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Application of Machine Learning for Panic Attack Detection using Health Wearable Sensors

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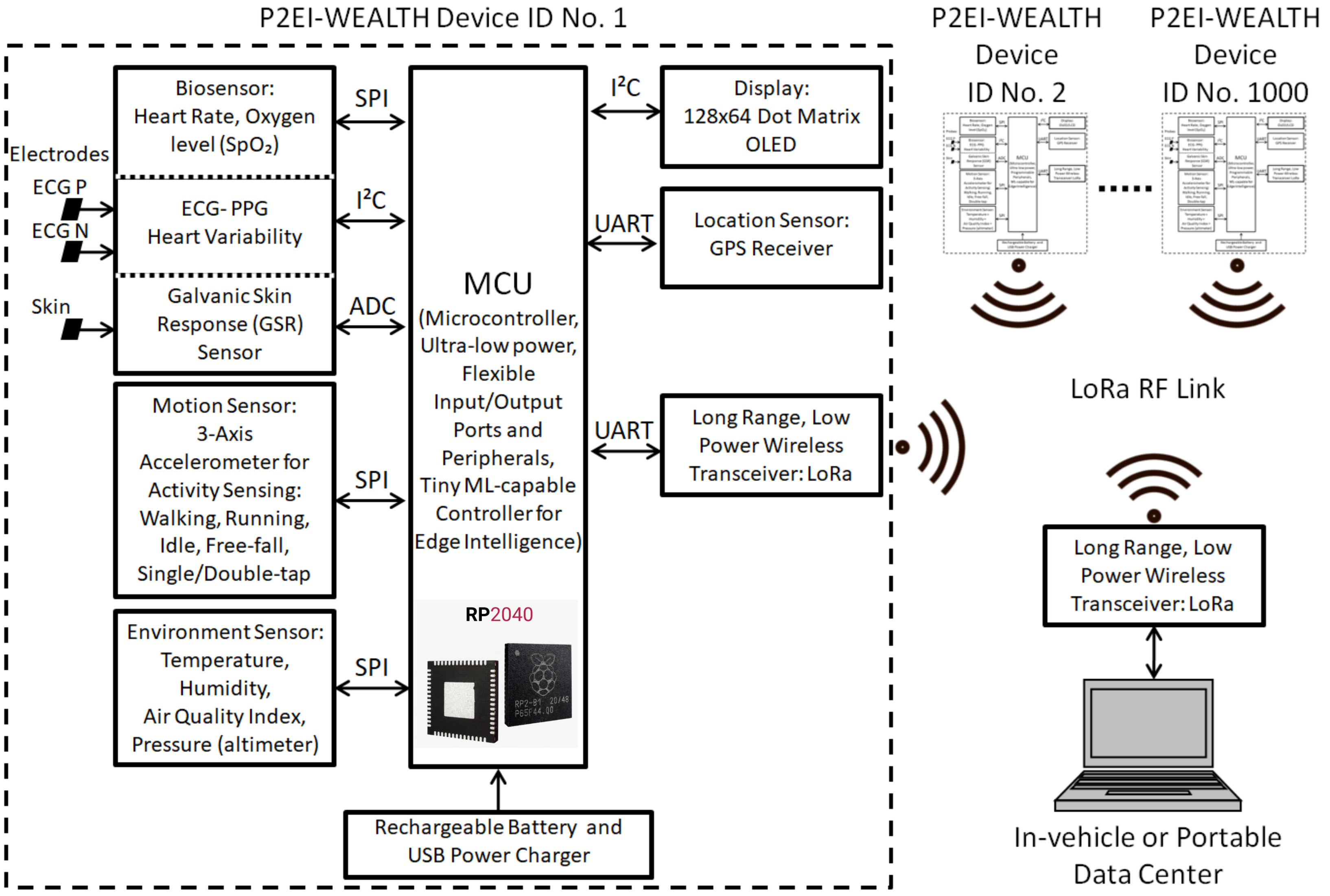
Background on the project

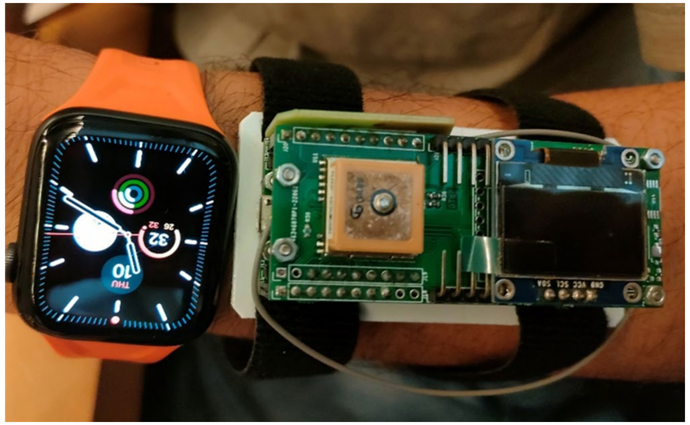
1. The indigenous people and the rescue operators in remote and dangerous vicinities cannot profit from the use of intelligent wearable health support system due to limited connectivity;

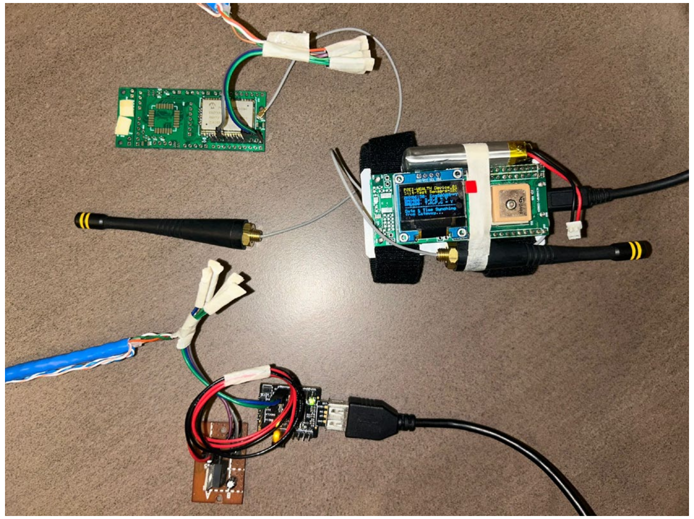
2. Current existing wearables are for individual purposes and not for common monitoring and intervention purposes;
3. Current wearables have multiple measurements from Physio sensors but not supported by edge-intelligence to be analyzed together for Psychological purposes.

P2EI-WEALTH

(**P**hysiological and **P**sychological **E**dge **I**ntelligence **WEA**rable **L**oRa **H**eal**TH**) System

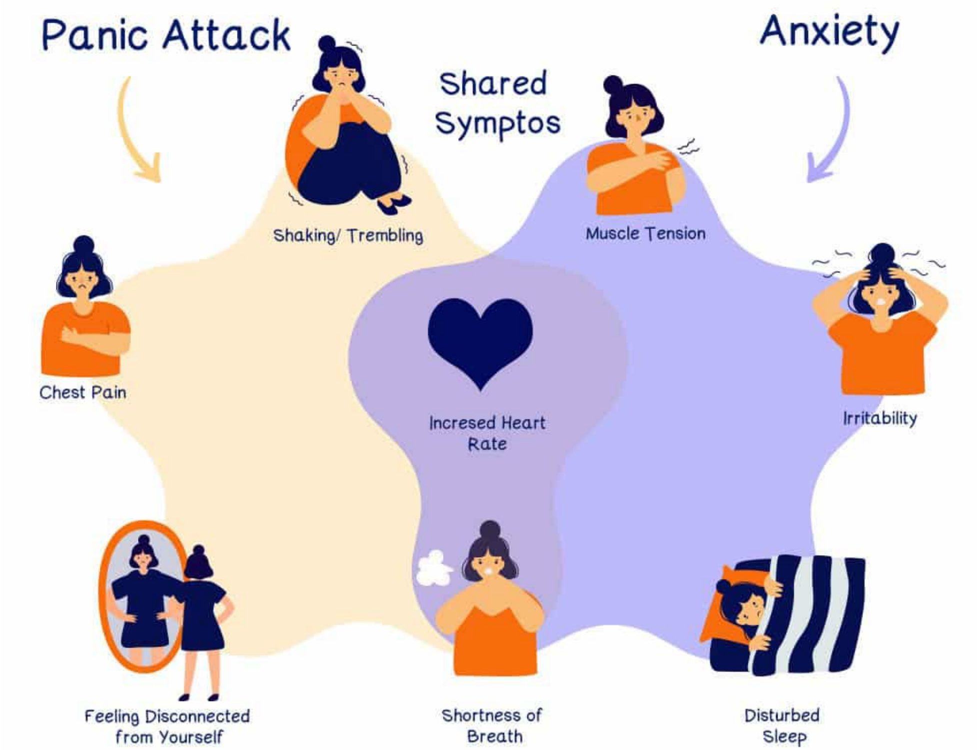






Background on Panic Attack

- **Description**: Sudden overwhelming surge of extreme panic or fear. Frequent episodes are onset for Panic disorder.
- **Triggers**: Long periods of stress, activities that lead to intense physical reactions, physical changes after illness, or a sudden change of environment.
- **Symptoms**:



Comparative Works

Authors	Title	Sensors data	Machine Learning technique
Henry et al., 2023	On the robustness of machine learning models for stress and **anxiety recognition** from heart activity signals	ECG, BVP	SVM, RF, XGBoost, 3 NN-based classifiers
Nath et al., 2021	Machine learning-based **anxiety detection** in older adults using wristband sensors and context feature	EDA, BVP	SVM, RF, LR
Tsai et al., 2022	**Panic attack prediction** using wearable devices and machine learning: development and cohort stud - Garmin Vívosmart 4 - Mobile apps	sleep, heart rate (HR), activity level, BDI, BAI, STAI-S, STAI-T, Air Quality Index	6 decision tree-based classifiers
Our work (**panic attack detection**)		HR, EDA, Body Temperature	11 classifiers (Decision Tree, KNN and SVM kernels)

**ECG – Electrocardiagram, PPG – Photopleytismogram, BVP – Blood volume Pulse, HR – Heart Rate, BDI - Beck Depression Inventory, BA - Beck Anxiety Inventory, STAI-S - State-Trait Anxiety Inventory state anxiety [STAI-S]*

Identification of Dataset

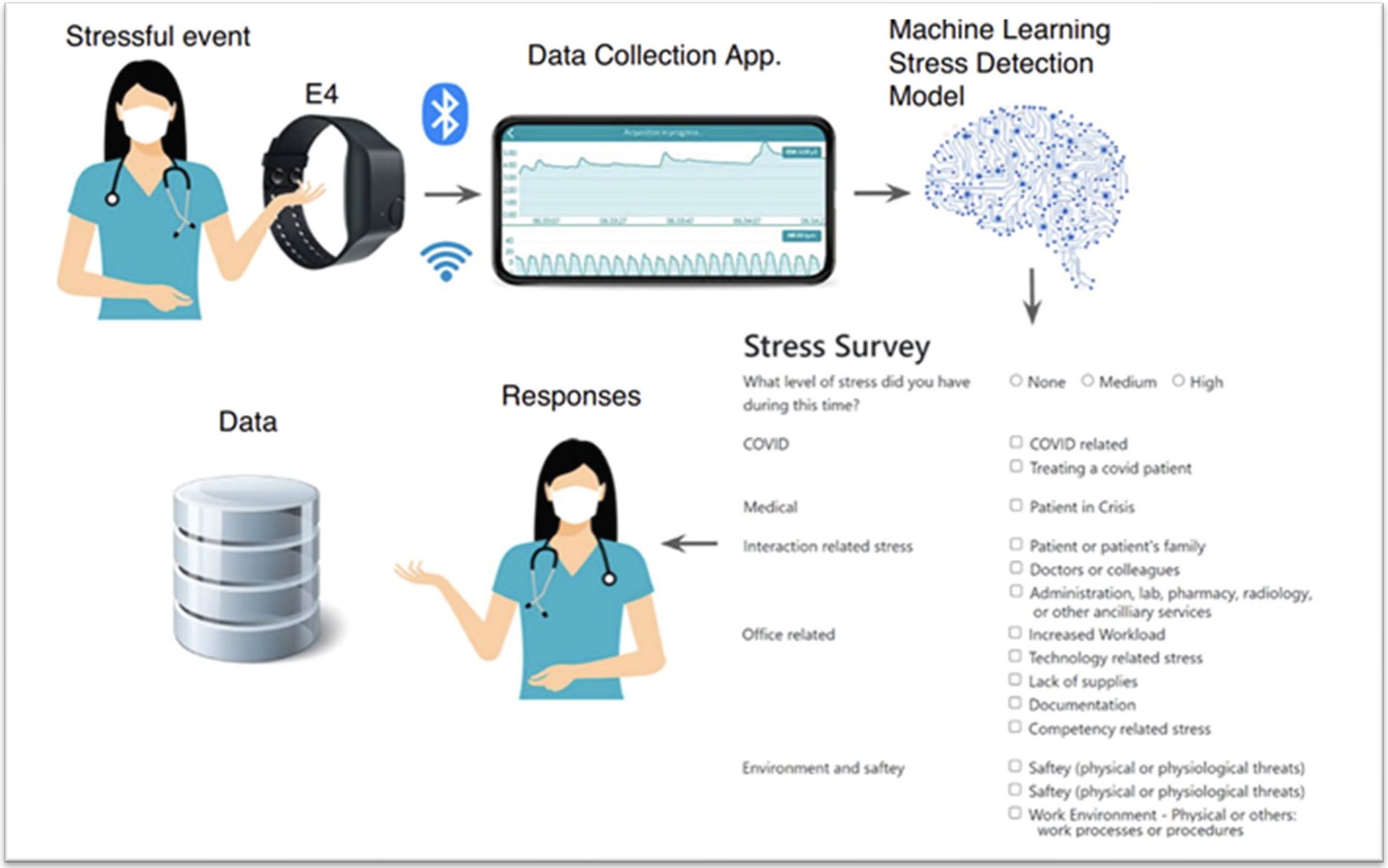


Figure 1. Explanation of the Dataset, Source: Nurse data [6]

Results (1):
Development of Rules for Panic Attack & Creation of Dataset

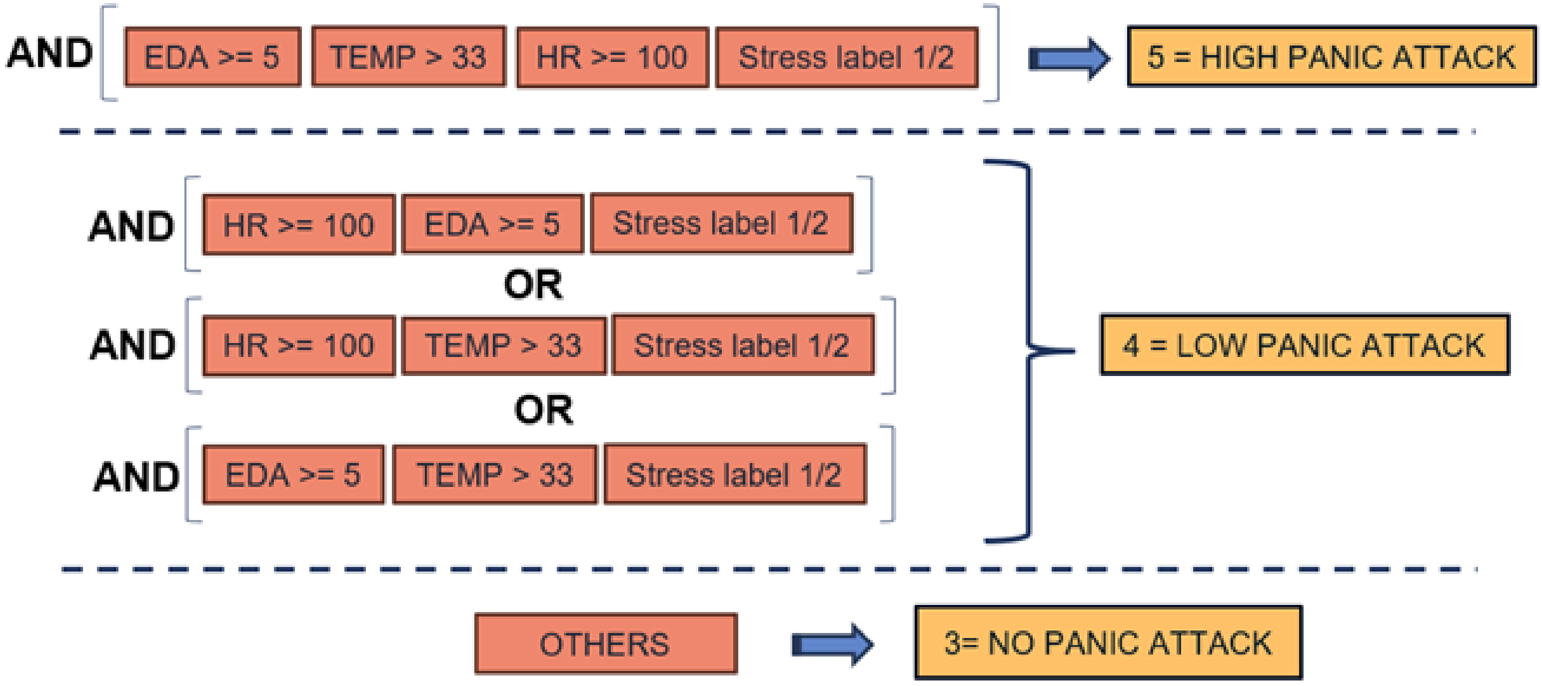


Figure 2. Classification rules of panic attack condition.

Results (2):
Creation of Dataset

Electrodermal Activity	Body Temperature	Heart Rate	Panic Attack Class
Continuous data	Continuous data	Continuous data	[3,4,5]
			3 – No panic attack
			4 – Low panic attack
			5 – High panic attack

Training Dataset	Testing Dataset	Validation Dataset
12 Nurses data	10-Cross Validation	3 Nurses data
11,509,052		104,857

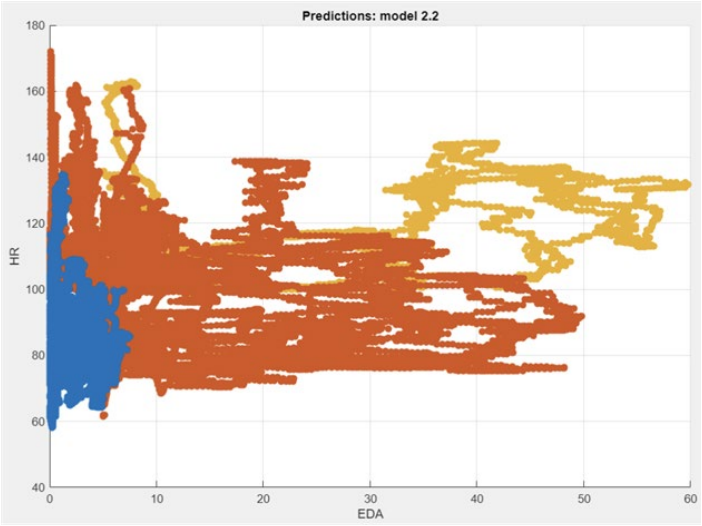


Figure 3: Scatter plot for all training data of Heart Rate (HR) vs ElectrodermalActivity (EDA)

Results (3)
Classification Performance

Machine Learning Model	Accuracy and Respective Nurses Dataset		
	Training (Full 12') Data (943718)	Validation (10% of 12') Data (104857)	Testing (3 Selected) Data (903752)
Fine Tree	100%	100%	99.96%
Medium Tree	100%	100%	99.96%
Coarse Tree	94.94%	94.89%	82.44%
Fine KNN	100%	100%	87.58%
Medium KNN	99.98%	100%	87.58%
Coarse KNN	99.82%	99.85%	87.81%
Cosine KNN	99.99%	100%	88.44%
Cubic KNN	99.98%	100%	86.92%
Weighted KNN	100%	100%	87.57%
Efficient Logistic Regression	91.88%	91.81%	74.01%
Efficient Linear SVM	91.69%	91.68%	74.04%

Table 3: Comparison of accuracy across different Machine Learning models.

Table 4: Comparison of accuracy across different Machine Learning models.

Machine Learning Model	Accuracy and Respective Nurses Dataset		
	Training (Full 12' Nurses Data) (943718)	Training (Full 12' Nurses Data) (943718)	Testing (3 Selected Nurses Data) (903752)
Fine Tree	Total cost : 0 Error rate : 0% Training time : 125.73s Model size : ∼7kB Prediction speed : ∼510000 obs/sec	Total cost : 0 Error rate : 0.0%	Total cost : 352 Error rate : 0.0%
Medium Tree	Total cost : 0 Error rate : 0% Training time : 118.67s Model size : ∼7kB Prediction speed : ∼570000 obs/sec	Total cost : 0 Error rate: 0.0%	Total cost : 352 Error rate : 0.0%
Coarse Tree	Total cost : 47743 Error rate : 5.1% Training time : 111.86s Model size : ∼5kB Prediction speed : ∼670000 obs/s	Total cost : 5361 Error rate : 5.1%	Total cost : 158723 Error rate : 17.6%
Coarse KNN	Total cost : 1736 Error rate : 0.2% Training time : 525.4s Model size : ∼64MB Prediction speed : ∼7800 obs/s	Total cost :161 Error rate : 0.2%	Total cost: 110143 Error rate : 12.2%
Cosine KNN	Total cost : 130 Error rate : 0.0% Training time : 21571s Model size : ∼44MB Prediction speed : ∼690 obs/s	Total cost : 0 Error rate : 0.0%	Total cost : 104508 Error rate : 11.6%
Cubic KNN	Total cost : 159 Error rate : 0.0% Training time : 17347s Model size : ∼64MB Prediction speed : ∼2900 obs/s	Total cost : 3 Error rate : 0.0%	Total cost : 118200 Error rate : 13.1%
Weighted KNN	Total cost : 0 Error rate : 0.0% Training time : 305.97s Model size : ∼64MB Prediction speed : ∼17000 obs/s	Total cost : 0 Error rate : 0.0%	Total cost : 112319 Error rate : 12.4%
Efficient Logistic Regression	Total cost : 76665 Error rate : 8.1% Training time : 462.97s Model size : ∼37kB Prediction speed : ∼370000 obs/s	Total cost : 8589 Error rate : 8.2%	Total cost : 234907 Error rate : 26.0%
Efficient Linear SVM	Total cost : 78409 Error rate : 8.3% Training time : 345.08s Model size : ∼37kB Prediction speed : ∼420000 obs/s	Total cost : 8722 Error rate : 8.3%	Total cost : 234635 Error rate : 26.0%

Conclusion

The study has proven that given a good rules, panic attack can be detected using werable sensors

Rooms for improvement include,

1. Integration to an edge device with limited ressources but at the same time can provide wireless communication capacity using tensorflow lite.
2. Comparative study with the same sensors/information as [5]
3. Seek more experts' advice on the design of the rules

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