



Hardware platform for detecting small flows with domestic water meters

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Metrology for Real-World
Domestic Water Metering



Introduction

Due to the importance of water for human beings, water leakage is considered a severe inconvenience even in small quantity. While for leakage in distribution networks, some convincing solutions are already on the field, more challenging appears to be the detection at the household level. Difficulties arise at different levels:

- Water sensors
- Algorithms
- Use of Smart Water Meters



Water sensors

Water sensors can be static (ultrasound) or mechanical:



- Cover a small part of the market
- High cost and limited battery life
- Measures flow rate [L/h]



- Cover a wide part of the market
- Low-cost
- Measures volume m^3



Algorithms

The main part of the literature about water leakage detection focuses on the comparison with consumption thresholds in terms of flow rate [L/h]. While this approach is fully compatible with the static meter output because these are flow meters, it does not fit entirely with volumetric mechanical meters, which measure volume [m³].

Minimum Night Flow (MNF)

- The pressure and flow are measured during night, where minimum consumer water usage is considered a minimum.
- Nightly consumption patterns are compared to previously and thereby outliers or sudden changes in MNF can be detected
- To avoid both missed detection and false alarms, the MNF value must result from analyzing and processing a large amount of data concerning household consumptions and consumer profiles.

Period With Null Consumption (PWNC)

- It represents a time interval characterized by null flow.
- If there is no leakage after the water meter, a certain number of PWNC should appear each day or in a lower time interval (a threshold).
- Continuous monitoring and comparison of these parameters with adequate thresholds could lead to leakage detection.



Water leakage detection

Two factors play a fundamental role in this challenge:

- The minimum flow rate that is still able to determine a change in the water meter output;
It depends on the water meter sensitivity and on the type of water meter. Meter sensitivity determines the minimum amount of leakage any algorithm will be able to detect.
- The promptness of the continuous monitoring of the water meter output.
It depends on the system adopted for the continuous automatic acquisition of the meter output.



Smart water meter

Requirements for a distributed water leakage detection solution:

- Compliance with existing water sensors
- Open to implementation of algorithms
- Smart metering features (digital, connected, etc..)





Regarding ultrasonic flow meters

- PWNC detection very easy (output value check);
- Digital (firmware controlled);
- Designed to be smart (featured with communication module);
- Battery life still limited.





Regarding mechanical register meters

- Volume meters;
- Not digital;
- Unconnected;
- Widespread;
- Cheap.





Add-on for water meter



- ✓ Compliance with existing water sensors
- ✓ Open to implementation of algorithms
- ✓ smart metering features (digital, connected, etc..)

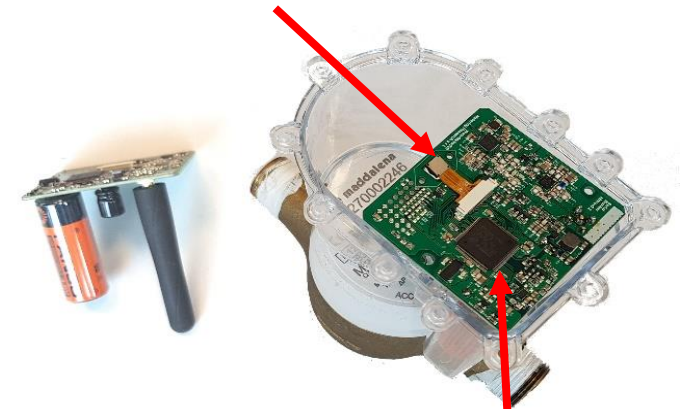


Digital add-on for mechanical register meters

In more detail, the add-on contains the following main components:

- The sensing module is an OV7670 low voltage CMOS image sensor that provides all the full functionality of a single-chip VGA camera and image processor in a small footprint package.
- The processing unit is the high-performance STM32F4. The selected MCU belongs to a family based on the general-purpose ARM®Cortex®-M4, which is widely used in several applications like automotive, medical equipment, industrial, motor driver, and many others.
- The communication part consists of: a Texas Instruments CC1120 chip as RF Transceiver and the SKY65367-11 chip as RF front-end module. The CC1120 chip is compliant with the standard EN 13757-4:2013, which regulates the WM-Bus operation in a short-range network. In the "Add-on", it has been configured to operate in wM-Bus N2a mode at maximum transfer power.
- The electronic device is battery powered with up to 2 low discharge lithium batteries, for a total maximum capacity of 7000mAh (3.6 V).

Camera Module



Embedded System



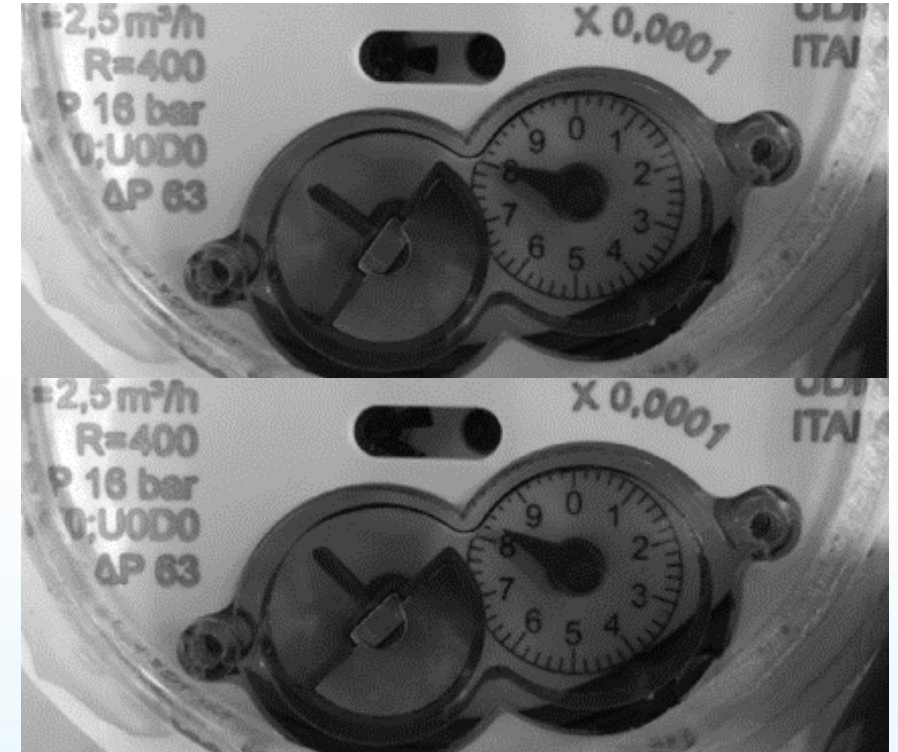
The leakage detection algorithm

The images acquired by the camera are processed to monitor the consumption and, overall, to detect the presence of small leakage, characterized by the absence of period with null consumption.

The analysis of the similarity/dissimilarity between successive images of the counter can be done using the Cross-Correlation evaluated as:

$$r(I_A, I_B) = \frac{\sum_j \sum_i (I_A(i, j) - \bar{I}_A) \cdot (I_B(i, j) - \bar{I}_B)}{\sqrt{\sum_j \sum_i (I_A(i, j) - \bar{I}_A)^2} \cdot \sqrt{\sum_j \sum_i (I_B(i, j) - \bar{I}_B)^2}}$$

where \bar{I}_A and \bar{I}_B are the mean values of the two images $I_A(i, j)$ and $I_B(i, j)$.





The leakage detection algorithm

The images acquired by the camera are processed to monitor the consumption and, overall, to detect the presence of small leakage, characterized by the absence of period with null consumption.

To monitor meter's display changings, at each n^{th} new frame acquisition (I_n) two different cross-correlation factors were calculated:

- $r_d(n) = r(I_n, I_{n-1})$
- $r_o(n) = r(I_n, I_0)$

where I_0 is the first image acquired.

a)



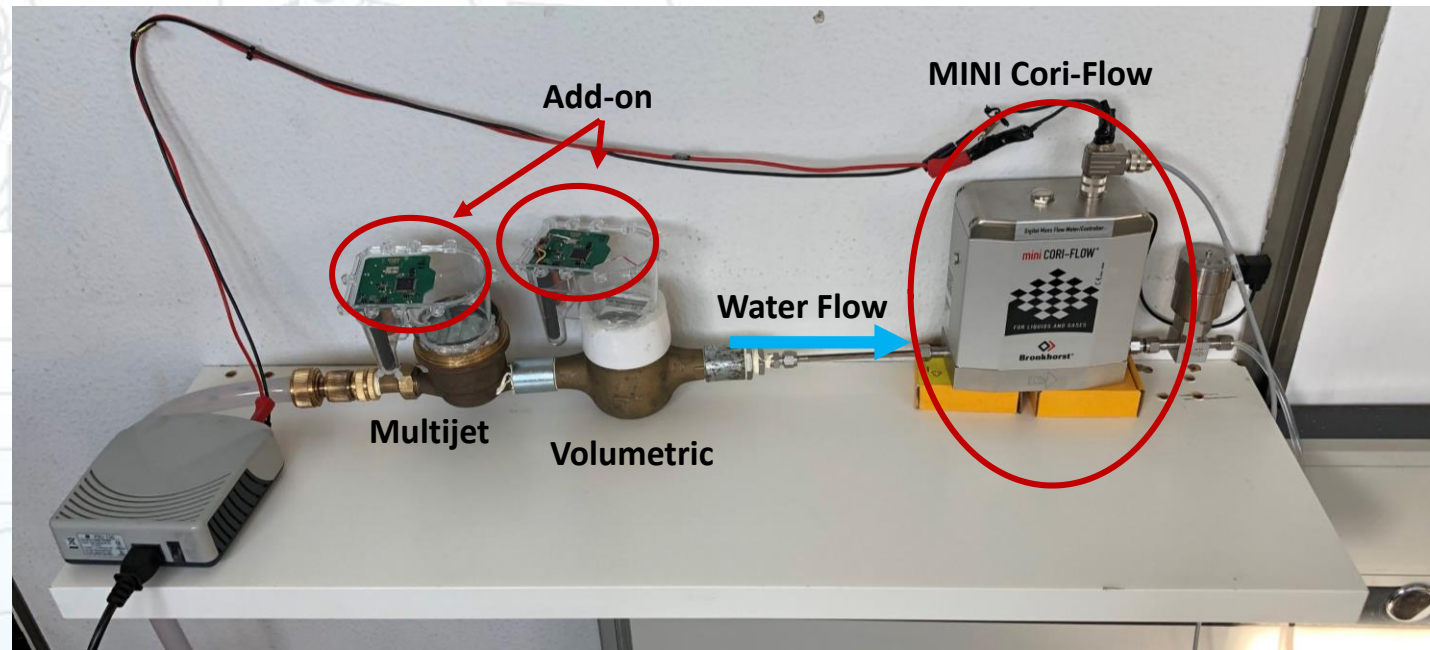
b)





The test rig

The measurement setup has been set in the laboratories of the University of Salerno, developing a test rig to generate a calibrated constant flow for more than one water meter mounted in series. It includes a precise and compact instrument to measure and control the water mass flow, which is based on the Coriolis measuring principle: MINI CORI-FLOW™ M15 by Bronkhorst



Thanks to the test rig feature described above, it was possible to carry out tests at flow rate values contained in the typical range of small domestic leakages [0,30] L/h



The water meters

The mechanical water meters employed belong to the two most widespread types of domestic water meter: multijet and volumetric (piston).



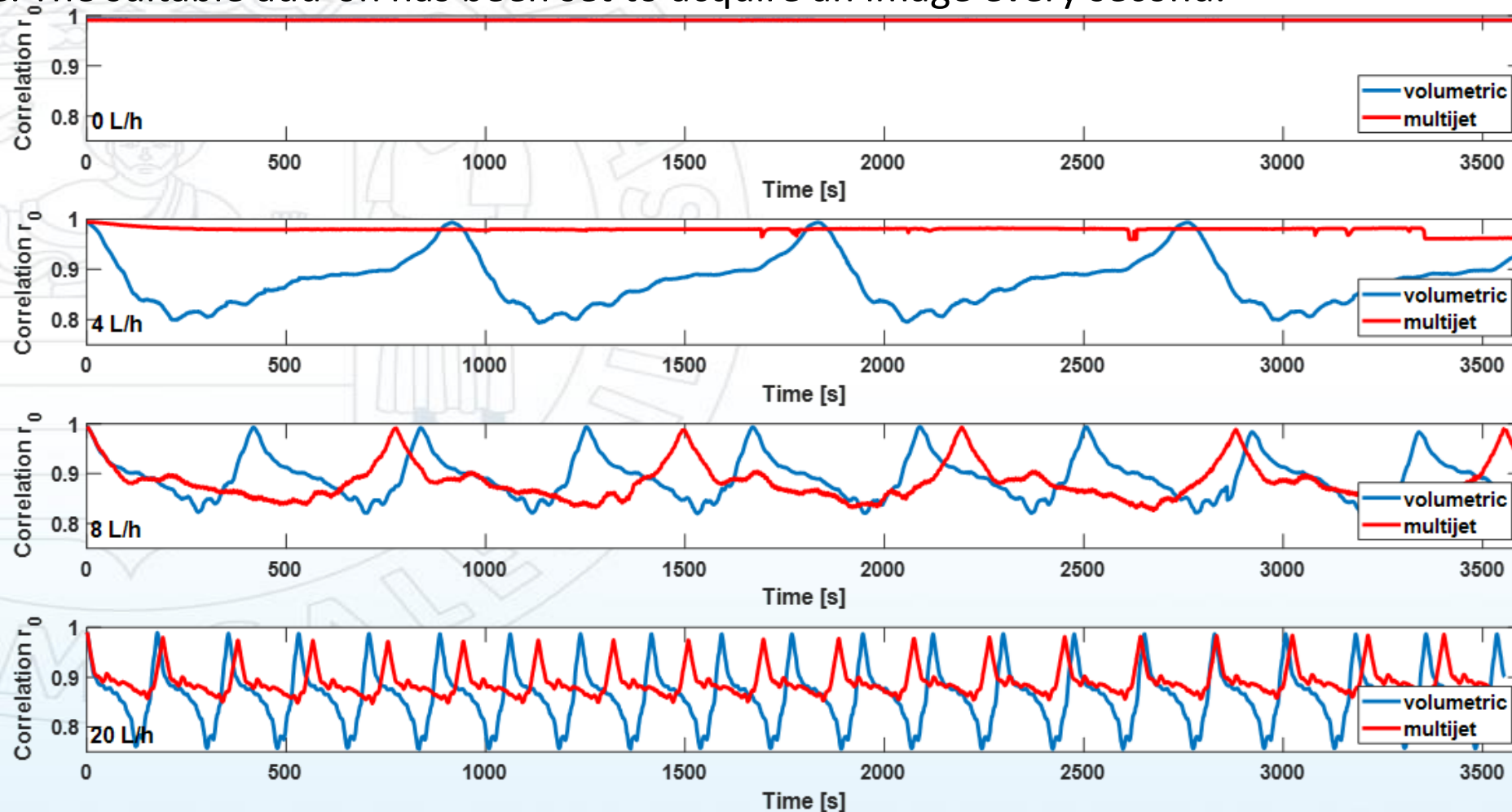
The last needle indicates with 0.0001 m^3 of resolution for both the water meters

METER	Size [inch]	Starting Flow [L/h]	Q ₁ [L/h]	Q ₂ [L/h]	Q ₃ [L/h]	Q ₄ [L/h]
Multi-jet	1/2"	7-8	15.6	25	2500	3130
Volumetric	1/2"	1	16	25.6	1600	2000



Static profiles

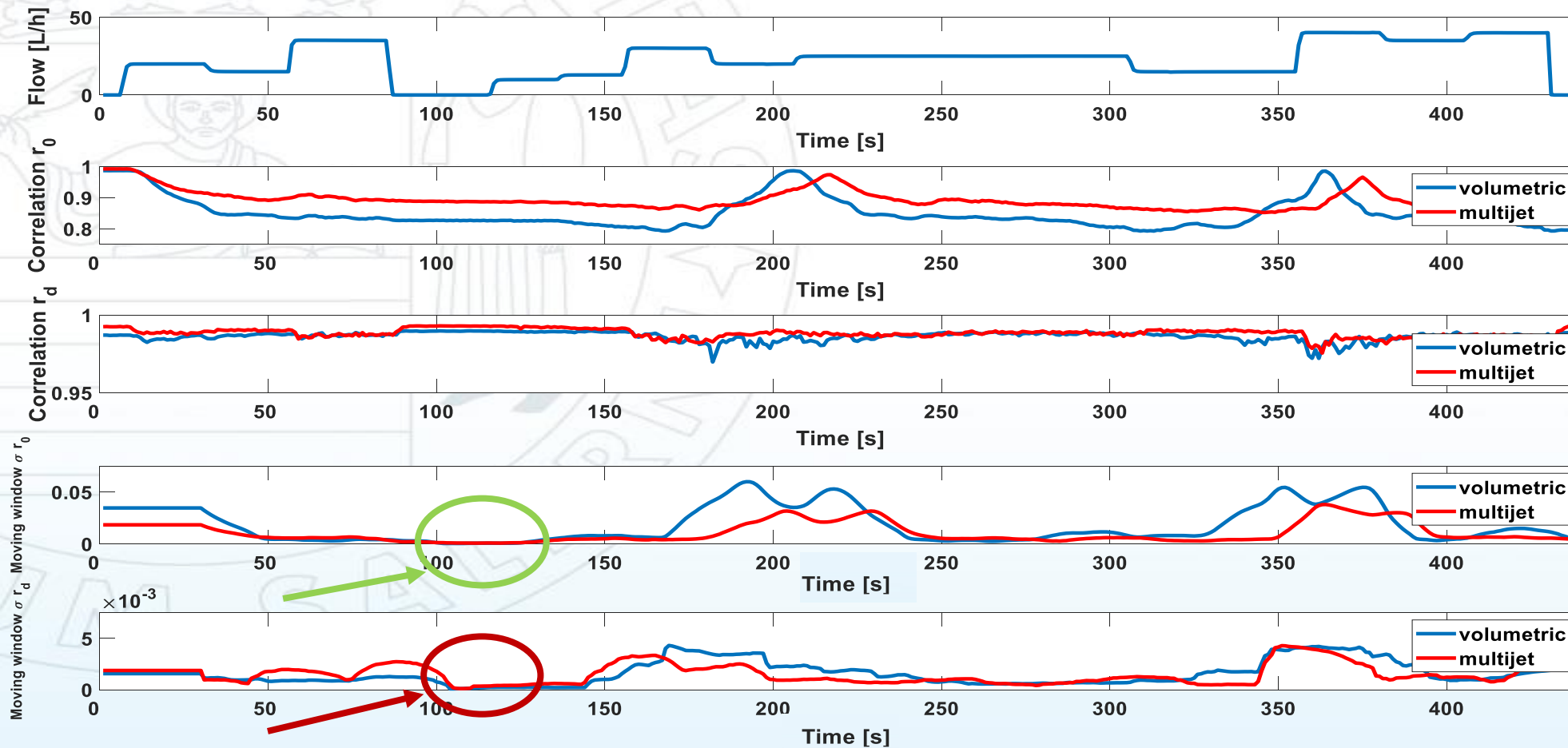
Several constant flows were generated by using the MINI CORI-FLOW: for every flow, a test of 3600s has been done. The suitable add-on has been set to acquire an image every second.





Dynamic profiles

Two profiles have been tested with a duration of 440 s. The profiles include a flow's variability in the range 0 to 30 L/h, including also some zero spots of several seconds.





An ongoing research:
Use of deep learning for leakage detection



Convolutional Neural Network

Convolutional Neural Networks (CNN) are a particular type of Artificial Neural Networks based on the visual cortex of animal world

CNNs are able to **classify and locate single or multiple objects** into an image

Classification



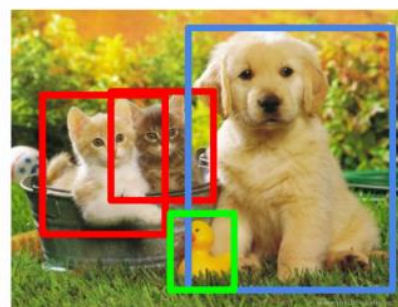
CAT

**Classification
+ Localization**



CAT

Object Detection



CAT, DOG, DUCK

**Instance
Segmentation**



CAT, DOG, DUCK

Single object

Multiple objects

Different **types** of features can be detected via several **filtering operations** carried out in **parallel** in each convolutional level



PWNC detection algorithm based on CNN



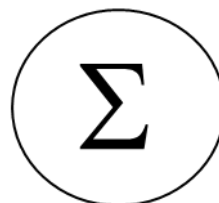
Shot #0



Shot #1

Frame rate 1s

+



-

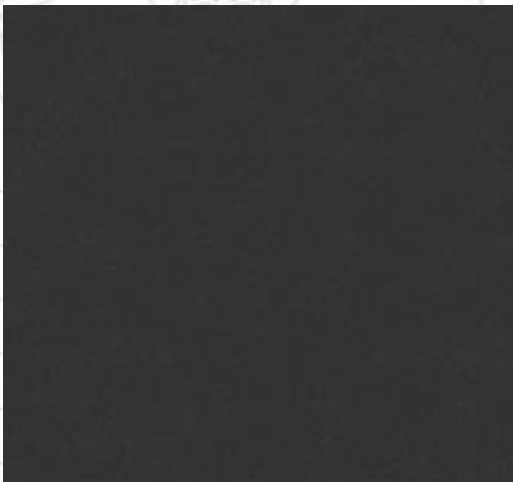


Computed difference



Training set

0 L/h



Class 0

8 L/h



Class 1

12 L/h



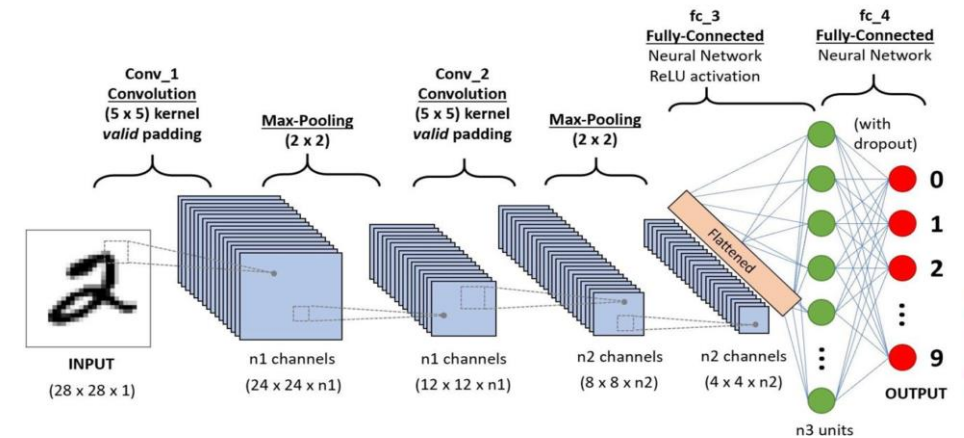
Class 2

Total of 4500 images equally distributed among the classes



CNN characteristics

- Seven convolutional level, with 16 filters
- Pooling level 2x2
- Fully connected ReLU activation layer
- Two dense level with 2048 hidden neurons and 3 output neurons
- Validation split of 25%;





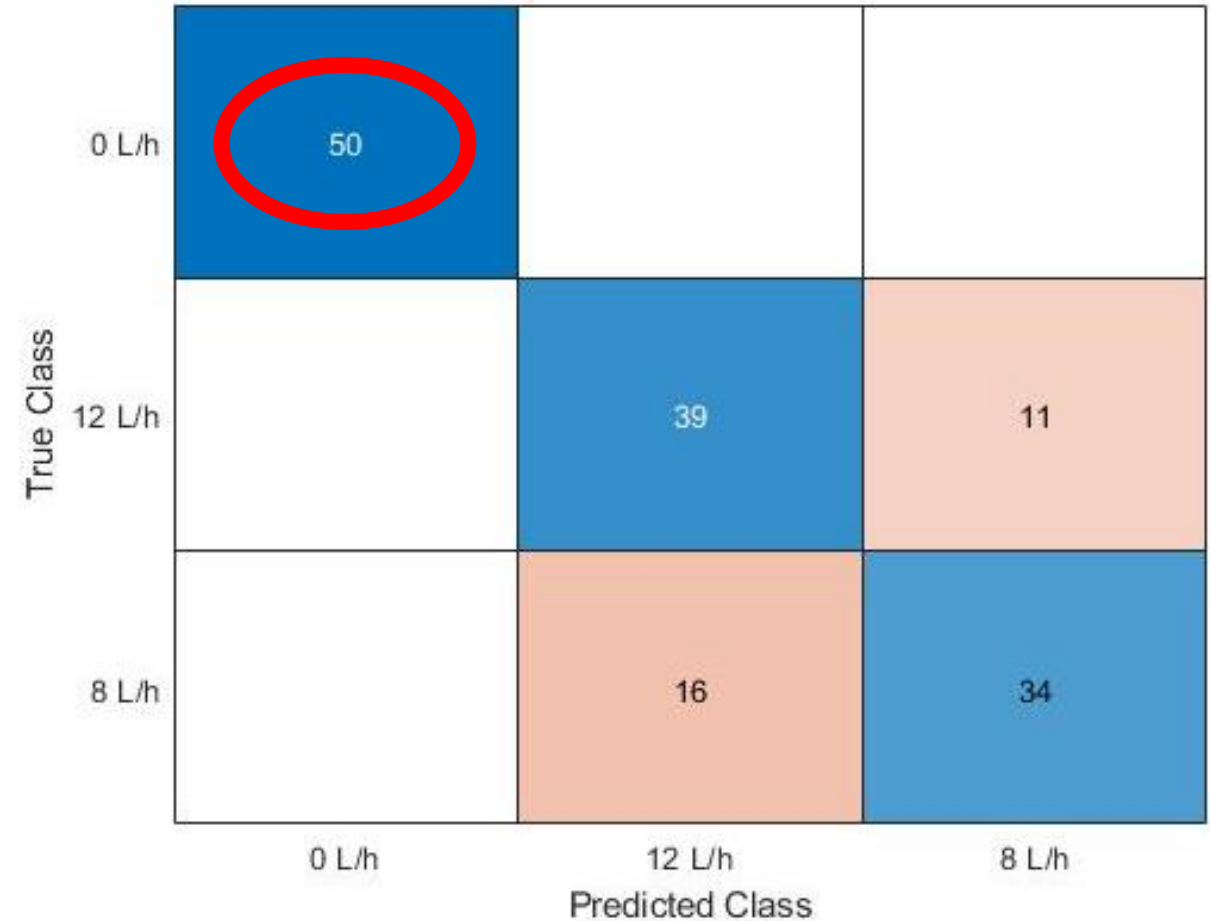
Testing - Results

- 50 predictions with 0 L/h
- 50 predictions with 8 L/h
- 50 predictions with 12 L/h

Class	Precision	Recall	F1score
0 L/h	1	1	1
8 L/h	0.76	0.68	0.72
12 L/h	0.71	0.78	0.74

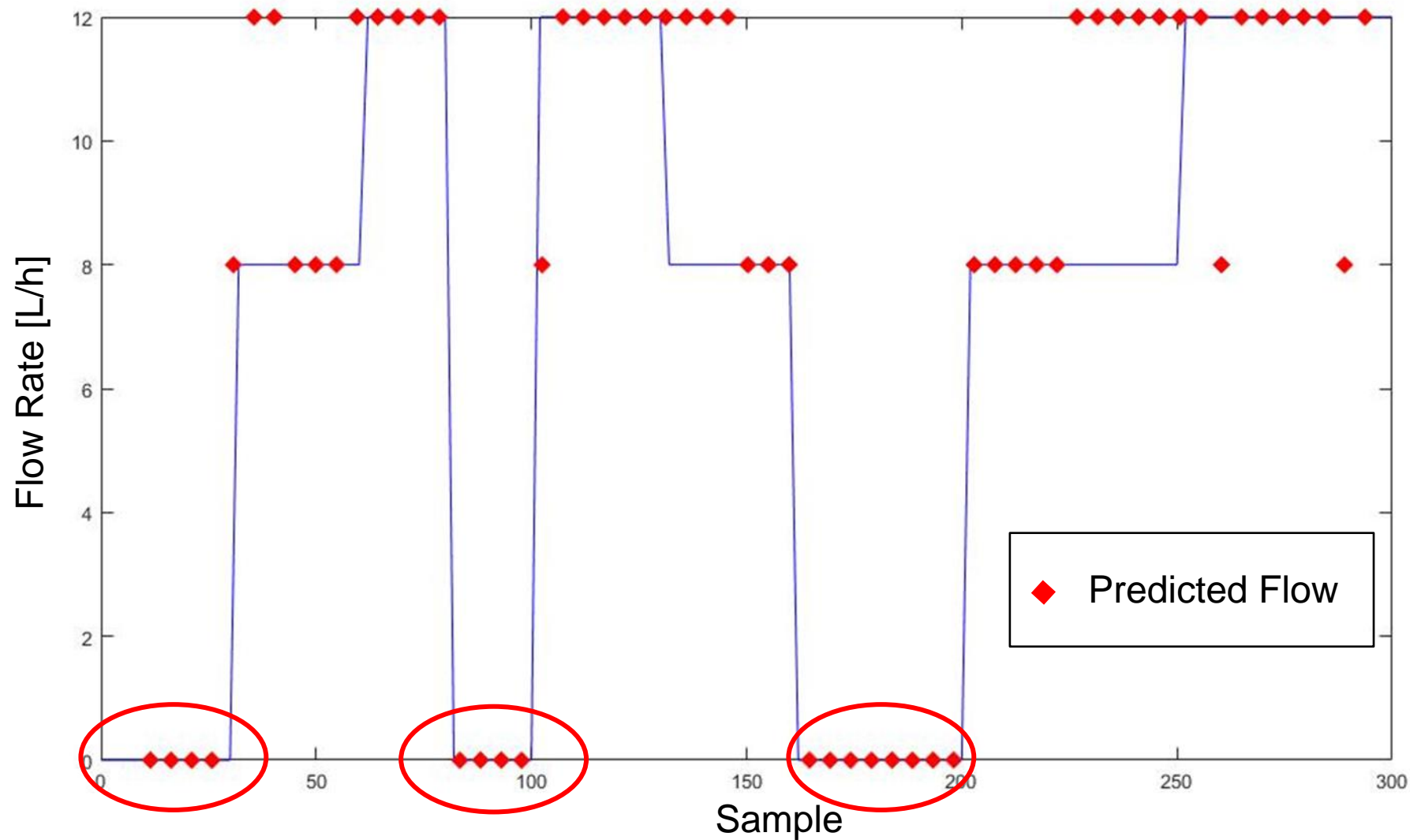
MacroF1=0.82

Confusion Matrix





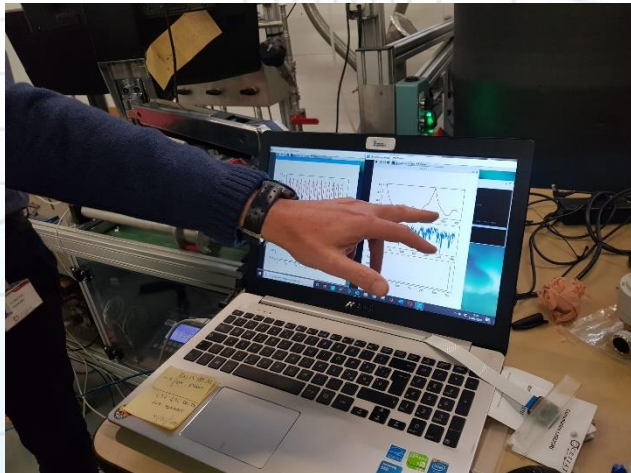
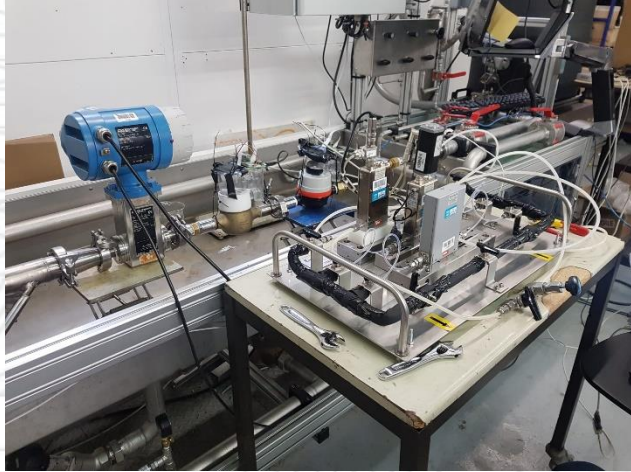
Test on real profiles



*Acquisition based on a dynamic profile.

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THANKS

for

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