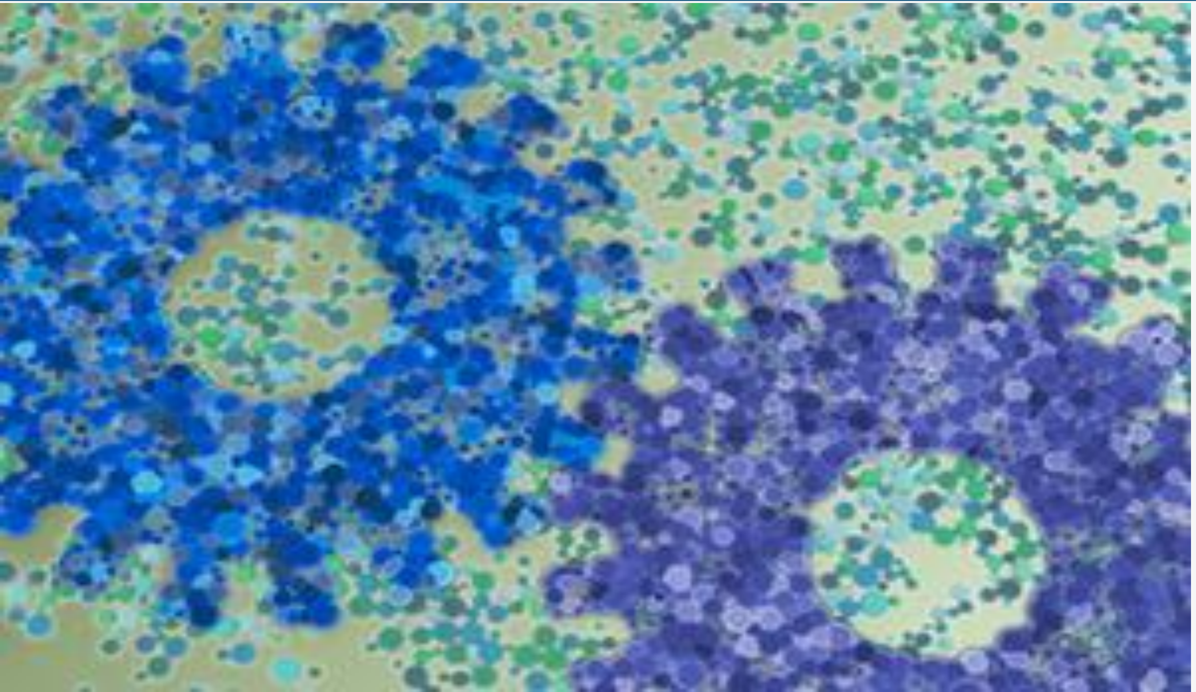
Data Analytics towards Predictive Maintenance for Industrial Ovens

A case study based on data analysis of various sensor data



Luigi Giugliano

LINKS Foundation

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European Union

COMPOSITION

COMPOSITION

Ecosystem for Collaborative Manufacturing PrOceSses – Intra- and Interfactory Integration and AutomaTION

Project Type
EU Funded - H2020
FOF-11-2016 - Digital automation

Project Domain
Industry 4.0, Digital Automation, Supply Chain Management

Project use cases
Scrap Metal Bidding Process, Fill-level Notification, Maintenance Decision Support, **Predictive Maintenance**, Component Tracking

Size
Innovation Action among 12 EU partners.

Duration
3 years (September 2016 – August 2019).

Data Analytics towards Predictive Maintenance for Industrial Ovens

A case study based on data analysis of various sensor data

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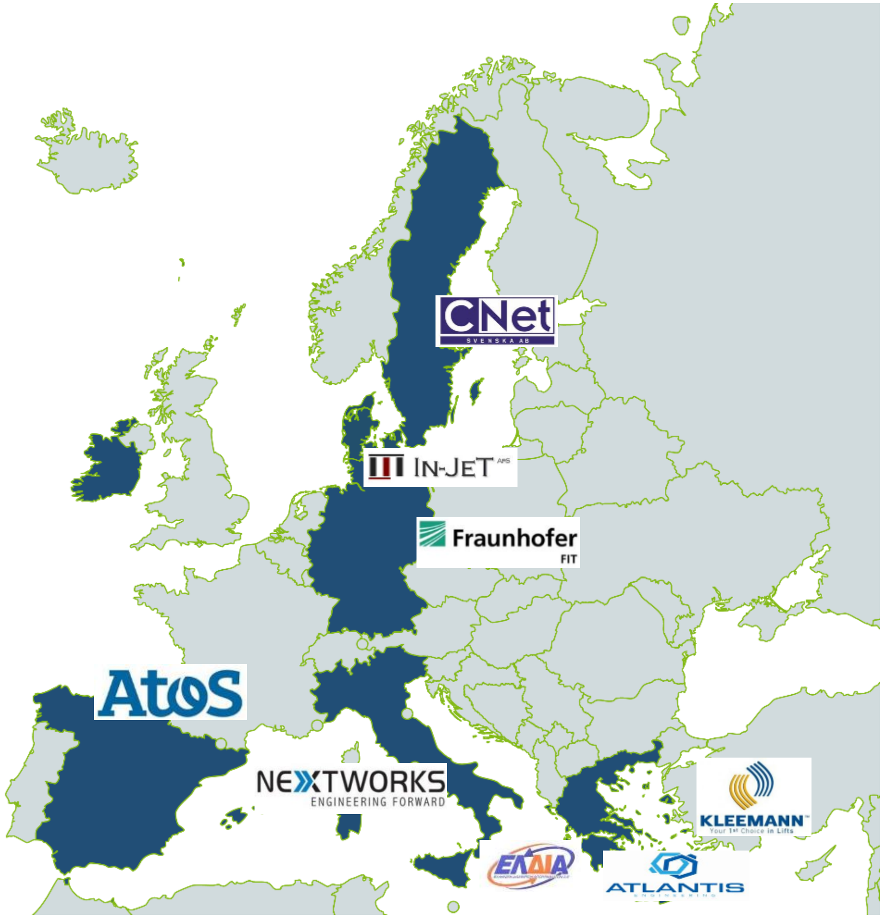


Predictive oven maintenance - *The challenge*

- Reflow soldering process requires very tight control of temperature
- Correct operation of the fans plays a crucial role in ensuring optimal operating conditions are maintained
- Fan breakdown leads to scrappage of all high value material inside the oven

PCBA

Fan failure → Non-compliant product → Scrappage

Predictive maintenance → Preventive maintenance → Scrappage decrease

Predictive oven maintenance - *The approach*

Objective

Present early detection of anomalies and failures using predictive analytics for industrial ovens and their application in a real-world oven

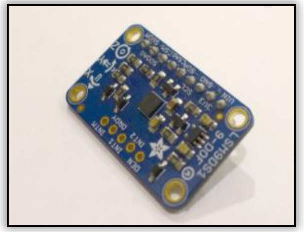
Two distinct approaches

- A technique based on **deployed sensors** for fault diagnosis based on acoustic data
  - → *An outlier detection analysis was implemented on acoustic sensor measurements*
- A technique based on **existing sensors** for oven failure prediction based on monitoring and log data
  - → *Deep learning techniques have been applied on existing sensor and event log data, especially temperature monitoring*

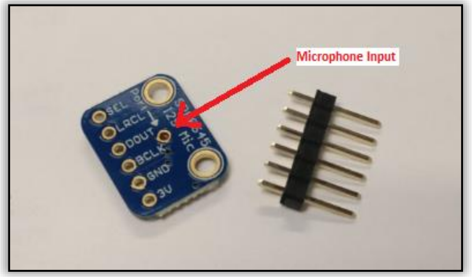
Acoustic sensors - *Deployment*

- **Investigated** several detection methods
  - Current Sensing
  - Vibration
  - Temperature
  - Acoustic

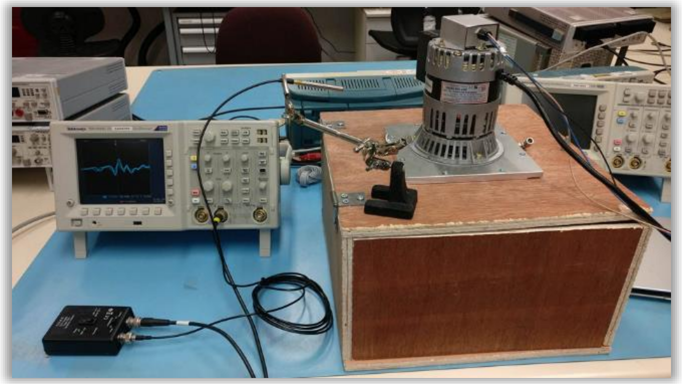
- **Acoustic chosen**
  - Ease of retrofit – Non invasive
  - Monitor zones reduce sensor count
  - Significant distinction between failing & good fans
- **Approach taken**
  - Lab based measurements to determine acoustic characteristics of a good and bad fan
  - Validate technique in flow solder oven in factory
  - Iterate implementation for robust operation


LSM9DS1 – Vibration / Thermal

G.R.A.S Free field Array microphone



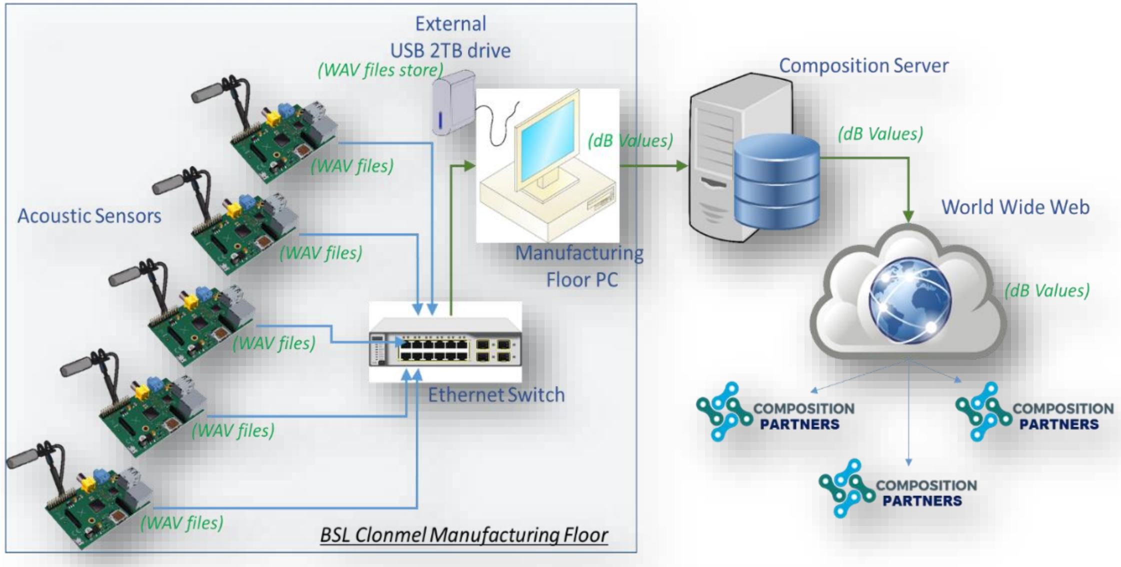
Knowles SPH0645 – mems microphone

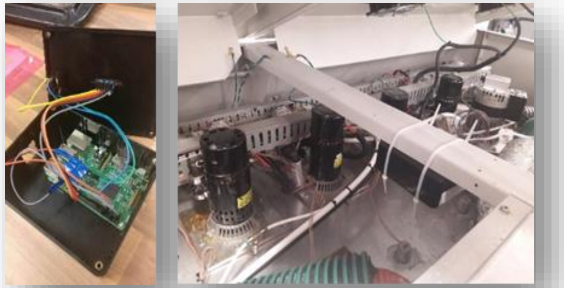


Acoustic sensors - *Deployment*

- **Implementation**
  - Raspberry Pi MEMS technology acoustic Sensors
  - Records 20 seconds of acoustic data every 5 minutes
  - Data is processed on the PC to output a single amplitude value per recording
  - Data sent to COMPOSITION server for processing

- **Operation**
  - When a fault condition is detected, the technician is alerted and identifies faulty fan, using zonal information
  - The system flags a fault condition BEFORE it affects the temperature profile
  - (Likelihood of failure over the next few days/weeks reported)





Sensors Positioned inside Oven

Acoustic outlier analysis for failure detection – *Method Overview*

Scope of the proposed method:

✓ Detect observations in the audio data measurements which deviate so much from the other samples as to indicate that there might exist a possible failure in the ovens

Dataset:

✓ Acoustic measurements from deployed IoT sensors – translated in dB amplitude values

Challenge:

✓ Absence of faulty acoustic measurements

Approach:

✓ Outlier analysis of the imbalanced dataset

✓ Implementation of well-known classification techniques

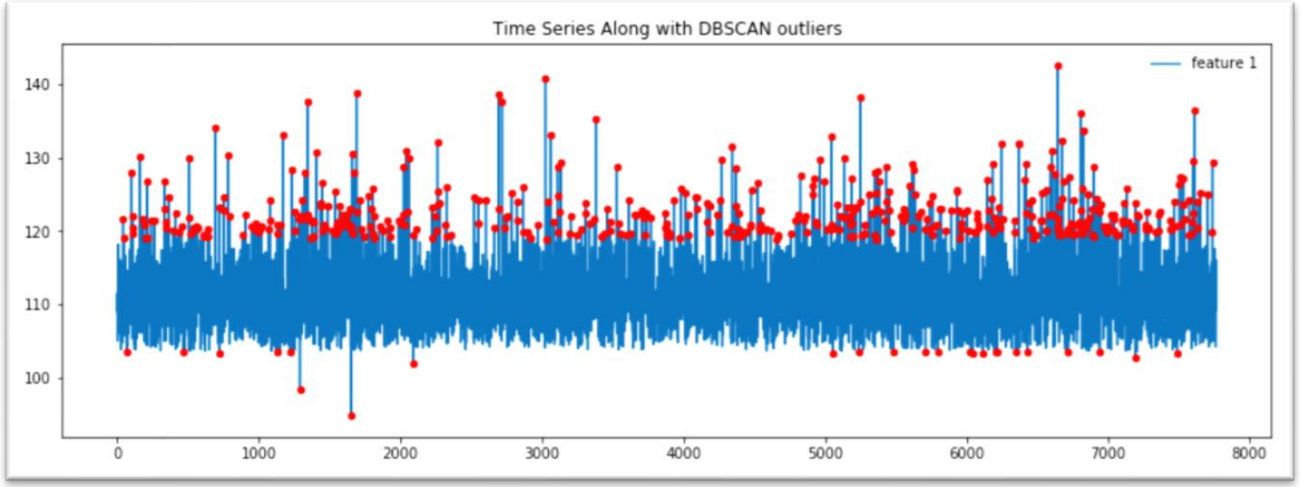
Acoustic outlier analysis for failure detection – *Method Overview*

Algorithms **implemented** and **compared**:

- **Mean Absolute Deviation (MAD)**
  - MAD value is calculated over a rolling window and the outliers lie between specific limits
- **Local Outlier Factor (LOF)**
  - Considers as outliers the samples that have a substantially lower density than their neighbours
- **Density-Based Spatial Clustering of Applications with Noise (DBSCAN)**
  - Clusters are created and outliers (noise) are assigned to the -1 cluster

Outcome:

- The lack of faulty data led to a quite small number of detected outliers
- **DBSCAN identified the most outlier points**, 1149 out of 7767 samples, which are noted as the faulty class for the classification process.



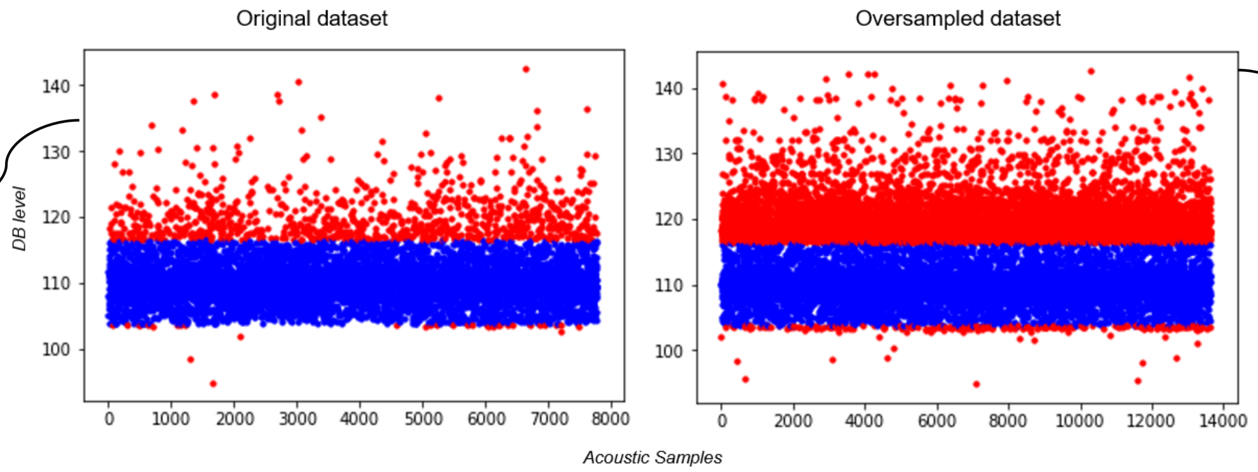
Acoustic outlier analysis for failure detection – *Preprocessing*

- **Imbalanced Dataset Problem -** faulty data are only 14% of the overall data points
  - classifiers are more sensitive to detecting the majority class and less sensitive to the minority class
  - biased classification output → always predicting the majority class

- **Oversampling -** Synthetic Minority Oversampling Technique (SMOTE)
  - re-sample the minority class
  - generate new samples by randomly sampling with replacement the current available samples

Original dataset:

- 86% positive class
- 14% negative class



SMOTE dataset:

- 50% positive class
- 50% negative class

Acoustic outlier analysis for failure detection – *SVM Classification/Prediction model*

SVM classifier used for training the new dataset

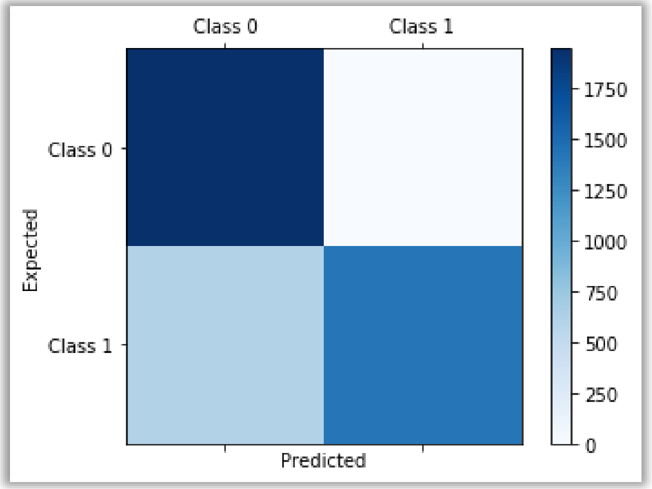
- **Two possible label classes**
  - faulted acoustic sample (=1)
  - non-faulted acoustic sample (=0)
- **Training dataset -** 70% of the overall dataset
- **Testing dataset** - 30% is used
- **SVM model parameters**
  - cost=0.5
  - kernel = Radial basis function kernel (RBF)

Evaluation results:

Metrics	Result
Accuracy	0.85
Precision	0.76
F1-score	0.86

Confusion Matrix:

- diagonal elements -predicted label is equal to the true label
- off-diagonal elements - mislabelled by the classifier



Outlier Prediction Model

Input New acoustic measurement → **Prediction model** → **Output** Fault/Non-fault class

Deep learning for predictive maintenance – *Method Overview*

Scope of the proposed method:

✓ Forecast future machine failures before they happen in order to diminish downtime and to prevent the scrappage of the oven content

Dataset:

✓ Legacy data, two sets of files:

- Data files
- Logs files

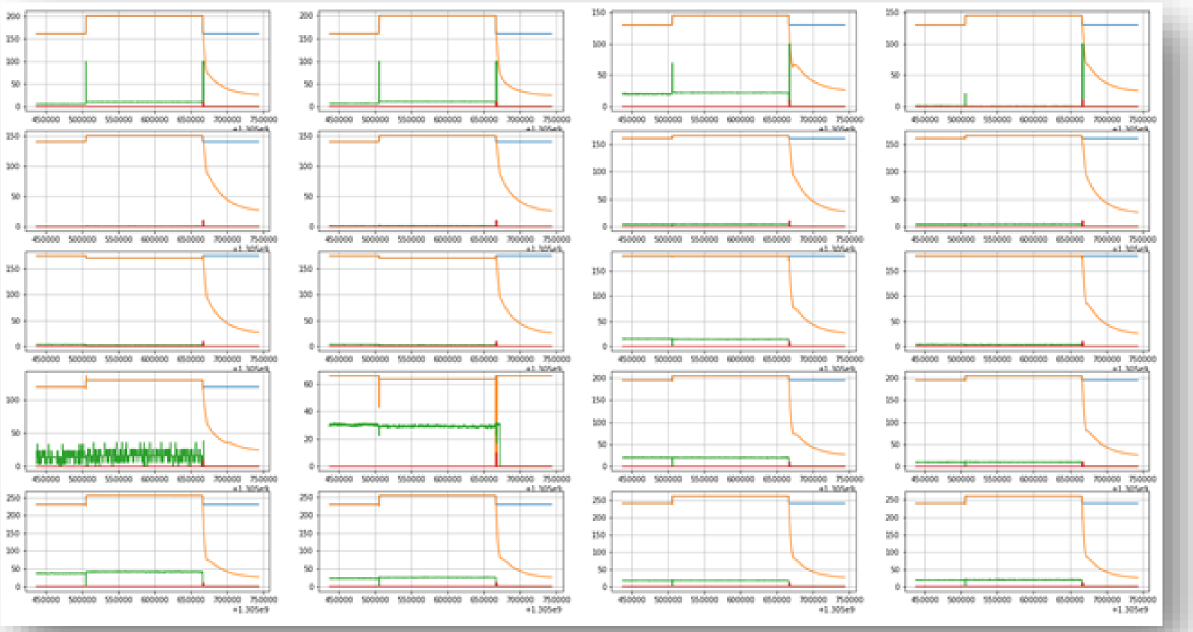
Challenge:

✓ High imbalance of the dataset

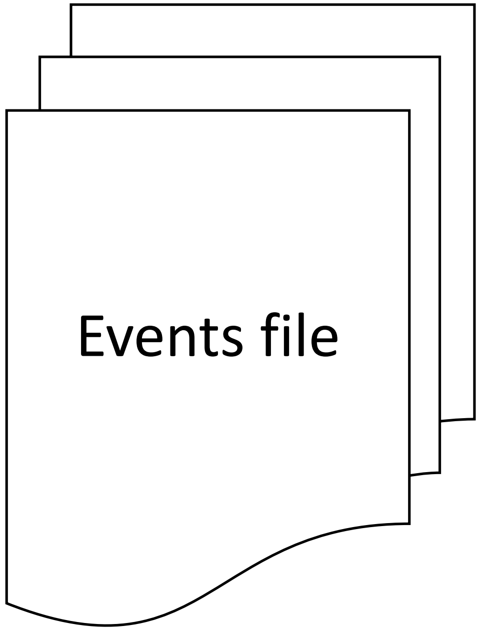
Approach:

✓ End-to-end deep learning solution to predict the failures of the machine

Deep learning for predictive maintenance – *Dataset*

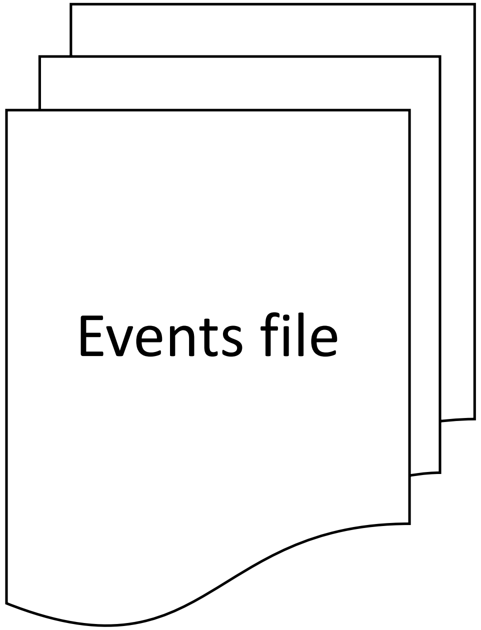


3 sensor values for each zone of the oven (20)



Machine generated logs

Deep learning for predictive maintenance – *Dataset*

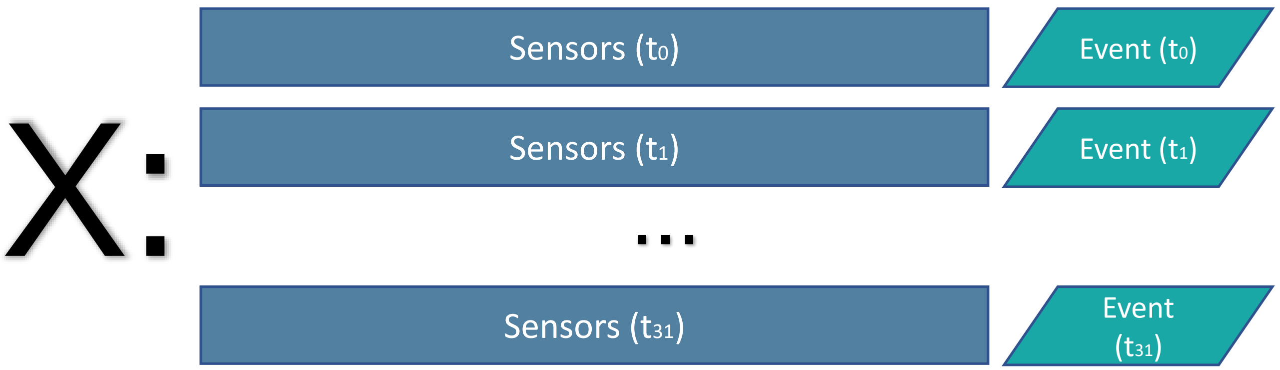


The logs are then filtered keeping only the "interesting" logs:

1. Flux Heater High Warning
2. **Hi Warning**
3. Lo Warning
4. **Hi Deviation**
5. PPM Level within limit
6. PPM Level has exceeded the amount set
7. High Water Temp Alarm Cool Down Loaded
8. Low Exhaust Alarm
9. Exhaust is insufficient
10. **Heat Fan Fault**

0 = all the other events

Deep learning for predictive maintenance – *Dataset*

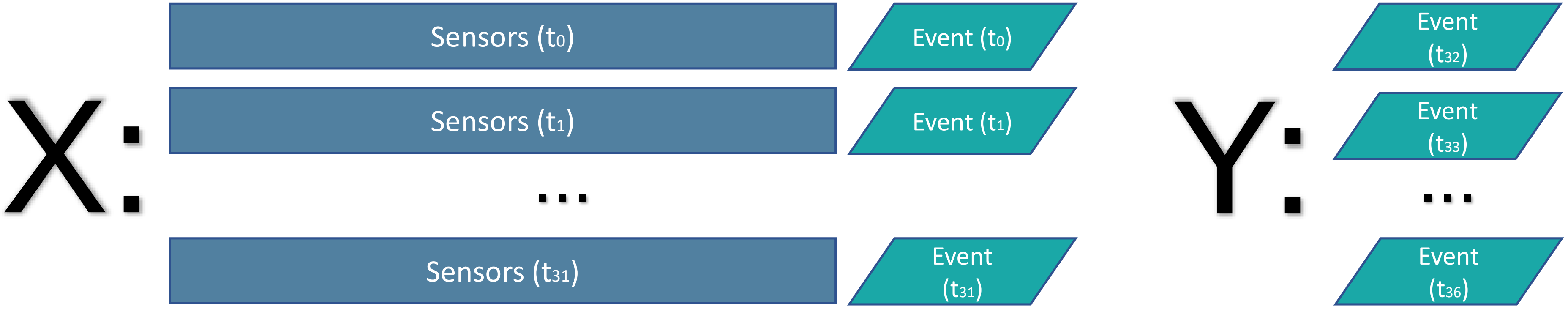


The events in the (both input and output) are transformed in One Hot Encoding.

The network will then work with a **time series of length 32** for each of the 71 features (sensors + events) and will try to predict the **future 5 events** in the form of OhE, thus a **timeseries of length 5.**

Summary: Using **160 minutes** of data to predict which event will occur in the next **25 minutes**

Deep learning for predictive maintenance – *Dataset*



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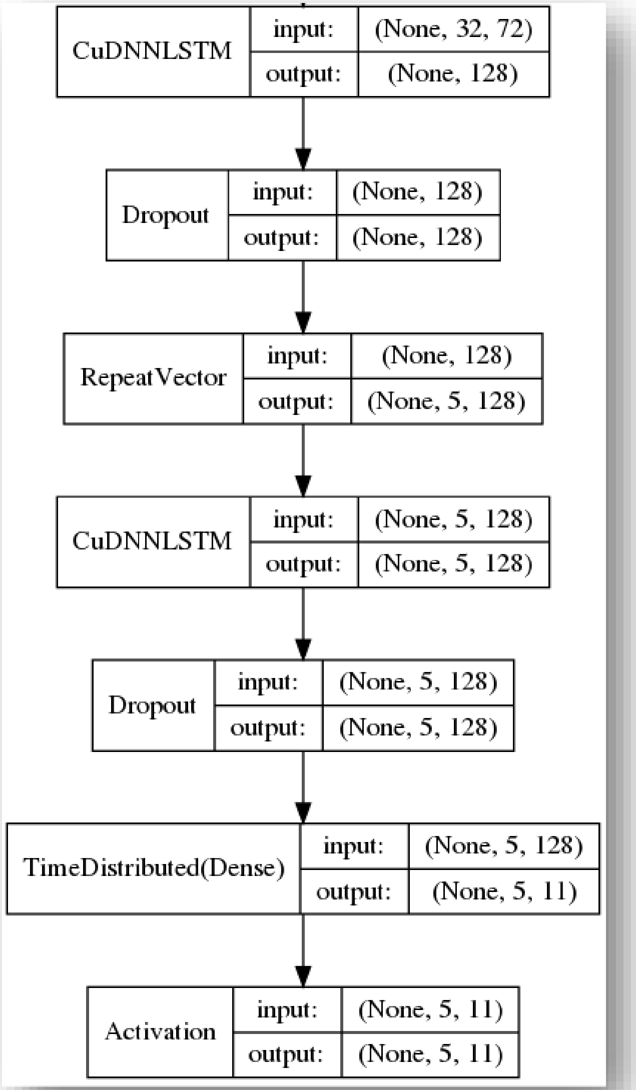
Deep learning for predictive maintenance – *Network Architecture*



The architecture of the network consists of a *seq2seq Encoder-Decoder* model

Model Configuration:

Encoder LSTM = 128 units
Decoder LSTM = 128 units

Optimizer = Adam
Learning Rate = 1e-5

Clip Norm = 1

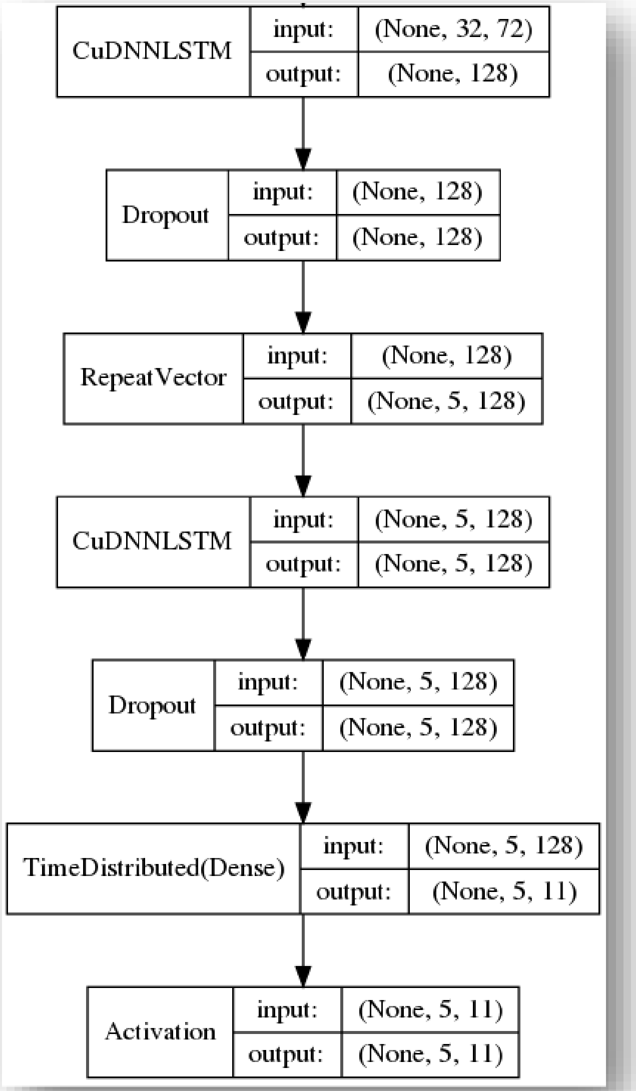
Label smoothing = 1e-4

*class weight used during training

Model output:

5 vector of length 11 (probability of events)

Deep learning for predictive maintenance – *Network Architecture*



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Label smoothing:

1 := 1 - ∈
0 := ∈ / (k -1)

K = length of OhE

Model output:
5 vector of length 11 (probability of events)

Deep learning for predictive maintenance – *Results*

Conf Matrix t(1)

Train/val/test = 80%/10%/10%

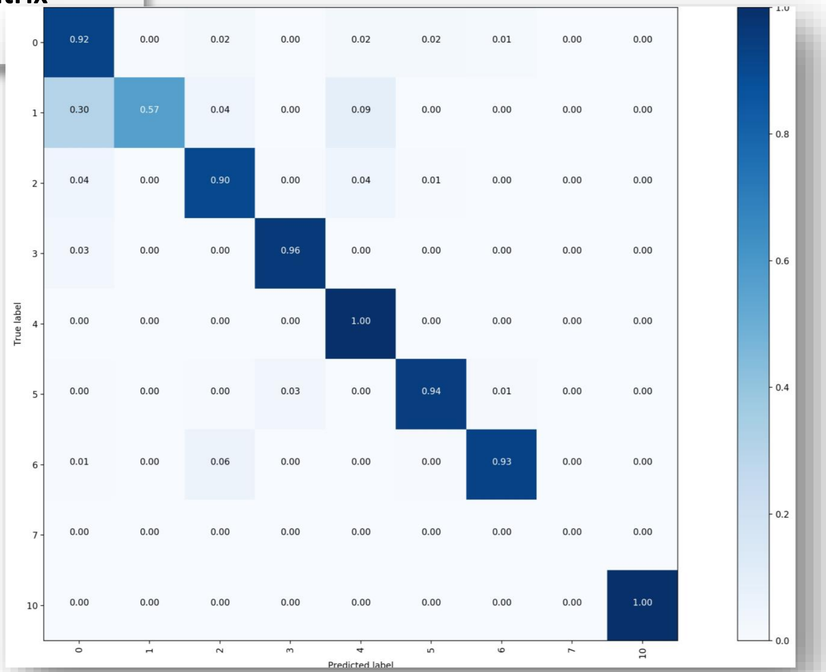
Evaluation results:

Metrics	Result
Accuracy	0.86
Precision	0.89
Recall	0.86
F1-score	0.87
MCC*	0.79

Those results are obtained as a mean of the metrics on the next five predicted events, indeed the first event (the one "less in the future") has higher score meanwhile the fifth event (the "more in the future") has the lowest overall score.

Deep learning for predictive maintenance – *Results*

Conf Matrix t(1)



Conf Matrix t(5)

Complete Evaluation results:

	Accuracy	F1-score	MCC
Event t1	0.93	0.92	0.87
Event t3	0.85	0.84	0.76
Event t5	0.81	0.80	0.69

Conclusion

The aim of this work was to exploit operational routine for **monitoring** of the system performance using the **already integrated** sensors of the oven and then **deploy extra sensors** (acoustic ones) in order to serve as **indicators** of a system’s health condition

Despite the limitations due to the **imbalanced dataset**, we formed a competent technique, capable of **detecting anomalies** and **failures** on a primitive phase aiming to improve both production and maintenance efficiency

The **predictive maintenance** approach we presented can constitute an assisting tool for **the decision support system** of industries towards the prevention of potential failure and securing of safe operation of machinery

Thanks for your attention

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