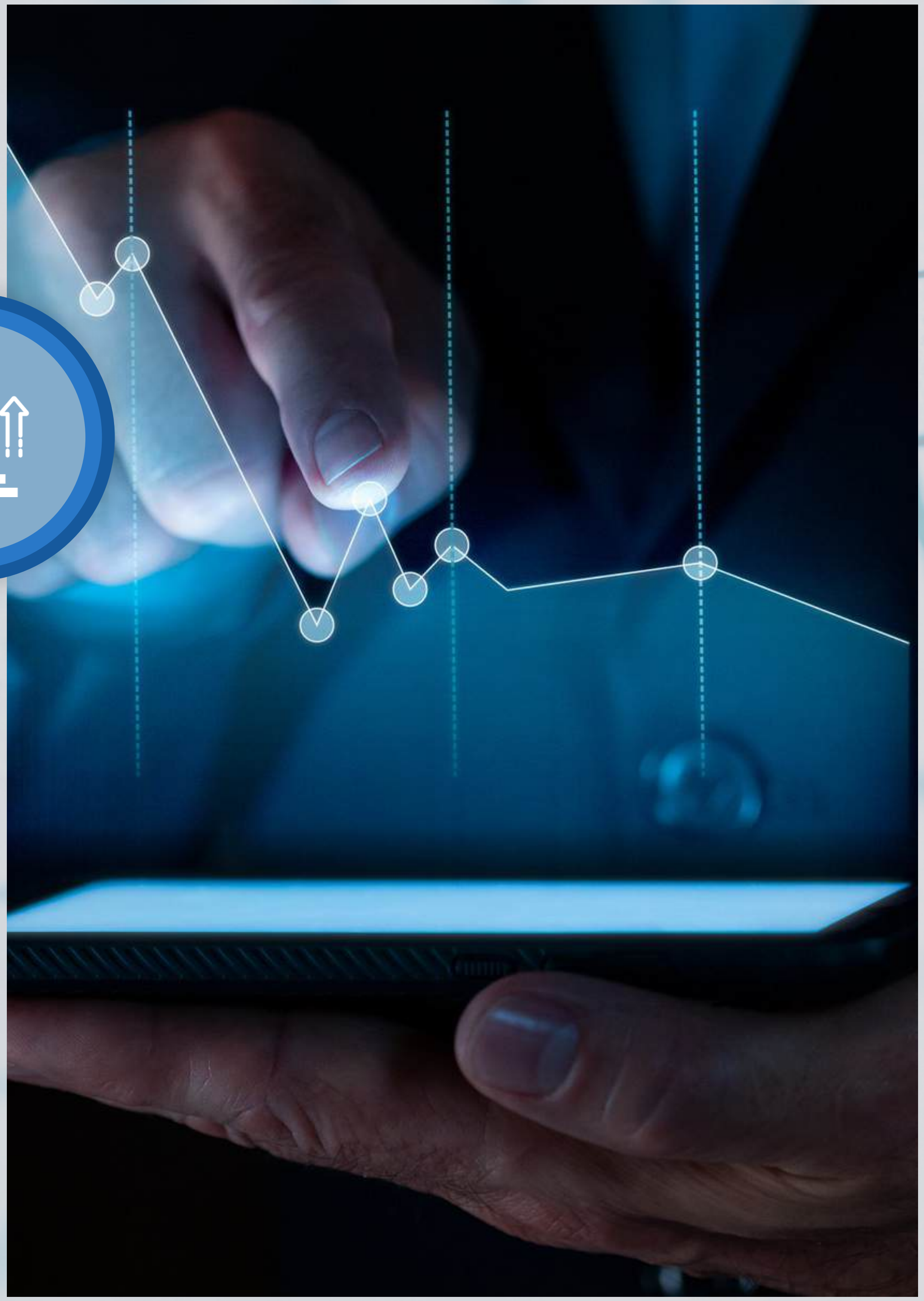
Signals :

- **Body Acceleration** - raw motion without gravity
- **Gravity Acceleration** - stationary tilt
- **Jerk** - how quickly you start / stop
- **Magnitude** - combined strength of X + Y + Z

Measure - X, Y, Z axes :



How We Summarize Each 2.56 s Window:



Mean
Your "average" motion
Smooths out spikes, shows overall trend

Median
Your "middle" motion
Ignores extreme outliers

Std Dev
How wildly you're moving
High when you're shaking or running

Min / Max
Lowest & highest movement
Captures sudden jumps (e.g., a step)

Bottom Line

We turn every 2.5 seconds of X/Y/Z sensor readings into a handful of simple numbers so our model can "see" patterns like walking vs. sitting.

EDA

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Workflow

Raw Data → Feature importance → PCA → t-SNE

2.56-s window into 561 features

into 434 features

into 50 PCs

2-D visual map of 6 activities

1.Feature Selection

- Combined normalized Mutual-Information and RandomForest scores into one "average importance" per feature.
- Sorted features by the combined score

Result - **434 out of 561 Features**

(94.9% total importance)

2. PCA on Selected Features

- Ran PCA on those 434 features.
- Selected Features captured 90% of the variance.

Result - **A compact 50-dimensional representation, removing low variance / noise directions.**

T-SNE
What & Why

t-SNE is a visualization tool

Measures **similarity** of each pair of high-dimensional samples, then arranges the points in **2-D** so that close neighbors stay close and distant ones spread apart.

Result - A scatter plot where tight blobs mark clear clusters

Why we need it ?

- We can't "see" 561- dimensional sensor features t-SNE turns them into an intuitive picture.
- Quickly shows whether the six activities naturally group into distinct clusters - before we train any model.

3. t-SNE

Projects the 50-dimensional PCA output down to 2D, preserving local neighborhoods.

Result - **Reveals tight clusters for each activity**

Key Insights

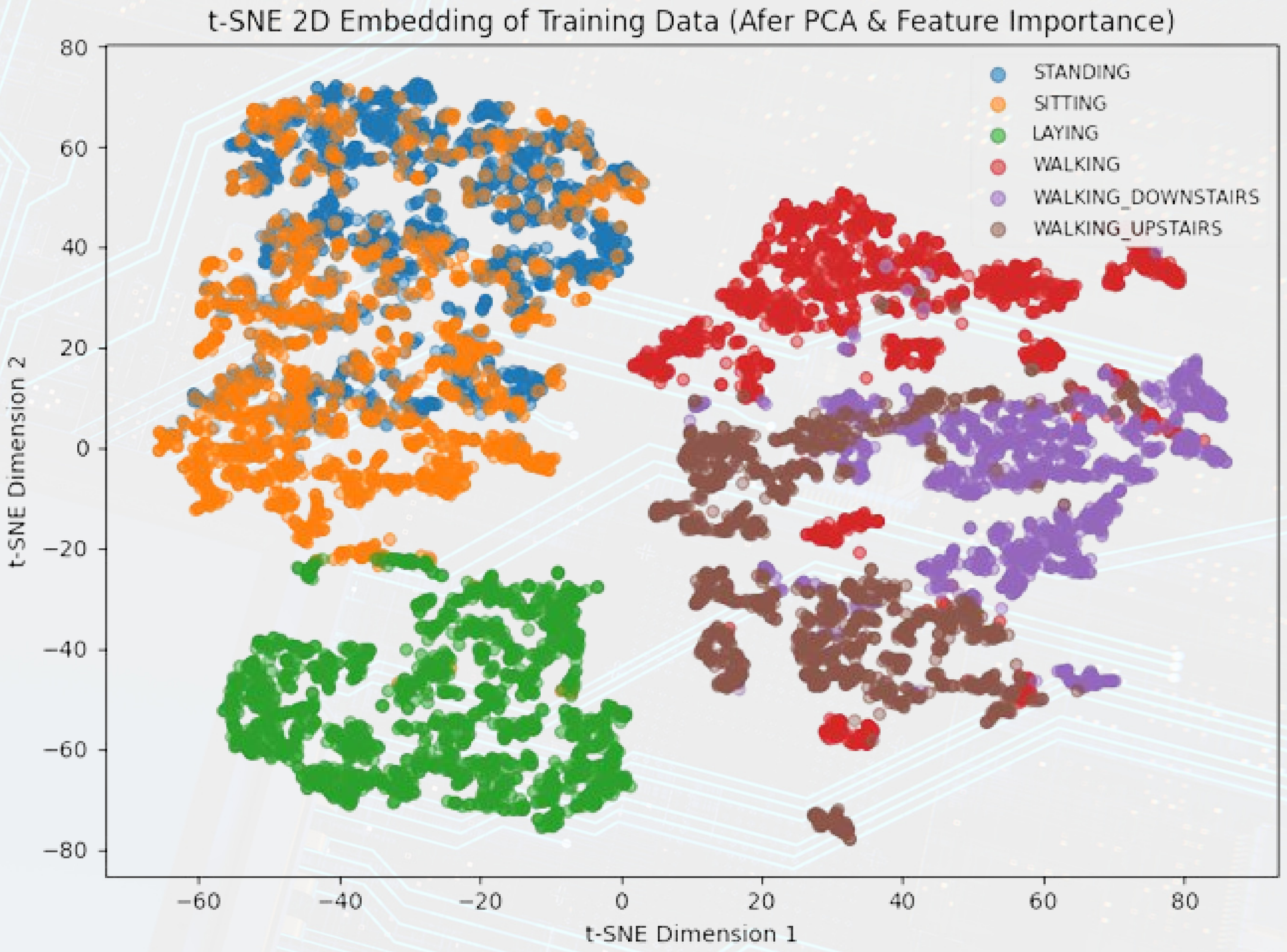
→ **Distinct regions:**
static (Sitting / Standing), stair (Up / Down), and level Walking each form their own islands.

→ **LAYING is alone:**
near-zero motion makes it uniquely separable.

→ **Up stairs vs. Down stairs:**
adjacent yet separate clusters - opposite vertical impulses.

→ **Walking island:**
periodic stride pattern keeps it apart from both static and stair groups.

→ **Sitting ↔ Standing overlap:**
minimal movement → occasional mix-ups.



Bottom Line:

A 2-D map still cleanly splits the six activities, confirming our features capture strong, learnable patterns.

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Model Architecture

FFNN

with **ReLU** activations

Hidden Layer

Each uses
L2 regularization
& **Dropout**,
(followed by Batch Normalization)

Final Layer

Final **softmax** layer -
6 neurons
(one per activity)

Optimizer

Optimized with **Adam**
(decaying LR)
and early stopping

Evaluation & Results

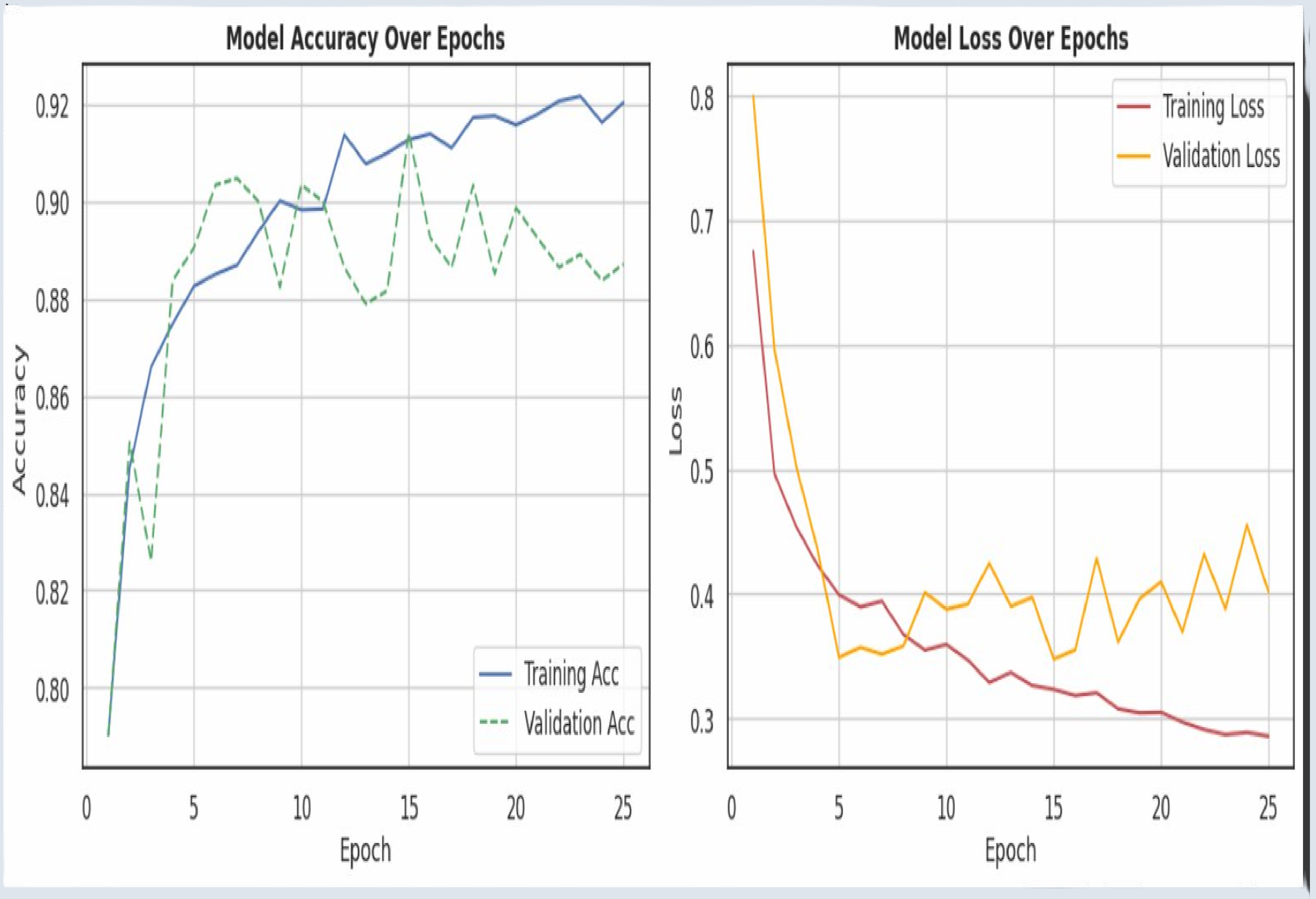
(On the Test Set)

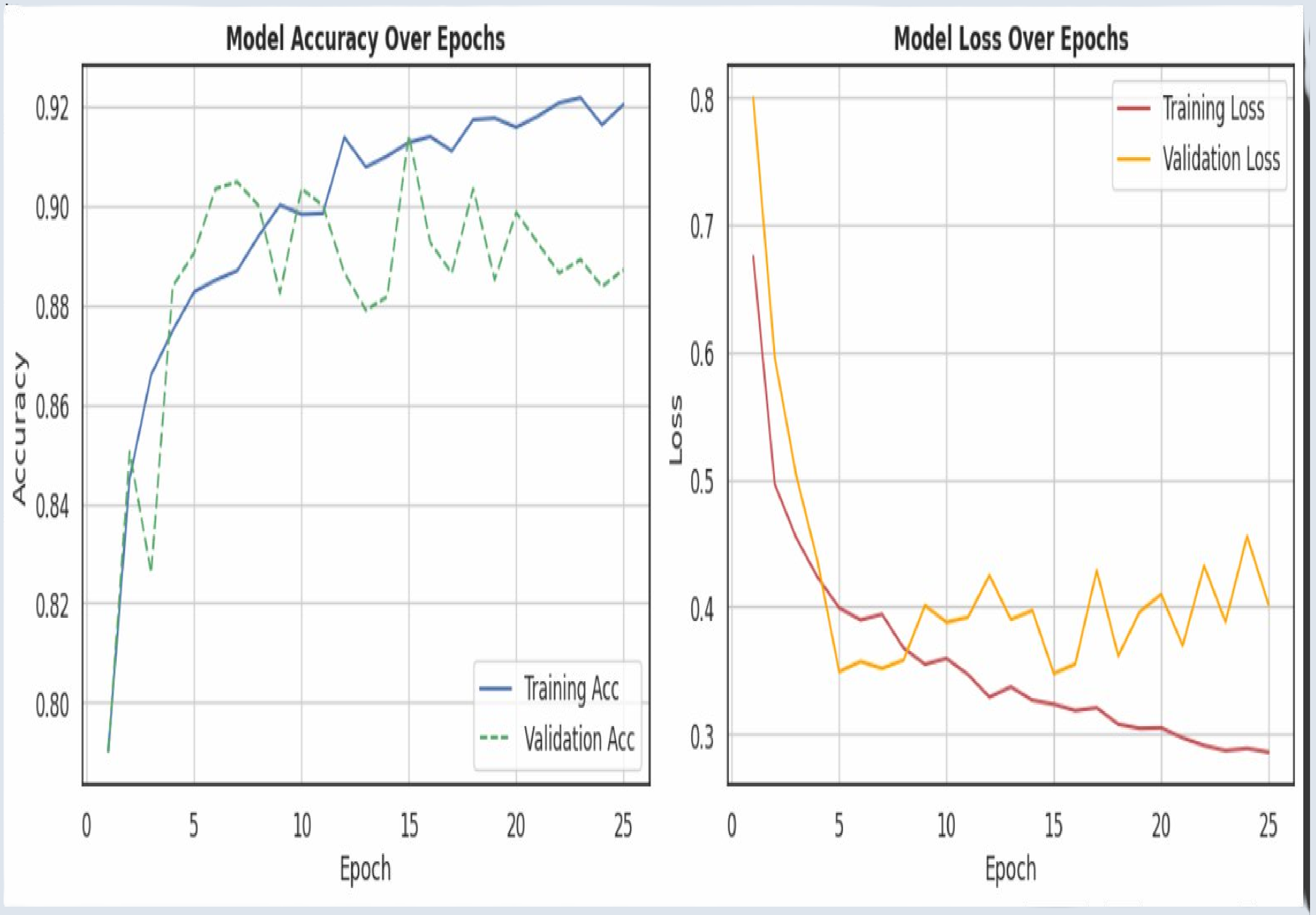
- **Accuracy - 0.88**

- **Macro Avg:**
  - **Precision -** 0.879
  - **Recall -** 0.877
  - **F1 -** 0.877

- **Weighted Avg:**
  - **Precision -** 0.88
  - **Recall -** 0.88
  - **F1 -** 0.88

Before Balancing...





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THANK YOU

FOR YOUR ATTENTION
AND PARTICIPATION

Any Questions ?