Indian Institute of Technology
Hyderabad

PIR-based Human Activity Recognition

Deep Learning Project (AI5100)

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Introduction

- The project focuses on developing models that can accurately classify human presence and activity states based on occupancy detection data collected using a synchronized Low-Energy Electronically-chopped Passive Infra-Red (PIR) sensor.
- Node deployed in residential and office environments.
- Each observation corresponds to 4 seconds of recorded human activity within the sensor's Field-of-View (FoV).

Dataset Overview:

- **Instances:** 7651 | **Features:** 59 | **Missing Values:** None

Dataset Overview

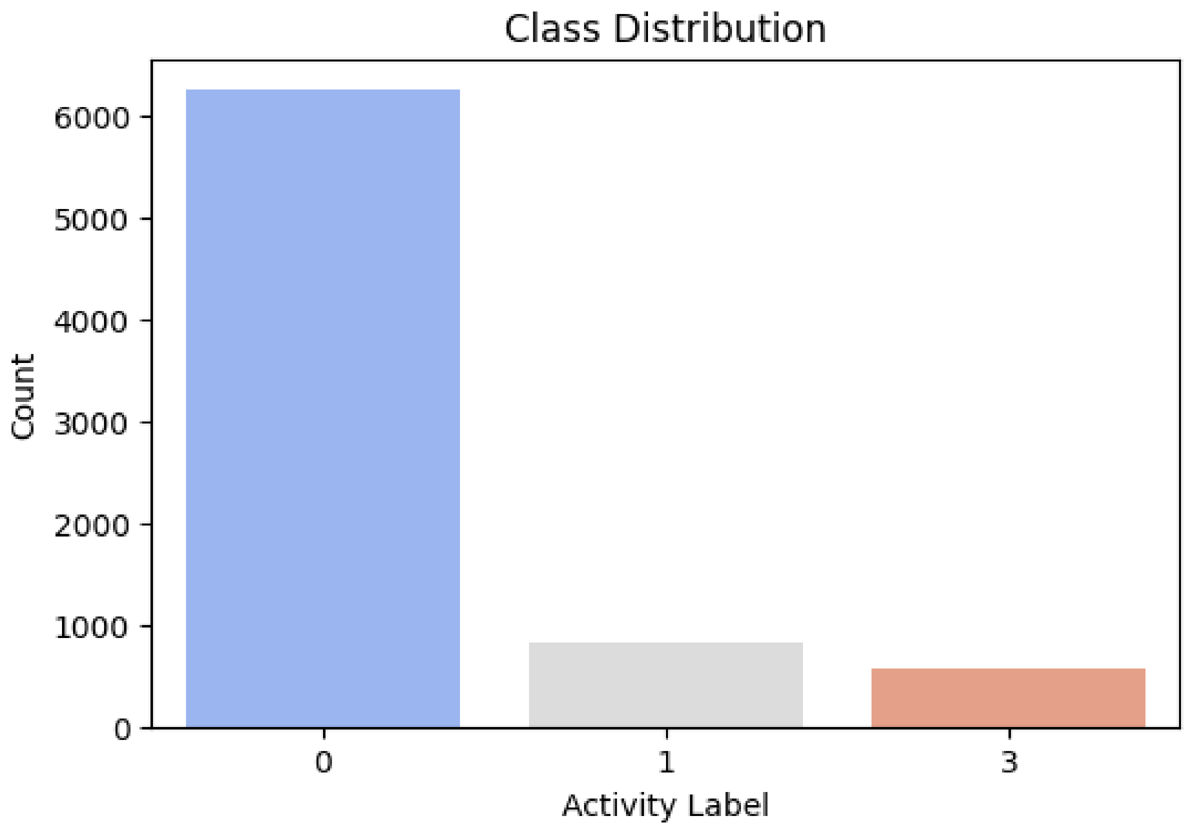
Key Features:

Date & Time: Timestamps for each observation.

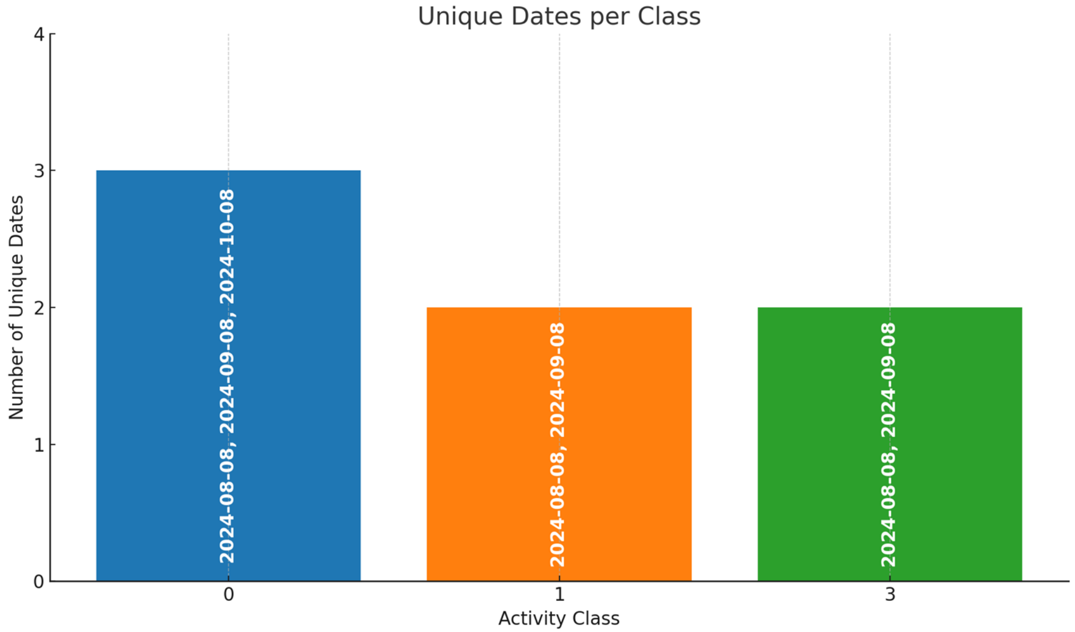
Labels: 0: Vacancy | 1: Stationary human presence | 3: Other activity/motion

Temperature_F: Ambient temperature in Fahrenheit.

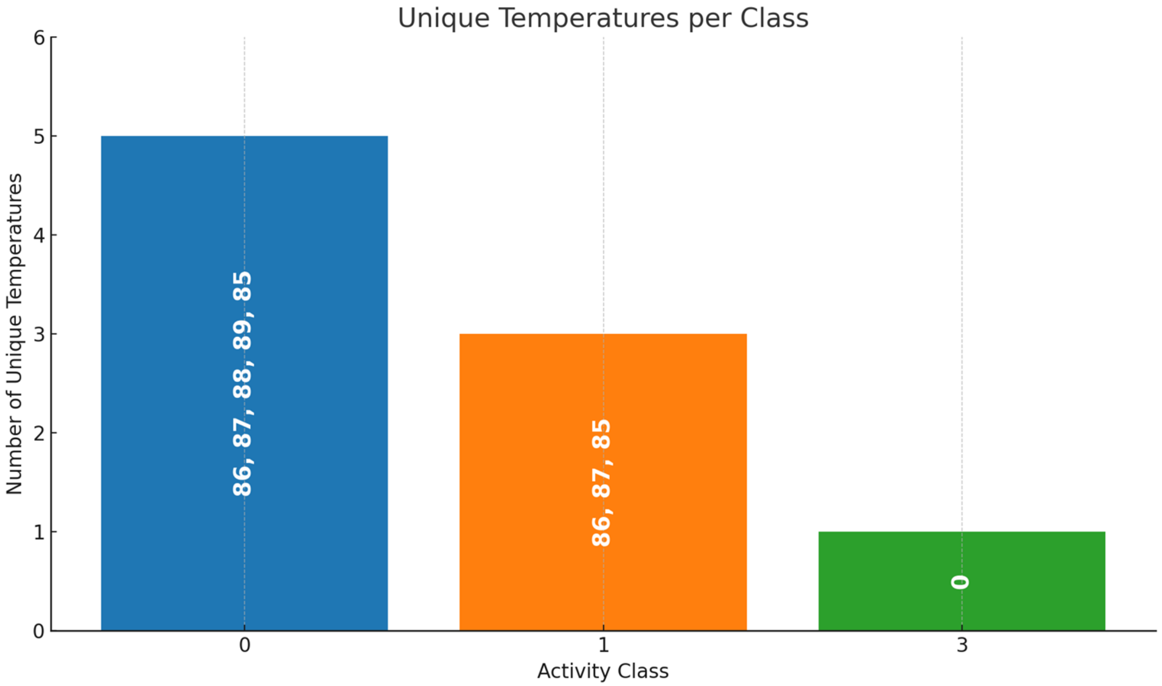
PIR_1 to PIR_55: Analog readings from 55 PIR sensors over each 4-second interval.



Imbalanced Dataset

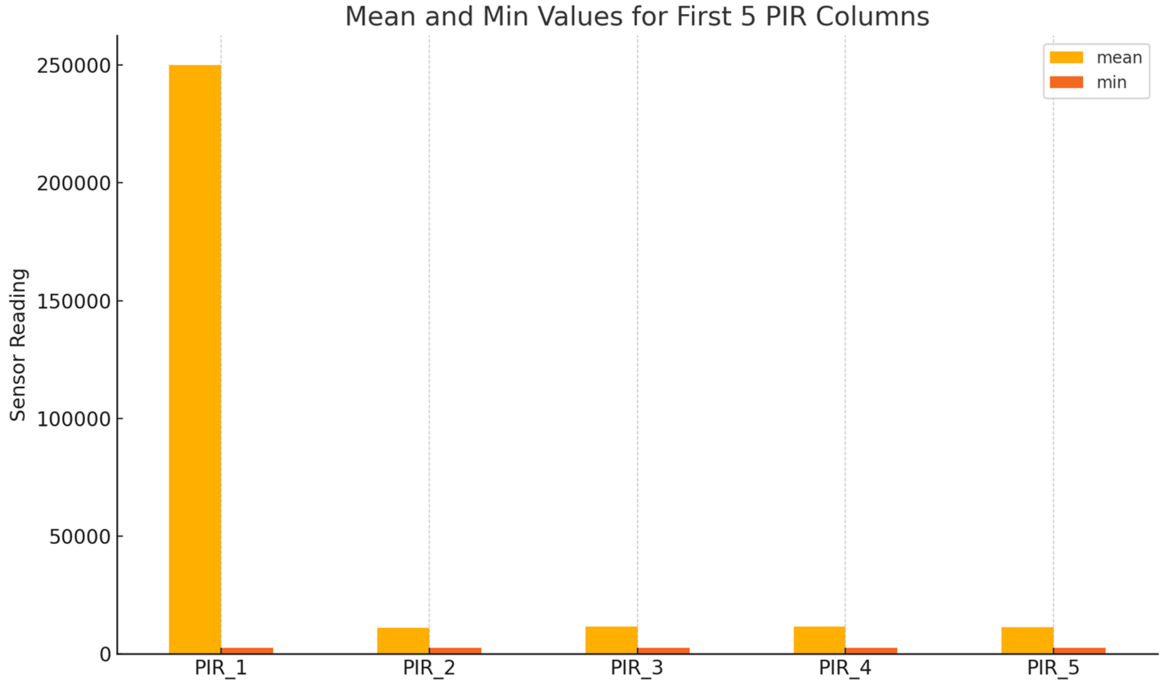


Checking unique dates per class



Checking unique temperature per class

Observation : temperature 0 only belongs to class 3



	PIR_1	PIR_2	PIR_3
count	7.651000e+03	7651.000000	7651.000000
mean	2.501256e+05	11013.891648	11517.838452
std	4.292998e+06	591.799276	656.683841
min	2.613000e+03	2615.000000	2614.000000
25%	1.033300e+04	10787.500000	11272.500000
50%	1.043100e+04	11002.000000	11557.000000
75%	1.056050e+04	11267.000000	11885.000000
max	1.116026e+08	16383.000000	16383.000000

PIR_1 columns values are significantly greater than other PIR columns.

Feature Engineering

Transform raw data into model-ready format.

Steps Followed:

1. **Features Used:** Used PIR_1 to PIR_55 as they directly relate to 4-second pattern + Temperature_F. Date & Time has been excluded due to performance degrade
2. **Temperature** = 0 → Always predicted as label 3 (Hard Coded, because of their 1-1 mapping)
3. **SMOTE** to handle class imbalance.
4. **StandardScaler** for normalization.

Model Selection

Model	Hidden Units	Epochs	Batch	Optimizer	Learning Rate	Dropout
ANN	128, 64	20	64	Adam	0.001	0.2
GRU	64	20	64	Adam	0.001	0.2
LSTM	64	20	64	Adam	0.001	0.2

Performed hyperparameter tuning on all models by varying the number of nodes, learning rates, batch size, number of layers, activation functions, etc.

Model Architecture

- Input: 56 features
- Layers:
  - LSTM (64 units)
  - Dropout (0.2)
  - Dense → Softmax output

Justification:

- Best validation loss, validation accuracy & macro F1.
- LSTM captures signal more better than CNN.
- Remembers signal trends across time.
- Handles vanishing gradient better than vanilla RNN.
- Beats ANN & GRU on both accuracy and stability.

Training and Evaluation

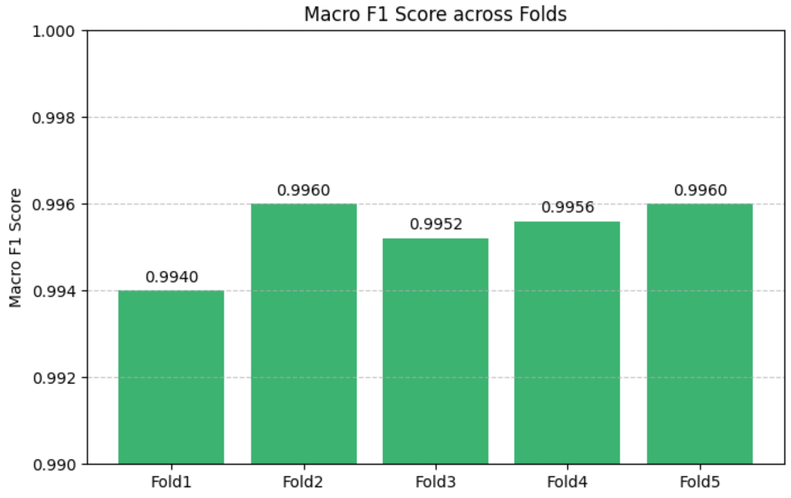
Validation Strategy – 5 Fold CV
Why Stratified?
•Preserves class balance across splits.
•Ensures fair and robust model testing.

Metrics Tracked:

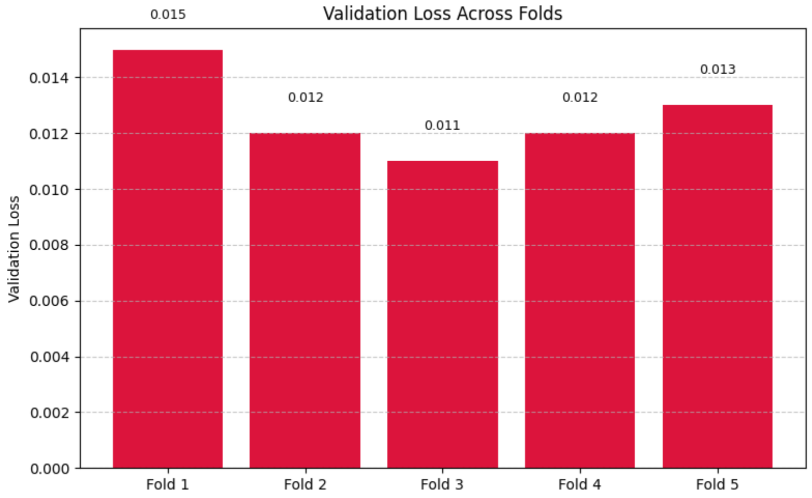
- **Accuracy/ Loss (train/val)**
- **Macro F1-Score**
- **Class-wise Precision, Recall, F1-score**
- **Confusion Matrix (per fold)**
- **Mean & Std Dev across folds**

Results

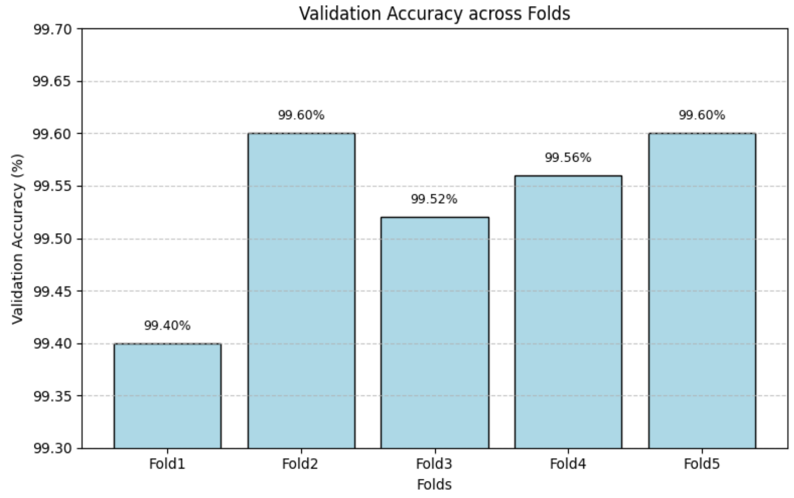
Macro F1 Score



Validation Loss

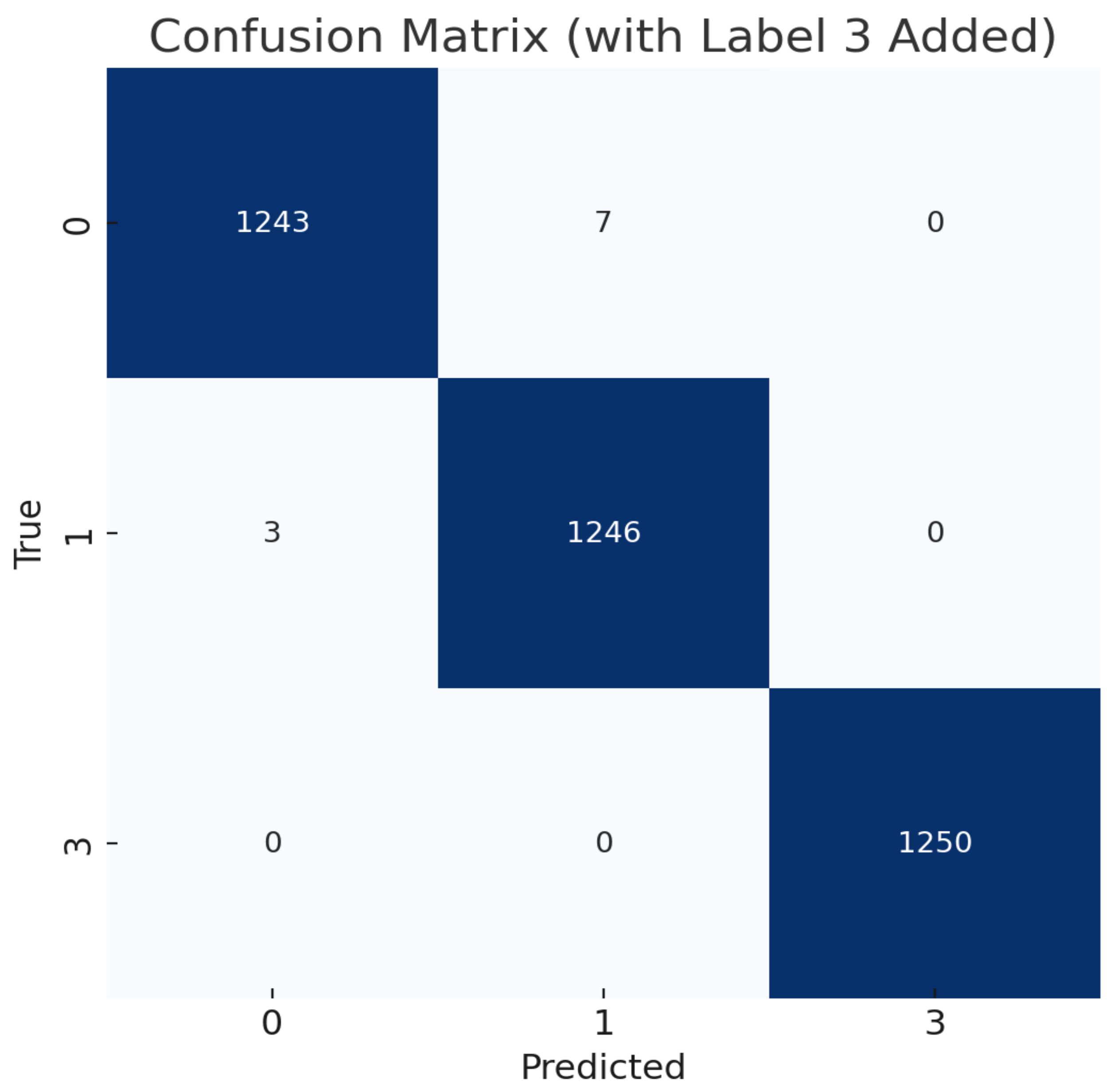


Validation Accuracy



Observations:

- Best validation fold (0.9960) chosen using Macro F1 score.
- Training and Validation losses decrease steadily.
- Training and Validation accuracies are consistently high (~99%).


Confusion Matrix (with Label 3 Added)
True
Predicted
0
1
3
1243
7
0
3
1246
0
0
0
1250

Model Performance

Metrics	Value
Average Training Accuracy	99.87 %
Average Validation Accuracy	99.62 %
Average Training Loss	0.0054
Average Validation Loss	0.0151
Average Macro F1 Score	0.9958

- Achieved **high accuracy** across folds: *Training – 99.87%*, *Validation – 99.62%*, indicating efficient learning strong model generalization.
- **Macro F1 Score** of 0.9958 shows balanced performance across all classes, even in the presence of potential class imbalance.
- Model shows excellent generalization and minimal overfitting.

Comparison Across Models

Models	Average Validation Accuracy(%)	Average F1 Score	Average Validation Loss
Multi-Layer Perceptron (MLP)	99.55 %	0.9948	0.0191
Long Short Term Memory (LSTM)	99.62 %	0.9958	0.0151
Gated Recurrent Unit (GRU)	99.59 %	0.9950	0.0167

NOTE: The best performing model is LSTM (Long Short Term Memory).

Thank You