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REPORT

AquaGuard: Quality Control for Bottled Water

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No.	Full name	Tasks
1	**Nguyen Tuan Tu – leader**	**Code model** Methodology part
2	**Tran Huu Manh**	**Code model** Conclusion part
3	**Pham Duc Manh**	**Prepare dataset** Result and Analysis part
4	**Ly Tan Phat**	**Prepare dataset** Quality control part
5	**Chau Nguyen Thanh Tai**	**Prepare dataset** Introduction part Reference part
6	**Nguyen Minh Thong**	**Prepare dataset** Data Collection part

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1. Introduction

Introduction to the Bottled Water Industry

The bottled water industry is one of the most dynamic and rapidly growing sectors in the global food and beverage market. Increasing consumer focus on health and wellness, convenience, and access to safe drinking water have propelled remarkable growth in recent years. Bottled water has even surpassed other packaged beverages, with consumers viewing it as a healthier alternative to sugary drinks. This expansion is expected to continue, driven by innovations in product offerings, sustainable packaging, and advanced distribution strategies.

Aquafina: A Leader in Quality and Innovation

Aquafina, a flagship brand owned by PepsiCo, has established itself as a trusted and globally recognized name in the bottled water industry. Known for its rigorous purification process, Aquafina has a substantial footprint in both domestic and international markets. Catering to health-conscious consumers, Aquafina benefits from PepsiCo's extensive distribution network, which has propelled its accessibility to a wide audience. Over the years, the brand's product portfolio has expanded to include flavored and sparkling water varieties, meeting a wide array of consumer preferences.

Vietnam's Bottled Water Market

In Vietnam, bottled water consumption has experienced a steady increase, attributed to concerns about tap water quality and a shift towards healthier beverage options. Leading brands such as Aquafina, LaVie, and Vĩnh Hảo dominate the market, with each brand adopting unique strategies to capture consumer interest. While the market remains highly competitive, there is potential for growth in premium and flavored bottled water segments, reflecting global trends in consumer preferences.

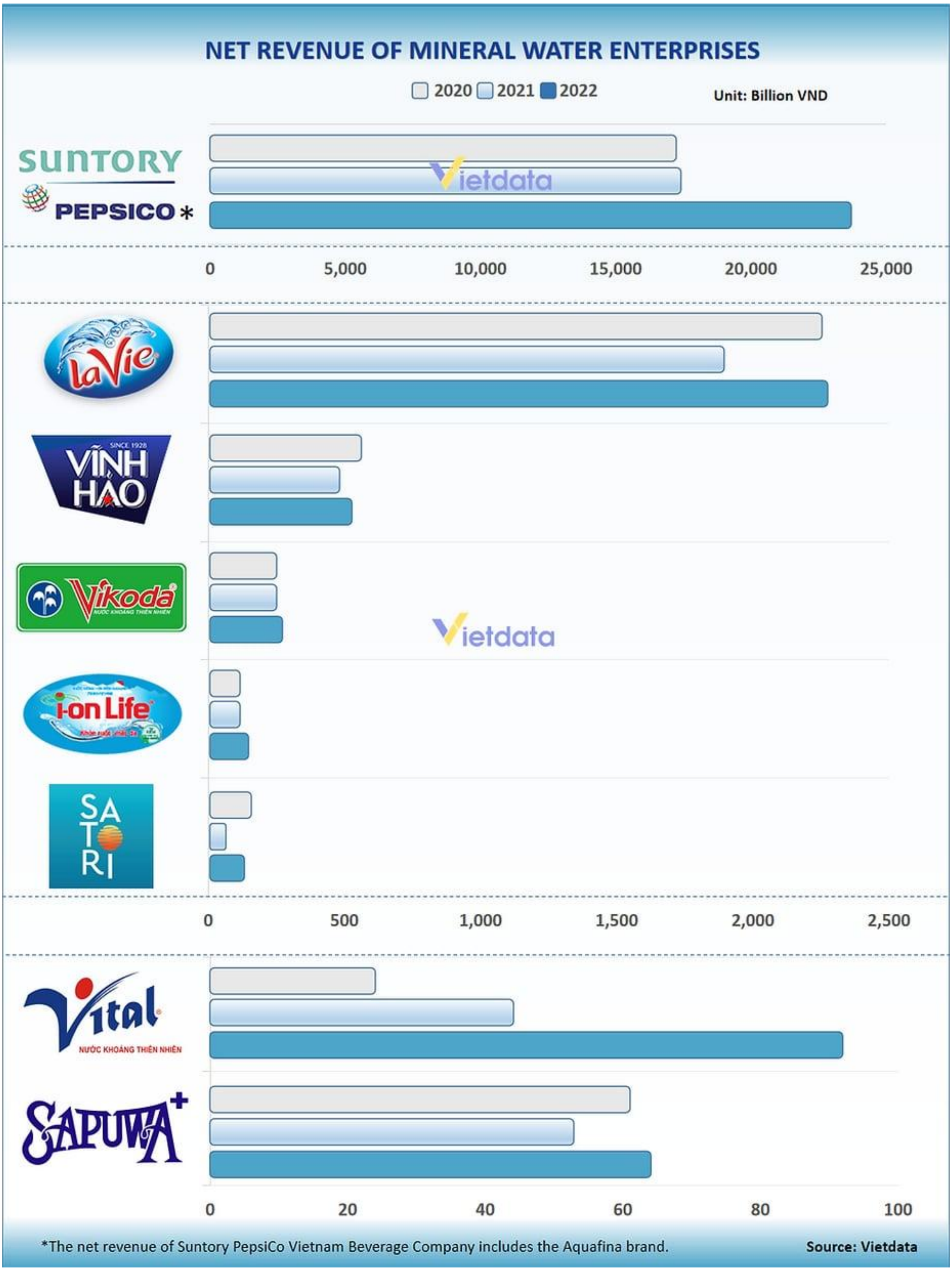

Figure 1. Aquafina and other competitors price

Competitive Landscape

- **Aquafina (PepsiCo):** Known for its stringent purification process and extensive distribution network, Aquafina holds a strong position in the

Vietnamese market. As shown in the revenue data, Suntory PepsiCo, which includes the Aquafina brand, leads the market with revenue surpassing 20,000 billion VND in 2022. This dominance reflects Aquafina's association with quality and reliability, making it a popular choice among urban consumers.

- **LaVie (Nestlé):** Leveraging Nestlé's brand reputation and extensive product range, LaVie is positioned as a premium brand in Vietnam, focusing on natural mineral water. The revenue chart indicates that LaVie is the second-largest player in the market, showing steady growth each year, reinforcing its appeal to health-conscious consumers who seek quality.
- **Vĩnh Hảo:** A local favorite, Vĩnh Hảo emphasizes its natural mineral water sourced from local springs, appealing to consumers who prioritize local products. Although Vĩnh Hảo's revenue is modest compared to Suntory PepsiCo and LaVie, it has shown some improvement over the years, highlighting its niche appeal within the domestic market.
- **Other Competitors:** Brands like i-On Life and Satori have also entered the market with unique selling points, such as alkaline water and a focus on sustainable packaging. However, their revenue remains significantly lower than the major players, with minimal growth over the years, indicating that while they meet niche demands, they are yet to capture a larger market share.

Market Trends

1. **Health-Conscious Choices**: Consumers are increasingly shifting away from sugary and carbonated drinks towards bottled water, seen as a healthier and more natural option.
2. **Sustainable Packaging**: There is a growing demand for environmentally friendly packaging solutions. Brands that focus on sustainability initiatives, such as recyclable or biodegradable packaging, are likely to gain consumer favor.
3. **Flavored and Functional Water**: Flavored and enhanced water varieties are gaining popularity, especially among younger consumers seeking unique tastes and health benefits.

Market Success and Potential Growth Opportunities

Aquafina has demonstrated impressive sales performance, significantly contributing to PepsiCo's bottled water revenue. Despite its robust positioning, there remains considerable growth potential within this competitive landscape. To capitalize on these opportunities, Aquafina could pursue initiatives such as expanding its flavored and functional water lines, investing in eco-friendly packaging, and leveraging digital marketing to engage health-focused younger consumers. Collaborations with wellness influencers and an increased presence in emerging markets could further enhance Aquafina's reach and capture the growing demand for premium, sustainable bottled water.

Objective

Defect detection for bottles primarily includes two methods: manual and optical inspection. Manual inspection generally requires workers to physically handle and visually examine each bottle. However, this approach has several limitations. First, it is inefficient and often time-consuming, especially in high-volume production, which can lead to bottlenecks. Second, the consistency of manual inspection results can fluctuate due to human factors such as attention span, experience, skill level, and fatigue. Third, tiny or subtle defects may go unnoticed, as they are challenging for the human eye to detect accurately. Additionally, inspectors' judgments can be influenced by personal experience, knowledge, emotions, and sometimes even subjective biases. Continuously inspecting bottles can also lead to physical strain and fatigue among employees. Given these limitations, many bottle manufacturers are shifting towards automated and semi-automated inspection methods, such as machine vision and sensor technologies, to improve the efficiency and accuracy of defect detection.

Figure 2. Defect detection in laboratory

This project aims to develop machine learning (ML) models for defect detection and quality assurance in Aquafina's bottled water manufacturing process, enhancing real-time quality control to ensure only top-quality products reach consumers.

Scope

The project focuses on identifying and classifying defects in Aquafina water bottles using a combination of YOLO (You Only Look Once) for object detection and Instance Segmentation. This approach bolsters real-time quality control and ensures consistent high quality.

Importance of the Project

1. **Consumer Safety**: Ensuring that each bottle of water is clean and free from harmful substances like bacteria, chemicals, or heavy metals is critical to protecting consumer health.
2. **Regulatory Compliance**: Aquafina's products must meet regulatory standards set by agencies like the FDA and other local bodies to ensure safety and quality.
3. **Brand Reputation**: Consistent quality control helps maintain Aquafina's positive brand image, preventing potential damage from quality issues.
4. **Efficiency and Cost Reduction**: Early defect detection reduces waste, minimizes the risk of product recalls, and optimizes production costs and time.

5. **Consistency in Product Quality**: This project supports Aquafina's commitment to delivering consistent quality, taste, and safety for every bottle, regardless of where or when it is produced.

By implementing advanced ML techniques in quality control, Aquafina can strengthen its market position, enhance operational efficiency, and uphold its commitment to consumer safety and satisfaction.

1.1. Introduction to Supply Chain Management (SCM)

Supply Chain Management (SCM) refers to the coordination of business operations and information flow from raw material suppliers to end users. Effective SCM improves customer satisfaction, reduces costs, and streamlines processes. It has evolved into a strategic advantage in industries like manufacturing, retail, healthcare, and technology.

1.2. SCM Implementation

SCM implementation involves planning, integrating, and executing, with alignment of

internal processes, technology selection, and external partnerships. Technologies like IoT, analytics, ERP, and blockchain enhance visibility and trust. Challenges include system integration, cultural differences, and inconsistent performance metrics, requiring strong leadership and communication to overcome.

1.3. Benefits of SCM

- Cost Reduction: Optimized supply chains cut costs through improved efficiency
- Customer Satisfaction: SCM enhances delivery speed and product availability
- Agility: Agile SCM responds swiftly to market changes
- Risk Management: Enhanced visibility aids in managing risks like supply disruptions
- Collaboration: SCM fosters stronger partnerships and innovation through collaboration

2. Data Collection

2.1. Data Sources

- Total of images/frames: 2898
- Dataset size: train: 2662 images, validate: 236 images

- The method involves simultaneously recording videos from different angles using smartphones, providing a more comprehensive dataset. This approach enables a more robust analysis of supply chain processes, capturing diverse perspectives and enhancing data accuracy for improved decision-making.

Type of detected bottle	**Description**	**Image**
1. BrokenCap	This label refers to a bottle with a damaged or broken cap, which may compromise the seal and product integrity.	
2. Cap	This label indicates the presence of a cap in a standard, undamaged condition, confirming the bottle is sealed properly.	
3. DentedBody	This label represents bottles with a dented or damaged body, affecting the bottle's appearance and potentially its structural integrity.	

4. Label	This label signifies that the bottle has a correctly placed label, confirming proper packaging presentation.	
5. NoCap	This label is assigned to bottles missing a cap, which could lead to product contamination or spillage.	
6. NoLabel	This label identifies bottles that are missing a label, impacting brand visibility and regulatory compliance.	

7. WrongLabel	This label denotes bottles with incorrectly placed or mismatched labels, affecting product identification and brand integrity.	

Table 1. Types of defection

2.2. Output Structure

result.csv file has columns: Bottle ID, Monitoring Date, Defect Type (dented, missing cap, etc.)

	A	B	C	D	E
1	Bottle ID	Label Status	Bottle Cap Status	Bottle Body Status	Monitoring date
2	1	Wrong Label	OK	Dented	11/12/2024 0:41
3	2	OK	OK	OK	11/12/2024 0:41
4	3	No Label	Broken	Dented	11/12/2024 0:41
5	4	OK	OK	OK	11/12/2024 0:41
6					

Figure 3. result.csv

3. Methodology

3.1. Preprocessing for input (dataset)

Frame Extraction: Frames are extracted from videos at key intervals to capture different states of bottles.

Data Augmentation: Techniques such as Rotation are used to increase dataset size and variety.

To prepare the dataset for training with YOLO v11, each image requires specific masks to be drawn on each object, followed by labeling the class. Here, we use the software Labelme, which supports object mask drawing.

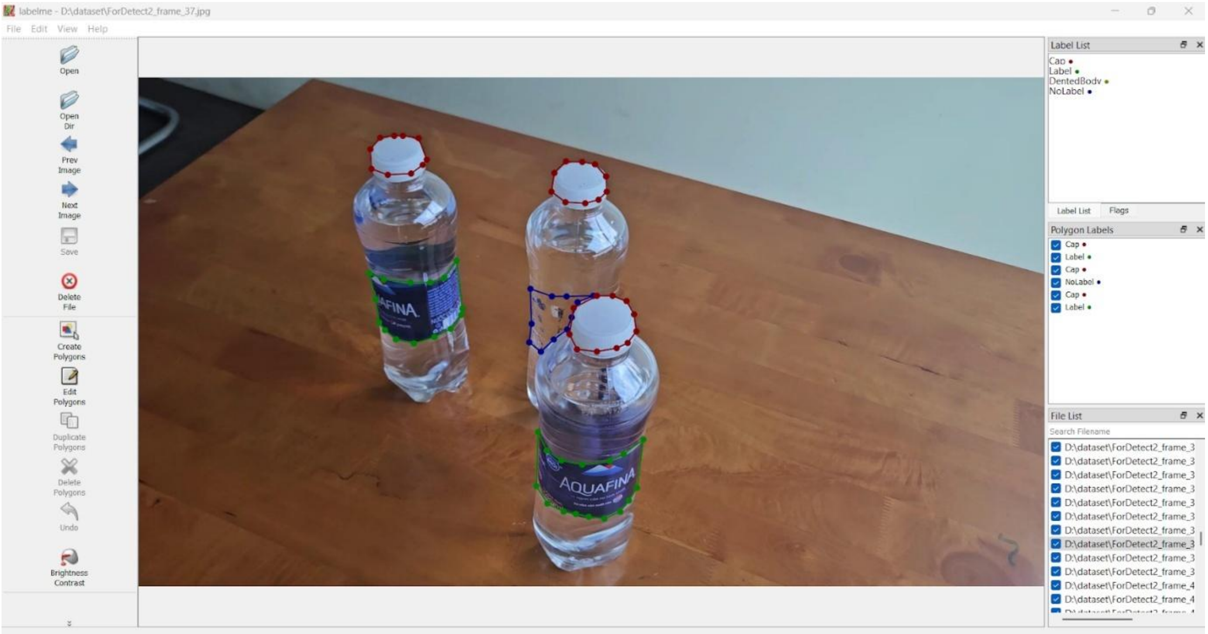

Figure 4. labelme's interface

Note: The more detailed the object, the more accurate the detection will be.

Next, we use Roboflow (https://app.roboflow.com/), a comprehensive platform for managing, annotating, and augmenting datasets for computer vision projects. With this app, we utilize the augmentation feature to increase the diversity of images, helping the model analyze more effectively.

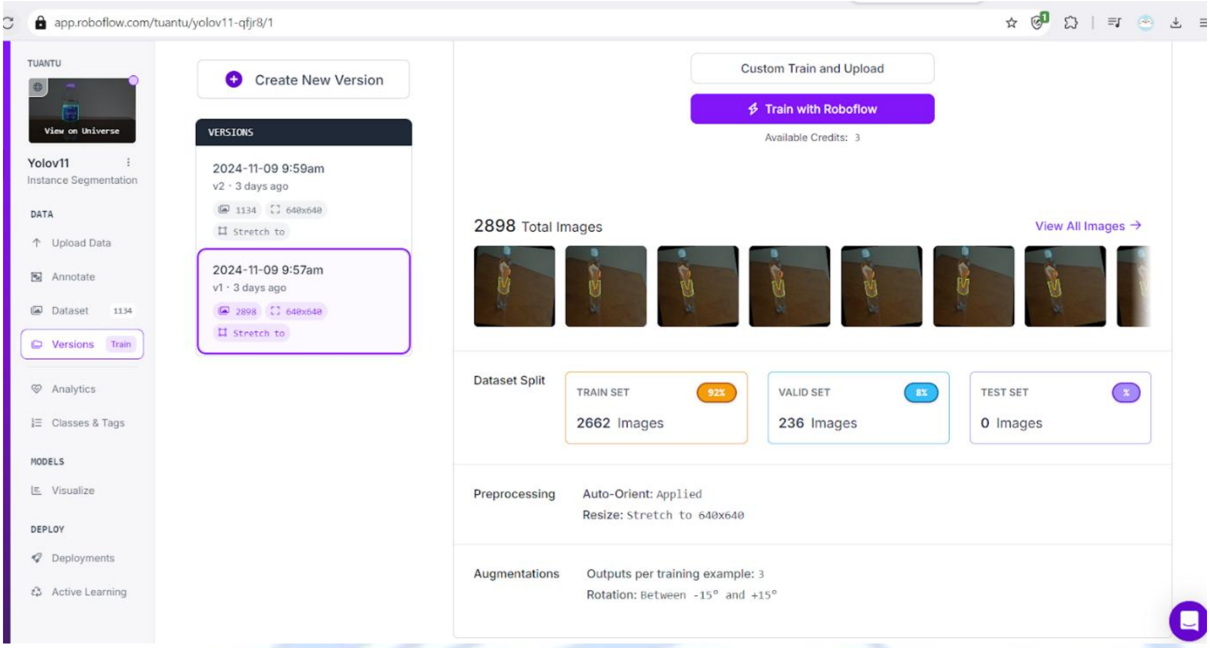

Figure 5. Roboflow manages dataset

Thus, the dataset preparation is complete.

3.2. Machine Learning Model Development

YOLO (You Only Look Once) is a deep learning model designed for real-time object detection tasks. Unlike traditional methods that divide an image into multiple parts and process them separately, YOLO analyzes the entire image in a single pass (hence "Only Look Once") and generates bounding boxes as well as class predictions for each object in the image.

Some reasons for choosing YOLO in a water bottle quality inspection project include:

- **High Accuracy**: Newer versions of YOLO have improved accuracy, especially in detecting small and hard-to-recognize defects. This helps ensure that only standard-quality products reach consumers.
- **Real-Time Performance**: YOLO can process images in real time, allowing for rapid defect detection without slowing down the production line. This enables real-time error detection and rejection of defective products while they are still on the line, minimizing costs and enhancing production efficiency.

For the water bottle quality inspection task, we will need to use two models: one for object detection and another for instance segmentation to mark dents on the bottles. Specifically, we use YOLO v3 for the Object Detection task and YOLO v11 for instance segmentation to address this issue

Yolo evolution time line:

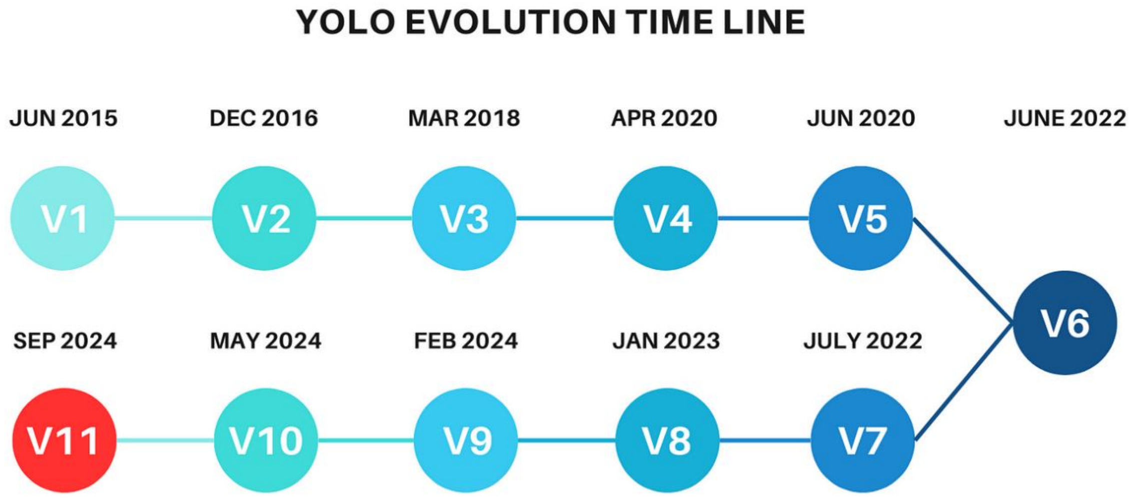

Figure 6. Yolo evolution time line

Object Detection with YOLOv3:

- YOLO is used to identify and locate water bottles in each frame.
- The real-time performance of YOLO allows it to quickly and accurately detect bottles in high-speed production lines.

Defect Classification with YOLOv11:

- Once the bottle is detected, YOLOv11 is applied to the identified object to classify defects.
- YOLO v11 is a new architecture in the YOLO model series (released on September 27, 2024), optimized for high-accuracy and high-speed detection and classification of defects on production lines. YOLOv11 introduces a more efficient architecture with C3K2 blocks, SPFF (Spatial Pyramid Pooling Fast), and enhanced attention mechanisms like C2PSA.

This is the architecture of YOLO v11.

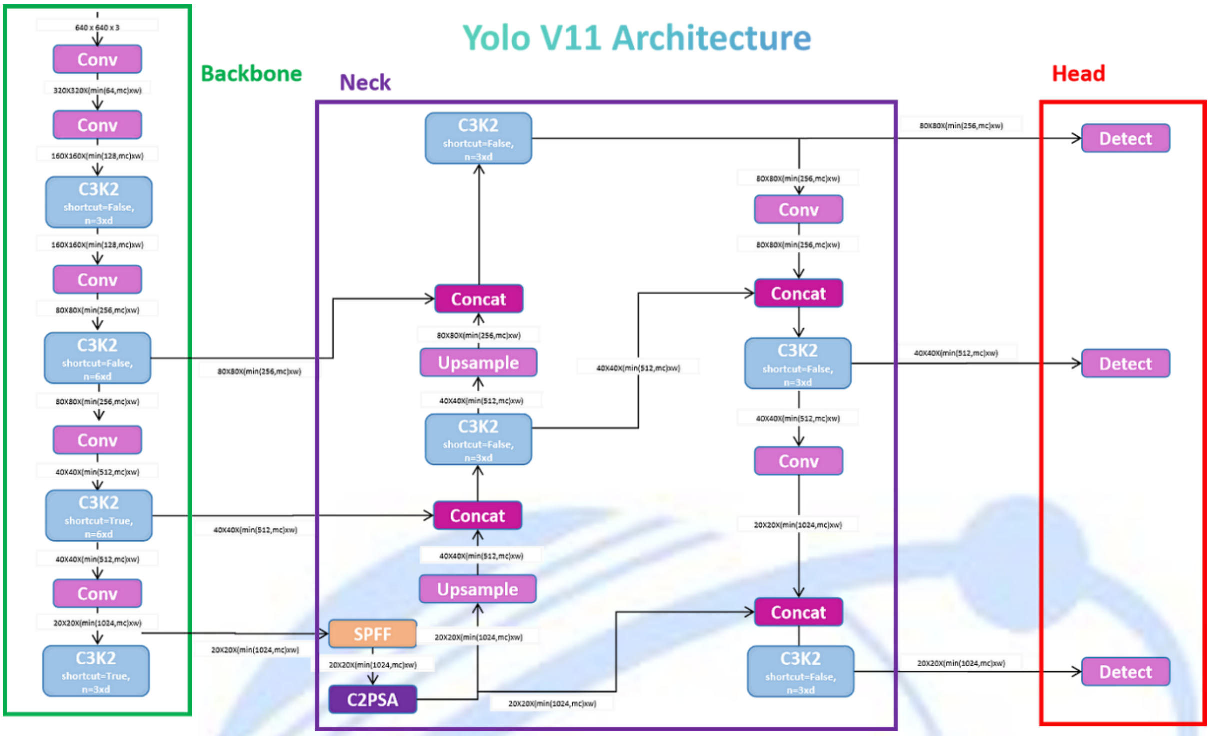

Figure 7. YOLO v11 architecture

The architecture of the YOLO v11 model is divided into three main parts: Backbone, Neck, and Head.

1. Backbone

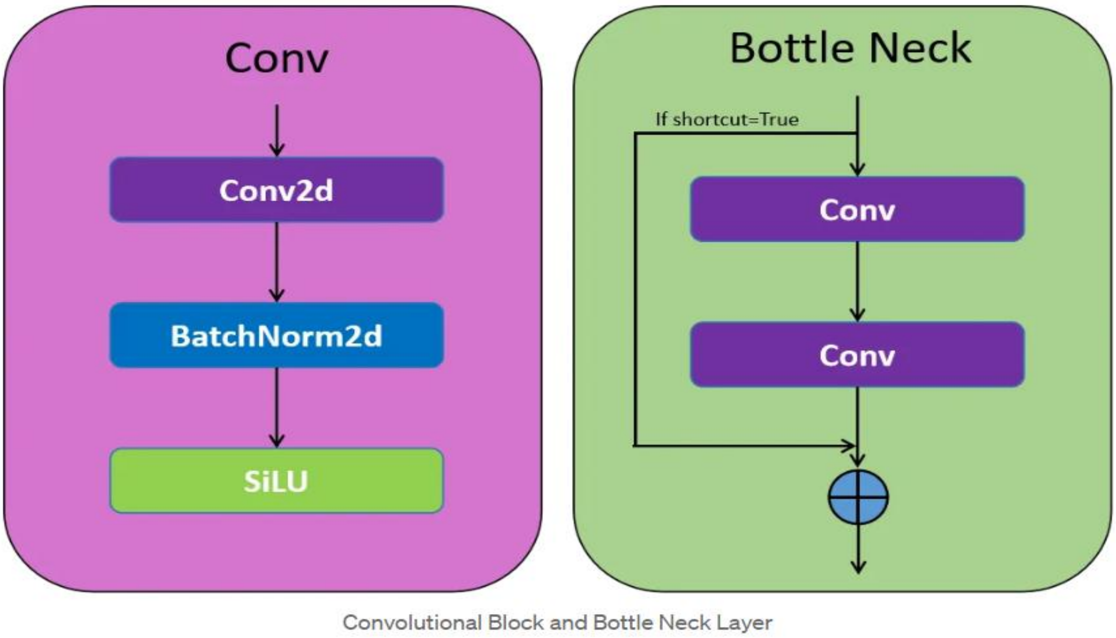

Figure 8. Backbone

a. Convolutional Block

2D Convolutional Layer: First, the input data passes through a 2D Convolutional Layer. This layer uses a small filter (e.g., 3x3) to "scan" across the entire image, performing a convolution operation on each small region to extract spatial features from the image, such as edges, corners, or more complex patterns.

Batch Normalization: After the convolutional layer, the data moves through a Batch Normalization layer. This layer normalizes the data to reduce the effect of "internal covariate shift," allowing the model to learn faster and more stably. **Internal Covariate Shift** refers to the change in the distribution of network activations caused by changes in network parameters during training.

Specifically, Batch Normalization operates by:

1. Normalizing the output values from the convolutional layer, adjusting them to a distribution with a mean close to 0 and a standard deviation close to 1 by calculating the mean and standard deviation of the input batch.
2. Normalizing the input by subtracting the mean and dividing by the standard deviation.

$$X_{\text{normalized}} = \frac{X - \text{mean}}{\text{std}}$$

With X as each value in the batch

3. Apply Two Learned Parameters (**Scale (γ)** and **Shift (β)**) if Necessary:
   - **Scale (γ)**: Adjusts the "stretch" of the data after normalization, allowing the model to expand or contract the range of feature values in the output.
   - **Shift (β)**: Offsets the normalized data, shifting it up or down as needed to better fit the model's learning requirements.

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathbf{BN}_{\gamma,\beta}(x_i)$$

with:

- x_i: the input value after normalization (with mean 0 and standard deviation 1) based on the batch.

- γ (scale): a parameter that adjusts the distribution's "stretch," expanding or contracting the range of values.
- β (shift): a parameter that adjusts the position, shifting the mean of the distribution.
- y_i: the final output value after applying scale and shift.

The notation $BN_{\gamma,\beta}(x_i)$ indicates that the value x_i has been normalized by Batch Normalization using the parameters γ and β.

SiLU Activation Function: Finally, the output from Batch Normalization passes through the SiLU (Sigmoid Linear Unit) activation function. This function introduces non-linearity, enabling the model to learn more complex features and adjust values to highlight important characteristics.

SiLU(x)=$x*\sigma(x)$, where $\sigma(x)$ is the logistic sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}.$$

YOLO v11's use of SiLU instead of simpler activation functions like ReLU offers specific advantages: With ReLU, all negative values are set to 0, leading to a loss of some information. In contrast, SiLU allows negative values to pass through with values close to zero (due to the sigmoid function's properties). This helps retain more information from the input data, especially meaningful features with negative values, allowing the model to learn more effectively.

b. Bottle Neck

The Bottle Neck is a sequence of convolutional blocks that can use a **shortcut** parameter to determine whether or not to include a shortcut connection. The **shortcut** parameter is set to optimize the model's learning process:

- When **shortcut** = **True**, a shortcut connection is used, allowing the input of the block to be directly passed to the output, which helps retain more information.
- When **shortcut** = **False**, the shortcut connection is removed, and only the result from the convolutional layers is retained, suitable for cases where it is not necessary to maintain information from the input.

The Bottle Neck helps reduce the number of parameters and optimize computation, while also improving the learning efficiency of deeper layers.

c. C2F (YOLOv8)

The C2F (Cross Stage Partial Focus) block is developed from the CSP (Cross Stage Partial) network, with its primary goal being to optimize computational efficiency and preserve features during the feature extraction process.

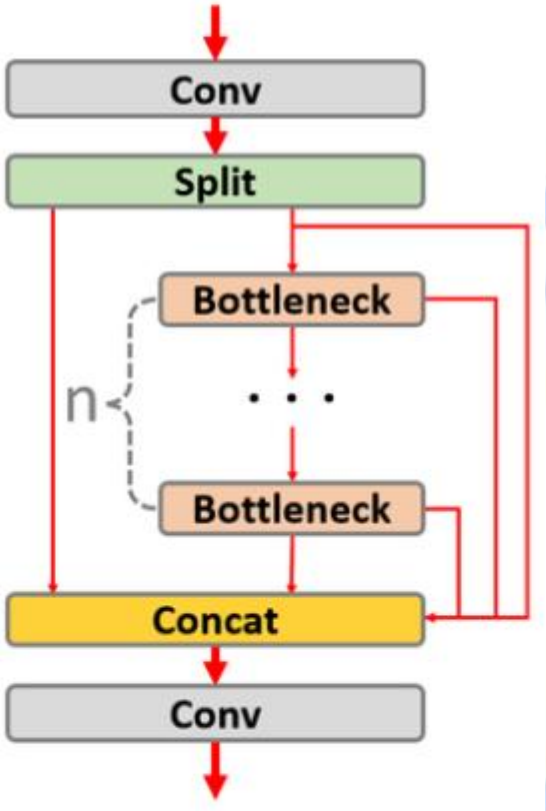

Figure 9. C2F block

- This block includes an initial Conv Block (convolutional block).
- Then, the output of this Conv Block is split into two equal parts (with channels divided in half).
- These two parts are then passed through a series of Bottle Neck layers.
- The results from each layer are concatenated and then passed through a final Conv Block.

-> This enhances the connections between feature maps without redundant information.

d. C3K2

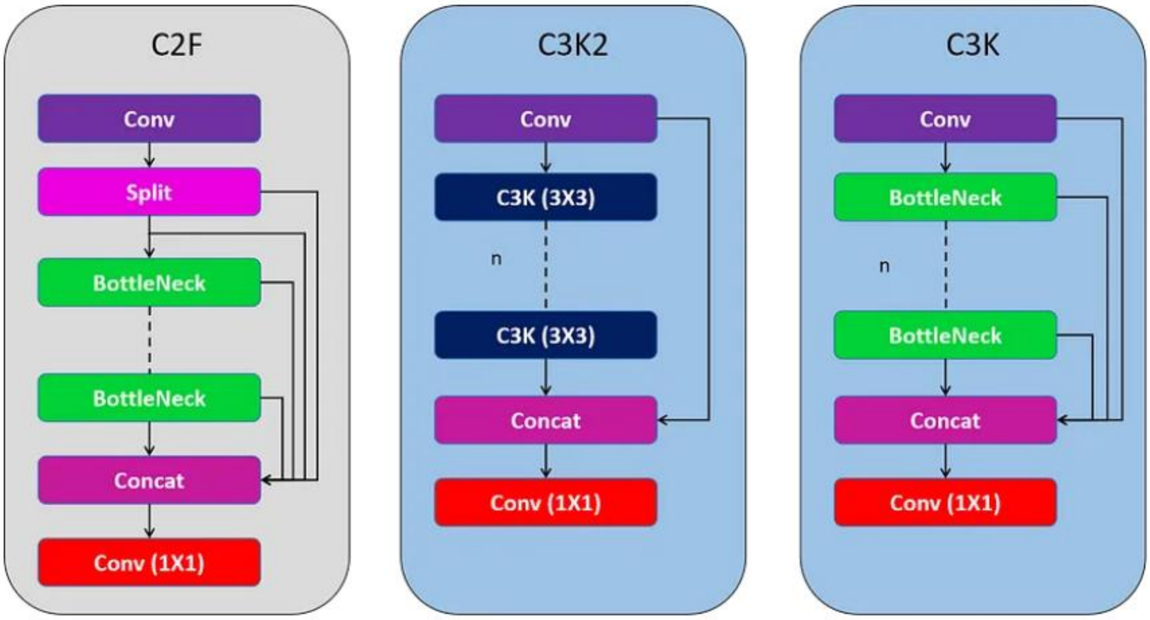

Figure 10. C3K2 block

The **C3K2** block is an important component in the Backbone architecture of YOLOv11, designed to optimize feature extraction with lower computational costs.

C3K2 is based on the CSP (Cross Stage Partial) structure, which enhances the flow of information in the network by splitting the feature map and applying small convolutions (3x3) on each part, then combining them. This approach improves the model's ability to represent features without requiring too many parameters, making the model more efficient.

Structure of C3K and C3K2:

- **C3K**: The input passes through an initial Conv Block, followed by a series of Bottle Neck layers with concatenation operations and ends with a final Conv Block.
- **C3K2**: Uses the C3K structure to process information. This block starts and ends with two Conv layers, with a series of C3K blocks in between. The outputs from the Conv Block and the last C3K block are concatenated and passed through the final Conv Block.

2. **Neck**

SPFF (Spatial Pyramid Pooling Fast): Used by YOLO v11 to improve the detection of objects of various sizes, especially small objects, which has been a challenge in previous YOLO versions.

SPFF operates by:

- Performing multiple MaxPooling operations with different kernel sizes to extract information from different regions in the image at various scales.
- Concatenating the results from each pooling operation to create a feature map that contains information across multiple resolutions.

This design ensures that small objects and details are preserved and recognized by the model.

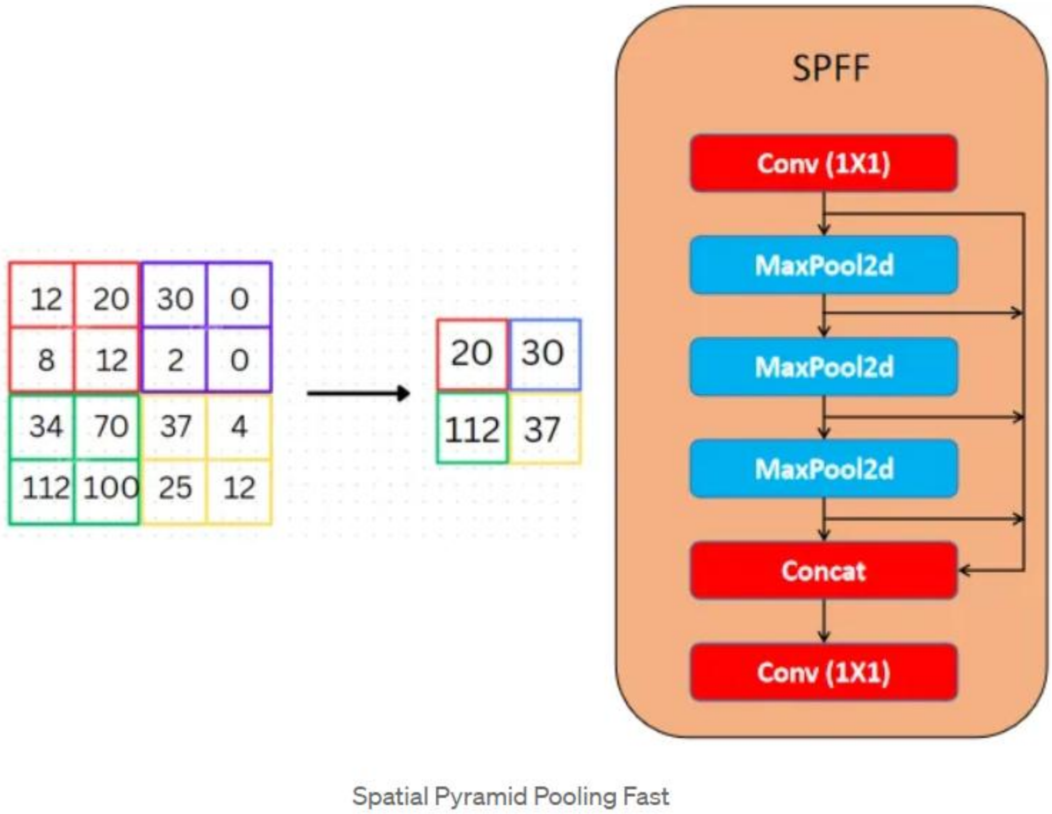

Figure 11. Neck

Upsampling is a technique to increase the size of the feature map in the YOLOv11 model, primarily used in the Neck section to restore details and combine information from layers of different resolutions. This technique enhances the ability to detect small objects and recover details lost through pooling and convolutional layers, enabling the model to detect objects more effectively and accurately.

Attention Mechanisms: C2PSA Block

C2PSA (Cross Stage Partial with Spatial Attention) has been improved for use in YOLO v11 to help the model focus on important regions in the image, such as small or partially obscured objects.

- **PSA (Position-Sensitive Attention)**: PSA applies an Attention layer to focus on key regions, then combines the output with the original input. This output then passes through a Feed-Forward Neural Network (FFN) and Convolutional layers, resulting in enhanced retention of critical details within the image.
- **C2PSA**: uses two PSA modules running on separate branches and then concatenates them, allowing the model to efficiently focus on spatial information while maintaining both speed and accuracy.

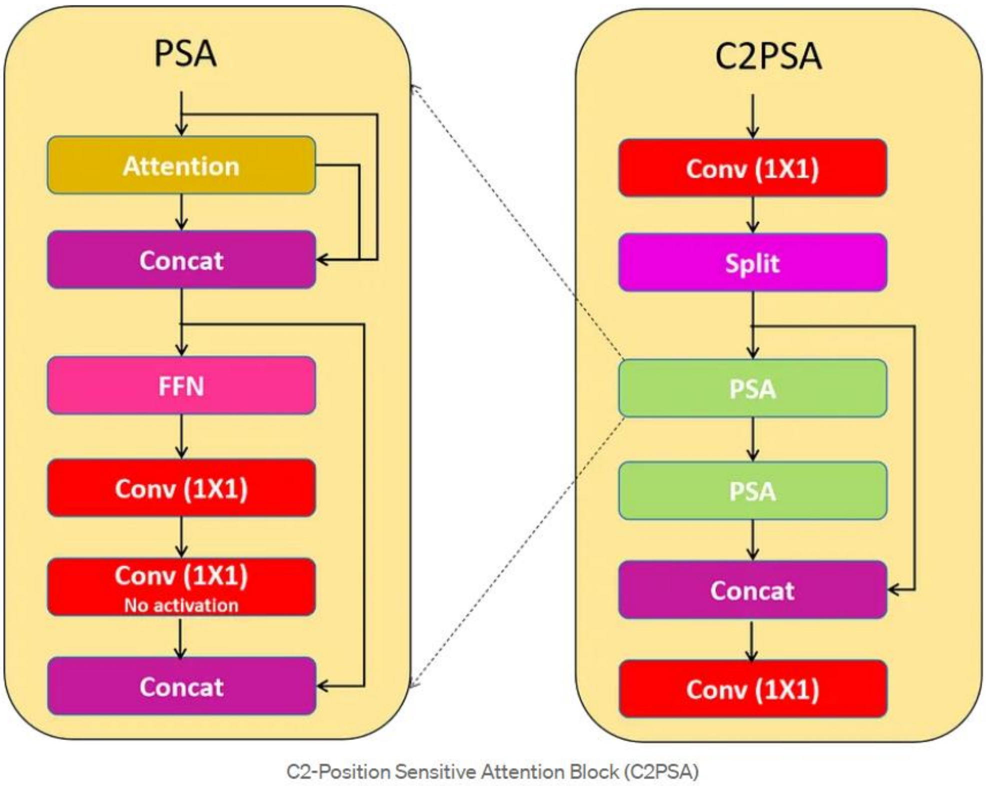

Figure 12. C2PSA block

3. **Head**

The **Head** is responsible for object detection through multi-scale predictions. Similar to previous versions, YOLO v11 uses three feature maps of different sizes to detect objects of varying sizes (small, medium, and large).

The Head uses three feature maps from the backbone and neck: **P3**, **P4**, and **P5**.

- **P3**: Detects small objects with high resolution.
- **P4**: Detects medium-sized objects at medium resolution.
- **P5**: Detects large objects with more generalized features at low resolution.

The use of a multi-scale prediction head allows YOLO v11 to efficiently recognize objects of varying sizes, ensuring high accuracy and the ability to detect both fine details and large objects within the same image.

Ways to train data:

Directory Structure:

- **train/images/:** Directory containing images for training.
- **train/labels/:** Directory containing label files corresponding to each image in the training set.
- **valid/images/:** Directory containing images for validation.
- **valid/labels/:** Directory containing label files corresponding to each image in the validation set.
- **dataset.yaml:** where we define our dataset so that YOLO can use it during training. It specifies the paths to the data and the classes in the dataset, helping the model understand what it needs to process and predict.

After completing the configuration, we trained YOLOv11 for 30 epochs with a batch size of 8 using segmentation mode and the model yolo11m-seg.pt

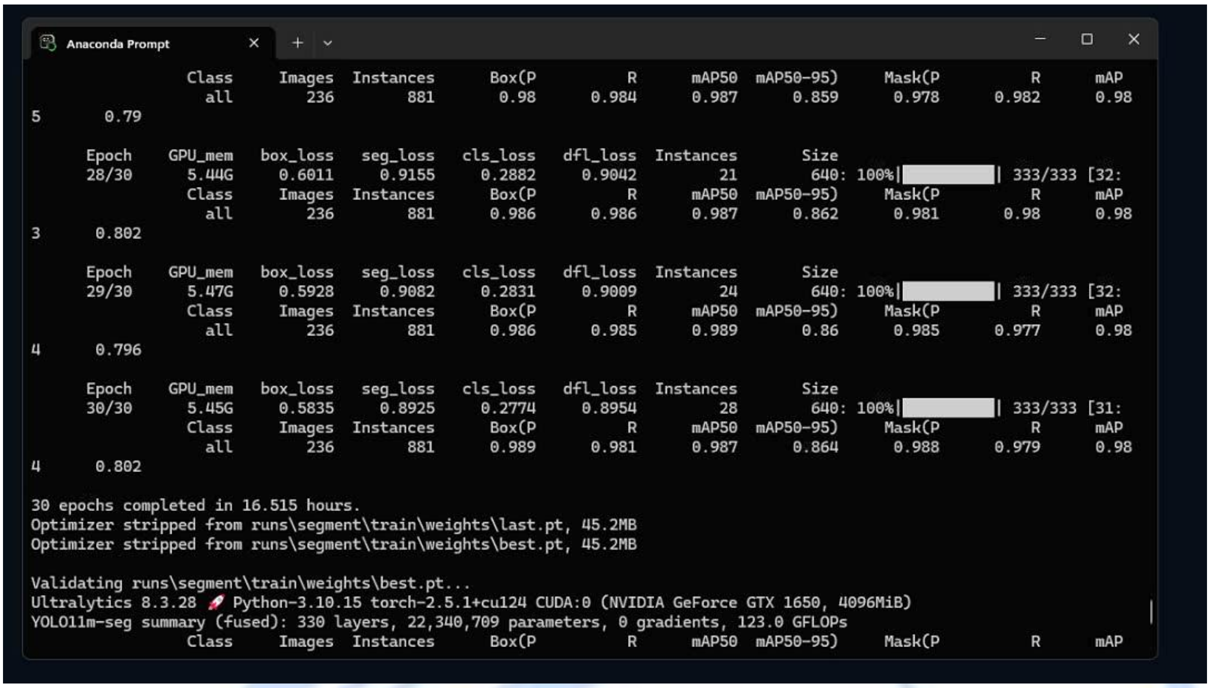

Figure 13. Train data process

The image above shows the training results of the YOLOv11 model for the segmentation task, run for 30 epochs and completed in 16.515 hours.

The weight files will be saved in runs\segment\train\weights, where there are two files: best.pt and last.pt. The last.pt file is the weight file from the final epoch, while best.pt is the weight file with the highest accuracy. Here, we use best.pt.

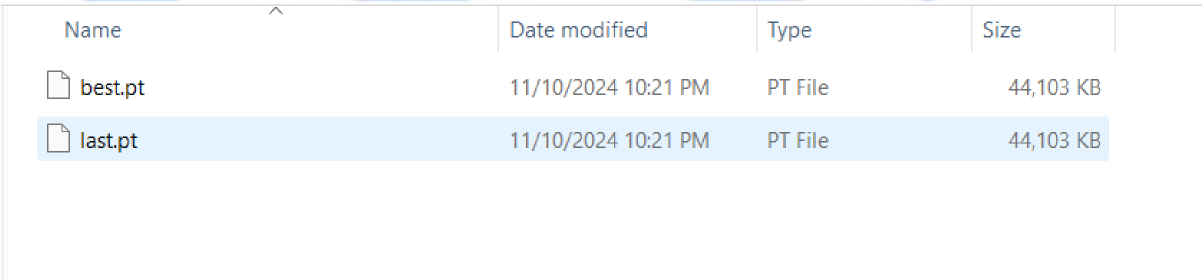

Figure 14. Weight file

Accuracy:

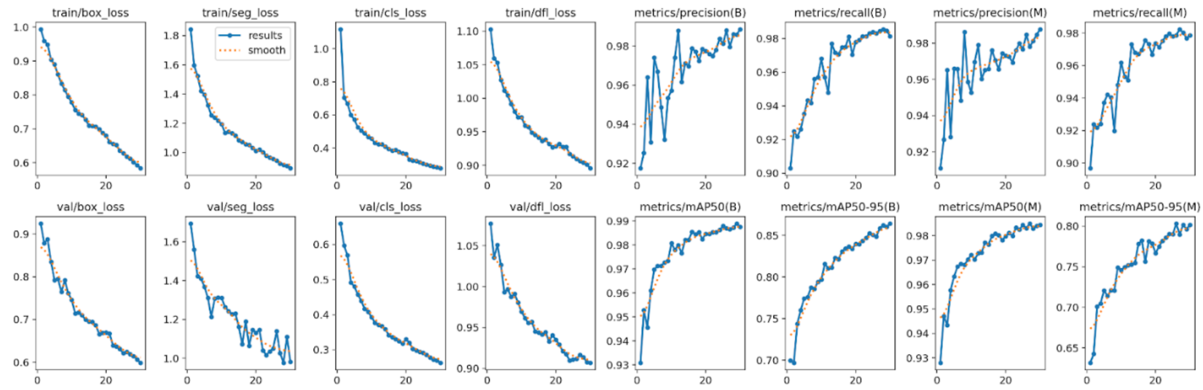

Figure 15. Accuracy results

The chart shows the training and evaluation process of the YOLOv11 segmentation model across epochs:

- **Train and Validation Loss**: The types of loss (box_loss, seg_loss, cls_loss, dfl_loss) on both the training and validation sets gradually decrease, indicating that the model is learning stably and effectively in predicting bounding boxes, segmentation, and classification.
- **Precision and Recall**: Precision and Recall steadily increase on the training set, especially for objects in bounding boxes (B) and mask segmentation (M), demonstrating that the model is becoming increasingly accurate in detection and segmentation.
- **mAP Scores**: The mAP@0.5 and mAP@0.5-0.95 metrics also increase over epochs, showing improved recognition capability as the model learns more deeply.

This result confirms that the YOLOv11 segmentation model achieves high performance and has the ability to accurately detect and segment objects after training.

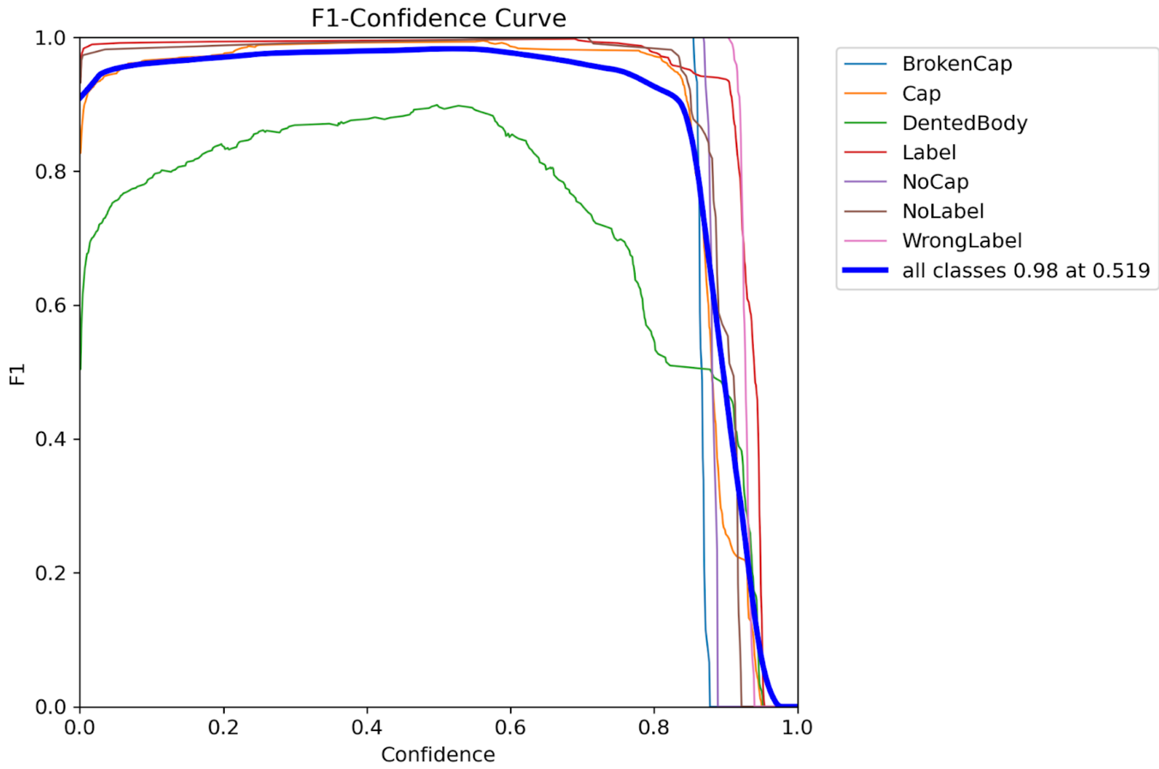

Figure 16. F1-Confidence Curve

F1-Confidence Curve: The F1-Confidence curve shows that all classes achieve a maximum F1-score of 0.98 at a Confidence threshold of 0.519. This demonstrates the high and stable performance of the model. The DentedBody class has a lower F1-score at higher Confidence thresholds, reflecting the difficulty in detecting this class.

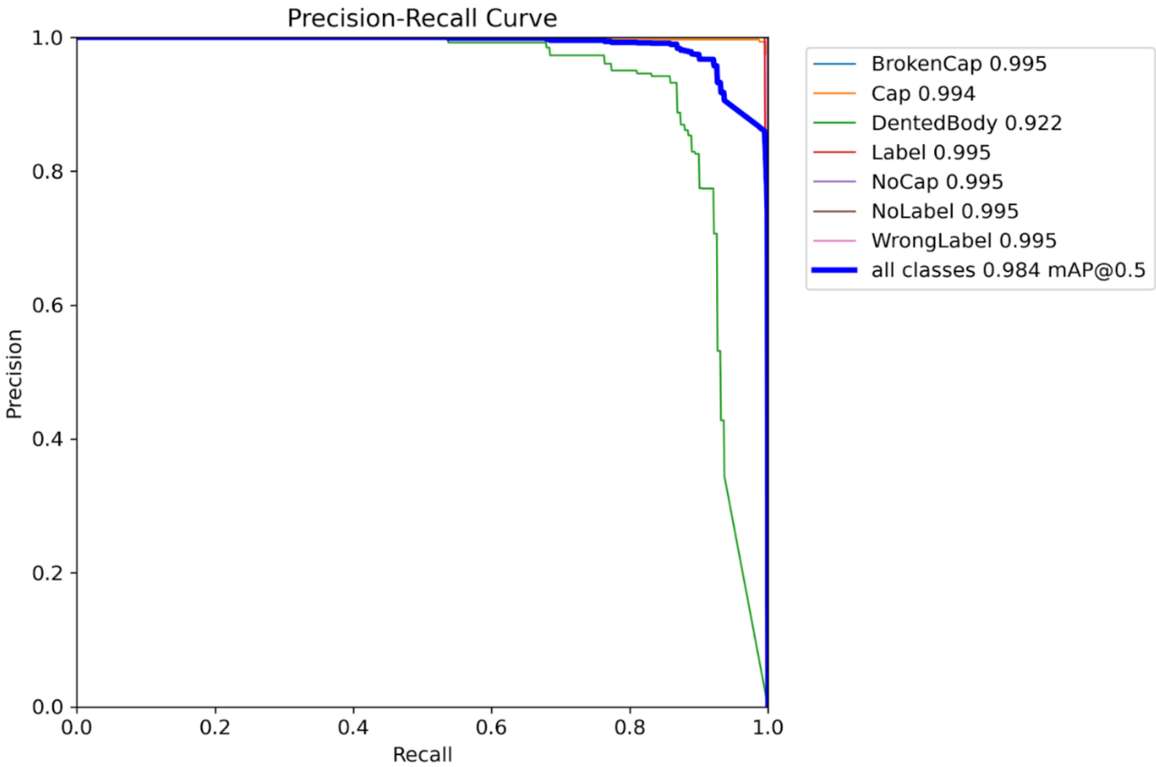

Figure 17. Precision-Recall Curve

Precision-Recall Curve: The model achieves an mAP@0.5 of 0.984 across all classes, with classes such as BrokenCap, Cap, Label, NoCap, and NoLabel nearly reaching the maximum (0.995). However, the DentedBody class has a lower result (0.922), indicating that detection performance needs improvement for this class.

Evaluation on validation dataset

Figure 18. Validate dataset

This image shows YOLOv11's predictions on the validation set, accurately detecting Cap, Label, and BrokenCap in various frames. The results demonstrate effective segmentation of bottle components, highlighting the model's strong performance.

Applying YOLO-based Defect Detection in Quality Control for Bottle Manufacturing

This approach applies YOLO-based object detection and segmentation to monitor the quality of bottles in a production line. The system continuously processes video frames from the production environment, identifying and tracking each bottle as it passes through detection boundaries. Here's how it works:

1. Dual Model Setup: A YOLO detection model identifies bottles on the conveyor belt, while a separate segmentation model analyzes detected regions of interest (ROIs) to verify specific bottle components (such as cap and label).
2. Real-time Tracking and Status Update: Each bottle is assigned a unique ID and tracked as it moves through detection boundaries. Key attributes like bottle cap status, label accuracy, and bottle body are updated in real-time. If the cap or label is missing or incorrect, the system marks the bottle accordingly.
3. Information Panel: A dynamically updated information panel displays the ID, status of each bottle. This includes label status, cap status, production batch number, and any detected defects, allowing operators to monitor quality visually.
4. Extended ROIs and Segmentation Analysis: The system expands each detected bottle's bounding box to capture additional context for segmentation. This allows the segmentation model to assess detailed features, such as label integrity and cap presence, providing higher accuracy in defect detection.
5. Threshold-based Filtering: Objects that remain undetected after a set threshold are removed from tracking, and the system only tracks objects within designated boundaries. This helps maintain real-time processing efficiency.

The detection confidence threshold was set based on an analysis of the **F1-Confidence**, **Precision-Confidence**, and **Recall-Confidence** curves. By examining these metrics, an optimal confidence threshold of **0.519** was chosen, where the model achieves a maximum F1-score of **0.98** across all classes, ensuring a balanced trade-off between precision and recall.

Limitation

One limitation of this approach is the time required for training and processing, as it was run on a local machine. Training on a local system without high-performance hardware significantly increased the overall time, potentially delaying the deployment of the model in real-time applications. To overcome this, future improvements could include using cloud-based or high-performance computing resources to accelerate the training and inference processes.

In addition to computational constraints, the dataset presents another limitation. Since it was created by recording and manually extracting frames, it lacks diversity in terms of lighting, angles, and bottle variations. This lack of diversity may affect the model's ability to generalize well to different production environments. Future improvements could involve collecting a more diverse dataset with varying conditions to enhance the model's reliability.

4. Real-Time Quality Control

4.1. General process

Complete bottling process flow chart of bottled water making process as below:

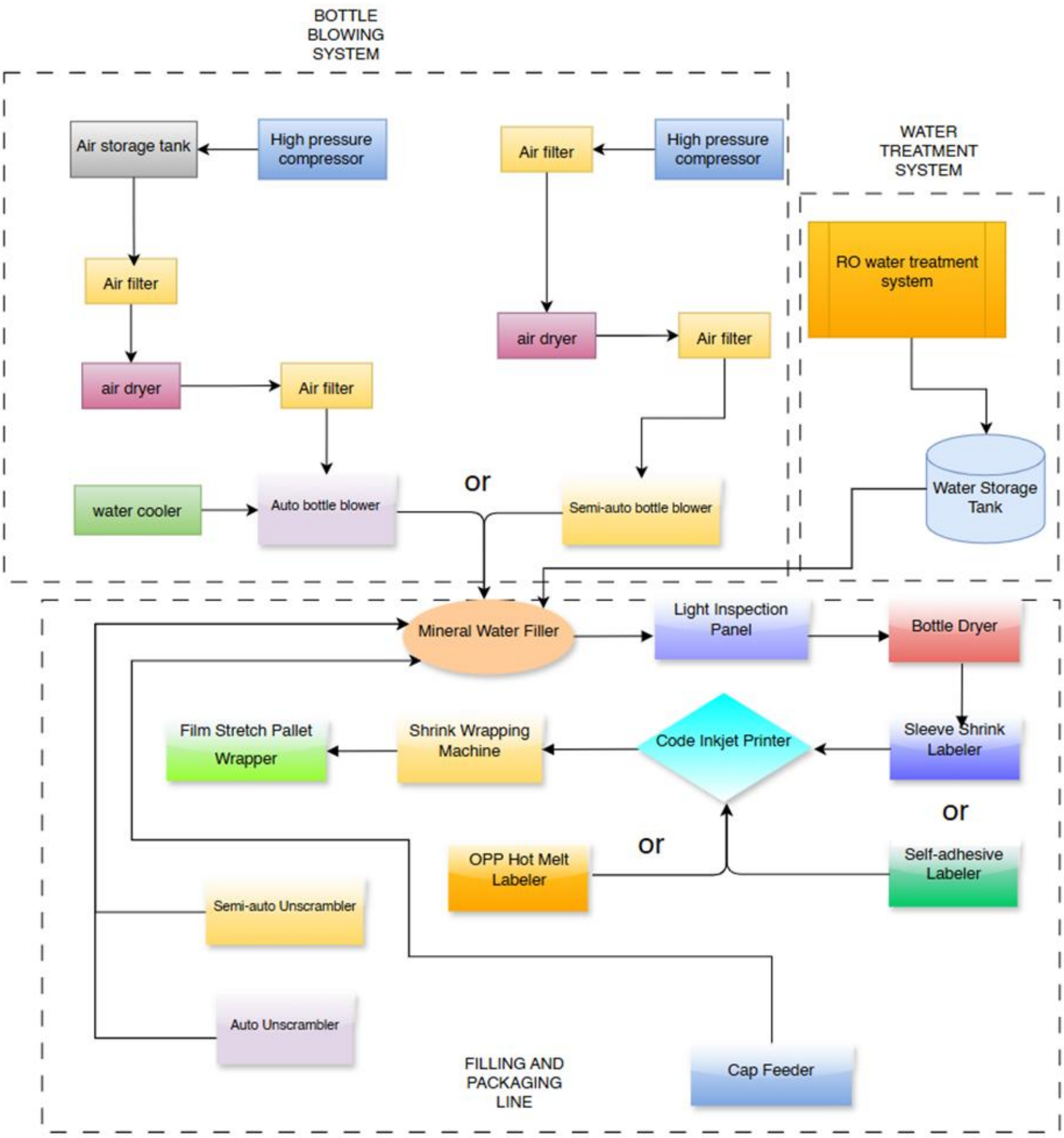

Figure 19. Manufacturing process

The bottling plant process involves several key stages, each critical to ensuring the quality and safety of the final product. From water treatment and purification to the actual bottling process, every step is carefully controlled and monitored. Our bottling process flow chart illustrates the journey of water through various bottled water machines, including filtration systems, filling equipment, and packaging lines.

4.1.1. Water Treatment System – Section 1

- The system begins with an RO (Reverse Osmosis) water treatment unit, which purifies the water to make it suitable for drinking or bottling.
- After treatment, the water is stored in a water storage tank, ready for use in the bottling process.

4.1.2. Bottle Blowing System – Section 2

- This system includes an air storage tank connected to high-pressure compressors and air filters to ensure clean, dry air for bottle formation.
- Air dryers and filters prepare the air, which then feeds into either an automatic or semi-automatic bottle blower.
- A water cooler is also used in the process to maintain optimal air and equipment temperatures during bottle blowing.

4.1.3. Filling and Packaging Line – Section 3

- Bottles are fed into a mineral water filler where they are filled with treated water.
- Filled bottles pass through a light inspection panel for quality control and are then dried.
- They can be labeled with either a sleeve shrink labeler or a self-adhesive labeler.
- A code inkjet printer is used for labeling product information, followed by options for shrink wrapping or pallet wrapping.
- Semi-auto and auto unscramblers are employed to organize the bottles before capping, while a cap feeder provides caps for sealing.

Especially, Aquafina has unique steps of HydRO-7 System in WATER TREATMENT – SECTION 1:

Figure 20. Water treatment in Auquafina

- Prefiltration: The water undergoes an initial filtration process to remove larger particles, such as sand and sediment, preparing it for the subsequent purification stages.
- Charcoal Filtration: The water passes through activated carbon filters, which help remove chlorine, organic compounds, and other substances affecting taste and odor.
- Reverse Osmosis: In this critical step, the water is forced through semi-permeable membranes, effectively removing dissolved solids, minerals, and other impurities, resulting in purified water.
- Ultraviolet Light Sterilization: The purified water is exposed to ultraviolet (UV) light, which inactivates any remaining microorganisms, ensuring the water's microbial safety.
- Polishing Filters: Additional filtration steps are employed to refine the water's taste further and remove any remaining impurities.
- Ozonation: Ozone, a powerful oxidant, is introduced into the water to provide an extra level of disinfection and maintain its freshness.
- Final Polish: Before bottling, a final filtration step ensures the water's purity and optimal taste.

Because we do not perform water purity testing, WATER TREATMENT SYSTEM does not require monitoring. To control quality, we focus on section FILLING AND PACKAGING LINE and BOTTLE BLOWING SYSTEM.

4.2. Quality control

Quality control means ensuring that a good or service conforms to specifications and meets customer requirements by monitoring and measuring processes and making any necessary adjustments to maintain a specified level of performance.

Case study of other competitor company, specifically Coca Cola

Coca-Cola was founded in 1886 by pharmacist Dr John S Pemberton in Atlanta, Georgia. Coca-Cola Company is the worlds largest marketer, distributor and manufacturer of non-alcoholic beverage syrups and concentrate, and produces close to 400 brands.

According Report on Coca Cola's Quality Management System (QMS) (24th Sep 2021), Coca Cola uses both Quality Control (QC) and Quality Assurance (QA) throughout its production process.

In QC and QA, state of the art computers checks all aspects of the production process, maintaining consistency and quality by checking the consistency of the formula, the creation of the bottle (blowing), fill levels of each bottle, labelling of each bottle, overall increasing the speed of production and quality checks, which ensures that product demands are met.

Every bottle is also checked to ensure that it is at the correct fill level and has the correct label. This is done by a computer which every bottle passes through during the production process. Any faulty products are taken off the main production line. Should the quality control measures find any errors, the production line is frozen up to the last good check that was made.

In addition, Coca-Cola controls its customer satisfaction by having a code on the bottles it produces. This means that if there is a fault, then that code can by entered into the Coca-Cola database and they can find out what plant it was produced at and where it was distributed to. This helps customer satisfaction because if there is a faulty group of Coke bottles then they can be recalled before any other customer finds problems with a particular batch of Coke products.

To sum up, Coca Cola emphasizing both internal and external aspects related to product delivery and customer satisfaction:

Internal (Production Process):

- **Automated Quality Checks:** Coca-Cola employs advanced computer systems to oversee all stages of production, from ingredient consistency to bottle creation, fill levels, and labeling. These systems enhance production speed and accuracy, maintaining high-quality standards.

- **Error Detection and Correction:** Every bottle undergoes quality checks to confirm proper fill levels and labels. Any defective products are removed from the main line, and if errors are detected, the production line is halted until the last verified check, minimizing faulty products reaching the market.

External (Delivery and Customer Satisfaction):

- **Traceable Codes:** Each bottle is marked with a unique code that allows Coca-Cola to trace production details, including the plant and distribution route. In case of a defect, this enables Coca-Cola to efficiently track and recall specific batches before they reach other customers, enhancing customer satisfaction and brand trust.

Especially, quality control practices in manufacturing that is conducted after YOLO model finds the defect detection:

4.2.1. Internal control

To ensure that any defective product is identified, marked, and removed from the production process before reaching the consumer.

Process: Defective bottles identified in the production line are promptly marked and removed to maintain quality standards. Specific checkpoints are set up to detect common issues, with each type of defect leading to a focused check of the corresponding subsystem.

Defects and Related Processes:

Defect Types	Inspection Point	Solution
Broken cap No cap No label Wrong label	Filling and Packaging Line	Bottles with these defects are pulled aside for inspection and correction in the Filling and Packaging Line, ensuring that no bottles without caps or labels proceed.

Dented body	Bottle Blowing System	Bottles found with body defects are separated from the line and inspected to prevent further production issues in the Bottle Blowing System.

Table 2. Internal control

Upon detection of any defective bottles, the following actions are taken based on the type and severity of the defect:

Remanufacturing: Bottles can be reprocessed without the need to purchase new materials, helping to increase Aquafina's revenue.

On the other hand, the cost of remanufacturing can sometimes be quite expensive, depending on the specific product defect that needs to be fixed. This is the market price we have gathered:

- **Cost of bottle shells**: For bottles intended for limited reuse, businesses should focus on selecting suitable shell types with optimal plastic quality. It's essential to differentiate customer segments and determine whether bottle stretching technology is required to decide on the thickness of the plastic. The average cost of a single bottle shell varies from 200 to 500 VND per bottle, depending on the type of plastic used.
- **Cost of labels for bottles**: For small water bottles, there is no need for shrink wrap around the bottle body as with 20-liter bottles; instead, only shrink wrap for the bottle cap is used (optional based on the business's preference and environmental initiatives to reduce waste). Bottle stamps now serve the function of shrink wrap for the bottle body. The cost of these stamps is relatively low and is typically sold by weight (kilograms).
- **Cost of electricity, water, and production labor**: The production cost for bottles is generally low, especially when combined with jars, and the daily production volume is typically not very high.
- **Cost of shrink film and containers**: Depending on the facility, there will be specific designs and criteria for selecting the appropriate type of packaging. The cost of shrink film is around tens of thousands of VND per kilogram, while the price of water barrels varies based on type, ranging from a few thousand to several tens of thousands of VND per barrel.

Thus, to optimize costs, we must consider various factors, including the costs of water and electricity required to produce the bottles. If a bottle is missing a label, we can simply replace it with a new one, as label costs are relatively low when purchased in bulk. However, if the bottle is entirely defective, including the bottle body, we will need to consider the next solution, which is removal.

Removal: Bottles that cannot be repaired or reused are removed from the production line and disposed of appropriately to prevent contamination of finished goods.

Defective water bottles can be donated to Aquafina campaigns. Aquafina's Marketing Strategy on mixed promotion is characterized by a diverse combination of traditional and modern advertising activities such as: newspapers, billboards, social media, television, events, combining Influencer product promotion... to enhance brand presence and create appeal to customers on different channels: Aquafina Vietnam International Fashion Week and Campaign “Regeneration Station”.

Figure 21: Inspired by creating fashion from plastic bottles

These efforts are expected to drive Aqua's revenue growth in the future through effective marketing campaigns.

This internal control process ensures high product quality and operational efficiency by addressing defects promptly and accurately.

4.2.2. External control (extend)

To ensure that products meet customer requirements and are delivered to retailers with the highest quality, aligning with both functional standards and customer satisfaction expectations.

Process: External control involves thorough inspections and functional testing of finished products before shipment to retailers. This process verifies that each bottle meets customer requirements and quality standards, flagging any defects for real-time intervention to prevent defective items from reaching the consumer.

Defects and Related Processes:

Defect Types	Description	Inspection Point	Solution
Quality Defects Post-Production	Visible quality issues, such as label misprints, cap alignment, or physical damage that may have occurred during handling or packaging.	Final Quality Assurance (QA) Check	Bottles with identified quality defects are flagged and held back from shipment. Immediate intervention allows the QA team to either resolve the defect or prevent it from affecting the supply chain.
Functional Defects	Issues related to functionality, such as leakage, improper sealing, or other factors affecting the bottle's usability.	Functional Testing Phase	Bottles that fail functional testing are pulled from the final shipment and assessed for potential causes. Defects identified here prevent faulty products from reaching end-users, enhancing customer satisfaction.

Table 3. External control

Upon identifying defects in the external control phase, the following actions are implemented to maintain customer trust and ensure quality assurance:

Return and Repair: Defective products are returned to the production line if repairable, or removed and reprocessed.

Replacement or Refund: If defects are detected post-delivery to retailers, defective products are either replaced with new ones or refunded to resolve any customer concerns.

This external control system not only verifies product quality at the final stages but also enables rapid responses to quality concerns, ensuring only the best products reach consumers and retailers.

5. Results and Analysis

I use the Yolo model to detect errors in water bottles. This is the detection interface when implemented on a water bottle with ID 3:

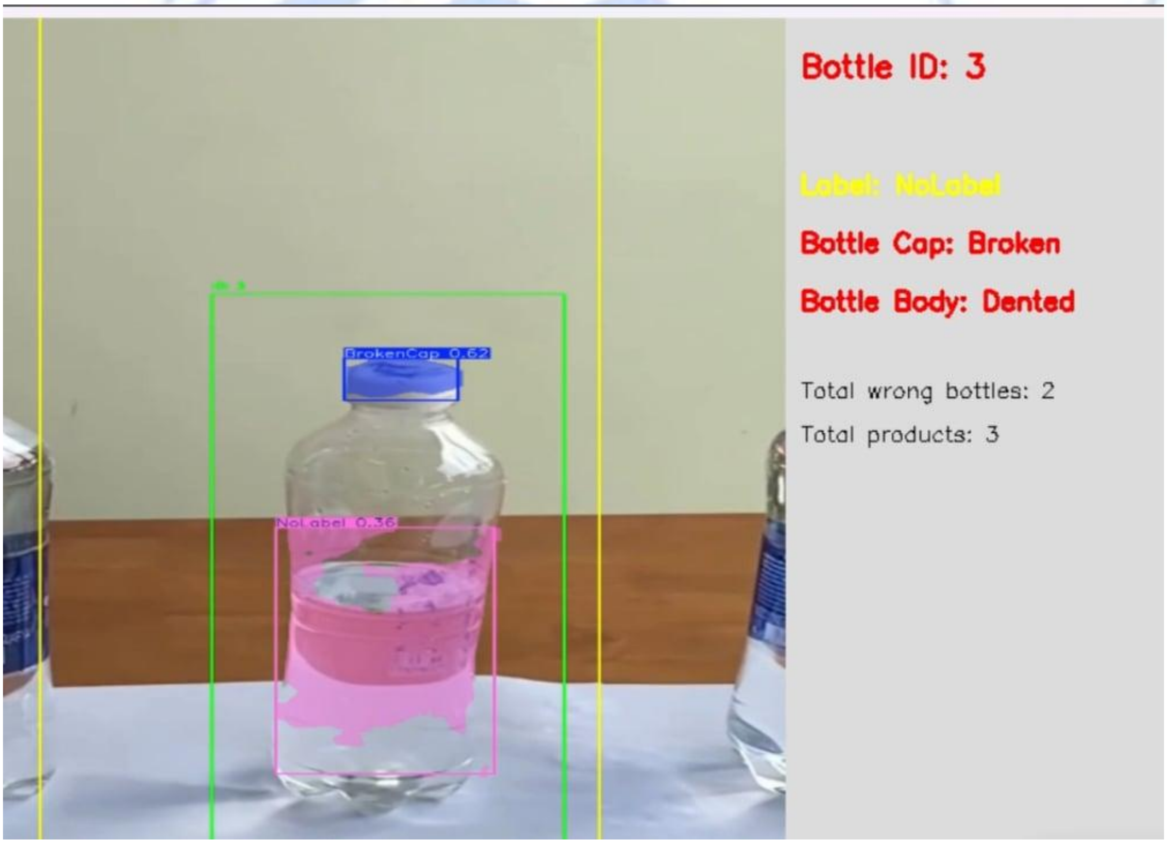

Figure 22. Detection interface

- NoLabel 0.36: water bottle without label with confidence level = 0.36.
- Broken 0.62: water bottle with broken cap with confidence level = 0.62.

- Dented: water bottle with dented body.
- Total wrong bottles: total water bottle found defective -> marked and removed from the line.
- Total products: total water bottle in main line.

Dented body: due to Bottle Blowing System – Section 2

Broken cap and no label: due to Filling and Packaging Line – Section 3

→ Several different defects were found on the bottle, thus we recommend that this bottle should be recycled.

6. Conclusion

Summary

This project successfully implemented the YOLO model to enhance quality control in Aquafina's bottled water production process. Through this technology, the system can automatically detect and classify production errors in real-time, ensuring that products meet high-quality standards before reaching the market.

The inspection system detects common defects, such as broken caps, mislabeling, or dented bottle bodies, minimizing the likelihood of faulty products passing through quality checks. By automating this process, YOLO technology not only improves the accuracy and speed of defect detection but also reduces manual inspection costs and labor.

Additionally, the system records data from each production batch for analysis, allowing Aquafina to continuously optimize and improve its production processes. With features that track and alert on defects as soon as they are detected, the system ensures that even minor errors are promptly identified, helping maintain Aquafina's product quality and brand reputation in the market.

Limitations:

Currently, the system faces certain limitations that impact its overall performance. One significant limitation is the data set, which lacks sufficient volume and diversity. This restricts the model's ability to generalize well to all possible variations and defects that could appear in the production process, limiting its effectiveness in identifying less common or unusual issues.

Additionally, the model struggles with detecting small dents or subtle deformations on the bottles. Due to limited training on these finer details, the model has not yet learned to accurately identify minor defects. This can result in missed detections for small damages, which, although subtle, may still affect the product’s quality.

Future Work:

In future work, further training will be conducted to improve the model's accuracy and ensure more consistent and seamless outputs. This additional training will aim to fine-tune the detection and classification capabilities, minimizing any minor discrepancies that could impact quality control.

Moreover, integrating additional models, such as EfficientDet for multi-scale object detection and UNet for finer segmentation, is planned to increase the reliability of the system. By combining YOLO with these models, the system could leverage YOLO's real-time detection speed, EfficientDet's capacity for handling objects at different scales, and UNet’s precision in segmenting small, detailed areas. This hybrid approach aims to reduce the occurrence of false positives and negatives, thus enhancing the robustness and dependability of the quality control system for production lines.

Together, these improvements will support even higher quality standards, ensuring a comprehensive and adaptable solution that aligns with Aquafina's commitment to excellence in its product offerings.

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