Indoor localization based on fingerprint of BLE and Wi-Fi using Machine Learning

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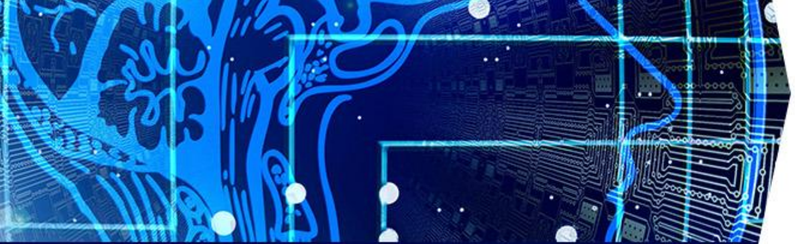

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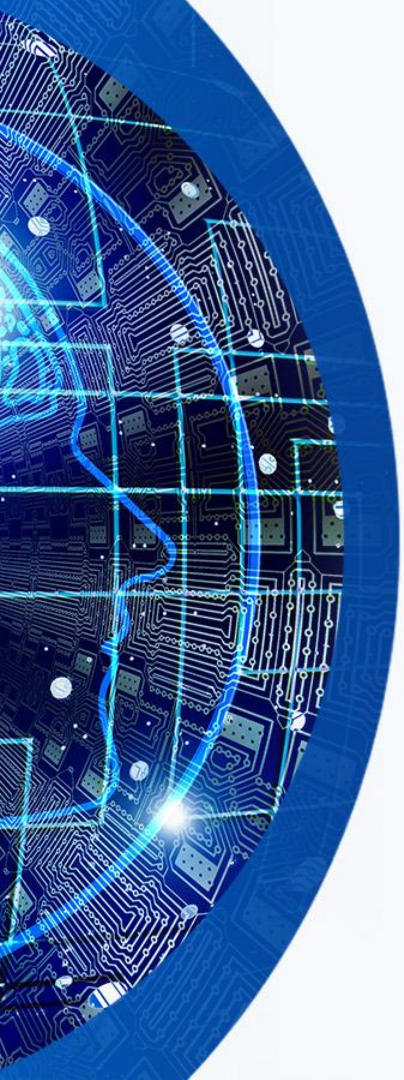
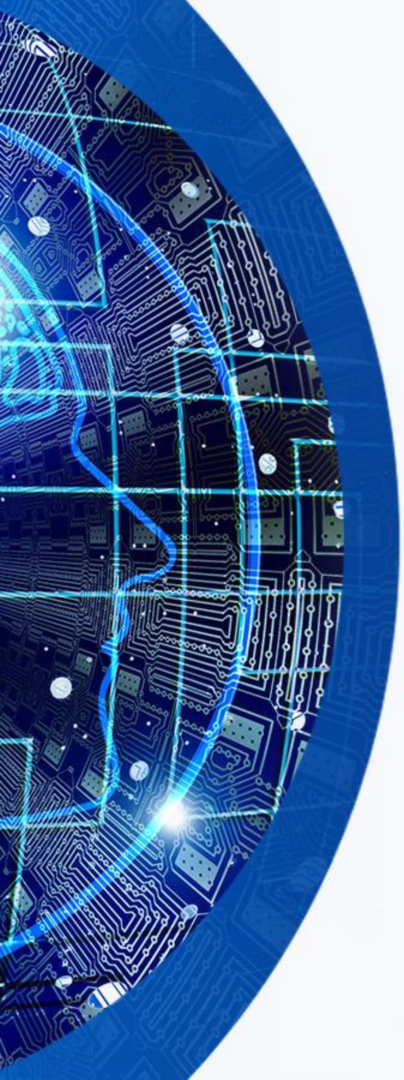


Abstraction

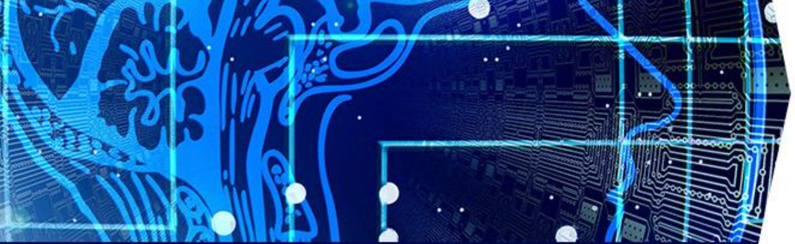
- **Fingerprint of BLE**
- **Data Collection using Raspberry pi 4 B+**
- **Data preprocessing using Received Signal Strength Indicator (RSSI) filtering methods**
- **Implementation of supervised learning methods**
- **Evaluate learning models**

- **Scripts are available in:**
- https://github.com/JaberBabaki/Indoor-Localization-with-ML/tree/author-01
- https://www.kaggle.com/ashkangoharfar/indoor-localization-using-ble-and-wifi



Introduction

- **Indoor Localization in Business**
- **(Global Positioning System)GPS**
- **Indoor Localization methods:**
  - Time of Arrival(ToA)
  - Time Difference of Arrival(TDoA)
  - Angle of Arrival(AoA)
  - Location Fingerprinting
- **Location Fingerprinting** connects location-dependent characteristics such as received signal strength (RSS), from known access points to a location, and uses these characteristics to infer the location.
- **Data Collection**
- **Data Preprocessing**
- **Implementation of machine learning methods**



Related Works

[1] G. De Blasio, A. Quesada-Arencibia, C. R. García, J. C. Rodríguez-Rodríguez and R. Moreno-Díaz, "A Protocol-Channel-Based Indoor Positioning Performance Study for Bluetooth Low Energy," in IEEE Access, vol. 6, pp. 33440-33450, 2018, doi: 10.1109/ACCESS.2018.2837497., 206-212

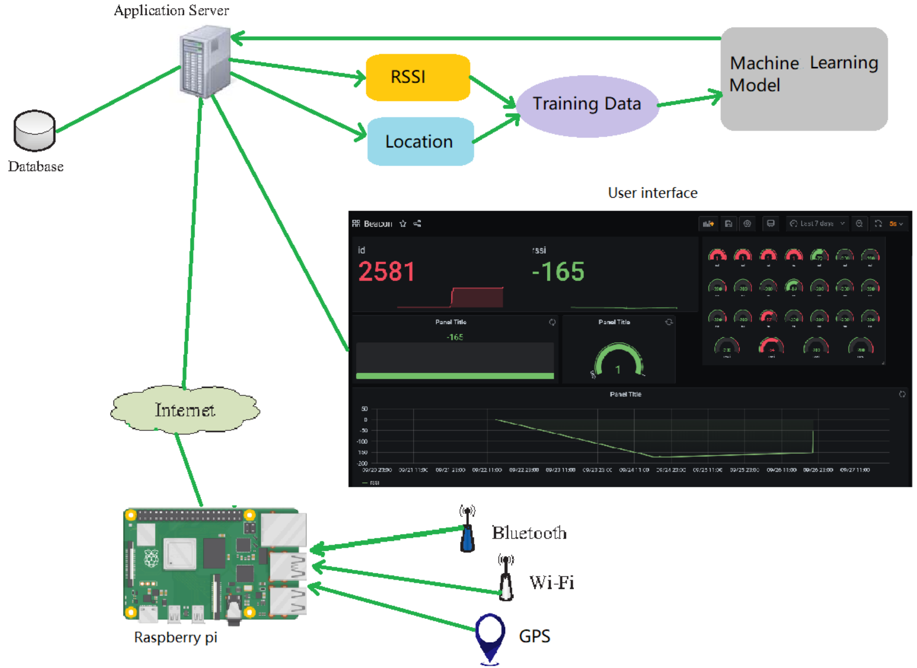
[2] Yu-Chi Pu and Pei-Chun You. “Indoor positioning system based on BLE location fingerprinting with classification approach”. In: Applied Mathematical Modelling 62 (2018), pp. 654–663.

[3] Wei Zhang, Kan Liu, Weidong Zhang, Youmei Zhang, and Jason Gu, “Deep Neural Networks for wireless localization in indoor and outdoor environments,” Neurocomputing, vol. 194, pp. 279-287, 2016

[4] M. Mohammadi, A. Al-Fuqaha, M. Guizani and J. Oh, "Semisupervised Deep Reinforcement Learning in Support of IoT and Smart City Services," in IEEE Internet of Things Journal, vol. 5, no. 2, pp. 624-635, April 2018, doi: 10.1109/JIOT.2017.2712560.

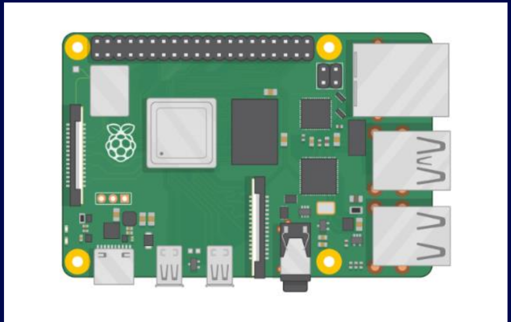
System Architecture

- An optimum System Architecture for BLE, Wi-Fi, and LoRaWAN protocols
- Hardware Devices
  - Raspberry Pi 4 B+
  - 5 Beacons
- Wireless Network
- Application Server
- Database
- Training Phase
- User interface : Grafana



Hardware Devices

Raspberry Pi



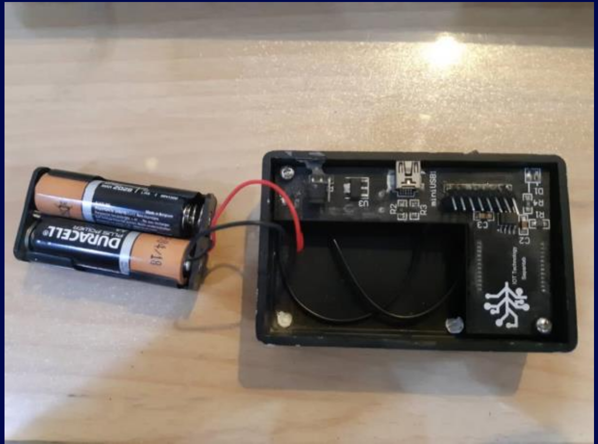
- Works as a Gateway
- Collect Data
- Train Data
- API

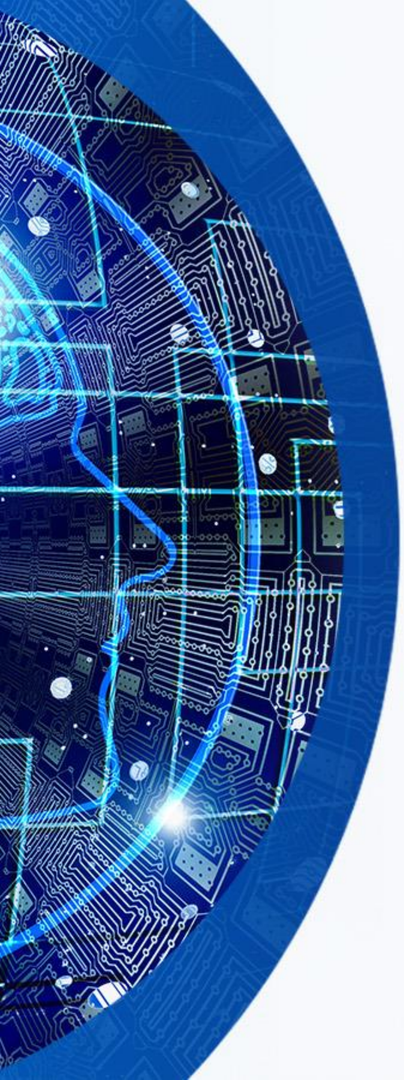
Wi-Fi

- ESP8266

Bluetooth Low Energy(BLE)

- Modes : Advertising or Connection
- Channel 38, 39 and 40
- iBeacon and Eddystone BLE profiles
- Bluetooth 5
- Low power
- NRF52832





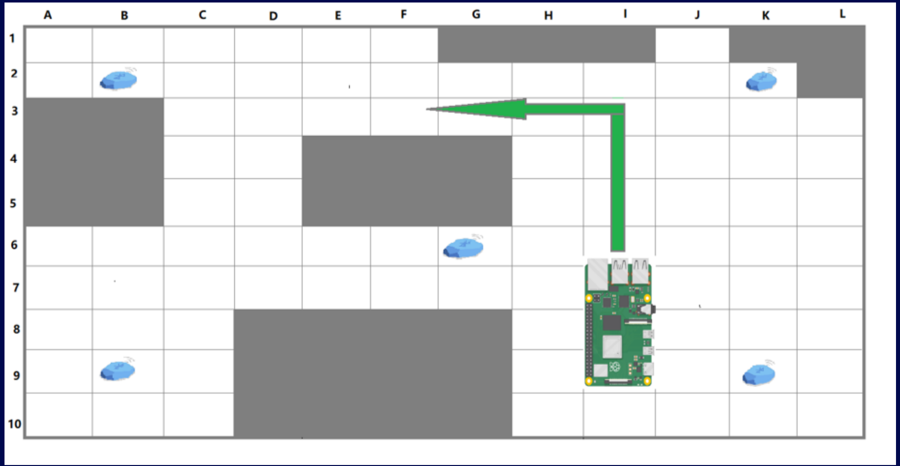
Learning Phase

- **Data Collection**
- **Data Preprocessing**
- **Supervised Learning**
- **Deep Learning**

Data Collection

Map:

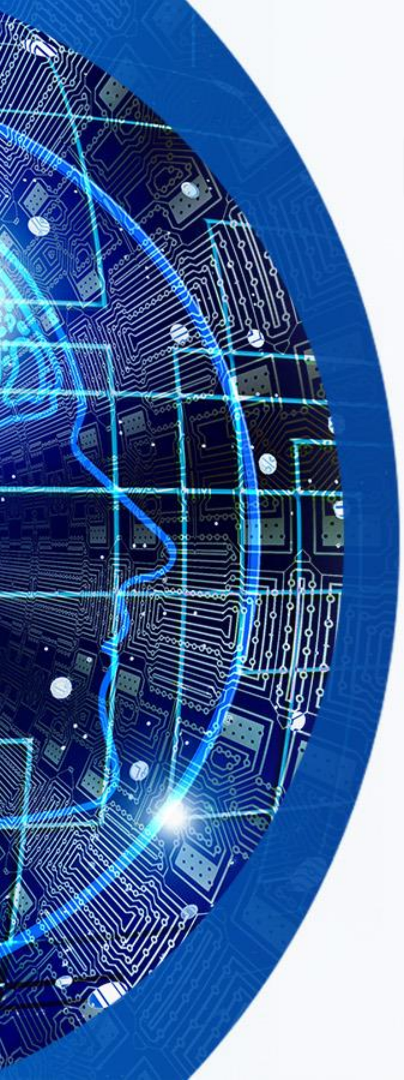
- Walk in the map using Predetermined Scenario



Dataset:

B2 10/2/2020 5:59:12 PM

	A	B	C	D	E	F	G
1	location	date	beacon1	beacon2	beacon3	beacon4	beacon5
2	A10	########	-72	-75	-59	-85	-79
3	A10	########	-67	-71	-57	-79	-76
4	A10	########	-77	-67	-64	-82	-84
5	A10	########	-72	-61	-63	-68	-79
6	A10	########	-67	-56	-64	-72	-82
7	A10	########	-67	-52	-62	-72	-80
8	A10	########	-73	-56	-67	-68	-85
9	A10	########	-66	-55	-71	-64	-90



Data Preprocessing

- **Signal is affected by the APs transmit power & antenna as well as the clients antenna**
- **RSSI [5]**
  - Actual RSSI + Antenna Gain = Displayed RSSI
  - RSSI < -90 dBm: this signal is extremely weak, at the edge of what a receiver can receive.
  - RSSI -67dBm: this is a fairly strong signal.
  - RSSI > -55dBm: this is a very strong signal.
  - RSSI > -30dBm: your sniffer is sitting right next to the transmitter
- **Signal to Noise (SNR)**
  - Actual RSSI + Antenna Gain = Displayed RSSI
- **Filter Noisy RSSI Discrete Signal:**
  - Kalman Filter[10]
  - FFT Filter
  - Gray Filter

$$A_0 = \frac{1}{N}\sum_{n=1}^{N} y(t_n) \quad B_0 = B_{N/2} = 0 \quad A_{N/2} = \frac{1}{N}\sum_{n=1}^{N} y(t_n)\cos(n\pi) \qquad (4)$$

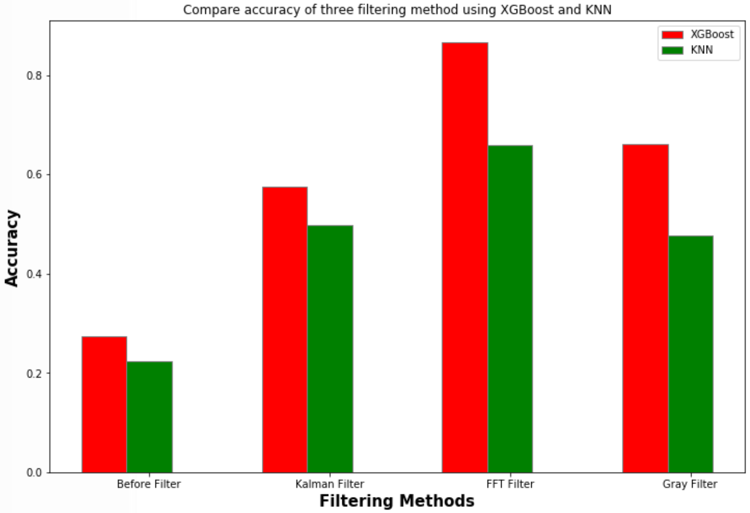
$$A_p = \frac{2}{N}\sum_{n=1}^{N} y(t_n)\cos\left(\frac{2\pi pn}{N}\right) \quad \text{where } p = 1 \ldots N/2 - 1 \qquad (5)$$

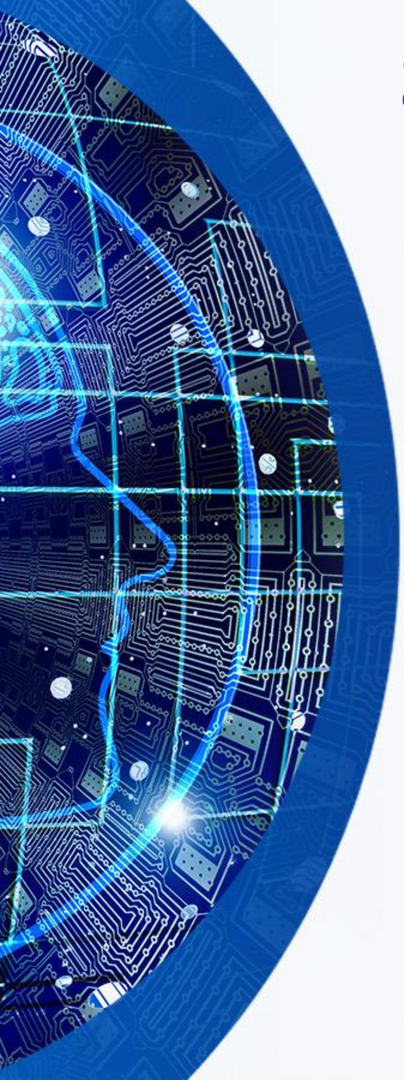
$$B_p = \frac{2}{N}\sum_{n=1}^{N} y(t_n)\sin\left(\frac{2\pi pn}{N}\right) \quad \text{where } p = 1 \ldots N/2 - 1 \qquad (6)$$

where $t_n = n\Delta t$, $\Delta t = \frac{T}{N}$, $\omega_p t = \frac{2\pi pn}{T}$, $N = R_0\ size$

The Fourier coefficient set is the basis to define an Inverse Discrete Fourier Transform (IDFT) to regenerate the RSSI signal:

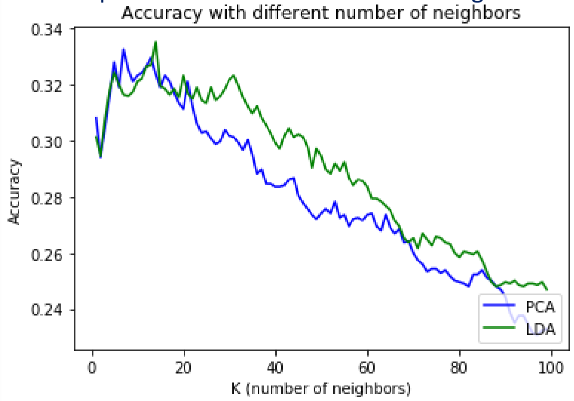
$$f(t_n) = \frac{1}{2}A_0 + \sum_{p=1}^{M}[A_p\cos(\omega_p t) + B_p\sin(\omega_p t)] \qquad (7)$$

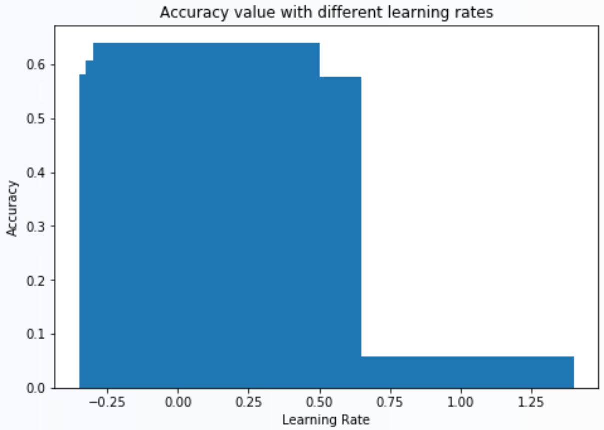


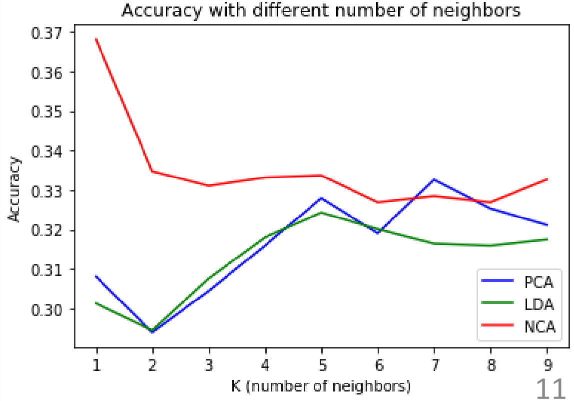


Supervised Learning Methods

- **K-Nearest Neighbors (KNN)[6]**
- **KNN with Dimensionality Reduction:** Dimensionality Reduction is the transformation of data from a high-dimensional space into a low-dimensional space so that the low-dimensional representation retains some meaningful properties of the original data, ideally close to its intrinsic dimension.
  - Principal Component Analysis (PCA)
  - Linear Discriminant Analysis (LDA)
  - Neighborhood Components Analysis (NCA)
- **Decision Tree**
- **Gradient Boosting**
  - Learning Rate: 0.05, 0.075, 0.1, 0.25, 0.5, 0.75, 1
- **Logistic Regression**
  - Solver: newton-cg, lbfgs, liblinear, sag, saga
- **Support Vector Machine (SVM)[6]**
  - Kernels: linear, RBF, sigmoid

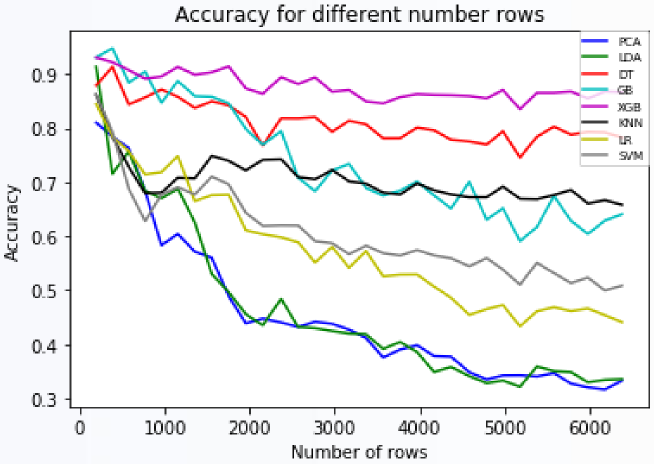


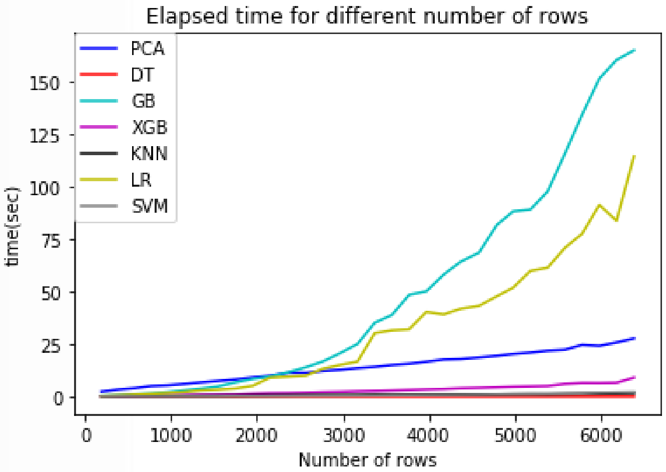




Supervised Learning Methods

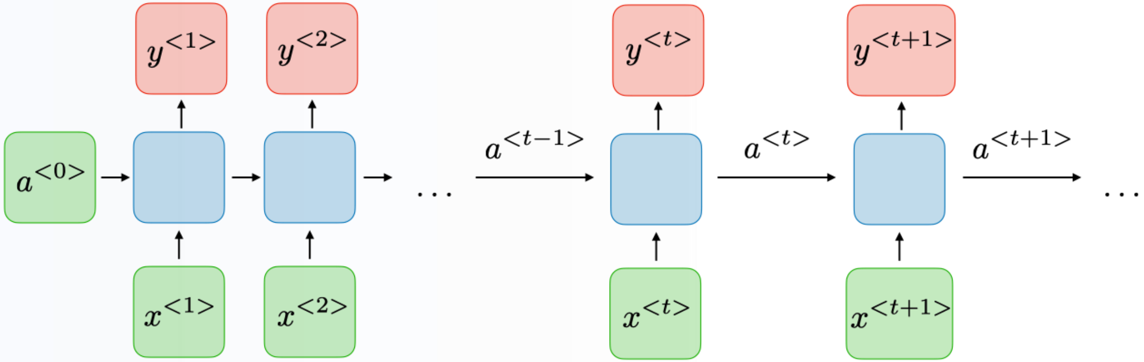
- **Boost Learning (XGBoost):** Boost Learning is an optimized distributed gradient boosting algorithm designed to be highly efficient, flexible and portable. It implements machine learning algorithms under the Gradient Boosting framework. XGBoost provides a parallel tree boosting (also known as GBDT, GBM) that solve many data science problems in a fast and accurate way.





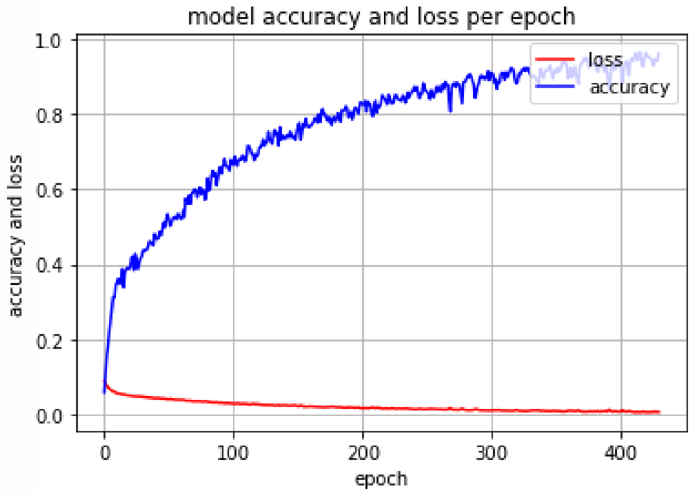
Deep Learning

- **Recurrent Neural Network (RNN)[9]:** Connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior.
  - **Long short-term memory (LSTM):** Unlike standard feedforward neural networks, LSTM has feedback connections. It can not only process single data points, but also entire sequences of data.
  - **Gated Recurrent Unit (GRU):** GRU is like a long short-term memory (LSTM) with a forget gate, but has fewer parameters than LSTM, as it lacks an output gate.



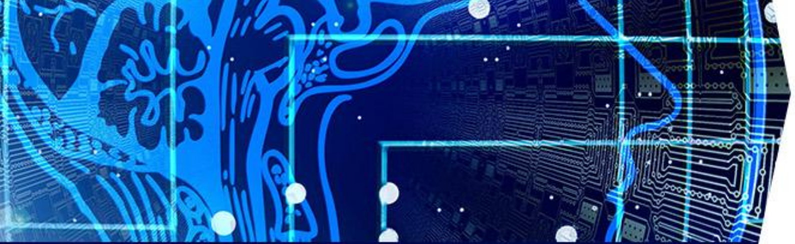
Deep Learning

- **LSTM Layer Parameters:**
  - Implementation of One-hot Encoding for Labels
  - Loss Function: binary_crossentropy
  - Optimizer: adam
  - Activation Function: softmax
  - Train Data: 70% -> choose randomly
  - Test Data: 30% -> others
  - X_train shape: (889, 5, 5)
  - y_train shape: (889, 55)
  - epochs=430
  - loss: 0.0505 - accuracy: 0.5748




```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_4 (LSTM)                (None, 150)               93600
_________________________________________________________________
dense_4 (Dense)              (None, 55)                8305
=================================================================
Total params: 101,905
Trainable params: 101,905
Non-trainable params: 0
_________________________________________________________________
```

Conclusion

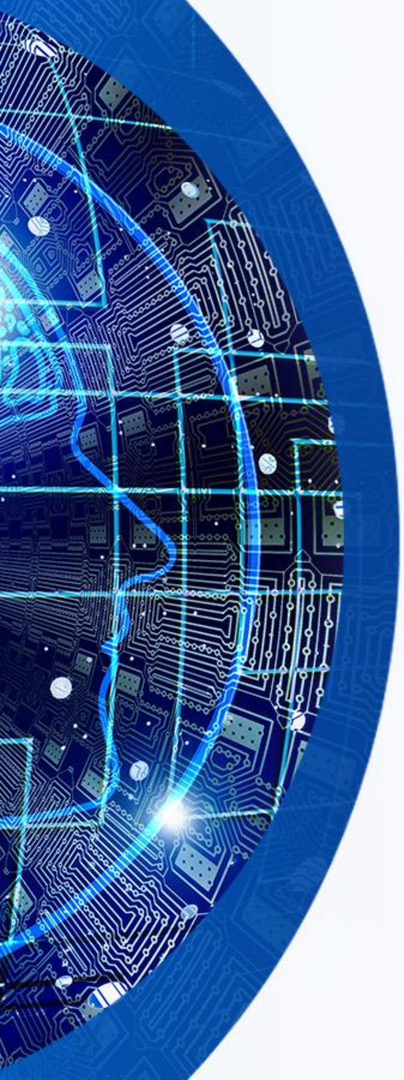


What to do next?

- Design Embedded System for Data Collection
- Develop a Hardware in order to scan QR code of each Label during Data Collection
- Add hidden layer to Neural Network
- Make a Library
- AWS IoT Core

AWS IoT Core

- Connect IoT devices to the AWS cloud without the need to provision or manage servers[7]
- How devices should behave, are they going to be sending sensor data
- Receiving instructions to control transducers
- balenaCloud : The container-based platform for deploying IoT applications[8]



References

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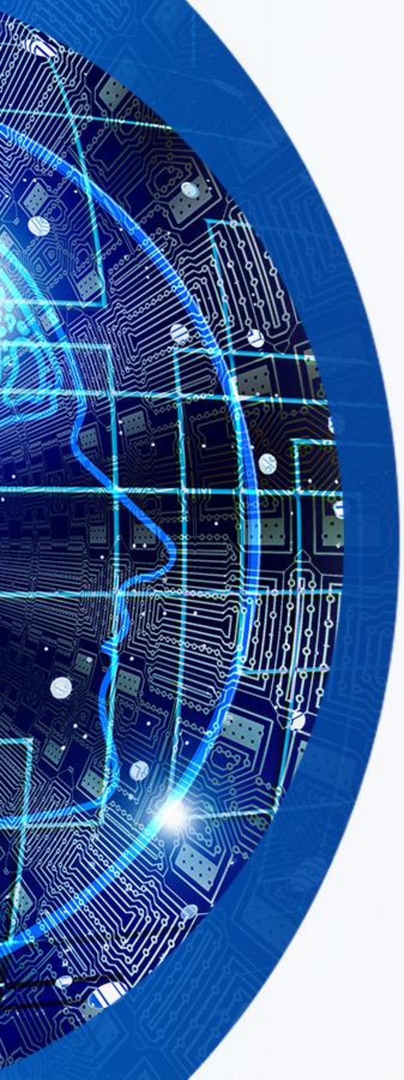

Thank you for your attention