IBAAS 2024
TECHNICAL LECTURE SERIES

Revolutionizing Smelter Operations: Early Detection of Anodic Incidents with AI

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MAESTRIA SOLUTIONS

Introduction

Anode Materials and Lifespan

Benefits of Predicting Time to Failure

Challenges in Predicting Time to Failure

Predictive Maintenance in Aluminum Production

Advanced Predictive Models

Early Anomaly Detection

Methods and Tools: A Quick Overview

The Weibull Distribution

Neural Networks

Recurrent Neural Networks

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The AI Roadmap Used

Early Stopping

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Receiver Operating Characteristic Curves

The AI Roadmap Used

Dataset and Data Processing

Details on the Dataset of Smelter A

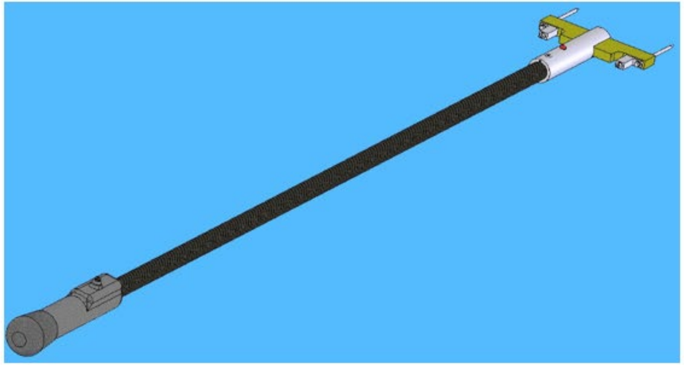
Data Collection and Preprocessing

Exploratory Data Analysis

Main Features of mVa mV Measuring Forks from Maestria use for the measurement campaign by Smelter A and Smelter B

Equipment Used

mVa unit specificities



- Ultra lightweight, ergonomic for the operators
- Long charge battery;
- Pre-programmed measurement sequence;
- Time-stamped mV data;
- Full potline and anode configuration;
- Typically less than 1 minute for scanning an entire cell;
- Sound and visual validation of the quality of the mV reading;
- Built-in memory stores mV data for transfer at the end of the run;
- Built-in display, joystick, LED.

Data Sampling and Representation

Feature Engineering

Results and Discussion

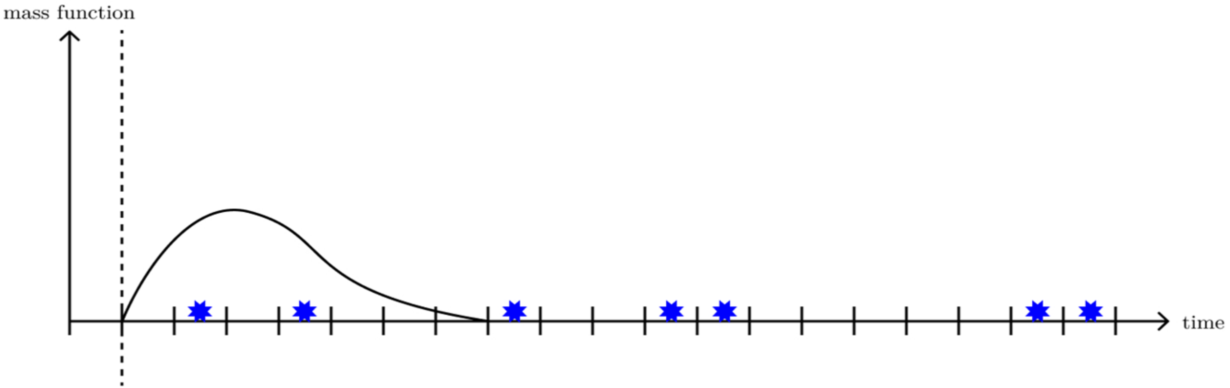
Overview of Results

Smelter A and Smelter B

Our Goals

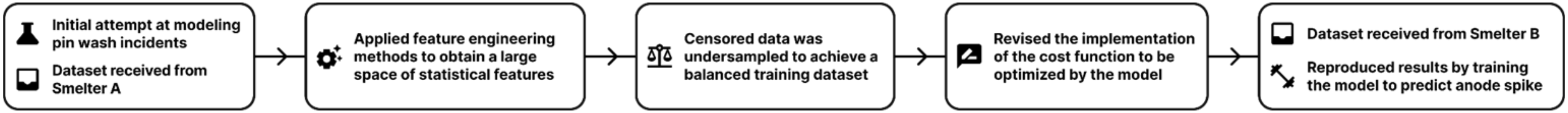
The models used make it possible to predict the time until the next incident occur ("Expected time to failure"), as well as the corresponding confidence interval.

These predictions can be made over a time anticipation window of 1 to 5 days



The tools and the process

- **The development of the "Deep Learning" predictive model was done in an iterative manner**



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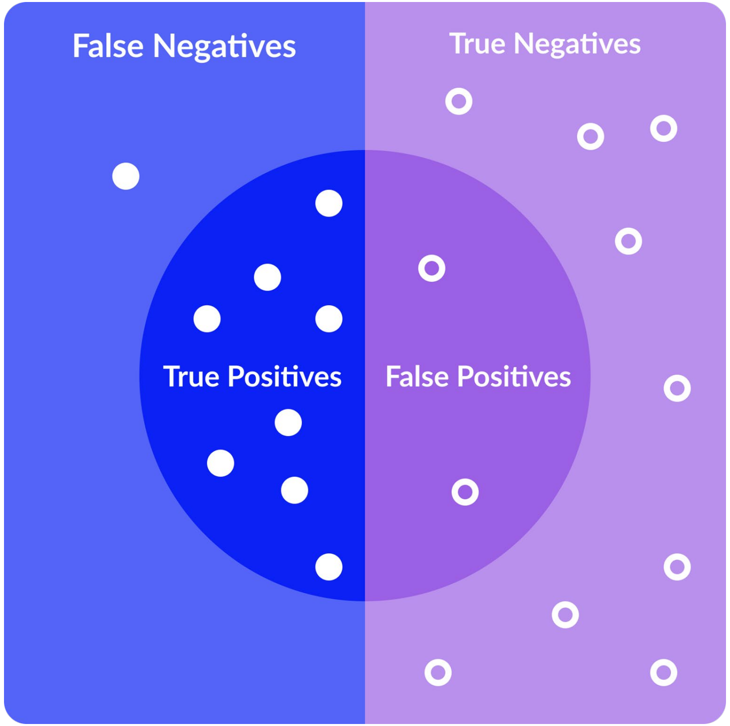
Model performance indicators



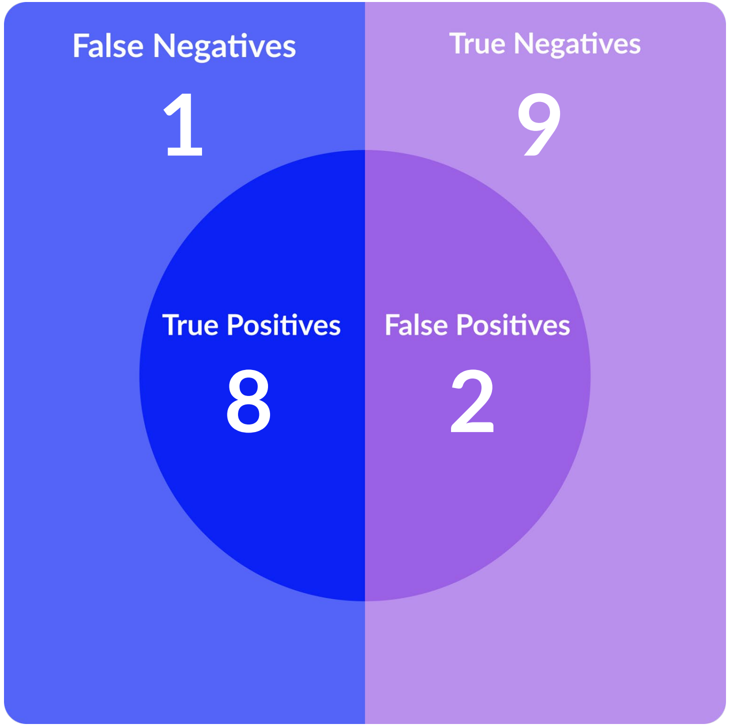
$$\textit{precision} = \frac{\textit{true positives}}{\textit{true positives} + \textit{false positives}}$$

$$\textit{recall} = \frac{\textit{true positives}}{\textit{true positives} + \textit{false negatives}}$$

Recall = The proportion of actual positive instances that are correctly identified by a model. In other words, it measures how well a model detects all the actual positive cases.

Source: https://en.wikipedia.org/wiki/Precision_and_recall

Model performance indicators



$$\textit{precision} = \frac{\textit{true positives}}{\textit{true positives} + \textit{false positives}} = \frac{8}{8 + 2} = 80\%$$

$$\textit{recall} = \frac{\textit{true positives}}{\textit{true positives} + \textit{false negatives}} = \frac{8}{8 + 1} = 89\%$$

In this example, the operator will carry out 2 unnecessary actions out of the 10 actions to be carried out and will miss one anomaly out of 9

Source: https://en.wikipedia.org/wiki/Precision_and_recall

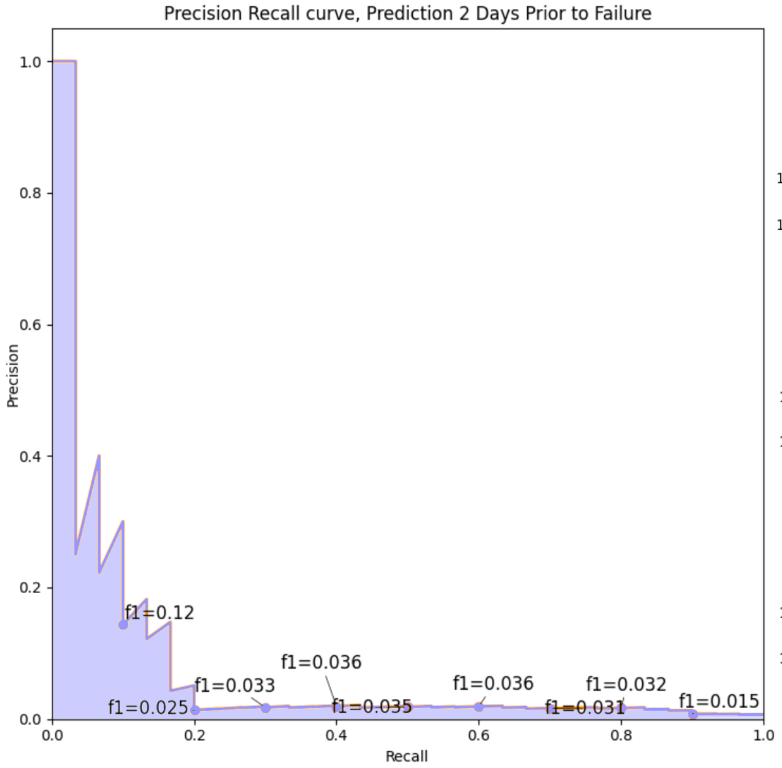
Some steps

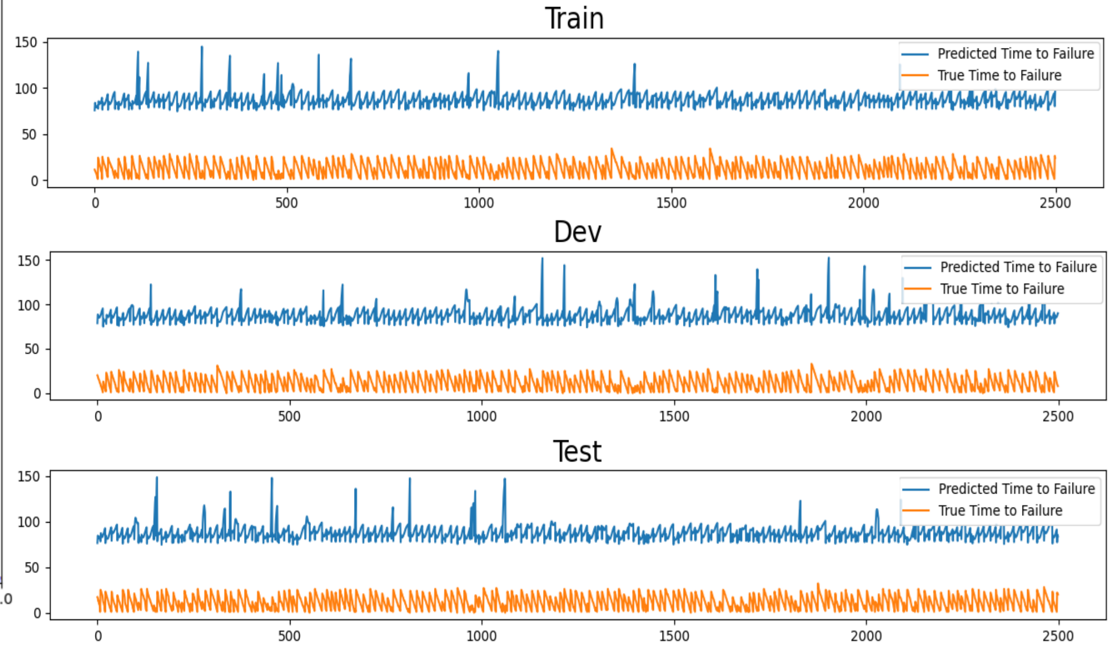
Initially, the detection core of the model was improved (optimization of the concordance index) on the "pin wash" of Smelter A, then the studies (optimization of the precision / recall couple) were carried out on the Smelter 2 data.

Actual data has been shared to allow:
A data set allowing the model to be developed
A data set allowing the model to be validated
A data set allowing the performance of the model to be evaluated

NB:
The results are sensitive to the anticipation time window which must be consistent with the frequency of mV measurements
Note that the model is only based on the mV data provided by Maestria solutions and may be enriched by the integration of others cell/anode data.

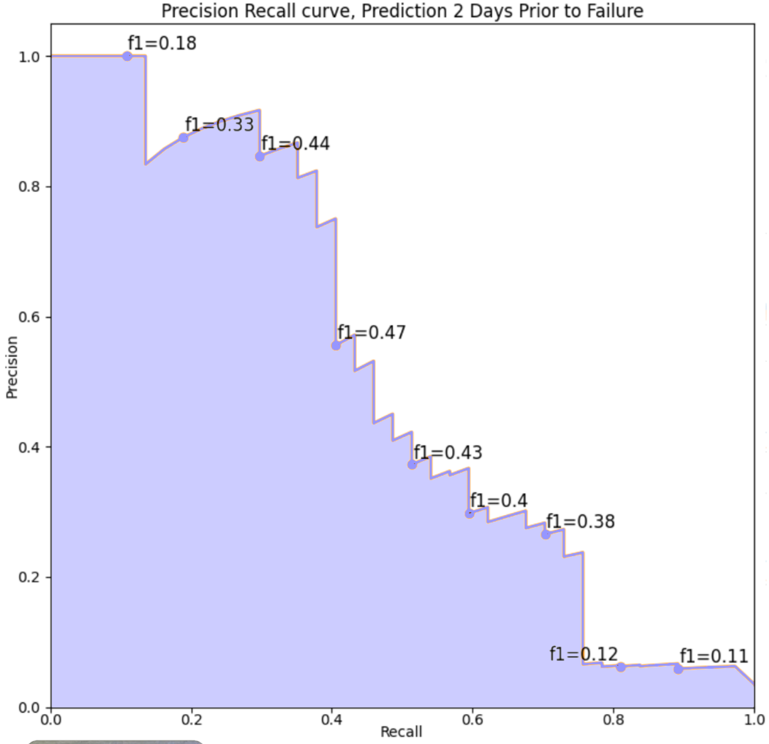
Early version of the model Smelter A / Pin wash

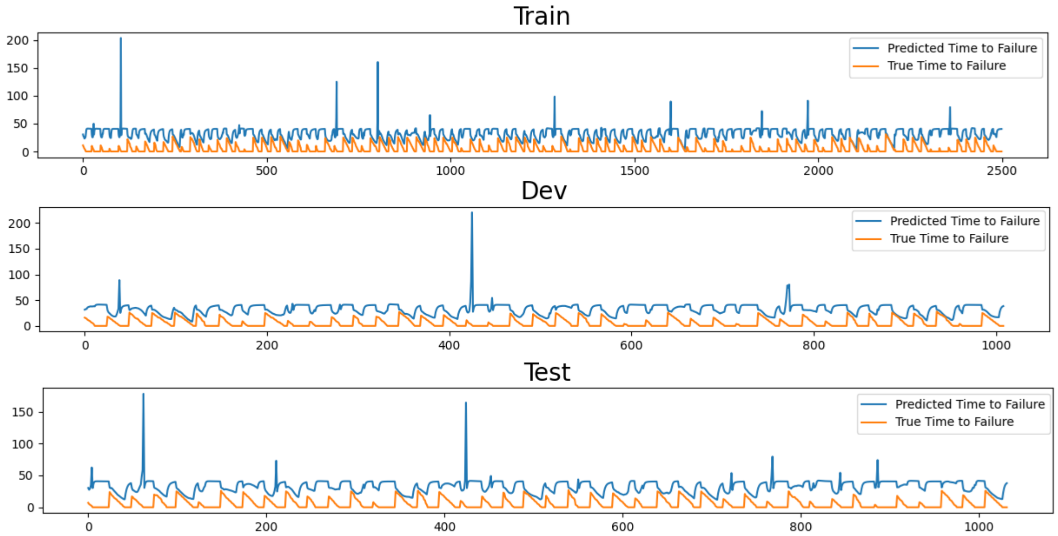




Slighty upgraded version of the model Smelter A / Pin wash

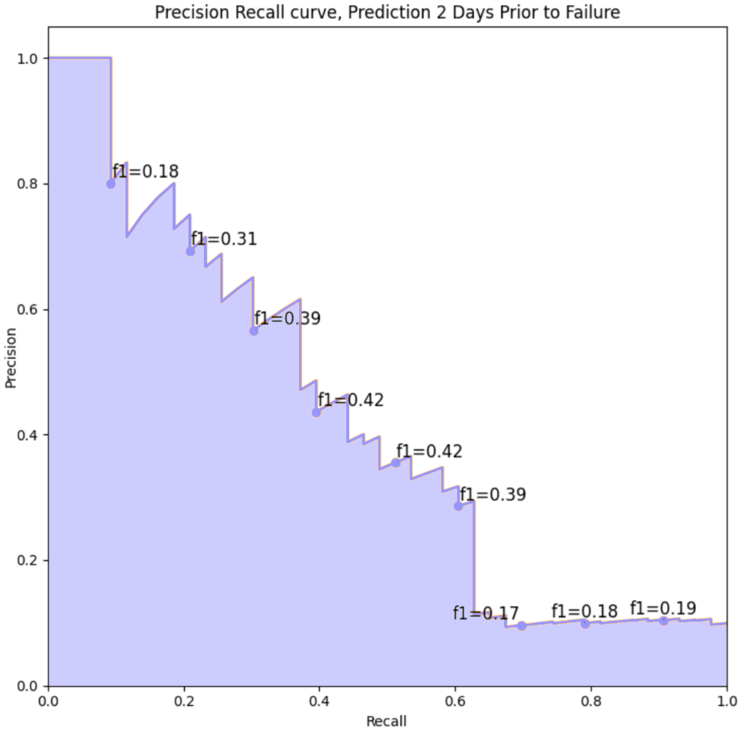
Then we balanced the data for Pin Wash

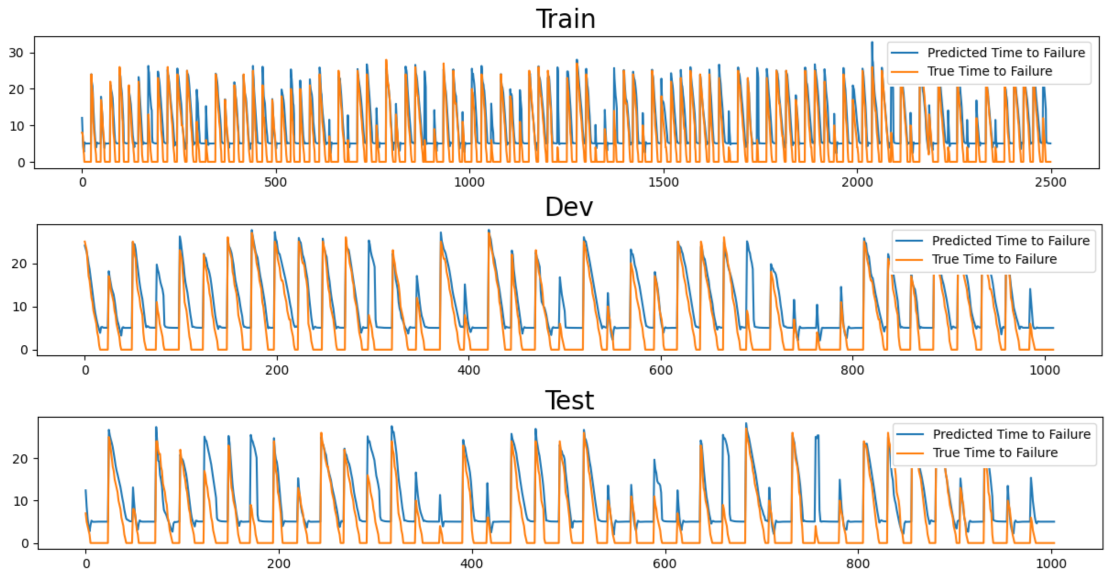




Model optimisation – Smelter A / Pin wash

Then we improved the internal functions and optimized the "cost" functions for Pin Wash to help on the next step

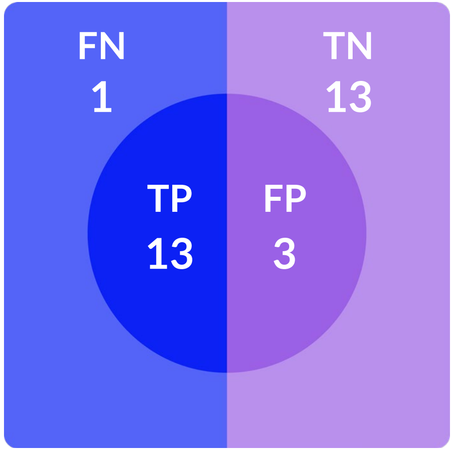




The results – Smelter B/ Spike – 2 Days anticipation

Incident type	**SPIS (Spike)**
Days window	**2 days**

Total number of incident actually occurred on the floor	**14**
Number of incidents predicted correctly 2 days before (TP)	**13**
Number of false positive prediction (FP)	**3**

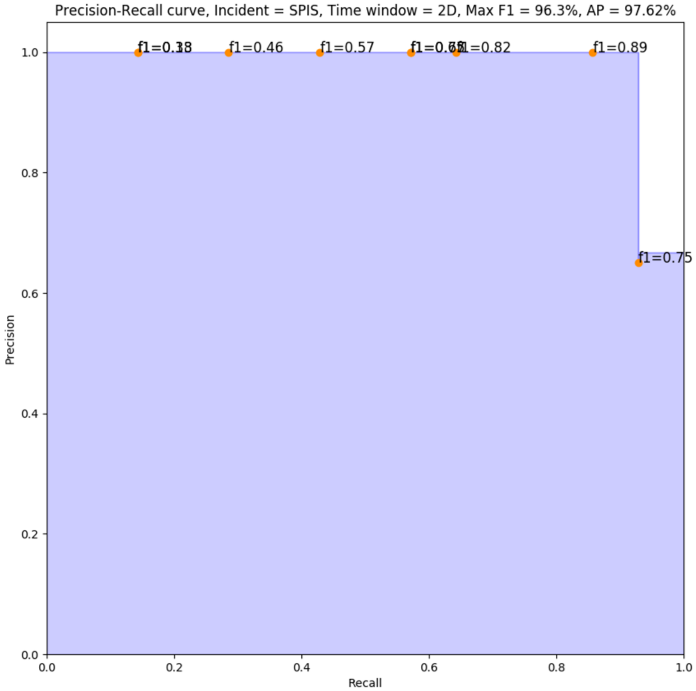


Precision = (True Positives / Total Positives)

= 13 / 16 = **81 %**

Recall = (True Positives / Total Real Incidents)

= 13 / 14 = **93 %**



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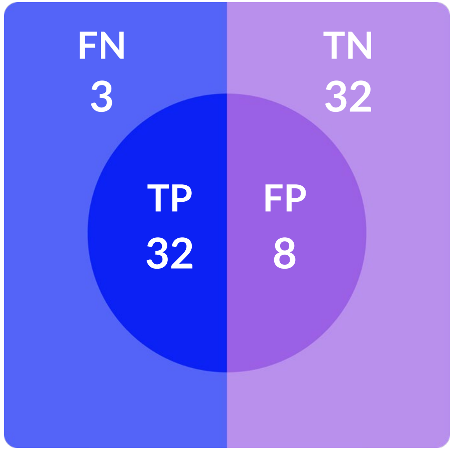
The results – Smelter B/ Spike – 5 Days anticipation

Incident type	**SPIS (Spike)**
Days window	**5 days**

Total number of incident actually occurred on the floor	**35**
Number of incidents predicted correctly 2 days before (TP)	**32**
Number of false positive prediction (FP)	**8**

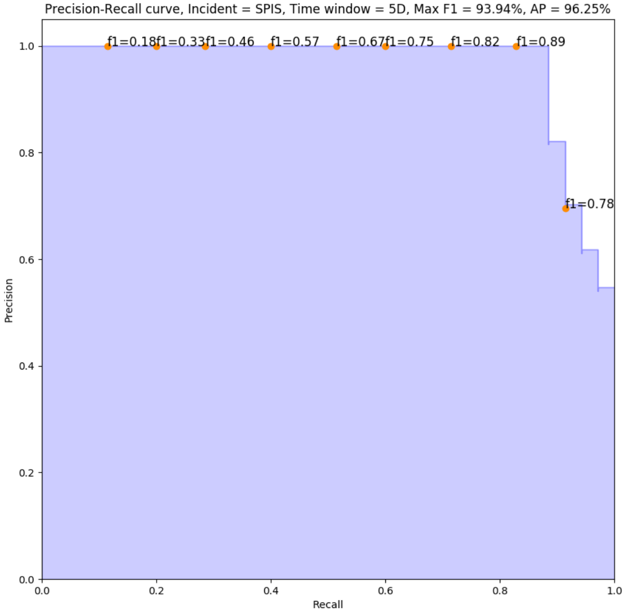


Precision = (True Positives / Total Positives)

= 32 / 40 = **80 %**

Recall = (True Positives / Total Real Incidents)

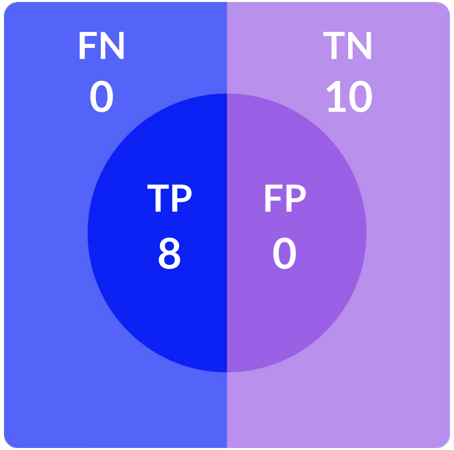
= 32 / 35 = **91 %**



The results – Smelter B/ Fallen Block – 2 Days anticipation

Incident type	**FBLU (Fallen Block)**
Days window	**2 days**

Total number of incident actually occurred on the floor	**8**
Number of incidents predicted correctly 2 days before (TP)	**8**
Number of false positive prediction (FP)	**0**

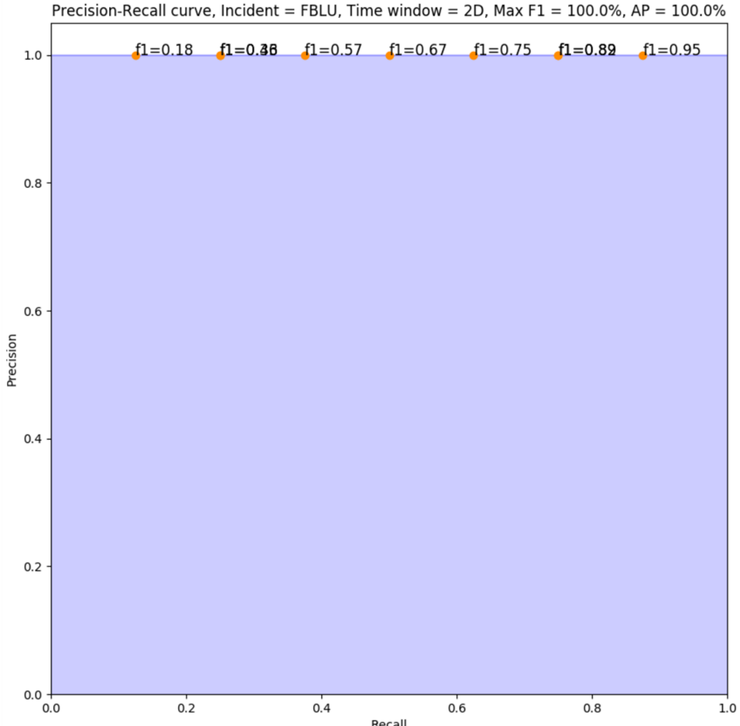


Precision = (True Positives / Total Positives)

= 8 / 8 = **100 %**

Recall = (True Positives / Total Real Incidents)

= 8 / 8 = **100 %**



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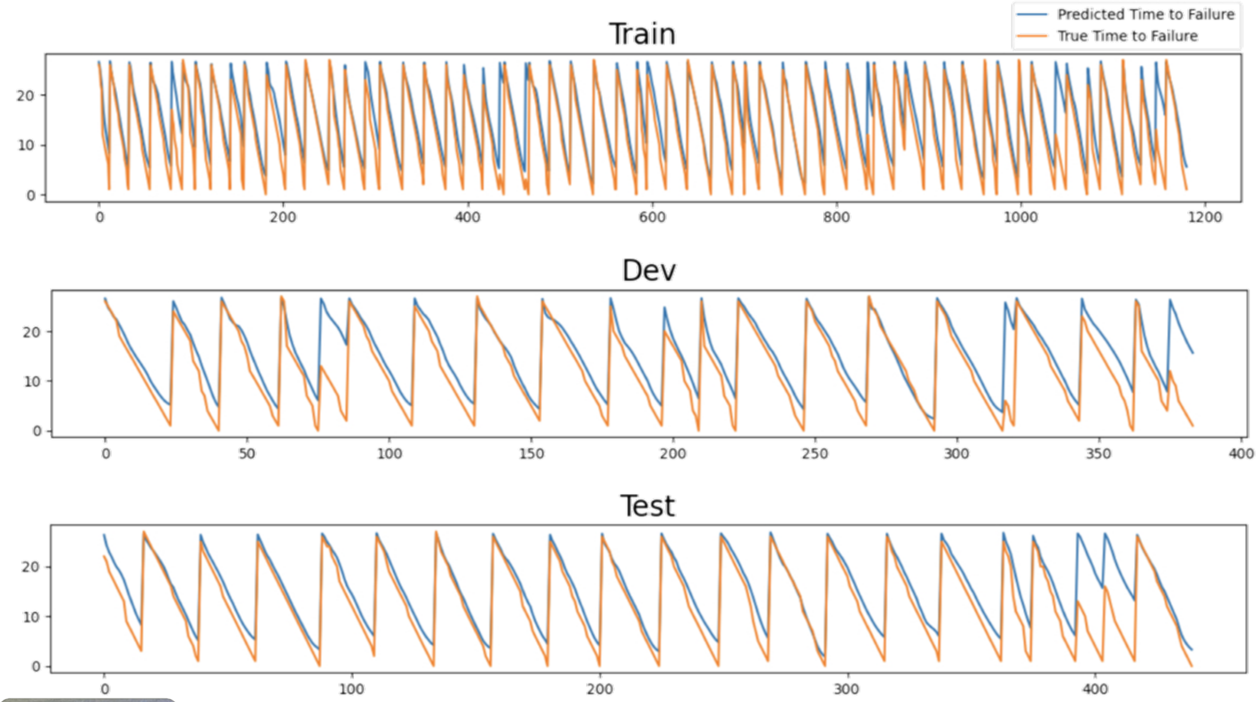
The Way Forward: Expanding the Dataset and Exploring New Failure Categories

In search of early detection of incidents by accurately predicting the timing of their occurrence



Future Work

Our future work can focus on improving the model's performance by incorporating additional features, such as the anode's maintenance history, or by using more advanced machine learning techniques, such as transfer learning or ensemble methods. Additionally, the model can be applied to predict other types of incidents in the aluminum smelting process.

Conclusion

Predictive maintenance and early anomaly detection will transform the aluminum production industry by enhancing operational efficiency, reducing downtime, and minimizing maintenance costs. Aluminum producers can proactively address potential issues and optimize their production processes by leveraging advanced sensor technologies and machine learning algorithms.

It will be essential to use these tools in the future and the sooner we do it, the more efficient and profitable we can be...

If you are interested by those results you can contact me for further information...

Thank you for your attention, and I hope you found this presentation informative and insightful. I'd like to express my gratitude to the International Bauxite, Alumina and Aluminium Society for inviting me to share my expertise with you. It's been a pleasure connecting with all of you, and I look forward to continuing the conversation on how Artificial Intelligence can revolutionize smelter operations.

As we conclude today's session, I'd also like to take a moment to wish you all a wonderful holiday season and a happy, prosperous New Year! May 2025 bring you joy, success, and continued growth for you. Thank you again, and I wish you all a great day!

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