CIIIT INTERNSHIP

TASK ASSIGNED: AUTOMATED DEFECT DETECTION IN CASTED METAL PARTS

PROJECT DESCRIPTION

To develop a computer vision-based system capable of autonomously inspecting and identifying defects or imperfections in casted metal parts.

The system utilizes state-of-the-art deep learning techniques to automate the quality control process, ensuring that only high-quality parts proceed to further manufacturing stages.

By leveraging the power of artificial intelligence (AI) and machine learning (ML), the system enhances accuracy, consistency, and efficiency in defect detection

SOLUTION

STEP 1: DATA PROCESSING

Collecting, balancing, splitting, preprocessing, and augmenting a dataset of casted metal part images to train machine learning models for defect detection.

STEP 2: MODEL TRAINING

Fine tune the pretrained model and train prepared data on Classification model.

STEP 3: MODEL PERFORMANCE ANALYSIS/TESTING

Test the model on various untested samples and analyse training and validation parameters

DEPLOYMENT

The classification model is versatile and deployable across a variety of environments, including Luxonis OAK, Raspberry Pi, NVIDIA Jetson, Docker containers, web pages, and Python scripts, tailored to the specific application requirements.

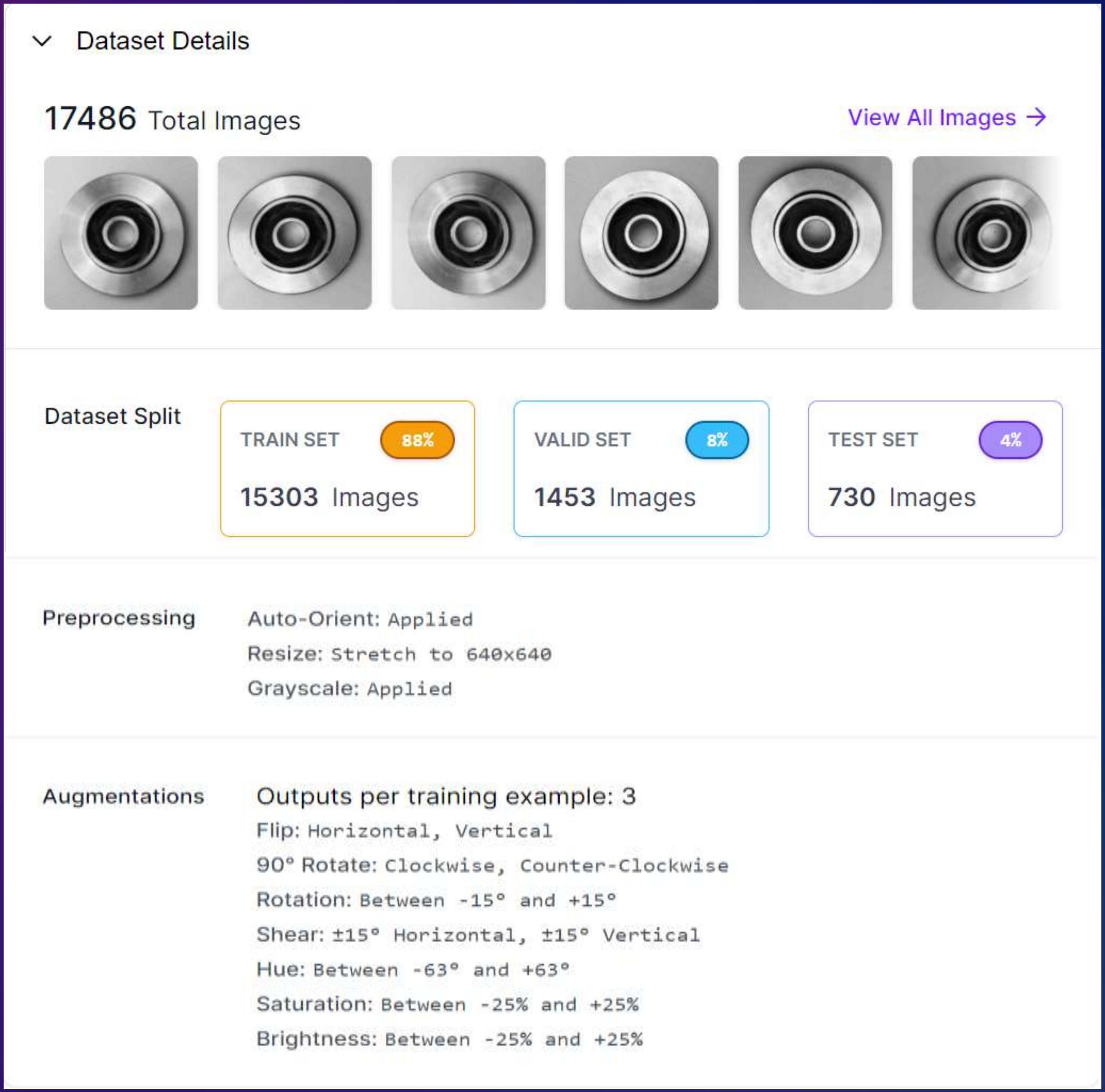
STEP 1: DATA PROCESSING

Description of Each Class Type:

The project involves classifying casted metal parts into two categories:

Defective Parts: This class includes casted metal parts that exhibit one or more defects or imperfections. Defects can range from surface irregularities, cracks, or incomplete casting.

Non-Defective Parts: This class comprises casted metal parts that meet the required quality standards and exhibit no detectable defects.



MODEL TRAINING

MODEL SUMMARY:

The model architecture consists of MobileNet V2 as a feature extractor, followed by Global Average Pooling and a Dense layer for prediction.

TOTAL PARAMETERS

The MobileNetV2 has 2.5 million non-trainable parameters, while the Dense layer has 1.2 thousand trainable parameters.

TRAINABLE VARIABLES

There are two trainable variables in the model: weights and biases in the Dense layer.The model was trained for 20 epochs on the specified dataset.

MODEL COMPILATION

The model was compiled using RMSprop optimizer with a learning rate of 0.0001 and binary cross-entropy loss (from_logits=True) since it provides linear output for binary

BASE MODEL

MobileNet V2 was used as the base model, pre-trained on ImageNet.

TOTAL PARAMETERS

The last classification layers were excluded, and feature extraction was performed using the "bottleneck layer" for better generality.

FEATURE EXTRACTION:

The MobileNetV2 has 2.5 million non-trainable parameters, while the Dense layer has 1.2 thousand trainable parameters.

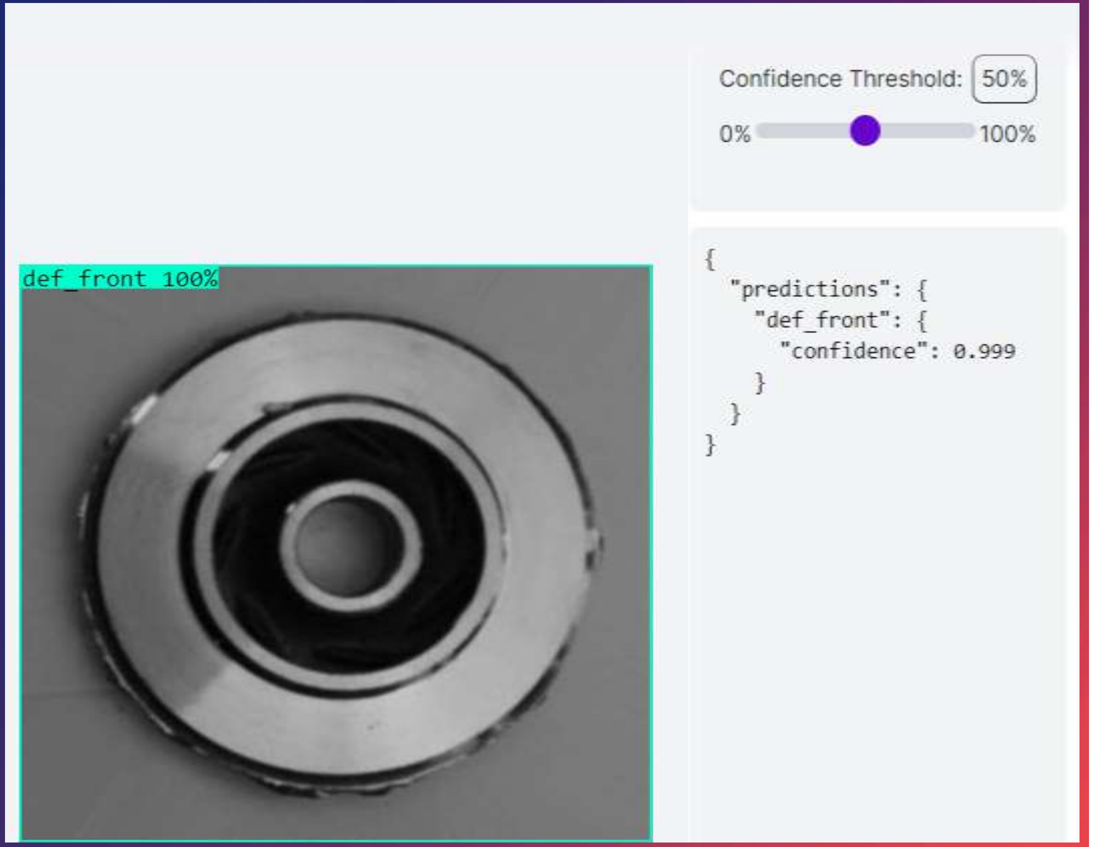
GLOBAL AVERAGE POOLING DENSE LAYER :

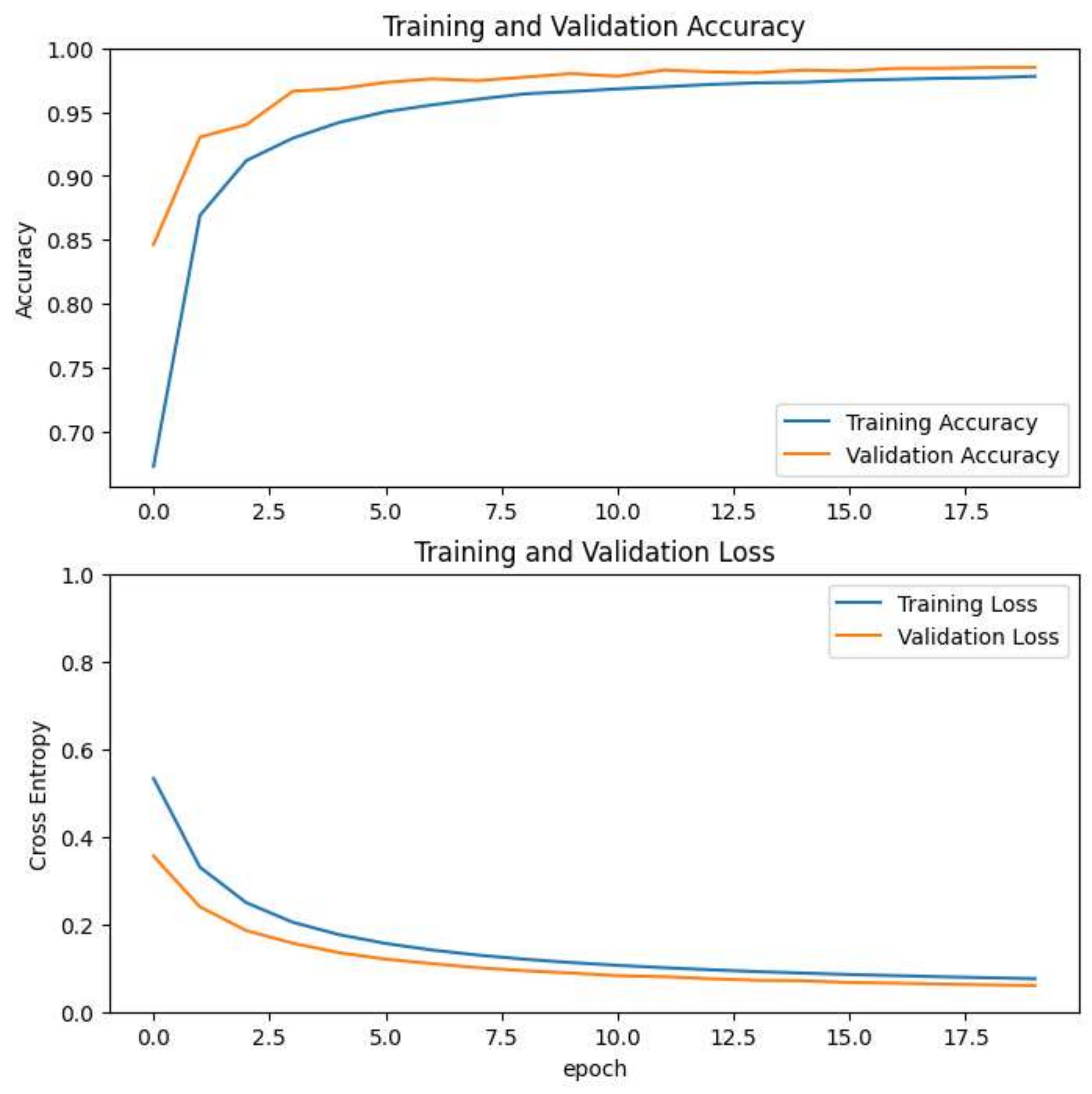
Features were converted into a single 1280-element vector per image using Global Average Pooling.

A Dense layer was added to produce a raw prediction value (logit) for binary classification.

TEST RESULTS

- Training accuracy: 99.95%
- Validation accuracy: 99.66%
- Test Accuracy: 99.45%





THANK YOU

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