Aircraft Fuselage Defect Detection Using CNN

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ECEN 5060

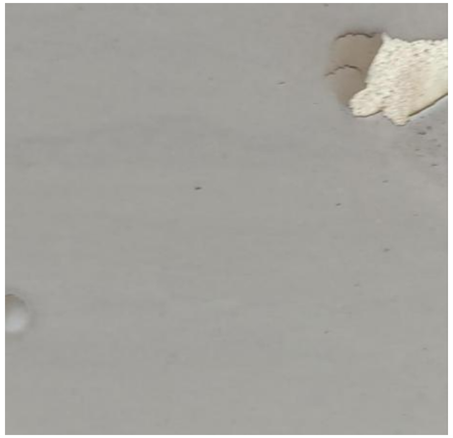
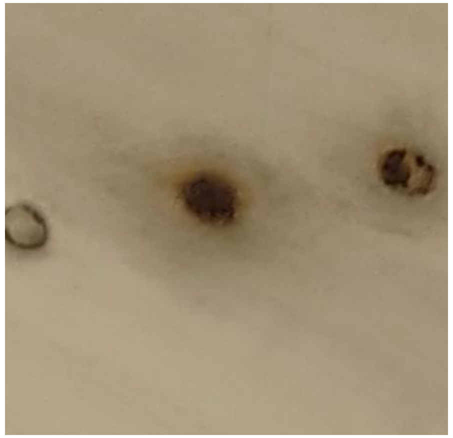
Project Overview

- Goal: Detect defects on aircraft fuselage surfaces.
- Strategy: Train CNN on limited labeled data.
- Expand dataset through pseudo-labeling.

Dataset

- 5601 images total
- 389 labeled images, 5212 unlabeled
- 4 defect classes: Scratch, Paint Peel, Rivet Damage, Rust
- High resolution: 1120 × 960 pixels
- x,y image coordinates of each defect



Data Preprocessing

- Resize images to 250 × 250 pixels.
- Labels extracted from COCO JSON annotations.
- Multi-label binarization for multi-defect cases.
- Augmentation: rotations, flips, color jitter.

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Model Architecture:
CNN(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=500000, out_features=128, bias=True)
  (fc2): Linear(in_features=128, out_features=4, bias=True)
)

Total Parameters: 64005732
Trainable Parameters: 64005732
```

Model Architecture

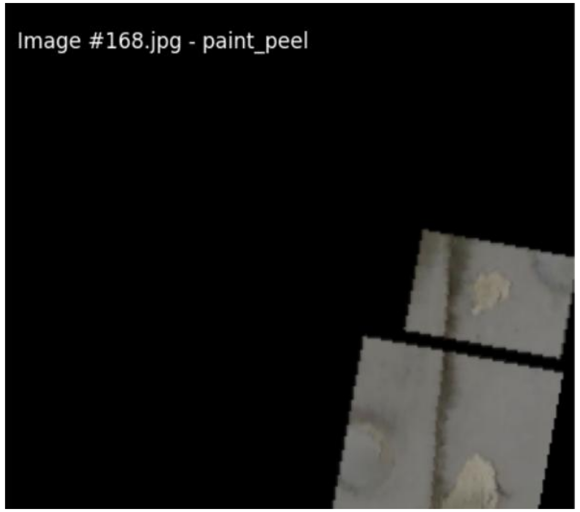
- Simple CNN:
  - 2 convolutional layers
  - Max pooling, ReLU activations
  - 2 fully connected layers
- Output: 4 defect probabilities (sigmoid)

Training Setup

- Optimizer: Adam
- Loss: Binary Cross-Entropy
- Batch Size: 30
- Learning Rate: 0.001
- Device: GPU if available

Paint Peel

Original Image



Scratch

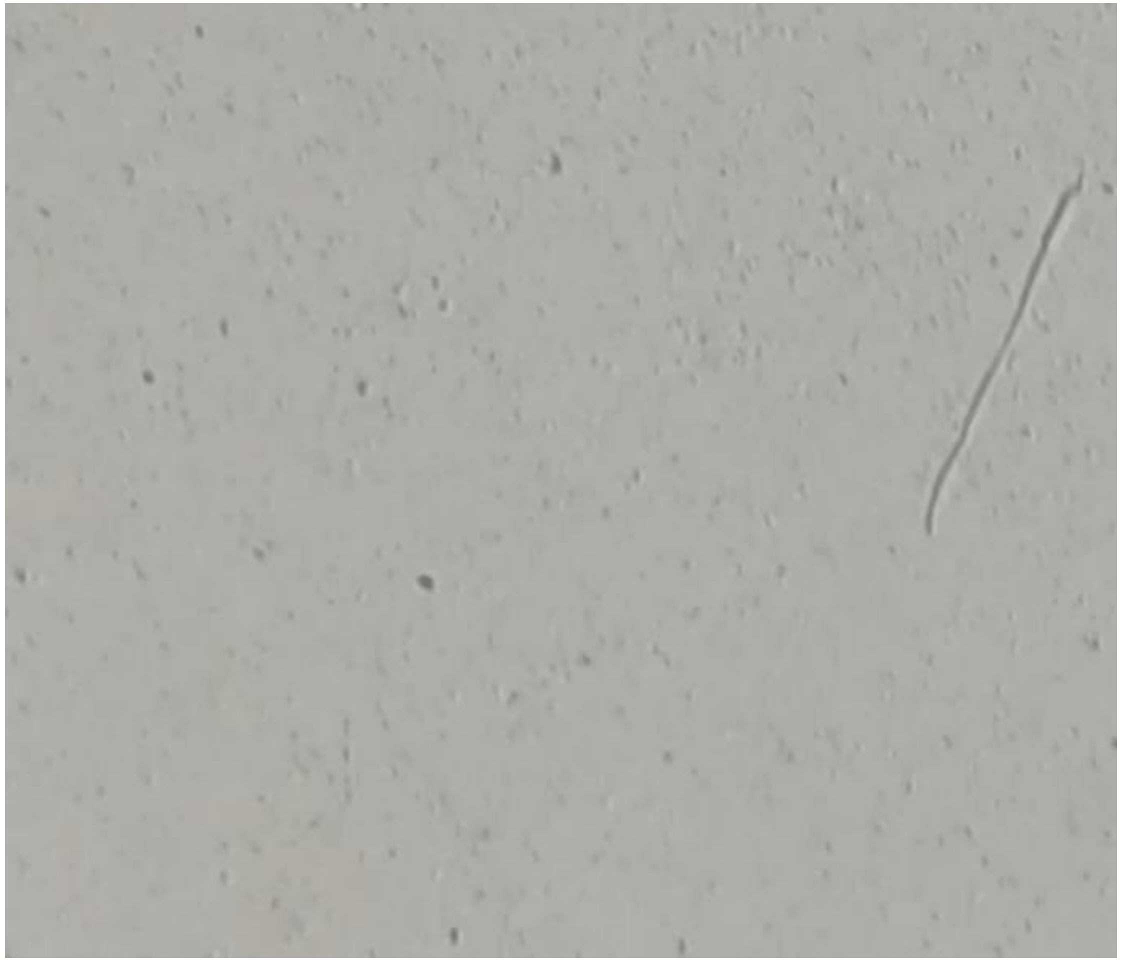



Image #067.jpg - scratch

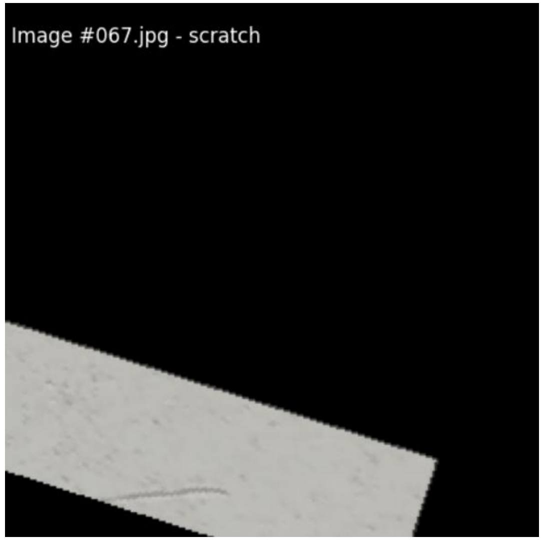


Image #067.jpg - scratch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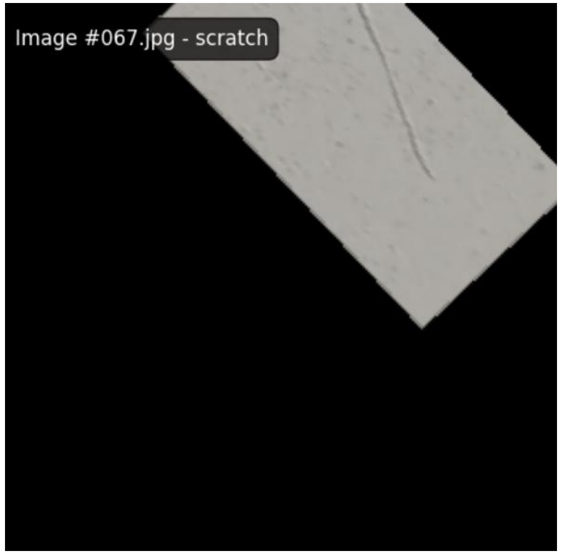
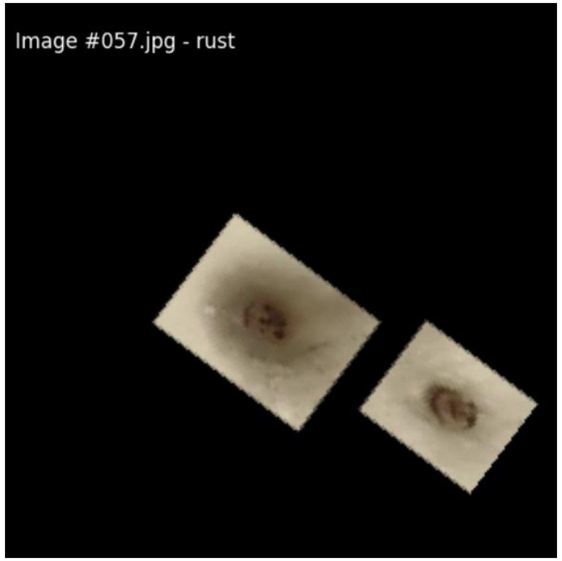
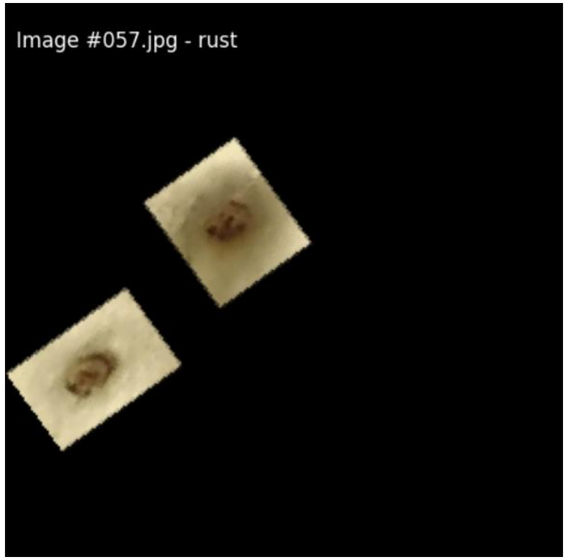


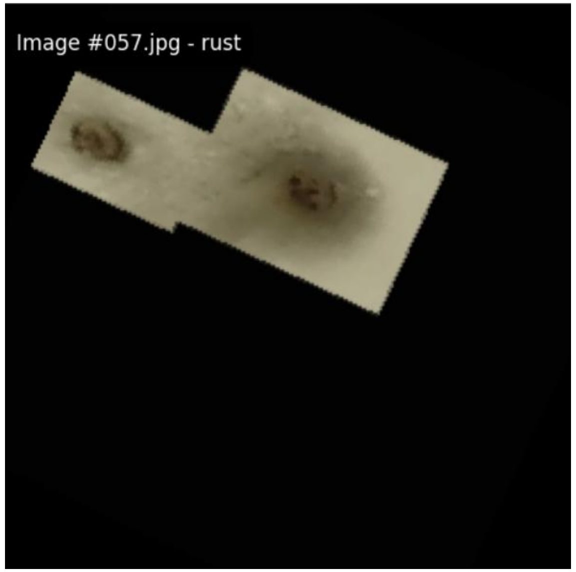
Image #067.jpg - scratch

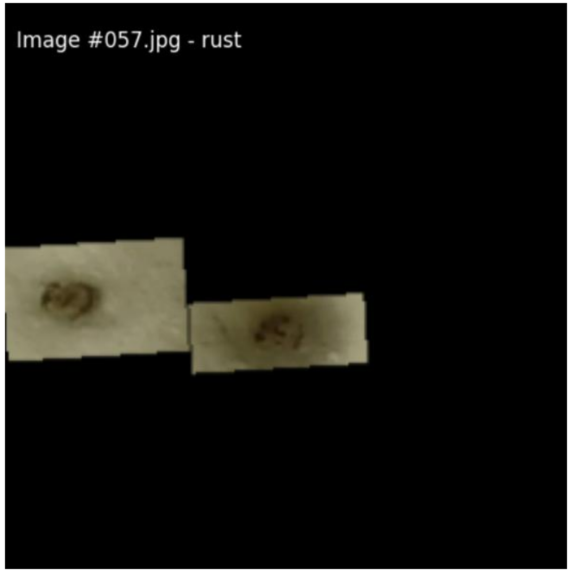
Rust

Original Image









Rivet Damage

```
Model Architecture:
CNN(
  (conv1_7x7): Conv2d(3, 8, kernel_size=(7, 7), stride=(1, 1), padding=(3, 3))
  (conv1_5x5): Conv2d(3, 8, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
  (conv1_3x3): Conv2d(3, 8, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(24, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=123008, out_features=128, bias=True)
  (fc2): Linear(in_features=128, out_features=4, bias=True)
)

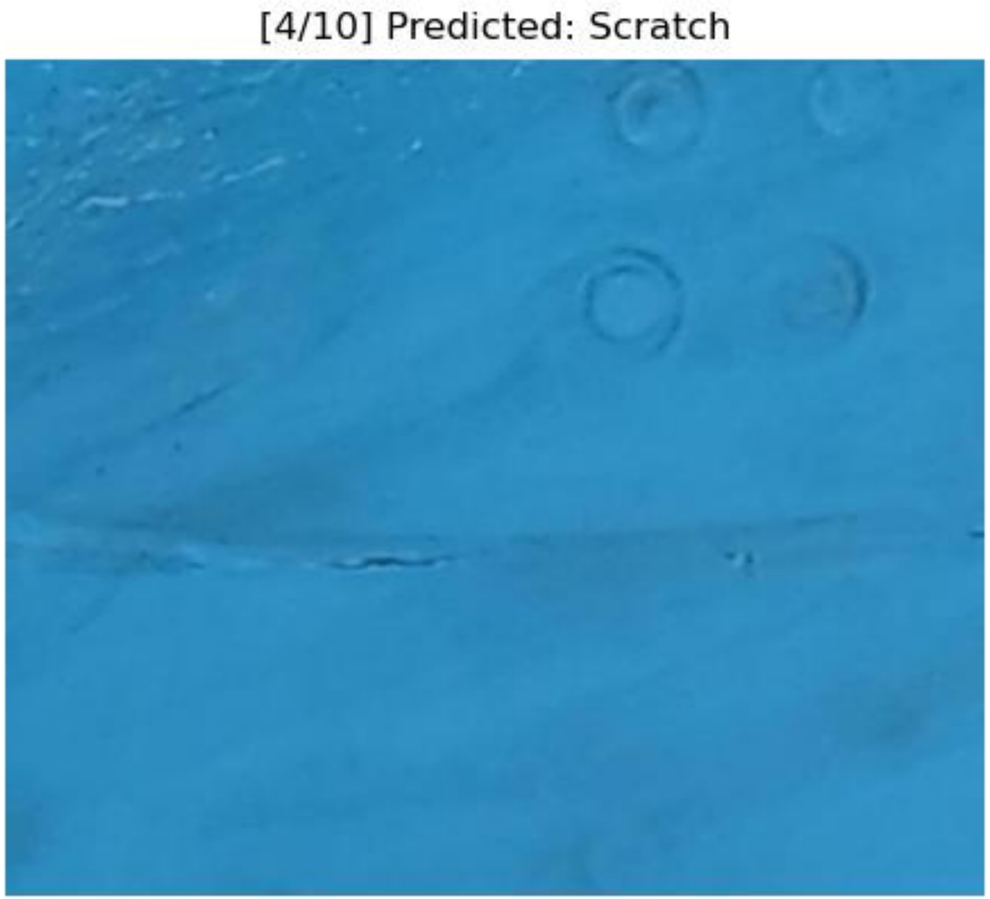
Total Parameters: 15754628
Trainable Parameters: 15754628
```

Final Model Architecture

- Best CNN:
  - 3 parallel convolutional layers in the first layer
  - 3 layers concatenated together
  - Max pooling, ReLU activations
  - 2 fully connected layers
- Output: 4 defect probabilities (sigmoid)

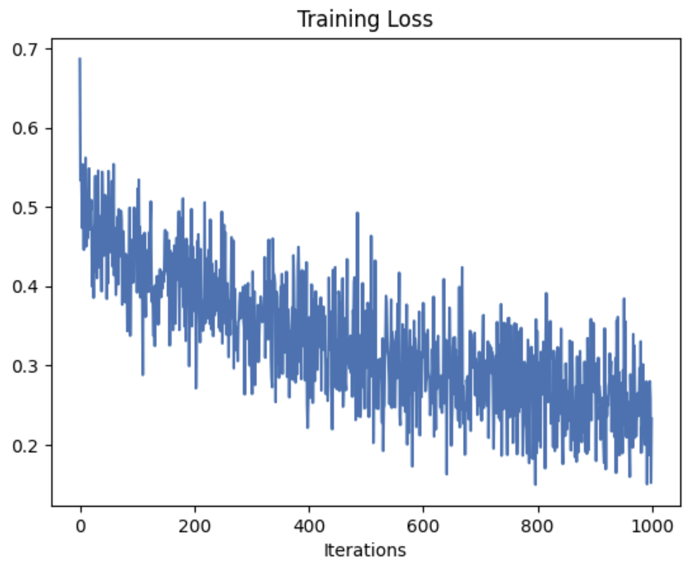
Pseudo-Labeling Unlabeled Data

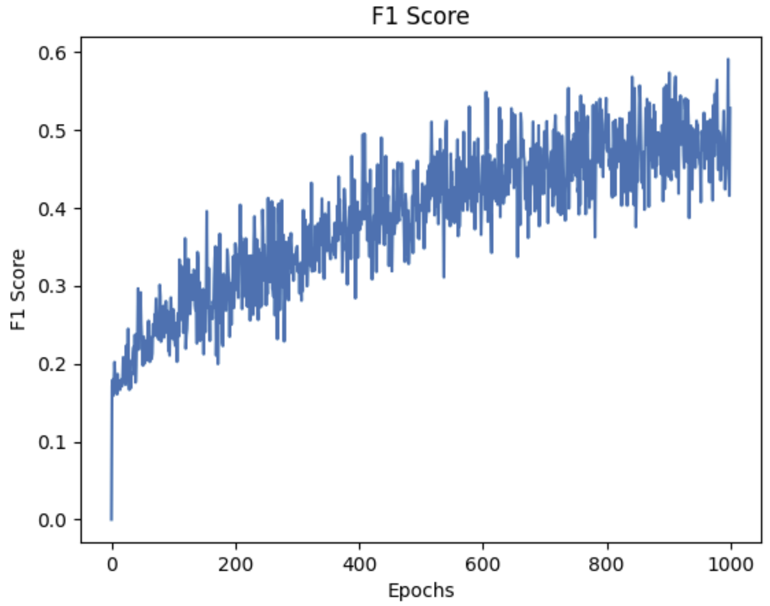
- Model predicts labels on 5212 images.
- Threshold: probability > 0.4 = label assigned.
- Results saved to CSV.
- Created a larger labeled dataset.



Key Outcomes

- Built a working multi-label classifier.
- Pseudo-labeled entire unlabeled dataset.
- Set up for future semi-supervised learning.
- Ready to move toward object detection.



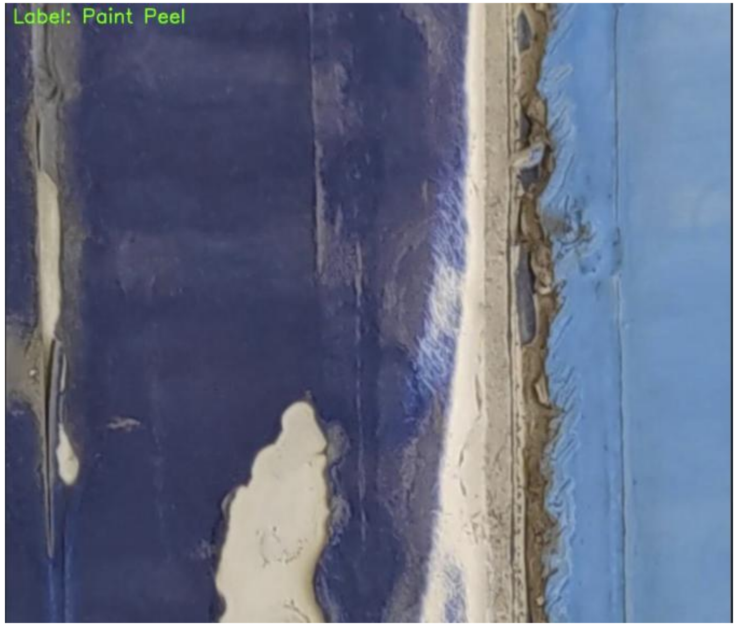


Classification Report

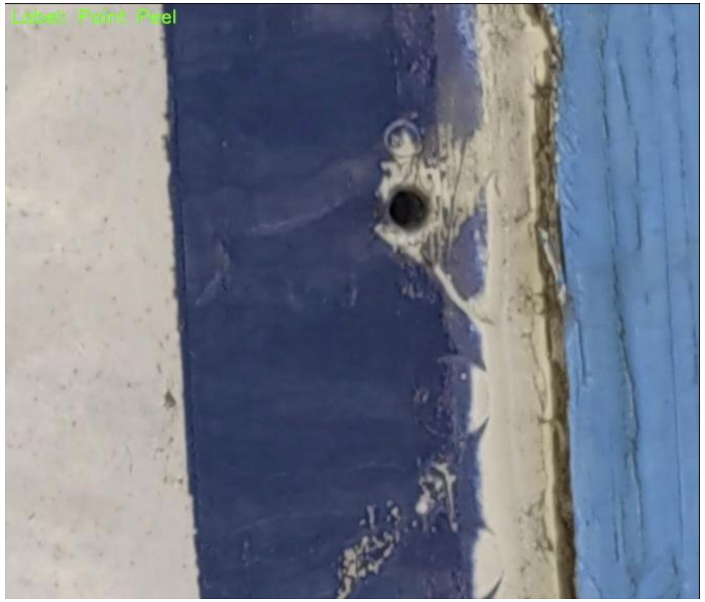
	precision	recall	f1-score	support
paint_peel	1.00	0.10	0.18	20
rivet_damage	0.50	0.71	0.59	7
rust	0.50	0.14	0.22	14
scratch	0.66	0.89	0.76	37
micro avg	0.64	0.54	0.58	78
macro avg	0.67	0.46	0.44	78
weighted avg	0.70	0.54	0.50	78
samples avg	0.54	0.54	0.54	78


Label: Paint Peel

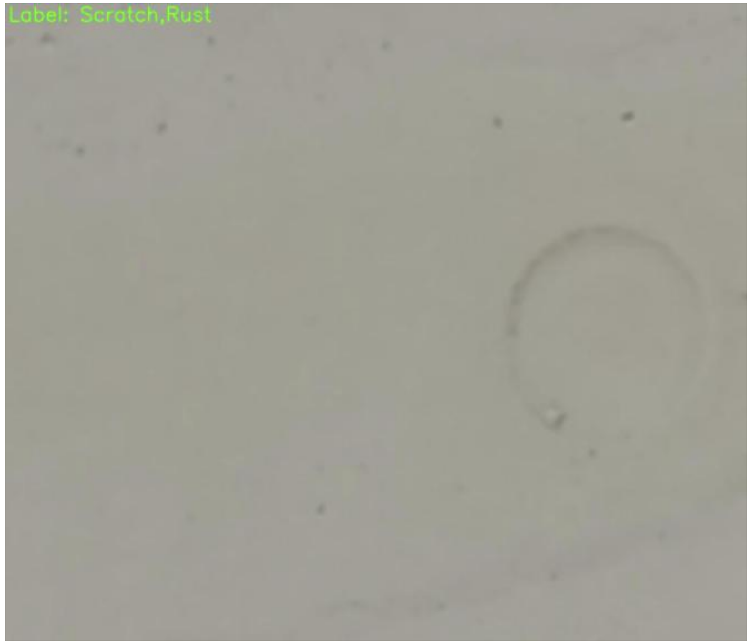

Label: Paint Peel

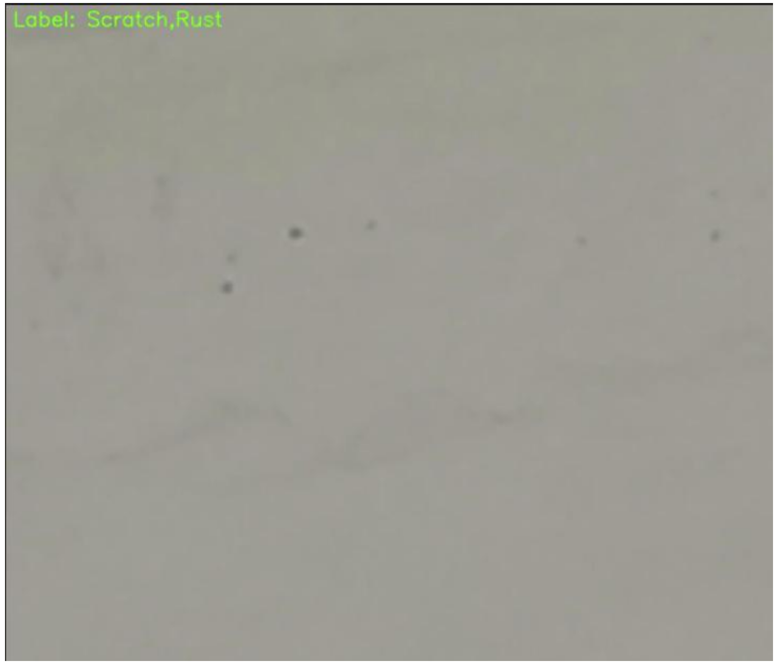

Label: Paint Peel


Label: Scratch,Paint Peel


Label: Paint Peel


Label: Paint Peel

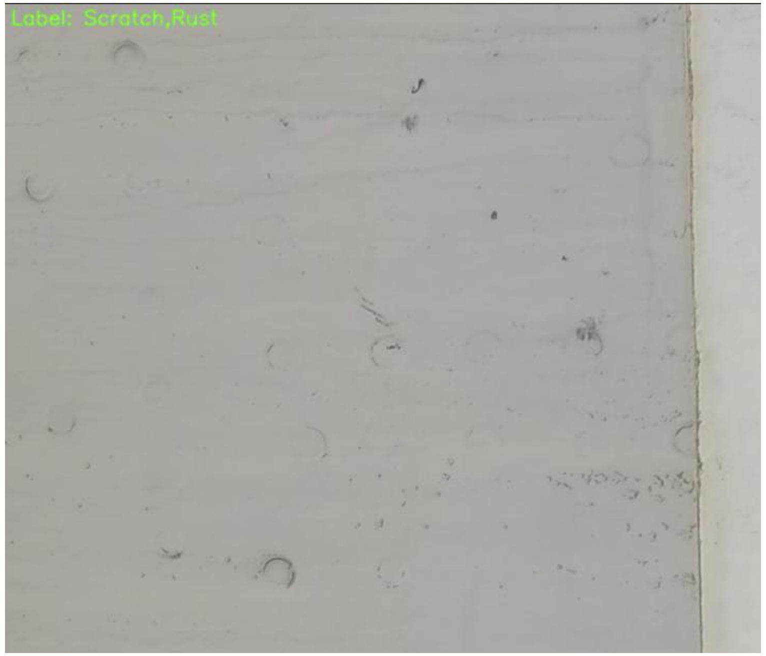

Label: Scratch,Rust


Label: Scratch,Rust


Label: Scratch,Rust


Label: Scratch,Rust

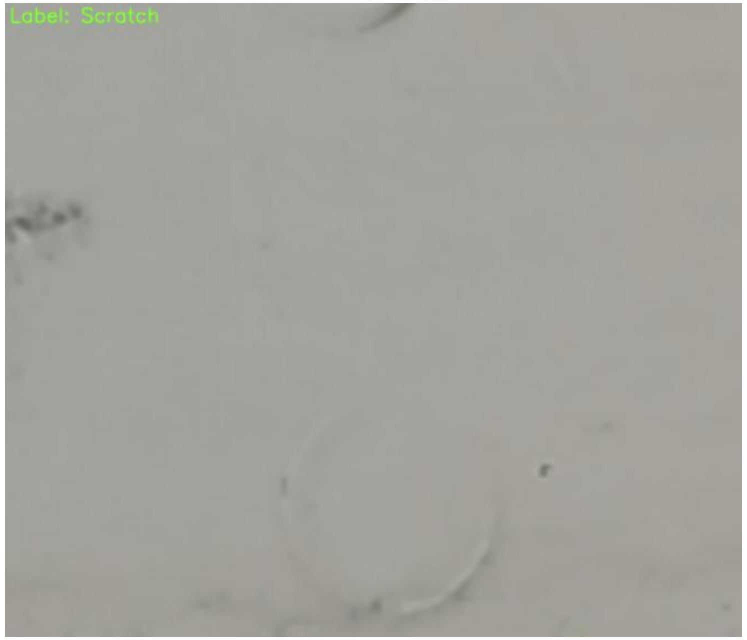

Label: Scratch,Rust

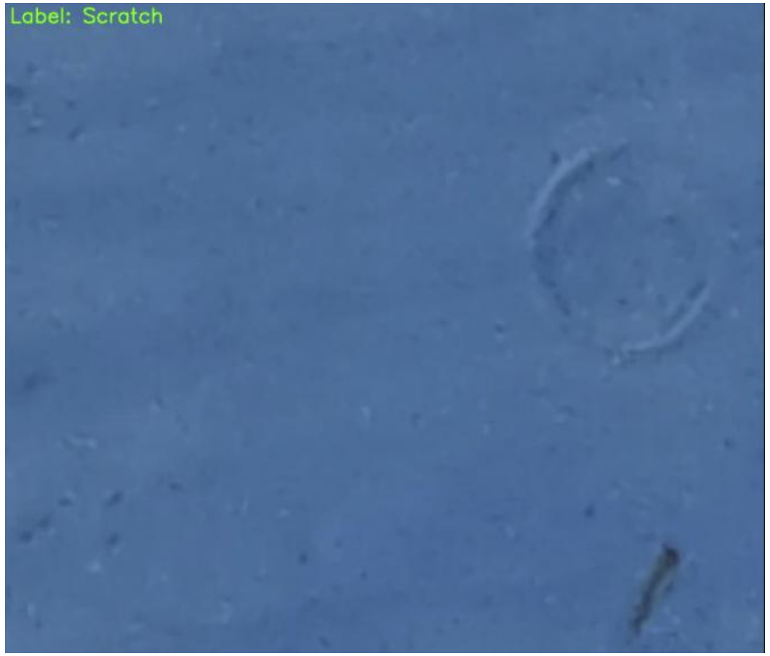

Label: Scratch,Rust

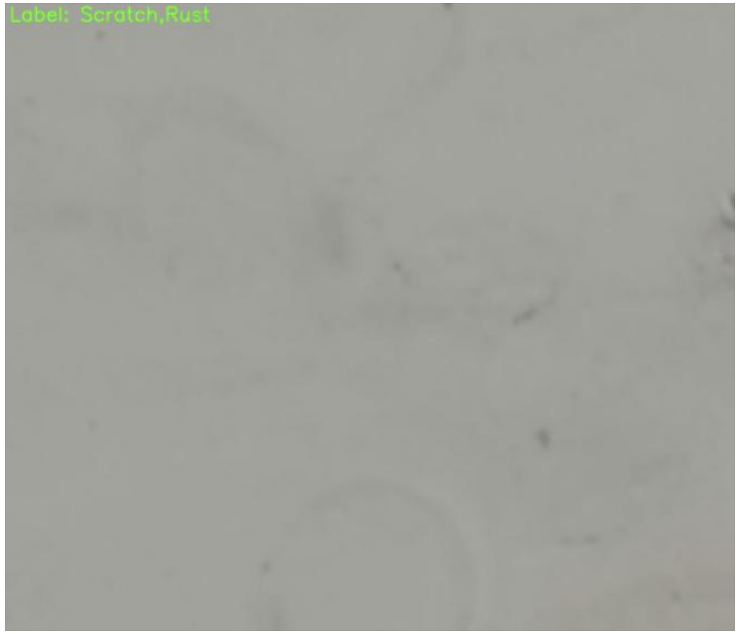

Label: Scratch,Rivet Damage
Label: Rivet Damage
Label: Rivet Damage,Rust
Label: Rivet Damage
Label: Rivet Damage
Label: Rivet Damage

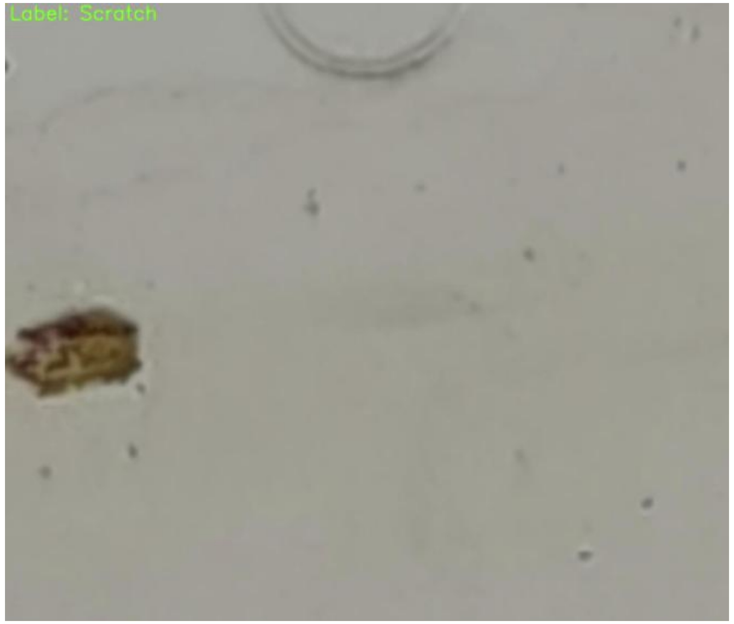

Label: Scratch


Label: Scratch


Label: Scratch


Label: Scratch


Label: Scratch,Rust


Label: Scratch

Challenges and Solutions

Small initial labeled set → solved with balancing and augmentation

Lack of multi-class labels → pseudo-labeling unlabeled images.

Classification of sprawling defects → solved with expanded masking.

Future Work

- Retrain model with expanded dataset.
- Improve model (larger CNNs, transfer learning).
- Move to object detection models.

Conclusion

- End-to-end defect detection pipeline created.
- Dataset expanded significantly.
- Strong foundation for future work.

Questions?