AUTOMATIC STEEL DEFECT USING DEEP LEARNING AND COMPUTER VISION

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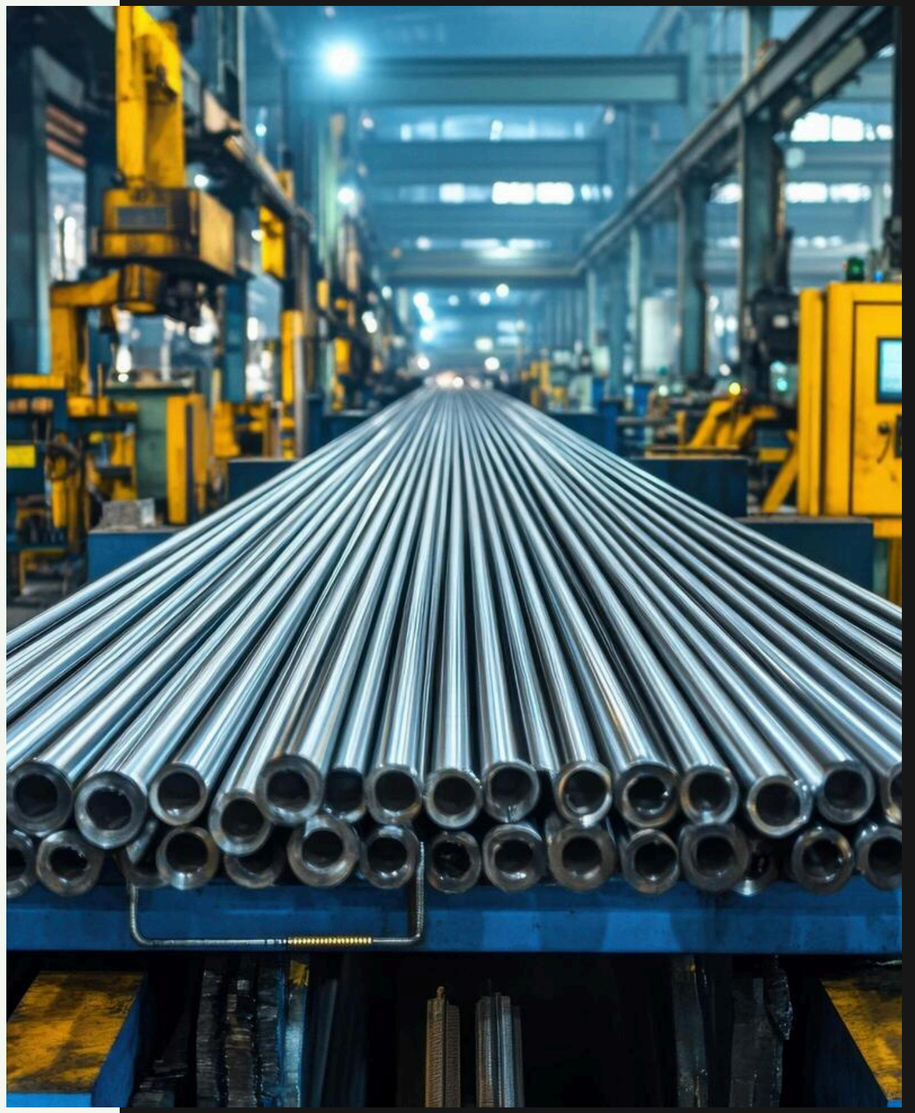
INTRODUCTION

Steel manufacturing is highly susceptible to surface defects such as scratches, cracks, and pitting, which affect both the product's quality and structural integrity. Traditional manual inspection methods are labor-intensive and prone to error. To address these challenges, this project implements an automated system for defect detection using deep learning.



Problem Statement

The manual inspection of steel surfaces is prone to error, inefficient, and unsuitable for large-scale production lines. Automating defect detection is essential to maintain high-quality standards

Objectives

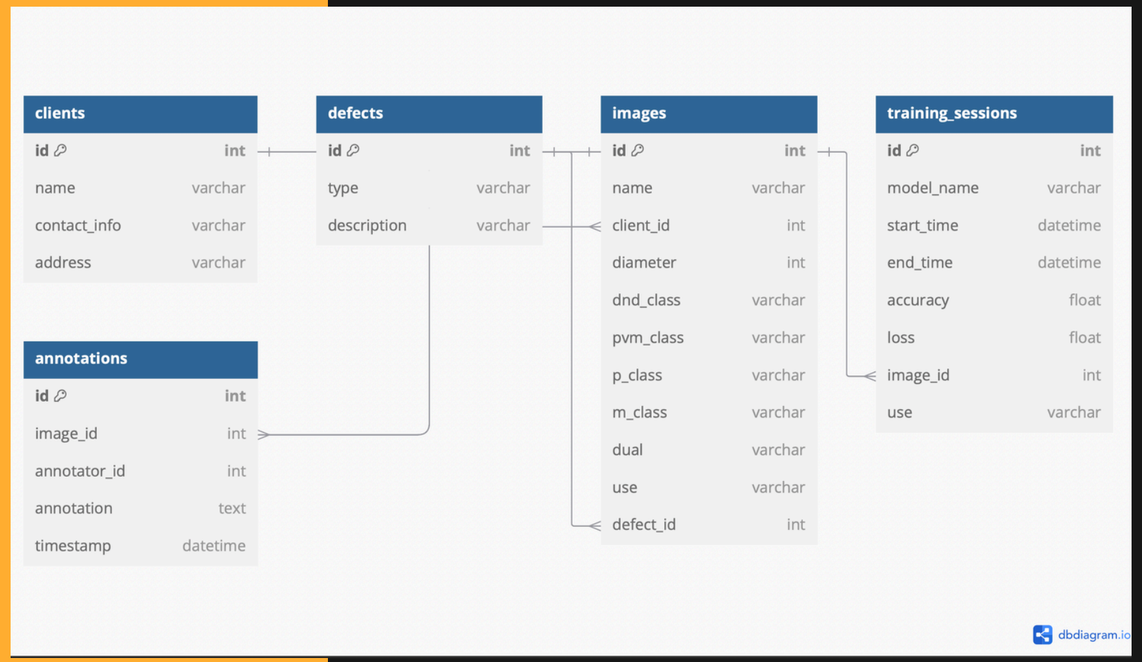
- Develop a deep learning model to detect and classify six types of steel defects.
- Deploy the model in a user-friendly web interface for real-time defect detection.
- Improve quality control in steel production by reducing manual intervention

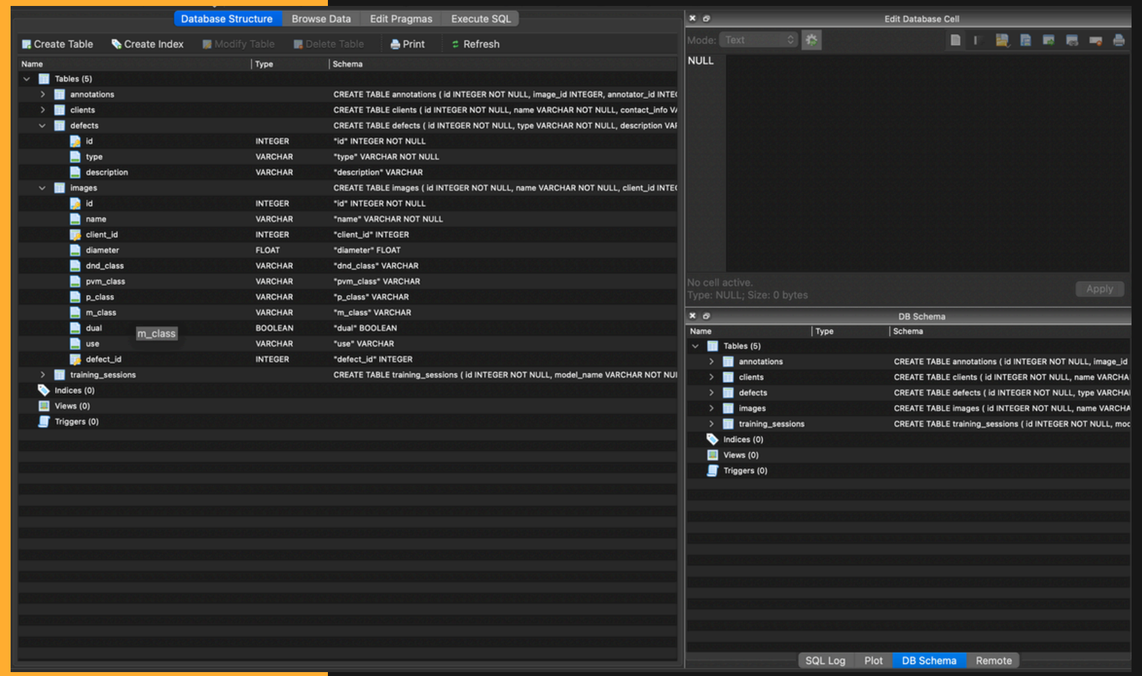
METHODOLOGY

This project follows a structured methodology that involves data collection, preprocessing, model development, training, and deployment. The ResNet50 model was selected for its ability to handle complex visual features. The model was trained using transfer learning, and deployed via a web interface built with Streamlit for real-time predictions.

Steps:

- Data Collection
- Preprocessing (Rescaling, Augmentation)
- Model Training (ResNet50)
- Deployment (Streamlit)





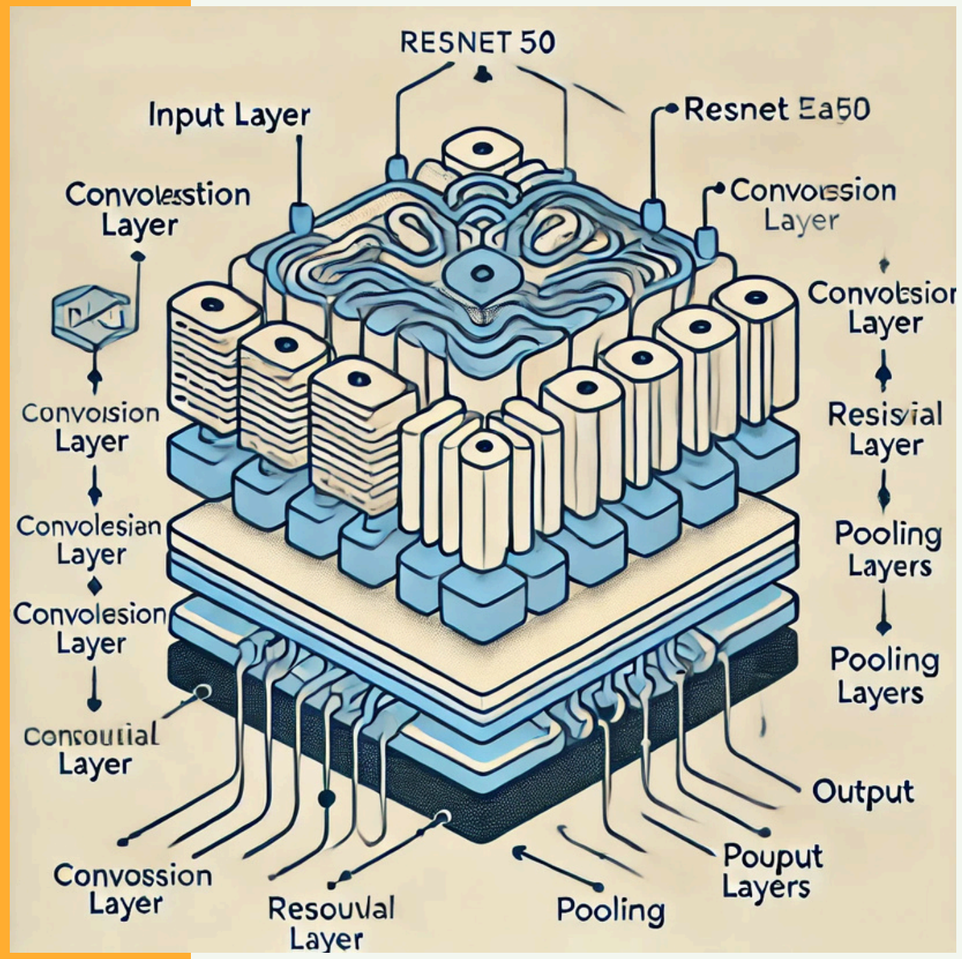
Data Collection and Preprocessing

- The dataset comprises steel surface images provided by iSEND. These images were categorized into six defect types: Crazing, Inclusion, Patches, Pitted Surface, Rolled-in Scale, and Scratches.

Preprocessing steps included:

1. Rescaling the images to 224x224 pixels.
2. Normalizing pixel values between 0 and 1.
3. Augmentation techniques such as flipping, rotation, and zoom to create a robust model.

Model Architecture



- The ResNet50 architecture, a 50-layer deep convolutional neural network (CNN), was used to classify the defects. It uses residual connections to improve training stability and performance.
- We used transfer learning, where the model was pre-trained on ImageNet and fine-tuned on our steel defect dataset

Architecture Layers:

- Pre-trained ResNet50 model without top layers
- Global Average Pooling
- Dense layers
- Softmax output layer for six classes.

Result & Performance

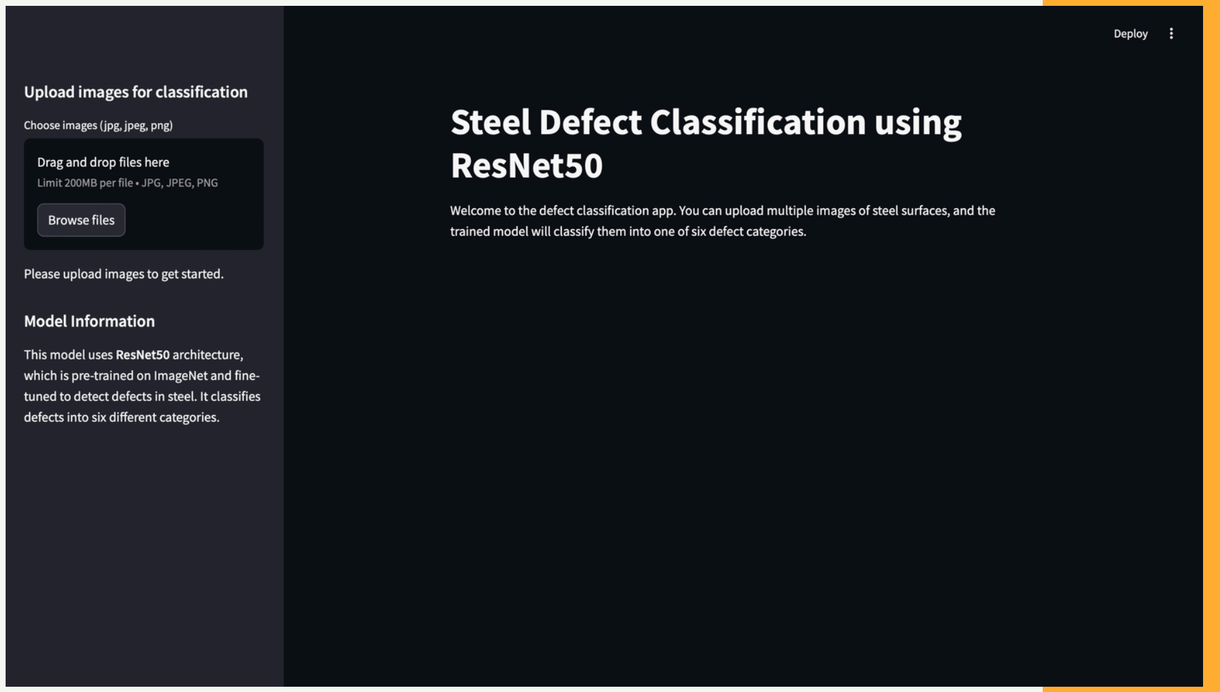
The model was trained and validated using an 80-20% data split. It achieved an accuracy of 83% after fine-tuning, with precision and recall metrics showing strong performance in detecting common defect types such as Scratches and Patches

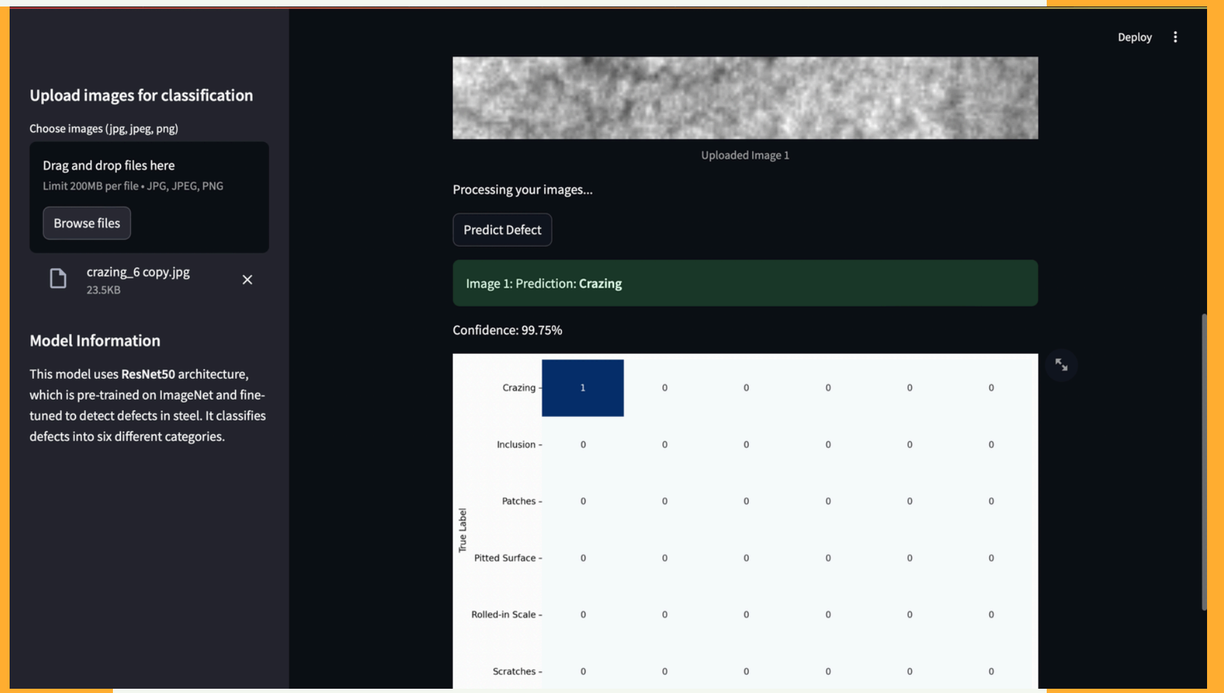
Key Performance Metrics

- Accuracy: 83%
- Precision: Strong for "Scratches" and "Patches"
- Recall: Moderate for "Pitted Surface

Deployment

- The model was deployed using Streamlit, providing an intuitive interface for operators to upload steel surface images and receive real-time defect classification results. The interface allows non-technical users to easily interact with the system.
- The system is accessible via a web interface and can handle multiple images at once



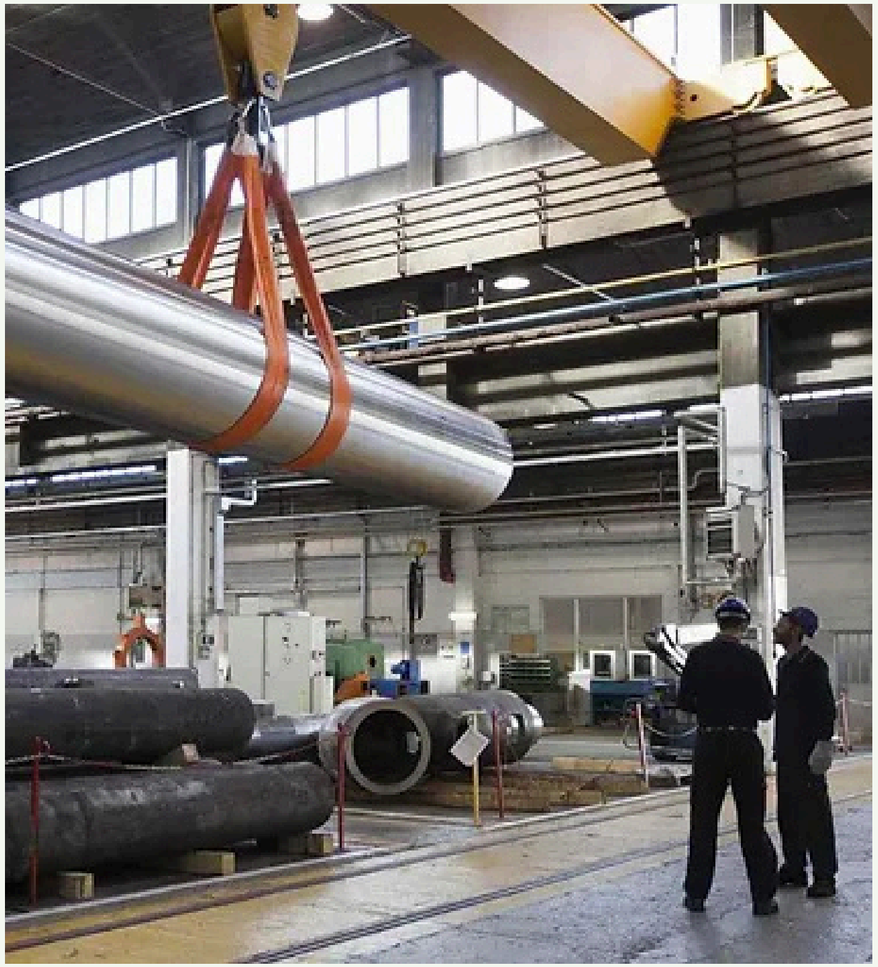


Conclusion & Future works

- This project successfully developed an automated system for steel defect detection using ResNet50 and achieved an accuracy of 83%. The deployment of the model in a Streamlit interface made it accessible for real-time use on the production floor.

Future Work:

1. Further improvements in class imbalance handling.
2. Incorporating more diverse defect types.
3. Exploring real-time IoT-based deployment.




Thank You