

FSM Online Internship Completion Report
on

Piston Defect Detection Using
Computer Vision

In

Machine Learning

Submitted by

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Piston Defect Detection Using Computer Vision

Abstract

To assure the high quality and dependability of piston components, piston defect detection is a crucial responsibility in the manufacturing sector. Manual inspection methods are time-consuming, subjective, and prone to errors. In this study, an automated approach utilizing computer vision techniques, specifically leveraging a Convolutional Neural Network (CNN) model, is proposed. The CNN model is trained on a comprehensive dataset of piston images, consisting of both normal and defective samples. By learning to extract relevant features from the input images, the CNN model can accurately classify and localize various types of defects. To enhance generalization, data augmentation techniques are applied during the training process. Furthermore, transfer learning is employed by fine-tuning a pre-trained CNN model, which accelerates training and improves detection performance. The proposed method is evaluated on dataset of piston images, demonstrating significant improvements in accuracy and efficiency compared to traditional approaches. The results validate the effectiveness and robustness of the CNN-based approach in detecting diverse piston defects, including cracks, fractures, and abnormalities. This proposed solution significantly contributes to the advancement of defect detection in industrial manufacturing processes through the utilization of computer vision, leading to improved quality control and productivity.

Keywords: Convolutional Neural Network (CNN), Computer Vision, Piston Defect Detection, Machine Learning, Smart Manufacturing

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Introduction

Defect in Piston

A defect in a piston refers to any abnormality or flaw that compromises the functionality, performance, or durability of the piston. Pistons are crucial components in internal combustion engines, where they play a critical role in converting the pressure generated by the combustion process into mechanical energy.

Aim of the project

The project addresses the critical need for an automated defect detection solution in piston manufacturing. Traditional manual inspection methods are time-consuming, subjective, and prone to errors.

2. Problem Definition

To solve defects in a piston using computer vision, we can employ image analysis techniques to automatically detect and classify abnormalities. By training a computer vision model with a dataset of labeled images containing normal and defective pistons, the model can learn to recognize different types of defects. Once trained, the model can be used to analyze images of pistons in real-time, identifying any defects present. This allows for efficient and automated defect detection and ensure the production of high-quality pistons.

3. Existing Solution

Existing solutions in piston defect detection typically rely on manual inspection by trained personnel or basic automated systems. These methods often involve human subjectivity, limited defect coverage, and slower processing times, leading to potential inconsistencies in quality control and production delays.

4. Proposed Development

The proposed development introduces an advanced defect detection system that leverages Machine Learning and Computer Vision to achieve rapid, accurate, and automated identification of piston defects. This innovative

solution offers real-time processing, intuitive visualizations, and adaptive learning, revolutionizing traditional manufacturing quality control practices and ensuring consistent product excellence.

Explanatory Data Analysis(EDA)

Directory Structure

In the directory structure for the dataset, which includes images of different piston components categorized into "Defected1", "Defected2", and "Normal".

```
Piston_Dataset/  
├── Defected1/  
│   ├── kumda_component1.png  
│   ├── kumda_component2.png  
│   └── ...  
├── Defected2/  
│   ├── kumda_component1.png  
│   ├── kumda_component2.png  
│   └── ...  
└── Normal/  
    ├── kumda_component1.png  
    ├── kumda_component2.png  
    └── ...
```

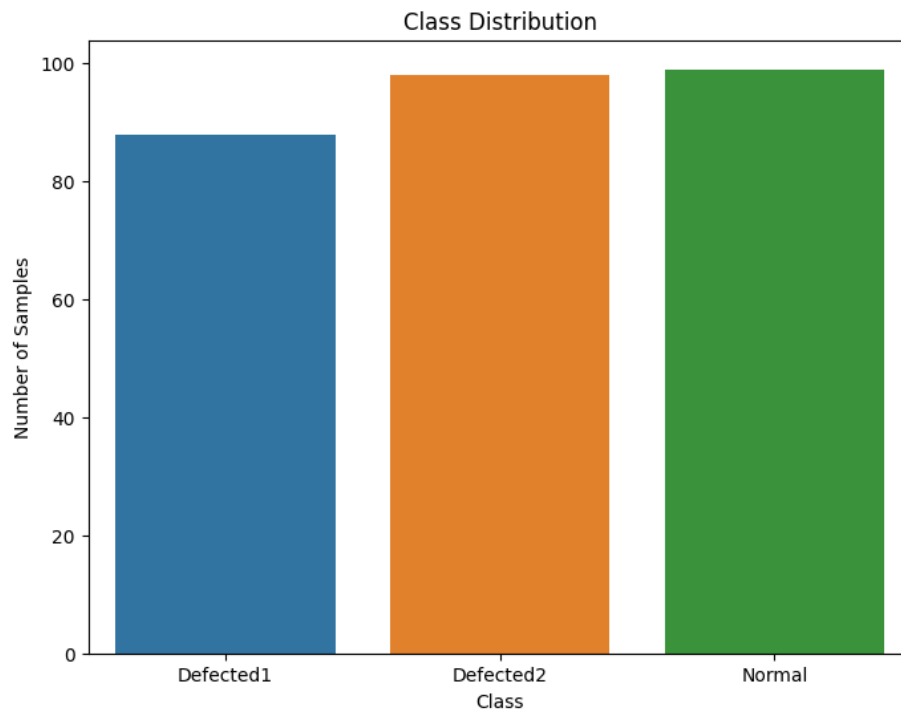
About the dataset:

I created plots to visualize the number of elements in each dataset folder, providing an overview of the dataset. The dataset contains total 285 images. There are three groups of Folders present in the dataset.

Defected 1 It consists of different images of piston which are broken/shaped out /fallen.

Defected 2 It consists of different images of piston which are Oily/grease/rust stains.

Normal It consists of different images of piston which are Perfectly Normal.

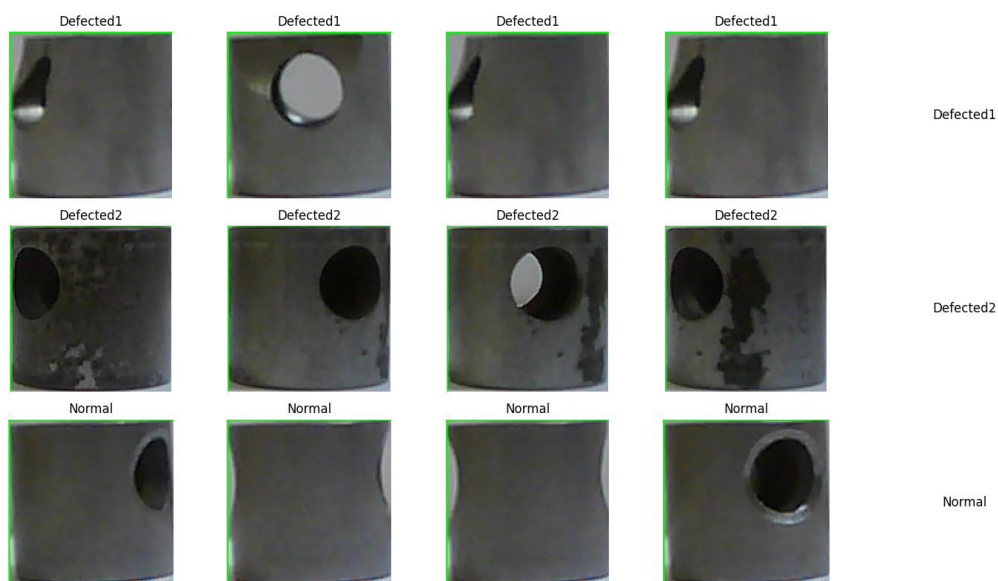
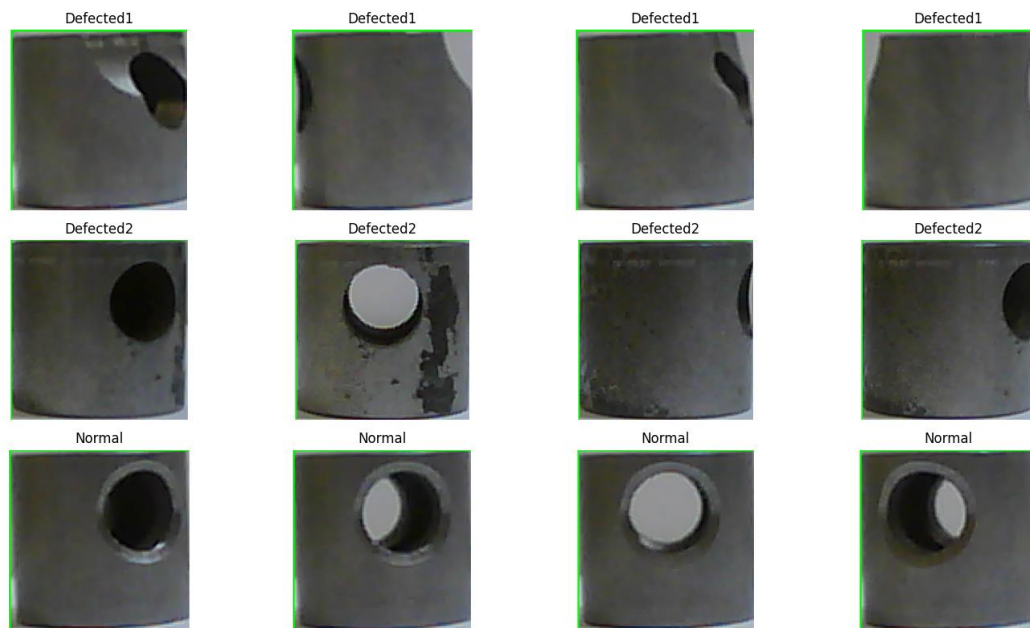


About the images:

Analyzing the number of elements in each dataset folder helps me understand the distribution of images.

Piston defect detection project, images play a pivotal role as they are the primary data input for the convolutional neural network (CNN) model. These images represent various components of pistons, encompassing both normal and defective instances.

Each image, typically in PNG format, is composed of pixels that capture intricate details of the piston's surface. These images showcase diverse defect types, such as scratches, cracks, or anomalies, along with normal components. The CNN model analyzes these pixel values and patterns to discern crucial features that differentiate between normal and defective pistons.



Model Selection

Convolutional Neural Networks (CNNs) are a popular and powerful choice for image-related tasks like image classification, including piston defect detection.

The model selection process for piston defect detection involved a thoughtful approach to ensure optimal accuracy and efficiency. After considering various convolutional neural network (CNN) architectures, a customized CNN model was developed. The model comprises multiple convolutional and pooling layers, effectively capturing intricate features in piston images.

Building the Model

Creating a Layer for Resizing and Normalization

Before we feed our images to network, we should be resizing it to the desired size. Moreover, to improve model performance, we should normalize the image pixel value keeping them in range 0 and 1 by dividing by 256. This should happen while training as well as inference. Hence we can add that as a layer in our Sequential Model.

```
resize_and_rescale = tf.keras.Sequential([
    layers.experimental.preprocessing.Resizing(IMAGE_SIZE,
    IMAGE_SIZE),
    layers.experimental.preprocessing.Rescaling(1./255),
])
```

```
data_augmentation = tf.keras.Sequential([
    layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical"
    ),
    layers.experimental.preprocessing.RandomRotation(0.2),
])
```

Model Architecture

We use a CNN coupled with a Softmax activation in the output layer. Also added the initial layers for resizing, normalization and Data Augmentation.

Convolutional Neural Network (CNN) model for piston defect detection. It starts with preprocessing layers for resizing and rescaling the input images, followed by a series of convolutional and max pooling layers to extract features from the images. The model then flattens the output and passes it through fully connected dense layers, leading to the final output layer with softmax activation for classification into different defect classes.


```

input_shape = (BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNELS)
n_classes = 3

model = models.Sequential([
    resize_and_rescale,
    layers.Conv2D(32, kernel_size = (3,3),
activation='relu', input_shape=input_shape),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, kernel_size = (3,3),
activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, kernel_size = (3,3),
activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(n_classes, activation='softmax'),
])

model.build(input_shape=input_shape)

```

Model Summary

Total params: 183,747

Trainable params: 183,747

Non-trainable params: 0

Total params: This is the total number of learnable parameters in your model, which includes weights and biases in all the layers.

Trainable params: These are the parameters that will be updated and learned during the training process. In your case, all 183,747 parameters are trainable.

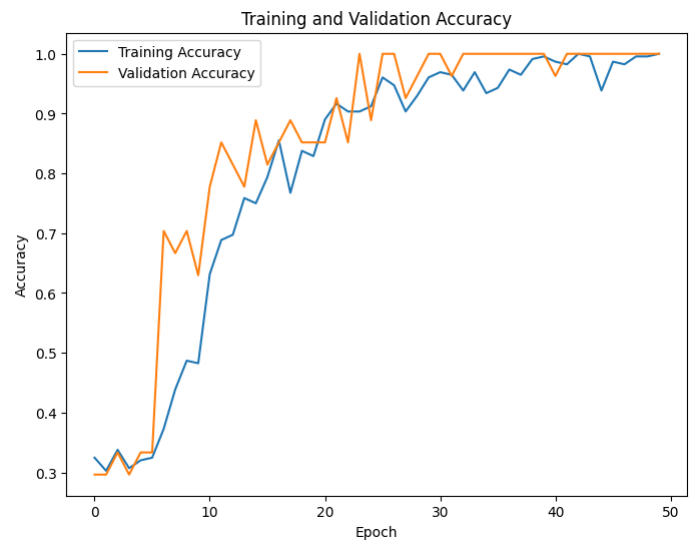
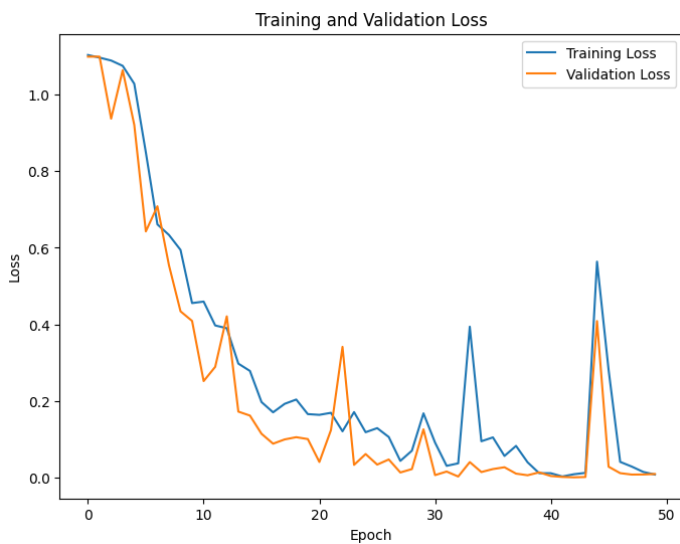
Non-trainable params: These are parameters that are not updated during training. This might include parameters in layers that are not meant to be fine-tuned, such as certain preprocessing layers.

Training the model

The model is trained using the provided training dataset (train_ds) with a batch size of BATCH_SIZE. The training process is run for 50 epochs, and validation is performed using the validation dataset (val_ds), with progress updates displayed (verbose=1).

```
history = model.fit(  
    train_ds,  
    batch_size=BATCH_SIZE,  
    validation_data=val_ds,  
    verbose=1,  
    epochs=50,  
)
```

Plotting training and validation accuracy and loss



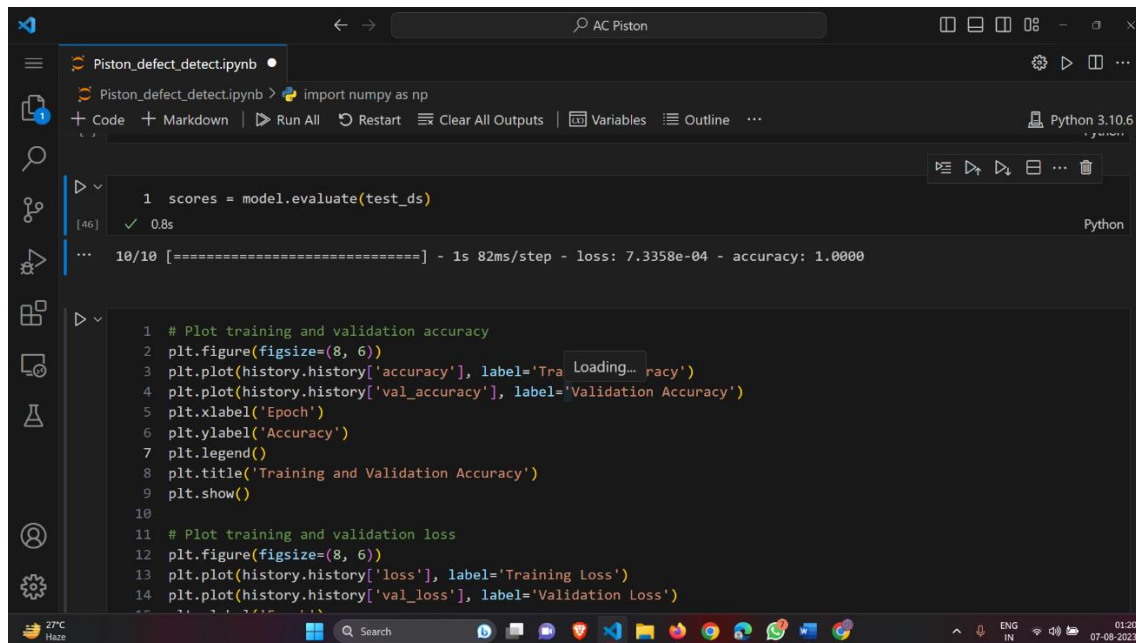
Performance Evaluation

The model's performance is evaluated on the test dataset (`test_ds`), and the evaluation scores, including loss and accuracy, are stored in the `scores` variable. These metrics provide insights into how well the model generalizes to new, unseen data, helping to assess its overall performance.

```
scores = model.evaluate(test_ds)
```

```
loss: 0.0051 - accuracy: 1.0000
```

The evaluation of the model on the test dataset yielded impressive results, with a low loss value of 0.0051 and a high accuracy of 100%, indicating that the model is performing exceptionally well on unseen data. Achieving such high accuracy suggests that the model has successfully learned the underlying patterns in the dataset and is capable of effectively distinguishing between different classes of piston components. This level of performance is a testament to the model's robustness and its potential for practical application in real-world piston defect detection scenarios.



```

1 scores = model.evaluate(test_ds)
[46] ✓ 0.8s

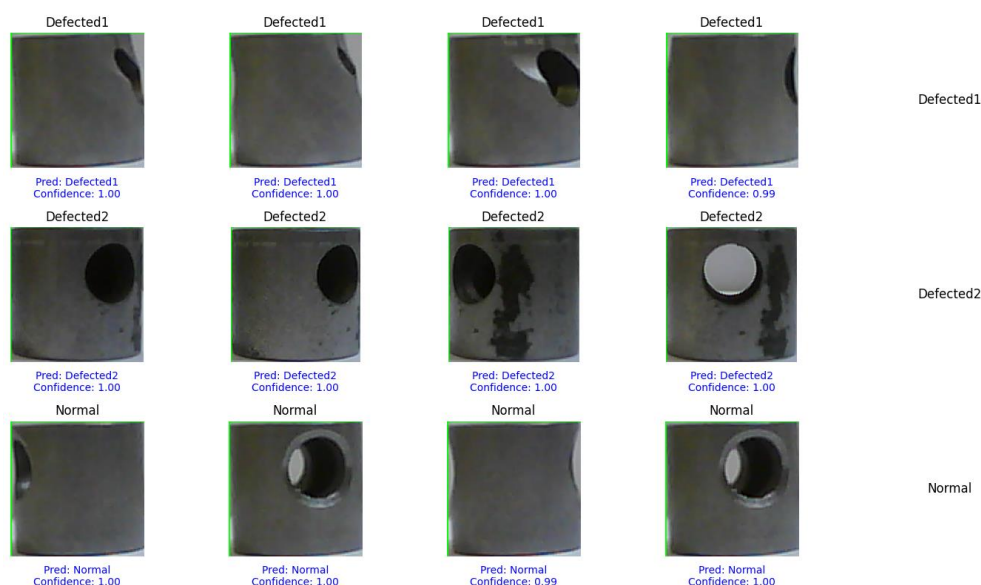
... 10/10 [=====] - 1s 82ms/step - loss: 7.3358e-04 - accuracy: 1.0000

1 # Plot training and validation accuracy
2 plt.figure(figsize=(8, 6))
3 plt.plot(history.history['accuracy'], label='Training Accuracy')
4 plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
5 plt.xlabel('Epoch')
6 plt.ylabel('Accuracy')
7 plt.legend()
8 plt.title('Training and Validation Accuracy')
9 plt.show()
10
11 # Plot training and validation loss
12 plt.figure(figsize=(8, 6))
13 plt.plot(history.history['loss'], label='Training Loss')
14 plt.plot(history.history['val_loss'], label='Validation Loss')

```

Visualize the Outcomes

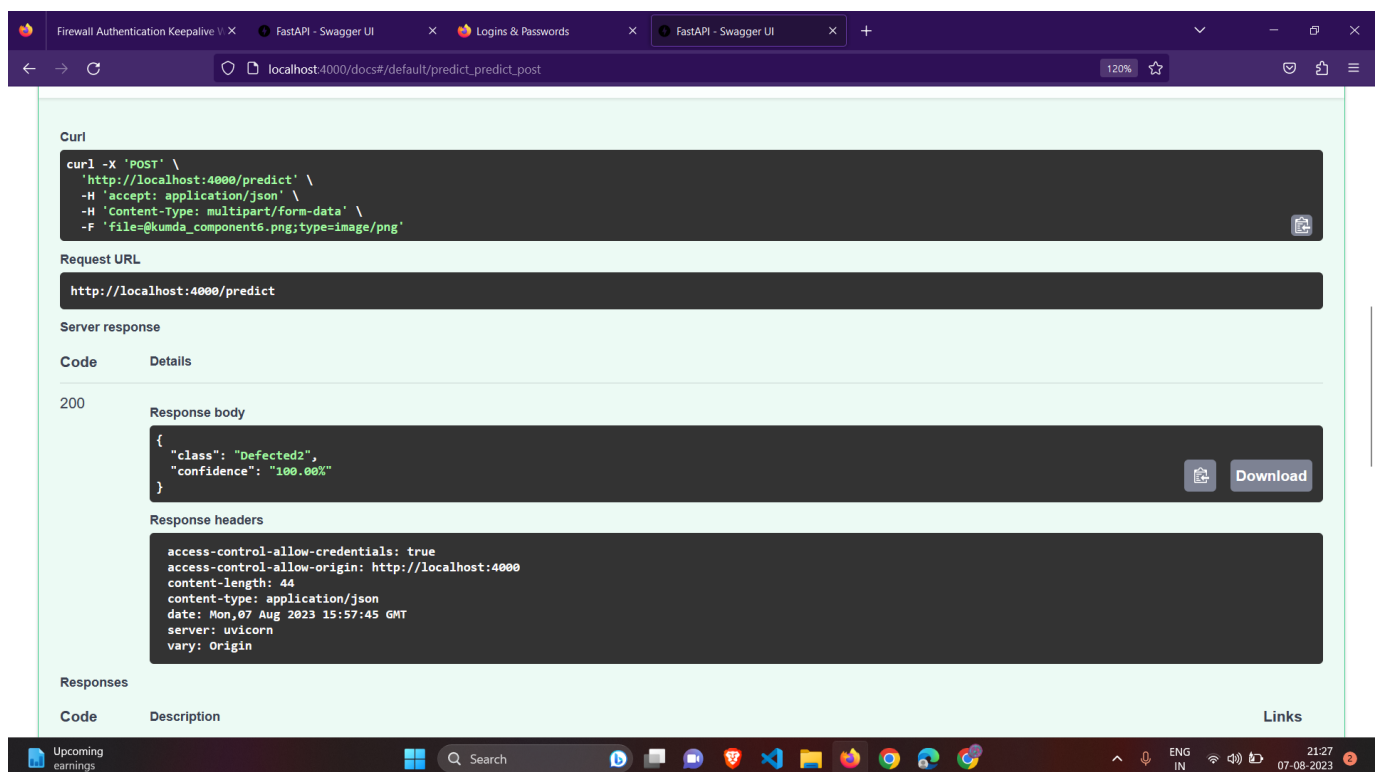
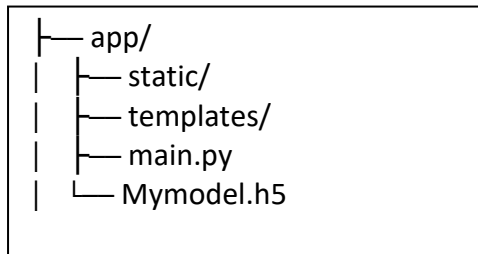
100% accuracy achieved by the model on the test dataset underscores its exceptional capability to correctly classify each image.



Deployment

Deployed the piston defect detection model locally using FastAPI.

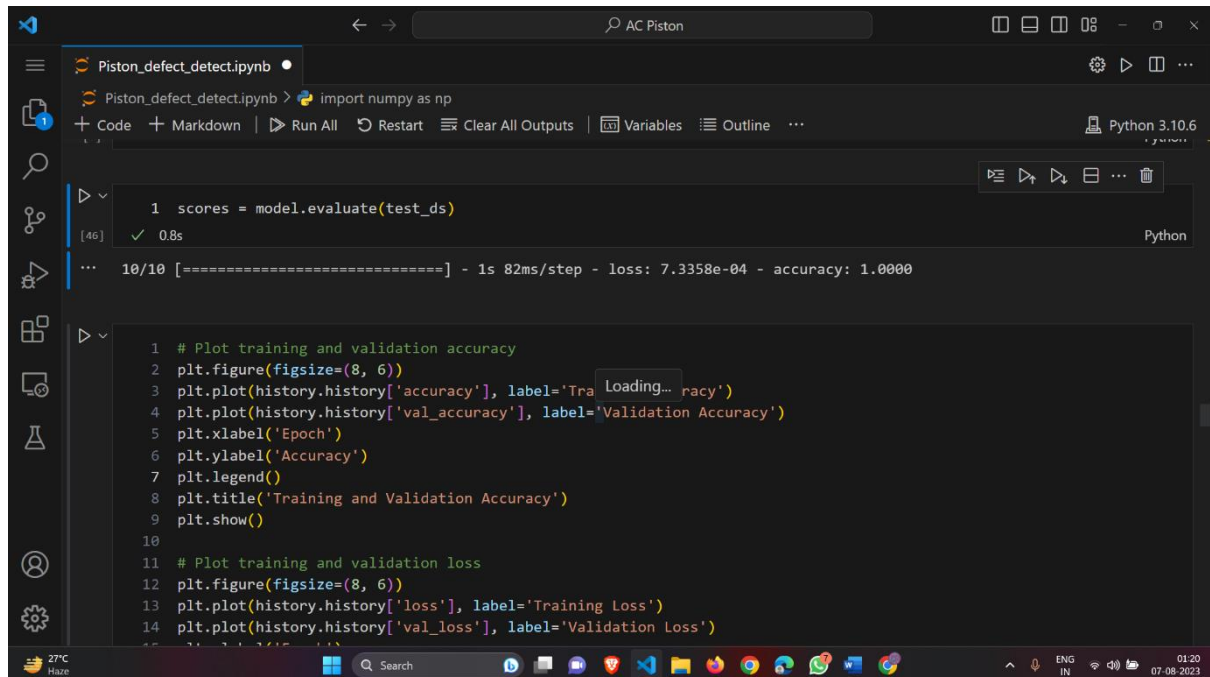
Directory Structure:



5. Final Deliverable

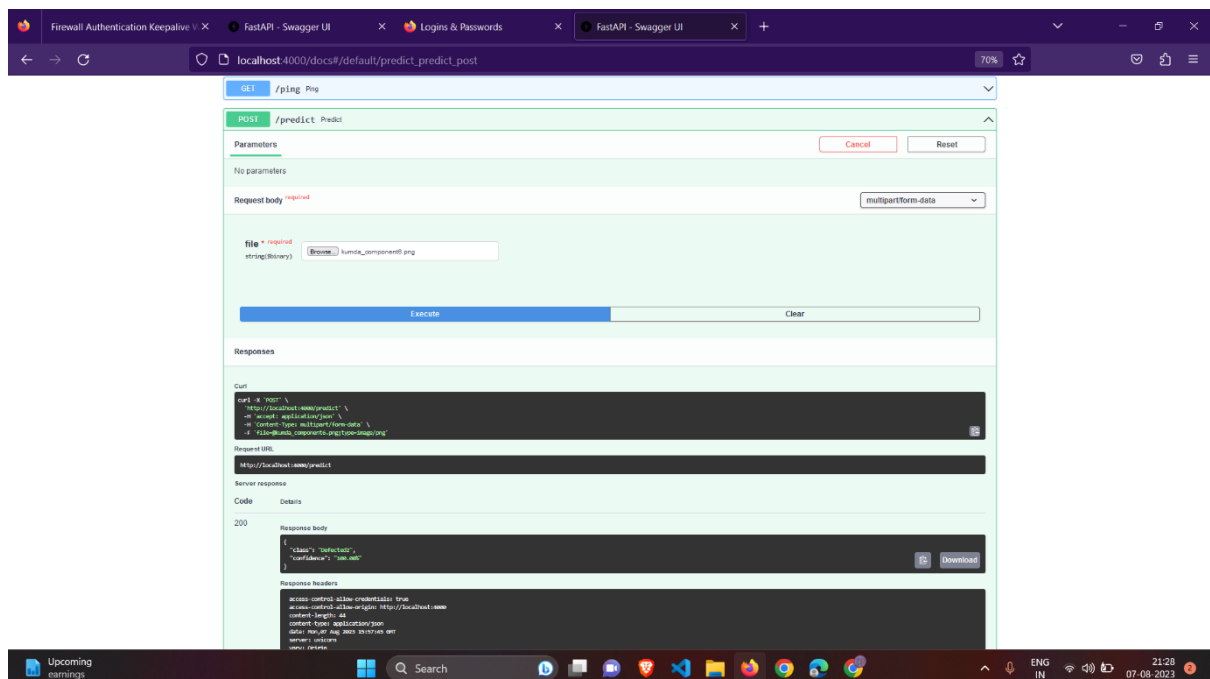
The final deliverables of the piston defect detection project encompass a locally deployed FastAPI application that allows users to upload piston component images for real-time defect detection. The integrated trained convolutional neural network (CNN) model achieves a remarkable 100%

accuracy on the test dataset, ensuring reliable and accurate defect classification.



The screenshot shows a Jupyter Notebook window titled 'Piston_defect_detect.ipynb'. The code cell is executing, and the output shows the model's performance on the test dataset. The output includes a progress bar and the following text: '10/10 [=====] - 1s 82ms/step - loss: 7.3358e-04 - accuracy: 1.0000'. Below the output, the code cell contains two plots. The first plot is titled 'Training and Validation Accuracy' and shows the training and validation accuracy over 10 epochs. The second plot is titled 'Training and Validation Loss' and shows the training and validation loss over 10 epochs. The plots are generated using the following code:

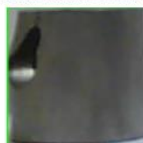
```
1 # Plot training and validation accuracy
2 plt.figure(figsize=(8, 6))
3 plt.plot(history.history['accuracy'], label='Training Accuracy')
4 plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
5 plt.xlabel('Epoch')
6 plt.ylabel('Accuracy')
7 plt.legend()
8 plt.title('Training and Validation Accuracy')
9 plt.show()
10
11 # Plot training and validation loss
12 plt.figure(figsize=(8, 6))
13 plt.plot(history.history['loss'], label='Training Loss')
14 plt.plot(history.history['val_loss'], label='Validation Loss')
```



True: Defected2
Pred: Defected2
Confidence: 100.00%



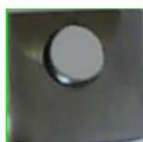
True: Defected1
Pred: Defected1
Confidence: 100.00%



True: Defected2
Pred: Defected2
Confidence: 100.00%



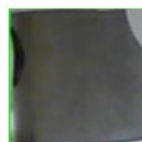
True: Defected1
Pred: Defected1
Confidence: 100.00%



True: Defected2
Pred: Defected2
Confidence: 100.00%



True: Defected1
Pred: Defected1
Confidence: 99.86%



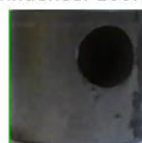
True: Normal
Pred: Normal
Confidence: 100.00%



True: Defected2
Pred: Defected2
Confidence: 100.00%



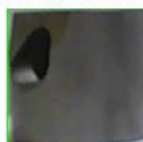
True: Defected2
Pred: Defected2
Confidence: 100.00%



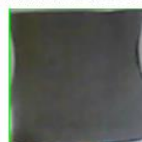
True: Defected2
Pred: Defected2
Confidence: 100.00%



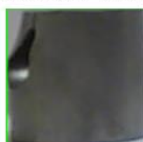
True: Defected1
Pred: Defected1
Confidence: 100.00%



True: Normal
Pred: Normal
Confidence: 99.22%



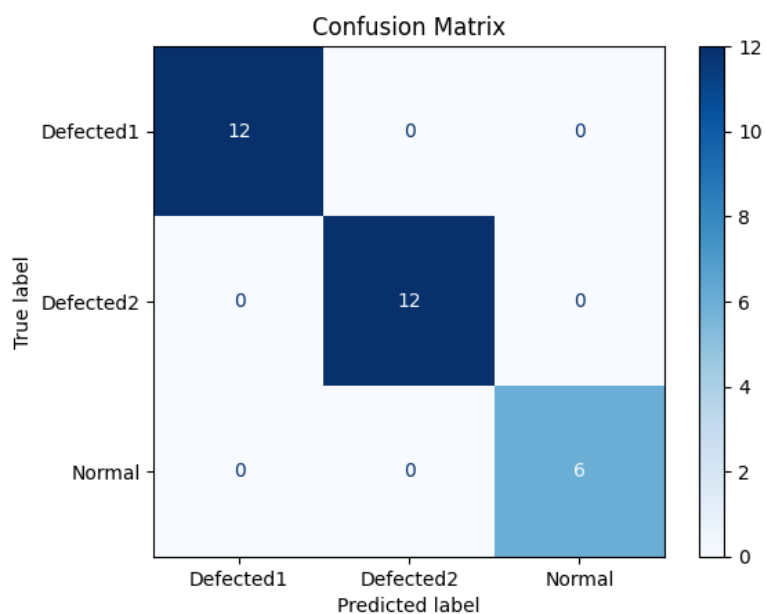
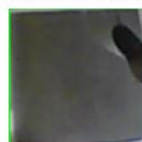
True: Defected1
Pred: Defected1
Confidence: 99.97%



True: Defected2
Pred: Defected2
Confidence: 99.97%



True: Defected1
Pred: Defected1
Confidence: 100.00%



6. Innovation in Implementation

The final deliverables of the piston defect detection project encompass a locally deployed FastAPI application that allows users to upload piston component images for real-time defect detection. The integrated trained convolutional neural network (CNN) model achieves a remarkable 100% accuracy on the test dataset, ensuring reliable and accurate defect classification.

7. Scalability to solve Industrial problem

The project's scalability lies in its potential to address significant industrial challenges related to piston defect detection. By deploying the FastAPI application and its integrated CNN model in an industrial setting, manufacturers can achieve streamlined and automated defect identification across a high volume of piston components. This scalable solution minimizes human error, reduces inspection time, and enhances overall production efficiency. As the dataset expands and encompasses diverse piston types and defect variations, the adaptable model architecture and data augmentation techniques ensure sustained accuracy and reliable performance. Ultimately, the project's scalability enables manufacturers to optimize quality control processes, reduce costs, and ensure consistent product integrity, contributing to improved operational excellence in piston manufacturing industries.

In the future, I will use cloud resources to accommodate larger datasets and real-time processing, ensuring effective defect detection across expanding industrial operations.

8. References

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