PLC BASED WATER FILLING STATION WITH BOTTLE DETECTION

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Supervised by

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Department of Computer Engineering

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Submitted to the department of computer engineering in the partial fulfillment of the requirements for the degree of Bachelors in Computer Engineering.

Department of Computer Engineering

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CERTIFICATE

PLC BASED WATER FILLING STATION WITH BOTTLE DETECTION

(Please tick the relevant SDG(s) linked with FYDP)

SDG No	Description of SDG	SDG No	Description of SDG
SDG 1	No Poverty	SDG 9	Industry, Innovation, and Infrastructure ✓
SDG 2	Zero Hunger	SDG 10	Reduced Inequalities
SDG 3	Good Health and Well Being	SDG 11	Sustainable Cities and Communities
SDG 4	Quality Education	SDG 12	Responsible Consumption and Production ✓
SDG 5	Gender Equality	SDG 13	Climate Change
SDG 6	Clean Water and Sanitation	SDG 14	Life Below Water
SDG 7	Affordable and Clean Energy	SDG 15	Life on Land
SDG 8	Decent Work and Economic Growth ✓	SDG 16	Peace, Justice and Strong Institutions
		SDG 17	Partnerships for the Goals

UNDERTAKING

We certify that research work titled “PLC BASED WATER FILLING STATION WITH BOTTLE DETECTION” is my own work. The work has not been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged / referred.

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DEDICATION

This thesis and project are dedicated to our parents and siblings for their constant love, encouragement, and support. Their belief in our abilities and sacrifices have been crucial in enabling us to reach this milestone. Their support has provided us with the strength and inspiration to pursue our goals.

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ABSTRACT

This study introduces an automated liquid filling station with advanced bottle detection capabilities, designed to enhance efficiency and precision across various industries. The system employs a Programmable Logic Controller (PLC) to govern the entire process, incorporating sophisticated components such as a shaft encoder for precise bottle positioning and AI technology for bottle detection and classification. Additionally, an automated bottle capping mechanism is implemented to ensure seamless operation from filling to sealing.

Water filling stations are prevalent in industries like beverages, pharmaceuticals, and cosmetics. Traditional systems often rely on solenoid valves for controlling liquid flow, IR sensors for bottle detection, and DC motors for conveyor belt movement. While these methods are functional, they frequently lack the precision and adaptability necessary for high-efficiency production lines, leading to issues such as inaccurate filling levels, misaligned bottles, and frequent maintenance needs.

To address these challenges, the proposed methodology integrates advanced technologies to refine the filling process. The PLC serves as the central controller, coordinating various components to ensure smooth operation. A shaft encoder accurately measures the distance of bottles on the conveyor belt, ensuring they stop precisely at the filling point. AI-powered camera systems continuously monitor the conveyor, detecting and classifying upright bottles to ensure only correctly positioned bottles are filled. Following the filling process, the system transitions to the capping stage, utilizing a gear motor and CNC guide for precise sealing. The AI system also detects anomalies, such as misaligned or unstable bottles, pausing the system to prevent errors.

This approach demonstrates the potential of PLC-based automation in industrial processes, highlighting the benefits of integrating advanced components and AI technology. The system provides a glimpse into the future of efficient and intelligent manufacturing technologies, paving the way for enhanced productivity, reliability, and quality assurance in manufacturing environments. By leveraging these innovations, industries can achieve higher levels of operational efficiency and product consistency, thereby meeting the increasing demands of modern production standards.

Keywords: PLC, VFD, Induction Motor, Shaft Encoder, Yolov8, Gear motors, CNC rail guide, Cap holder.

TABLE OF CONTENTS

Number *Page*

LIST OF FIGURES

LIST OF TABLES

Chapter 1
Introduction

Bottle filling and capping machines have been a cornerstone of the packaging industry for many years. Initially, these procedures were entirely manual, relying heavily on human labor, which frequently resulted in errors and slow output rates. Manual filling and capping were not only time-consuming but also inconsistent, leading to variations in product quality. As technology advanced, the development of automated machines significantly transformed these activities, dramatically increasing productivity and precision. Early automated systems, though primitive with limited capabilities, laid the groundwork for future innovations. These early machines performed repetitive operations, freeing operators to focus on oversight and quality control, but they had limitations in terms of flexibility and adaptability[1].

The evolution of bottle filling and capping machines has paralleled the broader advancements in automation technology. Today's machines incorporate modern technologies such as sensors, computer vision, and programmable logic controllers (PLCs). These advancements have enabled machines to fill and seal bottles rapidly and precisely, adapting to different bottle shapes and sizes. This adaptability is crucial in industries like food and beverage, pharmaceuticals, and cosmetics, where products come in a variety of forms and packaging types. Modern automated systems not only improve productivity and consistency but also enhance the overall efficiency of manufacturing processes. They lead to increased output and reduced labor expenses, as fewer human operators are needed to manage the machines[2].

The integration of automated solutions also enables improved quality control and traceability, which are critical for regulatory compliance and customer safety. The ability to maintain consistent filling levels and secure capping is vital for ensuring product safety and quality. This consistency is especially important in industries with stringent regulatory requirements, such as pharmaceuticals and food and beverages, where any deviation can lead to significant health risks or legal repercussions. Automated systems can also generate detailed logs and reports, which are essential for traceability and accountability in manufacturing processes[3].

Despite the significant advancements in automation, the industry continues to face challenges. One of the primary hurdles is managing delicate or unusually shaped bottles. Automated systems must be designed to handle a wide variety of bottle shapes and sizes without compromising on speed or accuracy. This requires sophisticated sensors and control algorithms that can quickly adapt to different types of bottles. Ensuring seamless integration into existing production lines is another challenge. Many manufacturing facilities have legacy systems that are not easily compatible with modern automated machines. Integrating new technology with old systems can be complex and costly, requiring careful planning and execution[3].

Enhanced automation has resulted in more exact filling levels and consistent capping, which, in turn, enhances product quality. Safety features and real-time monitoring have reduced the likelihood of contamination and mishaps, making modern automated systems more reliable and safer to operate. Real-time monitoring systems can detect issues such as bottle misalignment or spillage and take corrective actions immediately. This proactive approach minimizes downtime and prevents product wastage. Additionally, automated systems can be equipped with advanced cleaning and sterilization features, further reducing the risk of contamination[4].

The use of PLCs in modern bottle filling and capping machines plays a crucial role in achieving these benefits. PLCs offer precise control over various processes, ensuring that each step of the filling and capping operation is executed accurately and efficiently. PLCs can be programmed to handle different types of products and packaging, providing the flexibility needed to switch between different production runs quickly. This flexibility is essential in today's fast-paced manufacturing environment, where production lines must be able to adapt to changing market demands rapidly[4].

In this project, a Siemens PLC is the heart of the system, controlling the conveyor belt, filling section, and sensors to automate the bottle filling and capping process. The use of a Siemens PLC ensures high reliability and performance, as Siemens is a leading manufacturer of industrial automation equipment. The PLC coordinates the actions of various components, such as the shaft encoder, which measures the distance of bottles on the conveyor belt to ensure they stop accurately at the filling point. This precision is critical for achieving consistent filling levels and avoiding spillage[5].

To enhance the system's capabilities further, the YOLO v8 algorithm, running on a Raspberry Pi, is employed for bottle detection and classification. YOLO (You Only Look Once) is a state-of-the-art object detection algorithm known for its speed and accuracy. By using YOLO v8, the system can detect and classify bottles in real-time, ensuring that only correctly positioned bottles are filled. The Raspberry Pi, a cost-effective and versatile computing platform, processes the data from the camera and communicates with the PLC to control the filling process. This combination of advanced AI and robust industrial automation technology results in a highly efficient and reliable bottle filling and capping system[6].

The shift towards automation in bottle filling and capping not only increases productivity but also minimizes human error and operational downtime. Automated systems can operate continuously without the need for breaks, leading to higher production rates. By reducing human intervention, the risk of errors due to fatigue or inattention is minimized. Automated systems are designed to perform routine maintenance tasks, such as cleaning and lubrication, further reducing downtime and maintenance costs[6].

By implementing such a system, industries can address challenges related to increasing production volume, cost reduction, and safe operations. Automated bottle filling and capping systems are particularly beneficial in high-demand industries where large quantities of products need to be processed quickly and accurately. These systems can handle high production volumes without compromising on quality, ensuring that products meet stringent quality standards[7].

The potential benefits of a PLC-based automatic filling and capping system are demonstrated through this project. By combining technologies like YOLO v8, Raspberry Pi, and Siemens PLC, the project aims to provide an efficient solution to industry challenges. The integration of these technologies showcases the power of modern automation in transforming manufacturing processes. The use of AI for bottle detection and classification highlights the potential of combining machine learning with traditional automation technologies to achieve higher levels of efficiency and precision[7].

Furthermore, the project emphasizes the importance of safety and efficiency in manufacturing operations. The system is designed to detect anomalies, such as misaligned or unstable bottles, and pause the operation to prevent errors. This proactive approach ensures that only correctly positioned and stable bottles are filled and capped, reducing the risk of product defects and ensuring the safety of the final product[8].

The advancements in industrial technology have significantly influenced production processes across various industries. The application of reliable automation technology can enhance both the quality and quantity of production outcomes. Traditional manufacturing systems, reliant on manual operations, often face higher production costs and decreased efficiency. As industries strive to improve their production methods, they are increasingly turning to systems that are effective, efficient, and economical[8].

Programmable Logic Controllers (PLCs) play a crucial role in modern automation, offering precise control over various processes. The ability to program PLCs to handle different tasks and adapt to changing production requirements makes them invaluable in modern manufacturing environments. PLCs can be integrated with other automation technologies, such as sensors, cameras, and AI algorithms, to create highly efficient and flexible production systems[8].

The evolution of automation in bottle filling and capping is a testament to the rapid advancements in industrial technology. Over the years, manufacturers have recognized the need for precision and consistency, particularly in sectors where product integrity is paramount. The introduction of programmable logic controllers (PLCs) has been revolutionary, providing a level of control and adaptability that was previously unattainable with manual operations. PLCs have enabled machines to perform complex tasks with high accuracy, ensuring that each bottle is filled to the correct level and sealed properly. This precision is crucial for maintaining product quality and meeting regulatory standards, which are becoming increasingly stringent in many industries.[9].

In addition to PLCs, the integration of computer vision and artificial intelligence (AI) has further enhanced the capabilities of automated systems. Computer vision technologies allow machines to 'see' and analyze the production line in real time. This capability is particularly useful for detecting anomalies such as bottle misalignment, foreign objects, or variations in bottle shape and size. AI algorithms can then process this visual data and make real-time decisions to adjust the machine's operations, ensuring that only correctly positioned bottles are filled and capped. This level of intelligence and adaptability is essential for high production standards and minimizing waste[9].

The use of advanced sensors and monitoring systems also plays a critical role in modern bottle filling and capping machines. Sensors can detect various parameters, such as the presence and position of bottles, the flow rate of the liquid, and the torque applied during capping. These sensors provide continuous feedback to the PLC, allowing for precise control and adjustments during the filling and capping process. Real-time monitoring systems can alert operators to any issues, such as blockages or leaks, enabling quick resolution and preventing potential downtime. This proactive approach to maintenance and troubleshooting is key to maintaining high productivity levels and reducing operational costs[10].

Moreover, the integration of the YOLO v8 algorithm on a Raspberry Pi adds a layer of sophistication to the bottle detection and classification process. YOLO v8, being a state-of-the-art object detection algorithm, can process images quickly and accurately, identifying different types of bottles and ensuring they are properly aligned before filling. The use of Raspberry Pi, a compact and affordable computing platform, makes it feasible to implement such advanced algorithms in industrial settings. This combination of AI and affordable hardware highlights the potential for cost-effective solutions that do not compromise on performance or reliability[10].

The shift towards automation also addresses the need for scalability in manufacturing processes. As consumer demand fluctuates and new products are introduced, manufacturers must be able to scale their operations efficiently. Automated systems can be easily programmed to handle different bottle sizes and types, allowing for rapid changes in production lines without significant downtime. This flexibility is crucial for companies looking to stay competitive in dynamic markets. Furthermore, automated systems can operate continuously, increasing production capacity and enabling manufacturers to meet high-volume orders within tight deadlines[11].

Safety and compliance are other critical areas where automation provides significant benefits. Automated filling and capping systems can be designed with built-in safety features to protect both the product and the operators. For instance, machines can be programmed to shut down automatically if a malfunction is detected, preventing potential accidents. Additionally, automated systems ensure consistent adherence to regulatory requirements by maintaining precise control over filling volumes and capping torque. This consistency is essential for avoiding regulatory penalties and ensuring customer satisfaction, particularly in industries where product safety and quality are paramount[11].

The economic benefits of adopting advanced bottle filling and capping automation are substantial. Automated systems reduce the need for extensive manual labor, significantly cutting labor costs and reducing the risk of human error. This cost-saving aspect is particularly advantageous for large-scale manufacturers who operate around the clock. Additionally, automation leads to faster production cycles, allowing companies to meet market demands more promptly and efficiently. The initial investment in automated machinery is quickly offset by the long-term savings in labor, increased production rates, and reduced wastage, making it a financially sound strategy for businesses aiming for growth and sustainability[12].

The environmental impact of manufacturing processes is a growing concern in today's industrial landscape. Automated systems contribute to more sustainable practices by minimizing waste through precise control over filling and capping operations. Reduced spillage and overfilling lead to less product waste, which not only saves resources but also reduces the environmental footprint of the manufacturing process. Additionally, modern automated systems are often designed with energy efficiency in mind, utilizing advanced motors and control systems that consume less power. This focus on sustainability helps companies align with environmental regulations and corporate social responsibility goals, making automation a key component of eco-friendly manufacturing practices[12].

In conclusion, bottle filling and capping machines are critical in today's manufacturing landscape for ensuring efficient and reliable output across a wide range of industries. These machines ensure product safety and quality by maintaining constant filling levels and secure capping in various industries, including food, beverage, pharmaceutical, and cosmetics. They also enable rapid line changes, allowing manufacturers to easily swap between different products and sizes. Additionally, these machines help reduce labor costs and minimize human error, further enhancing production efficiency. Advanced automation and integration capabilities also allow for seamless coordination with other production line equipment. As technology continues to evolve, the importance and functionality of bottle filling and capping machines will only grow, driving innovation and productivity in manufacturing.

1.1 Problem Statement

Design and implement an automated bottle filling and capping system that utilizes PLC, Raspberry Pi, and computer vision technology. This system should be capable of accurately detecting and classifying unstable bottles in real time, ensuring smooth operation and product consistency. By automating these processes, we aim to enhance efficiency and safety while minimizing waste. The system should be re-programmable to adjust for different bottle types and production needs, allowing for versatility in various applications.

1.2 Aim And Objectives

The main aim and objective of our FYP is:

- Design and implement an automated bottle filling and capping system that utilizes PLC and computer vision technology to efficiently manage the production line.
- Integrate a computer vision system that can accurately detect and classify unstable bottles in real time to ensure smooth operation and maintain product quality.
- Develop a control system for the controllers that coordinates the filling and capping processes with precision, improving accuracy and minimizing potential errors.
- Optimize the system's performance to enhance speed, safety, and efficiency in production, thereby reducing waste and downtime while maintaining consistent product quality.

1.3 Project Scope And Limitations

The project scope involves designing and constructing the hardware components of an automated bottle filling and capping system, including PLC-based filling control, Arduino Uno for capping control, and a Raspberry Pi-integrated camera for computer vision. It will integrate computer vision to detect and classify unstable bottles in real-time and will assess the system's performance focusing on accuracy, speed, and reliability. The entire design and implementation process will be documented. The project limitations include focusing on implementing existing computer vision and object detection techniques rather than developing new algorithms. The system is specifically designed for the automated bottle filling and capping process and may not integrate with other unrelated systems. Additionally, it may be confined to handling specific types of bottles and operating within a defined production environment.

Chapter 2
Literature Review

This chapter examines existing research on the design of automatic bottle filling and coatings, including integration of PLC, Raspberry Pi, and Arduino Uno We examine the progress made in that these areas and their relationship to the objectives of our project. This review examines various approaches to using computer vision for quality management, with the aim of identifying best practices and emerging technologies that are relevant to our profession.

Our literature search primarily used Google Scholar and IEEE Xplore to identify relevant papers and research published from 2015 onwards. We reviewed highly respected conferences such as IEEE conferences for the most up-to-date research. Keywords include ”bottle filling,” ”PLC-based system,” ”computer vision,” ”YOLO algorithm,” and ”capping system.” This comprehensive analysis allows us to understand the pros and cons and related work of innovation and potential opportunities in the focus areas of our business.

2.1 Conveyor Belt Movement and Control Systems

Research on conveyor belt systems emphasizes the important role they play in packaging and lining shipping bags. Most of the time, the PLC controls the movement, ensuring smooth operation and synchronization. Proximity sensors detect the presence of bottles on the conveyor and start or stop movement accordingly. These systems not only increase efficiency but also help maintain product quality by reducing the chances of spillage and damage during transit. They are essential components in automated production lines, contributing to consistent output and streamlined operations. Additionally, conveyor belts help in reducing manual labor, lowering the risk of workplace injuries and allowing workers to focus on more complex tasks that require human intervention[1].

Conveyor belt systems are designed to be durable and reliable, handling the rigorous demands of continuous operation in industrial environments. The materials used in constructing these belts are often resistant to wear and tear, ensuring long service life and minimal maintenance. Furthermore, conveyor systems can be customized to fit the specific needs of different industries, whether it’s for handling food products, pharmaceuticals, or heavy machinery parts[2].

One system uses a rotary conveyor driven by a synchronous motor, controlled by a PLC to ensure a continuous flow from the filling section to the capping section. Another system focuses on a flat belt conveyor driven by a DC motor to move bottles under a solenoid valve for filling, showing versatility in handling a variety of bottle sizes. These examples highlight the adaptability of conveyor systems in accommodating different production requirements and bottle specifications, making them suitable for diverse industrial applications. Such systems also offer scalability, allowing manufacturers to upgrade or modify the setup as needed. In addition, these systems can be integrated with other automated equipment, such as robotic arms for packaging and palletizing, further enhancing production capabilities[3].

The integration of advanced sensors and control systems in conveyor belts provides greater precision and control over the manufacturing process. Sensors can monitor various parameters, such as speed, temperature, and load, providing real-time data that can be used to adjust operations on the fly. This capability is particularly important in industries where precise control over the production process is critical, such as in pharmaceuticals and electronics. Enhanced monitoring and control lead to better quality assurance and compliance with industry standards and regulations[4].

Apart from motor-driven systems, other methods such as pneumatic conveyors have been analyzed for better handling of small bottles. Comparisons between pneumatic and motor-driven conveyors have shown faster transport times for pneumatic systems, albeit at higher power costs. Pneumatic conveyors are particularly effective in scenarios where gentle handling of delicate items is crucial, minimizing the risk of breakage. Additionally, they can be more flexible in layout, accommodating complex production line designs. The use of air pressure to move products also reduces the need for mechanical components, which can lower maintenance requirements and extend the system's operational life[5].

The choice between pneumatic and motor-driven conveyor systems depends on various factors, including the type of product being handled, the required speed of operation, and the overall production goals. For instance, pneumatic systems might be more suitable for high-speed production lines where rapid product movement is essential, while motor-driven systems could be better for heavier or more robust items. Evaluating these factors helps manufacturers select the most appropriate conveyor system for their specific needs, ensuring optimal performance and efficiency[6].

Automation integrates sensors with IoT devices to enhance monitoring and control. For example, the use of RFID tags to track the movement of barrels near the conveyor has shown improvements in system performance and reduced errors. This integration allows for real-time data collection and analysis, leading to better decision-making and increased operational efficiency. Moreover, IoT-enabled systems can provide predictive maintenance alerts, reducing downtime and extending the lifespan of the equipment. IoT integration also facilitates remote monitoring and control, enabling managers to oversee production processes from anywhere, thus increasing flexibility[7].

The use of IoT in conveyor systems also supports advanced analytics, helping manufacturers identify patterns and trends that can inform future improvements. By analyzing data from IoT sensors, companies can gain insights into operational inefficiencies, equipment wear and tear, and other critical factors. This data-driven approach allows for continuous improvement, ensuring that conveyor systems remain at peak performance. Additionally, IoT can support energy management initiatives by monitoring and optimizing the power usage of conveyor systems, contributing to sustainability goals[8].

2.2 Bottle Capping Techniques And Automation

Bottling is an important part of the bottling process, ensuring the authenticity of the final product. Studies examine passive coating systems, often incorporated into filling lines. For example, automation of bottle capping systems of different sizes using PLC Logix-Pro simulation demonstrates how sensors and capping mechanisms can be integrated for efficiency. These systems streamline the production process, minimizing manual intervention and enhancing the speed and accuracy of bottling operations. Automation also contributes to maintaining consistent product quality by ensuring each bottle is capped to precise specifications[9].

The implementation of PLC-based systems allows for easy adjustments and scalability, accommodating various bottle sizes and production demands. With the integration of sensors, the capping process becomes more responsive and adaptable, reacting swiftly to any changes or discrepancies in the production line. This adaptability is crucial in industries where product variations are frequent, ensuring that the capping process remains efficient and reliable. Furthermore, automated systems reduce the risk of contamination and product tampering, thereby enhancing the overall safety and integrity of the bottled products[10].

A landmark study describes the capping mechanism in detail using a torque sensor that ensures that the torque is tightened to the correct specification, thus reducing the risk of leakage and contamination. Furthermore, the use of magnetic cap heads improves accuracy and reduces mechanical weaknesses compared to traditional methods. Advanced techniques, such as robotic arm coverings, have been developed to control high-speed production lines. These systems use optical technology to precisely place lids on bottles, greatly increasing productivity and reducing human error. The integration of these advanced mechanisms ensures that the capping process is not only efficient but also highly precise, minimizing the chances of defective products reaching the market[11].

The use of torque sensors in capping mechanisms provides real-time feedback, allowing for immediate adjustments to ensure consistent performance. This real-time monitoring is vital in maintaining the integrity of the bottling process, especially in high-speed production environments where even minor deviations can lead to significant issues. Moreover, magnetic cap heads offer a non-contact method of securing caps, reducing wear and tear on machinery and extending the lifespan of the equipment. These innovations highlight the ongoing advancements in bottling technology, aimed at improving efficiency, reliability, and product safety[12].

The integration of machine learning and artificial intelligence (AI) into bottling and capping processes has also shown promising results in enhancing operational efficiency and product quality. Recent studies have explored the use of AI algorithms to predict and adjust the filling and capping parameters in real-time. For instance, by analyzing historical data and real-time sensor inputs, these algorithms can optimize the filling speed and volume, as well as the capping torque, to accommodate variations in bottle size, shape, and material. This not only ensures consistent product quality but also reduces the risk of equipment wear and tear, thereby extending the lifespan of the machinery. AI-driven systems can also detect anomalies and potential failures early, allowing for preventive maintenance and minimizing downtime[13].

AI and machine learning technologies bring a new level of intelligence to the bottling process, enabling systems to learn from past data and continuously improve their performance. These technologies can identify patterns and trends that human operators might overlook, leading to more informed decision-making and efficient operations. By automating the adjustment of parameters based on real-time data, AI systems help maintain optimal conditions for bottling and capping, reducing waste and improving overall productivity[14].

In addition, the use of adaptive control algorithms in capping machines, which adjust capping torque in real time based on bottle cap characteristics, ensures consistent quality in different batches. This adaptability is crucial for maintaining uniformity across various production runs, especially when dealing with different types of bottles and caps. Adaptive control systems enhance the flexibility of the capping process, allowing manufacturers to easily switch between products without compromising quality. This results in more efficient production lines and higher satisfaction among consumers due to the consistent quality of the final products[15].

The ability to fine-tune capping parameters in real-time ensures that each bottle is sealed perfectly, reducing the likelihood of leaks or contamination. This precision is particularly important in industries such as pharmaceuticals and food and beverages, where product safety is paramount. Adaptive control algorithms also help in optimizing resource usage, as they can adjust operations to use the minimum required force and energy, leading to cost savings and a reduced environmental footprint. These advancements in capping technology reflect the broader trend towards smarter, more efficient manufacturing processes that leverage the power of AI and automation to achieve superior results[16].

2.3 Bottle Detection

Computer vision (CV) plays an important role in the automation of canning devices. Techniques such as the YOLO (You Only Look Once) algorithm have been widely discussed for use in object recognition and bottle detection. Using the COCO dataset, these models are trained to achieve greater accuracy in detecting bottles on conveyor belts. Convolutional neural networks (CNNs) are also used to identify defects in bottles, providing further control. The integration of CV systems into bottling lines enhances the precision and reliability of the entire process, ensuring that only defect-free bottles proceed to the next stages of production. This automated inspection significantly improves quality control, reducing the likelihood of defective products reaching consumers[17].

In addition to improving defect detection, CV systems streamline the overall production workflow by enabling faster identification and sorting of bottles. By automating these tasks, companies can achieve higher throughput and reduce bottlenecks that may occur during manual inspections. This efficiency translates into increased productivity and lower operational costs, as fewer resources are needed to manage the inspection process[18].

The incorporation of deep learning into edge computing has been investigated to reduce latency in bottle detection systems. This approach allows for real-time processing and decision-making at the production level, increasing productivity and reducing reliance on centralized computing resources. Practical applications have shown that implementing CV systems in bottling lines not only provides more accurate identification but also reduces operational costs by eliminating the need for manual inspection. The use of edge computing ensures that data processing occurs close to the source, minimizing delays and enhancing the responsiveness of the system[19].

Edge computing also enhances the scalability of CV systems, allowing manufacturers to expand their operations without overwhelming their central data processing capabilities. By distributing the computational load across multiple edge devices, companies can maintain high performance even as production demands increase. This decentralized approach also improves system resilience, as edge devices can continue to operate independently if the central system experiences issues. Overall, the integration of deep learning and edge computing in CV systems represents a significant advancement in manufacturing automation[20].

Furthermore, CV technology supports predictive maintenance by monitoring the condition of production equipment in real-time. By analyzing visual data, these systems can detect early signs of wear and tear, enabling timely maintenance and reducing the risk of unexpected breakdowns. This proactive approach helps maintain continuous production and extends the lifespan of machinery, resulting in cost savings and improved operational efficiency. Additionally, the data collected by CV systems can be used to refine and optimize production processes, leading to ongoing improvements in quality and productivity[21].

The use of CV systems also enhances worker safety by automating hazardous inspection tasks and reducing the need for human intervention in potentially dangerous environments. By relying on automated systems to perform these inspections, companies can minimize the risk of accidents and injuries, ensuring a safer workplace. This technological shift not only protects workers but also aligns with regulatory requirements and industry standards, fostering a culture of safety and compliance.

Table 2.1: PLC Paper Comparison

Feature	Garbage Detection (2023)	Plastic Detection (2024)	Surface Defect Detection (2024)	Object Detection (2023)	Bottled Water Identification (2019)	Water Bottle Defect Detection (2022)
	Detection Systems					
Focus	Detecting garbage, possibly bottles	Identifying plastic items	Detecting defects on plastic bottle surface	Identifying objects, possibly bottles	Identifying bottled water and fraud	Detecting defects in water bottles
Method	YOLOv3 deep learning model	CNN deep learning model	LFF YOLO deep learning model with multi-view imaging	Deep learning (unspecified)	Spectroscopy and CNN	CNN
Target Material	Various, including plastic	Plastic	Plastic	Various, including bottles	Bottled water	Plastic
Strengths	Good real-time performance	May work well for embedded systems	Addresses various views and surface defects	Not specified	Identifies specific types of bottles and fraud	Focuses on defect detection
Weaknesses	Not specifically designed for bottles	May not generalize well to different plastic types	Requires multiple cameras	Not specified	Requires specialized equipment	Limited to defect detection
Suitability for Bottles	Moderate	Moderate	High (for surface defects)	Moderate	High	High

The table summarizes various detection systems and their characteristics. Garbage detection uses the YOLOv3 model, offering good real-time performance but only moderate suitability for bottles. Plastic detection employs CNN models, which work well for embedded systems but might not handle various plastic types effectively. Surface defect detection uses LFF YOLO with multi-view imaging, providing high accuracy for surface defects but requiring multiple cameras. Object detection utilizes unspecified deep learning models, with unclear strengths and weaknesses, offering moderate suitability for bottles. Bottled water identification combines spectroscopy and CNN, excelling in identifying and preventing fraud but needing specialized equipment. Lastly, water bottle defect detection uses CNN to focus on defects in plastic bottles, effective for quality control but limited to defect detection.

2.4 Comparative Analysis

Comparative analysis provides insight into the efficiency and accuracy of different automation strategies. For instance, studies comparing YOLOv3 and YOLOv2 models for bottle recognition reveal that YOLOv3 has a higher recall score, indicating better recognition, while YOLOv2 demonstrates higher accuracy. Additional comparisons of different conveyor belt materials, such as rubber, plastic, and stainless steel, assess their suitability in various canning environments. Findings suggest that stainless steel belts, despite their higher cost, offer superior durability and cleanliness, making them ideal for specific beverage brands. Moreover, analysis of the economic impact of automation technology in bottling plants concludes that initial investments in advanced systems like robotic capping and CV-based monitoring are offset by long-term gains in productivity and quality assurance. This holistic view highlights the importance of selecting the right automation technologies and materials to optimize efficiency and ensure consistent product quality in bottling operations[22].

2.5 Base Paper

The paper titled ”Water Bottle Filling Conveyor Design Based on Programmable Logic Controller” presents an automated bottle filling system utilizing PLC-based control, which is widely used in various industries for its efficiency and practicality[1]. The system employs PLC devices to control mineral water bottle filling operations using input-output (I/O) facilities. Input devices such as push buttons and infrared sensors, coupled with PLC outputs including DC motors, solenoid valves, and linear solenoids, enable precise control over the filling process. The design and implementation of the system involve several electronic components, including PLCs, DC motors, infrared sensors, photo sensors, solenoid valves, solenoid linear actuators, and digital counters. PLCs are chosen for their digital operation, programmable memory, and ability to perform various functions such as logic, sequencing, timing, counting, and arithmetic operations, making them suitable for controlling automated processes.

The hardware design includes mechanical components such as conveyor systems driven by DC motors, as well as electronic modules interfaced with the PLC to control sensors and actuators. Software design follows the hardware configuration, with programming logic implemented to control the operation of the conveyor system based on sensor inputs and system requirements. Testing and analysis of the system demonstrate the functionality of each electronic module, including infrared sensors, photo sensors, solenoid valves, linear solenoids, digital counters, and conveyor systems[1].

Overall, the paper provides a detailed overview of the design and implementation of an automated bottle filling conveyor system based on PLC control. While the study focuses on simulation-based analysis, it offers valuable insights into the potential benefits of automation in improving production effectiveness, efficiency, and cost savings. However, further research and development are necessary to address practical challenges and ensure successful real-world implementation, such as hardware compatibility, sensor integration, and system reliability.

Table 2.2: Yolo Paper Comparison

Authors (Year)	Paper Title	Institution	Focus	Strengths	Weaknesses
Syahban Rangkuti et al. (September 2023)	Design of Conveyor System for Water Bottle Filling Using PLC	Faletehan University, Indonesia	Design of conveyor system for filling bottles using PLC	Discusses conveyor design; Provides insights into conveyor-based filling systems	Limited details on PLC programming and sensor integration
Abdulrahim Mahrez et al. (2022)	PLC-Controlled Liquid Filling System for Bottles of Various Sizes	Sabratha University, Libya & Zarqa University, Jordan	Design of PLC-controlled filling system for bottles of different sizes	Detailed design process and simulation; Component selection considerations; Use of TIA Portal V17	Lack of real-world testing data or performance evaluation
Md. Liton Ahmed et al. (2019)	Design of Automatic Bottle Filling System Using PLC	Khulna University of Engineering & Technology, Bangladesh	Development of a bottle filling system with PLC controller	Offers basic design concept; Provides foundation for understanding bottle filling process	Lack of specifics on PLC programming and sensor types
Ameer L. Saleh et al. (December 2017)	PLC Based Automatic Liquid Filling System For Different Sized Bottles	University of Misan, Iraq	PLC-based filling system for various bottle sizes	Addresses bottle size variation; Potential for increased productivity and flexibility	Lack of detailed information on PLC programming and sensor integration
D.Baladhandabany et al. (March 2015)	PLC-Based Automatic Liquid Filling System	INFO Institute of Engineering, India	Creation of a PLC-based liquid filling system for industrial use	Includes multiple filling nozzles; User-defined volume selection; Focus on cost-effectiveness	Limited to filling one bottle at a time; Restricted range of bottle sizes; Lack of real-world testing information

Across these studies, common strengths include detailed design processes, component selection considerations, and potential for increased productivity and flexibility. However, they often share weaknesses such as limited details on PLC programming, sensor integration, and lack of performance evaluation data.

Chapter 3
Design & Methodology

The design and methodology chapter of the PLC-based liquid filling station with bottle detection project provides a comprehensive overview of the project's goals, technologies, and methodologies. It emphasizes the integration of advanced automation technologies to improve the efficiency and precision of the liquid filling process. The chapter highlights the use of the Siemens PLC S7-1211 DC/DC/DC as a central component, along with other sophisticated components, to ensure smooth operation throughout the filling and capping processes[1].

This chapter will detail the systematic selection of components, the design of mechanical and electrical systems, the development of control software, and the implementation of safety measures to achieve a reliable and effective liquid filling station. The project begins with a thorough system overview to provide context for the design choices and methodologies employed. The subsequent sections delve into the rationale behind the selection of each component, such as the Sinamics G110 variable speed drive and SPG S8125GS-TCE induction motor, which are critical for maintaining precise control over the filling and capping processes[2].

By integrating Yolo v8 AI technology, the system can continuously monitor and classify bottles on the conveyor, ensuring accurate and efficient operations. The methodology includes detailed descriptions of the mechanical design, electrical schematics, and control system architecture. Each design aspect is meticulously planned to ensure compatibility and optimal performance. The software development section will discuss the programming of the PLC and the integration of AI for bottle detection[3].

It not only serves as a blueprint for the liquid filling station but also as a testament to the meticulous planning and execution required for such endeavours. Through a synthesis of innovative technologies and methodical approaches, the chapter underscores the project's commitment to setting new benchmarks in efficiency, precision, and reliability within the realm of liquid filling automation. This detailed exploration highlights the depth of research and development undertaken to ensure the system's robustness and adaptability to diverse operational environments. The chapter addresses the process flow, outlining each step from manual bottle placement to the automated capping process, while emphasizing safety to protect both operators and equipment[4].

3.1 System Overview

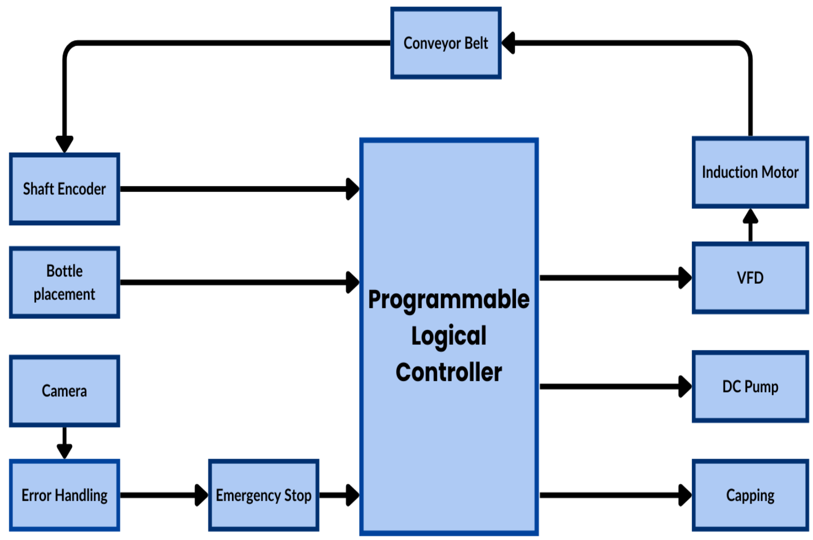


Fig 3.1: Methodology

The operational sequence of the filling station commences with the manual placement of a bottle onto the conveyor belt, initiating a meticulously orchestrated series of actions. As the bottle progresses along the conveyor belt, a Shaft Encoder E6B2-CWZ6C 1000P/R 2M diligently tracks its position, facilitating precise filling at the designated point. Utilizing the Siemens Sinamics G110 variable speed drive, the pump dispenses the exact volume of liquid, ensuring optimal filling accuracy. The seamless integration of the Yolo v8 AI system guarantees continuous monitoring of bottle orientation and positioning, ensuring optimal alignment for efficient filling operations[5].

Upon completion of the filling process, the system seamlessly transitions to the capping phase, characterized by a meticulously engineered mechanism comprising two gear motors, a CNC rail guide, a cap holder, and a motor bracket, meticulously calibrated to ensure precise and efficient sealing. Throughout this phase, the vigilant oversight of the AI system ensures prompt detection of any deviations or anomalies, promptly pausing operations to maintain stringent standards of accuracy, safety and overall quality of the end product and setting new benchmarks in liquid filling automation[6].

3.2 Hardware Components

3.2.1 Siemens PLC S7-1211 DC/DC/DC

Fig 3.2: PLC S7-1211 DC/DC/DC

The Siemens PLC S7-1211 DC/DC/DC is the central control unit of the liquid filling station. It is chosen for its robust performance, reliability, and ease of integration with various industrial components. The PLC controls all aspects of the system, including the conveyor belt, filling pump, and capping mechanism. Its DC/DC/DC configuration indicates that it operates with DC power inputs and outputs, making it suitable for the various motors and sensors used in the system. The PLC's programmability allows for precise control over the filling and capping processes, ensuring accuracy and consistency in operation.

This PLC model was selected due to its compact size, which is suitable for the space constraints of the system. The PLC is responsible for managing and coordinating the various components of the filling station, including the conveyor belt, water pump, and capping mechanism. The PLC is programmed using Siemens' TIA Portal software, which allows for the development of complex logic and algorithms to control the filling and capping processes[5]. The PLC communicates with other components of the system, such as the variable speed drive and the AI camera, using industrial communication protocols like Profibus or Profinet. This allows for real-time monitoring and control of the entire system.

3.2.2 Siemens Sinamics G110 Variable Speed Drive

Fig 3.3: Variable Speed Drive G110

The Siemens Sinamics G110 Variable Speed Drive is an essential component in the liquid filling station, used to control the speed of the SPG S8125GS-TCE induction motor. This drive offers precise control over the motor's speed, allowing for optimal performance and energy efficiency. One of the key features of the Sinamics G110 is its ability to regulate the motor's speed dynamically, based on the system's requirements.

This is important in the filling station, as different parts of the process may require different speeds. For example, the motor may need to run at a slower speed during the filling process to ensure accuracy, and then at a higher speed during the bottle transport phase. The Sinamics G110 is also known for its reliability and durability, making it suitable for industrial applications like the liquid filling station.

Its compact design allows for easy integration into the system, and its user-friendly interface simplifies setup and operation. Overall, the Siemens Sinamics G110 Variable Speed Drive plays a crucial role in the liquid filling station, ensuring that the SPG S8125GS-G61 induction motor operates efficiently and effectively throughout the filling process.

3.2.3 SPG S8125GS-G61 Induction Motor

Fig 3.4: Induction Motor SPG S8125GS-TCE

The SPG S8125GS-G61 induction motor is a key component in the liquid filling station, responsible for driving the conveyor belt and other mechanical components. This particular motor was selected for its high efficiency, reliability, and compatibility with the system's requirements. The motor's specifications, including its power rating and speed, were chosen to match the operational needs of the conveyor belt.

The motor is designed to provide smooth and continuous operation, ensuring that bottles are transported efficiently along the conveyor line. The motor is controlled by the PLC, which regulates its speed and direction based on the filling station's operational requirements. This allows for precise control over the bottle transport process, ensuring that bottles are positioned correctly for filling and capping.

Overall, the SPG S8125GS-G61 induction motor plays a critical role in the liquid filling station, providing the power and reliability needed for the system to operate smoothly and efficiently.

3.2.4 Shaft Encoder E6B2-CWZ6C 1000P/R 2M

Fig 3.5: Shaft Encoder E6B2-CWZ6C

The Shaft Encoder E6B2-CWZ6C 1000P/R 2M is a critical component in the liquid filling station, used for measuring the distance and speed of the conveyor belt and bottles. This encoder provides precise feedback to the PLC, allowing for accurate control of the bottle transport process.

The "1000P/R" designation indicates that the encoder has 1000 pulses per revolution, providing high resolution for precise positioning. This high resolution is essential for ensuring that bottles are accurately positioned for filling and capping.

The encoder's "2M" designation indicates that it has a 2-meter cable, which is suitable for connecting the encoder to the PLC over a relatively short distance. This allows for easy integration into the system without the need for additional cabling.

Overall, the Shaft Encoder E6B2-CWZ6C 1000P/R 2M plays a crucial role in the liquid filling station, providing accurate feedback to the PLC to ensure precise control over the bottle transport process.

3.2.5 Conveyor Belt

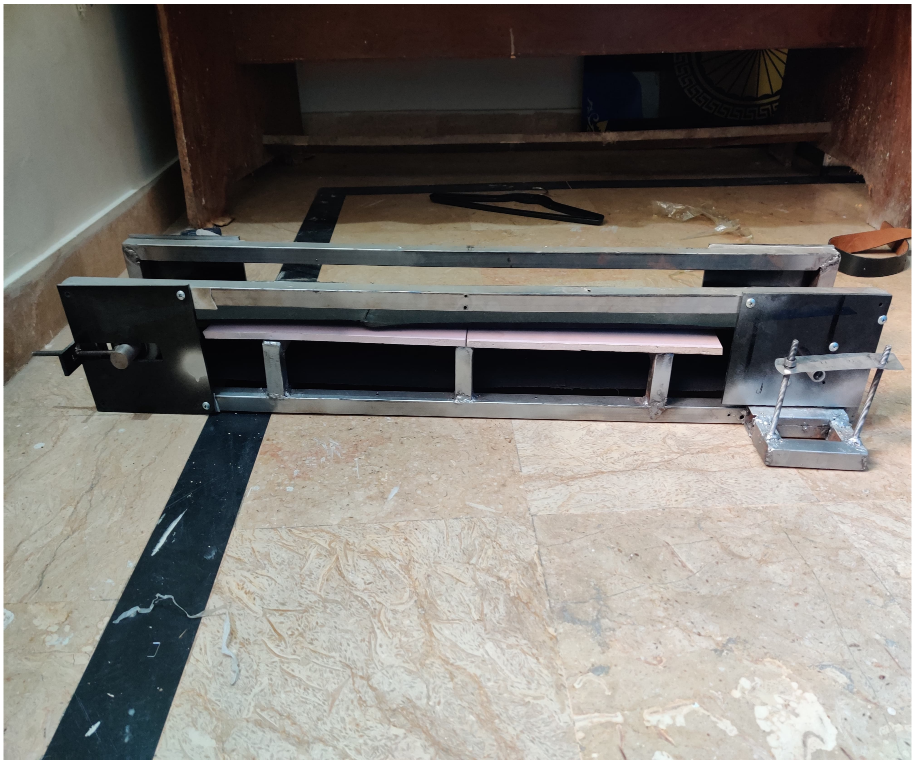


Fig 3.6: Conveyor Belt

The conveyor belt in the liquid filling station is a key component that facilitates the movement of bottles through the filling and capping processes. It consists of a 3-foot-long metal structure with plastic rollers at both ends. The belt itself is made of rexine sheet, a durable and flexible material that is ideal for conveying bottles without causing damage.

The metal structure provides a stable base for the conveyor belt, ensuring smooth and consistent movement. The plastic rollers at the ends allow for easy rotation of the belt, facilitating the transport of bottles along the conveyor line. The rexine sheet belt is chosen for its durability and resistance to wear and tear.

It is also easy to clean, which is important for maintaining hygiene in the filling station. Overall, the conveyor belt is a critical component in the liquid filling station, providing a reliable and efficient means of transporting bottles through the filling and capping processes.

3.2.6 DC Water Pump

Fig 3.7: DC Water pump

The DC water pump is tasked with dispensing liquid into bottles with precision and consistency. Its selection hinges on several factors, including compatibility with the PLC and the ability to maintain a controlled flow rate. The DC water pump operates independently, driven solely by power input. This standalone operation simplifies its integration into the system while ensuring reliable performance. The pump's mechanism involves a series of components working in tandem to facilitate fluid transfer. When activated, the pump draws liquid from a reservoir or supply source and propels it through a system of pipes or tubing to the designated filling point.

Its efficiency and reliability are paramount in maintaining the throughput and accuracy of the filling process. In the liquid filling station, the DC water pump's operation is optimized for efficiency and speed. Rather than adjusting flow rates dynamically, the pump is typically activated for a predetermined duration, precisely calibrated to dispense the required volume of liquid into each bottle. The pump has a filling speed of 10 liters per minute, it may only need to run for approximately 3 seconds to fill a standard 500ml bottle. This time-dependent approach streamlines operations, minimizing energy consumption and maximizing throughput without compromising accuracy.

3.2.7 Raspberry Pi

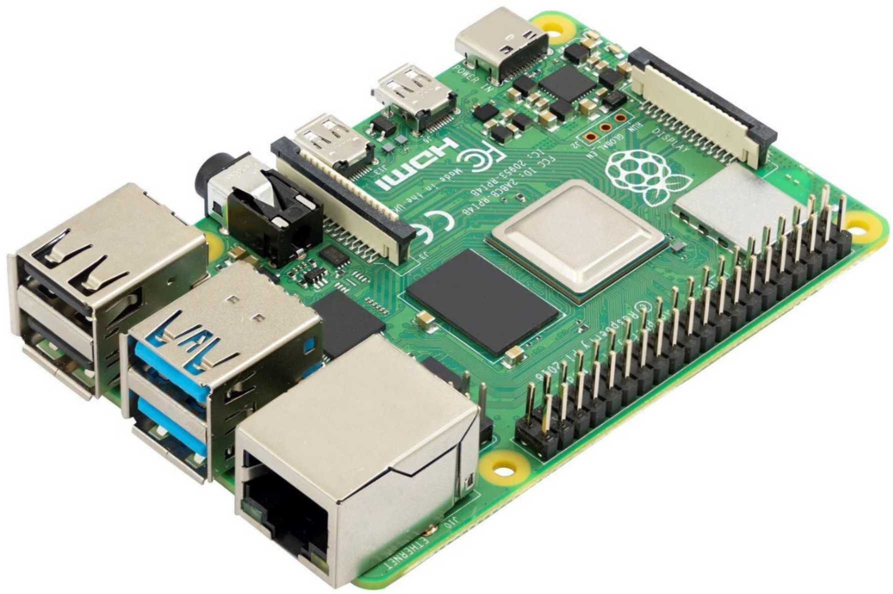


Fig 3.8: Raspberry Pi 4 Model B

The Raspberry Pi 4 Model B is a highly capable and flexible single-board computer designed for a broad range of applications. It is equipped with a powerful quad-core processor, ample memory options, and robust connectivity features, making it suitable for everything from basic educational projects to advanced industrial applications[14]. Its compact size and affordable price point further enhance its appeal, enabling users to deploy it in various innovative solutions, including home automation, IoT projects, and media centers.

In the context of object detection, the Raspberry Pi 4 Model B is particularly effective due to its enhanced processing power and support for advanced software frameworks like TensorFlow and OpenCV. We are utilizing the Raspberry Pi 4 Model B for a bottle detection system on a conveyor belt, aimed at ensuring bottles are correctly positioned before filling. The system checks whether a bottle is placed straight or tilted; if a bottle is detected to be tilted, an emergency button is triggered to stop the conveyor. The Raspberry Pi then communicates this status to the PLC S7-1200, which acts as the main controller for the bottle filling station. This integration ensures precise control and timely interventions, enhancing the efficiency and safety of the filling process.

3.2.8 Camera for AI

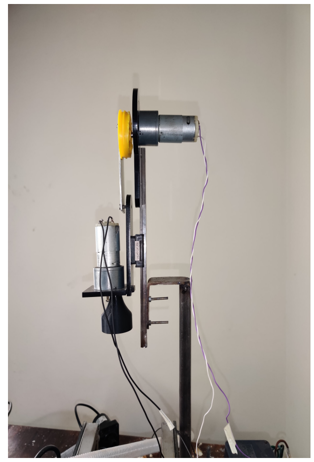
Fig 3.9: Camera ArduCam 15MP

The camera integrated with Yolo v8 AI technology is a pivotal component for real-time bottle detection and classification[17]. This camera continuously monitors the conveyor belt, identifying upright bottles and ensuring they are correctly positioned for filling and capping. The use of Yolo v8 enhances the system's ability to detect misalignment's or anomalies, triggering pauses or adjustments as necessary to maintain operational integrity. The camera's high resolution and AI capabilities ensure accurate monitoring, contributing to the system's overall efficiency and reliability.

The Arducam camera, operating at 30 frames per second (fps), is an excellent companion to the Raspberry Pi 4 Model B for object detection tasks. This high frame rate allows for smooth and accurate real-time video capture, essential for applications requiring precise motion detection and analysis. When connected to the Raspberry Pi 4, the Arducam leverages the board's robust processing capabilities to efficiently run computer vision algorithms using frameworks like OpenCV and TensorFlow. This combination is particularly effective in dynamic environments, such as monitoring a conveyor belt for bottle orientation, where the camera continuously feeds video to the Raspberry Pi.

3.2.9 Bottle Capping Mechanism

(a) Capping Mechanism Front



(b) Capping Mechanism Side

Fig 3.10: Overall Capping Mechanism

The bottle capping mechanism is designed for automated capping of bottles after filling. It consists of several components, including steel rails, two 12V gear motors, and a cap holder. The first gear motor is responsible for providing rotary motion to lift the second gear motor up and down along the steel rails. This vertical movement is crucial for positioning the cap holder over the bottle for sealing. The second gear motor's role in the capping mechanism is pivotal for securely sealing the bottle. Its clockwise rotation drives the cap holder, which is positioned over the bottle neck, ensuring a tight seal. This rotational motion provides the necessary torque to twist the cap onto the bottle threads, creating a secure closure that prevents leaks or spills.

The control of each gear motor through a relay connected to the PLC is a crucial aspect of the capping process. The PLC sends precise ON and OFF signals to the relays, dictating the start and stop of each motor's operation. This control mechanism allows for synchronized movement between the two motors, ensuring that the lifting and rotating actions occur in sequence and with the correct timing. As a result, the capping process is not only accurate but also efficient, minimizing the risk of errors and ensuring that each bottle is sealed correctly before moving to the next stage of the filling process.

Additionally, the mechanism is welded onto the conveyor base, providing stability and ensuring that the capping process is synchronized with the bottle transport process. Overall, the bottle capping mechanism is an integral part of the liquid filling station, ensuring that bottles are securely sealed after filling, ready for distribution.

3.3 Hardware Specification Sheet

Table 3.3: Hardware Specification Sheet

Component	Model	Specifications
Siemens PLC	Simatic S7-1200 CPU 1211C DC/DC/DC	Power Supply: 20.4-28.8V DC Digital Inputs: 6 x 24V DC Digital Outputs: 4 x 24V DC Analog Inputs: 2 x 0-10V DC Program/Data Memory: 50 KB
Variable Speed Drive	Siemens Sinamics G110	Power Supply: Single Phase 200-240V AC, 50-60Hz Output Power: 0.75kW (1 HP) Output Frequency: 0-650Hz Input Current: 10A Overload Capacity: 150% for 60 seconds
Induction Motor	S8125GS-G61	Operating Voltage: 220V AC Rated Speed: 1500 RPM Power Output: 0.75kW (1 HP)
Shaft Encoder	E6B2-CWZ6C	Resolution: 1024 pulses per revolution Power Supply: 5-24V DC Output: Incremental
Gear Motor	—	Operating Voltage: 6-12V DC Rated Speed: Varies depending on the model Torque: Varies depending on the model
Raspberry Pi 4	Model B	CPU: Quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz Memory: 2GB, 4GB, or 8GB LPDDR4-3200 SDRAM Networking: Gigabit Ethernet Wireless: 2.4GHz and 5.0GHz IEEE 802.11ac wireless Bluetooth: Bluetooth 5.0, BLE USB: 2 x USB 3.0 ports, 2 x USB 2.0 ports Video Output: 2 x micro HDMI ports (up to 4Kp60 supported) Power Supply: 5V DC via USB-C connector
Camera	Camera Board v1.3	Resolution: 5 Megapixels Video: 1080p at 30fps, 720p at 60fps, 640x480p at 90fps Interface: CSI-2 Operating Voltage: 3.3V (supplied by Raspberry Pi)

3.4 PLC Software’s

3.4.1 Rockwell Automation’s Studio 5000

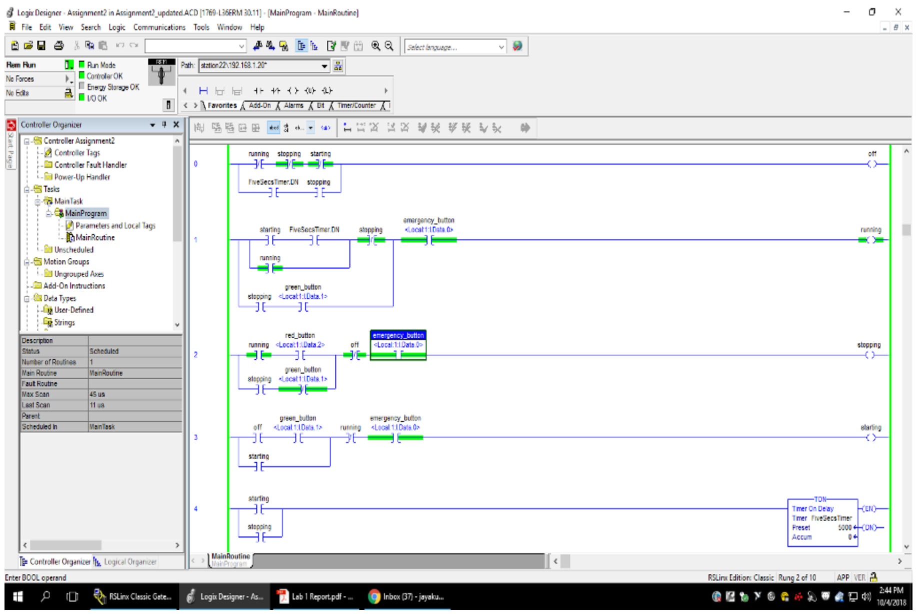


Fig 3.11: Studio 5000

Studio 5000, from Rockwell Automation, is a popular software platform for programming Allen-Bradley PLCs. It offers a range of features for programming, configuration, and diagnostics. Studio 5000 provides a common environment for programming various Allen-Bradley controllers, facilitating consistency across different automation projects. Its strengths lie in its compatibility with Rockwell Automation’s hardware and extensive support ecosystem. However, it may have a steeper learning curve compared to TIA Portal, especially for users transitioning from other platforms.

One notable advantage of Studio 5000 is its extensive support ecosystem, which includes a wealth of resources such as online forums, training courses, and technical documentation. This robust support network is invaluable for users seeking assistance with troubleshooting, optimization, or learning new features. Additionally, Rockwell Automation’s widespread presence in the industrial automation market ensures that users have access to a wide range of compatible hardware components and accessories, offering flexibility in system design and scalability. Despite its steeper learning curve, particularly for those transitioning from other platforms, Studio 5000’s comprehensive feature set and strong support infrastructure make it a compelling choice for industries relying on Allen-Bradley PLCs.

3.4.2 Mitsubishi's GX Works3

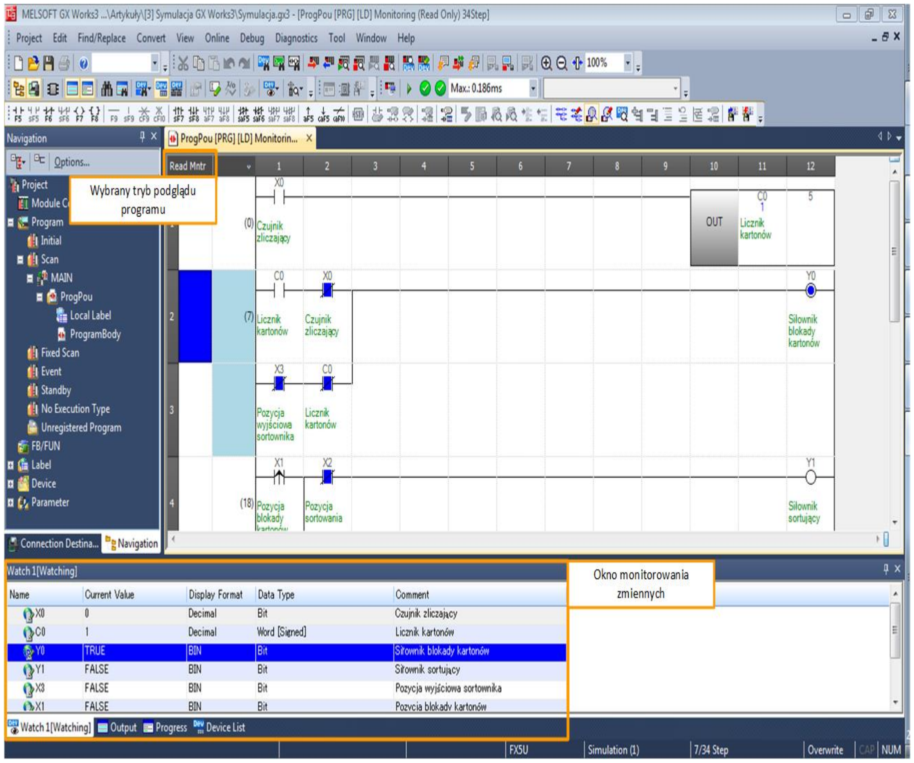


Fig 3.12: GX Works

GX Works3 is Mitsubishi Electric's programming software for its PLCs and other automation devices. It offers a range of programming and debugging tools tailored for Mitsubishi hardware. GX Works3 provides a user-friendly interface and supports various programming languages, including ladder logic, structured text, and function block diagram. While it is well-suited for Mitsubishi PLCs, its integration capabilities with third-party devices and systems may be more limited compared to TIA Portal[9].

In the context of project, GX Works3's optimization for Mitsubishi Electric's PLCs and automation devices offers tailored programming and debugging tools that can enhance productivity and efficiency. The user-friendly interface of GX Works3 ensures that both novice and experienced programmers can navigate the software seamlessly, expediting the development process. Given the diverse programming languages supported by GX Works3, including ladder logic, structured text, and function block diagram, you have the flexibility to choose the most suitable programming approach for your project. However, it's essential to consider potential limitations in integration capabilities with third-party devices and systems, particularly if interoperability across heterogeneous automation environments is a crucial requirement for your project.

3.4.3 Control Expert

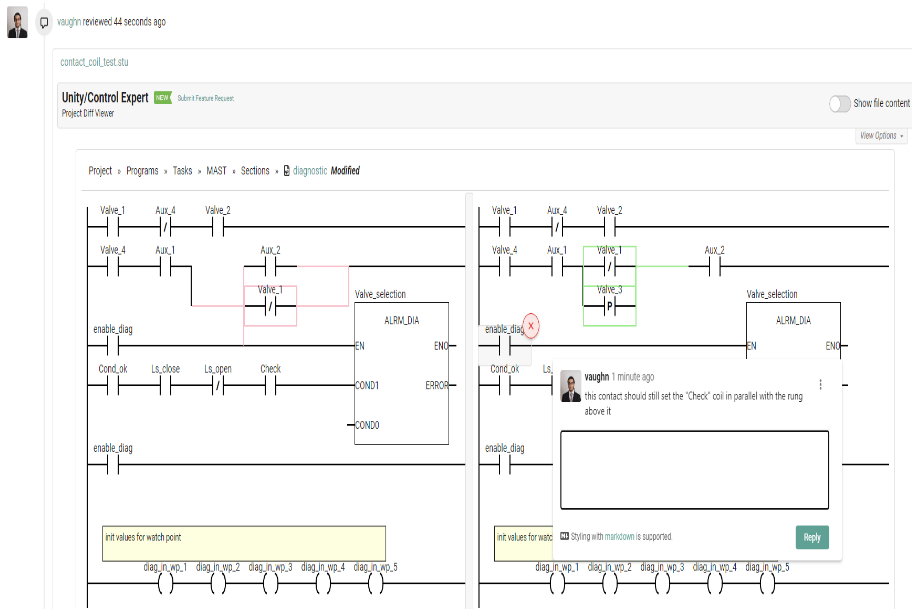


Fig 3.13: Control Expert

EcoStruxure Control Expert, previously known as Unity Pro, is Schneider Electric's software for programming its Modicon PLCs. It offers a comprehensive set of tools for programming, simulation, and debugging. EcoStruxure Control Expert supports multiple programming languages and provides advanced features for complex automation applications. It integrates well with Schneider Electric's ecosystem of automation solutions, offering seamless connectivity and interoperability. However, its compatibility may be limited to Schneider Electric's hardware, unlike TIA Portal's broader support for various manufacturers[8].

EcoStruxure Control Expert's comprehensive set of tools for programming, simulation, and debugging is well-suited for addressing the complexities of your bottle detection and filling system. Its support for multiple programming languages and advanced features tailored for complex automation applications empower you to tackle the diverse requirements of your project with confidence. The seamless integration with Schneider Electric's ecosystem of automation solutions enhances connectivity and interoperability within your system, ensuring smooth communication between Schneider Electric hardware and software components. However, it's important to note that EcoStruxure Control Expert's compatibility may be limited to Schneider Electric's hardware, potentially impacting its applicability in environments utilizing equipment from different manufacturers.

3.4.4 Sysmac Studio

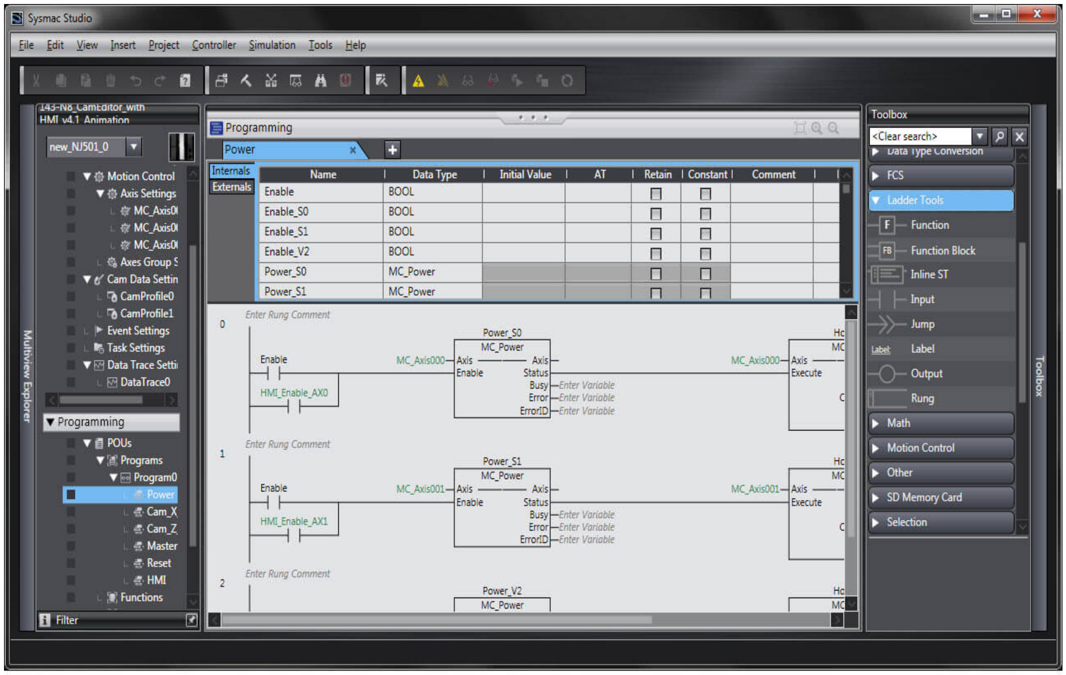


Fig 3.14: Sysmac Studio

Sysmac Studio is Omron's integrated development environment for programming its PLCs, motion controllers, and other automation devices. It offers a range of programming languages and tools for efficient development and maintenance of automation systems. Sysmac Studio provides features like simulation, monitoring, and debugging to streamline the programming process. While it is well-suited for Omron hardware, its compatibility with third-party devices and systems may be more limited compared to TIA Portal[10].

Sysmac Studio's integrated development environment offers a streamlined approach to programming your bottle detection and filling system, allowing you to efficiently develop and maintain automation systems tailored to your specific needs. The range of programming languages and tools available in Sysmac Studio enables you to implement the necessary logic and functionality required for precise bottle detection and accurate filling processes. Features such as simulation, monitoring, and debugging facilitate rapid iteration during the development cycle, ensuring that your system meets performance requirements effectively. However, it's essential to consider potential limitations in compatibility with third-party devices and systems, as this may impact interoperability and integration capabilities in heterogeneous automation environments.

3.4.5 TIA Portal V18

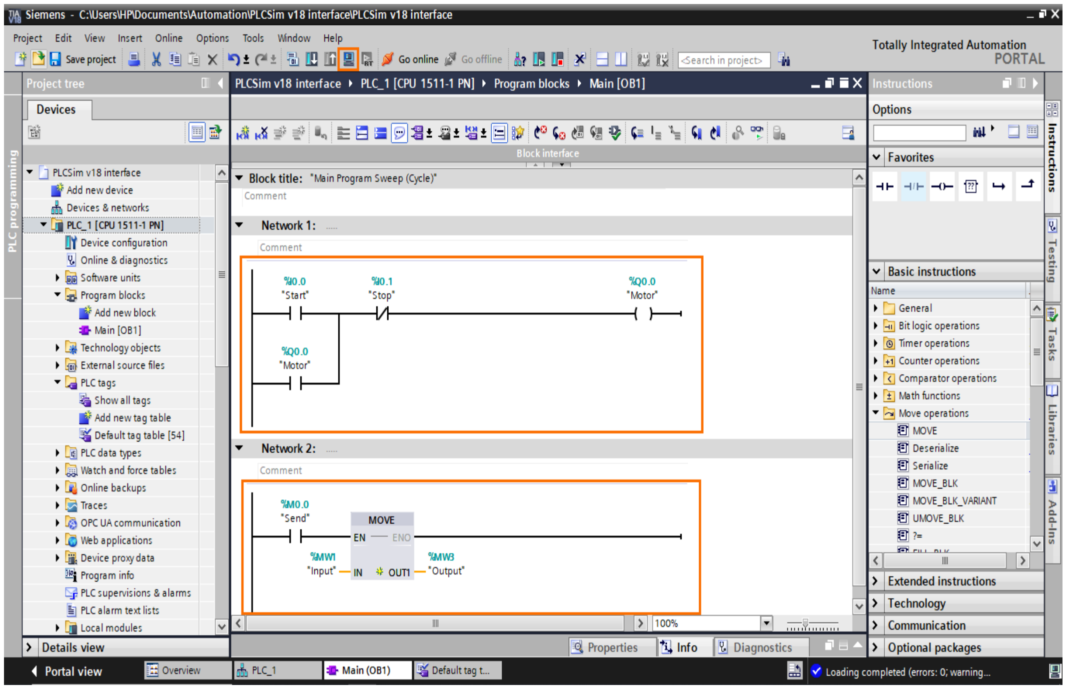


Fig 3.15: TIA Portal V18

TIA Portal, developed by Siemens, offers a comprehensive suite of tools for configuring, programming, and diagnosing Siemens PLCs, such as the S7-1200. Its user-friendly interface and integration capabilities make it a preferred choice for industrial automation projects. TIA Portal streamlines the development process with features like drag-and-drop programming, simulation tools, and extensive diagnostics, enabling efficient project implementation and maintenance. Moreover, TIA Portal's reputation for reliability and robustness further solidifies its position as a leading platform in the automation industry[10].

In the context of our bottle detection and filling system project, TIA Portal V18 emerges as the ideal choice for several reasons. Firstly, its user-friendly interface significantly reduces the learning curve for our team members, ensuring a smooth transition and accelerating the implementation process. With intuitive features and a well-organized layout, TIA Portal V18 empowers our engineers to focus on developing the functionality of the system rather than grappling with complex software navigation. Additionally, its extensive documentation and online resources provide valuable support throughout the development cycle, aiding in troubleshooting and optimization tasks.

Furthermore, TIA Portal's comprehensive suite of tools caters to every stage of the automation life-cycle, from initial configuration to ongoing diagnostics and maintenance. This holistic approach streamlines our development process, allowing us to efficiently tackle challenges at each stage without the need for multiple software platforms or disjointed workflows. Whether it's configuring PLCs, programming logic, or diagnosing issues, TIA Portal V18 provides a cohesive environment that fosters collaboration and productivity among our team members. Moreover, its modular architecture allows for scalability, enabling us to easily expand our system in the future to accommodate growing needs or additional functionalities.

Furthermore, the extensive compatibility of TIA Portal V18 with Siemens hardware is particularly advantageous for our project. Since we are utilizing Siemens PLCs, such as the S7-1200, TIA Portal's seamless integration with these devices ensures optimal performance and reliability. This compatibility not only simplifies the setup and configuration process but also minimizes compatibility issues, reducing the risk of errors and downtime during system operation. Additionally, TIA Portal's support for various communication protocols facilitates interoperability with other devices and systems, enhancing the flexibility and versatility of our automation solution.

Additionally, TIA Portal V18 offers advanced features for Human-Machine Interface (HMI) design and simulation, further enhancing its appeal for our project. With built-in HMI development tools, we can create intuitive and visually appealing interfaces for operators to monitor and control the bottle detection and filling process. The ability to simulate the system behavior within TIA Portal V18 allows us to validate our logic and HMI designs before deployment, ensuring that the system operates as intended and minimizing the risk of costly errors or rework. Furthermore, TIA Portal's support for multi-language interfaces enables us to cater to diverse user needs and preferences, enhancing user satisfaction and usability.

In summary, TIA Portal V18 stands out as the preferred choice for our bottle detection and filling system project due to its user-friendly interface, comprehensive tool set, compatibility with Siemens hardware, and advanced features for HMI design and simulation. By leveraging TIA Portal V18, we can streamline our development process, enhance collaboration, and ultimately deliver a robust and efficient automation solution tailored to our specific requirements.

3.5 PLC Software's Comparison

Table 3.4: PLC Software Comparisons

Features	TIA Portal V18	Studio 5000	GX Works3	Control Expert	Sysmac Studio
Manufacturer	Siemens	Rockwell Automation	Mitsubishi Electric	Schneider Electric	Omron
PLC Support	S7-300, S7-1200, S7-1500	ControlLogix, Compact-Logix	MELSEC Series	Modicon M340, M580	NJ/NX Series
Programming Languages	LAD, FBD, STL, SCL	LAD, FBD, ST	LAD, ST, SFC, FBD	LD, ST, FBD, IL, SFC	LD, ST, FBD, SFC
User Interface	Integrated, Intuitive	Modern, User-friendly	Comprehensive, Modular	Advanced, Graphical	Flexible, Integrated
Simulation Capabilities	Yes	Yes	Yes	Yes	Yes
Hardware Configuration	Comprehensive	Extensive	Detailed	Extensive	Comprehensive
SCADA Integration	Seamless with WinCC	Compatible with FactoryTalk	Compatible with MC Works64	Seamless with Citect SCADA	Compatible with CX-Supervisor
Learning Curve	Moderate	Moderate	Moderate	Steep	Moderate

3.6 PLC Programming Languages

Ladder Logic, Structured Text, Function Block Diagram, and Instruction List are four widely used programming languages in the realm of Programmable Logic Controllers (PLCs). Each language offers unique advantages and is tailored to specific programming needs and preferences. In the following sections, we will delve into the details of each programming language, exploring their syntax, functionality, and applications in industrial automation. By understanding the intricacies of these languages, we can make informed decisions when selecting the most suitable approach for programming PLCs in various automation projects.

3.6.1 Structured Text

Structured Text represents a more advanced approach to PLC programming compared to ladder logic, leveraging text-based coding skills and knowledge of programming languages. While it may present a steeper learning curve initially, structured text offers greater flexibility and power for handling complex automation tasks. Programmers familiar with other text-based languages find structured text easier to work with, as it allows for the use of loops, conditional statements, and mathematical operations, enabling precise control and calculations.

However, debugging structured text programs can be more challenging due to the lack of visual representation, requiring a deeper understanding of the code and programming concepts. In certain projects requiring complex algorithms and calculations, such as sensor fusion or advanced control algorithms, structured text may offer significant advantages over ladder logic. Its flexibility and ability to handle intricate logic make it suitable for tackling sophisticated automation tasks.

However, structured text may demand more programming expertise and involvement, potentially increasing development time and complexity compared to ladder logic. Despite these challenges, structured text remains a valuable tool for projects demanding precise control and calculations, offering advanced capabilities beyond the scope of ladder logic. While structured text provides advanced capabilities for complex automation tasks, its adoption may not be suitable for all projects, especially those emphasizing simplicity and ease of understanding.

In comparison to ladder logic, which offers a more straightforward visual representation of program logic, structured text requires a deeper understanding of programming concepts and syntax. Maintenance and troubleshooting of structured text programs may necessitate the involvement of programmers, limiting accessibility to technicians and electricians without programming experience.

Overall, the decision to use structured text depends on the specific requirements and complexity of the automation project, weighing the benefits of advanced functionality against the challenges of increased complexity and programming expertise required.

3.6.2 Function Block Diagram (FBD)

Function Block Diagram (FBD) programming language offers a graphical representation that utilizes interconnected function blocks to depict program elements. FBD's modular approach allows for the creation of reusable blocks, making it particularly suitable for applications with complex data flow and interaction between program elements. The graphical nature of FBD simplifies understanding, as users can visualize program logic through the interconnected function blocks. Troubleshooting FBD programs benefits from this visual representation, though understanding the functionality of each block may require some knowledge of the underlying code or function it represents.

Despite its advantages, FBD may pose challenges for beginners, especially when dealing with intricate programs. In projects requiring modular programming and advanced data flow control, Function Block Diagram (FBD) offers significant advantages over ladder logic. Its graphical representation facilitates the visualization of program logic, enhancing understanding and maintainability. The modular nature of FBD allows for the breakdown of complex functions into reusable blocks, improving program clarity and scalability. However, like structured text, FBD may require a deeper understanding of programming concepts and function blocks, potentially increasing development time and complexity compared to ladder logic.

Despite these challenges, FBD remains a valuable tool for projects requiring modular programming and advanced data flow control, offering flexibility and scalability beyond the capabilities of ladder logic. While Function Block Diagram (FBD) provides benefits in terms of modularity and scalability, its adoption may introduce additional complexities and challenges compared to ladder logic. The graphical representation of function blocks offers a visual way to represent program logic, making it easier to understand for some users. However, troubleshooting and debugging FBD programs may still require expertise to identify issues within individual function blocks or interactions between blocks. Additionally, maintenance of FBD programs may require someone with an understanding of the function blocks used, potentially limiting accessibility to technicians and electricians without programming experience.

Overall, the decision to use FBD depends on the specific requirements of the automation project, weighing the benefits of modularity and scalability against the challenges of increased complexity and maintenance requirements.

3.6.3 Instruction List

Instruction List (IL) is a text-based programming language that utilizes mnemonics to represent instructions, similar to assembly language programming. IL offers a low-level approach to PLC programming, providing precise control over individual instructions and memory locations. While IL may be challenging to learn and understand for those without prior experience with programming languages, it offers a high degree of flexibility and control for advanced automation tasks.

However, understanding IL programs requires knowledge of the specific instructions and commands used, and the logic flow can be difficult to follow compared to visual languages like ladder logic or FBD. In certain projects requiring fine-grained control and optimization, such as low-level manipulation of PLC memory and registers, Instruction List (IL) may offer significant advantages over ladder logic. Its text-based nature allows for direct access to individual instructions, making it suitable for implementing custom algorithms and optimization techniques.

However, the complexity of IL programs and the need for expertise to understand and debug them may pose challenges for teams with limited programming experience. Despite these challenges, IL remains a valuable tool for projects requiring precise control and optimization, offering capabilities beyond the scope of visual programming languages like ladder logic. While Instruction List (IL) provides advanced capabilities for low-level control and optimization, its adoption may introduce additional complexities and challenges compared to ladder logic.

The text-based nature of IL requires users to have a deep understanding of the specific instructions and commands used, as well as the underlying hardware architecture of the PLC. Debugging IL programs can be challenging due to the lack of visual representation, making it difficult to pinpoint errors or issues. Additionally, maintenance of IL programs typically requires a programmer's involvement, limiting accessibility to technicians and electricians without programming experience.

Overall, the decision to use IL depends on the specific requirements of the automation project, weighing the benefits of low-level control and optimization against the challenges of increased complexity and maintenance requirements.

3.6.4 Ladder Logic

Ladder logic, a cornerstone of industrial automation, combines simplicity with robust functionality, making it a preferred choice for diverse applications. Its intuitive graphical nature facilitates rapid comprehension of program flow, simplifying troubleshooting and maintenance tasks. Moreover, its compatibility with various PLCs ensures versatility and ease of integration, contributing to its widespread adoption across industries.

In our bottle detection and filling system automation project, we opted for ladder logic due to its simplicity and compatibility with our team's skill set, primarily consisting of technicians and electricians. The visual representation of ladder logic enabled rapid development and debugging of the PLC program, allowing us to efficiently address any challenges during implementation. Furthermore, its widespread usage in the industry ensured that our team members were familiar with its concepts, reducing training requirements and accelerating the project timeline.

Compared to other programming languages like structured text, function block diagram, and instruction list, ladder logic stands out for its unparalleled ease of understanding and intuitive visual representation. While these languages offer advanced capabilities, ladder logic's simplicity and familiarity made it the preferred choice for our project. By leveraging ladder logic, we streamlined development, enhanced collaboration, and ensured the successful deployment of our bottle detection and filling system, effectively meeting project requirements.

Furthermore, the flexibility of ladder logic allows for easy modifications and expansions as project requirements evolve over time. Its modular structure facilitates scalability, enabling seamless integration of new functionalities or adjustments to existing processes without significant disruptions. This adaptability is particularly beneficial in dynamic industrial environments where operational needs may change frequently.

In summary, ladder logic's combination of simplicity, versatility, and ease of integration makes it an indispensable tool in industrial automation projects like ours. Its intuitive nature empowers technicians and electricians to effectively control and monitor complex processes, ensuring efficiency, reliability, and ultimately, the success of automation initiatives.

3.7 PLC Programming Languages Comparison

Table 3.5: Comparison of PLC Programming Languages

Features	Ladder Logic	Structured Text	Function Block Diagram	Instruction List
Ease of Use	Easy to follow	Needs Programming language knowledge	Graphical, Logic can be complex	Requires understanding commands
Troubleshooting	Easy to trace program flow	Requires debugging skills	logic flow visually trackable	Difficult to find errors
Maintenance	Easy for technicians	Needs programmers	May need programmer involvement	Needs programmers
Flexibility	Versatile	Powerful for complexity	Good for modular programming	Somewhat limited flexibility
Industry usage	Widely used	Commonly used for complex tasks	Commonly used for specific applications	Less commonly used

3.8 Integrated Development Environments (IDEs)

An Integrated Development Environment (IDE) is a software application that provides comprehensive facilities for software development, including a source code editor, build automation tools, and a debugger, all within a single interface to enhance productivity. Visual Studio Code (VS Code), an open-source IDE by Microsoft, supports various programming languages and offers features like IntelliSense, integrated debugging tools, and built-in Git for version control. It is widely used for tasks including web development and data analysis but lacks GPU acceleration for complex model training. Google Colab, a cloud-based IDE for data science and machine learning, offers a Jupyter notebook interface, real-time collaboration, free GPU/TPU access, and integration with Google Drive, making it ideal for training and testing ML/DL models.

3.8.1 Visual Code

Visual Studio Code is widely acclaimed for its versatility and extensive features tailored for software development, including Python programming. However, when it comes to machine learning tasks such as object detection and classification, VS Code lacks built-in support for GPU acceleration. As a result, training deep learning models on local computing resources can be time-consuming and inefficient, especially for large-scale datasets. While VS Code offers a user-friendly interface and robust code editing capabilities, its limitations in GPU support may hinder the productivity and performance of machine learning projects, prompting users to seek alternative platforms like Google Colab for GPU-accelerated model training.

3.8.2 Google Colab

Google Colab stands out as a powerful platform for developing machine learning models, thanks to its provision of free access to GPU resources. This GPU acceleration significantly expedites the training process for deep learning models, particularly for tasks like object detection and classification, which often involve complex neural network architectures and large datasets. Moreover, Colab offers seamless integration with popular machine learning libraries such as TensorFlow and PyTorch, along with pre-installed dependencies, streamlining the development workflow. With Colab's cloud-based infrastructure, users can leverage its scalable computing resources without the need for expensive hardware investments, making it an accessible and cost-effective solution for machine learning projects.

The decision to opt for Google Colab over Visual Studio Code for object detection and classification tasks boils down to the availability of GPU acceleration and cloud-based computing resources. Google Colab's seamless integration with GPUs allows for faster model training and experimentation without the need for expensive hardware investments. Moreover, Colab's collaborative features facilitate team collaboration and knowledge sharing, enhancing productivity and efficiency. While Visual Studio Code offers a robust development environment for Python programming, its lack of native GPU support limits its suitability for computationally intensive tasks like deep learning. Overall, Google Colab's combination of GPU acceleration, cloud-based infrastructure, and collaborative features makes it the preferred choice for developing and deploying object detection and classification models.

3.9 Object Detection Algorithms

Object detection is a pivotal aspect of computer vision, involving the identification and localization of objects within an image or video. This technology is essential in various applications, from autonomous driving to industrial automation. For our PLC-based bottle filling station, several models can be employed for effective object detection, including Faster R-CNN, SSD, YOLOv3, YOLOv4, YOLOv8, RetinaNet, DSSD, and Mask R-CNN. Each model offers unique strengths in terms of accuracy, speed, and resource requirements. We will explore the details and suitability of these models for our specific application next. Effective object detection is critical for optimizing the efficiency and accuracy of our bottle filling station, ensuring seamless operation and minimizing errors. By carefully evaluating the strengths and limitations of each model, we can make an informed decision to select the most suitable approach for our PLC-based system.

3.9.1 Faster R-CNN

Faster R-CNN stands out in the realm of object detection for its remarkable accuracy, leveraging a two-stage architecture to meticulously identify objects within images. Its methodology involves employing a region proposal network (RPN) to generate potential object locations, followed by a subsequent network to classify these proposed regions. This approach yields highly precise results, making it suitable for applications where exact object recognition is critical. However, this accuracy comes at the cost of speed, as Faster R-CNN tends to have a slower response time compared to some other algorithms. Additionally, it necessitates a substantial amount of training data and hardware resources, making it more resource-intensive to deploy and maintain.

In our PLC-based bottle filling station project, Faster R-CNN could be instrumental in ensuring precise detection of bottles moving along the conveyor belt. Its high accuracy aligns well with the need for accurate identification of bottles to facilitate efficient filling operations. However, the slower response time may pose challenges in a real-time production environment, potentially impacting the overall throughput of the system. Furthermore, the requirement for a significant amount of training data and hardware resources may increase the complexity and cost of implementing Faster R-CNN within our system. Therefore, while it offers unparalleled accuracy, careful consideration must be given to the trade-offs in speed and resource utilization.

3.9.2 Single Shot MultiBox Detector (SSD)

SSD strikes a balance between accuracy and speed in object detection tasks, making it a versatile choice for various applications. Its single-shot architecture enables faster response times compared to two-stage detectors like Faster R-CNN, while still maintaining satisfactory accuracy levels. SSD achieves this by predicting object bounding boxes and class probabilities directly from feature maps at multiple scales, streamlining the detection process. While it may not match the accuracy of more complex algorithms, its efficiency makes it suitable for real-time applications where speed is paramount. However, SSD still requires moderate training data and hardware resources, although less than Faster R-CNN.

In our PLC-based bottle filling station project, SSD could provide an optimal solution for quickly and accurately identifying bottles on the conveyor belt. Its balanced performance in terms of accuracy and speed aligns well with the real-time processing requirements of our system. By leveraging SSD, we can ensure swift detection of bottles without compromising on accuracy, thereby enhancing the overall efficiency of the filling station. Moreover, SSD's moderate training data and hardware resource requirements make it a practical choice for implementation within our system, offering a good compromise between performance and resource utilization.

3.9.3 You Only Look Once (YOLO) v3

YOLOv3 is renowned for its exceptional speed in object detection tasks, making it a preferred choice for real-time applications. Its single-stage architecture processes images as a whole to generate bounding boxes and class predictions simultaneously, resulting in rapid detection. However, this speed may come at the expense of accuracy compared to more complex algorithms like Faster R-CNN. Despite this trade-off, YOLOv3 remains highly efficient and requires only moderate training data and hardware resources, making it accessible for various applications.

In our PLC-based bottle filling station project, YOLOv3's speed could be advantageous for swiftly identifying bottles on the conveyor belt in real-time. Its ability to process images quickly aligns with the fast-paced nature of production environments, ensuring timely detection of bottles for efficient filling operations. While YOLOv3 may sacrifice some accuracy compared to other algorithms, its rapid response time and moderate resource requirements make it a practical choice for our system.

3.9.4 You Only Look Once (YOLO) v4)

YOLOv4 builds upon the success of its predecessor, aiming to improve both accuracy and speed in object detection tasks. It incorporates various enhancements and optimizations to achieve a better balance between these two crucial metrics. With a focus on real-time performance, YOLOv4 strives to maintain high accuracy levels while delivering faster response times compared to previous versions. This makes it a compelling choice for applications requiring rapid object detection without compromising on precision. However, like other YOLO variants, YOLOv4 may not achieve the same level of accuracy as more complex algorithms like Faster R-CNN.

In our PLC-based bottle filling station project, YOLOv4 could offer significant advantages in quickly and accurately identifying bottles on the conveyor belt. Its improved performance in terms of both accuracy and speed makes it an attractive option for ensuring efficient operation of the filling station. By leveraging YOLOv4, we can achieve fast and reliable bottle detection, facilitating seamless integration into our production environment.

3.9.5 RetinaNet

RetinaNet is renowned for its exceptional accuracy in object detection tasks, making it a preferred choice for applications where precise identification of objects is paramount. It achieves this high level of accuracy through a novel focal loss function that addresses the class imbalance issue inherent in many object detection datasets. By focusing on both localization and classification, RetinaNet delivers robust performance across various object scales and aspect ratios. However, this high accuracy comes with a trade-off of slower response times compared to faster algorithms like YOLOv3. Additionally, RetinaNet requires a significant amount of training data and hardware resources, making it more resource-intensive to deploy and maintain.

In the context of our PLC-based bottle filling station project, RetinaNet could offer unparalleled accuracy in detecting bottles on the conveyor belt. Its advanced capabilities in handling object scales and aspect ratios ensure precise identification of bottles, minimizing false positives and negatives. However, the slower response time may pose challenges in a real-time production environment, potentially impacting the overall throughput of the system.

3.9.6 Dense Detection and Segmentation Detector (DSSD)

DSSD represents a significant advancement in object detection algorithms, offering not only accurate object detection but also segmentation masks around objects. This additional capability allows for more detailed analysis and understanding of object shapes and boundaries.

In our PLC-based bottle filling station project, DSSD's ability to provide segmentation masks around detected objects could offer valuable insights into the shapes and boundaries of bottles on the conveyor belt. This detailed information can enhance the precision of object detection and facilitate more advanced analysis of bottle characteristics. However, the slower response time may pose challenges in a real-time production environment, potentially affecting the efficiency of the filling station. Furthermore, the requirement for a high amount of training data and hardware resources may increase the complexity and cost of implementing DSSD within our system. Therefore, while it offers advanced capabilities, careful consideration must be given to the trade-offs in speed and resource utilization.

3.9.7 Mask R-CNN

Mask R-CNN represents a significant advancement in object detection algorithms by extending the capabilities of Faster R-CNN to include instance segmentation. This means that not only can Mask R-CNN accurately detect objects within an image, but it can also generate precise segmentation masks outlining the boundaries of each detected object instance. However, the complexity of instance segmentation comes with a trade-off of slower response times compared to traditional object detection algorithms. Additionally, Mask R-CNN requires a significant amount of training data and hardware resources, making it more resource-intensive to deploy and maintain.

In the context of our PLC-based bottle filling station project, Mask R-CNN could offer valuable insights into the precise shapes and boundaries of bottles on the conveyor belt. However, the slower response time may pose challenges in a real-time production environment, potentially impacting the efficiency of the filling station. Furthermore, the requirement for a significant amount of training data and hardware resources may increase the complexity and cost of implementing Mask R-CNN within our system. Therefore, while it offers advanced capabilities, careful consideration must be given to the trade-offs in speed and resource utilization.

3.9.8 Yolo V8

YOLOv8 prioritizes real-time performance. Compared to its predecessors (YOLOv3 and YOLOv4), it boasts significant speed improvements without sacrificing significant accuracy. This is crucial in your project, where quick and accurate bottle detection is essential for smooth operation and avoiding malfunctions. YOLOv8 achieves its speed through a lightweight architecture. This translates to lower computational demands, making it ideal for deployment on industrial PLCs which may have limited processing power compared to high-end computing systems. This efficient design allows for seamless integration with your PLC system.

While some algorithms like Faster R-CNN offer higher accuracy, their processing times are often too slow for real-time industrial scenarios. YOLOv8 strikes a perfect balance between speed and accuracy, crucial for reliable bottle detection in your filling station. This balance ensures both efficient operation and a low risk of errors or missed detections.

3.10 Object Detection Models Comparison

Table 3.6: Comparison of Object Detection Models

Factor	Factor R-CNN	SSD	YOLOv3	YOLOv4	RetinaNet	DSSD	Mask R-CNN
Accuracy (mAP)	70-80	70-80	50-70	60-70	70-80	60-70	70-80
Response Time (ms)	100-500	20-100	10-50	8-30	40-150	30-100	200-500
Weight (MB)	100	50	40	35	50	70	150
Training Data	High	High	Moderate	Moderate	High	High	High
No of Epochs	High	Moderate	Moderate	Moderate	High	High	High
Hardware Requirements	High	Moderate	Moderate	Moderate	High	High	High

Chapter 4
Implementation & Testing

4.1 Hardware Implementation

This section provides a detailed overview of our PLC-based bottle filling station, covering its architecture, layout, construction, component placement, and circuit design. We explore the 3D layout with a labelled diagram, discuss conveyor construction, component placement, and strategic positioning of critical operations such as filling, capping, and object detection. Additionally, we outline the circuit design governing system operation, offering insights into its functionality. Detailed explanations follow in subsequent sections.

4.1.1 Design Visualization

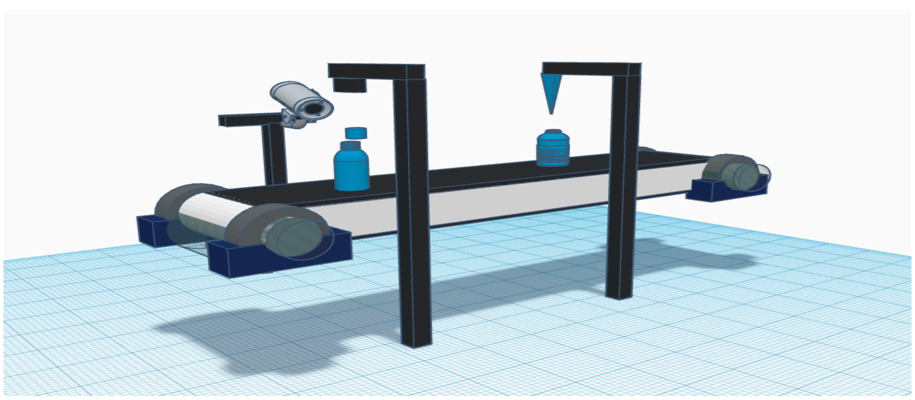


Fig 4.16: 3D Design Back View

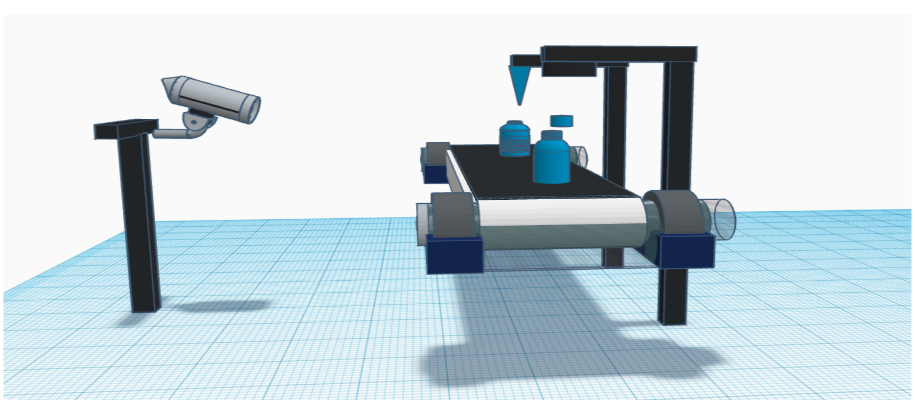


Fig 4.17: 3D Design Front View

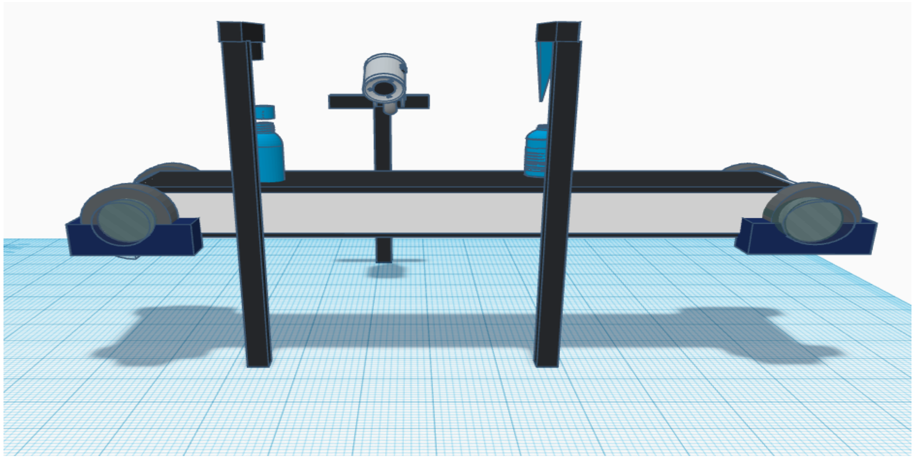


Fig 4.18: 3D Design Side View

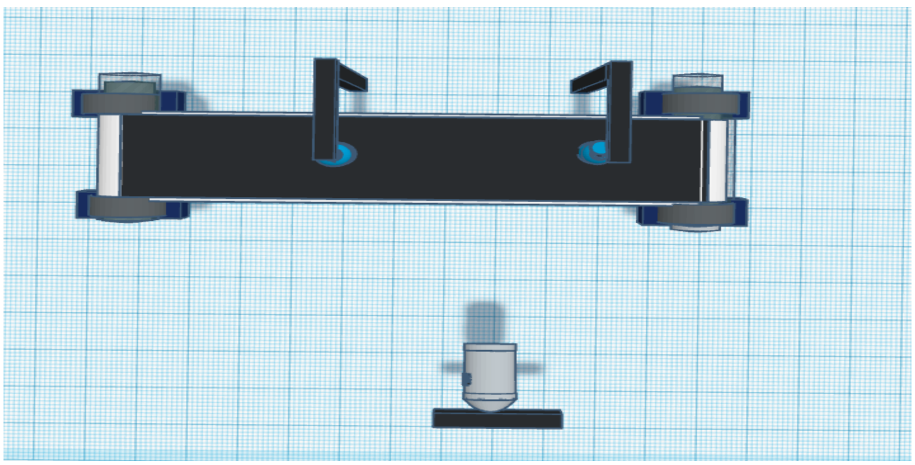


Fig 4.19: 3D Design Top View

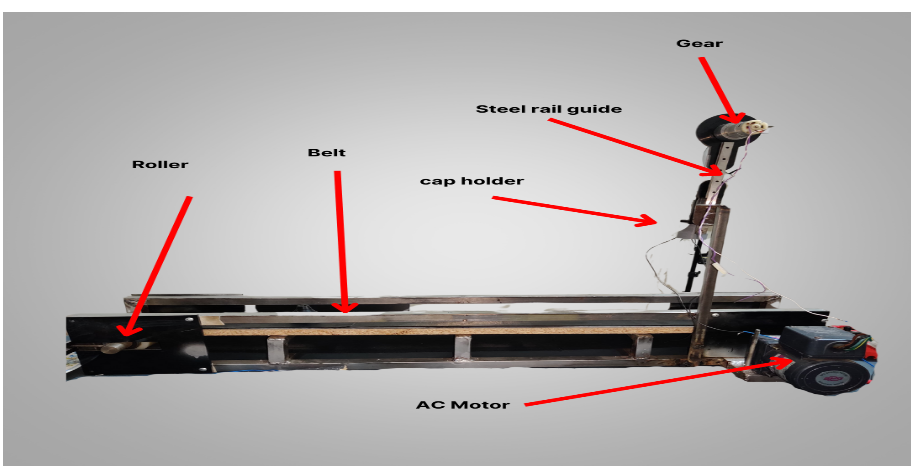


Fig 4.20: 3D Design Labelled Diagram

4.1.2 Component Placement

Conveyor belt design is integral to our PLC-controlled bottle filling station, ensuring smooth and uninterrupted bottle transport across manufacturing lines. The conveyor system eliminates jams and errors that might impede filling. Construction begins with a robust frame, typically made of steel or aluminum, providing structural integrity and support. Once the frame is complete, a rubber conveyor belt is secured with tensioning devices and fasteners. We chose high-grade resin for its toughness, flexibility, and wear resistance. The belt's dimensions are customized to meet customer specifications and accommodate specific bottle sizes.

Maintaining proper belt tension is crucial for guiding bottles correctly and preventing slippage, which can cause jams or improper bottle movement. Tensioning devices make maintenance and adjustments simpler, ensuring optimal conveyor performance. Proper alignment is also key to preventing jams and production disruptions. Rollers and guides help keep the belt centered and provide guidance, requiring regular inspection and maintenance. Additionally, frequent checks on the belt's wear and tear, as well as the condition of the tensioning devices, are essential to prevent unexpected breakdowns. Regular lubrication of moving parts further enhances smooth operation and extends the lifespan of the conveyor system.

Our design includes features like removable panels or doors for easy maintenance access, as well as safety measures like guards and emergency stop switches to protect employees. The goal is precise maintenance and design to ensure the efficient operation of the bottle filling station, leading to consistent quality products and outputs. Using high-grade materials and meticulous construction, our PLC-controlled system guarantees seamless bottle filling and enhances overall station effectiveness and efficiency.

In addition to the physical construction, the integration of the PLC (Programmable Logic Controller) is critical for the automated control of the conveyor system. The PLC ensures precise timing and coordination of the bottle filling process, adjusting speeds and stops as needed to match production requirements. This automation reduces human error, increases production speed, and allows for easy adjustments to be made for different bottle sizes and filling volumes. By combining advanced mechanical design with sophisticated control systems, we provide a reliable and efficient solution for modern bottle filling operations.

4.1.3 Filling Location

In our PLC-based bottle filling station project, determining the suitable location for the filling process is critical to ensure the efficiency and accuracy of bottle filling operations. The layout of the filling station is meticulously designed to incorporate the filling mechanism in a centralized position along the conveyor belt's trajectory. This centralized placement allows bottles to pass through seamlessly, ensuring optimal alignment with the filling mechanism for precise and consistent filling.

The selection of the ideal location for filling takes into account various factors, including accessibility, alignment with the conveyor belt, and proximity to the liquid supply source. Typically, the filling mechanism is installed above the conveyor belt at an optimal height to facilitate the smooth transfer of liquid into the bottles without the risk of spillage or splashing. Moreover, the layout of the filling station ensures sufficient clearance between the filling mechanism and other components of the conveyor system, preventing any interference during the operation.

In our setup, we utilize a 12V DC pump connected to the PLC via a relay. This configuration allows for seamless integration with the PLC, which operates at a voltage of 24V DC. The conveyor system spans approximately 38 to 40 inches, with the filling station strategically positioned along its path. After a specific distance, the capping system is placed, ensuring that both processes can work in parallel. To optimize the filling process, we introduce a 1-second delay before filling begins. This delay allows the motor to start and stabilize before commencing the filling operation, ensuring uniform and accurate filling within the specified 3-second time frame.

Once the shaft encoder detects that a bottle has reached the designated filling zone, it sends a signal to the PLC, triggering the activation of the filling mechanism. This precise coordination between the shaft encoder and the bottle detection system ensures that the liquid is released into the awaiting bottle at the right moment. By leveraging the rotational feedback from the shaft encoder, we achieve precise control over the filling process, enhancing operational efficiency and maintaining consistent product quality in our bottle filling station.

4.1.4 Capping Location

In our PLC-based bottle filling station, achieving a proper seal on bottles post-filling is paramount, and the capping process plays a central role in ensuring this outcome. To execute this task efficiently, we've integrated two gear motors into the system. The first motor is responsible for positioning the capping mechanism over the bottle, while the second motor tightens the cap securely. This dual-motor setup allows for precise control, ensuring consistent and reliable performance throughout the capping process.

As bottles progress along the conveyor belt, they reach the designated capping zone where the capping mechanism is strategically positioned. Upon bottle detection, the first gear motor is promptly activated, initiating the lowering of the capping mechanism with precision timing to align it optimally with the bottle. This meticulous alignment minimizes the risks of misalignment, ensuring a seamless capping operation. Following this, the second gear motor swiftly engages to tighten the cap securely onto the bottle, completing the process in a mere 0.2 seconds. Notably, capping occurs simultaneously with the filling process, maximizing overall throughput and operational efficiency.

To ensure precise control over motor timing and movement, we've implemented a sophisticated control algorithm that coordinates actions based on sensor signals detecting bottle presence. This algorithm orchestrates the deployment and tightening of the capping mechanism accurately and efficiently, further enhancing the reliability of the capping process. Additionally, to bolster reliability and balance, we've welded the capping system to the conveyor belt, providing stability and minimizing vibrations during operation, thereby optimizing performance.

Furthermore, our capping mechanism is engineered to withstand the rigors of continuous industrial operation. Utilizing high-quality materials and components, we've enhanced durability while minimizing maintenance requirements. Regular inspections and servicing protocols are implemented to uphold the performance of the gear motors, ensuring consistent and reliable bottle sealing. By prioritizing reliability and durability, we can confidently maximize up time and productivity, meeting production targets with ease.

4.1.5 Camera Location

In our PLC-based bottle filling station project, selecting the appropriate location for the camera is crucial for efficient and accurate object detection. The camera serves as a critical component for identifying and tracking bottles as they move along the conveyor belt, enabling precise control and coordination of various processes within the system. To ensure optimal performance, we have chosen a camera with specific specifications tailored to our requirements.

The selected camera boasts impressive specifications, including a frame rate of 30 frames per second (fps) and a resolution of 1080p with 8 megapixels (MP). These specifications are carefully chosen to strike a balance between image quality and processing speed, allowing for high-resolution imagery while maintaining a real-time processing capability suitable for object detection tasks. The high frame rate ensures smooth and fluid motion capture, essential for accurately tracking fast-moving objects such as bottles on the conveyor belt.

In terms of placement, the camera is strategically positioned to provide comprehensive coverage of the bottle filling station's operational area. It is typically mounted overhead, providing a bird's eye view of the conveyor belt and the surrounding environment. This vantage point offers optimal visibility of the bottles as they move along the conveyor, enabling the camera to capture clear and detailed images for accurate object detection.

Additionally, the camera's placement is optimized to minimize blind spots and maximize coverage of the entire conveyor belt area. Careful consideration is given to factors such as lighting conditions, glare, and potential obstructions to ensure optimal performance of the camera system. By strategically positioning the camera, we can effectively monitor and track bottles throughout the filling process, facilitating precise control and coordination of filling, capping, and other operations.

Integrating the camera with the Raspberry Pi 4 Model B adds another layer of versatility and capability to our bottle filling station's object detection system. The Raspberry Pi serves as a powerful and flexible computing platform, capable of handling image processing tasks efficiently. By connecting the camera directly to the Raspberry Pi, we leverage its computational power to perform real-time analysis and decision-making based on the captured images.

4.1.6 Circuit Schematic

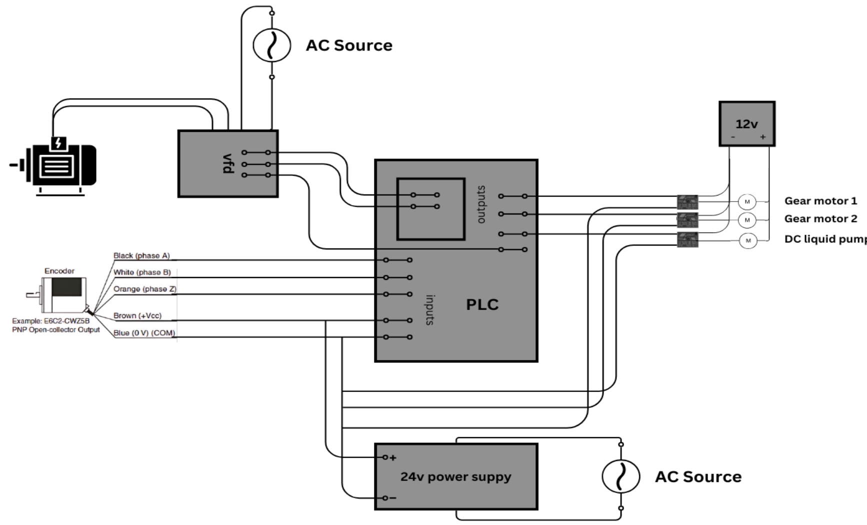


Fig 4.21: Schematic Diagram

4.2 Software Implementation

The software implementation section outlines the integration and coordination of various hardware components using software protocols and logic. This project employs Siemens PLC, Raspberry Pi, and other devices to create a fully automated bottle filling station. The software controls the interaction between the Variable Frequency Drive (VFD), motors, shaft encoder, DC pump, capping mechanism, camera, and Raspberry Pi. By leveraging advanced object detection algorithms like YOLOv8 and precise ladder logic programming, the system ensures efficient and accurate bottle detection and filling processes.

This section describes the interfacing and programming required to manage each component. We will discuss the software techniques used to interface the VFD and motor, shaft encoder, DC pump and capping system, and the communication between Raspberry Pi and PLC. Additionally, the process of creating a custom dataset for object detection and the overall working of the camera setup will be covered. The final part will present the complete ladder logic code with detailed explanations to illustrate the control flow and decision-making process within the system.

4.2.1 Interfacing of VFD & Motor

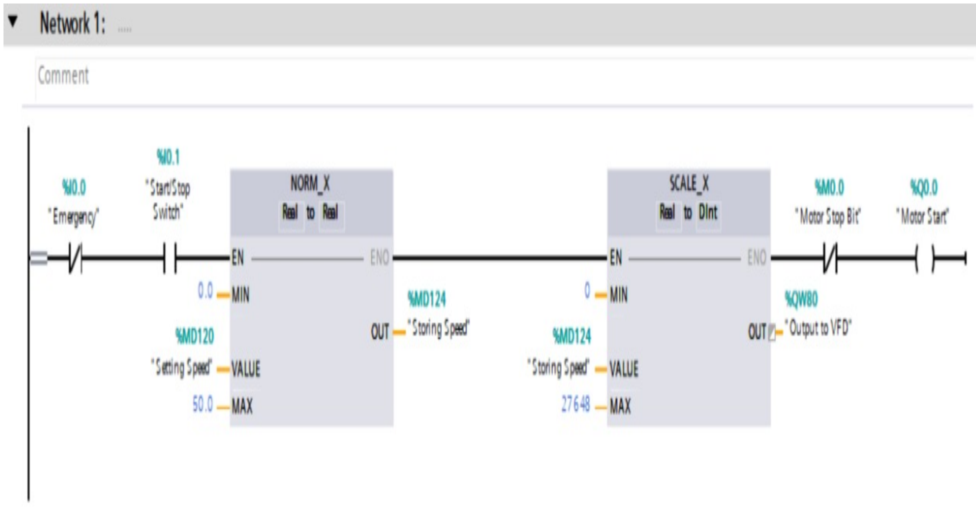


Fig 4.22: VFD & Motor Ladder Logic

Interfacing the Variable Frequency Drive (VFD) with the induction motor involves setting up communication protocols and control signals that allow the PLC to manage motor speed and torque. The Siemens Sinamics G110 VFD converts the fixed-frequency AC supply into a variable-frequency output, which controls the motor speed. The configuration parameters, such as ramp-up and ramp-down times, maximum and minimum speeds, and torque limits, are programmed into the VFD to match the motor's operational requirements. This setup ensures precise control over the motor, allowing for smooth and efficient operation of the conveyor belt.

To interface the VFD with the PLC, digital and analog signals are used. The PLC sends a reference speed signal to the VFD using an analog output (0-10V or 4-20mA), which the VFD interprets to adjust the motor speed accordingly. The VFD also provides feedback on the motor's status and speed through digital outputs and analog inputs, enabling the PLC to monitor the system and make necessary adjustments. Industrial communication protocols like Modbus or Profibus can be employed for more detailed control and monitoring, enhancing the system's functionality. Programming the PLC involves creating a control loop that adjusts the motor speed based on the conveyor's load conditions and bottle filling requirements. The ladder logic code processes inputs from sensors and devices, such as a shaft encoder, to dynamically adjust the motor speed and ensure smooth bottle movement. Safety features and fault detection mechanisms handle scenarios such as motor overload, conveyor jams, or emergency stops. This control scheme ensures optimal performance and efficiency of the bottle filling station.

4.2.2 Interfacing of Shaft Encoder

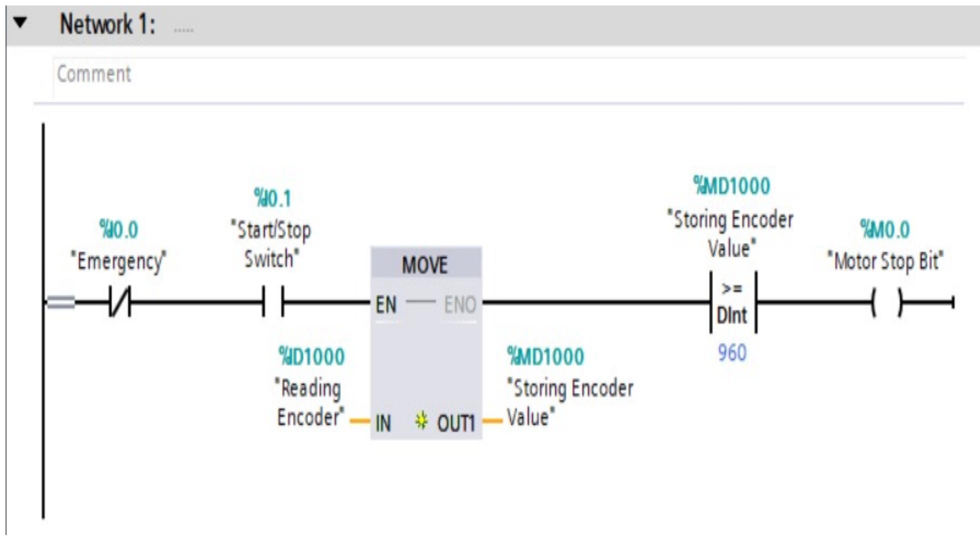


Fig 4.23: Shaft Encoder Ladder Logic

The shaft encoder provides feedback on the position and speed of the motor shaft, which is essential for the accurate operation of the conveyor system in the filling station. The Omron E6B2-CWZ6C encoder used in this project generates pulses as the shaft rotates, with each pulse corresponding to a specific increment of rotation. The encoder outputs three channels: A, B, and Z. Channels A and B provide quadrature output, allowing the PLC to determine the direction of rotation, while the Z channel produces a single pulse per revolution, which can be used for homing and resetting the position count.

To interface the shaft encoder with the PLC, the encoder's output channels are connected to the PLC's high-speed counter inputs. These inputs are specifically designed to handle the rapid pulse signals generated by the encoder. The PLC is programmed to count these pulses and calculate the shaft's position and speed in real-time. This real-time feedback is crucial for maintaining the synchronization between the conveyor belt's movement and the filling and capping processes. The PLC uses this data to ensure that bottles are correctly positioned for each operation, adjusting the conveyor speed and position as needed. In the ladder logic code, the pulse count from the encoder triggers specific actions within the control system. For example, the code can be programmed to start the filling process once a bottle is detected in the correct position based on the encoder's feedback. By continuously monitoring the encoder signals, the PLC ensures that the filling and capping mechanisms operate in precise coordination with the conveyor belt, reducing the risk of errors and improving overall system efficiency.

4.2.3 Interfacing of DC Pump and Capping

The DC pump and capping mechanism are integral components of the bottle filling station, ensuring that each bottle is accurately filled and securely capped. This section details the interfacing of the DC pump and the dual-motor capping mechanism with the PLC, explaining how these components work together to achieve precise filling and reliable capping.

The DC pump is controlled by the PLC to ensure accurate filling of each bottle. The pump's speed and operation duration are adjusted based on the bottle size and the required fill level. The interfacing process involves connecting the pump's power supply and control inputs to the PLC's digital outputs. The PLC sends control signals to start and stop the pump, which are triggered based on the position of the bottles detected by sensors and the shaft encoder. In the ladder logic code, sequences are created to start the pump when a bottle is in the correct position and to monitor the fill level using sensors. The PLC stops the pump once the desired fill level is reached. This ensures that each bottle is filled accurately without overfilling or underfilling, maintaining product quality and reducing waste.

Achieving a proper seal on bottles post-filling is paramount, and the capping process is crucial for this. Our capping mechanism uses two gear motors: one for positioning the capping mechanism over the bottle and the other for tightening the cap securely. As bottles move along the conveyor belt, they reach the capping zone where the first gear motor positions the capping mechanism. Upon detecting a bottle, the first motor lowers the capping mechanism to align it optimally with the bottle, minimizing the risks of misalignment. Once aligned, the second gear motor engages to tighten the cap securely in just 0.2 seconds. This rapid and precise operation ensures that the capping process does not hinder the conveyor flow.

To interface the capping mechanism with the PLC, the control inputs of both gear motors are connected to the PLC's digital outputs. The control algorithm, embedded in the PLC's ladder logic, coordinates the actions of both motors based on sensor signals detecting bottle presence. This ensures the capping mechanism deploys and tightens the cap accurately and efficiently. The ladder logic code for both the DC pump and the capping mechanism includes error handling routines. These routines address potential issues such as pump malfunctions or caps not being properly applied. For the pump, sensors monitor the fill level and detect any discrepancies, prompting the PLC to stop the pump and alert the operator if necessary. For the capping mechanism, if the system detects a misalignment or improper sealing, it stops the conveyor and triggers an alarm. To ensure stability and minimize vibrations, the capping system is welded to the conveyor belt, optimizing performance. The capping mechanism is designed for continuous industrial operation, using high-quality materials and components to enhance durability and minimize maintenance. Regular inspections and servicing protocols are in place to maintain the performance of the gear motors, ensuring consistent and reliable bottle sealing. By prioritizing reliability and durability, the system maximizes uptime and productivity, meeting production targets efficiently. This robust setup ensures that the bottle filling station operates smoothly, with minimal interruptions and high efficiency, maintaining product quality and operational consistency.

In addition to the primary functions of filling and capping, the system also incorporates advanced diagnostics to predict and prevent potential failures. By integrating predictive maintenance algorithms within the PLC, the system can analyze the operational data from the pump and capping motors to forecast when maintenance is required. This proactive approach helps in scheduling maintenance activities during planned downtimes, reducing unexpected interruptions and extending the lifespan of the components. The integration of such intelligent diagnostics is crucial for maintaining the overall efficiency and reliability of the bottle filling station.

Another critical aspect of the system is the adaptability to different bottle sizes and types. The PLC can be programmed to adjust the pump's speed and the capping mechanism's position based on the specific bottle being processed. This flexibility is achieved through modular programming and adjustable mechanical components, allowing quick changeovers between different production runs. The ability to handle various bottle sizes without significant downtime enhances the versatility of the bottle filling station, making it suitable for a wide range of applications in the beverage industry.

Finally, the bottle filling station is designed with user-friendly interfaces to facilitate easy operation and monitoring. The control panel, equipped with a touch screen HMI (Human-Machine Interface), allows operators to easily set parameters, monitor real-time performance, and access diagnostic information. Training for operators is simplified through intuitive graphical interfaces and step-by-step guides displayed on the HMI. By focusing on ease of use and comprehensive monitoring capabilities, the system ensures that operators can effectively manage the production process, promptly respond to any issues, and maintain optimal performance and efficiency.

4.2.4 Interfacing Raspberry Pi with PLC

The Raspberry Pi 4 Model B serves as a secondary controller and processing unit for object detection and classification tasks within our PLC-based bottle filling station. It communicates with the Siemens PLC to coordinate actions based on the detection results. The primary communication method between the Raspberry Pi and the PLC is through digital I/O or industrial communication protocols like Modbus TCP/IP or Profinet, ensuring reliable and fast data exchange.

In the software implementation, the Raspberry Pi runs a YOLOv8-based object detection algorithm to identify and classify bottles on the conveyor belt. This algorithm processes images captured by the Raspberry Pi Camera Board, detecting the presence and orientation of bottles. The detection results, such as identifying a tilted or upright bottle, are then transmitted to the PLC as digital signals. For instance, if a tilted bottle is detected, the Raspberry Pi sends a specific digital signal to the PLC, triggering an emergency stop sequence to prevent further processing errors. The PLC ladder logic is programmed to respond to these signals by executing predefined actions, such as stopping the conveyor, activating alarms, or initiating corrective measures. This setup ensures seamless integration of the object detection system with the overall control logic of the bottle filling station, enhancing operational efficiency and reliability. By leveraging the processing power of the Raspberry Pi for advanced image analysis and the robust control capabilities of the PLC, the system can effectively manage the bottle filling and capping processes with high precision.

Furthermore, the integration allows for real-time monitoring and diagnostics. The Raspberry Pi can log detection data and system performance metrics, which can be used for further analysis and optimization of the production process. This real-time data logging is critical for continuous improvement initiatives, as it provides valuable insights into the performance of the detection system and the overall efficiency of the bottle filling station. By analyzing these logs, operators and engineers can identify patterns, predict potential issues, and implement improvements to enhance productivity and reduce downtime.

Additionally, the use of the Raspberry Pi adds a layer of flexibility to the system, allowing for future upgrades and modifications. The open-source nature of the Raspberry Pi ecosystem means that new algorithms, sensors, and functionalities can be integrated without major overhauls to the existing system.

4.2.5 Overall Ladder Logic Code with Explanation

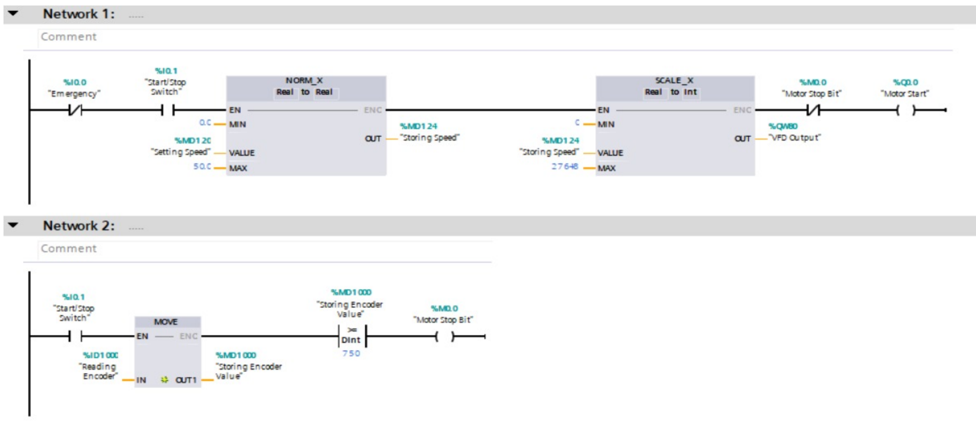


Fig 4.24: Ladder Logic Part 01

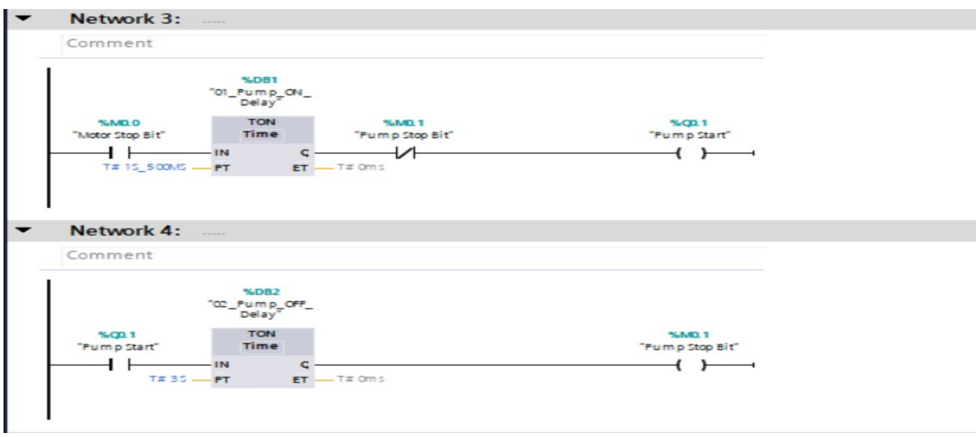


Fig 4.25: Ladder Logic Part 02

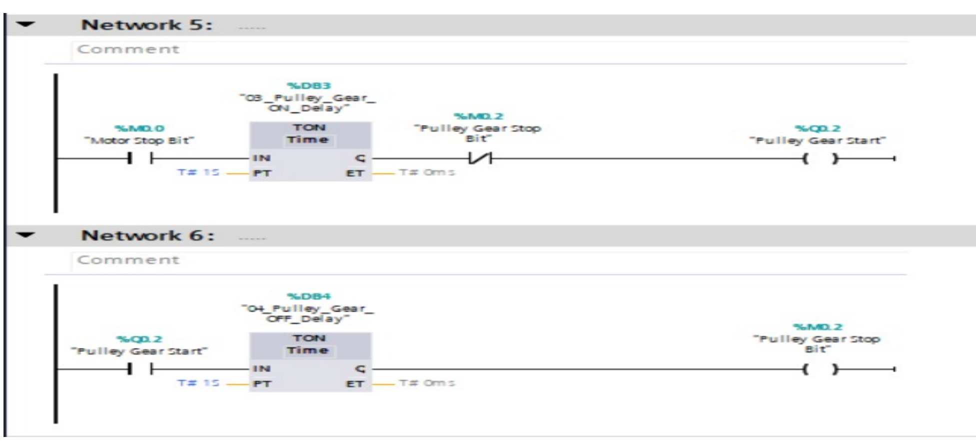


Fig 4.26: Ladder Logic Part 03

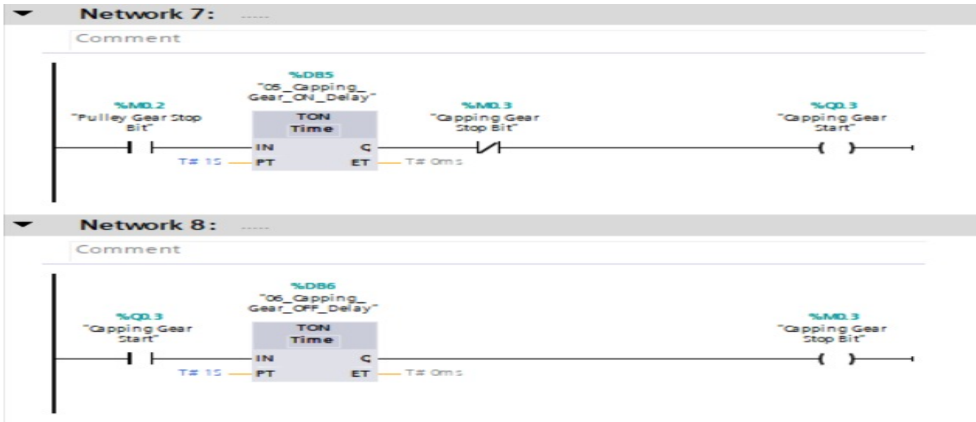


Fig 4.27: Ladder Logic Part 04

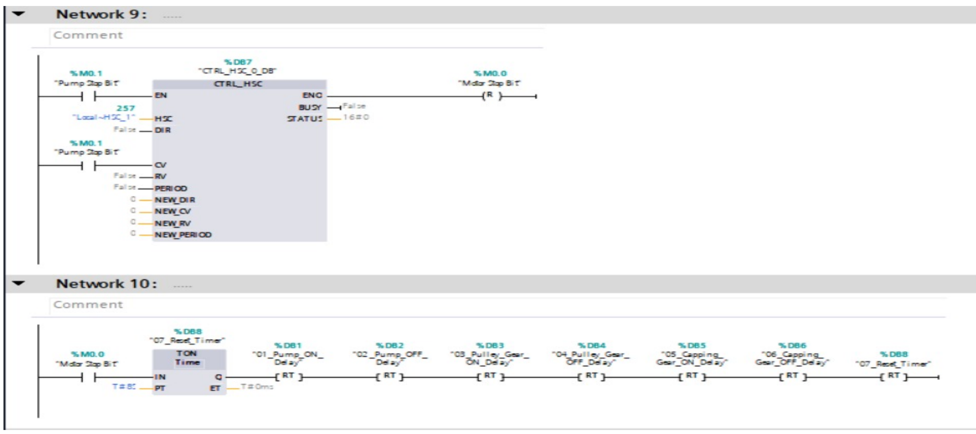


Fig 4.28: Ladder Logic Part 05

The ladder logic code is the backbone of the PLC-based control system, managing the interactions between various components to ensure smooth and efficient operation. The code is structured to handle inputs from sensors, control outputs to actuators, and implement decision-making logic based on the real-time conditions of the system. The main sections of the ladder logic include initialization routines, input processing, control sequences for the VFD and motor, and error handling. The initialization routines set up the PLC, configuring timers, counters, and initial states for various components. Input processing involves reading signals from sensors, such as the shaft encoder and position sensors, and updating the internal state of the system accordingly. Control sequences manage the operation of the VFD and motor, ensuring that the conveyor belt runs at the desired speed and adjusts based on the detected bottle positions. Error handling routines monitor the system for any anomalies, such as tilted bottles or pump malfunctions, and trigger appropriate corrective actions, such as stopping the conveyor or activating alarms.

4.2.6 Custom Dataset Making

Creating a custom dataset for the object detection algorithm is a critical step in training the YOLOv8 model to accurately identify and classify bottles on the conveyor belt. The process begins with capturing a large number of images using the Raspberry Pi Camera Board. These images should depict bottles in various states, including upright, tilted, and empty, so model can generalize well to different scenarios encountered.

Fig 4.29: Dataset Sample

Once the images are collected, the next step is annotation. Tools like Roboflow are commonly used for this purpose. Annotation involves drawing bounding boxes around the bottles in each image and labeling them with class names such as ”straight” or ”tilted”. This step is crucial as it provides the model with the necessary information to learn the differences between the various bottle states. The annotations are saved in a format compatible with the YOLOv8 training pipeline, typically in the YOLO or COCO format, which standardizes how objects are represented in the dataset.

After annotating the images, the dataset is split into training and validation sets. The majority of the images are used for training, allowing the model to learn and adjust its parameters. A smaller subset is reserved for validation to evaluate the model's performance and ensure it is not over-fitting. The training process involves feeding the images and their corresponding annotations into the YOLOv8 training pipeline, where the model learns to minimize detection and classification errors.

4.2.7 Overall Working of Camera with Explanation

The camera setup is integral to the bottle detection and classification process. The Raspberry Pi Camera Board v1.3 captures high-resolution images of bottles on the conveyor belt in real-time. These images are then processed by the YOLOv8 object detection algorithm running on the Raspberry Pi 4 Model B. The camera is connected to the Raspberry Pi via the CSI port, and the pi-camera library in Python is used to manage image capture and processing.

The camera continuously captures frames at a specified frame rate, ensuring that each bottle on the conveyor is monitored. These frames are fed into the YOLOv8 algorithm, which performs object detection to identify bottles and classify them as either ”straight” or ”tilted”. The real-time processing capability of the Raspberry Pi, combined with the efficiency of YOLOv8, ensures that detection and classification are performed swiftly and accurately.

The detection results are then communicated to the Siemens PLC, which controls the subsequent actions. For instance, if the algorithm detects a tilted bottle, the Raspberry Pi sends a signal to the PLC to trigger an emergency stop, preventing the tilted bottle from proceeding further down the conveyor. This integration of camera, object detection, and PLC control ensures the efficient and accurate operation of the bottle filling station, minimizing errors and ensuring quality control.

4.3 Testing And Debugging

Testing and debugging are pivotal phases in developing the PLC-based liquid filling station, ensuring every component operates efficiently. Procedures cover the conveyor, motor speed variation, encoder, filling mechanism, capping mechanism, and camera system. These tests rigorously validate functionality under diverse conditions. The conveyor undergoes checks for smooth operation and bottle alignment, while motor speed tests ensure precise adjustments for consistent filling. Encoder tests verify position accuracy crucial for control. Filling mechanism tests confirm accurate fill levels and responsiveness, and capping mechanism tests ensure secure sealing. Camera system tests assess Raspberry Pi’s object detection in varied bottle orientations. Thorough testing and detailed debugging not only validate individual components but also ensure seamless integration across the system. By identifying and resolving issues early, teams optimize performance, enhance reliability, and deliver a robust solution meeting operational needs with minimal downtime.

4.3.1 Testing of Conveyor

The conveyor is a critical component of the liquid filling station, responsible for transporting bottles through various process stages. Testing ensures its smooth operation and reliability. Initially, mechanical integrity is checked to ensure all parts are securely fastened and aligned. A power-on test follows to verify consistent movement without jerking or stalling, confirming the conveyor's structural stability. Speed settings undergo rigorous testing to align with operational requirements. Various speeds are tested, and actual speeds are measured against expected values, with adjustments made as necessary to motor controller settings. Responsiveness to control signals is assessed by sending commands from the PLC—start, stop, and speed adjustments—and observing smooth execution without delays.

Under load conditions, the conveyor is tested with bottles of different sizes and weights to assess performance under maximum load, ensuring it operates without slowing down or causing bottles to tip over. Identified issues during testing prompt mechanical adjustments or software modifications to optimize performance and reliability. Regular maintenance and periodic checks are essential to maintain conveyor efficiency and prevent downtime, continuous operation and meeting production demands effectively.

Furthermore, continuous monitoring and data logging enhance conveyor performance assessment over time. Real-time data collection allows for trend analysis, identifying potential wear or mechanical stress early. This proactive approach to maintenance helps mitigate risks of unexpected failures, optimizing conveyor lifespan and operational uptime. By integrating robust testing protocols and proactive maintenance strategies, the conveyor system in the liquid filling station ensures reliable, efficient bottle transport throughout the production process.

Additionally, integration with the PLC system ensures that the conveyor operates in sync with other station components, facilitating seamless automation and workflow coordination. This integration enables the PLC to orchestrate timing and synchronization between the conveyor, filling mechanisms, capping processes, and other station operations. By centralizing control through the PLC, operators can monitor and adjust conveyor performance in real-time, responding promptly to operational changes or production demands. This centralized control also enhances troubleshooting capabilities, allowing for quick identification and resolution of issues that may arise during operation.

4.3.2 Motor Speed Variation

Testing motor speed variation is crucial to guarantee optimal performance of the Sinamics G110 variable speed drive and the SPG S8125GS-TCE induction motor throughout the filling process stages. Beyond calibration, the testing process delves into real-world scenarios by assessing how the motor copes with varying loads. This involves adjusting the conveyor's load with different numbers of bottles to observe the motor's ability to maintain consistent speed. It's akin to testing a runner's endurance under different weights—they need to sustain pace regardless of additional burden, ensuring reliable operation during production cycles.

The system undergoes rigorous evaluation for its responsiveness to sudden load changes, akin to a motor vehicle's ability to accelerate smoothly from a standstill. By swiftly adapting to fluctuating demands, the motor not only maintains speed but also ensures operational stability, crucial for uninterrupted production flow. This aspect highlights the precision and resilience required in industrial settings, where each component's performance impacts overall efficiency and output consistency. Thermal performance testing is critical to assess the motor's endurance over prolonged operation periods. Similar to athletes enduring endurance tests, the motor is evaluated under sustained stress to ensure it remains within safe operating temperatures. This comprehensive assessment ensures that cooling systems effectively dissipate heat, preventing overheating issues that could jeopardize both motor longevity and operational reliability. These tests not only validate operational capabilities but also underscore the importance of robust engineering and meticulous testing in maintaining peak performance in industrial applications.

Beyond technical tests, ensuring the motor speed variation aligns with operational needs involves practical considerations. Operators play a crucial role in monitoring and fine-tuning motor performance based on real-time production demands. This human oversight complements automated systems by providing contextual insights and making on-the-spot adjustments to optimize efficiency. Just as a skilled conductor directs an orchestra, operators synchronize motor speeds with filling station activities, ensuring harmonious operation and minimizing downtime.

Continuous improvement in motor speed variation testing utilizes production data and operator feedback to refine control strategies, optimizing speed profiles for dynamic conditions. This iterative approach blends human expertise with technology, ensuring operational efficiency and adaptability to industry standards.

4.3.3 Testing of Encoder (6 rpm)

The Shaft Encoder E6B2-CWZ6C 1000P/R 2M is crucial for ensuring precise bottle positioning during the filling process. Testing this encoder at a specific speed of 6 rpm involves meticulous steps to validate its accuracy and reliability. Initially, calibration is conducted by comparing its readings with a known reference, ensuring that the output pulses correspond correctly to the expected number per revolution at the designated speed.

Once calibrated, integration into the conveyor system is essential, where practical tests under operational conditions commence. Placing bottles on the conveyor allows observation of how effectively the encoder tracks each bottle's position. The encoder must consistently provide precise position data to the PLC, facilitating accurate timing for halting the conveyor at the correct filling point. Testing also encompasses the encoder's response to various speeds and direction changes, ensuring it maintains accuracy regardless of operational dynamics.

Durability and reliability assessments involve subjecting the encoder to continuous operation over extended periods and varying environmental conditions. These tests include exposure to different temperatures and humidity levels to verify the encoder's resilience in diverse operating environments. Any issues identified, such as inaccuracies in position data or intermittent signal loss, prompt recalibration, adjustments in mounting, or replacement of faulty components. The overarching goal remains ensuring the encoder delivers dependable and precise position data, crucial for maintaining efficient and accurate bottle filling operations.

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4.3.4 Filling Testing

Testing the filling mechanism involves rigorous evaluations to ensure precise and efficient liquid dispensing into bottles within a specified timeframe. Initially, calibration is pivotal to verify that the nozzles dispense the correct volume of liquid within the designated 3-second window. This process entails meticulous measurement of output, followed by adjustments to flow rate and pressure settings to achieve desired dispensing accuracy.

Subsequent testing under operational conditions involves placing bottles on the conveyor and executing the filling process. Programmed pauses by the PLC at the filling station for 3 seconds allow the nozzles to dispense liquid, followed by a 1-second delay before the conveyor moves the next bottle. The system's accuracy and consistency are critically evaluated through multiple cycles, ensuring uniformity in liquid volume dispensed into each bottle. Variations prompt adjustments to the flow control system, ensuring consistent filling volumes across production runs.

Additionally, rigorous testing includes evaluating the delay mechanism to ensure precise timing of the 1-second interval between bottles. Monitoring system responses to PLC commands confirms the consistent timing of delays across cycles, ensuring smooth conveyor operation. Testing under varying load conditions, such as different bottle sizes and liquid viscosities, further validates the filling mechanism's capability to perform reliably under diverse operational scenarios. Any identified issues, whether related to inconsistent filling volumes or timing delays, are promptly addressed through software refinements or mechanical adjustments. This comprehensive testing approach aims to optimize the filling mechanism's accuracy and efficiency, thereby enhancing overall productivity and ensuring reliable performance in demanding manufacturing environments.

Furthermore, continuous monitoring and maintenance protocols are essential to sustain optimal performance of the filling mechanism over time. Regular inspections and data analysis help identify potential issues early, allowing for proactive adjustments and preventive maintenance. This proactive approach not only minimizes downtime but also enhances system reliability and longevity. By continuously optimizing operation and addressing potential concerns promptly, manufacturers can maintain consistent product quality and throughput, meeting production goals efficiently.

4.3.5 Capping Testing

The testing of the capping mechanism focuses on ensuring it securely seals bottles within precise time constraints. Initially, calibration verifies that the gear motor and CNC guide operate within specified time frames, starting with a 0.2-second initial delay, followed by a 1-second capping period, and concluding with a second 0.2-second gear engagement delay. Testing begins by isolating the capping system to assess timing and mechanical performance. This includes observing the gear motor's response to control signals to ensure it engages and disengages at the correct intervals. Each timing element—from the initial delay to the capping duration and subsequent gear engagement—is meticulously tested to ensure adherence to specified timings.

Next, integration with the conveyor and filling systems tests the capping mechanism under operational conditions. Bottles move through the filling process and then reach the capping station, where the system engages the mechanism according to programmed timings. Multiple cycles verify the accuracy and consistency of the capping process, with each bottle inspected to ensure tight seals. Any discrepancies, such as loose caps or misalignments, prompt adjustments to the gear motor or CNC guide settings to maintain consistent performance.

Furthermore, comprehensive testing includes evaluating the capping mechanism's performance under different load conditions, using bottles of various sizes and cap types. This ensures the system's capability to handle diverse scenarios effectively. Issues identified during testing, such as timing inaccuracies or mechanical failures, undergo resolution through software adjustments or hardware modifications. The overarching objective is to ensure the capping mechanism operates with precision and efficiency, securely sealing each bottle to uphold product integrity and enhance system productivity.

Additionally, ongoing monitoring and maintenance protocols are essential to uphold the capping mechanism's reliability and performance over time. Regular inspections and performance evaluations help detect potential issues early on, enabling proactive adjustments and preventive maintenance measures. This proactive approach not only minimizes downtime but also enhances operational continuity and product quality assurance. By implementing robust maintenance strategies and continuous monitoring, manufacturers can ensure that the capping mechanism operates optimally throughout its lifecycle, supporting consistent production outputs and meeting customer expectations reliably.

4.3.6 Testing of Camera

The camera system, powered by Yolo v8 AI technology, is essential for detecting and classifying bottles on the conveyor. Testing involves critical steps to ensure its accuracy and reliability. Initial calibration includes adjusting settings like the matrix, f1 core, and confidence threshold (ranging from 0.56 to 0.86).

The camera undergoes isolated testing to assess its ability to detect and classify objects of various shapes and sizes accurately. It must maintain confidence levels within the specified range, with adjustments made to settings as needed for improved accuracy. Integrated into the conveyor system, the Yolo v8 system continuously monitors and accurately detects upright bottles, providing real-time data to the PLC for precise control over bottle positioning and process management.

Testing also includes evaluating the camera's performance in detecting anomalies such as misaligned or unstable bottles. The system responds promptly to anomalies by signaling the PLC to pause the conveyor, preventing disruptions in the production process. Furthermore, rigorous testing under different environmental conditions ensures consistent performance in varied operational scenarios, guiding adjustments in software or hardware to optimize detection and classification accuracy.

Chapter 5
Results & Discussions

5.1 System Performance

In our PLC-based bottle filling station project, system performance is paramount to ensure the seamless operation of the production line. Speed is a critical aspect, as it directly influences the throughput of the system, which encompasses the entire process from bottle detection to filling and capping. A higher throughput rate allows for more bottles to be processed within a given time-frame, ultimately increasing production efficiency. To achieve optimal speed, the PLC control system must be finely tuned to minimize processing delays at each stage of the filling process. This involves optimizing sensor response times, refining control algorithms for precise actuator movements, and ensuring smooth conveyor operation.

Reliability is another key consideration for system performance, particularly in industrial settings where downtime can result in significant production losses. The PLC-based control system must demonstrate robust reliability, capable of consistently performing its functions without errors or failures. This entails implementing redundant components and failover mechanisms to mitigate the risk of system disruptions. Regular maintenance and preventive measures, such as sensor calibration and equipment inspections, are essential to identify and address potential issues before they escalate into critical failures. Additionally, incorporating diagnostic features into the control system enables real-time monitoring of system health, allowing for proactive maintenance and troubleshooting.

Scalability is essential to accommodate fluctuations in production demand, ensuring that the bottle filling station can adapt to varying throughput requirements. The PLC control system should be designed with scalability in mind, allowing for easy integration of additional equipment or expansion of production lines as needed. This flexibility allows manufacturers to increase production during periods of high demand or reduce operations during quieter times, ensuring efficient use of resources and operational effectiveness. Additionally, modular design principles support easy upgrades and adjustments to the system structure, safeguarding the bottle filling station against changing production requirements in the future.

In addition to speed, reliability, and scalability, another crucial aspect of system performance in our PLC-based bottle filling station project is accuracy. Bottle detection and recognition accuracy are paramount to ensure that the correct bottles are identified and processed accurately throughout the production line. This involves precise sensor calibration, accurate object detection algorithms, and robust control strategies to minimize errors and ensure consistent performance. High accuracy in bottle detection and recognition contributes to product quality, reduces waste, and enhances overall system efficiency.

5.2 Bottle Detection and Recognition Accuracy

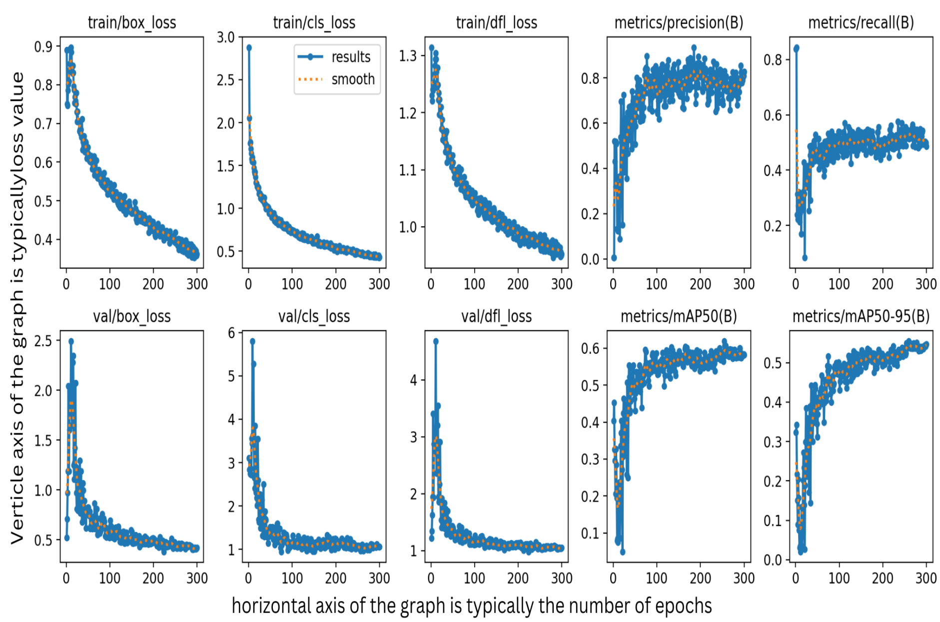

Fig 5.30: Model Training Graph

The confusion matrix presented in this image offers a detailed view of the bottle detection model's performance, likely the YOLOv8 model mentioned in the background information. This matrix effectively visualizes how the model distinguishes between bottles and background elements, providing crucial insights into its strengths and weaknesses. Examining the diagonal elements reveals that the model performs reasonably well in correctly identifying both bottles and background. Specifically, 21 instances were correctly identified as bottles by both versions of the model, 24 instances were correctly identified as bottles by the updated version, and 33 instances were correctly classified as background.

However, the matrix also highlights some misclassifications that warrant attention. For instance, 2 instances of bottles (v1) were misclassified as background, 1 instance of a bottle (v1) was misclassified by the updated version, and 7 instances of bottles (updated version) were misclassified as background. Additionally, 40 instances of background were misclassified as bottles by v1, and 2 instances of background were misclassified as bottles by the updated version.

These results indicate that while the model generally performs well, there is room for improvement, particularly in reducing false positives (background misclassified as bottles) and false negatives (bottles misclassified as background). The updated version (v1) appears to have made some progress in reducing false positives, but it still struggles with false negatives. To enhance the model's performance, the team could focus on several strategies. Expanding the training dataset to include a more diverse range of bottle shapes and sizes could help the model better recognize various bottle types. Fine-tuning the model's parameters to better distinguish bottles from background elements could reduce misclassifications. Implementing data augmentation techniques could improve the model's ability to generalize to new situations. Additionally, optimizing lighting conditions in the bottle filling station could help reduce ambiguity in image capture, potentially leading to more accurate detections. By addressing these areas, the team can work towards improving the overall accuracy and reliability of the bottle detection system, ultimately enhancing the efficiency of the PLC-based bottle filling station and minimizing errors in the production process.

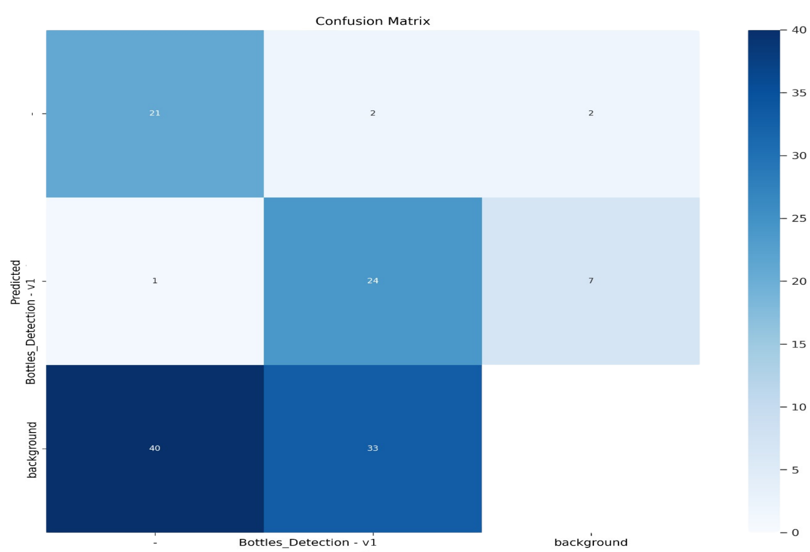

Fig 5.31: Model Confusion Matrix

The multi-panel graph presented in this image provides a comprehensive view of the bottle detection model's training process and performance metrics over time. Each panel in the graph represents a different aspect of the model's learning and evaluation, offering valuable insights into its development and potential areas for improvement. The top row of the graph displays three key loss functions: train&box_loss, train&cls_loss, and train&dfl_loss.

All three of these loss functions show a consistent downward trend throughout the training process, indicating that the model is improving in its ability to predict bounding boxes, classify objects, and learn relevant features. The train&box_loss, which likely relates to the accuracy of bounding box predictions, shows a steady decrease over time. This suggests that the model is becoming increasingly precise in locating and sizing the bounding boxes around detected bottles.

The train&cls_loss, representing the classification loss, also demonstrates a downward trend, indicating that the model is improving its accuracy in distinguishing bottles from background elements. The train&dfl_loss, possibly related to feature learning, exhibits a similar pattern of improvement. The bottom row of the graph displays corresponding validation losses, which closely mirror the patterns seen in the training losses. This parallel decrease in both training and validation losses is a positive sign, suggesting that the model is generalizing well to unseen data and not overfitting to the training set.

The right side of the graph showcases various performance metrics that provide additional insights into the model's capabilities. The metrics/precision(B) and metrics/recall(B) both show improvement over time, indicating that the model is getting better at correctly identifying bottles when it predicts them and finding all the bottles present in the images, respectively. The metrics/mAP50(B) and metrics/mAP50-95(B), which represent mean Average Precision at different IoU (Intersection over Union) thresholds, demonstrate steady improvement throughout the training process. These metrics reflect an overall enhancement in detection performance across various levels of precision. The graph uses both raw data points (in blue) and smoothed trend lines (in orange) to help visualize the overall trends amidst the natural fluctuations in the data.

The graph shows effective learning and improvement in bottle detection, but there's still room for enhancement. Precision and recall metrics haven't plateaued, suggesting potential for further training or fine-tuning.

In our PLC-based bottle filling station, the accuracy of bottle detection and recognition plays a pivotal role in ensuring the efficiency and reliability of the entire production process. Currently, with an accuracy of 85 percent achieved using the YOLOv8 model, there is room for improvement to enhance the precision of object detection. Improving accuracy involves several strategies, including refining the training data to encompass a more diverse range of bottle shapes, sizes, and orientations. Additionally, fine-tuning the parameters of the YOLOv8 model, such as adjusting the confidence threshold and anchor box dimensions, can further optimize detection performance. Implementing techniques like data augmentation and transfer learning may also help enhance the model's ability to generalize to unseen bottle variations, improving overall accuracy.

One of the primary challenges we face in bottle detection accuracy is ensuring that bottles are precisely positioned under the filling pump and capping mechanism. This requires robust alignment mechanisms and precise control algorithms to accurately place the bottles at the designated spots. Implementing vision-based alignment systems or integrating additional sensors for feedback control may help address this challenge and improve detection accuracy. By leveraging advanced computer vision techniques and optimizing control strategies, we can enhance the accuracy of bottle detection and recognition, minimizing errors and maximizing the efficiency of the filling station.

Another aspect that can contribute to improving bottle detection and recognition accuracy is the optimization of lighting conditions within the bottle filling station environment. Variations in lighting, such as shadows or glare, can affect the performance of object detection algorithms by altering the appearance of bottles in images. Implementing uniform lighting setups or using specialized lighting techniques, such as diffused lighting or back-lighting, can help mitigate these issues and ensure consistent object visibility for the detection system.

Additionally, employing light sensors or color correction algorithms to dynamically adjust lighting parameters based on environmental conditions can further enhance detection accuracy. By addressing lighting challenges effectively, we can improve the robustness and reliability of bottle detection and recognition in our PLC-based filling station, ultimately optimizing overall system performance.

5.3 Liquid Filling Accuracy

Liquid filling accuracy is critical for maintaining product quality and consistency in our PLC-based bottle filling station. With a filling time of 3 seconds per bottle, ensuring precise control over the filling process is essential to prevent overfilling or underfilling. Achieving accurate filling involves calibrating the filling pump to dispense the correct volume of liquid consistently. This calibration process may include adjusting parameters such as flow rate, pump speed, and filling duration to achieve the desired fill level for each bottle.

In our project, the challenge lies in optimizing the filling process to minimize liquid wastage while maintaining high throughput. This requires fine-tuning the filling parameters to achieve the desired fill level with minimal overfilling or spillage. By continuously monitoring and optimizing the filling process, we can ensure consistent product quality and minimize material waste, contributing to the overall efficiency of the bottle filling station.

Another aspect crucial for liquid filling accuracy is the compatibility of the filling system with different types of liquids, each with its unique viscosity and flow characteristics. Adapting the filling process to accommodate variations in liquid properties ensures consistent fill levels across different products without compromising accuracy. Moreover, integrating safety features such as overflow prevention mechanisms and automated shut-off systems can prevent spillage and ensure operator safety. By addressing these challenges and implementing robust control strategies, we can enhance liquid filling accuracy in our PLC-based bottle filling station, ensuring reliable performance and product quality.

5.4 Capping Mechanism Performance

The performance of the capping mechanism is crucial for securely sealing bottles and preventing leaks or contamination in our PLC-based bottle filling station. With a capping time of 1 second per bottle, the capping mechanism must operate swiftly and accurately to cap each bottle effectively. Ensuring reliable capping performance involves optimizing the capping motor's speed and torque to apply the appropriate amount of force to seal the bottle cap securely. Additionally, proper alignment of the bottle and cap is essential to ensure that the cap is positioned correctly before sealing.

One challenge we encounter in capping mechanism performance is maintaining consistent torque and pressure during the capping process to prevent over-tightening or under-tightening of bottle caps. This requires precise control over the capping motor's speed and torque output, as well as real-time monitoring of torque feedback to adjust the capping force dynamically. Implementing advanced torque control algorithms and integrating torque sensors into the capping mechanism can help address this challenge and ensure uniform capping performance across all bottles. By optimizing the capping process for speed, accuracy, and reliability, we can minimize the risk of defective seals and ensure product integrity throughout the bottling process.

Another aspect crucial to capping mechanism performance is the compatibility between the bottle and cap designs. Variations in bottle and cap sizes, shapes, and materials can impact the sealing process and lead to inconsistencies in capping performance. Therefore, conducting thorough testing and validation of different bottle and cap combinations is essential to ensure compatibility and optimize capping efficiency. Additionally, regularly inspecting and maintaining the capping equipment, including cleaning and lubricating moving parts, can help prevent mechanical failures and ensure smooth operation. By addressing these challenges and implementing robust control and maintenance procedures, we can enhance the performance and reliability of the capping mechanism in our bottle filling station.

5.5 Overall System Efficiency

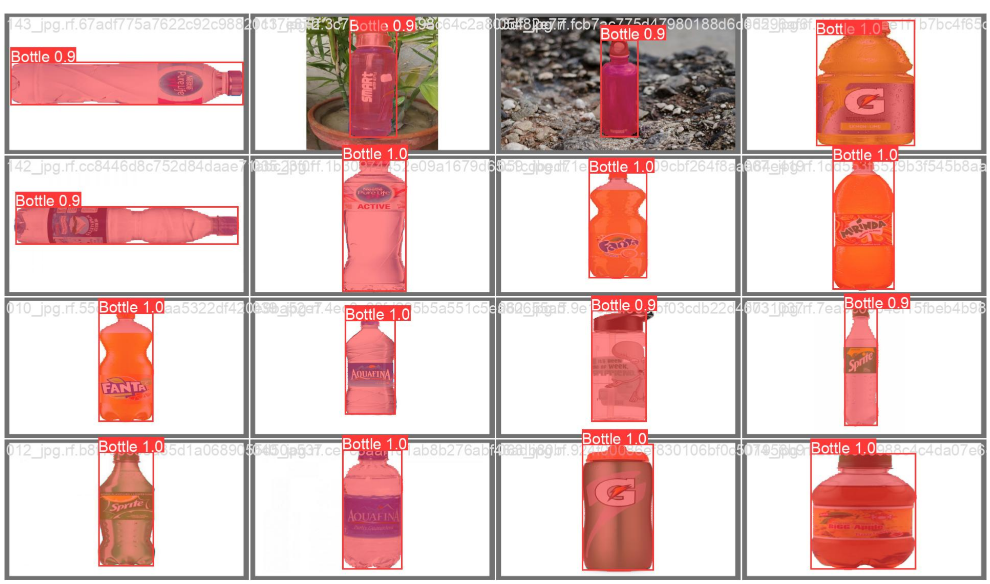

Fig 5.32: Validation Results

The overall efficiency of our PLC-based bottle filling station is a holistic measure of its productivity, reliability, and resource utilization. Efficiency encompasses various aspects, including throughput, up-time, energy consumption, and material usage. Maximizing system efficiency involves optimizing each component of the bottling process to minimize waste, reduce downtime, and maximize output. This requires continuous monitoring and optimization of system performance metrics, such as cycle time, fill rate, and error rate, to identify areas for improvement and implement corrective measures.

One challenge we face in optimizing overall system efficiency is balancing speed and accuracy in the bottle filling and capping processes. While increasing throughput by reducing cycle time can improve productivity, it may also compromise accuracy if not managed properly. Therefore, it is essential to strike a balance between speed and accuracy by implementing control strategies that prioritize both aspects simultaneously. Additionally, minimizing energy consumption and material waste through efficient use of resources and recycling initiatives can further enhance system efficiency and sustainability. By continuously optimizing system performance and implementing efficiency-enhancing measures, we can ensure that our PLC-based bottle filling station operates at peak efficiency, delivering high-quality products while minimizing costs and environmental impact.

Another significant aspect of overall system efficiency involves optimizing operational processes and resource management to maximize productivity and minimize waste. While we may not currently utilize proactive maintenance strategies or monitoring technologies, there are still opportunities to enhance efficiency through other means. For instance, streamlining the bottle filling and capping processes to minimize idle time and maximize throughput can significantly improve overall system efficiency. By optimizing workflow layouts, reducing bottlenecks, and fine-tuning operational parameters, we can enhance productivity and resource utilization without relying on advanced monitoring systems.

Chapter 6
Conclusion And Future Work

6.1 Conclusion

This research presents a comprehensive study and implementation of an automated bottle filling and capping system using PLC and computer vision technologies. The key findings underscore the effectiveness of integrating PLCs with computer vision to enhance operational efficiency and accuracy in industrial bottling processes. One of the significant contributions is the development of a robust control system that coordinates the filling and capping operations with high precision, thereby minimizing errors and maintaining consistent product quality. Additionally, the incorporation of a computer vision system capable of real-time detection and classification of unstable bottles has proven instrumental in ensuring smooth operation and reducing downtime.

The project successfully achieved its primary objectives, including the design and construction of the hardware components, implementation of the control algorithms, and integration of computer vision for quality control. Testing and evaluation of the system demonstrated its capability to handle various types of bottles with a high degree of accuracy and reliability. The use of the YOLOv8 model for object detection achieved an accuracy rate of 85%, highlighting the potential for further improvements through fine-tuning and data augmentation.

Overall, this research contributes to the field by providing a scalable and efficient solution for automated bottling processes, with potential applications in various industrial settings. The methodology and findings can serve as a foundation for future advancements in automated production lines, leveraging the strengths of PLCs and computer vision technologies.

6.2 Future Work

While the current study has demonstrated the viability and benefits of an automated bottle filling and capping system, several avenues for future research and development remain. Future work could focus on refining the training data, employing advanced techniques like transfer learning, and exploring alternative object detection models to achieve higher precision rates.

Another potential direction is the expansion of the system's capabilities to handle a broader range of bottle types and production environments. This could involve developing adaptive algorithms that can adjust to different bottle shapes, sizes, and materials without requiring significant manual reconfiguration. Additionally, incorporating more sophisticated alignment and feedback mechanisms, such as advanced vision-based alignment systems, could further improve the precision and efficiency of the bottling process.

Addressing the limitations of the current study, such as its focus on existing computer vision algorithms rather than the development of new ones, could also be a valuable pursuit. Research into novel object detection and classification techniques tailored specifically for industrial applications could yield significant performance enhancements. Finally, the integration of proactive maintenance and real-time monitoring systems could greatly enhance the system's reliability and longevity. By implementing predictive maintenance strategies and advanced diagnostic tools, future iterations of the system could preemptively address potential issues, reducing downtime and maintenance costs.

6.3 Concluding Remarks on overall project

The completion of this project marks a significant step forward in the automation of industrial bottling processes, demonstrating the practical benefits of combining PLCs with computer vision technologies. The automated bottle filling and capping system developed herein not only meets the initial objectives but also sets a new standard for efficiency, accuracy, and scalability in the field.

This project's significance lies in its potential to transform how bottling operations are conducted, offering a template for other industries to follow. The system's ability to reduce human error, increase production speed, and maintain high product quality can lead to substantial improvements in operational efficiency and cost savings. Furthermore, the knowledge gained and the methodologies developed through this research contribute valuable insights to the broader field of industrial automation.

In summary, the project's outcomes have broad implications for enhancing automated production lines. By addressing current limitations and exploring future research directions, this work can pave the way for even more advanced and efficient automated systems. The impact of this project is expected to resonate across various sectors, ultimately contributing to the advancement of industrial automation technologies.

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ABBREVIATIONS

PLC:	Programmable Logic Controller
HMI:	Human-Machine Interface
VFD:	Variable Frequency Drive
PID:	Proportional-Integral-Derivative
RPM:	Revolutions Per Minute
MP:	Megapixels
FPS:	Frames Per Second
I/O:	Input/Output
SCADA:	Supervisory Control and Data Acquisition
TCP/IP:	Transmission Control Protocol/Internet Protocol
MTBF:	Mean Time Between Failures
OEE:	Overall Equipment Effectiveness
DCS:	Distributed Control System
FAT:	Factory Acceptance Testing
SAT:	Site Acceptance Testing
IEC:	International Electrotechnical Commission
TIA:	Totally Integrated Automation
CAD:	Computer-Aided Design
RTU:	Remote Terminal Unit
CPU:	Central Processing Unit
RAM:	Random Access Memory
I2C:	Inter-Integrated Circuit Protocol
DIP:	Digital Image Processing
YOLO:	You Only Look Once
CNN:	Convolutional Neural Network
AI:	Artificial Intelligence

ANNEXURE A: PROGRAMMABLE LOGIC CONTROLLER

SIEMENS

Data sheet **6ES7211-1AE40-0XB0**

SIMATIC S7-1200, CPU 1211C, COMPACT CPU, DC/DC/DC, ONBOARD I/O: 6 DI 24V DC; 4 DO 24 V DC; 2 AI 0 - 10V DC, POWER SUPPLY: DC 20.4 - 28.8 V DC, PROGRAM/DATA MEMORY: 50 KB

General information	
Product type designation	CPU 1211C DC/DC/DC
Firmware version	V4.2
Engineering with	
• Programming package	STEP 7 V14 or higher
Supply voltage	
Rated value (DC)	
• 24 V DC	Yes
permissible range, lower limit (DC)	20.4 V
permissible range, upper limit (DC)	28.8 V
Reverse polarity protection	Yes
Load voltage L+	
• Rated value (DC)	24 V
• permissible range, lower limit (DC)	20.4 V
• permissible range, upper limit (DC)	28.8 V
Input current	
Current consumption (rated value)	300 mA; CPU only
Current consumption, max.	900 mA; CPU with all expansion modules

ANNEXURE B:SHAFT ENCODER

Incremental 40-mm-dia. Rotary Encoder

E6B2-CWZ6C 1000P/R 2M

Image

Rotary Encoder, 1000 P/R, 5 to 24 VDC, NPN open collector, Cable length 2 m

Encoding method	Incremental Shaft model
Resolution	1000 P/R
Output phases	A, B and Z
Control output	NPN open collector
Connection method	Pre-wired models (Cable length: 2 m)

Ratings / Performance

As of March 13, 2024

Categorise		Incremental Shaft model
Diameter		40 mm dia.
Power supply voltage		5 to 24 VDC (-5% to +15%) Ripple (p-p) 5% max.
Current consumption		80 mA max.
Resolution		1000 P/R
Inrush current		Approx. 9 A (0.3 ms)
Output phases		A, B and Z
Control output	Output type	NPN open collector
	Load power supply voltage	30 V max.DC
	Sink current	35 mA max.
	Residual voltage	0.4 V max. (at sink current 35 mA)
Starting positional point		Equipped
Max. response frequency		100 kHz
Phase difference on output		90±45 ° between A and B (1/4 T ± 1/8 T)
Rise and fall times of output		1 μs max. (Cable length: 2 m max., output voltage: 5 V, load resistance: 1 kΩ)
Starting torque		0.98 mN.m max.
Moment of inertia		1 x 10^{-6} kg.m^2 max.
Shaft loading		Radial: 30 N Thrust: 20 N
Max. permissible rotation		6000 r/min

ANNEXURE C: INDUCTION MOTOR

25W

INDUCTION MOTOR, REVERSIBLE MOTOR
□80mm TERMINAL BOX TYPE

INDUCTION MOTOR - CONTINUOUS RATING

SIZE mm sq.	Type	Poles	Output (W)	Voltage (V)	Frequency (Hz)	Duty	Rated Load Current (A)	Rated Load Speed (rpm)	Rated Load Torque (kg-cm)	Rated Load Torque (N-m)	Starting Torque (kg-cm)	Starting Torque (N-m)	Capacitor (uF)
80	S8I25GA-T S8I25GA-T1	4	25	1ø 110	60	Cont.	0.51	1600	1.60	0.160	1.80	0.180	6.0
	S8I25GB-T S8I25GB-T1	4	25	1ø 220	60	Cont.	0.23	1550	1.65	0.165	1.80	0.180	1.5
	S8I25GC-T S8I25GC-T1	4	25	1ø 100	50	Cont.	0.57	1250	2.00	0.200	1.45	0.145	6.0
					60		0.52	1550	1.65	0.165			
	S8I25GD-T S8I25GD-T1	4	25	1ø 200	50	Cont.	0.30	1250	2.00	0.200	1.45	0.145	1.5
					60		0.29	1500	1.70	0.170			
	S8I25GX-T S8I25GX-T1 S8I25GX-TCE S8I25GX-T1CE	4	25	1ø 220	50	Cont.	0.23	1200	2.10	0.210	1.10	0.110	1.3
				1ø 240			0.25		2.20	0.220	1.30	0.180	
	S8I25GU-T S8I25GU-T1 S8I25GU-TCE S8I25GU-T1CE	4	25	3ø 200	50	Cont.	0.26	1300	1.95	0.195	3.50	0.350	-
					60		0.24	1550	1.65	0.165	2.90	0.290	
	S8I25GT-T S8I25GT-T1 S8I25GT-TCE S8I25GT-T1CE	4	25	3ø 220	50	Cont.	0.28	1350	1.90	0.190	4.20	0.420	-
					60		0.24	1600	1.60	0.160	3.50	0.350	
	S8I25GS-T S8I25GS-T1 S8I25GS-TCE S8I25GS-T1CE	4	25	3ø 380	50	Cont.	0.14	1250	2.00	0.200	3.15	0.315	-
					60		0.12	1500	1.70	0.170	2.50	0.250	
				3ø 400	50	Cont.	0.14	1250	2.10	0.210	3.50	0.350	
					60		0.12	1500	1.80	0.180	2.75	0.275	
				3ø 415	50	Cont.	0.15	1300	1.95	0.195	3.75	0.375	
					60		0.13	1550	1.65	0.165	3.00	0.300	
				3ø 440	50	Cont.	0.15	1300	2.10	0.210	4.40	0.440	
					60		0.13	1550	1.80	0.180	3.40	0.340	

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by Attaullah Manzoor

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