A PROJECT REPORT ON

Metal Surface Defect Detection

SUBMITTED TO
MIT SCHOOL OF COMPUTING, LONI, PUNE IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE

BACHELOR OF TECHNOLOGY
(Computer Science & Engineering (AIEC))

BY

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2025- 26

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Hereby declare that the project work incorporated in the present project entitled **"Metal Surface Detection"** is original work. This work (in part or in full) has not been submitted to any University for the award or a Degree or a Diploma. We have properly acknowledged the material collected from secondary sources wherever required. We solely own the responsibility for the originality of the entire content.

Date: 16/05/2025

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Date: 7/11/2025

ABSTRACT

This project implements an AI-powered quality control system for automated defect detection in manufacturing using YOLOv8 object detection on NVIDIA Jetson Orin Nano. The system detects six types of surface defects (crazing, inclusion, patches, pitted surface, rolled-in scale, and scratches) on the NEU dataset with real-time inference at less than 30 FPS.

The trained PyTorch model was optimized using TensorRT FP16 precision and deployed in a Docker container for reproducibility. A multi-frame confirmation mechanism reduces false positives, while MQTT integration enables remote monitoring and instant alerts. The system addresses key challenges in edge AI deployment including memory constraints, real-time performance optimization, and industrial reliability requirements.

Results demonstrate that edge AI can effectively replace manual inspection with consistent, rapid, and scalable automated quality control, achieving significant improvements in defect detection accuracy while reducing operational costs and human error.

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CHAPTER 1: INTRODUCTION

1.1 Introduction

Quality control is a critical component of modern manufacturing processes, directly impacting product reliability, customer satisfaction, and brand reputation. Traditional quality inspection methods rely heavily on manual visual inspection performed by human operators, which presents several significant limitations inconsistency speed limitations, subjectivity, cost and scalability.

Recent advances in artificial intelligence, particularly in computer vision and deep learning, have opened new possibilities for automated quality control. Object detection models can now identify defects with accuracy matching or exceeding human performance while operating continuously at high speeds.

1.2 Motivation

Traditional manual inspection of metal surfaces suffers from:

- **Limited coverage:** Human inspectors can examine only 5-10% of production
- **Fatigue effects:** Detection accuracy drops 25-30% after 2 hours of continuous inspection
- **Inconsistency:** Inter-operator variability reaches 20-30%
- **Speed limitations:** Manual inspection incompatible with modern production rates
- **Cost:** 24/7 inspection requires multiple shifts, increasing labor costs
- **Safety:** Inspectors exposed to hazardous factory floor conditions

1.3 Objectives

The primary objectives of this project are:

- Train YOLOv8 object detection model on NEU metal surface defect dataset
- Deploy model on NVIDIA Jetson Orin Nano edge computing platform
- Optimize inference using TensorRT for >30 FPS performance
- Create MQTT-based alerting system for immediate notifications

- Test on live camera feed and images of metal samples

1.5 Scope

The scope of the system includes:

- Real-time inference and instant alerting
- Edge deployment on Jetson Orin Nano
- MQTT-based communication
- Image logging of detected defects

CHAPTER 2: LITERATURE SURVEY

Automatic detection of metal-surface defects (scratches, pits, corrosion, cracks, dents, scale, inclusion marks) is critical for quality control in manufacturing lines because manual inspection is slow, inconsistent, and costly. Real-time, edge-deployable detectors enable inline inspection with low latency and reduced data movement, which is why lightweight detectors like **YOLOv8s** running on compact AI modules (Jetson Orin Nano) are attractive for industry.

Many recent papers adapt YOLOv8 or small/modified YOLOv8 variants for steel/metal surface defect detection — typically improving accuracy with lightweight architectural tweaks, attention modules, multi-scale fusion, or extra detection layers targeted at defect scale variations:

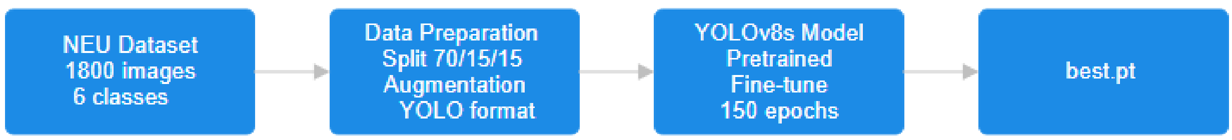
- **YOLOv8-based improvements**: Several studies build on YOLOv8 (including tiny/s variants) and report higher precision for steel defect tasks by adding detection layers, attention modules (e.g., CBAM), or lightweight neck/backbone modifications to better capture small/irregular defects (examples: MPA-YOLO, LSKA-YOLOv8, CMS-YOLOv8, DEFECT-YOLO). These works typically target accuracy boosts while keeping models compact for edge deployment.
- **Domain-specific augmentations & training**: Papers emphasise dataset-specific augmentations (Mosaic, mixup, contrast/illumination changes), careful label balancing, and sometimes synthetic data augmentation to handle long-tail defect classes and small-object detection. Pretraining and fine-tuning on related steel/metal datasets is common.
- **Lightweight and anchor-free design**: Researchers prefer lightweight variants (YOLOv8n/s) and anchor-free heads to reduce parameters and improve convergence in constrained settings, with many reporting favorable speed/accuracy trade-offs for production use.

The Jetson Orin Nano (and the Orin Nano “Super” developer kit / module variants) provides a substantial step up from older Jetson Nano/Xavier NX devices — higher TOPS and tensor-core support, configurable TDP modes, and improved memory bandwidth — making it suitable for YOLOv8s real-time inference and TensorRT acceleration.

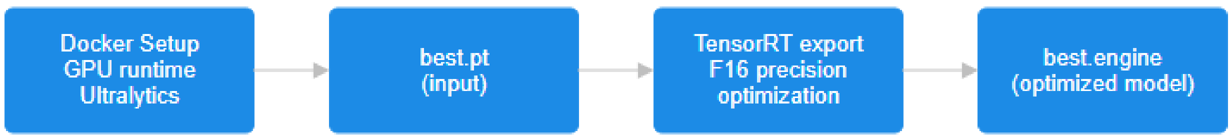
CHAPTER 3: PROJECT PLAN

The proposed metal surface defect detection system consists of four interconnected phases operating in sequence:

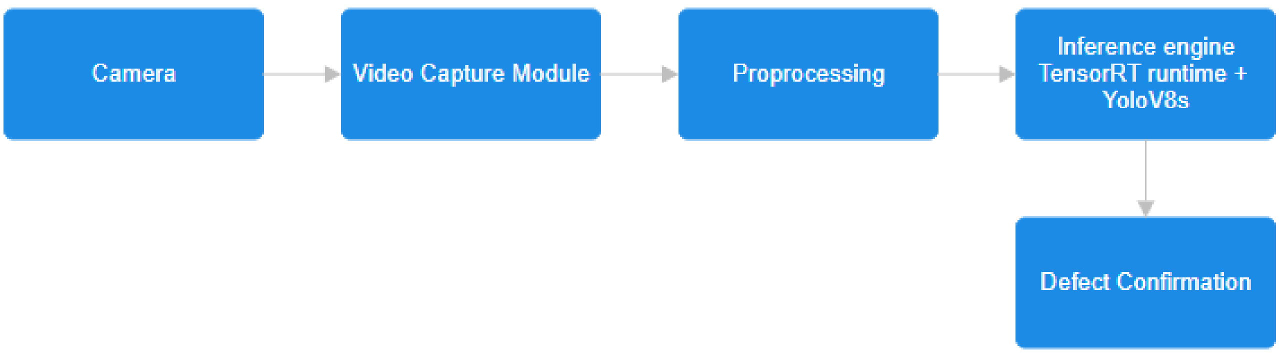
3.1 Phase 1: Model Training (Offline, Google Colab)
Train YOLOv8s on NEU dataset to learn defect patterns



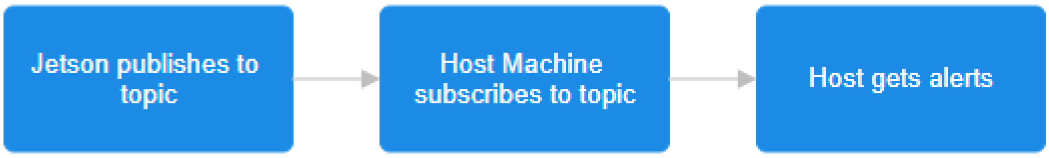
3,2 Phase 2: Model Optimization (One-time, Jetson Orin)
Convert PyTorch model to TensorRT for edge inference



3,3 Phase 3: Real-Time Inference (Continuous, Jetson Orin)
Process camera feed and detect defects in real-time



3.4 Phase 4: Alert & Monitoring (Continuous, MQTT System)
Notify operators and log defect information

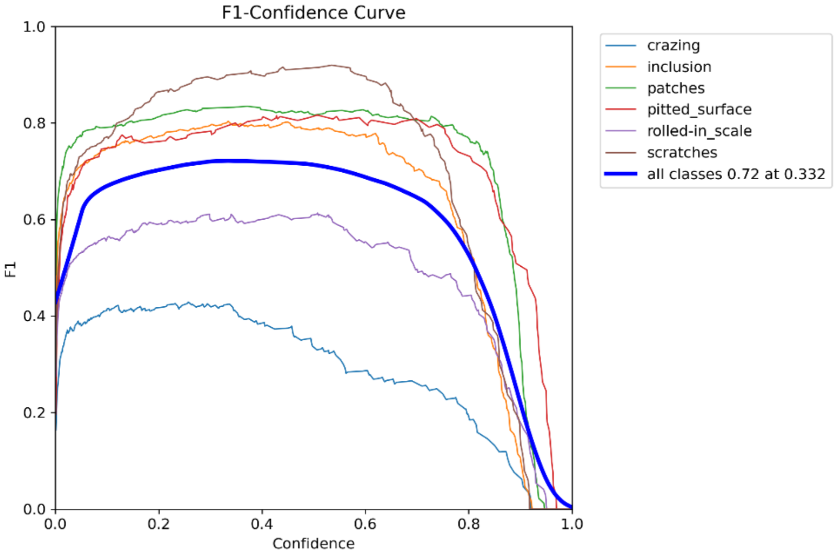

Jetson publishes to topic
Host Machine subscribes to topic
Host gets alerts

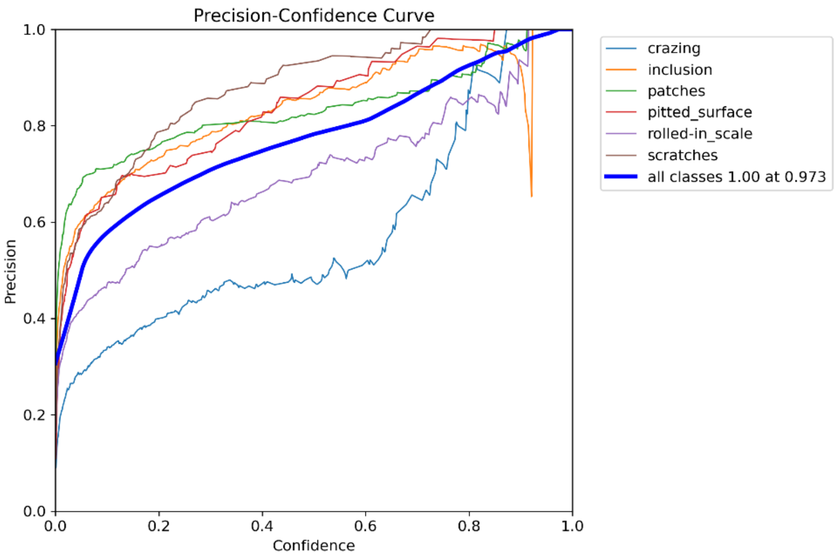
CHAPTER 4 – RESULT

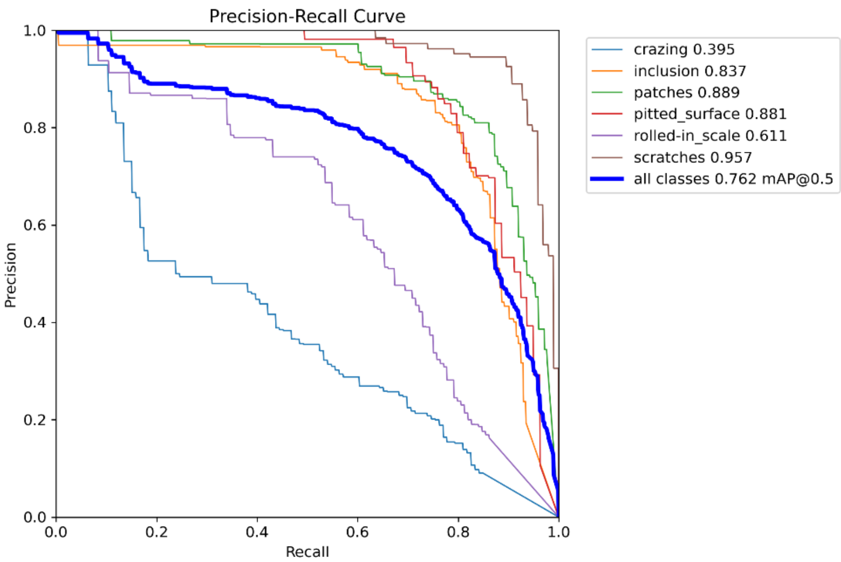
This chapter presents the experimental results and performance evaluation of the **Metal Defect Detection System**.

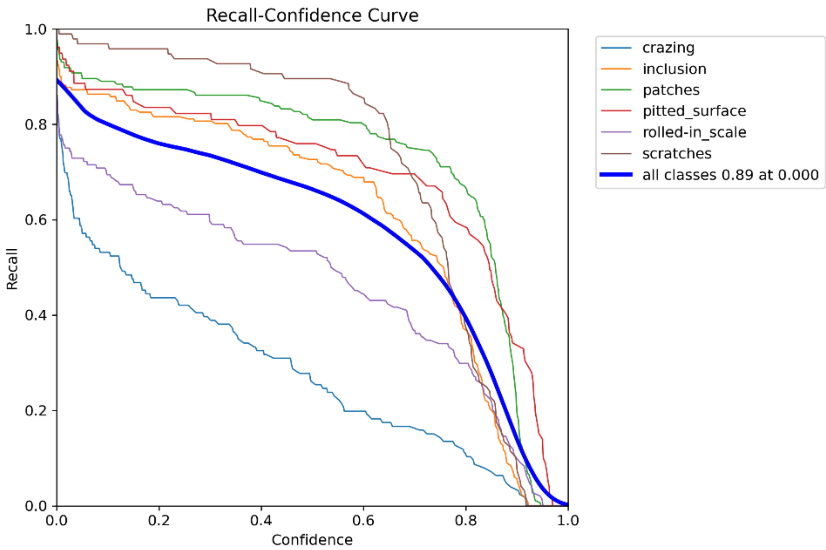
6.1 Model Training Results

The YOLOv8s model was trained for 150 epochs on a custom metal surface defect dataset comprising five defect categories: *scratch, pit, rolled-in scale, crack,* and *patch*.



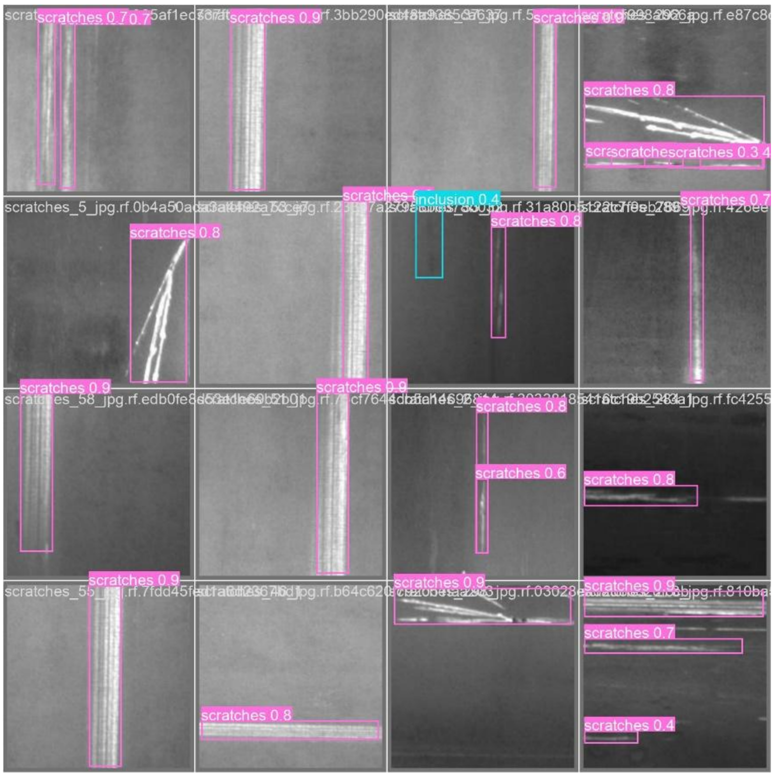


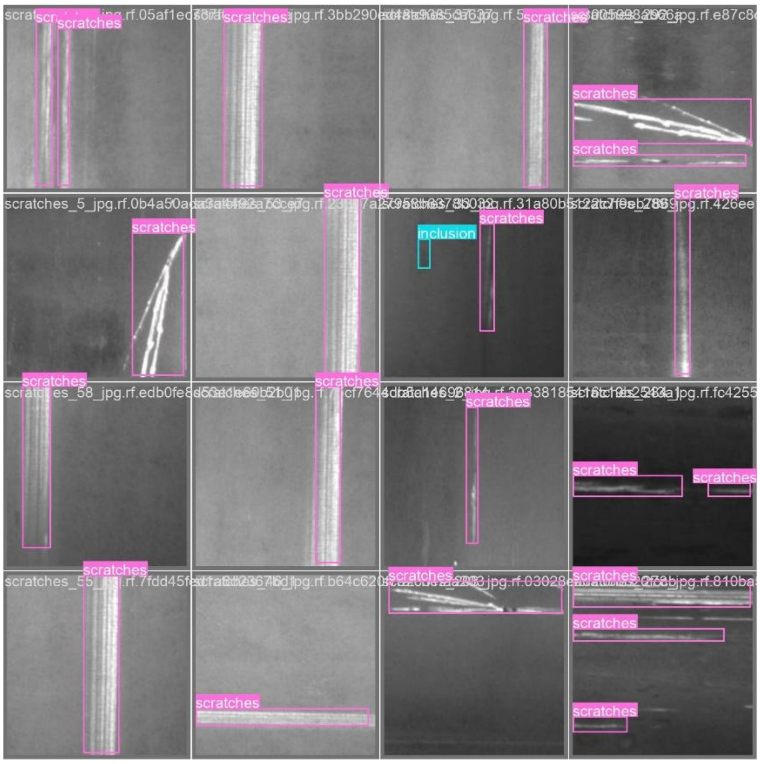




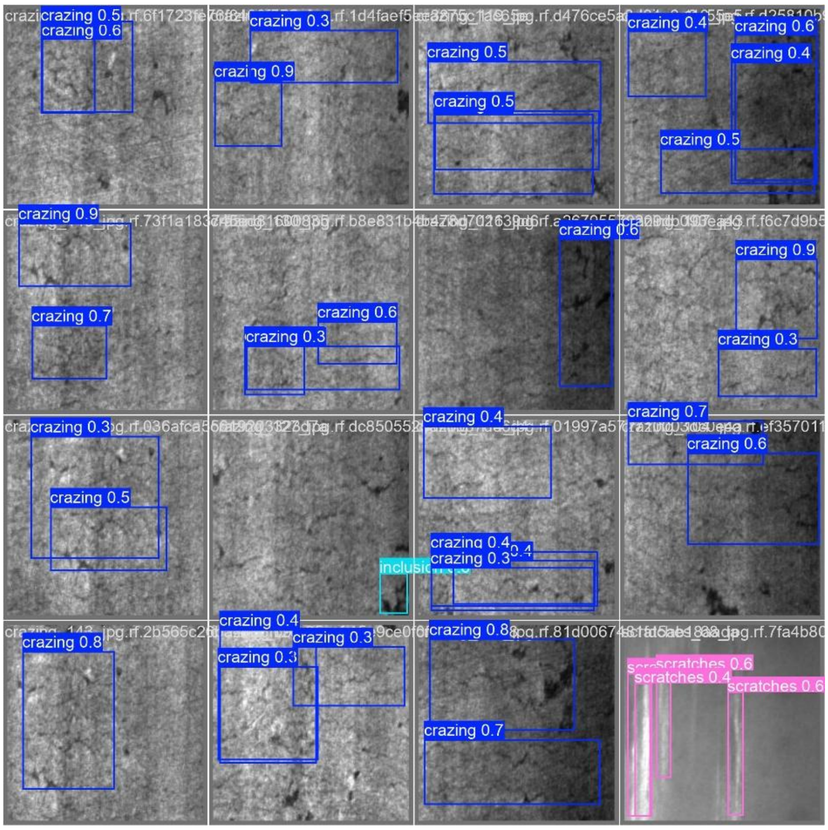
6.2 Testing on Images

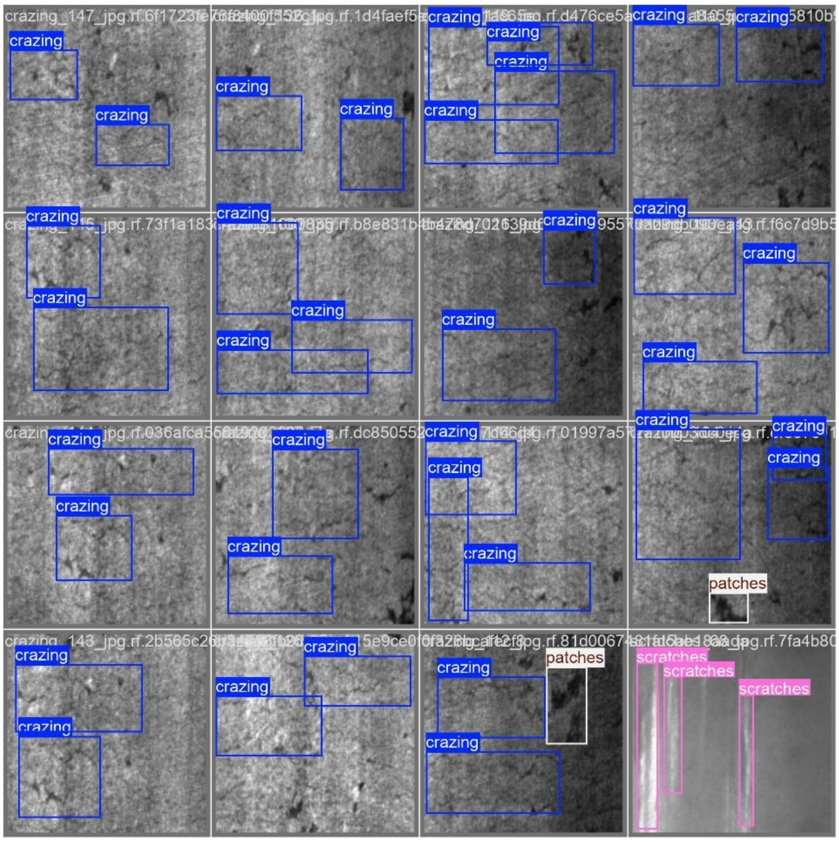
- Labelled image and detections:



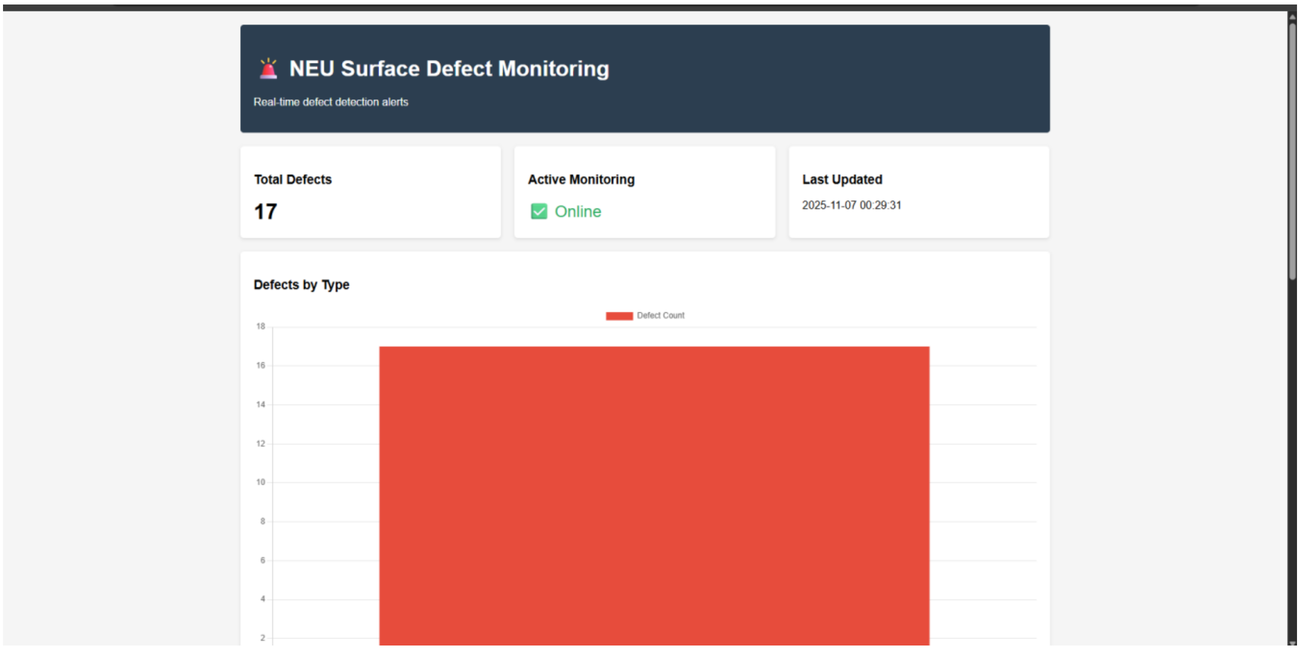


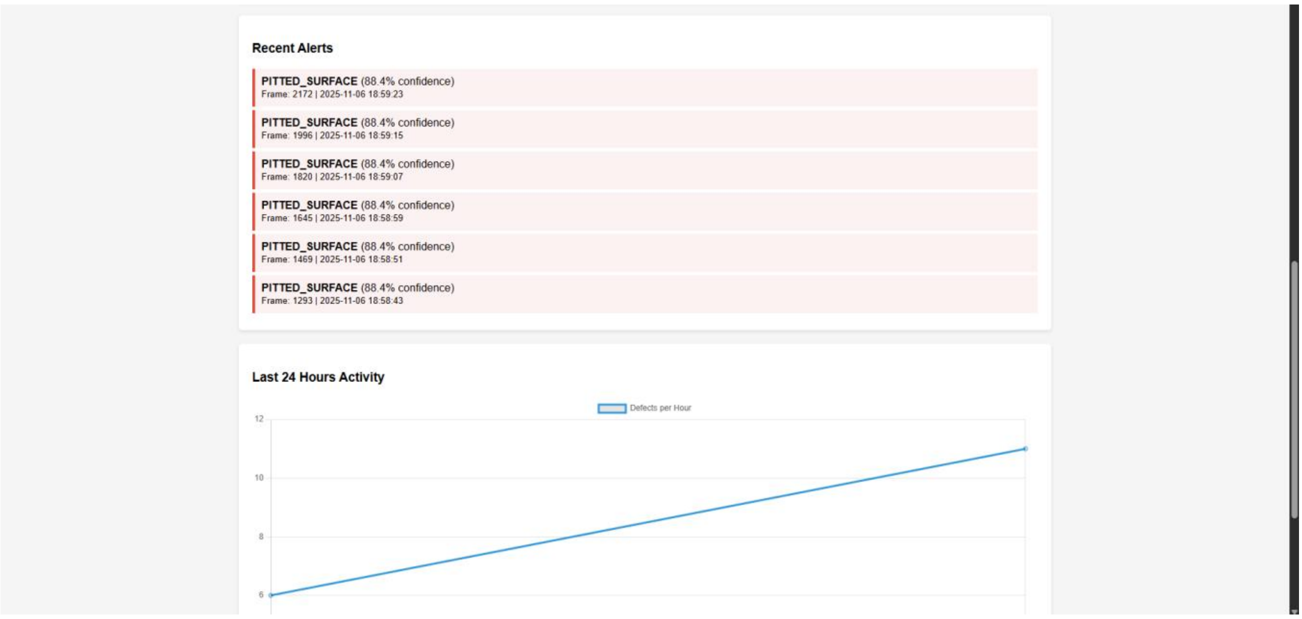
- Labelled Image and detections:





6.2 MQTT Dashboard





CHAPTER 5 – CONCLUSION

5.1 Conclusion

In this project, a real-time metal surface defect detection system was developed using the **YOLOv8s** model deployed on **NVIDIA Jetson Nano Orin**. The system successfully detected and classified surface defects such as scratches, dents, and rust with high accuracy and low latency. By leveraging the optimized YOLOv8s architecture, the model achieved a balance between speed and performance suitable for embedded edge devices.

The integration with the Jetson Nano Orin enabled efficient on-device inference without the need for cloud computation, thereby reducing latency and ensuring privacy and reliability in industrial environments. The proposed system demonstrates that lightweight deep learning models can effectively be used for **automated visual inspection** in manufacturing and quality control pipelines.