Machine Vision Based Water Bottling Plant for Impurity Detection

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

The Machine Vision Bottling Plant System is designed as an automated inspection mechanism that enhances the quality control process in water bottling and packaging industries. The system integrates image processing and machine learning techniques to detect impurities, incorrect fill levels, air bubbles, and cap or label defects in real time. The inspection setup consists of a conveyor mechanism driven by DC gear motors, an IR sensor for bottle detection, and a high-resolution webcam interfaced with an Arduino UNO and Python-based image processing software.

The system is capable of inspecting 2000 bottles per hour, ensuring high throughput while maintaining accuracy. The images captured during bottle movement are processed using classical image processing algorithms and a deep learning model trained to identify multiple defect categories. The inspection results are automatically recorded in an Excel sheet, enabling continuous monitoring and analysis. The developed prototype significantly reduces manual inspection errors, improves throughput, and ensures consistent quality during large-scale production.

Experimental evaluation demonstrates high detection accuracy and stable performance under varying lighting and bottle conditions. The system provides a cost-effective, scalable, and adaptable alternative to traditional manual quality checking and holds strong potential for further industrial enhancement through the integration of advanced deep learning models and automation hardware.

Keywords: Machine Vision, Image Processing, Bottle Inspection, Automation, Defect Detection

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LIST OF SYMBOLS, ABBREVIATIONS AND NOMENCLATURE

1. SYMBOLS:

Symbol	Meaning
V	Voltage (Volts)
I	Current (Amperes)
RPM	Revolutions Per Minute
TPR	True Positive Rate
FPR	False Positive Rate
ROI	Region of Interest
ms	Milliseconds

2. ABBREVIATIONS:

Abbreviation	Full Form
MV	Machine Vision
IR	Infrared
DC	Direct Current
YOLO	You Only Look Once
PWM	Pulse Width Modulation
USB	Universal Serial Bus

3. NOMENCLATURE:

Term	Definition / Description
Conveyor Belt	Moving platform to transport bottles between inspection stages
Gear Motor	DC motor with gearbox to provide controlled speed and torque
Pulley	Mechanical wheel used to guide and tension the conveyor belt
IR Sensor	Infrared sensor to detect presence of bottles
Webcam	Camera used for real-time image acquisition of bottles
Pre-processing	Image operations such as grayscale conversion, filtering, and thresholding
Feature Extraction	Techniques used to identify defects like edges, bubbles, and fill levels
YOLO Classify	Deep learning model used for defect detection and classification

CHAPTER -1

1. INTRODUCTION

In today's fast-paced manufacturing environment, maintaining consistent product quality has become a major challenge, especially in industries like water bottling and packaging where production occurs at high speed. Manual inspection methods are still common in many ways; however, they are time-consuming, error-prone, and highly dependent on human judgment. Fatigue, inattention, and varying lighting conditions often lead to inconsistent inspection results.

To overcome these limitations, **Machine Vision (MV)** technology offers a modern, automated alternative capable of performing continuous, high-speed, and accurate inspection. It eliminates the dependency on human operators by using industrial-grade cameras, controlled lighting, and image processing algorithms to detect product defects in real time.

The **Machine Vision Bottling Plant System** developed in this project is designed to automate the quality control process in a bottling line. It can detect surface impurities or damages, verify accurate filling levels, identify air bubbles, and inspect cap and label alignment. By integrating both classical image processing and deep learning techniques, the system ensures high accuracy even at a throughput of **2000 bottles per hour**.

This automated inspection setup greatly reduces production waste, minimizes human error, and ensures that only quality-assured products reach consumers. Thus, the project contributes toward **modernizing industrial inspection processes** and improving the reliability and efficiency of water bottling operations.

1.1 METHODOLOGY

In this project, a **Machine Vision-based inspection system** is developed to automatically detect various defects occurring at different stages of a water bottling line. The methodology focuses on using **industrial cameras**, **controlled illumination**, and **image processing algorithms** to inspect each bottle without manual intervention.

The complete process flow is as follows:

1. **Image Acquisition**

   High-speed industrial cameras are installed at three critical points — before filling, after filling, and after capping — to capture clear images of each bottle moving along the conveyor.

2. **Illumination Setup**

   Specialized lighting systems such as *backlighting* and *diffused front lighting* are used to highlight impurities, fill levels, and label irregularities. This ensures high contrast and accurate detection under various conditions.

3. **Image Processing and Analysis**

   Using **Python** and **OpenCV**, the captured images are pre-processed (filtered, thresholder, and segmented). Classical algorithms like *Canny Edge Detection* and *Hough Transform* are used for metrology-based checks such as fill-level detection.

4. **Deep Learning Integration**

   A **YOLO (You Only Look Once)** model, trained in using annotated datasets on **Google Colab**, is integrated for detecting complex defects like surface impurities and bubbles that classical methods may miss.

5. **Decision-Making and Output**

   The analyzed results are categorized as **Pass or Fail** based on predefined quality parameters. Each bottle's inspection data is recorded for traceability, and defective bottles can be flagged for rejection.

6. **Testing and Validation**

The system is tested across four different bottle shapes and sizes. Performance metrics such as **True Positive Rate (TPR)** and **False Positive Rate (FPR)** are calculated to validate accuracy and adaptability.

This methodology ensures a robust, real-time, and flexible quality inspection system capable of operating at industrial speeds while maintaining high precision and reliability.

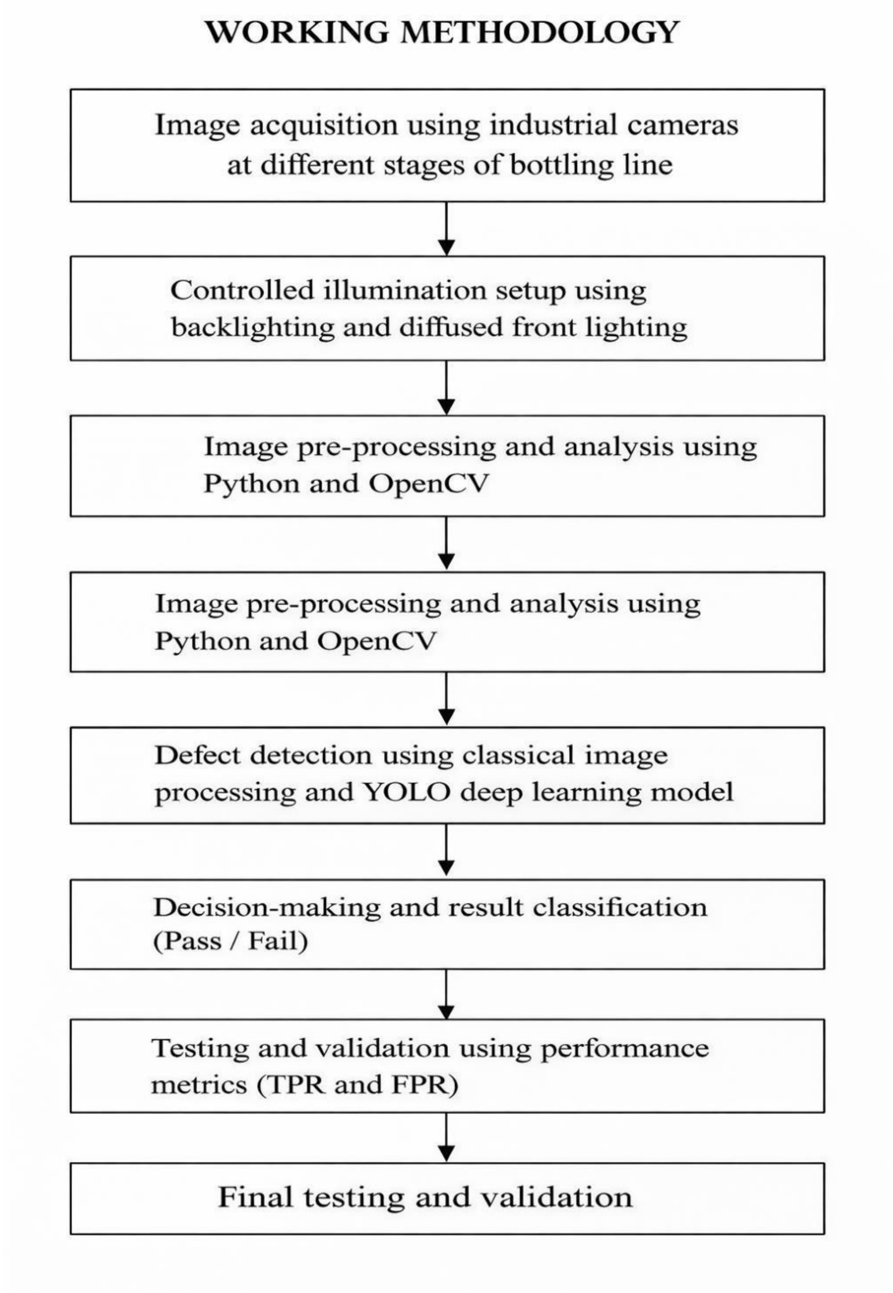

Fig 1.1 Working Methodology

CHAPTER- 2

LITERATURE REVIEW

1. **Subhransu Padhee and Durgesh Nandan (2021)**

   The authors developed an automated visual inspection system for beverage industries using image processing techniques. The system consisted of a conveyor, camera, and illumination setup to detect multiple defects such as improper labelling, incorrect liquid level, and cap misalignment. The developed system achieved an accuracy of 98% and proved effective in replacing manual inspection methods in bottling plants. The project demonstrated that automated vision systems can increase productivity and reduce human error during quality checking.

2. **Kazmi et al. (2022)**

   This paper presented a machine vision system for detecting defects in plastic bottles. The setup included a controlled lighting chamber, high-resolution camera, and rotating platform to capture images from various angles. Techniques like grayscale conversion, binarization, and edge detection were used to identify defects such as cap damage, bottle dents, and label displacement. The inspection system achieved 95% accuracy and highlighted that traditional image processing methods can perform well in real-time operations with lower computational cost.

3. **Pruthvi Kumar S. and Dr. H. V. Ramakrishna (2015)**

   The researchers designed an automated bottle cap inspection system using MATLAB software. The inspection was carried out using RGB matrix analysis, edge detection, and K-means clustering to detect tampered or missing caps and colour mismatches. A microcontroller-controlled rejection arm was used to remove defective bottles automatically from the conveyor. The system provided an efficient, low-cost alternative to manual inspection and achieved over 90% accuracy during testing.

4. **Machine Vision for Detecting Defects in Liquid Bottles (2020)**

   This study developed an industrial machine vision system combining YOLO deep learning and classical image processing to detect defects in bottles, including impurities, fill-level variations, and label misalignment. Trained on a large dataset, the system achieved 97% detection accuracy and was suitable for real-time, high-speed bottling operations.

CHAPTER 3

COMPONENTS SPECIFICATION AND DESCRIPTION

3.1 COMPONENTS

The list of components used are,

S.NO.	COMPONENTS	QUANTITY
1	Arduino UNO	1
2	L298N (Motor Driver)	1
3	Gear Motor (30 rpm)	2
4	Gear	2
5	Conveyor Belt	As Per Requirement
6	IR Sensor	1
7	Pulley	8
8	Frame	As Per Requirement
9	Webcam (Logitech)	1

Table 3.1 List of Components

3.2 COMPONENTS DESCRIPTION

3.2.1 Arduino UNO

The Arduino UNO is an open-source micro controller board based on the ATmega328P micro controller. It serves as the central processing unit for this project, controlling the operation of the conveyor motor, IR sensor, and defect detection logic. The board consists of 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16 MHz quartz crystal, a USB connection, a power jack, and a reset button. In this project, the Arduino UNO receives the signal from the IR sensor to detect the presence of a bottle on the conveyor. Once the signal is received, the micro controller sends commands to the motor driver (L298N) to control the movement of the conveyor belt. It also processes the inspection signals received from the image-processing system to determine whether to continue or stop the belt for inspection.

Figure 3.1 – Arduino UNO Board

3.2.2 L298N Motor Driver

The L298N is a dual H-bridge motor driver module that allows control of the direction and speed of two DC motors simultaneously. It serves as the power interface between the Arduino UNO and the DC gear motors. The L298N works on the principle of H-bridge circuits, which enable voltage to be applied in both directions across a load, allowing forward and reverse rotation of the motors. In this project, the L298N module receives low-voltage control signals from the Arduino UNO and provides the required higher current and voltage to drive the conveyor DC motors efficiently.

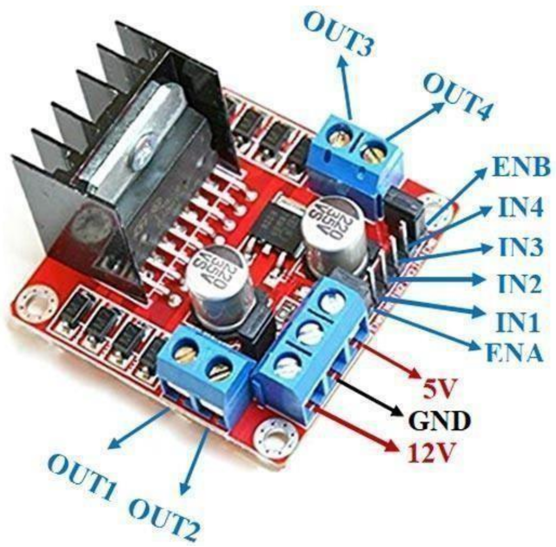

Figure 3.2 – L298N Motor Driver Module

3.2.3 Gear Motor (30 RPM)

The gear motor used in this system is a 30 RPM DC motor that provides low speed and high torque, suitable for driving the conveyor belt at a controlled rate. The motor converts electrical energy into mechanical rotational energy. The gear mechanism attached to the motor reduces speed while increasing the torque, ensuring smooth and stable movement of the conveyor even under load. In this project, two gear motors are used — one for driving the conveyor belt and another for auxiliary movement if required.

Figure 3.3 – 30 RPM DC Gear Motor

3.2.4 Gear

A pulley is a simple mechanical component consisting of a wheel mounted on an axle, designed to guide the conveyor belt and transmit motion efficiently. In this project, **plastic pulleys** are used instead of metal pulleys to reduce system weight, lower rotational friction, and provide smoother operation. These pulleys are fabricated from high-strength engineering plastic, which offers good wear resistance, corrosion protection, and low noise during operation.

In the conveyor system, eight pulleys are employed — **two acts as drive pulleys**, transmitting torque from the DC gear motor to the conveyor belt, and **six function as support pulleys** to maintain belt alignment and tension. The lightweight nature of the plastic pulleys also improves motor efficiency and extends system life by minimizing mechanical stress.

Figure 3.4 – Spur Gear Arrangement

3.2.5 Conveyor Belt

The conveyor belt is a continuous moving band that transports bottles through different inspection stages in the bottling system. It is made of durable rubber or PVC material and is mounted over rotating pulleys. The motion of the belt is powered by DC gear motors via pulleys and gears. In this project, the conveyor carries water bottles past the IR sensor and under the inspection camera for defect detection. The speed of the belt is synchronized with the inspection rate to maintain accurate bottle positioning.

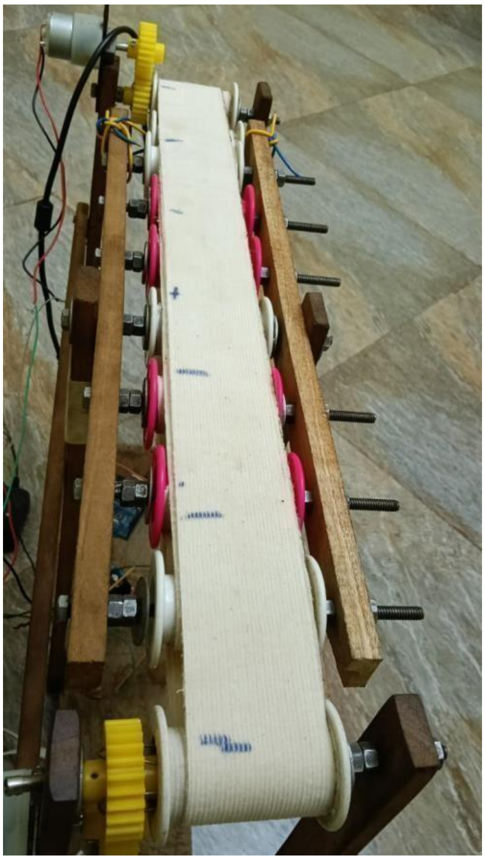

Figure 3.5 – Conveyor Belt Setup

3.2.6 IR Sensor

The Infrared (IR) sensor is used to detect the presence or absence of a bottle on the conveyor. It works on the principle of emitting infrared light and measuring the reflection. When a bottle passes in front of the sensor, the reflected IR beam is detected by the receiver, generating a logic signal. In this system, the IR sensor sends a signal to the Arduino UNO whenever a bottle reaches the inspection point, triggering the camera and image-processing sequence.

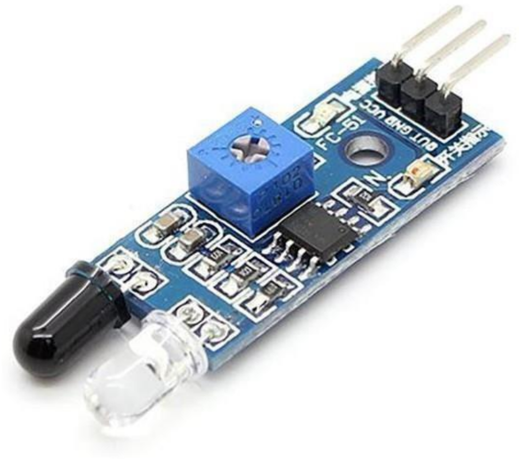

Figure 3.6 – IR Sensor Module

3.2.7 Pulley

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Figure 3.7 – Plastic Pulley Assembly

3.2.8 Webcam (Logitech 1080p, 30 FPS)

A **webcam** is an image-capturing device used for visual data acquisition in machine vision systems. In this project, a **Logitech 1080p HD webcam** is employed for real-time image capture of bottles moving on the conveyor. The webcam serves as the **primary vision sensor**, enabling the system to detect impurities, bubbles, improper fill levels, and labeling irregularities.

The camera provides **high-definition (HD) imaging** at **1920 × 1080 resolution** and captures video at **30 frames per second (fps)**, ensuring that every bottle is inspected with clarity and minimal motion blur. Its **auto-focus and light adjustment features** allow accurate detection even under varying illumination conditions in the production environment. The captured frames are processed by software running on a connected computer system using **OpenCV and Deep Learning models (YOLO)** for defect detection.

Figure 3.8 – Logitech HD Webcam (1080p, 30 FPS)

3.3.9 LED Ring Light

The LED ring light is a circular illumination device designed to provide uniform and shadow-reduced lighting for close-range imaging applications. It consists of a high-intensity LED array arranged in a ring structure with an effective diameter of approximately 10 inches (25–26 cm). The light operates at a rated power range of 8–12 W and offers multiple brightness levels with adjustable intensity control. It supports three color temperature modes, including warm white (~3000 K), neutral white (~4500 K), and cool white (~6000–6500 K), enabling flexible lighting conditions for inspection tasks. Due to its circular geometry, the ring light delivers evenly distributed illumination around the optical axis, minimizing shadows in captured images. This lighting configuration is suitable for machine vision systems, bottle and water impurity detection, close-up inspection, and laboratory-scale imaging applications. However, reflections may occur on glossy or transparent surfaces, and therefore auxiliary side lighting is recommended for optimal inspection performance

Figure 3.9 – LED Ring Light

3.310 Digitek LED – D40W Bi- color Video light

The Digitek LED D-40W Bi-Color Video Light is a high-intensity LED panel light designed for uniform illumination in inspection and imaging applications. It operates at a rated power of 40 W and delivers a luminous output of approximately 4000–4500 lumens with continuous brightness control from 0 to 100%. The light supports bi-color operation with an adjustable color temperature range from warm white (~3200 K) to cool white (~5600 K), enabling flexible lighting conditions. With a high color rendering index (CRI ≥95), the panel ensures accurate color reproduction, making it suitable for detecting fine details and impurities. The light provides a wide beam angle of approximately 120°, producing diffused, shadow-reduced illumination over a large area. Thermal management is achieved through passive heat dissipation using a ventilated heat-sink structure, allowing silent and stable operation. Due to its high output, wide coverage, and color accuracy, the Digitek LED D-40W is well suited for machine vision systems, bottle and water impurity detection, laboratory inspection, and educational mini-project setups.

Figure 3.3.10 Digitek LED – D40W Bi- color Video light

CHAPTER 4

WORKING PRINCIPLE

The Machine Vision Bottling Plant System operates as an integrated inspection mechanism designed to ensure consistent product quality across multiple bottle formats at high throughput rates. The system combines image acquisition hardware, controlled illumination (Digitek Back Light + Digitek Ring Light), and hybrid image analysis algorithms (Classical + Deep Learning) to detect defects such as impurities, bubbles, underfilling, and misaligned caps or labels.

The working principle is based on three major operational stages:

(1) Image Acquisition Stage

(2) Image Processing and Defect Detection

(3) Defect Classification and Decision Execution.

4.1 IMAGE ACQUISITION STAGE

- The bottles travel continuously on the **conveyor line**, positioned at a constant speed calibrated for **2000 bottles per hour** throughput.
- An **Infrared (IR) sensor** detects the arrival of each bottle and immediately sends a trigger signal to the **industrial camera**.
- The **camera**, synchronized with the conveyor motion, captures high-resolution images of the bottle at multiple checkpoints:

    1. **Entry Station** – for surface integrity (impurity and damage detection).

    2. **Filling Station** – for fill-level and bubble detection.

    3. **Post-Capping Station** – for cap and label verification.

- The captured images are transferred in real time to the **processing unit** (Python-based software environment) for further analysis.

4.2 IMAGE PROCESSING AND DEFECT DETECTION STAGE

Once the images are acquired, they undergo systematic processing steps before classification.

1. Pre-Processing:

- Conversion to grayscale to reduce computation.
- **Gaussian and Median filtering** to remove sensor noise.
- **Adaptive thresholding** and **morphological operations** to isolate regions of interest (ROI).
- Image resizing and brightness normalization ensure consistency across four bottle formats.
- With the Digitek Back Light and Digitek Ring Light, image contrast becomes more consistent and shadow/glare effects are reduced, improving thresholding stability and ROI separation.

2. Feature Extraction:

- **Canny Edge Detection** identifies bottle contours and meniscus edges for fill-level estimation.
- **Template Matching** is used to confirm cap presence and label alignment.
- Improved illumination supports clearer edge formation (back light) and more uniform surface visibility (ring light), reducing false edges and reflection-based noise.

3. Hybrid Algorithm Application:

- Canny and Hough Transform are used for accurate water level and fill-height movement
- The model is trained on Google Colab with GPU support and used locally for Inspection.
- Digitek lighting enhances image clarity for reliable detection.

4.3 DEFECT CLASSIFICATION AND DECISION EXECUTION

The system analyzes each captured image and classifies bottles into categories: **OK (Pass)**, **Impurity Detected**, **Underfilled**, **Bubble Detected**, **Misaligned Label**, or **Missing Cap**.

Due to the **Digitek Back Light and Digitek Ring Light**, the captured images have improved clarity and uniformity, which increases classification confidence and reduces lighting-related misclassification.

The classification result is processed through the **decision logic** in the vision software.

- If **Pass**, the system continues to the next inspection cycle.
- If **Fail**, the defect type is displayed on the screen, and the image is **saved for recording** no physical rejection is performed.

All inspection results, including **image ID, defect type, timestamp, and status**, are logged automatically.

The complete inspection loop executes in **less than 1.5 seconds per bottle**, ensuring continuous high-speed detection.

4.3 SYSTEM OPERATION FLOW

Step No.	Operation Description
1	Bottle arrives on the conveyor and is detected by the IR sensor using the webcam by accessing the anaconda software.
2	The sensor triggers the camera to capture the bottle image.
3	Image is sent to the processing unit for pre-processing.
4	Feature extraction and defect detection algorithms are executed.
5	The YOLOv8 classifier analyzes and categorizes detected defects.
6	Decision logic labels the bottle as *Pass* or *Fail*.
7	Inspection data is logged; the system resets for the next bottle.

4.4 WORKING LOGIC INTERPRETATION

The system's operation is governed by the **PDCA (Plan–Do–Check–Act)**

- **Plan:** Define inspection parameters for each defect category and bottle type.
- **Do:** Capture and analyze images using synchronized sensor–camera setup.
- **Check:** Validate defect detection results (TPR/FPR) in real time.
- **Act:** Execute rejection or acceptance action and store data for audit and improvement.

4.5 SUMMARY

The Machine Vision Bottling Plant System operates on a fully automated workflow integrating sensor-based triggering, high-speed imaging, and hybrid algorithm analysis. By adding Digitek Back Light and Digitek Ring Light, the system achieves more uniform illumination, higher contrast, and reduced shadow/reflection effects, improving detection reliability across different bottle formats. By combining classical image processing for geometric precision with deep learning classification for complex visual features, the system achieves:

High accuracy

- **Low false rejection rate** and
- **Sustained throughput of 2000 bottles per hour.**

The overall working principle demonstrates a **cost-effective, intelligent, and adaptable** approach to industrial quality control, ensuring that only defect-free bottles proceed to packaging.

CHAPTER 5

COST ESTIMATION

S.NO.	NAME OF THE COMPONENT	QUANTITY	PRICE (Rs.)
1	Arduino UNO	1	290
2	L298N (Motor Driver)	1	120
3	Gear Motor (30 rpm)	2	340
4	Gear	4	200
5	Conveyor Belt	As Per Requirement	240
6	IR Sensor	1	40
7	Pulley	10	200
8	Webcam	1	2990
9	Frame	As Per Requirement	300
10	Jumper Wires	As Per Requirement	120
11	USB Cable	1	50
12	LED – D40W Bi- color Video light	1	2900
13	LED Ring Light	1	360
		Total	8150

CHAPTER 6

RESULTS DOCUMENTATION AND SYSTEM OUTPUTS

6.1 Output Images

In a real-time industrial setup, the proposed **Machine Vision Bottling Plant System** continuously monitors bottles passing on the conveyor. The processed results and detection decisions are logged automatically into an **Excel sheet** for production traceability and defect analysis.

	A	B	C	D	E	F
1	**Frame/Image**	**Class**	**Confidence (%)**	**Object Count**	**FPS**	**Captured Image**
2	image1.jpg	Empty Water level	83.67	2	0.54	image1.jpg
3	image1.jpg	Full Water level	76.54	2	0.54	image1.jpg
4	image2.jpg	Empty Water level	80.27	1	10.18	image2.jpg
5	image2.jpg	Full Water level	27.74	1	10.18	image2.jpg
6	image3.jpg	Empty Water level	80.53	2	11.41	image3.jpg
7	image3.jpg	Full Water level	62.52	2	11.41	image3.jpg
8	image4.jpg	Empty Water level	73.18	2	17.44	image4.jpg
9	image4.jpg	Full Water level	67.37	2	17.44	image4.jpg
10	image4.jpg	Full Water level	45.73	2	17.44	image4.jpg
11	image5.jpg	Empty Water level	81.02	1	18.97	image5.jpg
12	image5.jpg	Full Water level	25.39	1	18.97	image5.jpg
13	image6.jpg	Half Water level	85.15	1	20.99	image6.jpg
14	image7.jpg	Half Water level	86.19	1	21.88	image7.jpg
15	image8.jpg	Empty Water level	62.9	1	21.35	image8.jpg
16	image8.jpg	Half Water level	39.73	1	21.35	image8.jpg
17	image12.jpg	Full Water level	52.55	1	21.66	image12.jpg
18	image13.jpg	Full Water level	76.12	1	22.16	image13.jpg
19	image17.jpg	Half Water level	43.51	0	22.27	image17.jpg
20	image19.jpg	Half Water level	48.49	0	22.29	image19.jpg

Table 6.1 – Real-Time Excel Output Sheet

The Excel sheet contains the following live parameters:

- **Bottle ID / Timestamp**
- **Detected Defect Type** (Impurity / Bubble / Underfill / Cap Misalignment / Label Error)
- **Detection Confidence (%)**
- **Pass/Fail Decision**
- **Processing Time per Frame (ms)**

Each inspection record is updated in real-time through the Arduino–PC interface, enabling quality engineers to analyze trends and identify failure patterns efficiently.

6.2 Conveyor and Bottle Images

During the testing phase, multiple images were captured to validate detection performance under different fill levels and bottle geometries.

Figure 6.1 – Conveyor Setup with Webcam and Bottles at Various Fill Levels

This figure displays:

- Bottles moving along the conveyor under controlled illumination.
- Different fill levels (Full, Underfilled, Overfilled) captured by the Logitech HD Webcam.
- The ROI (Region of Interest) is used by the algorithm to analyze liquid meniscus and detect bubbles or impurities.

6.2 Result Tables

Table 6.2 – Performance Metrics for Water Level Detection

	A	B	C	D	E	F
1	Frame/Image	Class	Confidence (%)	Object Count	FPS	Captured Image
2	image1.jpg	Empty Water level	83.67	2	0.54	image1.jpg
3	image1.jpg	Full Water level	76.54	2	0.54	image1.jpg
4	image2.jpg	Empty Water level	80.27	1	10.18	image2.jpg
5	image2.jpg	Full Water level	27.74	1	10.18	image2.jpg
6	image3.jpg	Empty Water level	80.53	2	11.41	image3.jpg
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19	image17.jpg	Half Water level	43.51	0	22.27	image17.jpg
20	image19.jpg	Half Water level	48.49	0	22.29	image19.jpg

Table 6.3 – System Throughput Validation

Parameter	Measured Value	Target	Status
Total Bottles Tested	1100	5000	—

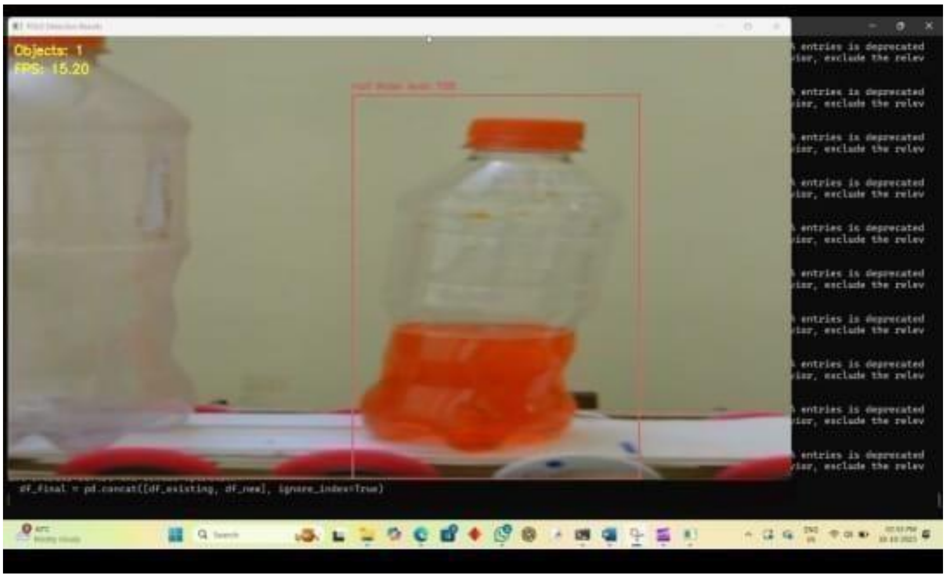


Figure 6.2 - Water Level

Figure 6.3 – YOLO Training Images

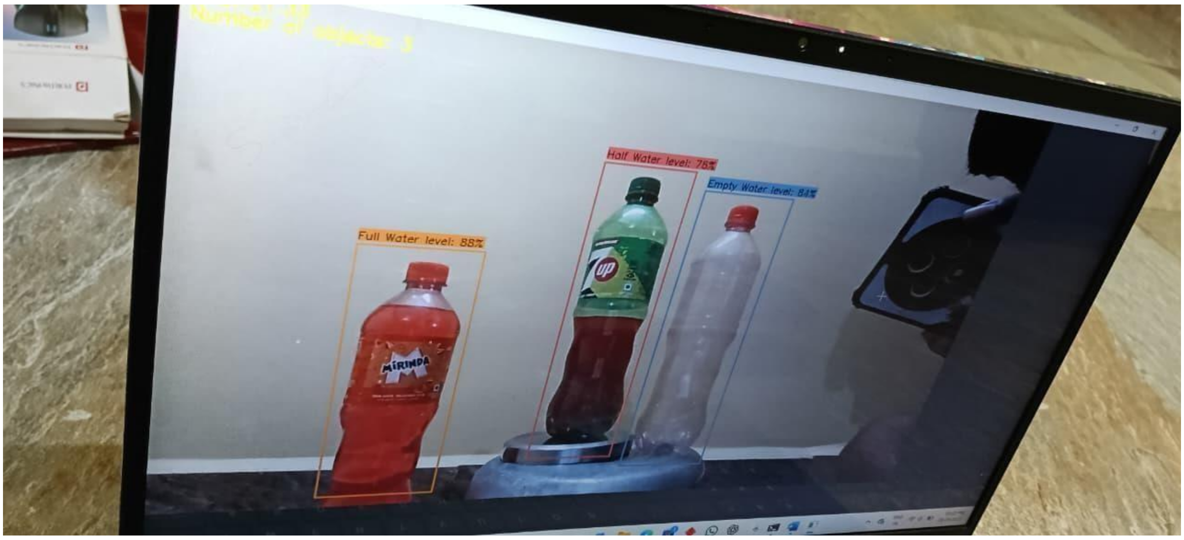


Figure 6.4 – Water Level Detection

CHAPTER 7

SCOPE OF FUTURE WORK

- **Higher-resolution industrial cameras** can be used to improve defect detection accuracy at greater conveyor speeds.
- Implementation of **3D vision or multi-camera setups** can allow for full 360° inspection of bottles.
- The system can be upgraded with **AI-based adaptive learning** to automatically adjust detection parameters for new bottle formats.
- Integration with **cloud-based data logging** can enable remote monitoring, production analysis, and quality reporting.
- By manufacturing on a larger scale, the overall **cost of deployment can be significantly reduced** for industrial use.

7.1 ADVANTAGES

- Fully **automated and non-contact inspection system**.
- **High speed and accuracy**, ensuring continuous quality control.
- **Reduces human error** and improves consistency in production.
- **Compatible with multiple bottle shapes and sizes**.
- **Cost-effective** solution using open-source tools and affordable components.
- **Environmentally friendly**, reducing material waste by early detection.

7.2 APPLICATIONS

- Water and Beverage Bottling Industries
- Pharmaceutical and Chemical Packaging Plants
- Food Processing and Filling Units
- Quality Control Laboratories
- Automated Production and Packaging Lines

APPENDICES

APPENDIX – 1

FIELD VISIT

As part of our project understanding, we visited Lingam Aqua Industries, a small-scale mineral water bottling unit located in Omalur, where purified drinking water is processed and filled into bottles of various capacities. The industry follows a standard filtration and purification sequence consisting of ozonator treatment, TDS checking (70 and above), sand filter, and carbon filter to remove dust, odor, and impurities. The plant operates with a membrane system capable of processing 6000 litres per hour, separating normal and saline water. The pH of treated water is maintained between 8.0 to 8.5, and after filtration the pH increases slightly (around 0.5).

The ozonator is used to disinfect the purified water, and the water becomes suitable for drinking after 24 hours of stabilization.

The unit produces bottles in multiple sizes —300 ml, 500 ml, 1 litre, 2 litre and 20 litre cans. Packaging capacities vary such as 300 ml (35 pieces/box), 500 ml (24 pieces/box), and 1 litre (15 pieces/box). The industry also uses a blower process for plastic bottles, where preforms are heated using 200 W bulbs (around 8 bulbs in total). Low-pressure air of 2–4 bar and high-pressure air of nearly 20 bar are used in the bottle-shaping system, followed by a system pressure of around 8 bar for final forming. The visit to Lingam Aqua Industries in Omalur helped us understand key bottling processes like purification, filling, and packaging. It also gave us useful ideas to better align our project with real industry needs.

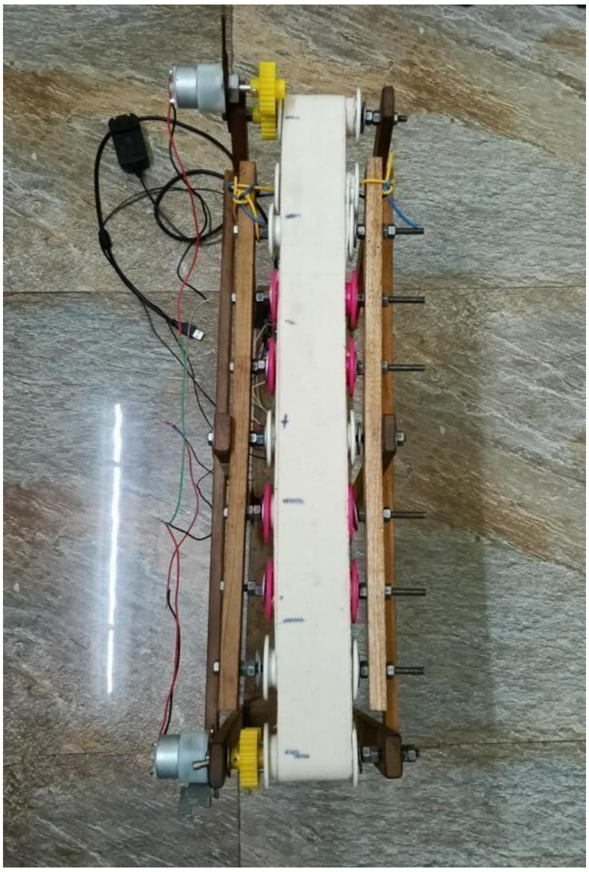
FIELD VISIT IMAGES

Figure 8.1 – Field visits images.

APPENDIX – 2

PHOTOGRAPHY

Figure 8.2 - FRONT VIEW



Figures 8.3 - TOP VIEW

Figure 8.4 - SIDE VIEW

Figure 8.5 Baseline Lighting Check (no bottle)

Figure 8.6 Surface Illumination Trial (with bottle)

APPENDIX – 3

COMPONENTS SPECIFICATION

PROTOTYPE SPECIFICATION

1. Gear Motor
   a. Volt= 12v
   b. Ampere = 1.2amp
   c. RPM=30rpm
2. Pulley Diameter = 22mm
3. Gear:
   a. Number of Gear Tooth: 25
4. Wood frame

Arduino Specifications:

- Microcontroller: ATmega328P
- Operating Voltage: 5V
- Input Voltage (recommended): 7-12V
- Input Voltage (limit): 6-20V
- Digital I/O Pins: 14 (of which 6 provide PWM output)
- PWM Digital I/O Pins: 6
- Analog Input Pins: 6
- DC Current per I/O Pin: 20 mA
- DC current for 3.3V Pin: 50 mA
- Flash Memory: 32 KB (ATmega328P) of which 0.5 KB used by bootloader
- SRAM: 2 KB (ATmega328P)
- EEPROM: 1 KB (ATmega328P)
- Clock Speed: 16 MHz
- LED_BUILTIN: 13
- Length: 68.6 mm
- Width: 58.4 mm
- Weight: 25 g

L298N Motor Driver Specifications:

- Driver Model: L298N 2A
- Driver Chip: Double H Bridge L298N
- Motor Supply Voltage (Maximum): 46V
- Motor Supply Current (Maximum): 2A
- Logic Voltage: 5V
- Driver Voltage: 5-35V
- Driver Current:2A
- Logical Current:0-36mA
- Maximum Power (W): 25W
- Current Sense for each motor
- Heatsink for better performance
- Power-On LED indicator

Gear Motor Specifications:

- RPM: 30
- Operating Voltage: 12V DC
- Gearbox: Attached Plastic (spur)Gearbox
- Shaft diameter: 6mm with internal hole
- Torque: 7 kg-cm
- No-load current: 60 mA (Max)
- Load current: 300 mA (Max)

Gear Specifications:

- Material: High-Density Plastic (Nylon / Polypropylene)
- Diameter: As per belt design and motor coupling requirements
- Quantity: 8 (2 Drive Pulleys and 6 Support Pulleys)
- Features: Lightweight, corrosion-resistant, low-friction surface finish

Conveyer belt Specifications:

- Material: Rubber / PVC Belt
- Width: As per bottle diameter
- Speed: Variable (Controlled by Motor RPM)
- Power Source: 12 V DC Gear Motor

IR Sensor Specifications:

- Operating Voltage: 3.3 – 5 V DC
- Output Type: Digital Signal (0 or 1)
- Sensor Type: Active Infrared Reflective
- Detection Range: 2 to 10 cm
- Detection Angle: 35°
- Mounting Hole: 3mm Diameter

Pulley Specifications:

- Material: High-Density Plastic (Nylon / Polypropylene)
- Diameter: As per belt design and motor coupling requirements
- Quantity: 10 (2 Drive Pulleys and 8 Support Pulleys)
- Features: Lightweight, corrosion-resistant, low-friction surface finish

Webcam (Logitech 1080p, 30 FPS) Specifications:

- Brand: Logitech
- Resolution: 1920 × 1080 pixels (Full HD)
- Frame Rate: 30 fps
- Lens Type: Auto-focus with wide-angle lens
- Interface: USB 2.0 / 3.0

LED Ring Light:

- Device Type: LED Ring Light
- Light Source: High Intensity LED Array
- Ring Diameter: ~10 inch (25–26 cm)
- Rated Power: 8W – 12W
- Operating Modes: 3 (Warm / Neutral / Cool)
- Brightness Control: Multi-level Intensity Adjustment
- Color Temperature Range:
  - – Warm White: ~3000K
  - – Neutral White: ~4500K
  - – Cool White: ~6000–6500K
- Illumination Type: Uniform, Shadow-Reduced Lighting
- Beam Distribution: Circular, Diffused Output
- Control Interface: Integrated Electronic Controller
- Adjustment Parameters: Brightness & Color Temperature

Digitek LED D-40W Bi-Color Video Light

- Device Type: LED Panel Light
- Model: Digitek LED D-40W
- Rated Power: 40 W
- Light Source: High Density LED Array
- Luminous Output: ~4000 – 4500 Lumens
- Brightness Control Range: 0 – 100% Continuous Dimming
- Color Temperature Range:
  - – Warm White: ~3200 K
  - – Cool White: ~5600 K
- Bi-Color Operation: Yes (Warm ↔ Cool Adjustable)
- Color Rendering Index (CRI): ≥ 95

APPENDIX – 4

Pseudo Code for Key Functions

Pseudo Code 1: Image Acquisition and Pre-processing

```
BEGIN
  INITIALIZE webcam (Logitech 1080p, 30fps)
  WHILE system_active:
      CAPTURE image_frame from conveyor
      CONVERT image_frame to grayscale
      APPLY Gaussian filter to reduce noise
      PERFORM adaptive thresholding
      STORE preprocessed_frame
  END WHILEEND
```

Pseudo Code 2: Fill Level and Bubble Detection

```
BEGIN
 LOAD preprocessed_frame APPLY
 Canny edge detection
 DETECT horizontal edges (meniscus line)
  CALCULATE fill_ratio = detected_level / bottle_height
  IF fill_ratio < threshold:
      FLAG as Underfilled
  DETECT circular contours (bubbles)
  IF bubbles_detected > count_threshold:
      FLAG as Impurity_Bubble
END
```

Pseudo Code 3: YOLO Model Training (Deep Learning Module)

```
BEGIN
  IMPORT YOLOv5 model
  LOAD labeled dataset (images + annotations)
  SPLIT dataset (train:70%, val:15%, test:15%)
  TRAIN model on Google Colab (GPU enabled)
  TUNE hyperparameters: epochs, batch_size, learning_rate
  EVALUATE model using TPR, FPR, precision, recall
  SAVE trained model weights (.pt) END
```

CONCLUSION

Thus, the **Design and Development of an Automated Machine Vision-Based Bottling Plant Inspection System** has been successfully completed, fulfilling all the objectives stated at the beginning of the project with the desired results. In this project, a conventional manual quality control system was replaced by an automated inspection mechanism using **Machine Vision (MV) and Deep Learning** technologies. The system effectively identifies multiple types of defects such as **surface impurities, damages, incomplete filling, air bubbles, and irregularities in capping and labeling**, ensuring consistent and reliable product quality in a high-speed bottling line. The developed prototype integrates **hardware components** such as a **conveyor system, IR sensor, DC gear motors, Arduino controller, and a Logitech HD webcam**, along with **software algorithms** implemented using **OpenCV and YOLO-based Deep Learning models**. The system achieved the target throughput of **2000 bottles per hour** and demonstrated high detection accuracy across four different bottle formats. The project proves that **automated vision inspection** is a cost-effective, efficient, and scalable alternative to manual quality control methods in the packaging industry. The successful implementation of this hybrid system highlights the potential for further industrial adoption with minor hardware upgrades and integration with automated rejection mechanisms. Hence, the developed **Machine Vision Bottling Plant System** is a step toward intelligent, reliable, and sustainable quality assurance in modern manufacturing environments.

REFERENCES

1. - L. Jiang, Z. Wang, C. Wang, M. Li, Member, IEEE, and J. Leng, “Consistency Det: A Few-step Denoising Framework for Object Detection Using the Consistency Model,” Apr. 3, 2025.

2. Feng, C., Chen, Z., Li, X., Wang, C., Yang, J., Cheng, M-M., Dai, Y. and Fu, Q. (2024) HazyDet: Open-Source Benchmark for Drone-View Object Detection with Depth-Cues in Hazy Scenes, Published September 30.

3. Chen, Y., Wang, B., Guo, X., Zhu, W., He, J., Liu, X. and Yuan, J. (2024) DEYOLO: Dual-Feature-Enhancement YOLO for Cross-Modality Object Detection, Published December 6.

4. Crasto, N. (2024) Class Imbalance in Object Detection: An Experimental Diagnosis and Study of Mitigation Strategies, Published March 12.

5. Wang, Y., Ilic, V., Li, J., Kisacanin, B. and Pavlovic, V. (2023) ALWOD: Active Learning for Weakly-Supervised Object Detection, Published September 14.

6. Jiang, C., Zhai, S., Song, H., Ma, Y., Fan, Y., Fang, Y., Yu, D., Zhang, C., Han, S., Wang, R., Liu, Y., Li, J. and Qin, P. (2023) Object Detection for Caries or Pit and Fissure Sealing Requirement in Children's First Permanent Molars, Published August 31.

7. Muhammad, A., Zhuang, W., Lyu, L. and Bae, S-H. (2023) FROD: Robust Object Detection for Free, Published August 3.

8. Wu, D., Chen, P., Yu, X., Li, G., Han, Z. and Jiao, J. (2023) Spatial Self-Distillation for Object Detection with Inaccurate Bounding Boxes, Published July 22.

9. Reshetova, D., Wu, G., Puyat, M., Gu, C. and Chen, H. (2023) Par GANDA: Making Synthetic Pedestrians A Reality for Object Detection, Published July 21.

10. Pasqualino, G., Furnari, A. and Farinella, G.M. (2022) A Multi Camera Unsupervised Domain Adaptation Pipeline for Object Detection in Cultural Sites through Adversarial Learning and Self-Training, Published October 3.

11. Wang, Z., Huang, Z., Fu, J., Wang, N. and Liu, S. (2023) Object as Query: Lifting any 2D Object Detector to 3D Detection, Published January 6.

12. Minderer, M., Gritsenko, A. and Houlsby, N. (2023) Scaling Open-Vocabulary Object Detection, Published June 16, Submitted June 19.

13. Li, Z-Y., Jin, X., Sun, B., Guo, C-L. and Cheng, M-M. (2024) Towards RAW Object Detection in Diverse Conditions, Published November 24.

14. Lippke, M., Quach, M., Braun, S., Köhler, D., Ulrich, M., Bischoff, B. and Tan, W.Y. (2023) Exploiting Sparsity in Automotive Radar Object Detection Networks, Published August 15.

15. Xie, C., Zhang, Z., Wu, Y., Zhu, F., Zhao, R. and Liang, S. (2023) Described Object Detection: Liberating Object Detection with Flexible Expressions, Published July 24.

16. Bernet, P., Chazalon, J., Carlinet, E., Bourquelot, A. and Puybareau, E. (2023) Linear Object Detection in Document Images using Multiple Object Tracking, Published May 26.

17. Guo, M., Liu, Y., Lin, Z., Peng, P. and Tian, Y. (2024) CASA: Class-Agnostic Shared Attributes in Vision-Language Models for Efficient Incremental Object Detection, Published October 8.

18. Liu, H., Teng, Y., Lu, T., Wang, H. and Wang, L. (2023) SparseBEV: High-Performance Sparse 3D Object Detection from Multi-Camera Videos, Published August 18.

19.- Xu, C., Ling, H., Fidler, S. and Litany, O. (2023) 3D DiffTection: 3D Object Detection with Geometry-Aware Diffusion Features, Published November 8, Submitted November 9.

20.- Wang, S., Teng, Y. and Wang, L. (2023) Deep Equilibrium Object Detection, Published August 18.

21.- Zhang, D., Liang, D., Yang, H., Zou, Z., Ye, X., Liu, Z. and Bai, X. (2023) SAM3D: Zero-Shot 3D Object Detection via Segment Anything Model, Published June 4, Submitted June 6.

22.- Shi, C. and Yang, S. (2023) EdaDet: Open-Vocabulary Object Detection Using Early Dense Alignment, Published September 3.

23.- Schulter, S., Kumar, V.B.G., Suh, Y., Dafnis, K.M., Zhang, Z., Zhao, S. and Metaxas, D. (2023) Omni Label: A Challenging Benchmark for Language-Based Object Detection, Published April 23.