# Remote Health Monitoring For Early Detection of Self harm Behavior Detection Using SDR Technology


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## Introduction

- More than 800,000 suicides occur annually worldwide. 75% of suicides occur in low- and middle-income nations (LMICs) [1].
- Increase in patients has led to a decrease in the number of doctors per patient, creating a vicious cycle where ignored or delayed diagnostics make patients more reliant on doctor's visits.
- Remote Patient Monitoring is a subcategory of homecare telehealth that allows to gather patient health data and send it to healthcare professionals.
- Providers can now track their patient's readings instantly using Cellular enabled medical devices such as Blood Pressure Monitor, Blood Glucose Meter, Pulse Oximeter & Weight Scale.
- SDR software radio is that the radio can be totally configured or defined by the software. It's more flexible, easy for prototyping, adaptable and cost effective

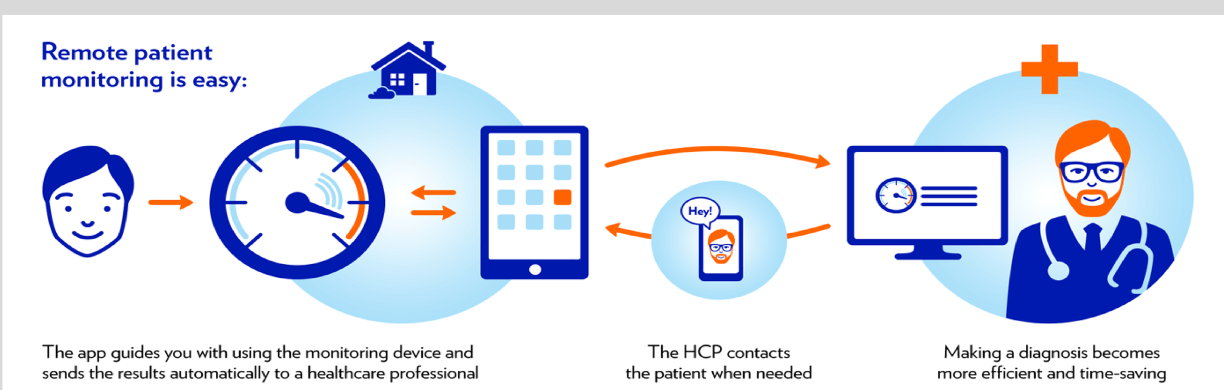


**Fig. 1** Remote Health Monitoring

## Objectives

The objectives of this project are to

- Designing a remote health monitoring prototype system using RF sensing for early detection of self-harming activity.
- Analyze the state-of-the-art Machine Learning Algorithms (MLA) performance on collected datasets in term of accuracy, prediction speed and training time.
- Developing a proactive approach system to ensure the two-way safety of subject health using Industry 5.0 health approach.

## Methodology

Self harming activities detection involves two steps:

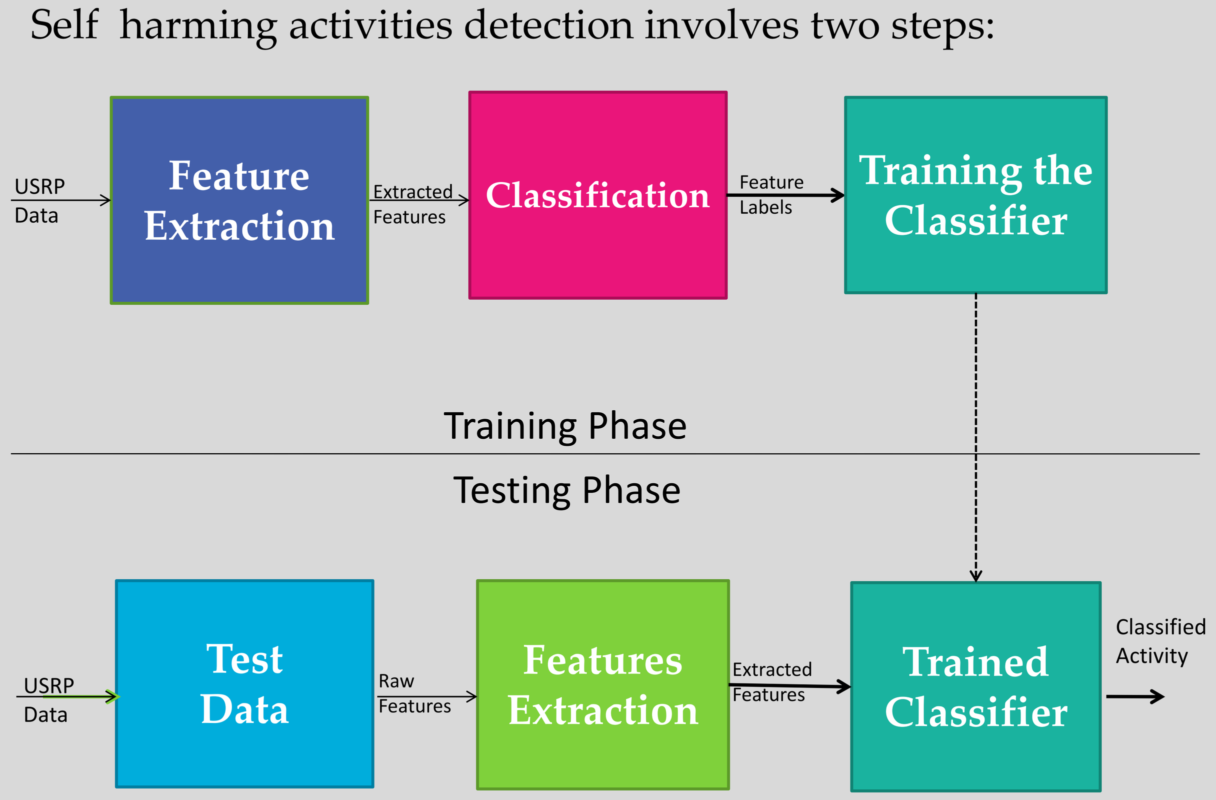


**Fig. 2** Self Harm Activities Recognition Process

## Literature Review

**Table 1.** Literature Review

| Technology/Reference | Detection | Classification Method | Accuracy |
|---|---|---|---|
| Radar [3] | Human Activities Recognition | Support Vector Machine (SVM) | 85.3% |
| Wi-Fi [4] | Human Activity and Fall Recognition | Fine kth Nearest Neighbor (FKNN) | 96.6% |
| RFID [5] | Mental Health Activity | Decision Tree (DT) | MSE 0.003 |
| NCS With RFID [6] | Sleep Monitoring | Support Vector Machine (SVM) | 91.6% |
| Camera based [7] | Human posture disorder using mobile | Nil | Nil |

## Flowchart

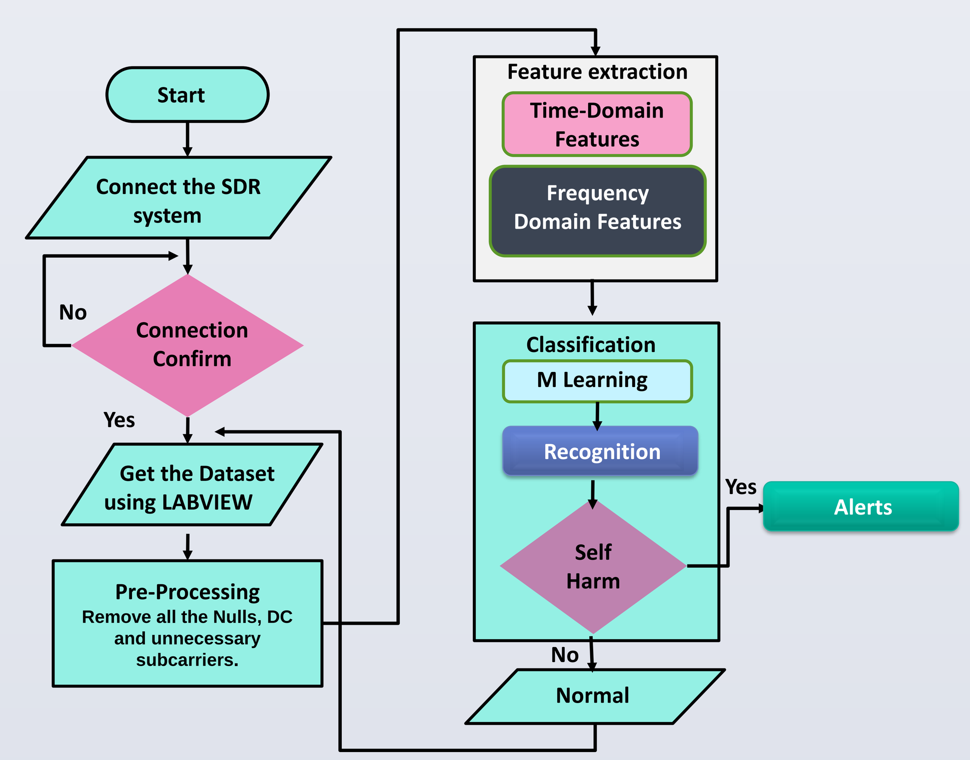


**Fig. 3** Flow Chart of proposed activity detection systems

## Considered Activities


| Sr.No | Subject Gender | Subject Age (Years) | Subject Height (cm) |
|---|---|---|---|
| 1 | Male | 19 | 172 |
| 2 | Male | 21 | 174 |
| 3 | Male | 26 | 160 |
| 4 | Male | 29 | 173 |
| 5 | Male | 26 | 170 |
| 6 | Male | 24 | 164 |

Considered Activities = 7
Total Subjects = 6
Number of Time Each Activity is Performed By Single Subject = 5

T Activities = ((7*5)*6) = 210 Activities

**Fig. 4** Considered Harming Activities For Dataset

## Waveforms

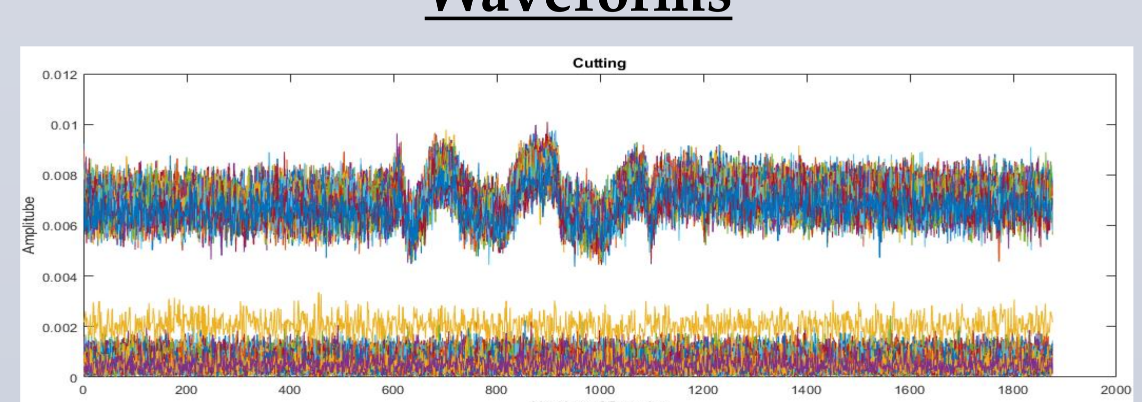


**Fig. 5** Raw Data Waveform Single Activity (Cutting)

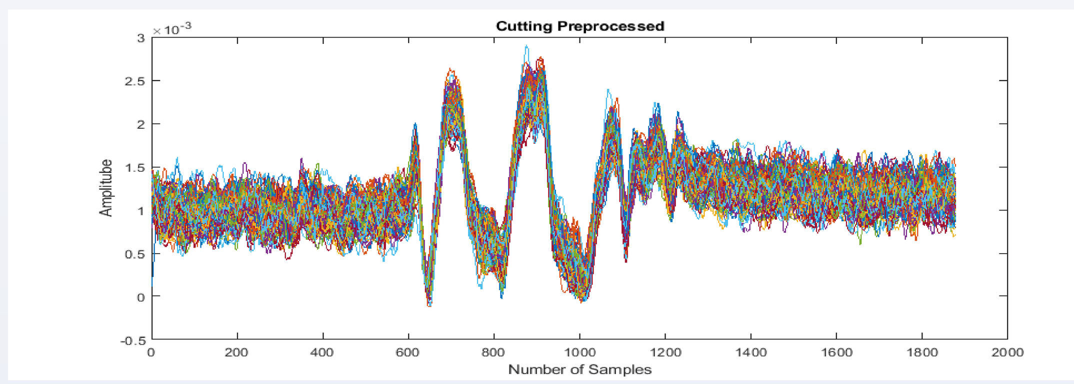


**Fig. 6** Pre processed Waveform Single Sctivity (Cutting)

## Communication Block Diagram

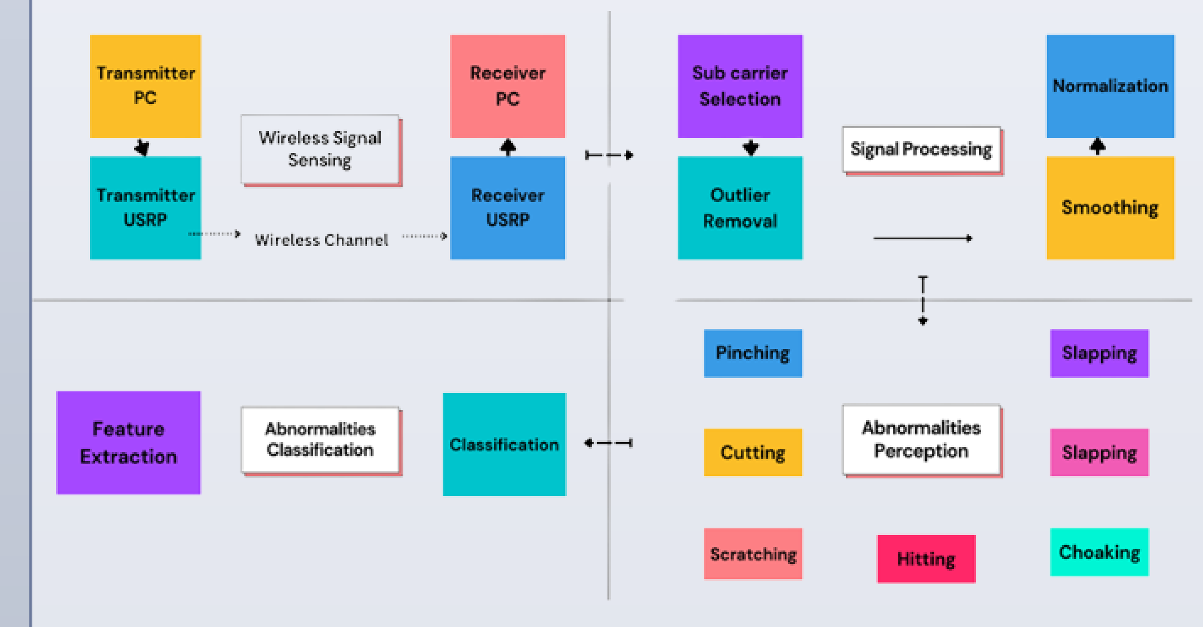


**Fig. 7** Proposed Communication Block Diagram

## System Model

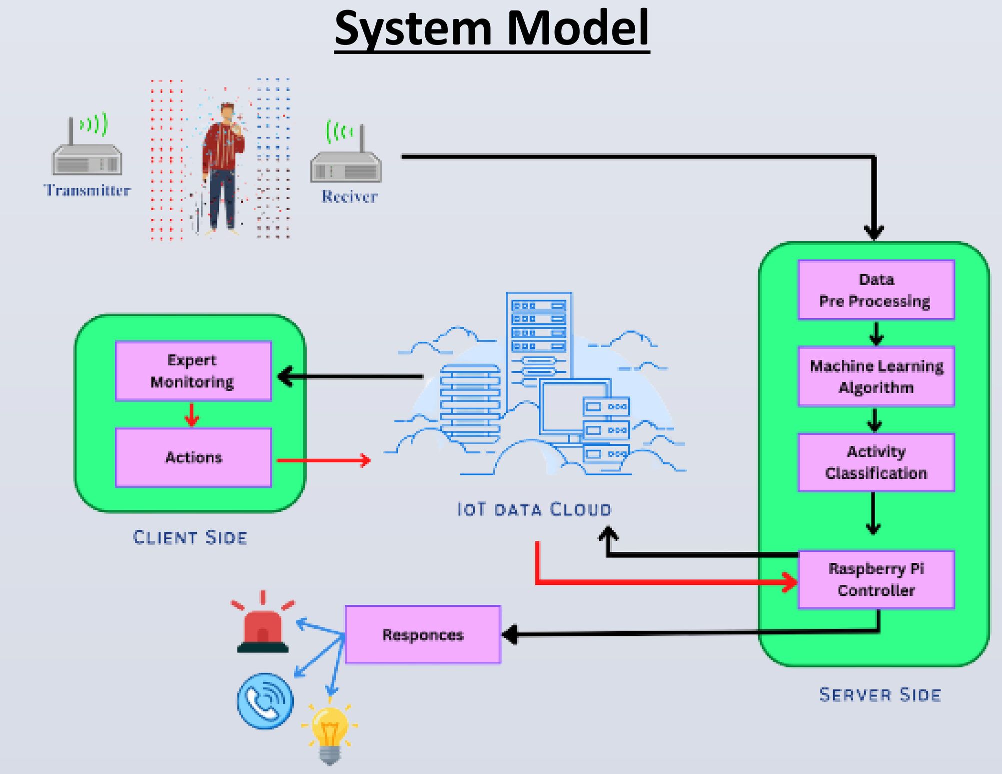


**Fig. 8** Proposed System Model

## Experimental Setup

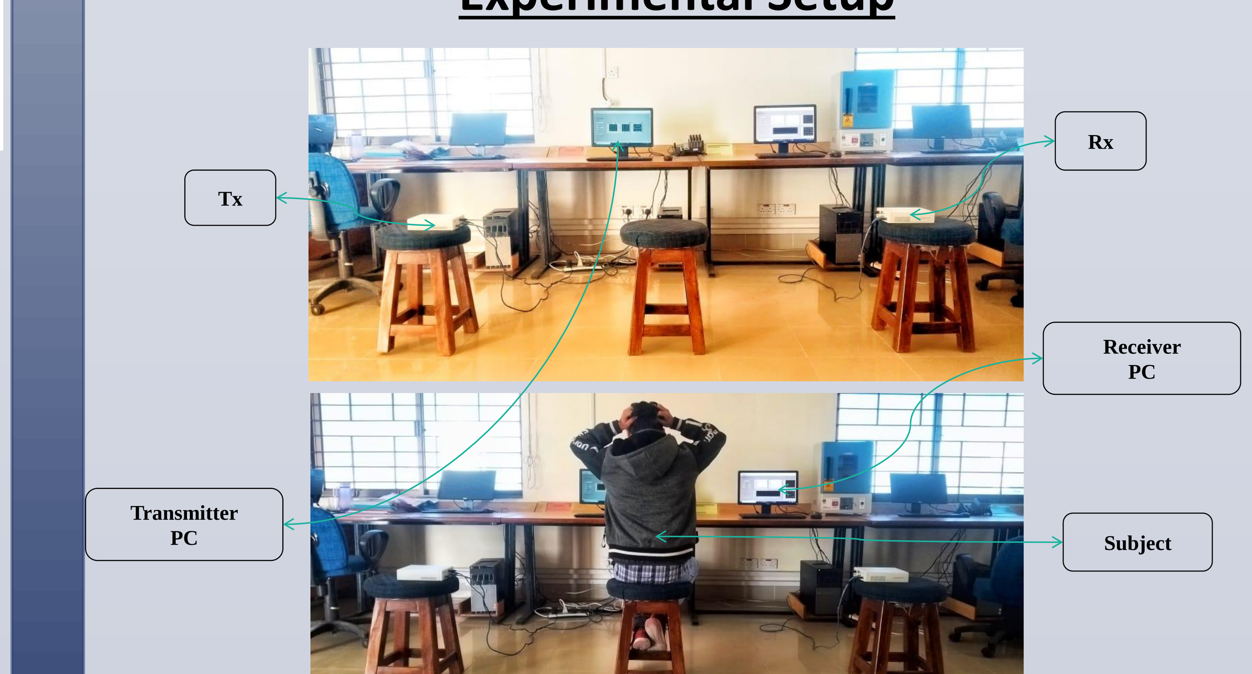


**Fig. 9** LAB Experimental Setup

## Classification Results

**Table 2. Machine Learning Performance Comparison**

| Model | Prediction Speed | St Deviation | Accuracy |
|---|---|---|---|
| K Nearest Neighbor | 32.66s | 0.32 | 89.23% |
| Random Forest | 246.25s | 0.32 | 95.63% |
| Decision Tree | 14.85s | 0.44 | 94.07% |
| XG Boost | 358.93s | 0.78 | 78.68% |
| CAT Boost | 436.71 | 0.46 | 94.64% |

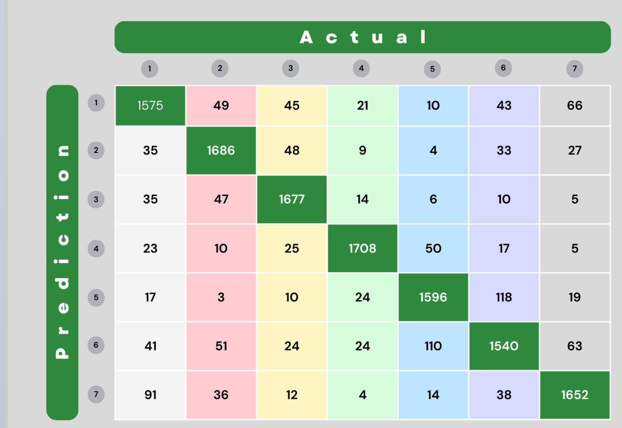

Fig. 10 Confusion Metrix for KNN

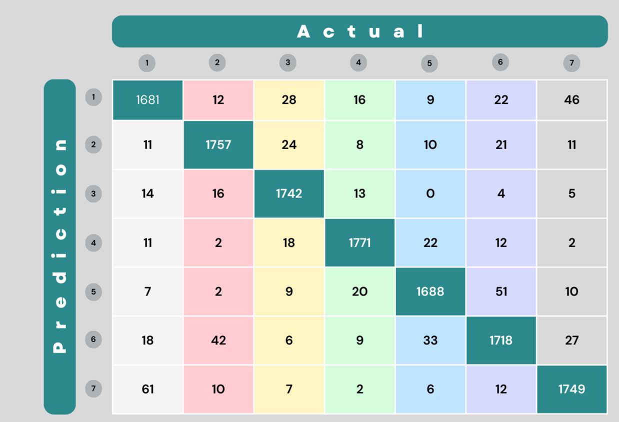

Fig. 11 Confusion Metrix for Decision Tree

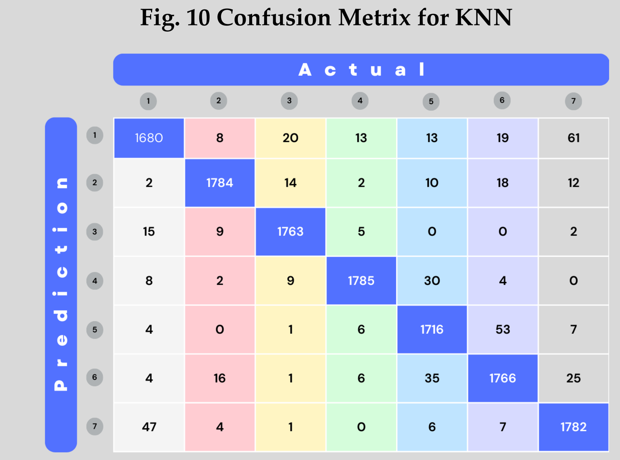

Fig. 12 Confusion Metrix for Random Forest

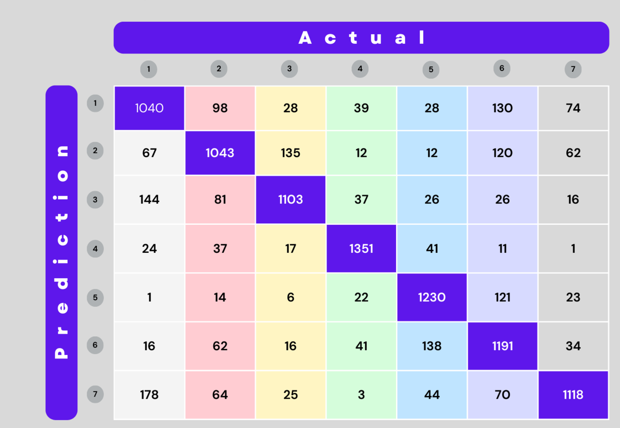

Fig. 13 Confusion Metrix for XG Boost

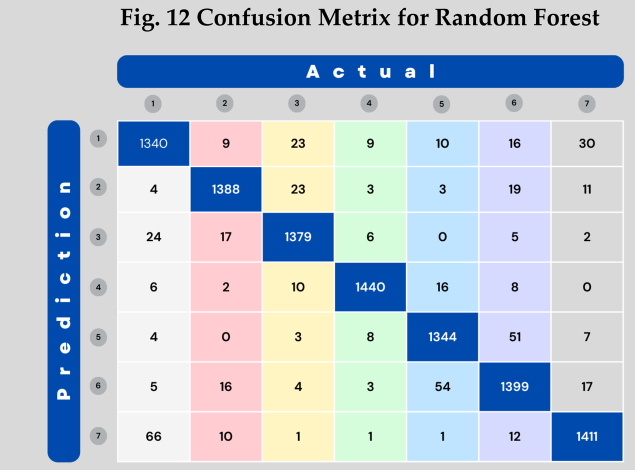

Fig. 14 Confusion Metrix for CAT Boost

## Conclusion

According to what we found in the confusion matrix that compares various machine learning algorithms. Random Forest have the highest accuracy of 95.63%, while CAT Boost is in second place , coming at 94.64%. Further more there will be performance tuning and the generation of possible alerts using the Raspberry pi 4, as one of our objective as to test and understand the state of art of newly developed algorithms for this kind of heatlh care applications. In order to accomplish this, our goal is to use the application for the harming activity detection.

## References


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