# Nurse Care Activity Recognition Based on Machine Learning Techniques Using Accelerometer Data

Team: MoonShot_bd

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# Introduction

## Activity Recognition

Recognizing the actions and goals from a series of observations based on sensor data

- **Predicting Movements**
- **Human Behavior Analysis**
- **Health Monitoring**
- **Elderly Care Service**
- **Smart Home**

# Introduction (cont’d)

## Nurse Care Activity Recognition

- **Automate documentation process**
- **Increase efficiency in care activities**

# Second Nurse Care Activity Recognition Challenge

- Lab accelerometer data (2 subjects)
- Field accelerometer data (6 subjects)
- 12 distinctive labeled activity
- Attached in right arm using armband
- **Sampling rate:** 60 Hz

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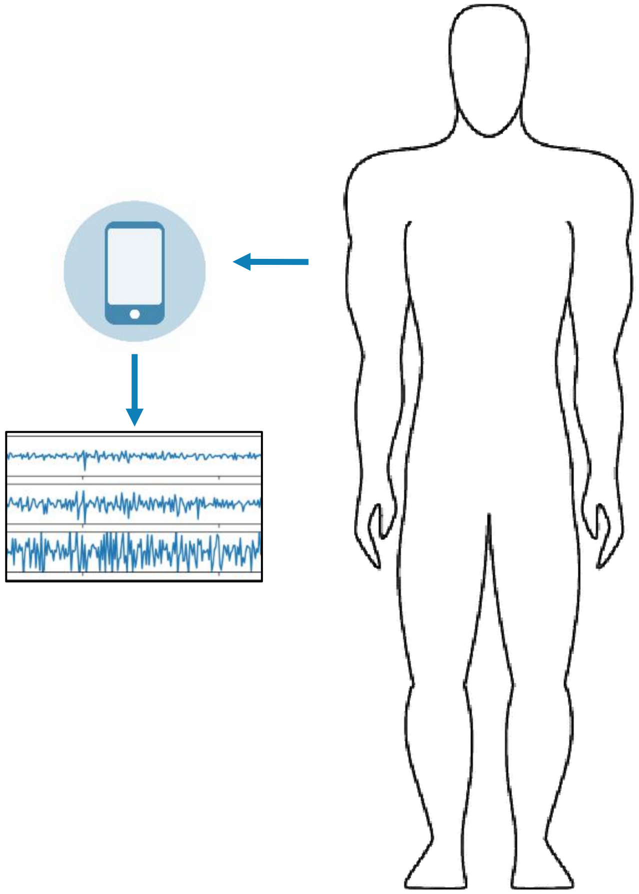

Figure (1): Collecting Accelerometer data using Smartphone

# Second Nurse Care Activity Recognition Challenge (cont'd)

| Principal Category | Activity Name | Label in Dataset | Activity Name |
|---|---|---|---|
| A | Help in Mobility | 1 | Guide (from the front) |
| | | 2 | Partial assistance |
| | | 3 | Walker |
| | | 4 | Wheelchair |
| B | Assistance in Transfer | 5 | All assistance |
| | | 6 | Partial assistance (from the front) |
| | | 7 | Partial assistance (from the side) |
| | | 8 | Partial assistance (from the back) |
| C | Position Change | 9 | To Supine position |
| | | 9 | To Right Lying position |
| | | 10 | To Left Lying position |
| | | 11 | Lower Body Lifting |
| | | 12 | Horizontal Movement |

Table (2): Different Labeled Activities in the Dataset

# Challenges

- Imbalanced data
- Irregular sampling rate
- Missing labels
- Dissimilarities between Lab data and Field data

# Methodology

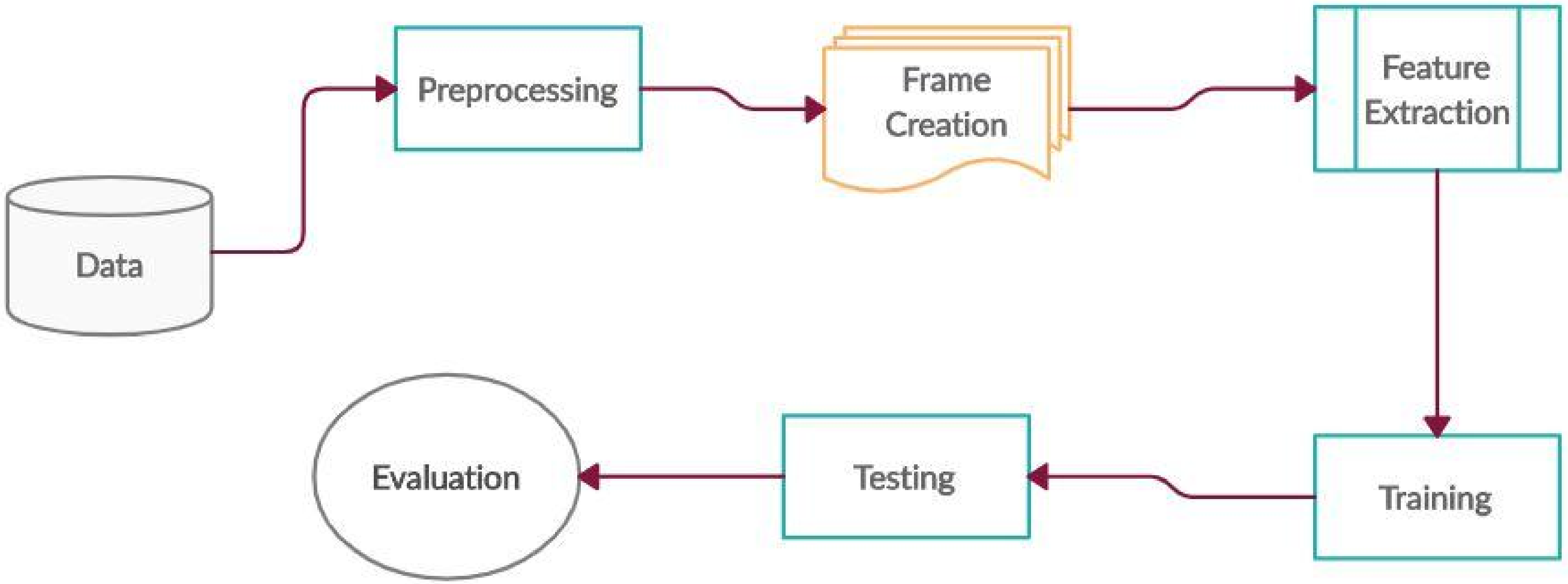


Figure (3): Overview of the methodology

# Preprocessing

- Integrating Lab and Field data
- Handling irrelevant data
- Normalizing the data

# Frame Creation

- Overlapping Sliding Window
- Frame size: 60
- Hop size: 10

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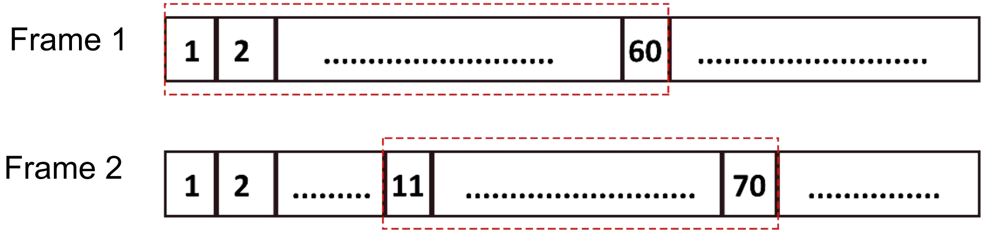


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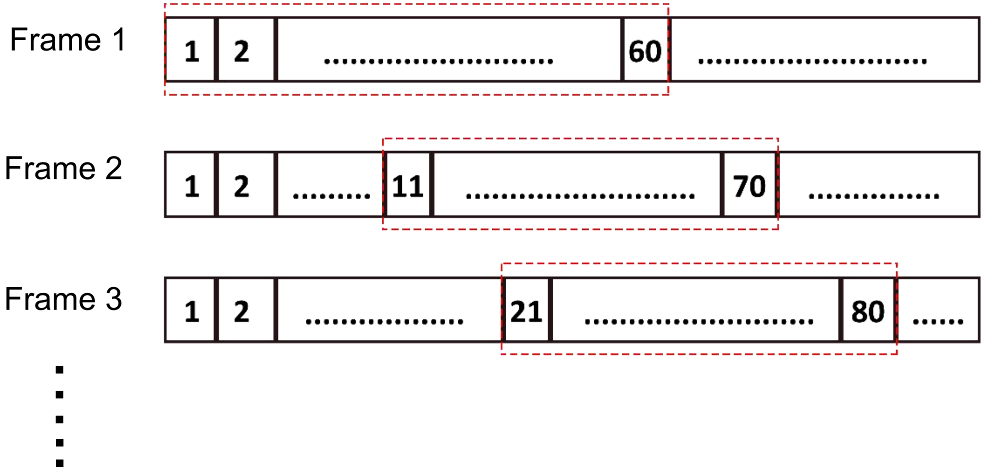


Figure (4): Overlapping Sliding Window

# Feature Extraction

We have chosen these five features empirically for extracting summarizing features from each window

- **Mean**
- **Median**
- **Mode**
- **Standard Deviation**
- **Variance**

# Recognition Algorithm

We experimented with-

- ✓ **Naïve Bayes**
- ✓ **SVM**
- ✓ **KNN**
- ✓ **Random Forest**
- ✓ **Multilayer Perceptron**

# Result Analysis

- KNN outperformed all other algorithm achieving 75% accuracy
- Multilayer Perceptron achieved 73%
- Random Forest got around 70% accuracy

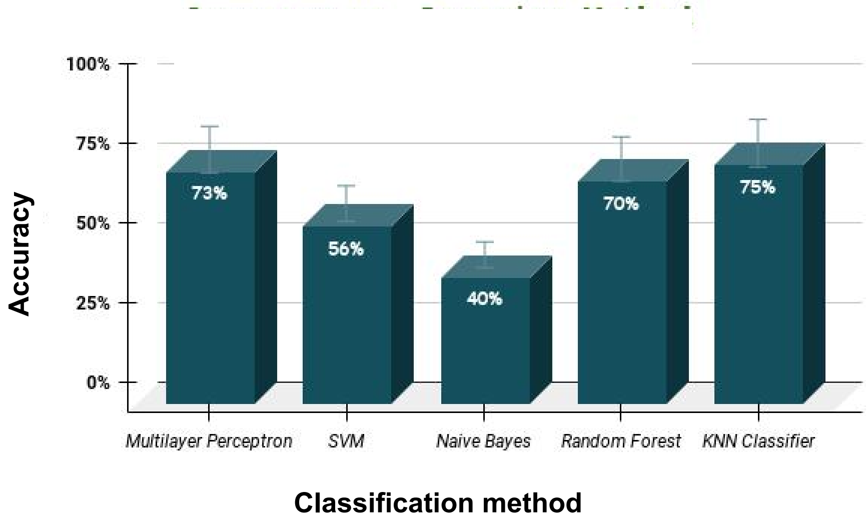


Figure (5): Accuracy in different algorithms

# Result Analysis (cont'd)

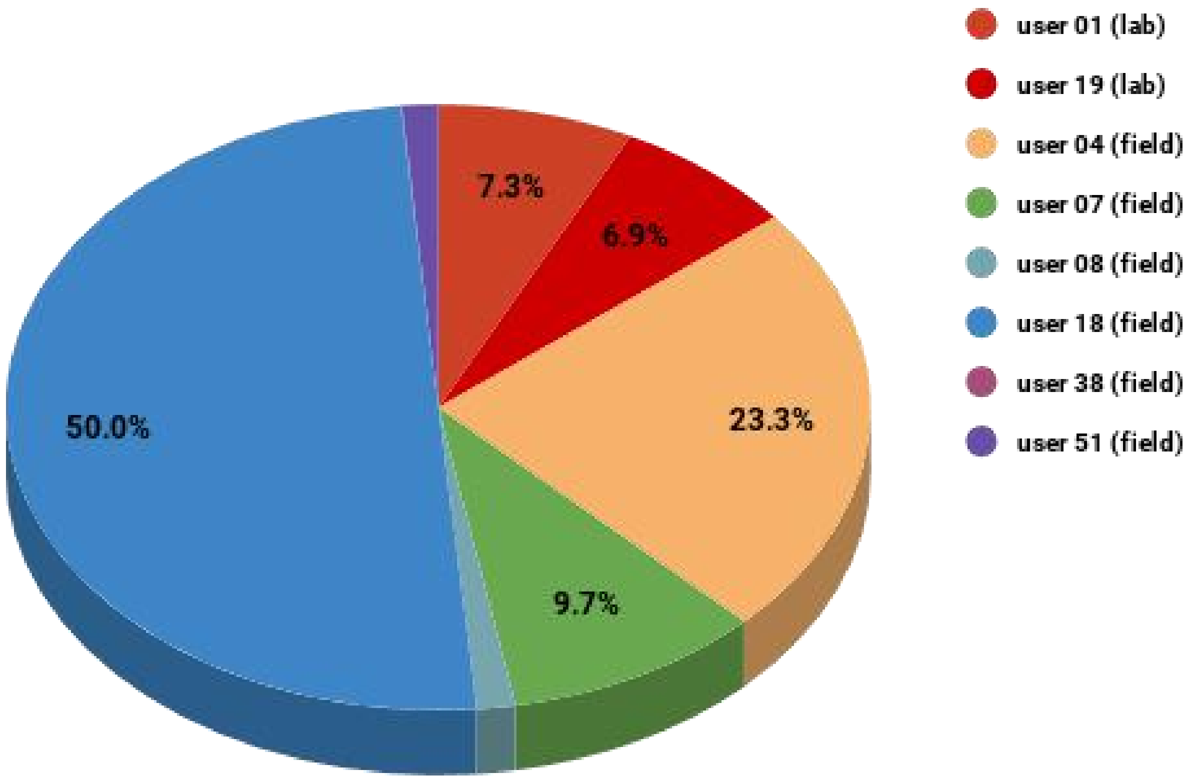


Figure (6): User wise data distribution

# Result Analysis (cont'd)

| Classifier (Accuracy) | Lab Data | | Field Data (Users) | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 19 | 4 | 7 | 8 | 18 | 38 | 51 |
| K Nearest Neighbor | 56% | 71% | 39% | 41% | 6% | 85% | 1% | 1% |
| Random Forest | 62% | 59% | 43% | 27% | 13% | 73% | 10% | 7% |
| Naive Bayes | 12% | 15% | 14% | 16% | 3% | 51% | 1% | 1% |
| Multilayer Perceptron | 62% | 71% | 40% | 41% | 6% | 86% | 1% | 1% |

Figure (7): User wise accuracy

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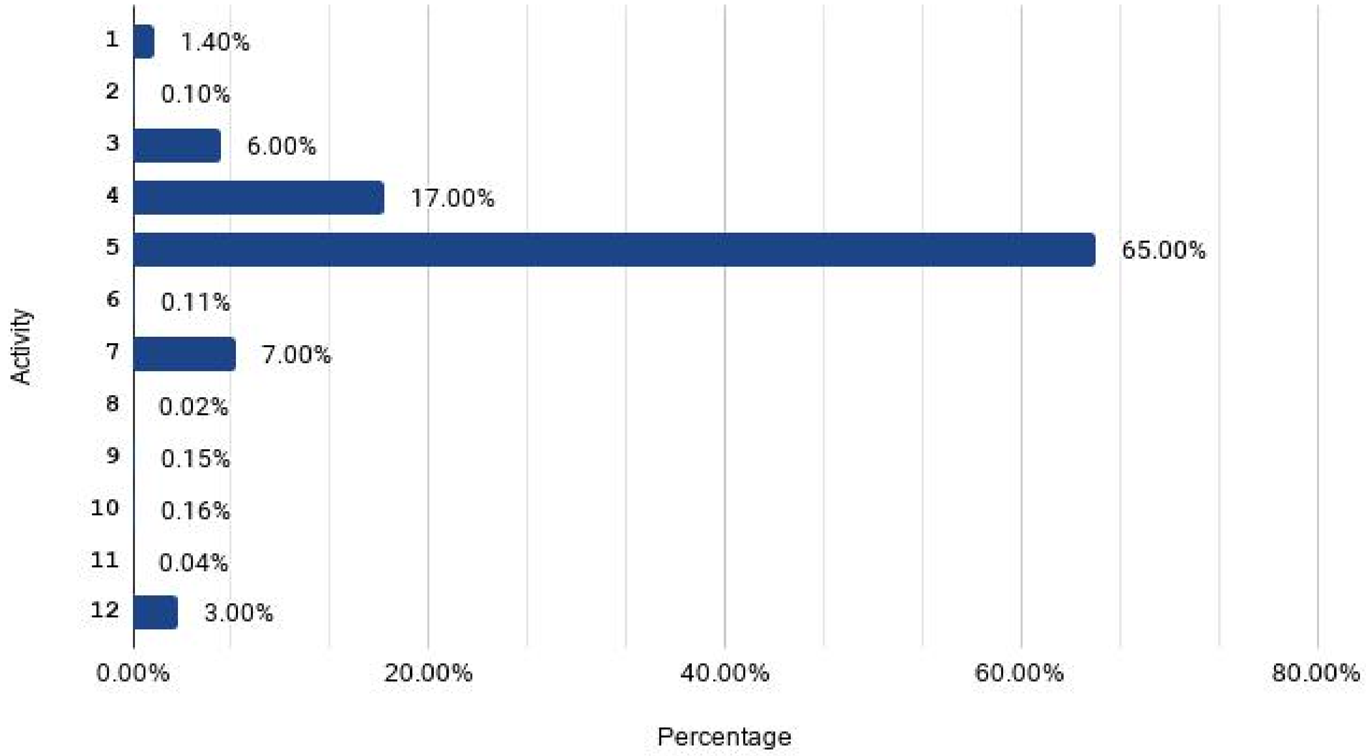


Figure (8): Activity wise data distribution

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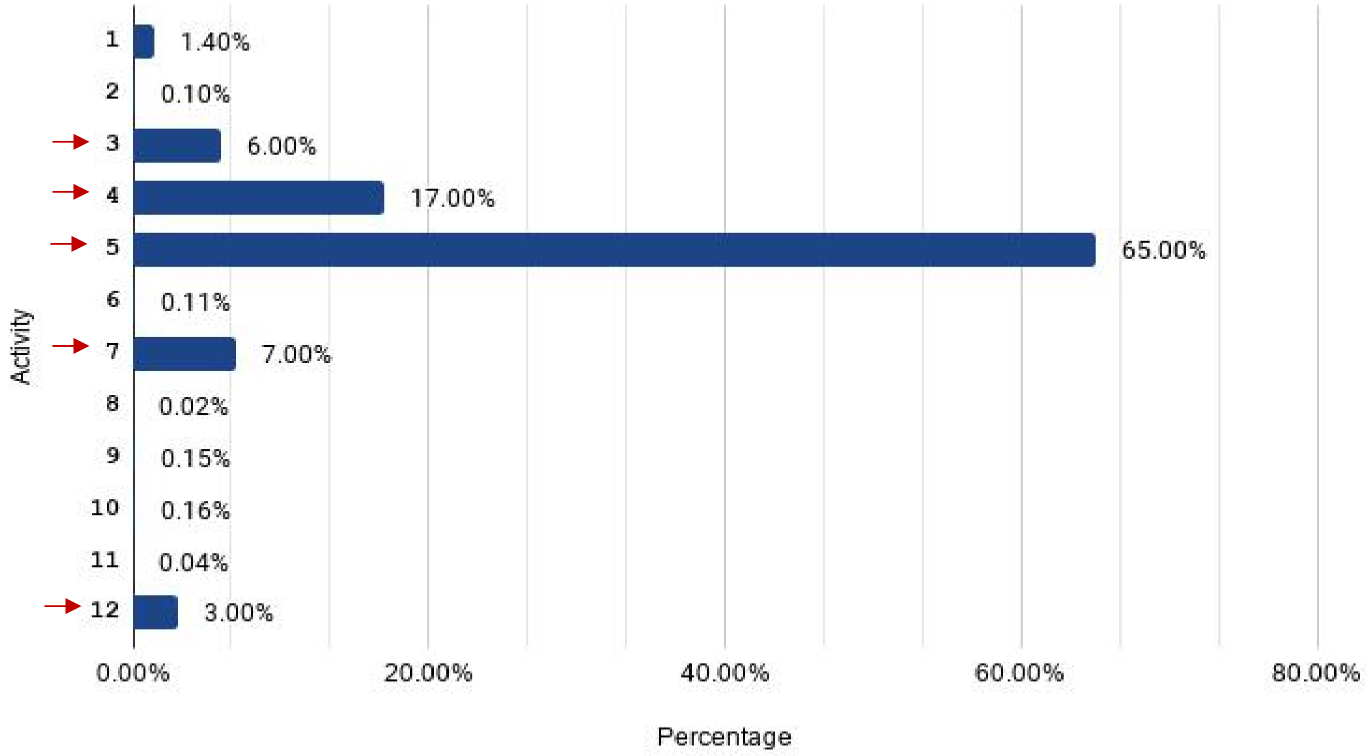


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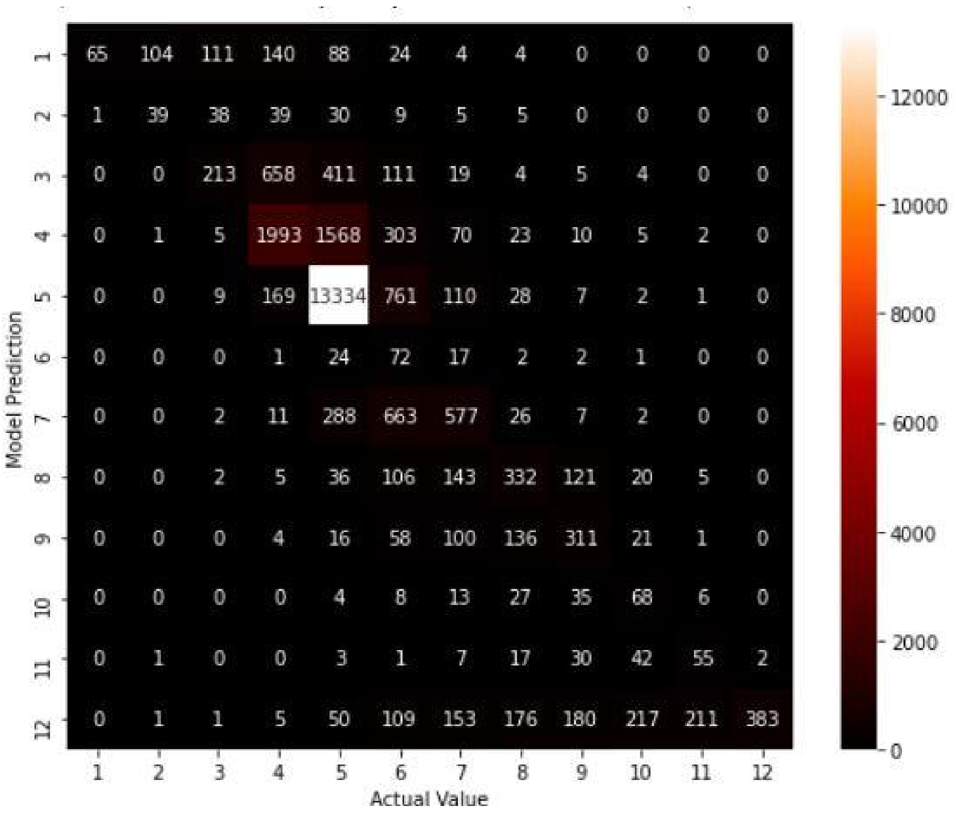


Figure (9): Confusion Matrix for Random Forest

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- Traditional Machine Learning algorithms can also be viable in complex activity recognition problems!

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- Traditional Machine Learning algorithms can also be viable in complex activity recognition problems!
- We wish to explore further possibilities in our future work
  - Feature Selection
  - Handling Imbalanced Data

# Thank You

## Any Questions?