Defect Detection in Welding using Thermal Image

1 **Introduction**

In modern industry, manual inspection processes are increasingly being replaced by automated, AI-driven solutions. Traditional weld defect inspection, performed by human operators, is often time consuming and inconsistent due to subjective judgment. To address these limitations, this project utilizes the YOLO-Pro model from Edge Impulse to automatically detect internal welding defects from thermal images. This edge-optimized model enables fast, accurate, and consistent defect detection, significantly reducing inspection time and eliminating human error. As Edge AI technology advances, YOLO-Pro based weld inspection is poised to become an essential tool for reliable and efficient industrial quality assurance.

2 **Methodology and Materials**

This section describes the experimental setup for data collection and the step-by-step methodology used for model training. The schematic of the setup is given below (fig 1),

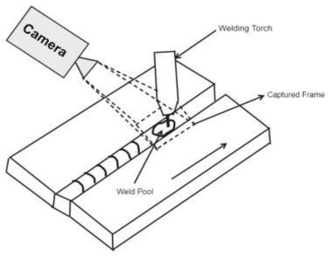

Fig. 1 schematic of setup

2.1 *Camera:*

The FLIR Lepton 3.5, a long wave infrared camera, was used for this study. It is designed for easy integration with mobile devices and other electronics. The camera captures infrared radiation and produces uniform thermal images with a nominal wavelength band of 8 to 14 microns and a thermal sensitivity of less than 50 mK.

2.2 *Experimental Setup:*

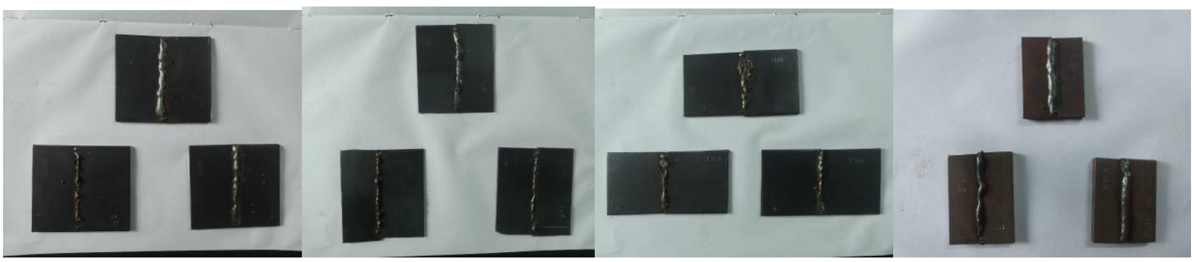

Fig. 2 Thickness samples - (a) 4MM , (b) 1.5*MM ,(c) 3MM ,(d)* 6*MM*

Mild steel samples of varying thicknesses (1.5mm, 3mm, 4mm, and 6mm) were welded (fig. 2) using MIG welding with different parameters, as detailed in Table 1. Since the metal is welded on different parameters several defects have been noted.

	Levels of Parameter	
Input parameters	**Value**	**Deviation**
Current (Ampere)	220	220 ± 30
Voltage (V)	16	16 ± 2

Table 1 Weld parameters

After the metal is welded the heat is present in it and then it is placed under the lepton 3.5 thermal camera which is connected to a raspberry pi. And the thermal image is seen as output. All the weld samples are placed under this setup (fig. 3) and thermal images are taken.

Fig 3 Complete setup

2.3 *Data Preprocessing:*

The raw output from the FLIR Lepton camera has a resolution of 160 x 120 pixels. All images were resized to 128 x 128 pixels and normalized to standardize the input data for the model.

2.4 *Data Augmentation:*

The initial dataset was limited and captured under stable conditions. To improve model robustness and accuracy, the image dataset was augmented using the Albumentations library.

An analysis of the raw dataset of 234 files revealed a significant class imbalance, as evidenced by the pixel distribution of the masks for each class (Fig. 4).

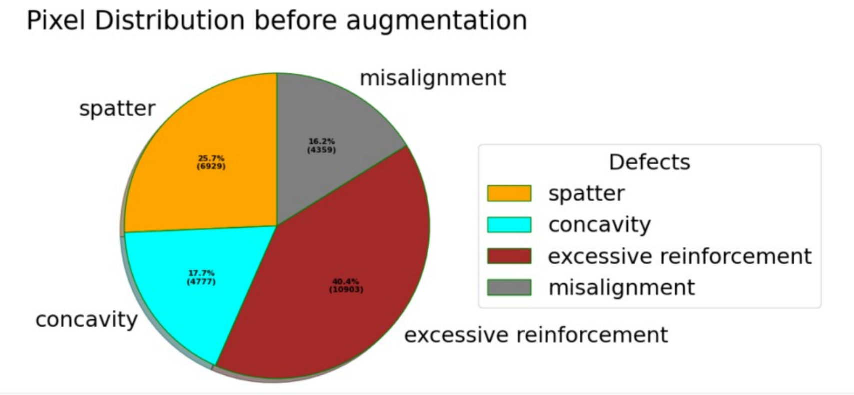

Fig. 4 Pixel distribution of masks before augmentation

To address this imbalance and improve generalization, several augmentation techniques were applied. These included adjustments to combat non-uniform illumination, such as modifying brightness and adding ISO noise to simulate grain. Horizontal and vertical flips were also used. The specific techniques and their parameters are listed in Table 2, with visual examples provided in Fig. 5.

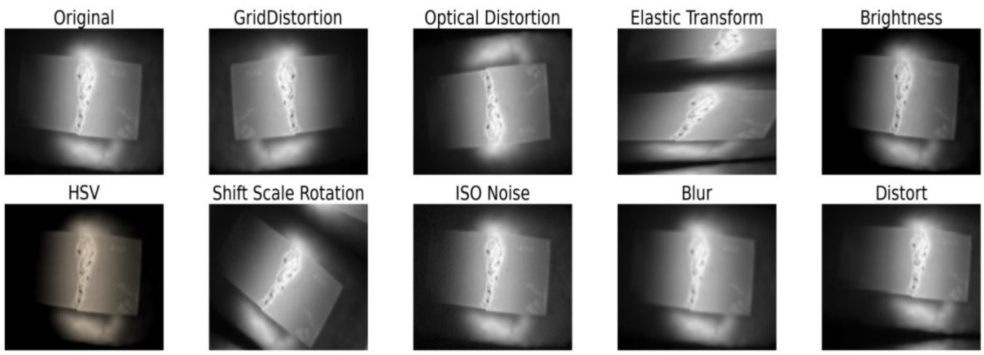

Fig. 5 Applied Data Augmentation techniques

Technique	**Parameters**
Grid Distortion	Num steps=4, distort limit=0.02
Optical Distortion	Distort limit=2, shift limit=0.5
Elastic Transform	Alpha=1, sigma=50, Alpha Affine=50
Brightness	limit=0.3, p=1
Hue Saturation Value	Hue shift limit=20, sat shift limit=50, val shift limit=50
Shift Scale Rotate	Shift limit=0.06, Scale limit=0.1, rotate limit=90
ISO Noise	Color shift=(0.03, 0.06), intensity=(0.3, 0.6)
Blur	Blur limit=3

Distort	grid=(3, 3)

Table .2 Data Augmentation parameters

3 MODEL AND PERFORMANCE:

The YOLO-Pro model, trained within the Edge Impulse platform, demonstrated strong potential for weld defect detection. It achieved a high precision score of 85.4%, indicating that when the model identifies a defect, it is correct most of the time. The model performed particularly well on medium and large objects, achieving mAP scores of 0.37 and 0.63, respectively. It also showed solid localization ability with a mAP@50 of 0.61.

These results underscore the model's capability for accurate and consistent identification of key defects. Furthermore, the model is highly optimized for deployment on resource-constrained hardware, requiring only 1.8 MB of RAM and 7.5 MB of flash memory, and runs efficiently using TensorFlow Lite.

With targeted improvements such as increasing the input resolution or enriching the dataset with more examples of small defects, the model's performance can be further enhanced to deliver even stronger detection capabilities across all object sizes.

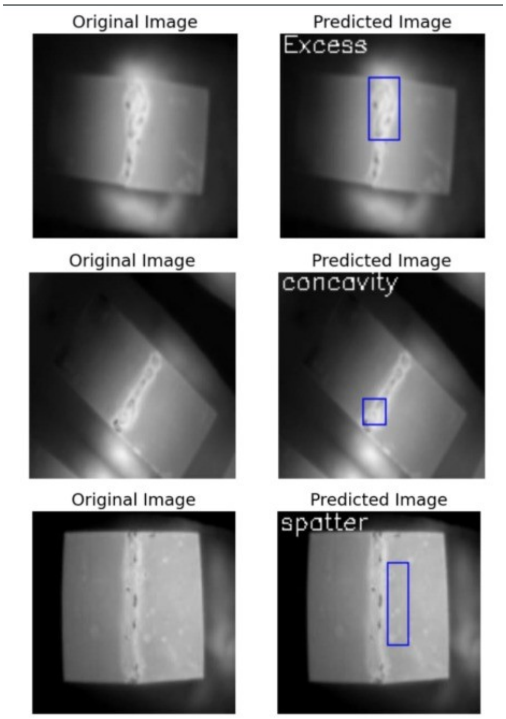

Fig. 6 Sample Predictions

MODEL OPTIMIZATIONS

Model optimizations can increase on-device performance but may reduce accuracy.

Quantized (int8)

Select

	IMAGE	OBJECT DETECTION	TOTAL
LATENCY	1 ms.	710 ms.	**711 ms.**
RAM	4.0K	1.8M	**1.8M**
FLASH	-	7.5M	-
ACCURACY			-

Unoptimized (float32)

Selected ✔

	IMAGE	OBJECT DETECTION	TOTAL
LATENCY	1 ms.	1,397 ms.	**1,398 ms.**
RAM	4.0K	6.4M	**6.4M**
FLASH	-	27.6M	-
ACCURACY			-

To compare model accuracy, run model testing for all available optimizations.

Run model testing

Estimate for Raspberry Pi 4 - Change target