

Bachelor Thesis



Tiny Machine Learning for Ultrasonic Object Classification A Naïve Bayes Approach on Red Pitaya



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Automotive



Automation



Daily Live



Objective

Human-Machine Interface Prototype

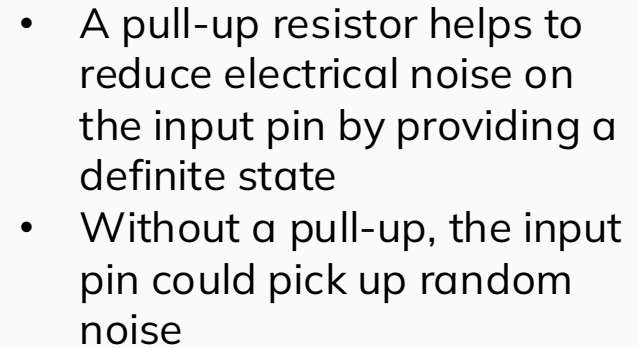
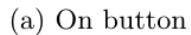
Develop an interface with buttons and LEDs for sensor features, bypassing the dependency on external software.

Naive Bayes Classifier Implementation

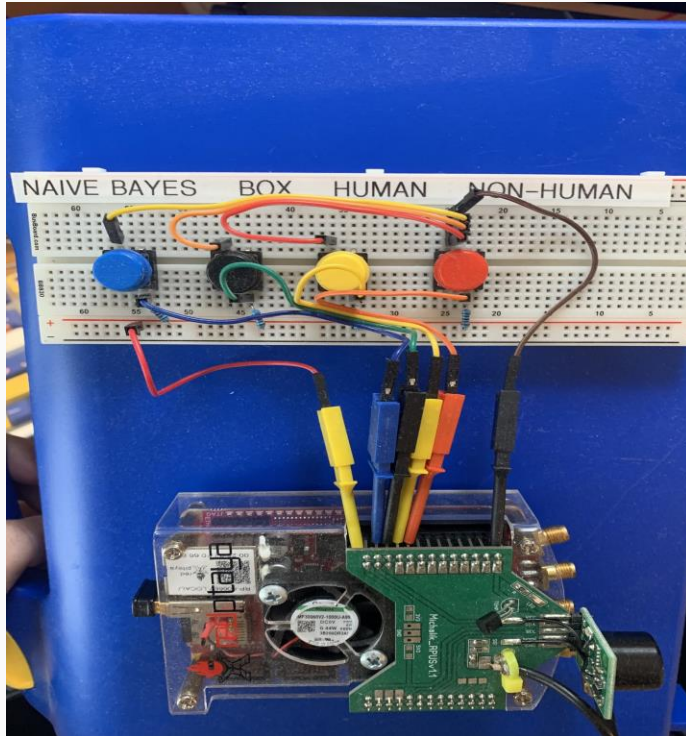
Utilize Naive Bayes as a probabilistic technique on the Red Pitaya platform for real-time classification.

Machine Learning Pipeline

Establish a flexible and updatable machine learning pipeline for effortless model modifications.

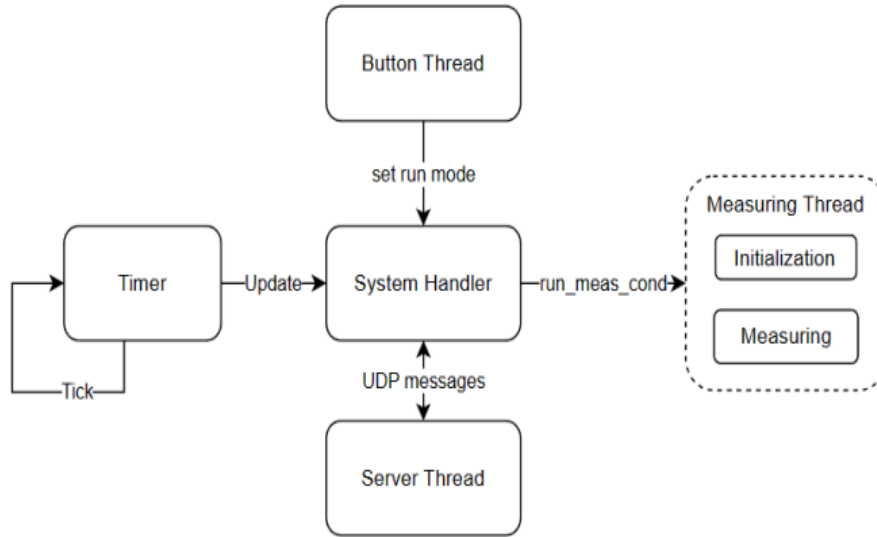


Hardware Setup



- **Button 1:** Saves object 1 sensor data as a binary file
- **Button 2:** Logs object 2 sensor data
- **Button 3:** Activates Box Classifier
- **Button 4:** Activates Naive Bayes Classifier
- **LED 1 (Class 0):** Lights up for class 0
- **LED 2 (Class 1):** Lights up for class 1
- **LED 3 (Classifier Mode):** On for Naive Bayes, off for Box Classifier
- **LED 6 (Learning Phase):** Indicates when the system is learning and saving data

Red Pitaya Architecture



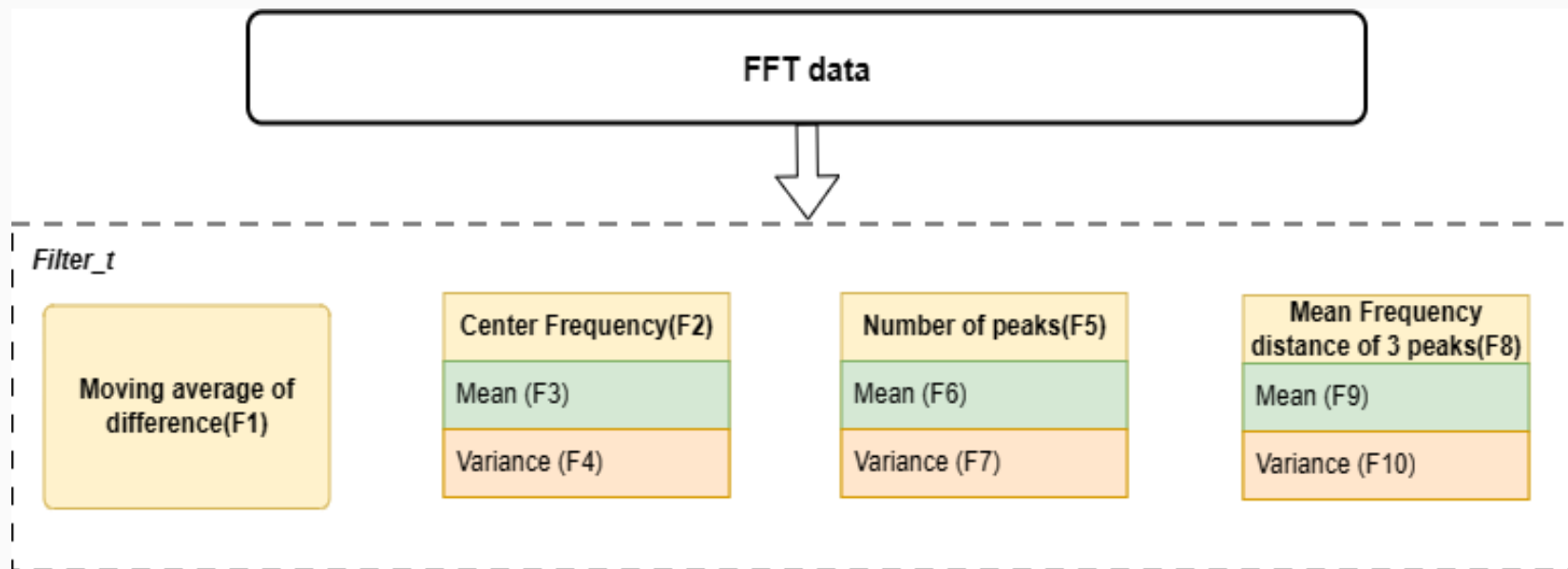
Button Thread: Manages button interrupts, storage, and prediction controls for standalone sensor operation.

Time Thread: Manages the measuring process with a 100ms cycle for consistent data acquisition.

Server Thread: Listens for UDP messages on port 61231 and parses commands for real-time classification.

Measure Thread: Initializes ADC and FFT process, running feature extraction processes.

Feature Extraction



Naïve Bayes Classifier

The general form of the Naive Bayes theorem for a class variable C and a dependent feature vector $O=(o_1,o_2,...,o_n)$ is given as follows:

Posterior Probability Class prior probability Likelihood probability

$$P(H = C_k | O = o) = \frac{P(H = C_k) \prod_{i=1}^n P(O_i = o_i | H = C_k)}{P(O_1 = o_1, \dots, O_n = o_n)}$$

Predictor prior probability

$$\hat{C} = \arg \max_{k \in \{1, \dots, K\}} \left[\log P(H = C_k) + \sum_{i=1}^n \log P(O_i = o_i | H = C_k) \right] \quad (3.7)$$

Key Principles:

- **Conditional Probability:** The classifier calculates the probability of a data point belonging to each class based on its features.
- **Feature Independence:** Despite its naive assumption, this classifier often performs surprisingly well in practice, even when the independence assumption is violated.
- **Prior Probability:** Represents the overall likelihood of each class in the dataset.
- **Posterior Probability:** The probability of a class given a set of features, which is computed using Bayes' theorem.

Sklearn

```
from sklearn.model_selection import  
train_test_split  
from sklearn.naive_bayes import  
GaussianNB
```

Metrics:

# Split	F1 Score:	0.82
and a	Accuracy(%):	0.82
X_train	Recall:	0.85
train_	Precision:	0.82
random		

```
# Train  
gnb = GaussianNB()  
model = gnb.fit(X_train, y_train)
```

Data Preparation and Splitting

- Split dataset into features (X) and target (y)
- Use train_test_split to divide data (80% train, 20% test)
- Ensure data is shuffled for randomness

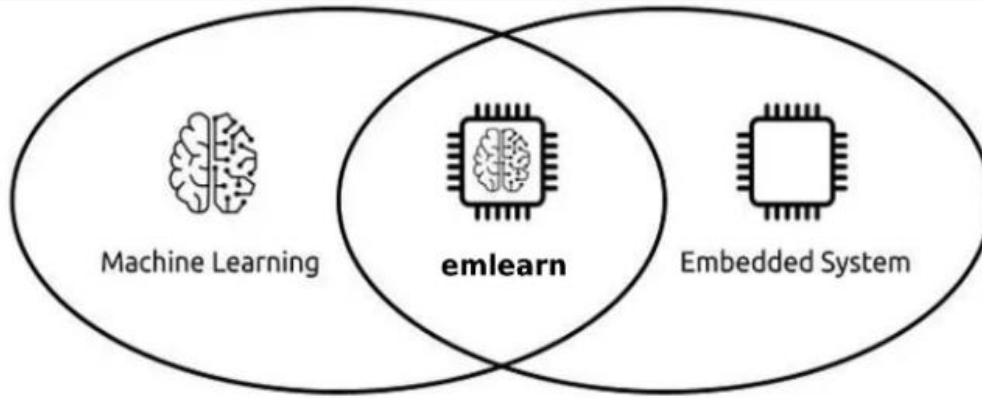
Choosing the Naive Bayes Model

- Select appropriate Naive Bayes variant (Gaussian, Multinomial, Bernoulli)
- Consider feature distribution when choosing

Model Evaluation

- Predict on the test set with model.predict(X_test)
- Calculate accuracy and other metrics

Emlearn



- No libc required
- No dynamic allocations
- Single header file include
- Support fixed-point math
- Support various machine learning algorithm, including Naïve Bayes as well
- Running on AVR Atmega, ESP8266, ESP32, ARM Cortex M (STM32), Linux

Emlearn on Red Pitaya

Algorithm 3: Emlearn Gaussian Naive Bayes on Red Pitaya

Input : `EmlBayesSummary(mean, std, stdlog2)`, Input values.

Output: Predicted class: either 0 (non-human) or 1 (human)

Function `EmlearnNaiveBayes()`:

- 1) Convert all input values to fixed point representation;
- 2) Calculate \ln of the PDF using a quadratic approximation;
- 3) Compute \ln of $N(\mu, \sigma^2)$ based on the standard $N(0, 1)$;
- 4) Utilize the function `eml_bayes_predict` to:
 - Compute the log-posterior probabilities for each class
 - Identify the class with the highest log-posterior probability

return Predicted class;

Model Summaries:

- Mean(μ)
- Standard Deviation(σ)
- Natural logarithm of std($\ln(\sigma)$)

Calculating likelihood probabilities

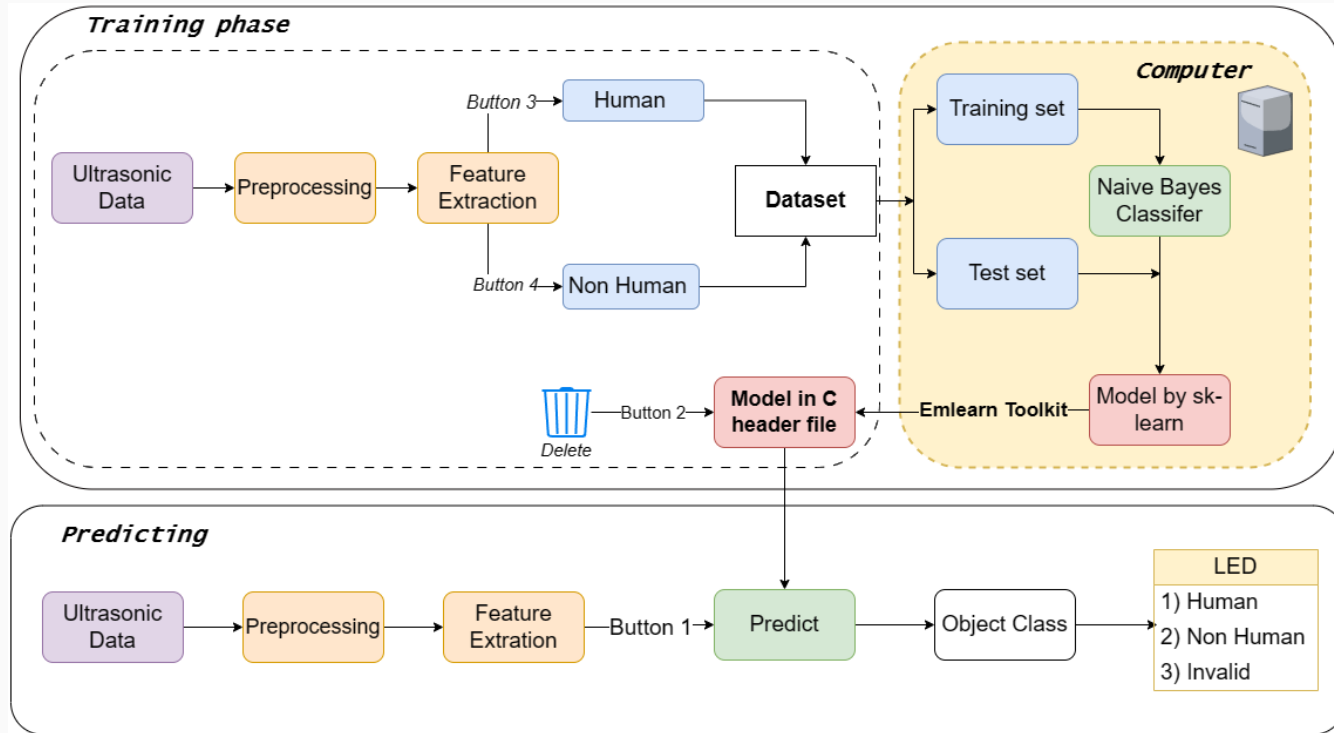
PDF of a Gaussian distribution in terms of the standard nor-mal distribution in logarithmic form, one can derive the following relationship:

$$\ln(f(x|\mu, \sigma^2)) = \ln(f(z)) - \ln(\sigma)$$

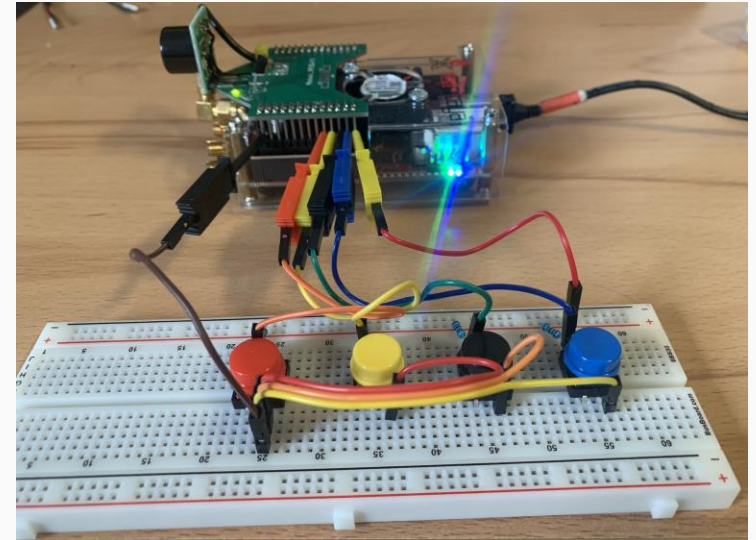
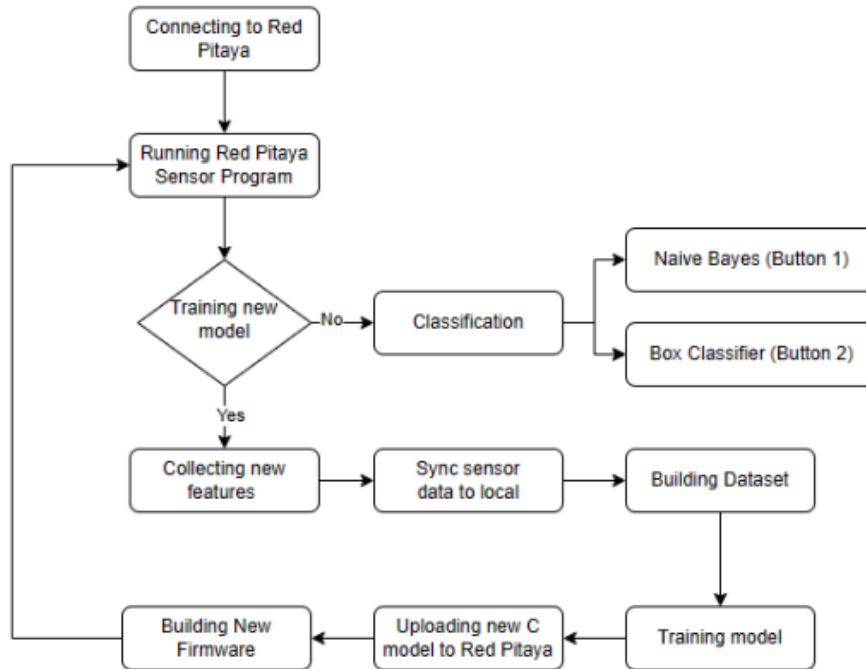
- $\ln(f(z))$: PDF of standard normal distribution using quadratic approximation
- $\ln(\sigma)$: is precomputed by sklearn model

Calculating posterior probabilities

Machine Learning Pipeline



Uploading a model





Smart sensor application



Device Info



Red Pitaya, SRF02



Waiting for connection...



Data Preprocessing

Building Dataset

☐ Seatbelt☐ Door☐ Movement

Sync:



Filename:



UDP Client

☐ Manual / Debug mode

Difference Average:

0.00

Center Frequency:

0.00

Number of Peaks:

0.00

Mean Peak Frequency Distance:

0.00



Programming

Programming Sensor



C Model:



Execute



Training model

Dataset:

☐ Emlearn model☐ Confusion matrix☐ RoC curve

Metrics:

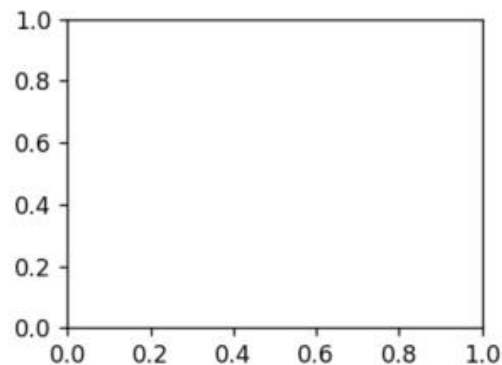
F1 Score: 0.00

Accuracy(%): 0.00

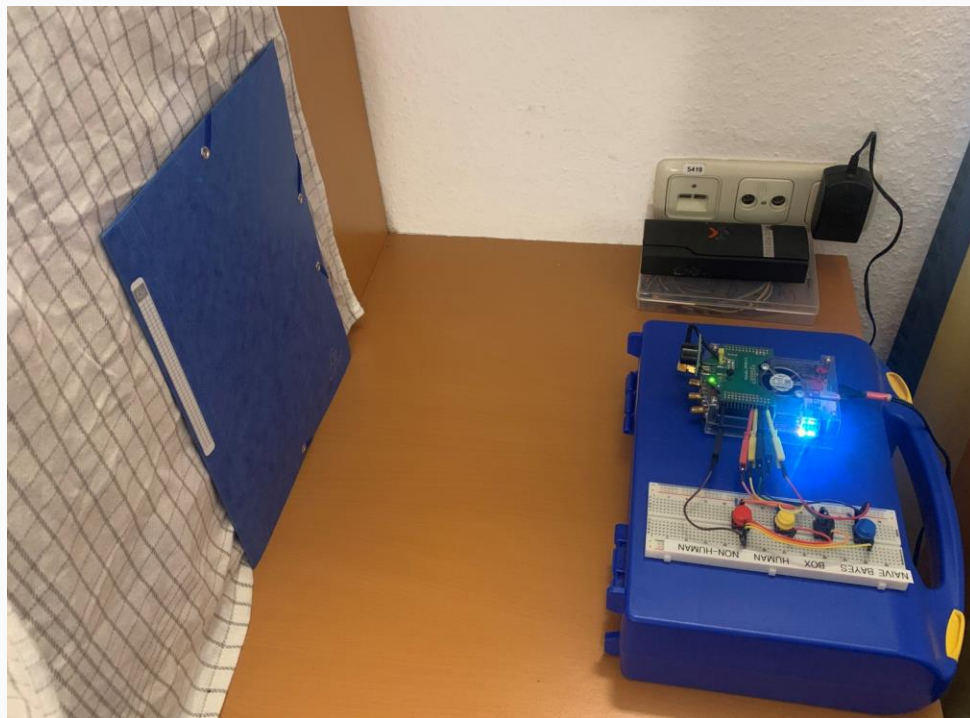
Recall: 0.00

Precision: 0.00

Debugging



Experimental setup







📍 Stable measuring condition

📍 Target Materials: Paper Board and Blanket

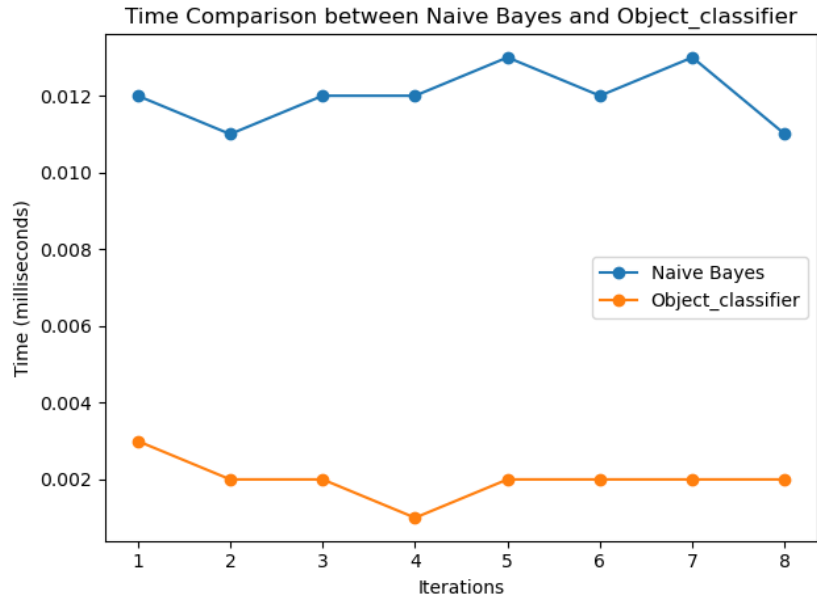
📍 Data Collection: 10 times/ measurement

- Exploring Sample Sizes
- Analyzing the Outcomes



04 Results & Discussion

Execution Time

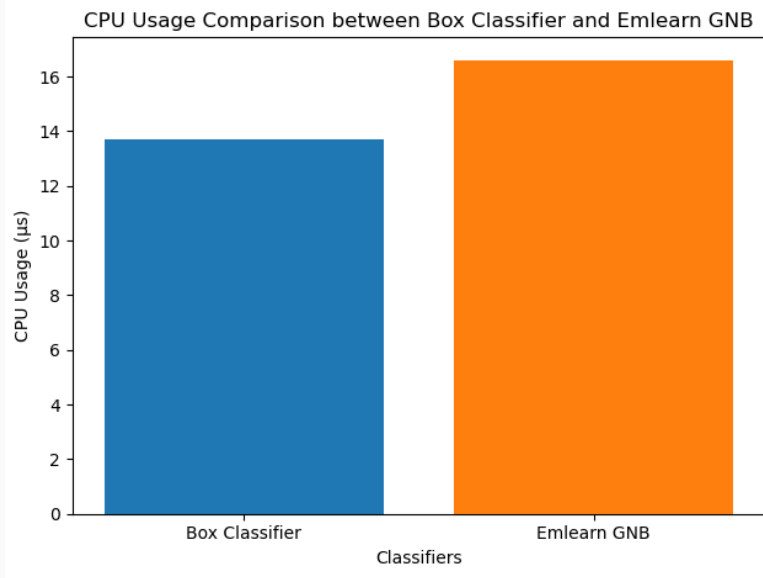


Utilizing time.h library

✧ 0.003(s) – Box Classifier

✧ 0.012(s) – Naïve Bayes

CPU Usage

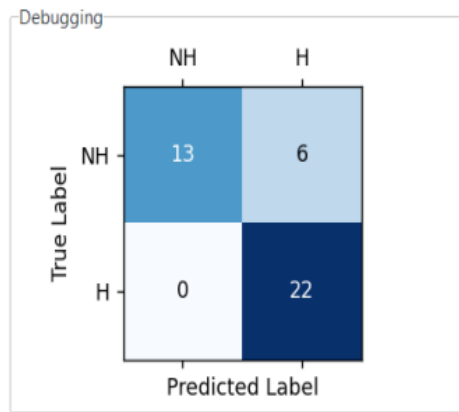


✧ 13(μs) – Box Classifier

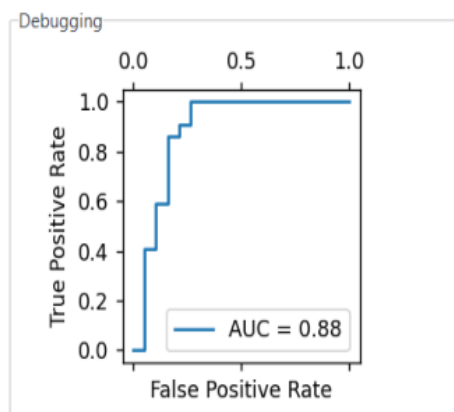
✧ 17(μs) – Naïve Bayes

- Emlearn's reliability in differentiating between objects
- Box classifier's need for calibrations and lower accuracy

Analysis of the results



(a) Confusion Matrix



(b) AUC Graph

Figure 5.8: Confusion Matrix with 200 samples

Confusion Matrix:

- Table showing model's prediction accuracy.
- **True Positives (TP):** Correct positive predictions.
- **True Negatives (TN):** Correct negative predictions.
- **False Positives (FP):** Incorrect positive predictions.
- **False Negatives (FN):** Incorrect negative predictions.
- **Used to calculate accuracy, precision, recall, F1-score.**

AUC Curve:

- Plots true positive rate vs. false positive rate.
- Measures model's ability to differentiate classes.
- **AUC of 0.5:** no class separation capacity.
- **AUC of 1.0:** perfect class separation.
- **Higher AUC indicates better model performance.**

Classification

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

Method	Number of Samples		
	200 samples	2,000 samples	20,000 samples
Sk-learn	85%	77%	96%
Real – world	90%	88%	82%



Future Work

- Sensor sensitivity
- Fourier Transform Limitation
- Algorithm Assumption
- Inability to recognize unknown objects

=> Advanced time-frequency based feature analysis techniques, such as the STFT and wavelet transform.



References

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Thanks!



Do you have any questions?

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