# Automated Bridge Corrosion Detection

## 1. Problem Statement

Automated detection of corrosion in bridges so that we can ensure safety, extend life, and perform inspections more quickly and reliably..

## 2. Motivation

- Public Safety: Bridges facilitate the continuous movement of people and goods, early detection of corrosion occurs before corrosion from neglect and should keep bridges from falling and people safe from harm.
- Inspector Safety: Inspectors inspect manual and outdoor inspections are always in hazardous situations. The automated nature will mitigate the impact of working in hazardous situations.
- Speed and Accuracy: Traditional methods take time, and are expensive, this project provides the scale and traverse the accuracy necessary to make informed asset management decisions which have been data driven.

## 3. Objectives

- A robust data pipeline that automatically enhances and prepares images for model training using Digital Image Processing (DIP).
- A functional U-Net deep learning model specifically architected for the semantic segmentation of corrosion.
- A trained and validated model capable of accurately classifying pixels as "corrosion" or "background" with measurable performance

## 4. Introduction

Bridges act as the arteries of transportation systems, with millions of vehicles traversing them every day. However, corrosion gradually weakens the structural components, reducing their strength, load capacity, and overall reliability. Traditional manual inspection methods are often subjective, inefficient, and time-consuming. With the advancement of Unmanned Aerial Vehicles (UAVs) equipped with high-resolution cameras capable of capturing images at centimeter-level detail, automated corrosion detection has become more feasible. In this study, a U-Net-based deep learning segmentation model is utilized to detect and quantify corrosion from UAV-captured images. The U-Net architecture enables fast, accurate, and pixel-level segmentation, making it an essential tool for the modern, data-driven process of bridge health monitoring.

## 5. Related Work

| Sr. No. | Name of the Study | Features | Methodology | Research Gaps Present |
|---|---|---|---|---|
| 1 | Computational Structural Condition Monitoring (CSCM, 2024) | Highlighted importance of dataset quality. | CNN-based detection | Limited to detection, no pixel-level quantification. |
| 2 | Journal of Civil Structural Health Monitoring (JCSHM, 2025) | Achieved high segmentation accuracy. | Transformer-based SegFormer. | Needs large datasets; computationally intensive. |
| 3 | Artificial Intelligence in Construction (AiC, 2025) | Reduced annotation workload. | Semi-supervised deep learning. | Accuracy lower than fully supervised approaches. |
| 4 | Structures Journal (2025) | Strong at identifying corrosion instances. | Mask R-CNN / YOLO. | Weak at measuring large, connected corrosion regions. |
| 5 | Heliyon Journal (2024) | Integrated detection with lifecycle models. | DL + BIM. | Vision models less advanced; focus mainly on integration. |
| 6 | Expert Systems with Applications (ESWA, 2025) | Good results in lab settings. | YOLOv8s-G. | Limited success in complex real-world bridge scenarios. |
| 7 | Machine Vision and Applications (MVA, 2025) | Combined CNN detail with Transformer context. | Hybrid Transformer-CNN. | Added complexity without clear performance advantages. |

## 6. Methodology

- **Dataset Preparation**

  Images and their corresponding corrosion masks were collected from multiple sources, including online repositories and drone captures. All images and masks were resized to 256×256 pixels for uniform input dimensions.

  A custom image enhancement (sharpening) function was applied to each image to improve edge clarity and make corrosion boundaries more visible. The masks were normalized to the [0,1] range and converted to tensors for pixel-wise learning.

- **Model Architecture**

  Instead of the heavy **SegFormer Transformer model**, we implemented a **U-Net-based convolutional architecture**.

  The U-Net consists of an encoder–decoder structure with skip connections:

  a. The encoder extracts hierarchical features from input images.
  b. The bridge connects the encoder and decoder to capture deep contextual information.
  c. The decoder reconstructs the segmentation mask while preserving spatial detail via skip connections.
     Each block uses Batch Normalization and ReLU activation to stabilize and speed up training.

  *This architecture was chosen because U-Net provides high segmentation accuracy with significantly lower computational demand than SegFormer, making it ideal for real-time or resource-limited environments like UAV inspection systems.*

- **Training Strategy**

  The model was trained using Binary Cross-Entropy (BCE) loss and optimized with the Adam optimizer (learning rate = 1e-4) for 15 epochs and a batch size of 4.

  During training, pixel-level accuracy was continuously tracked to evaluate segmentation performance.

- **Inference and Deployment**
  After training, the model can accept any uploaded image for prediction. The image undergoes the same enhancement and preprocessing steps before being passed through the trained U-Net.
  The model produces a **pixel-wise corrosion mask**

## 7. Conclusion

This project presents an automated corrosion detection pipeline using a U-Net-based deep learning model. Unlike transformer models such as SegFormer, which require large datasets and high-end computational resources, U-Net offers a balanced trade-off between performance and efficiency, making it suitable for practical field deployment.
The custom image enhancement preprocessing and skip-connected U-Net structure significantly improved segmentation precision, especially in complex and connected corrosion regions.
The model effectively achieves pixel-level corrosion segmentation, enabling precise quantification of corrosion spread and supporting future integration with bridge health monitoring systems.

## 8. References


[1] CSCM (2024) – CNN-based corrosion detection study.
[2] JCSHM (2025) – SegFormer-based semantic segmentation research.
[3] AiC (2025) – Semi-supervised deep learning approach.
[4] Structures (2025) – Mask R-CNN / YOLO for corrosion detection.
[5] Heliyon (2024) – Integration of DL with BIM.
[6] ESWA (2025) – YOLOv8s-G applied in corrosion detection.
[7] MVA (2025) – Hybrid Transformer-CNN research.