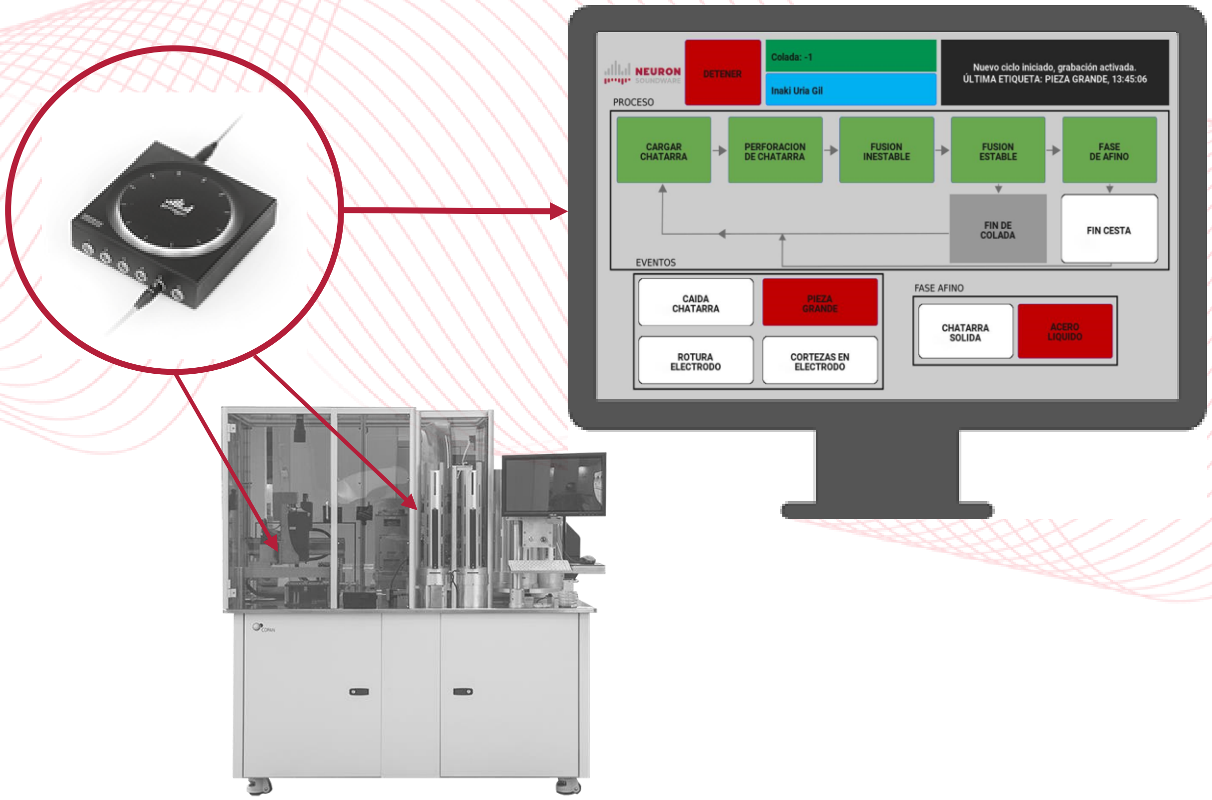
Quality Control Case Study

How to reshape end-of-line testing practices of mechanical units?



THE PRODUCTION PROCESS

The production assembles mechanical units that consist of a few tens of parts; it produces several types of units, and some customers require specific customizations. The assembly process is automated partially; complex tasks and low volume orders need to be handled by human workers. The production line assembles hundreds of units daily, and each assembled unit is tested for quality at the end of the line. Tests are run on test benches equipped with a noise recording system. Human operators perform the tests using their judgment and basic statistical methods.

THE QUALITY TESTING PROBLEM

The testing is time-consuming and requires manual work that is highly repetitive and tiring. Human operators need to be trained for a long time to be able to distinguish Bad pieces via noise with high confidence. Some pieces are judged as Good by some workers, while others may say they're Unsure or even mark them as Bad.

HIGH COSTS AND TOO MUCH WASTE

The manual testing method is costly by nature. Inconsistency of human judgment brings about additional costs. If there are doubts in a test, i.e., different workers have different opinions, units go to scrap/re-assemble, even though they might be Okay quality and functionality.

5 Steps by Neuron soundware

to improve the end-of-line testing process

1. Hardware and Installation

We used available customer data and integrated our hardware with the equipment in place (piezo-electric sensors). We backed the recording system with our nBox and similar sensors.

2. Data Collecting and Labeling

We collected data for a few weeks. We closely collaborated with the production operators, who we asked to label the recorded samples using our proprietary labeling app.

3. Algorithms Training and Validation

We developed two kinds of algorithms. Anomaly detection proved to be the better option for this use case in the end as classification was not accurate enough due to the issues in human labeling accuracy.

4. Final Deployment and User Training

We deployed the algorithm on our nBox edge device and integrated the detection service with the customer hardware in place. We trained the operators on how to use the AI solution and how to provide real-time feedback to us.

5. Continuous Service Improvement

Real-time feedback from operators helps us to improve accuracy further. We provide quarterly updates in the service model. We calibrate the algorithm to new production lines or types of products on a project basis.

BRINGING THE AI SOLUTION IN PLACE

We expected that the inconsistency of human labeling of Good/Bad units would make it difficult to collect a quality training data set. It indeed proved to be a limiting factor for the training of accurate classification algorithms. Therefore, we mostly focused on the development of a powerful anomaly detector which, when fed with vast amounts of data, could learn sound patterns in the Bad units. After several development iterations and live factory tests, the new automated AI-solution proved to be very accurate and reliable. The client decided to change the testing procedure and manually test only those units which crossed the threshold set for the automated AI test. At the end of the PoC, the volume tested manually decreased to 5%.

CUSTOMER TESTIMONIAL

“Neuron soundware reshaped our end-of-line testing practices of mechanical units. The initial precision and consistency of detection of faulty units, with only thee full days of audio data available, were surprising. We closed the trial project with **the amount of manual testing reduced by a staggering 95%.** We are now rolling out the solution to our other three production lines.”

Production engineer
A global supplier of mechanical units