Vinglabs Noesis Installation at ALPLA - A Technical Report

About ALPLA

ALPLA, otherwise **ALPLA Group** is an Austrian, international acting plastics manufacturer and plastics recycler headquartered in Hard, specializing in blow-molded bottles and caps, injection-molded parts, preforms and tubes. It is one of the largest producers of rigid plastic packaging solutions worldwide, with a total of **177 production plants** in over **45 countries**worldwide, approx. **22,100 employees** and annual sales of **€ 4.00 billion** in 2021. The annual production capacity of ALPLA's recycling companies, joint ventures and collaborations amounts to approximately **203,000 tonnes of rPET** (recycled PET) and **74,000 tonnes of rHDPE** (recycled HDPE). **ALPLA is the largest recycler of PET in Europe.**

Problem Statement

Vinglabs was tasked to install a monitoring system at one of **ALPLA's**subsidiary **PRT(PET Recycling Team)** in **Wöllersdorf, Austria**,**30km off Vienna**. The system was to be installed on top of a conveyor which was the input feed to the plant. The feed consisted of clear PET bottles(desirable) with other plastic impurities like non-clear PET bottles, non-clear PP bottles, cans, cardboards etc. The feed was traveling at a speed of **3m/s** and the conveyor was **1.8m wide**. PRT wanted the following analytics from the monitoring system -

- **Utilization Factor of the plant** - Fraction of time throughout the day when the conveyor was empty.
- **Opaque impurity detection** - For the PRT team, opaque bottles in the input stream were a big concern because even a tiny percentage could negatively affect the output.
- **Non food detection** - As the output of the PRT recycling plant is food grade PET flakes, it is imperative for them to know the amount of non food material in their input stream.
- **Real time analytics** - PRT wanted to eliminate the disconnect between the office and the plant floor by implementing a real time analytics system to be proactive rather than reactive.

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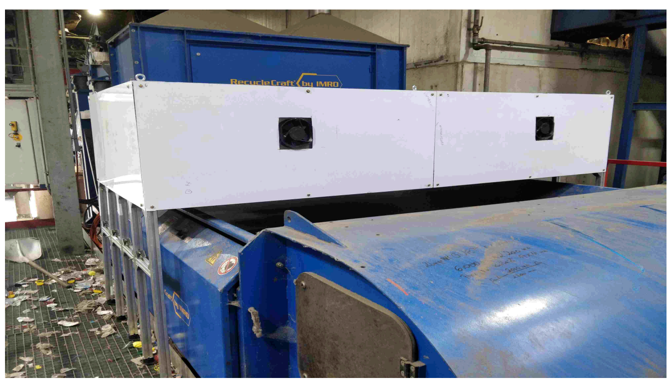
The Solution - Vinglabs Noesis



Camera Lens selection

The camera lens selection was crucial as the objects were traveling at a speed of **3m/s** and were spread on a **1.8 m wide** conveyor. Following things were to be kept in mind -

- The images would be clicked at **extremely low exposure to avoid motion blur.**
- Capturing images at **low exposure requires a lot of illumination** as lower the exposure, less light will enter the camera.
- The camera has to be a **global shutter** camera to avoid distortion caused due to objects moving at high speed.
- The camera should have a **high pixel size** so as to incorporate as much light as possible into the sensor.

- **Increasing pixel size comes at a tradeoff to resolution** as sensor size remains fixed.

Given these constraints, it was impossible to develop a single camera system that covers a FOV of **1.8m**. Thus it was decided to use **2 cameras** that would be adjacent to each other capturing the left and right half of the conveyor respectively.

Given these variables, the constant that could be relied upon was the resolution of the camera. Since it was known the minimum feature size (this is the minimum distance between the features that camera lens system can resolve) to be captured was **2mm**, the minimum resolution of the camera was determined to be **2MP**.

After carefully considering all the options, running some tests and availability constraints, it was decided to go forward with-

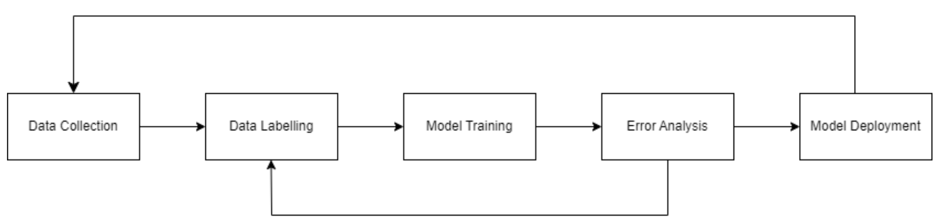
- **2 LUCID Vision Labs Triton™ TRI071S-CC, Sony IMX428, 7.1MP**
- **Color Camera coupled with Fujinon CF12ZA-1S 12mm f/1.8 Machine Vision C-Mount Lens. The IMX428 has a very large pixel pitch of 4.5um.**

Lighting

Capturing images at a very low exposure requires a lot of lighting to capture a well lit image. We used diffused rectangular LED light panels with a target lux of 10,000 on the surface of the conveyor.

System design of ML pipeline

The ML pipeline consisted of following parts -

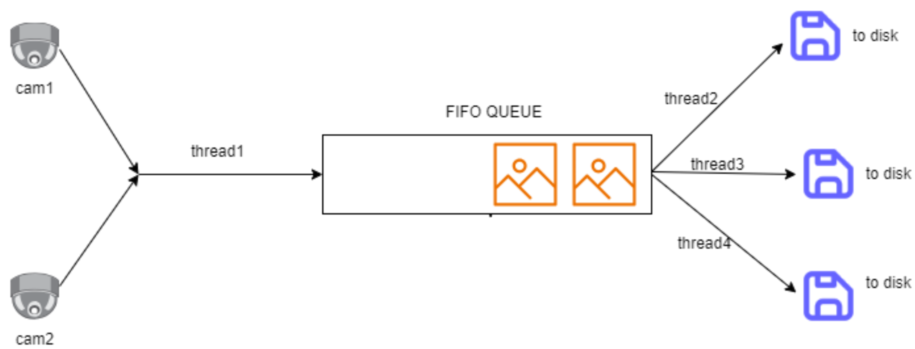


Machine Learning Loop

Data Collection

- In a fully operational plant, it is imperative to capture diverse data at different times throughout the day as capturing data only during particular hours may lead to the collection of a particular kind of data and thus lead to poor classifiers. Also, one cannot collect all the data as it would be impossible to manage such huge amounts of data.

- We decided to collect a burst of **1000 images every 30 minutes** throughout the day. The data would be saved to externally connected Solid State Drives and would be uploaded automatically to cloud(S3) whenever the images are not being clicked.
- To click and save images, a typical **multithreaded master-slave architecture was used with a queue in between.** One thread was responsible for clicking images and dumping into the queue and multiple threads were used for popping the queue and saving the image to disk.



Splitting up the problem into multiple parts with multiple classifiers

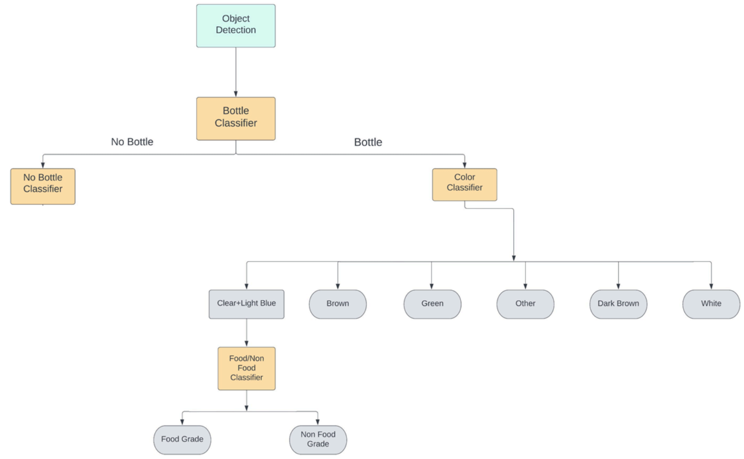
There are two ways to solve a complex ML problem.

- The first is to **train an end to end model** which takes in the captured images, does the object detection and classification(of type of object,color and food/non food) in one shot.
- The other way is to **split the problem into multiple sub problems and sub classifiers and combine the result**. This is always preferable as-

  1. It helps us track the real performance bottleneck of our pipeline thereby giving us a targeted approach to solve the problem.
  2. Smaller classifiers are easier to debug and run through the machine learning loop.

We split the problem into multiple classifiers as per the following flowchart -

VINGLABS TECHNOLOGIES PET RECYCLING TEAM A Member of the ALPLA Group ALPLA



PRT CLASSIFICATION CATEGORIES FOR LABELLING

The problem was split up into 1 object detection model, and 3 classifiers-

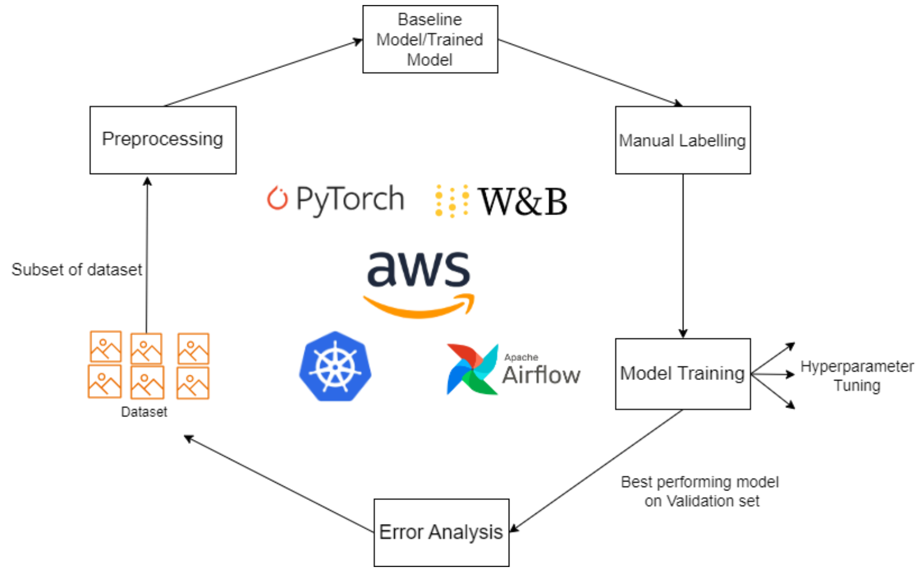
- **Object Detection** - YOLO and YOLO-like family of models
- **Bottle/Cans/Other Classifier** - Resnet, GoogleNet, Squeezenet, ShuffleNet, EfficientNet family of models
- **Color(Clear,Light Blue/Brown/Green/Black/Opaque/Other) Classifier** - Specially designed models of classification family to deal with colors.
- **Food/Non Food Classifier** - We used many visual markers like shape of the bottle, transparency, brands etc. to detect non food bottles in input stream. A combination of YOLO styled and classification styled model.

In the final deployment of models, the object detection model needed to process **8 images** and the **3 classifiers** needed to process **100 objects each**, all in **1 sec**.

Label - Train - Error Analysis loop

We extensively used **active learning** along with a team of multiple human labellers to label millions of images in a short amount of time. Following tools were used throughout this loop -

- **Pytorch** - To write models,training loops,data loaders etc.
- **Wandb** - To track models, dataset and training.
- **S3** - As object store.
- **Apache Airflow** - To orchestrate ETL pipelines involved in preprocessing.
- **Kubernetes** - To scale across different nodes for tuning hyperparameters.



Model Deployment

All the models were deployed locally on an **AGX JETSON ORIN** with the stream of images and models connected with a lightweight **RabbitMQ**. This enabled objects being retained even if there was a hit on execution speed of models. We were able to consistently clock **800ms for inference 8 images/sec** end to end which involved running multiple classifiers on **100 images/sec**.

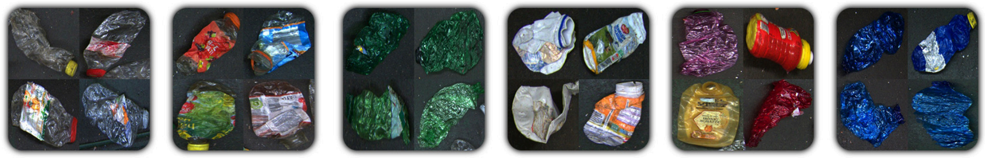
The Impact

Pet Recycling Team (PRT), a subsidiary of **ALPLA**, is a PET recycler in Europe. **Vinglabs** installed their system at PRT Wöllersdorf, Austria on **October 1st 2022**. Through real-time monitoring using Vinglabs proprietary AI **Noesis** and a highly interactive dashboard **Athena**, the installation achieved the following goals successfully -

- **Utilization factor of plant** - Through Noesis's real time bottle detection, it is now possible for stakeholders to monitor the plant throughput in real time, thus enabling them to detect the least productive times of the day to take corrective action.

Bottle Others Cans

- **Opaque impurity detection** - For PRT team, opaque bottles in input stream were a big concern because even a tiny percentage could negatively affect the output.Through Noesis's real time color detection, PRT is able to monitor and get notified about opaque percentage in input stream.Along with opaque bottle detection Noesis also detects bottles of different colors like green,blue etc. to give real time insights to the plant.

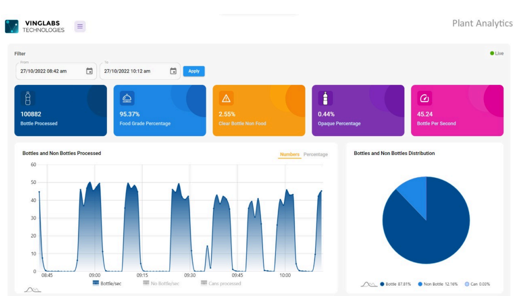


Clear Clear Sleeved Green Opaque Others Blue

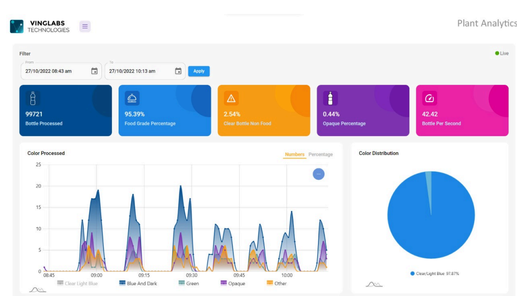
- **Non food detection** - As the output of PRT recycling plant is food grade PET flakes, it is imperative for them to know the amount of non food material in their input stream. Noesis uses many visual markers like shape of the bottle, transparency, brands etc. to detect non food bottles in input stream.

Food Non-Food

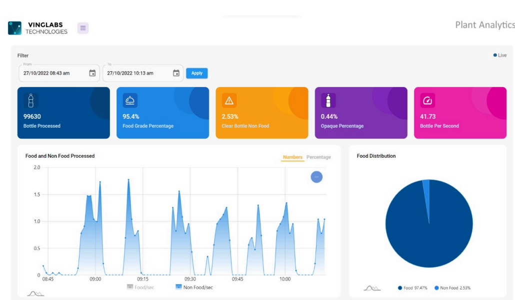
- **Visualizing analytics on Athena** - To visualize all the analytics and insights, Vinglabs has provided PRT with a highly interactive dashboard “Athena” which gives them live as well as historical view of insights generated by Noesis.



Throughput Analytics on Athena



Color Analytics on Athena



Food/Non food Analytics on Athena