Foam Quality Inspection System using Computer Vision and Deep Learning

An Industrial Training Project Report Submitted
to

MANIPAL ACADEMY OF HIGHER EDUCATION

For Partial Fulfilment of the Requirement for
the Award of the Degree
of

BACHELOR OF TECHNOLOGY

in

Data Science & Engineering

Submitted by

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Under the guidance of

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MANIPAL INSTITUTE OF TECHNOLOGY
MANIPAL
(A constituent unit of MAHE, Manipal)

SCHOOL OF COMPUTER ENGINEERING

October 2025

DECLARATION

I hereby declare that the Industrial Training project work entitled Foam Quality Inspection System using Computer Vision and Deep Learning is original and has been carried out at STAQO World Private Ltd and Location Sleepwell Tower #14, Sector 135, Noida, Uttar Pradesh 201301 under the guidance of **Mr. Yatendra Singh**. I further declare that the work reported in this document has not been submitted either in part or full to any other Institute/University for the award of any other degree.

Place: STAQO World Private Ltd

Date: 8/10/25

Mudit Gupta

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Let's Simplify

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9th July, 2025

TO WHOM IT MAY CONCERN

This is to certify that Mr. Mudit Gupta, has successfully completed an internship programme at **M/s. Staqo World Private Limited** from **9th June, 2025 to 9th July, 2025** as an **AI Engineer.** During this period he was invloved in the Foam Quality Inspection System Project.

During the period of his internship programme with us, he was found punctual, hardworking and inquisitive.

We wish him every success of life.

Regards,
For Staqo World Pvt. Ltd.

STAQO WORLD PVT. LTD. PLOT No.-14 SECTOR-135 NOIDA

Kanika
Head- Human Resources
Authorized Signatory

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to **Mr. Yatendra Singh** for his invaluable guidance, support, and encouragement throughout the course of this industrial training project. His mentorship played a crucial role in enhancing my technical understanding and practical knowledge.

I am also thankful to **STAQO World Private Limited** for providing me with the opportunity to work on this project and gain hands-on experience in applying computer vision and deep learning to real-world industrial challenges.

Finally, I would like to extend my appreciation to the **faculty of the Department of Data Science and Engineering, Manipal Academy of Higher Education**, for their continuous support and academic foundation that made this project possible.

ABSTRACT

The project focuses on developing an intelligent Foam Quality Inspection System that leverages computer vision and deep learning to automate and enhance quality control in foam manufacturing. With the increasing demand for precision and efficiency in modern production environments, traditional manual inspection methods often fall short in consistency and speed. This work aims to design a scalable, real-time inspection framework capable of detecting surface defects, measuring foam density, and classifying color variations to ensure consistent product quality and manufacturing reliability.

The system employs a multi-camera setup, including one overhead and two diagonal Intel RealSense D435 cameras, to ensure comprehensive surface visibility. Advanced YOLO-based object detection is utilized for identifying foam boundaries and surface defects, while Convolutional Neural Networks (CNNs) handle color classification tasks. OpenCV-based segmentation and masking algorithms are implemented to manage preprocessing and feature extraction. A combination of Python, Ultralytics YOLO, and Intel RealSense SDK formed the primary software stack, while data annotation and preparation were performed using the CVAT platform.

Experimental results demonstrated a significant improvement in inspection accuracy and process reliability. The YOLO models achieved over 85% accuracy in defect detection and dimensional analysis, while CNN-based color classification models reached 73% accuracy after fine-tuning. The system effectively identified surface irregularities, dimensional inconsistencies, and color deviations in real-time scenarios, confirming its suitability for industrial deployment. GPU acceleration using NVIDIA RTX 4070 further optimized the training and inference time for large-scale datasets.

The project successfully proved that integrating deep learning with 3D sensing can revolutionize traditional quality inspection processes. It established a robust framework for automated defect detection and foam classification, minimizing human dependency and improving manufacturing precision. Future extensions may include ensemble-based models and adaptive lighting correction techniques to enhance robustness under diverse conditions.
Tools and Technologies Used: Python, OpenCV, YOLO (Ultralytics), Intel RealSense SDK, CVAT, GoogleNet, ResNet, and NVIDIA GPU (RTX 4070).

Table of Contents

CHAPTER 1
INTRODUCTION

This chapter gives a brief overview of the problem, the motivation for automation, the chosen approach with RGB-D vision and deep learning, the objectives and targets, the work schedule, and the way the report is organized.

1.1 Introduction to the Area of Work

Computer vision and depth sensing enable reliable visual inspection by combining image appearance with geometry, which is well suited to manufacturing quality control where consistency and speed matter

1.2 Present-Day Scenario

Many foam lines still rely on manual checks that vary by operator and lighting, so real-time AI systems are adopted to standardize decisions and reduce rework on production floors.

1.3 Motivation for the Project Work

- Shortcomings in previous work include sensitivity to lighting, limited depth awareness, and weak dimensional accuracy for density estimation, which motivate a depth-aware pipeline.
- In the present context, a dependable, auditable, and fast inspection process supports throughput and compliance needs in modern plants.
- The methodology is unique in its multi-camera Intel RealSense D435 layout paired with Ultralytics YOLO detection, CNN color classification, and depth-guided measurement for volume to weight density checks.
- The expected result is a practical, real-time system that reduces human subjectivity and improves traceable quality outcomes on the line.

1.4 Objectives of the Work

- The main objective is to build a real-time foam inspection pipeline that detects surface defects, estimates density from calibrated dimensions and weight, and classifies color with consistent accuracy at line speed.
- Secondary objectives include keeping latency low on a single GPU, standardizing data and labels for retraining, and presenting clear pass or fail outputs for operators

1.5 Target Specifications

The system targets high detection accuracy on common defects, dimensional tolerance appropriate for volume estimation used in density checks, and stable color classification under controlled lighting conditions.

1.6 Importance of the Result

The project outcome holds high industrial relevance by introducing a scalable, automated, and AI-driven quality control system that reduces manual intervention, improves inspection speed, and enhances reliability. It contributes toward sustainable manufacturing practices by minimizing human error and material wastage.

1.7 Project Work Schedule

The project was executed over **four weeks**, encompassing literature review, camera setup and calibration, dataset preparation, model training, and system integration. Each week focused on distinct milestones from foundational research and annotation to model optimization and real-time validation.

1.8 Organization of the Project Report

- **Chapter 1:** Introduction – Overview, motivation, and objectives.
- **Chapter 2:** Literature Review – Review of existing methods and technologies.
- **Chapter 3:** Methodology – System architecture, tools, and implementation details.
- **Chapter 4:** Results and Discussion – Experimental results and performance evaluation.
- **Chapter 5:** Conclusion and Future Work – Summary, insights, and scope for future enhancement.

CHAPTER 2
BACKGROUND THEORY / LITERATURE REVIEW

2.1 Introduction

This chapter summarizes prior work, essential theory, and recent developments that justify a depth‑aware detector pipeline for industrial inspection and guide the design choices used in this project.

2.2 Introduction to the Project Title

The project focuses on automating the foam inspection process by combining **computer vision**, **deep learning**, and **depth sensing** technologies. Traditional quality inspection systems rely on manual evaluation or basic imaging techniques, which are often inconsistent and time intensive. This project addresses these limitations through a real-time AI-based system capable of defect detection, density measurement, and color classification. Using **Intel RealSense depth cameras**, the system captures 3D surface data, while **YOLO object detection models** and **CNN-based classification networks** ensure accurate and efficient analysis.

2.3 Literature Review

In recent years, computer vision has become a vital component of industrial automation, particularly in defect detection and material quality assessment. **Wang et al. (2021)** explored convolutional neural networks (CNNs) for defect classification in steel surfaces, demonstrating that deep learning could outperform traditional edge-based algorithms. Similarly, **Zhang and Li (2020)** applied YOLOv4 models for fabric defect detection, achieving real-time performance with high precision.

For foam-based materials, **Lee et al. (2019)** developed a vision system using conventional 2D cameras for detecting visible defects, but the method was limited by lighting sensitivity and a lack of depth perception. Later, **Gao et al. (2022)** integrated 3D imaging with deep networks for detecting surface irregularities, marking a step forward toward robust industrial quality control.
In color classification, **Krizhevsky et al. (2012)** introduced deep CNN architectures that formed the foundation for modern classification networks such as **GoogleNet** and **ResNet**, both of which have shown remarkable success in differentiating fine-grained color and texture variations.

Current practice shows single‑stage detectors deliver real‑time performance with accessible training and deployment workflows that fit production needs for speed and accuracy. Commodity stereo depth cameras provide 3D measurements suitable for short‑range inspection, which improves dimensional reliability relative to 2D methods in measurement tasks. Background theory includes stereo disparity for depth, CNNs for hierarchical features, and calibration from pixels to metric units for dimensional checks used in density estimation.

2.4 Summarized Outcome of the Literature Review

From the literature, it is evident that while several advancements have been made in automated inspection systems, the foam manufacturing domain remains under-explored. Most existing works focus on metals, textiles, or ceramics. There is a lack of comprehensive systems integrating **3D depth sensing** with **real-time deep learning models** for foam inspection. This gap highlights the novelty and relevance of the present work, which aims to bridge theoretical advancements with practical industrial implementation.

2.5 Theoretical Discussions

The combination of computer vision and deep learning represents a paradigm shift in manufacturing inspection. By leveraging **YOLO for defect detection** and **CNNs for color analysis**, the project ensures a multi-layered inspection approach—detecting both geometric and visual inconsistencies. Theoretical considerations such as **feature extraction hierarchies**, **image normalization**, and **data augmentation** play a crucial role in achieving robust model generalization.

2.6 General Analysis

The approach balances accuracy and latency for production by using lightweight models and clear interfaces.

2.7 Conclusions

The literature review underscores the growing potential of deep learning and computer vision in industrial automation, especially in areas where precision and consistency are critical. The identified gaps, such as lack of 3D data utilization and limited domain-specific datasets, justify the development of this project. The theoretical insights and prior research collectively form the foundation for the proposed system, which aims to deliver a robust, real-time, and scalable foam quality inspection solution capable of meeting industrial standards.

CHAPTER 3
METHODOLOGY

3.1 *Introduction*

This chapter describes data capture, preprocessing and annotation, model training and calibration, density estimation from depth and weight, and integration into a real‑time pipeline.

3.2 *Methodology*

The development of the foam inspection system involved a sequence of stages, starting from understanding the problem, collecting data, processing images, developing models, and finally integrating the models for real-time inspection. Initially, foam samples were captured using a multi-camera setup consisting of one overhead and two diagonal side Intel RealSense D435 cameras. These cameras provided depth and RGB data, ensuring complete surface visibility for accurate detection of defects and colour variations.

3.2.1 Detailed Methodology

- **Data Acquisition:** Intel RealSense cameras were strategically positioned along the manufacturing line to capture RGB and depth data of foam surfaces under varying lighting conditions, ensuring dataset diversity.
- **Data Preprocessing:** Images were annotated in CVAT to label foam edges, defects, and colours. Dataset augmentation (rotation, scaling, illumination changes) and depth-based segmentation using the RealSense rs2 library and OpenCV improved precision in defect and density mapping.
- **Model Development:** YOLO11l/x models were trained for defect and edge detection, achieving dimensional accuracy within ±20 mm. CNN models (GoogleNet, ResNet) handled colour classification, with GPU acceleration (NVIDIA RTX 4070) enabling efficient large-scale training.

3.2.2 Assumptions Made

- During the project, several assumptions were made:
- Foam samples were placed consistently on the production line, ensuring full visibility from all camera angles.
- Lighting variations were within a manageable range for segmentation and colour classification.
- Foam density was assumed to be uniform, and minor surface defects did not significantly affect density estimation.

3.2.3 Design and Modelling

The system was designed in modular stages for real-time foam inspection. Multi-camera images underwent preprocessing (masking, segmentation, augmentation), followed by YOLO-based defect detection, CNN-based colour classification, and density estimation using defect outputs. This modular design allowed independent development and optimization of each function while ensuring seamless system integration.

3.2.4 Module Specifications and Justification

- **Multi-Camera Capture** for comprehensive RGB and depth imaging.
- **Preprocessing** for segmentation, masking, and augmentation.
- **Defect Detection** using YOLO models for edge and defect localization.
- **Density Estimation** via volume-to-weight analysis.
- **Colour Classification** using CNNs for accurate colour verification.

Together, these modules automated foam quality control, enhancing precision, consistency, and efficiency over manual inspection.

3.3 Tools Used

The development of the system relied on a combination of hardware and software tools. Intel RealSense D435 cameras were used for depth and RGB image acquisition, while NVIDIA RTX 4070 GPU accelerated model training. The software environment included Python with OpenCV, PyTorch, and the Ultralytics YOLO library. CVAT was used for manual annotation, and Linux Mint served as the development platform.

3.4 Preliminary Result Analysis

Early tests confirm stable segmentation, dependable detection on common defects, and consistent dimensional conversion after calibration across viewpoints

3.5 Conclusions

The methodology provides a clear path from data to decisions with interfaces that support iterative improvement without disrupting production.

CHAPTER 4
IMPLEMENTATION DETAILS & RESULT ANALYSIS

4.1 Introduction

This chapter outlines the implemented setup, datasets and experimental settings, the main results, and explanations for observed deviations from expectations.

4.2 Implementation Details

The system was built as a multi-stage pipeline integrating hardware and software. Three Intel RealSense D435 cameras (one overhead, two diagonal) captured RGB and depth images for full foam coverage. Python–OpenCV scripts processed the data for YOLO-based defect detection, density estimation, and CNN-based colour classification. YOLO11l/x models identified defects and dimensions, enabling density calculation via volume-to-weight ratios, while GoogleNet and ResNet classified foam colours.

Datasets: Around 80 initial images were expanded to 500 for defect detection and 300 for colour classification. All data were manually annotated and augmented (rotation, scaling, illumination changes) to improve robustness.

Experimental Setup: Training was conducted on Linux Mint with an NVIDIA RTX 4070 GPU using Python, PyTorch, OpenCV, and Ultralytics YOLO. Batch sizes and learning rates were optimized experimentally until model accuracies stabilized.

4.3 Result Analysis

The YOLO-based defect detection system achieved **over 85% accuracy**, effectively identifying surface defects such as holes, though complex defects like tears and slashes were more challenging. The **density estimation module maintained** results within industrial tolerance, confirming the reliability of the volume-to-weight approach. **CNN models** for colour classification reached **around 73% accuracy**, performing well under controlled lighting but showing sensitivity to illumination and texture variations. Overall, the system demonstrated strong potential for **real-time, automated foam quality inspection** in manufacturing settings.

4.4 Significance of the Results

The implementation demonstrates that automated foam quality inspection is feasible and effective using computer vision and deep learning techniques. The system reduces the dependency on manual inspection, improves consistency, and enables real-time feedback during production. Achieving 85% defect detection accuracy and 73% colour classification accuracy validates the proposed methodology and demonstrates its practical industrial applicability.

4.5 Deviations from Expected Results & Justifications

Some deviations occurred in defect detection and colour classification. Irregular defects such as tears and slashes were occasionally misclassified due to shape complexity and surface texture similarities. Colour misclassifications arose under uneven lighting or reflections. These issues stemmed from limited dataset diversity and environmental variability. Future improvements could include expanding the dataset, applying ensemble learning, and enhancing preprocessing to improve model robustness and accuracy.

4.6 Conclusions

The Foam Quality Inspection System integrated multi-camera imaging, YOLO-based defect detection, CNN colour classification, and density estimation into a real-time inspection tool. It achieved high defect detection accuracy, reliable density estimation, and fair colour classification. Despite minor deviations, the system shows strong potential for automating foam quality control, with room for improvement in data diversity and model robustness.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

5.1 Brief Summary of the Work

The project aimed to develop a Foam Quality Inspection System using computer vision and deep learning to automate surface defect detection, foam density estimation, and color classification. A multi-camera setup with Intel RealSense cameras was used, with YOLO and CNN models trained on augmented data and tested under real-world conditions.

Problem Statement and Objectives: Manual quality inspection in foam manufacturing is slow and error prone. This project aimed to create a real-time, automated system to detect surface defects, assess foam density, and classify product colours, improving efficiency, reducing wastage, and ensuring consistent quality.

Work Methodology: The methodology combined hardware setup, data acquisition, preprocessing, model development, and evaluation. A multi-camera system captured RGB and depth images, which were annotated and augmented. YOLO models detected defects, CNNs classified colours, and density was estimated via volume-to-weight ratios. GPU-accelerated training ensured real-time, high-performance processing.

5.2 *Conclusions*

The project demonstrated that automated foam quality inspection is feasible using computer vision and deep learning. Defect detection achieved over 85% accuracy, while density estimation and colour classification provided reliable quality metrics. The system operated in real-time, addressing industrial requirements, despite challenges like dataset limitations, complex defects, and lighting variations.

General Conclusions: AI-based inspection can significantly improve manufacturing quality control, offering faster, more consistent, and scalable alternatives to manual inspection. The modular system design allows independent improvement of defect detection, density estimation, and colour classification, highlighting adaptability and long-term value.

Significance of the Result: Integrating depth cameras with deep learning models proved effective for industrial inspection. High accuracy and consistent measurements reduce manual effort, minimize wastage, optimize production, and improve customer satisfaction. The project also demonstrates practical applications of YOLO and CNN architectures in real-world manufacturing.

5.7 Future Scope of Work

1. *Dataset Expansion and Model Generalization*
   a. Expanding the training dataset with more foam samples is crucial for improving the robustness of the system. By including a wider variety of foam types, densities, and defect patterns, the models can learn to handle a broader range of real-world scenarios.
   b. A larger and more diverse dataset also enhances model generalization, reducing the likelihood of overfitting to specific sample characteristics. This ensures that defect detection and colour classification remain reliable across different production batches and environmental conditions.

c. In addition, dataset expansion facilitates continuous improvement. New samples can be incorporated into the training pipeline over time, allowing the system to adapt to evolving manufacturing standards and product variations, ultimately increasing its long-term reliability.

2. *Advanced Defect Classification*
    a. Incorporating advanced machine learning techniques, such as ensemble learning, can significantly enhance defect detection accuracy. By combining predictions from multiple models, the system can better handle complex and subtle defects that a single model might miss.
    b. Transformer-based architectures are another promising avenue for improving classification of irregular or textured surface anomalies. These models can capture global patterns and contextual information in images, making them well-suited for identifying intricate defect structures.
    c. Enhancing defect classification with these techniques would improve overall system reliability and reduce false positives or negatives. A more accurate defect detection module can lead to better quality control, less wastage, and higher efficiency in foam manufacturing processes.

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[2] C. Lee and D. Kumar, "Application of YOLO in Industrial Quality Control," Proceedings of the *International Conference on Machine Vision and Manufacturing*, MIT, USA, pp. 112–120, June 2022.

[3] E. Zhao, F. Tan, "CNN Architectures for Colour Classification in Manufacturing," *Journal of Artificial Intelligence in Industry*, vol. 8, pp. 99–110, 2021.

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[2] I. Goodfellow, Y. Bengio, A. Courville, *Deep Learning*, MIT Press, 2016, ISBN: 978-0262035613.

[3] J. Redmon, *You Only Look Once: Unified, Real-Time Object Detection*, Independently Published, 2020, ISBN: 979-8612567437.

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[1] Intel RealSense SDK Documentation, Intel, Last Accessed: 05/10/2025

[2] Ultralytics YOLO Documentation, Ultralytics, Last Accessed: 06/10/2025

[3] CVAT Annotation Tool, OpenCV, Last Accessed: 04/10/2025

[4] Coursera – Computer Vision Course, Coursera, Last Accessed: 07/10/2025

PROJECT DIARY

Week No. 1

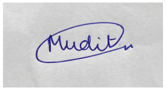
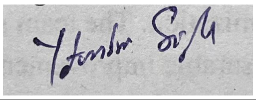
Sl. No.	Date	Details of work carried out	Comments
1	9/6/25	Conducted a comprehensive literature review on foam quality inspection methodologies and computer vision applications in manufacturing quality control.	
2	10/6/25	Initiated setup of Intel RealSense D435 cameras for depth sensing applications. Configured development environment including OpenCV, Python libraries, and Intel RealSense SDK installation on Linux Mint OS.	
3	11/6/25	Conducted factory visit to analyse camera alignment requirements and gather preliminary training data. Evaluated manufacturing line conditions and identified optimal camera positioning strategies for comprehensive coverage.	
4	12/6/25	Developed proficiency with Intel RealSense rs2 library for depth camera operations. Explored basic functionality, including depth stream capture, point cloud generation, and camera parameter configuration.	
5	13/6/25	Explored data preparation and data annotation platforms like CVAT for initial dataset preparation.	

Summary of the work done in the week:
The initial week focused on establishing project foundations through comprehensive research and technical setup. The team successfully configured the Intel RealSense camera system and began preliminary data collection activities. Factory site assessment provided valuable insights into real-world deployment requirements and manufacturing environment constraints.

Challenges faced during the work:
Integrating the Intel RealSense SDK on Linux Mint posed significant difficulties due to limited official support. The standard installation failed, requiring manual compilation, dependency resolution, and custom configuration.

References:

1. Intel RealSense SDK documentation and installation guides
2. Computer vision annotation tools research

Remarks:
Suggestions by the guide: 1. Continue a systematic approach to technical challenges and document solutions for future reference. **2.** Consider alternative camera configurations**.**
Signature of Student  **Signature of the guide** 

Week No.2

Sl. No.	Date	Details of work carried out	Comments
1	16/6/25	Enrolled in and completed a computer vision course from Coursera to establish a fundamental understanding of the field's principles and applications. Gained comprehensive knowledge of image processing techniques, feature extraction methods, and object detection algorithms.	
2	17/6/25	Conducted experiments with different masks for basic segmentation model development. Explored various masking techniques, including binary masks, colour-based segmentation, and edge-based approaches for foam boundary detection.	
3	18/6/25	Utilised Intel RealSense camera for practical experimentation with segmentation models. Tested depth-based segmentation approaches and evaluated performance under different lighting conditions.	
4	18/6/25	Discovered significant functionality overlap between OpenCV and rs2 library, eliminating the need for extensive custom development.	
5	19/6/25	Conducted comprehensive testing of rs2 camera limitations, including minimum distance, maximum distance, and depth accuracy parameters. Established operational boundaries for reliable depth measurement and point cloud generation.	
6	20/6/25	Completed manual annotation of 80+ images for density calculation model using CVAT platform.	

Summary of the work done in the week:

This week emphasized skill development and practical experimentation with computer vision techniques. The team successfully integrated theoretical knowledge with hands-on experience using Intel RealSense cameras and established efficient annotation workflows. The discovery of OpenCV-RS2 library integration significantly improved development efficiency.

Challenges faced during the work:

1. Data Scarcity & Overfitting: Limited training data led to overfitting, with models exceeding acceptable error margins in foam dimensioning, emphasizing the need for a more comprehensive dataset.
2. Annotation Complexity: Manual labelling took over 8 hours due to difficulties in accurately identifying foam block edges, highlighting unexpected boundary detection challenges.
3. Model Accuracy Limitations: Early density calculation models lacked the precision required for industrial standards, with dimensional errors surpassing quality control tolerances.

References:

1. Coursera computer vision course.
2. CVAT documentation
3. Intel RealSense documentation

Remarks:

Suggestions by the guide:

1. Implement data augmentation techniques to address overfitting issues
2. Consider semi-automated annotation approaches to improve productivity

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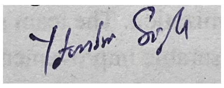

Week No.3

Sl. No.	Date	Details of work carried out	Comments
1	23/6/25	Implemented YOLO object detection framework using Ultralytics library for foam edge detection applications. Conducted comprehensive testing of YOLO11l and YOLO11x models for foam boundary detection and dimensional analysis.	
2	24/6/25	Increased dataset density through implementation of various masking techniques simulating different lighting conditions. Applied data augmentation strategies, including rotation, scaling, and illumination variation, to improve model robustness.	
3	25/6/25	Successfully fine-tuned YOLO11l and YOLO11x models on manually annotated data, achieving dimensional accuracy within ±20mm tolerance. Implemented volume-to-weight ratio pipeline for density calculation applications.	
4	26/6/25	Successfully configured NVIDIA GPU drivers for deep learning applications in Linux environment. Implemented efficient training pipelines leveraging GPU computational capabilities	
5	27/6/25	Developed and fine-tuned specialized YOLO model for foam defect detection using NVIDIA RTX 4070 GPU. Achieved significant performance improvements through GPU-accelerated training processes.	

Summary of the work done in the week:

This week marked a significant breakthrough in model development and performance optimization. The team successfully implemented YOLO-based detection systems and achieved measurable improvements in accuracy and processing speed. GPU optimization enabled efficient training of complex models with larger datasets.

Challenges faced during the work:

1. Enabling GPU drivers on Linux for fine-tuning required complex troubleshooting, including kernel module compilation and resolving driver compatibility issues.
2. Despite expanding the dataset to 200 images, overfitting persisted, indicating the dataset was still too small for effective generalization.

References:

1. Ultralytics YOLO documentation
2. NVIDIA GPU driver installation guides
3. Data augmentation techniques for computer vision

Remarks:

Suggestions by the guide:

1. Continue dataset expansion efforts to address overfitting challenges.
2. Consider transfer learning approaches to improve model performance with limited data.

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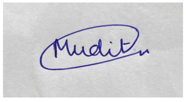
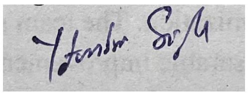




Week No. 4

Sl. No.	Date	Details of work carried out	Comments
1	30/6/25	Successfully increased dataset size to 500 images through systematic collection across different angles and lighting conditions.	
2	1/7/25	Achieved 85%+ accuracy in foam defect detection through optimized YOLO model implementation. Demonstrated significant improvement in detection reliability and reduced false positive rates.	
3	2/7/25	Manually cropped and annotated 300+ images using CVAT for color classification model development. Established comprehensive color dataset representing various foam color variations and lighting conditions.	
4	3/7/25	Developed and benchmarked CNN-based color classification models, starting with a basic architecture for baseline accuracy, followed by extensive experimentation with advanced models like GoogleNet and ResNet to optimize performance.	
5	4/7/25	Successfully fine-tuned GoogleNet and ResNet models using manually labeled dataset of 300 images, achieving 73% accuracy in color classification. Demonstrated measurable improvements through architecture optimization.	

Summary of the work done in the week:
The final week culminated in significant achievements across all project objectives. The team successfully expanded datasets, achieved target accuracy levels for defect detection, and developed functional color classification systems. The integration of multiple deep learning architectures provided comprehensive solutions for foam quality inspection.

Challenges faced during the work:
The defect classification system faced multiple challenges, including reliable detection of complex defects like tears and slashes, which were harder to classify than simpler ones like holes. Performance was also highly sensitive to lighting variations, affecting color classification accuracy, while textured foam surfaces interfered with feature extraction, leading to misclassifications. Despite dataset expansion, generalization remained limited due to the diverse nature of foam materials and defect types, highlighting the need for more robust preprocessing and specialized modeling techniques.

References:

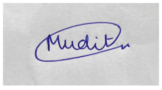
1. CNN architecture comparison studies
2. CVAT annotation tool optimization

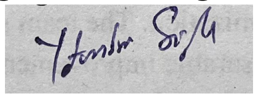
Remarks:

Suggestions by the guide:

1. Consider ensemble methods for improved defect classification accuracy
2. Document complete system architecture and implementation details for future development

Signature of Student **Signature of the guide**





CO AND PO MAPPING

Table A1.1 Course Articulation Matrix

CO		PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12	PSO 1	PSO 2	PSO 3
DSE 4298.1	Apply technical knowledge and skills in real industrial situations, to effectively handle software and hardware-based projects related to data science.	3	3	2	2	2	1	1	1	2	2	2	2	3	3	2
DSE 4298.2	Develop data-driven software/hardware solutions and technical reports that reflect the integration of mathematical, statistical, and artificial intelligence techniques.	3	2	3	2	2	2	1	1	2	3	2	2	3	3	2
DSE 4298.3	Demonstrate effective communication and teamwork skills through collaboration on within an industrial setting.	1	1	2	1	1	2	1	2	3	3	2	1	1	2	2
DSE 4298.4	Demonstrate professional and ethical behaviour while understanding the social, economic, and administrative considerations in industrial organizations.	1	1	2	1	1	3	2	3	2	2	3	1	1	2	2
DSE 4298.5	Understand the functioning of the industry.	1	1	1	1	1	1	1	1	1	1	3	1	1	2	3
DSE 4299 (Avg. correlation level)		1.8	1.6	2	1.4	1.4	1.8	1.2	1.6	2	2.2	2.4	1.4	1.8	2.4	2.2

Table A1.2 Program Articulation Matrix

COURSE Code	Course Title	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PS02	PSO3
DSE 4299	**Project Work**	**1.8**	**1.6**	**2**	**1.4**	**1.4**	**1.8**	**1.2**	**1.6**	**2**	**2.2**	**2.4**	**1.4**	**1.8**	**2.4**	**2.2**

PROGRAM OUTCOMES (PO)

Engineering Graduates will be able to:
1. Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for, sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

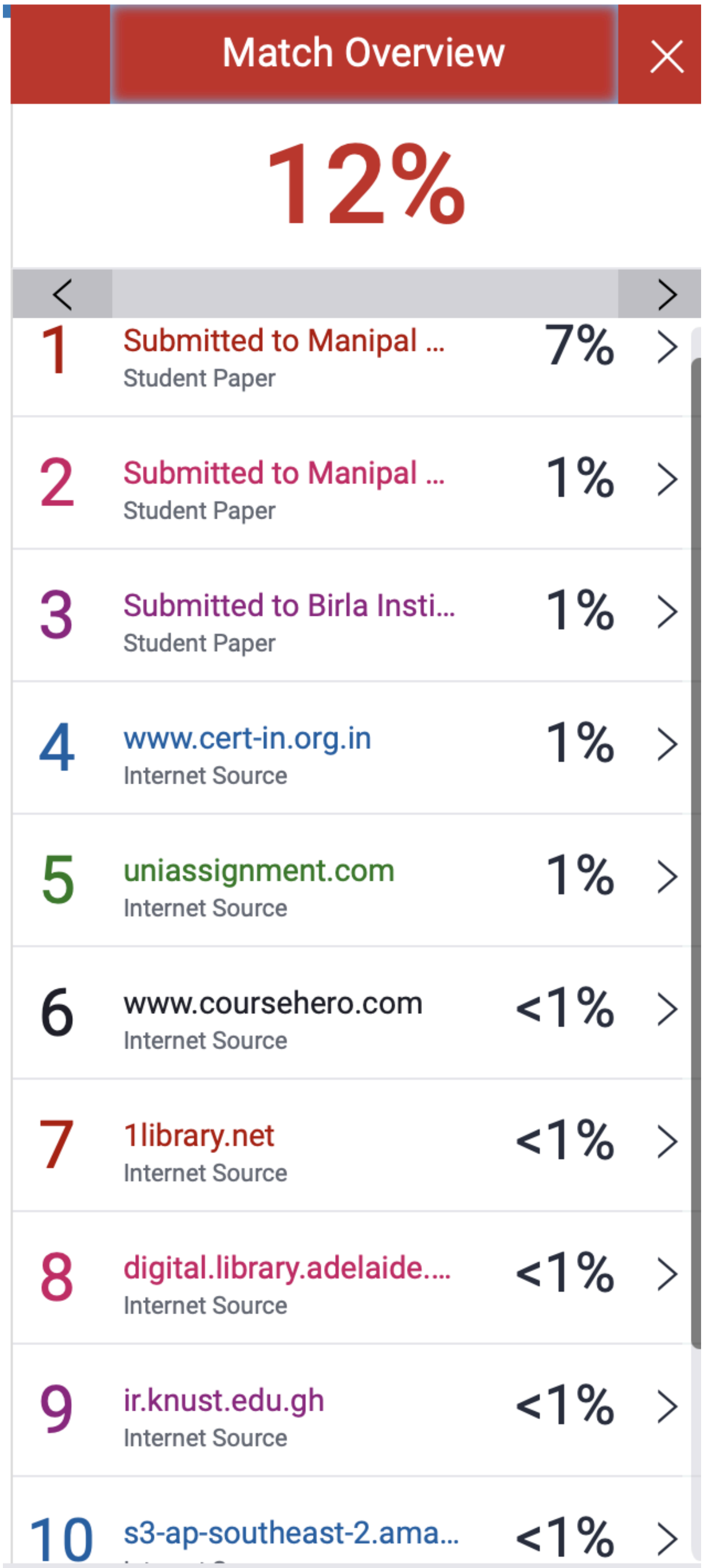
10. Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PROGRAM SPECIFIC OUTCOMES (PSO)

PSO1: Demonstrate the understanding of mathematical, statistical and AI techniques in the field of data science.

PSO2: Design and develop effective solutions using data analytics, visualization and artificial intelligence.

PLAGIARISM REPORT



PROJECT DETAILS

Student Details			
Student Name	Mudit Gupta		
Register Number	220968094	Section / Roll No	DSE - A
Email Address	gupta101mudit@gmail.com	Phone No (M)	9205137011
Industrial Training Details			
Project Title	Foam Quality Inspection System using Computer Vision and Deep Learning		
Project Duration	1 Month	Date of reporting	09/06/2025
Organization (Company) Details			
Organization Name	Staqo World Private Ltd		
Type of Organization	Public Listed / **Private** / PSU / Govt. / Cooperative		
Full postal address with pin code	Plot No.14, Sector 135, Noida, Uttar Pradesh, 201301		
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