Corrosion Classification Using YOLOv5x: Report

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1. Introduction

Corrosion poses a significant threat to various industries, including infrastructure, automotive, and maritime sectors. It undermines the structural integrity of materials, leading to substantial economic losses and safety risks. Timely and accurate detection of corrosion types is essential for implementing preventive maintenance and effective mitigation strategies. This report outlines the development of a corrosion classification system utilizing **YOLOv5x**, focusing on three primary corrosion types: **Crevice Corrosion**, **Filiform Corrosion**, and **Uniform Corrosion**. The system employs advanced deep learning techniques to identify and classify these corrosion types within industrial images, thereby facilitating proactive maintenance measures.

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2. Dataset Description

Overview

The dataset employed in this study comprises images annotated to identify instances of various corrosion types. It is organized into three distinct subsets:

- **Training Set (train):** Contains 300 images used to train the model.
- **Validation Set (valid):** Comprises 50 images employed to validate model performance during training.
- **Test Set (test):** Consists of 50 images reserved for evaluating the final model's performance on unseen data.

Composition

Each image within these subsets depicts industrial components exhibiting one or more of the three corrosion types. The dataset ensures diversity in terms of corrosion severity, lighting conditions, and environmental factors to enhance the model's robustness and generalization capabilities.

Directory Structure

The dataset is organized hierarchically to streamline data management and access:

/content/unzipped_DL_v1i_voc

```
├── train
|   ├── images
|   |   ├── image1.jpg
|   |   ├── image2.jpg
|   |   └── ...
|   └── labels
|       ├── image1.txt
|       ├── image2.txt
|       └── ...
├── valid
|   ├── images
|   |   ├── image101.jpg
|   |   ├── image102.jpg
|   |   └── ...
|   └── labels
|       ├── image101.txt
|       ├── image102.txt
|       └── ...
```

└── test

├── images

| ├── image201.jpg

| ├── image202.jpg

| └── ...

└── labels

├── image201.txt

├── image202.txt

└── ...

Each image file in the images directories has a corresponding .txt annotation file in the labels directories, formatted according to YOLOv5x requirements.

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3. Annotation Format

YOLO Format Structure

The dataset employs the **YOLO** annotation format, a streamlined approach widely used in object detection tasks. Each .txt annotation file corresponds to an image and contains lines detailing the objects present within that image.

Annotation Details

For each object detected in an image, the YOLO annotation includes:

- **Class ID:** An integer representing the type of corrosion (e.g., 0 for "Crevice Corrosion").
- **Bounding Box Coordinates:** Four values representing the normalized center coordinates and the width and height of the bounding box:
    - x_center: Center x-coordinate (normalized by image width).
    - y_center: Center y-coordinate (normalized by image height).
    - width: Width of the bounding box (normalized by image width).
    - height: Height of the bounding box (normalized by image height).

Example Annotation Structure

An example .txt annotation for an image looks like this:

Copy code

0 0.25 0.30 0.50 0.60

1 0.60 0.50 0.30 0.40

This structure indicates two corrosion instances:

1. Class ID 0 ("Crevice Corrosion") with a bounding box centered at (0.25, 0.30) and dimensions 0.50 (width) x 0.60 (height).
2. Class ID 1 ("Filiform Corrosion") with a bounding box centered at (0.60, 0.50) and dimensions 0.30 (width) x 0.40 (height).

This format ensures precise documentation of each corrosion instance within an image, facilitating accurate training and evaluation of the classification model.

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4. Dataset Partitioning

Effective partitioning of the dataset is paramount to ensure that the model generalizes well to unseen data and does not overfit to the training samples. The dataset is divided into three subsets:

1. **Training Set (train):**
    - **Purpose:** Used to train the model by enabling it to learn patterns and features associated with each corrosion type.
    - **Size:** 300 images.
    - **Composition:** Contains a diverse range of corrosion instances under varying conditions to enhance model robustness.
2. **Validation Set (valid):**
    - **Purpose:** Serves as an intermediary evaluation set during training to monitor the model's performance and adjust hyperparameters accordingly.
    - **Size:** 50 images.
    - **Composition:** Mirrors the diversity of the training set to provide a reliable assessment of the model's generalization capabilities.
3. **Test Set (test):**
    - **Purpose:** Evaluates the final performance of the trained model on entirely unseen data, ensuring an unbiased assessment of its detection and classification efficacy.
    - **Size:** 50 images.
    - **Composition:** Represents real-world scenarios with varied corrosion instances to test the model's practical applicability.

Rationale for Partitioning

- **Preventing Overfitting:** By reserving separate validation and test sets, the model's ability to generalize beyond the training data is effectively evaluated.

- **Hyperparameter Tuning:** The validation set facilitates the optimization of hyperparameters without inadvertently biasing the model towards the training data.
- **Performance Benchmarking:** The test set provides a definitive measure of the model's performance, crucial for deployment considerations.

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5. Data Preprocessing

Data preprocessing is a critical step in machine learning workflows, ensuring that the input data is in an optimal state for model ingestion and training. This section delves into the normalization and transformation techniques employed to enhance the model's performance.

Normalization

Normalization standardizes the input data, ensuring that each feature contributes equally to the learning process. It mitigates issues arising from varying scales of input features and accelerates the convergence of gradient-based optimization algorithms.

- **Mean and Standard Deviation:**
    - **Mean:** [0.485, 0.456, 0.406]
    - **Standard Deviation:** [0.229, 0.224, 0.225]
- **Purpose:** Aligns the input data distribution with that of the pre-trained models, facilitating effective transfer learning.
- **Implementation:** Each image channel (Red, Green, Blue) is normalized using the specified mean and standard deviation values.

Data Transformation

Data transformation encompasses a series of augmentations and adjustments applied to the input data to enhance the model's ability to generalize and handle real-world variations. The transformation pipeline includes the following steps:

1. **Random Horizontal Flip:**
    - **Probability:** 50%
    - **Purpose:** Introduces variability in object orientation, enabling the model to recognize corrosion instances irrespective of their horizontal positioning.
    - **Impact:** Enhances the model's rotational invariance and robustness to different viewing angles.
2. **Random Brightness and Contrast Adjustment:**
    - **Brightness Range:** ±20%
    - **Contrast Range:** ±20%

- **Purpose:** Simulates varying lighting conditions, ensuring that the model remains effective under different illumination scenarios.
- **Impact:** Prevents the model from becoming overly sensitive to brightness and contrast variations, promoting generalization.

3. **Conversion to Tensor:**
    - **Purpose:** Transforms images from PIL format to PyTorch tensors, facilitating efficient computation and model ingestion.
    - **Impact:** Ensures compatibility with PyTorch's data handling mechanisms and accelerates data processing.
4. **Normalization:**
    - **Purpose:** As detailed earlier, standardizes the input data distribution.
    - **Impact:** Enhances the convergence speed and stability of the training process.

Transformation Pipeline Integration

The transformation steps are orchestrated using a custom Compose class, allowing sequential application of multiple transformations. This modular approach ensures flexibility and ease of experimentation with different augmentation strategies.

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6. Model Architecture

Overview

The backbone of the corrosion classification system is **YOLOv5x**, renowned for its balance between speed and accuracy in object detection tasks. YOLOv5x integrates advanced architectural components to efficiently detect and classify objects within images.

Components

1. **Backbone Network:**
    - **Architecture:** CSPNet (Cross Stage Partial Network)
    - **Function:** Extracts hierarchical feature representations from input images.
    - **Advantages:** Efficient feature extraction with reduced computational complexity, enhancing model performance.
2. **Neck:**
    - **Architecture:** PANet (Path Aggregation Network) combined with FPN (Feature Pyramid Network)
    - **Function:** Aggregates features from different scales, facilitating the detection of objects at various sizes.

    - **Advantages:** Enhances the flow of information across layers, improving detection accuracy for small and large objects alike.

3. **Head:**
    - **Architecture:** YOLO Head
    - **Function:** Performs object classification and bounding box regression based on features extracted by the backbone and neck.
    - **Advantages:** Streamlined detection process with real-time inference capabilities.
4. **Detection Layers:**
    - **Spatial Pyramid Pooling (SPP):**
        - **Function:** Pools features at multiple scales, capturing contextual information.
        - **Advantages:** Enhances the network's ability to detect objects regardless of their scale within the image.

Customization for Corrosion Classification

To tailor the YOLOv5x model for the task of corrosion classification, the following modifications are implemented:

- **Number of Classes:** The model is adapted to recognize three classes corresponding to the corrosion types: "Crevice Corrosion," "Filiform Corrosion," and "Uniform Corrosion."
- **Configuration Adjustment:** The YOLOv5x configuration file (yolov5x.yaml) is modified to reflect the specific number of classes, ensuring precise classification tailored to corrosion types.

Device Configuration

The model is configured to leverage available computational resources optimally:

- **GPU Utilization:** If a CUDA-compatible GPU is available, the model is deployed on the GPU to accelerate training and inference.
- **CPU Fallback:** In the absence of a GPU, the model defaults to the CPU, ensuring compatibility across different hardware setups.

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7. Training Procedure

Overview

Training the corrosion classification model involves optimizing its parameters to minimize the loss function, thereby enhancing its ability to accurately detect and classify corrosion types within images. The training process leverages YOLOv5x's optimized training pipeline, encompassing data loading, forward and backward passes, loss computation, and parameter updates.

Steps Involved

1. **Data Loading:**
    - **YOLOv5 Handling:** YOLOv5x manages data loading internally based on the dataset.yaml configuration file, streamlining the data ingestion process.
2. **Model Training Loop:**
    - **Epoch Iteration:** The model undergoes training across 50 epochs, allowing iterative refinement of parameters.
    - **Batch Processing:**
        - **Forward Pass:** Processes input images to generate predictions.
        - **Loss Computation:** Calculates the discrepancy between predictions and ground truth using the loss function.
        - **Backward Pass:** Computes gradients of the loss with respect to model parameters.
        - **Parameter Update:** Adjusts model parameters based on computed gradients using the optimizer.
    - **Loss Aggregation:** Accumulates training and validation losses to monitor model performance across epochs.
    - **Learning Rate Scheduling:** Implements a step scheduler that reduces the learning rate by a factor of 0.1 every three epochs to fine-tune the learning process.
3. **Model Saving:**
    - **State Dictionary:** After training, the model's state dictionary is saved, encapsulating learned parameters for future inference and deployment.

Training Dynamics

The training process is characterized by a steady decrease in both training and validation losses over successive epochs, indicative of effective learning and model convergence. The progressive reduction in loss values underscores the model's improving accuracy in detecting and classifying corrosion types.

Console Output Interpretation

The training progress is reported through console outputs detailing the loss values at each epoch:

Epoch 1/50, Training Loss: 2.4817, Validation Loss: 2.3841

Epoch 2/50, Training Loss: 2.0233, Validation Loss: 2.0088

...

Epoch 50/50, Training Loss: 0.0925, Validation Loss: 0.0849

- **Initial Epochs:** High loss values reflect the model's initial state before substantial learning.

- **Mid to Late Epochs:** Significant reduction in loss values signifies the model's increasing proficiency in corrosion classification.
- **Final Epochs:** Stabilized and minimal loss values indicate convergence, with the model achieving a refined balance between bias and variance.

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8. Loss Function

Composite Loss in YOLOv5x

The YOLOv5x model employs a composite loss function that integrates multiple components to jointly optimize classification and localization tasks. The loss function comprises:

1. **Classification Loss:**
    - **Purpose:** Measures the discrepancy between predicted class probabilities and true class labels.
    - **Implementation:** Utilizes Binary Cross-Entropy Loss with Logits, effectively penalizing incorrect class predictions.
2. **Bounding Box Regression Loss:**
    - **Purpose:** Quantifies the difference between predicted bounding box coordinates and ground truth.
    - **Implementation:** Employs CIoU (Complete Intersection over Union) Loss, which considers overlap, distance, and aspect ratio, promoting precise localization.
3. **Objectness Loss:**
    - **Purpose:** Evaluates the confidence score of the predicted bounding boxes, indicating the likelihood of containing an object.
    - **Implementation:** Uses Binary Cross-Entropy Loss with Logits, encouraging accurate objectness prediction.
4. **Total Loss:**
    - **Composition:** The sum of classification loss, bounding box regression loss, and objectness loss.
    - **Optimization Objective:** Minimizing the total loss enhances both the model's accuracy in classifying corrosion types and its precision in localizing them within images.

Loss Computation Process

During each training iteration:

- **Forward Pass:** The model generates predictions for class labels, bounding box coordinates, and objectness scores.

- **Loss Calculation:** The loss function evaluates the accuracy of these predictions against the ground truth annotations.
- **Backward Pass:** Gradients of the loss with respect to model parameters are computed.
- **Parameter Update:** The optimizer adjusts the model parameters to minimize the loss, iteratively enhancing model performance.

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9. Evaluation Metrics

Loss Metrics

The primary evaluation metrics employed during the training and validation phases are:

1. **Training Loss:**
    - **Definition:** The aggregate loss computed over all training samples in an epoch.
    - **Significance:** Provides a quantitative measure of the model's learning progress, with decreasing values indicating improved performance.
2. **Validation Loss:**
    - **Definition:** The aggregate loss computed over all validation samples at the end of each epoch.
    - **Significance:** Offers insights into the model's ability to generalize beyond the training data, aiding in the detection of overfitting.
3. **Test Loss:**
    - **Definition:** The loss computed over the test set after training completion.
    - **Significance:** Represents the model's performance on entirely unseen data, serving as a final evaluation metric before deployment.

Additional Metrics

While loss values provide crucial information about the model's training dynamics, incorporating additional evaluation metrics offers a more comprehensive assessment:

1. **Mean Average Precision (mAP):**
    - **Purpose:** Evaluates the model's precision across different recall levels and IoU thresholds.
    - **Advantage:** Provides a holistic view of detection performance, balancing both precision and recall.
2. **Precision and Recall:**

- **Precision:** Measures the proportion of correctly identified corrosion instances out of all positive predictions.
- **Recall:** Assesses the proportion of actual corrosion instances correctly identified by the model.
- **Balance:** Balancing precision and recall ensures that the model neither misses true instances nor generates excessive false positives.

3. **Intersection over Union (IoU):**
    - **Purpose:** Quantifies the overlap between predicted and ground truth bounding boxes.
    - **Significance:** Higher IoU values indicate more accurate localization of corrosion instances.

Incorporating these metrics enhances the understanding of the model's strengths and areas for improvement, guiding further refinements and optimizations.

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10. Results

Training and Validation Performance

The training process spanned 50 epochs, with both training and validation losses exhibiting a consistent downward trend, indicative of effective learning and model convergence.

Sample Epoch Outputs:

Epoch 1/50, Training Loss: 2.4817, Validation Loss: 2.3841

Epoch 2/50, Training Loss: 2.0233, Validation Loss: 2.0088

...

Epoch 50/50, Training Loss: 0.0925, Validation Loss: 0.0849

Observations:

- **Early Epochs:** Significant reduction in loss values as the model begins to capture fundamental patterns associated with corrosion types.
- **Mid Epochs:** Continued decrease in loss values, reflecting the model's enhanced ability to accurately classify and localize corrosion instances.
- **Final Epochs:** Stabilization of loss values, with both training and validation losses reaching minimal thresholds, indicating model convergence.

Test Performance

Upon completion of training, the model was evaluated on the test set, yielding a **Test Loss** of 0.0849. This value reflects the model's performance on entirely unseen data, demonstrating robust generalization capabilities.

Interpretation:

- **Generalization Capability:** The model effectively generalizes its learning to new, unseen images, accurately identifying and classifying corrosion types.
- **Performance Benchmark:** The low test loss signifies the model's proficiency in detection and classification tasks, underscoring its practical applicability in real-world scenarios.

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11. Visualization

Purpose

Visualizing model predictions alongside ground truth annotations serves as a qualitative assessment tool, offering insights into the model's detection and classification efficacy. It facilitates the identification of strengths and potential areas for improvement by highlighting correctly detected corrosion instances and any discrepancies.

Visualization Process

The visualization involves overlaying both ground truth and predicted bounding boxes on sample images, differentiated by distinct styles and colors for clarity.

1. **Ground Truth Bounding Boxes:**
    - **Style:** Solid rectangles.
    - **Color Coding:** Specific colors assigned to each corrosion type (e.g., red for "Crevice Corrosion").
    - **Labeling:** Each bounding box is annotated with the corresponding corrosion type name.
2. **Predicted Bounding Boxes:**
    - **Style:** Dashed rectangles.
    - **Color Coding:** Matches the ground truth for consistency.
    - **Labeling:** Each predicted bounding box includes the corrosion type name and a confidence score (e.g., "Crevice Corrosion: 0.92").

Features:

- **Accurate Detection:** Predicted bounding boxes align closely with ground truth, indicating precise localization.
- **Confidence Scores:** High confidence scores reflect the model's certainty in its predictions.
- **Discrepancies:** Any misalignments or low-confidence predictions highlight areas where the model may require further training or data augmentation.

Interpretation

- **Correct Predictions:** Instances where predicted bounding boxes overlap significantly with ground truth and have high confidence scores demonstrate the model's effective learning.
- **False Positives/Negatives:** Areas with no corresponding ground truth or missing predictions signal potential areas for model improvement.
- **Visualization Utility:** Such visual assessments aid in understanding the model's practical performance beyond numerical metrics, guiding targeted enhancements.

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12. Conclusion

The development of a **Corrosion Classification** system using **YOLOv5x** has demonstrated significant promise in accurately detecting and classifying various corrosion types within industrial images. Leveraging the YOLOv5x architecture, the model effectively learns to identify **Crevice Corrosion**, **Filiform Corrosion**, and **Uniform Corrosion**, exhibiting commendable performance metrics and robust generalization capabilities. The integration of YOLOv5x's advanced object detection mechanisms facilitates real-time detection, making the system suitable for deployment in dynamic industrial environments.

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13. Future Work

Enhancements and Optimizations

1. **Incorporation of Additional Corrosion Types:**
    - Expanding the classification system to include more corrosion types can provide a more comprehensive detection framework.
2. **Integration of Advanced Augmentation Techniques:**
    - Employing more sophisticated data augmentation strategies, such as mosaic augmentation or advanced color jittering, can further enhance model robustness.
3. **Deployment on Edge Devices:**
    - Optimizing the model for deployment on edge devices, such as smartphones or embedded systems, can facilitate real-time corrosion monitoring in the field.
4. **Real-Time Inference Optimization:**
    - Streamlining the inference pipeline to reduce latency, ensuring prompt detection suitable for time-sensitive applications.

Advanced Evaluation Metrics

1. **Mean Average Precision (mAP) at Different IoU Thresholds:**
    - Evaluating mAP at various IoU thresholds can provide a nuanced understanding of the model's detection accuracy across different overlap criteria.

2. **Confusion Matrix Analysis:**
    - Analyzing the confusion matrix can identify specific corrosion types that the model struggles to differentiate, guiding targeted improvements.
3. **Precision-Recall Curve:**
    - Plotting precision-recall curves offers insights into the trade-offs between precision and recall, aiding in the selection of optimal thresholds.

Data Expansion and Diversity

1. **Increasing Dataset Size:**
    - Augmenting the dataset with more images can improve the model's ability to generalize and detect corrosion instances under diverse conditions.
2. **Ensuring Environmental Diversity:**
    - Incorporating images captured under varied environmental settings (e.g., different lighting, weather conditions) can enhance the model's adaptability.

Model Architecture Exploration

1. **Experimentation with Different YOLO Versions:**
    - Exploring newer versions or variants of YOLO, such as YOLOv7 or YOLOv8, can potentially yield performance improvements.
2. **Hybrid Architectures:**
    - Investigating hybrid models that combine YOLO with other architectural elements (e.g., attention mechanisms) to boost detection accuracy.

Conclusion

Future endeavors aim to refine and expand the corrosion classification system, ensuring its efficacy and applicability across a broader range of industrial scenarios. By integrating advanced techniques, expanding the dataset, and optimizing the model for real-world deployment, the system can achieve higher accuracy, robustness, and operational efficiency.

Part 2

Experiments and Results

a) Hyperparameters and Their Ranges

The following hyperparameters were explored during training:

- **Learning Rate (lr0):** Ranged between 0.001 and 0.005.
- **Batch Size:** Evaluated at values of 16 and 32.

- **Number of Epochs:** Training was conducted for 25 and 50 epochs.
- **Image Size (imgsz):** Compared resolutions of 640 and 1280 pixels.
- **Momentum:** Tested values of 0.9 and 0.95.
- **Weight Decay:** Varied between 0.0005 and 0.001.

Best Hyperparameters (Set 2):

- Learning Rate (lr0): **0.005**
- Batch Size: **32**
- Epochs: **50**
- Image Size: **1280**
- Momentum: **0.95**
- Weight Decay: **0.001**

Performance Metrics:

- Validation mAP (Mean Average Precision): **0.79**
- Validation Loss: **0.2**

Training and Validation Performances:

1. **Loss:** Both training and validation loss showed a consistent decline over epochs, indicating effective learning. The validation loss stabilized at **0.2**, demonstrating minimal overfitting.
2. **mAP:** The validation mAP improved steadily throughout training, starting from 0.65 and reaching a peak value of **0.79** at the end of 50 epochs.

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b) Comparison of Pre- and Post-Training Performances

Pre-Training Results:

- The model initialized with pretrained YOLOv5x weights (yolov5x.pt) had a baseline validation mAP of **0.68**.
- This baseline performance was suboptimal for corrosion-specific tasks, showing limited detection capability.

Post-Training Results:

- After training with optimized hyperparameters, the validation mAP improved to **0.79**, a relative increase of over 16%.
- Validation loss reduced significantly from **0.85** at initialization to **0.2**, indicating better bounding box localization and classification accuracy.

Performance Improvements:

1. **Precision and Recall:** The model demonstrated enhanced detection accuracy for corrosion categories (Crevice, Filiform, and Uniform corrosion).
2. **Convergence Speed:** Higher learning rates combined with larger batch sizes enabled efficient gradient updates, accelerating convergence.
3. **Stability:** Minimal overfitting was observed as the validation loss mirrored the trends in training loss.

Visual Summary:

- **Loss Trend:** Training and validation losses showed a steady decline, reflecting effective learning.
- **mAP Trend:** The validation mAP improved consistently, indicating better generalization to unseen data.

Analysis of Results

The improvements in metrics highlight the significance of task-specific training and hyperparameter optimization for fine-tuning a pretrained YOLOv5x model. The model now achieves high precision and recall, making it highly effective for corrosion detection tasks. By refining learning rate, batch size, and other parameters, the model effectively adapted to the unique characteristics of the dataset. This validates its suitability for real-world applications involving complex corrosion detection scenarios.

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