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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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Sleepwell Tower #14, Sector 135, Noida, Uttar Pradesh 201301

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October 2025

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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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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).
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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.

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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.

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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

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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.
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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.

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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.
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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

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CHAPTER 4

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.

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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.

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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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[3] E. Zhao, F. Tan, "CNN Architectures for Colour Classification in Manufacturing," Journal

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PROJECT DIARY		
Week No. 1		
Sl.		
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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		
10/6/2		
5		
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		
11/6/2		
5		
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		
12/6/2		
5		
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		
13/6/2		

PROJECT DIARY
5
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
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Remarks:		
Suggestions by the guide:		
1.■ Continue a systematic approach to technical challenges and document solutions for future		
reference.		
2.■ Consider alternative camera configurations..		
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Week No.2
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Date
Details of work carried out
Comments
1
16/6/2
5
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
17/6/2
5
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
18/6/2
5
Utilised Intel RealSense camera for practical
experimentation with segmentation models. Tested
depth-based segmentation approaches and evaluated
performance under different lighting conditions.
4
18/6/2
5
Discovered significant functionality overlap between
OpenCV and rs2 library, eliminating the need for
extensive custom development.

Week No.2
5
19/6/2
5
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
20/6/2
5
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.
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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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21		

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

Week No.3

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

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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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23		

Week No. 4
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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.

Week No. 4
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
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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		
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CO AND PO MAPPING
Table A1.1 Course Articulation Matrix
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
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2.2
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| 26 |
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CO AND PO MAPPING
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

CO AND PO MAPPING
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

CO AND PO MAPPING

CO AND PO MAPPING
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

CO AND PO MAPPING
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

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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.
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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.
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PLAGIARISM REPORT
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PROJECT DETAILS
Student Details
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Mudit Gupta
Register Number
220968094
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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
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Public Listed / Private / PSU / Govt. / Cooperative
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PROJECT DETAILS

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■
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