



**Politecnico
di Torino**

URBAN NOISE MONITORING

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ML4IOT
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Outline

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- Model Description
- MQTT
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- Conclusion

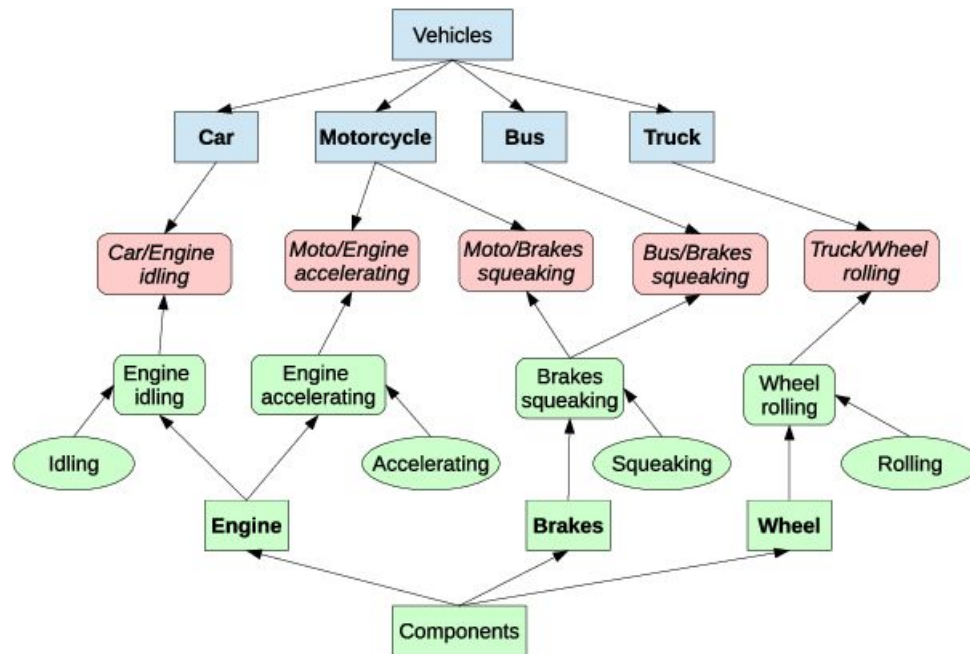
The MAVD-traffic dataset

MAVD => Montevideo Audio and Video Dataset.

The **MAVD-traffic** focuses on the most prevalent noise source in urban environments.

Two *basic levels* (Vehicles and Components) and a *subordinate* one.

Our system is focused on the **Vehicles** category.



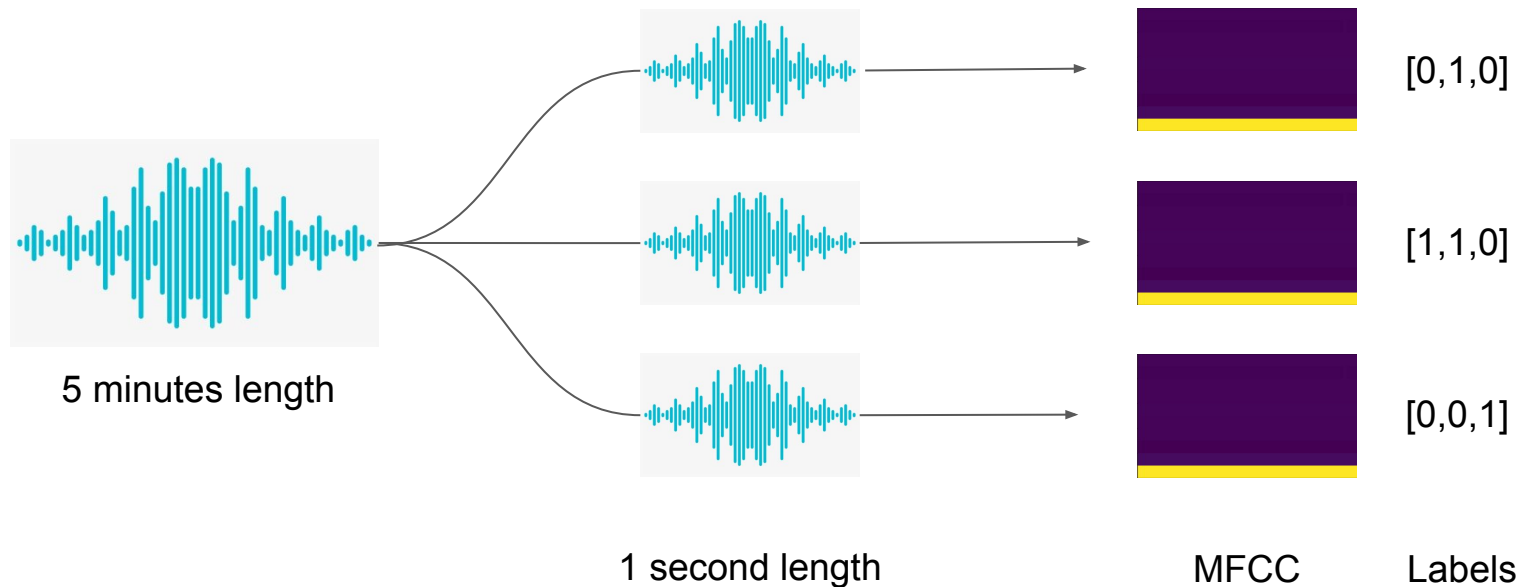
Random Forest and S-CNN

In the paper presenting the dataset, two strategies for classifying sounds are proposed: **Random Forest** and a **Convolutional Network** called S-CNN.

The **RF** receives as input a 20 mel–frequency cepstral coefficients (MFCC) using the energy in 40 mel bands. The MFCCs were calculated in frames of 40 ms overlapped 50% and using a Hamming analysis window.

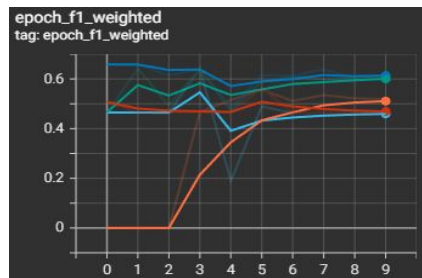
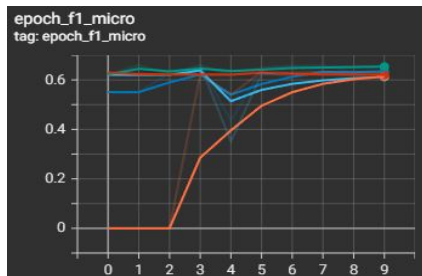
The input of the **CNN** instead, is a one–second length mel–spectrogram. The network implements three convolutional layers followed by three fully connected layers. The predictions are extracted thanks to a final sigmoid layer. In that way, the CNN is able to accomplish a multilabel detection if needed. The model has more than 2 millions of parameters and reaches a **global F1 score** of 55.5% on the Vehicles taxonomy.

Data Preprocessing



Model Performances

Validation



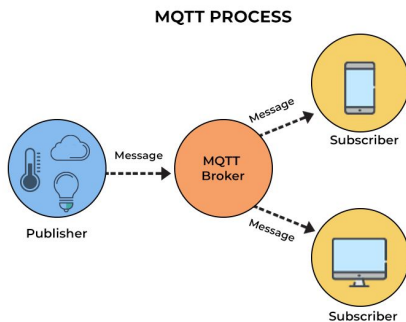
Test

Model	Params	F1 micro (or global)	F1 weighted	Latency in seconds (tflite)	Size in kb (tflite)
HMW	1×10^4	60.0%	45.0%	0.064	21
V1	2.1×10^6	60.0%	45.0%	0.060	7693
V1+WS	3.2×10^5	63.8%	62.1%	0.082	1152
V1+WS+DW	2.6×10^5	60.8%	45.4%	0.081	929
V1+WS+DW+WP	2.6×10^5	62.7%	62.7%	0.037	385
S-CNN	2.5×10^6	55.5%	-	-	-

MQTT

Within our main script we developed an MQTT client that will act as a **publisher**, taking the mac address, timestamp and prediction cast for the input on the edge and sending it to a subscriber under the topic “Montevideo”.

As for the [subscriber](#), it takes the information passed by the publisher and adds it to a Redis time series. These time series will be divided by the zones where the input was taken from. The prediction will be saved encoded by a number to correctly manage the time series restriction where it only takes integers as the value to be stored.



REST API

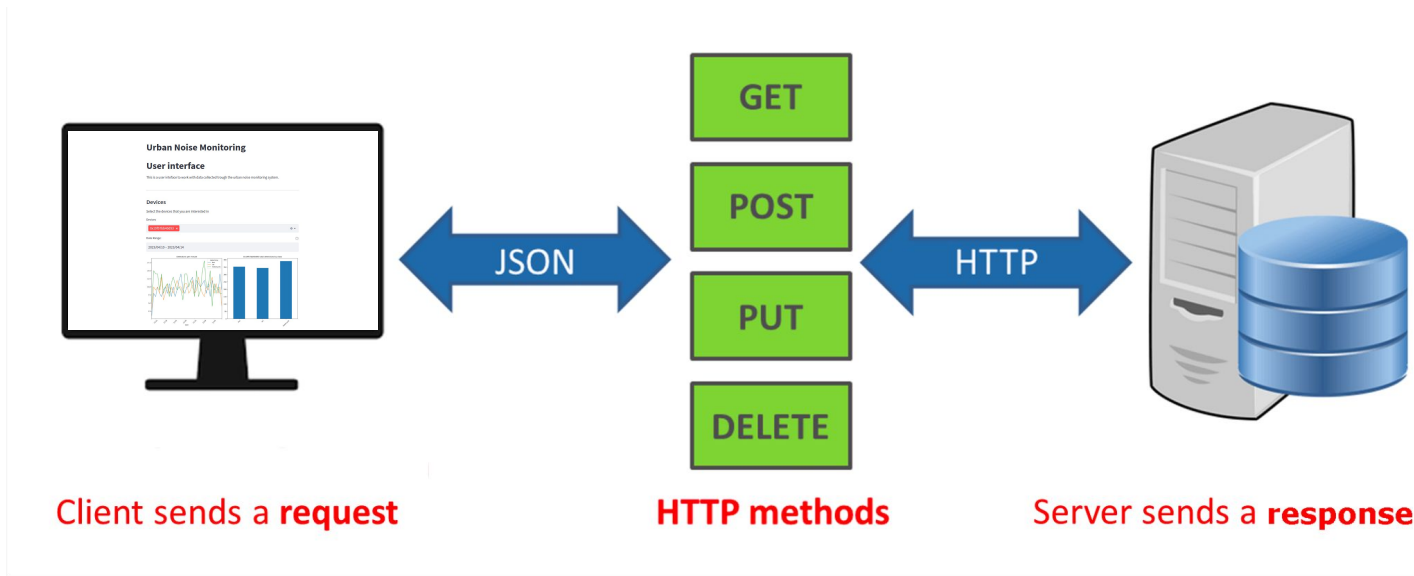
For the REST part we divided our work in 2 parts: **Server** and **Client**.

For the [server](#) part we created 4 endpoints to expose the redis time series information: `Zone()`, `Zones()`, `Device()` and `Devices()`.

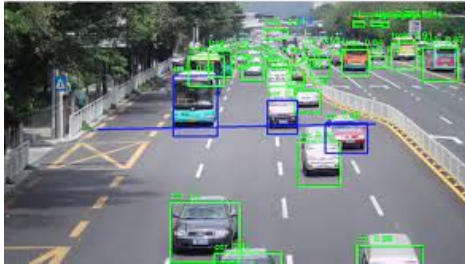
Inside the [client](#) is where we can use these functionalities, where **Zone()** will take the name of the zone, the start and end times as parameters to return the predictions corresponding to that period for the specified zone, or just the name in the case the deletion process for that zone is triggered. On the other hand **Zones()** will just display the names of the zones as a list.

Going further, the **Device()** endpoint will do the same as the `Zone()` endpoint, with the difference that the main parameter here is the mac address for a specific sensor and not the zone name. The same happens with the **Devices()** endpoint, that will print the mac addresses registered thus far instead of the zones names.

REST API



Future Works: Incorporating Video into the Model for Improved Results



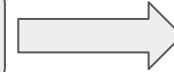
CNN + LSTM
Based on RGB
Videos



CNN
Based on MFCC



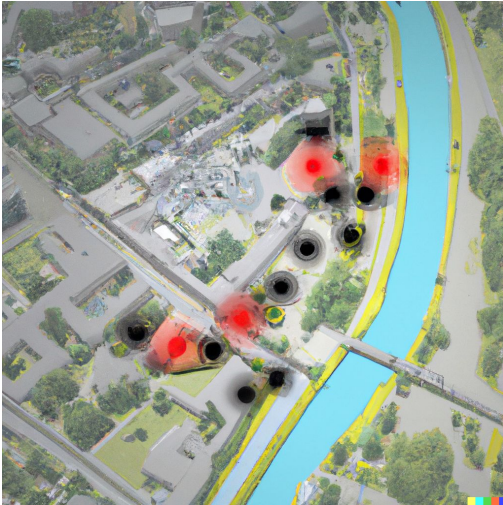
Fusion
Module



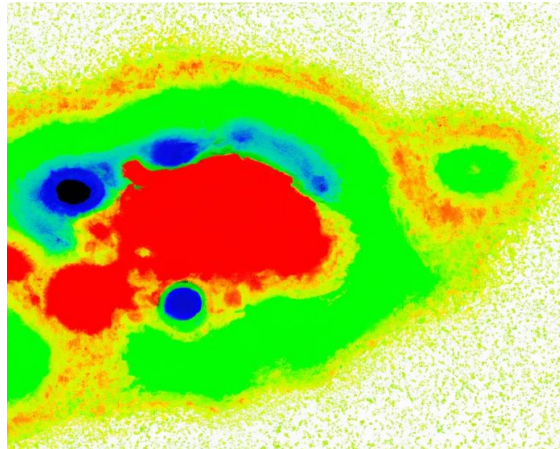
Output

Real World Applications

Traffic Monitoring



Pollution Monitoring



Public Infrastructure Development

