Analog Gauge Reading Using CNN Regression

A Deep Learning Approach for Automated Gauge Reading using CNN regression

---

Python v3.8 pytorch v1.10.2 torchvision v0.11.3 Version v1.0 platform Linux|Windows10 opencv python ^4.6.0

Authors:

- Guy Dahan

Submission:

- Supervising company: Captain's-Eye
- Project Instructor: Mr. Doron Oizerovich
- Project Supervisor: Dr. Jonatan Ostrometzky
- Faculty: Engineering
- Department: Digital Sciences for Hi-Tech
- Tel-Aviv University

TEL AVIV UNIVERSITY אוניברסיטת תל אביב

Table of Contents

Full Demo Video

Watch Demo at his link

Requirements

- Python 3.8
- PyTorch 1.10.2
- Torchvision 0.11.3
- Linux Ubuntu 20.04 LTS / 22.04 LTS / Windows 10 (Tested on all of them)

Project Directory Structure

```
├──src
│    ├──calibrator
│    ├──gauges
│    ├──model
│    └──utils
├──demo
└──docs
```

- `src` - Contains the source code of the project
  - calibrator - Contains the code for the Calibrator App
  - gauges - Contains the code for the Gauges classes
  - model - Contains the code for the CNN regression model
  - utils - Contains the code for the utility functions IE mathematical functions and image processing functions
- `docs` - Documentation and an academic poster made for the project
- `README.md` - The current document, serving as the final report for this project
- `settings.toml` - The project's local settings file. When cloned this will generate the default settings.
- `config.py` - This file will generate environment specific settings for the project, including the generation of data directories and their respective paths.

Installation

Two ways to install the package:

- Using Anaconda
- Using pip

Clone the repository, and run the following commands in the root directory of the repository:

Using Poetry

```
poetry install
```

Using Anaconda

```
conda create --name <env> --file requirements.txt
```

Settings file

This project is designed to be a flexible project, which will support quick and easy deployment of the project in different operating systems and scenarios. for that purpose, a settings file is created, which will generate automatically the project's configuration. The available settings are:

Setting	**Default Value**	**Effect**
DEV	"False"	DEV mode - No error checking for UI
GAUGE_CALIBRATION_FILE_XML	gauge_params.xml'	Name of the gauge calibration_data file
TRAIN_IMAGE_NAME	'train_image.jpg'	Name of the training image
NEEDLE_IMAGE_NAME	'needle_image.jpg'	Name of the needle image
TRAIN_SET_DIR_NAME	'train_set'	Name of the training set directory
XML_FILE_NAME	"camera_{}_analog_gauge_{}"	Name of the gauge calibration_data file
VALIDATION_SET_DIR_NAME	'validation_set'	Name of the validation set directory
REPORT_PLT_NAME	'test_report.png'	Name of the report plot
WINDOW_SIZE	[1500, 1500]	Default Calibrator app window size (width, height)
EDIT_IMAGE_SIZE	[500, 500]	Default edit image window size (pixels)
TRAIN_IMAGE_SIZE	64	Default train image size (pixels)
REPORT_PLT_SIZE	15	Default report plot size (inches)
LOSS_THRESHOLD	0.002	Threshold for the loss function
BATCH_SIZE	64	Batch size for dataset loading and training
BATCH_MULTIPLIER	3	Batch multiplier for building the dataset
EPOCHS	150	Number of epochs for training
LEARNING_RATE	0.001	Learning rate for the model
AUTO_ADD_EPOCHS	"True"	Automatically add epochs to the model when training if the loss is below the threshold
TORCH_SEED	147	Seed for the torch random number generator
NUM_WORKERS	1	Number of workers for dataset loading

Setting	Default Value	Effect
DEFAULT_MODEL_TYPE	"best"	Default model type for loading (best or latest)
MODEL_VERSION	"1.0"	Model version for saving
GAUGE_TYPES	['analog', 'digital']	List of gauge types supported by the app
TEST_REPORT_IMAGE_TILE	8	Number of images in the test report image tile

Usage

This application has three parts:

1. *Calibration* using UI - designed to be performed quickly and once only for each gauge
2. *Training* the CNN model specifically for the gauge using the automatically generated calibration data
3. *Reading* the gauge value using the trained CNN model

Demo

> ***NOTE:*** This project was designed completely to fit Captain's-Eye requirements, so it does not have any need for a native CLI interface. The application will give some feedback using the terminal regarding errors and progress.

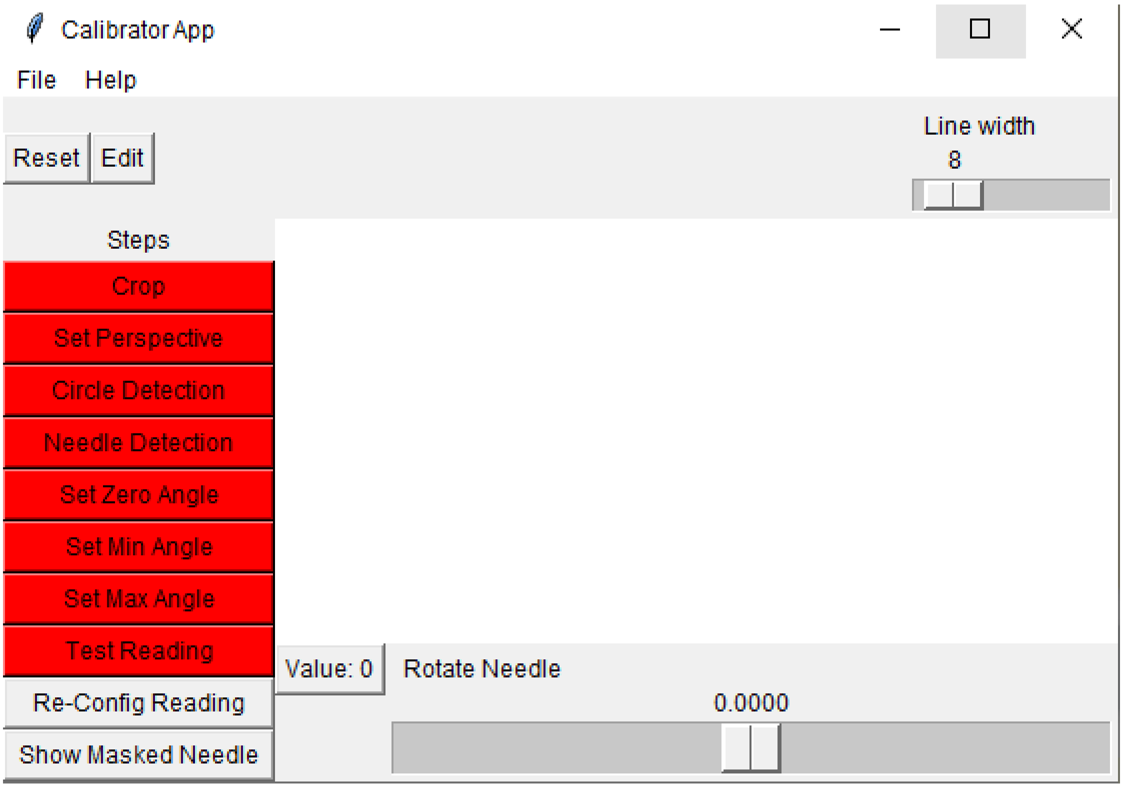
To perform calibration, a sample image is needed of gauge. Through this example I would walk you through the process of calibration, training and reading from a gauge using the code and image sample provided in the `demo` folder.

Calibrator App

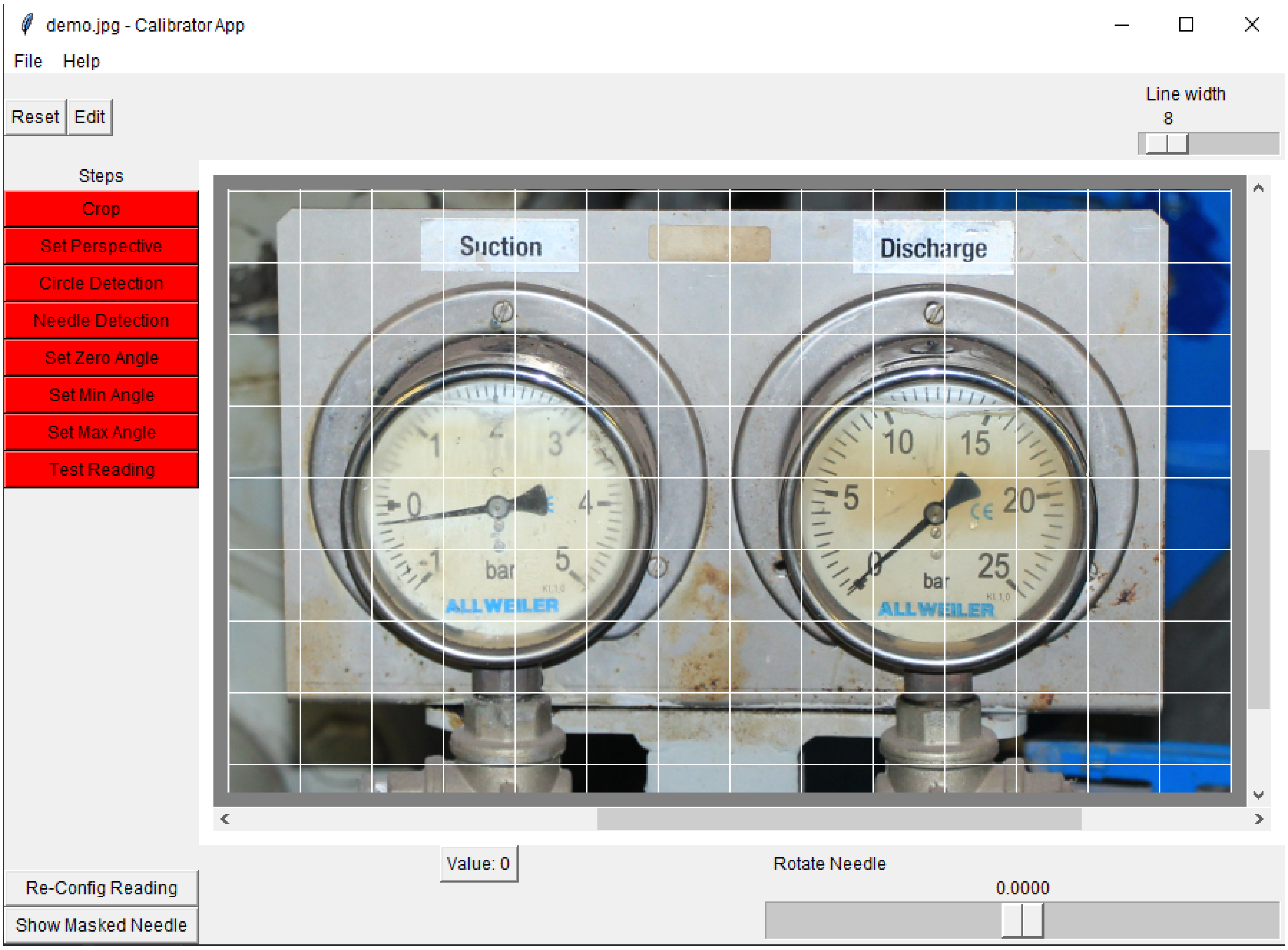
Got to `demo` directory and run:

```
python full_demo.py
```

The Calibrator App will open:



Click: `File` -> `Load Calibration Image`. A prompt will appear asking you to select the image. for this demo select the demo gauge in the `demo` folder.



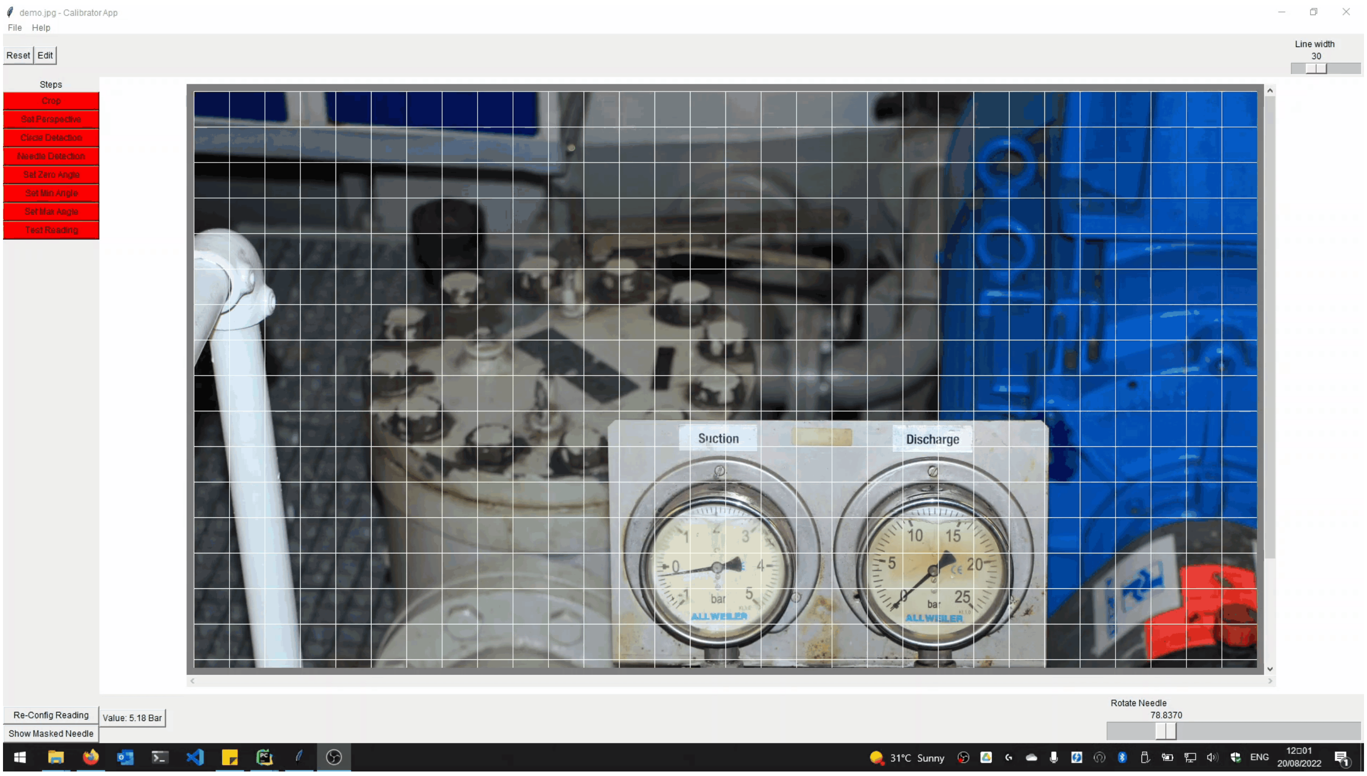
The Calibrator App is intuitive and easy to use. It also includes a user error-checking system, which can be disabled/enabled int the project's settings file using the `DEV` flag (set to `True` for no error checking).

The calibration steps show in red color on the left bar, indicating the which steps were not completed. The order of steps is top to bottom. Completed steps are shown in green color.

Step	Effect
Crop	Crop the image
Set Perspective	Fix perspective issues
Circle Detection	Detect manually/automatically circles in the image to find the gauge center
Needle Detection	Using a brush, the user marks the needle for the gauge
Set Zero Angle	Using the rotation bar, rotate to the center angle and mark it
Set Min Angle	Using the rotation bar, rotate to the minimal angle and mark it
Set Max Angle	Using the rotation bar, rotate to the max angle and mark it
Test Reading	Test the reading from the angles

Crop

Simply click the `Crop` button to crop the image.

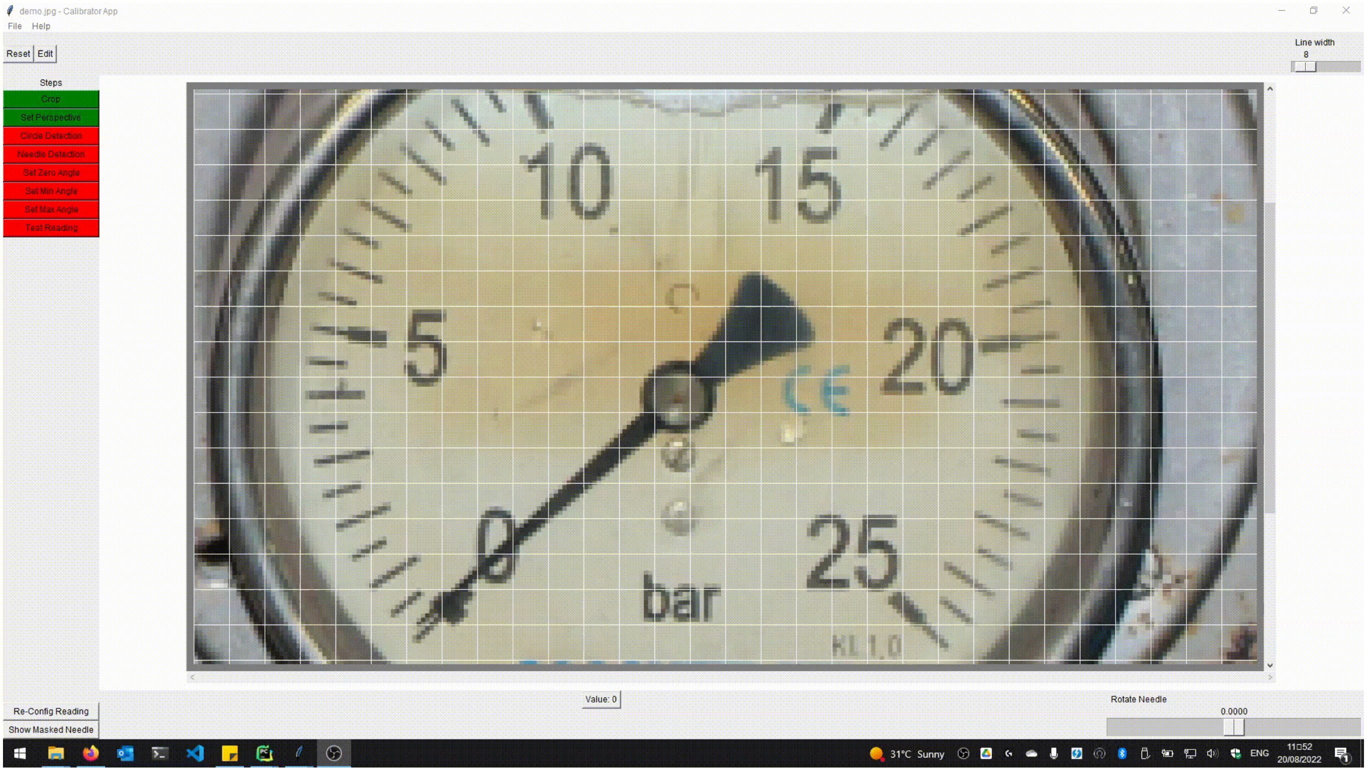


Set Perspective

Click the `Set Perspective` button to fix the perspective issues. Use either picking 4 points or manually tweaking the perspective bars.

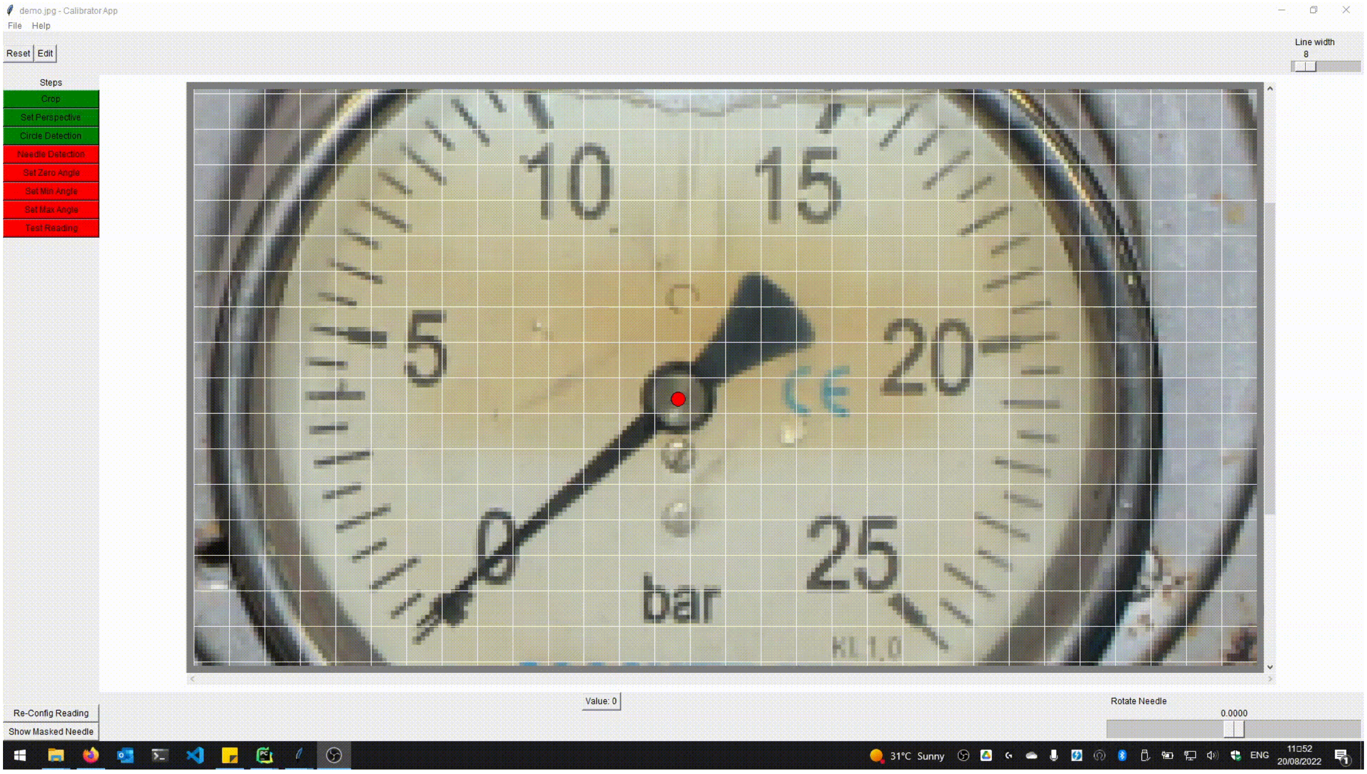
Circle Detection

When clicked, the app will try to automatically detect the gauge center. If it fails (visually examined by the user) Pick the center manually.



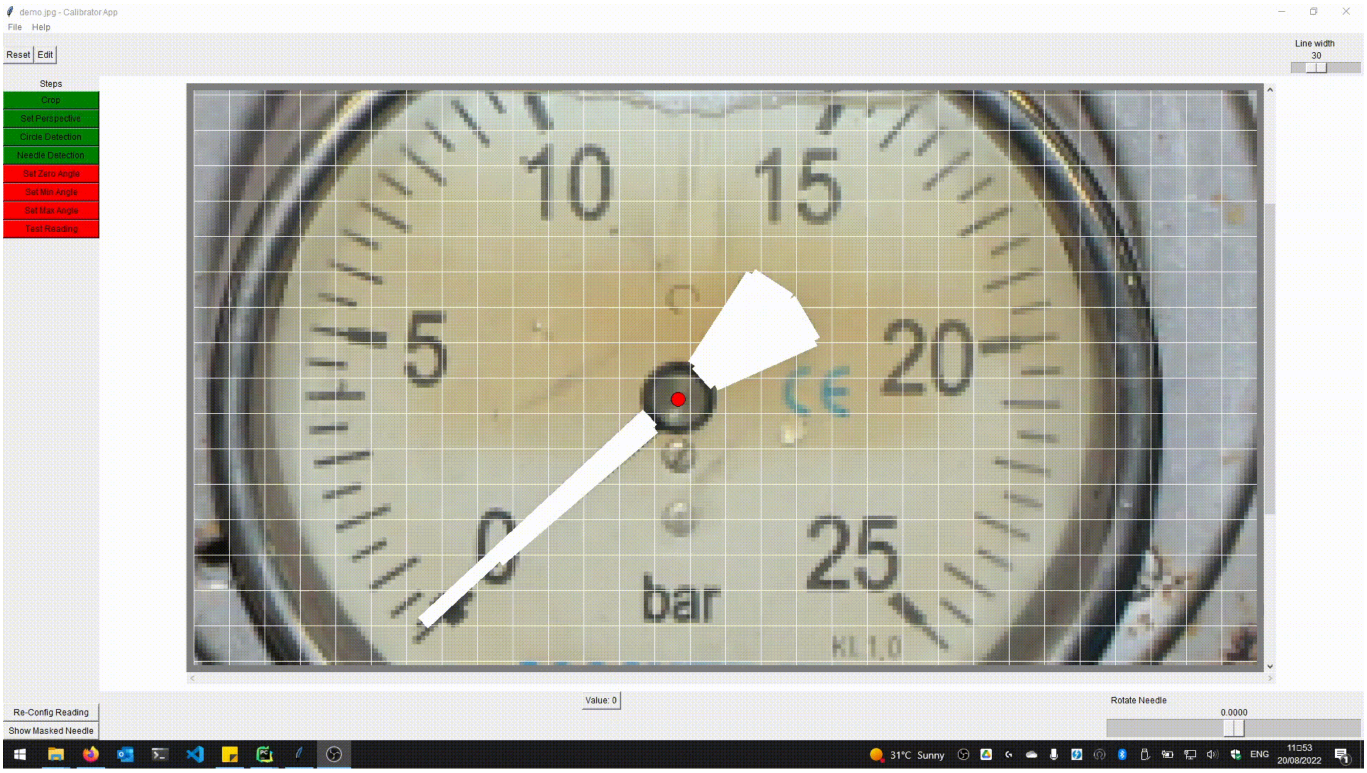
Needle Detection

Set the parameters for the gauge - max reading, min reading and units. Then simply draw the needle on the image. The size of the brush can be changed using the 'line width' slider.



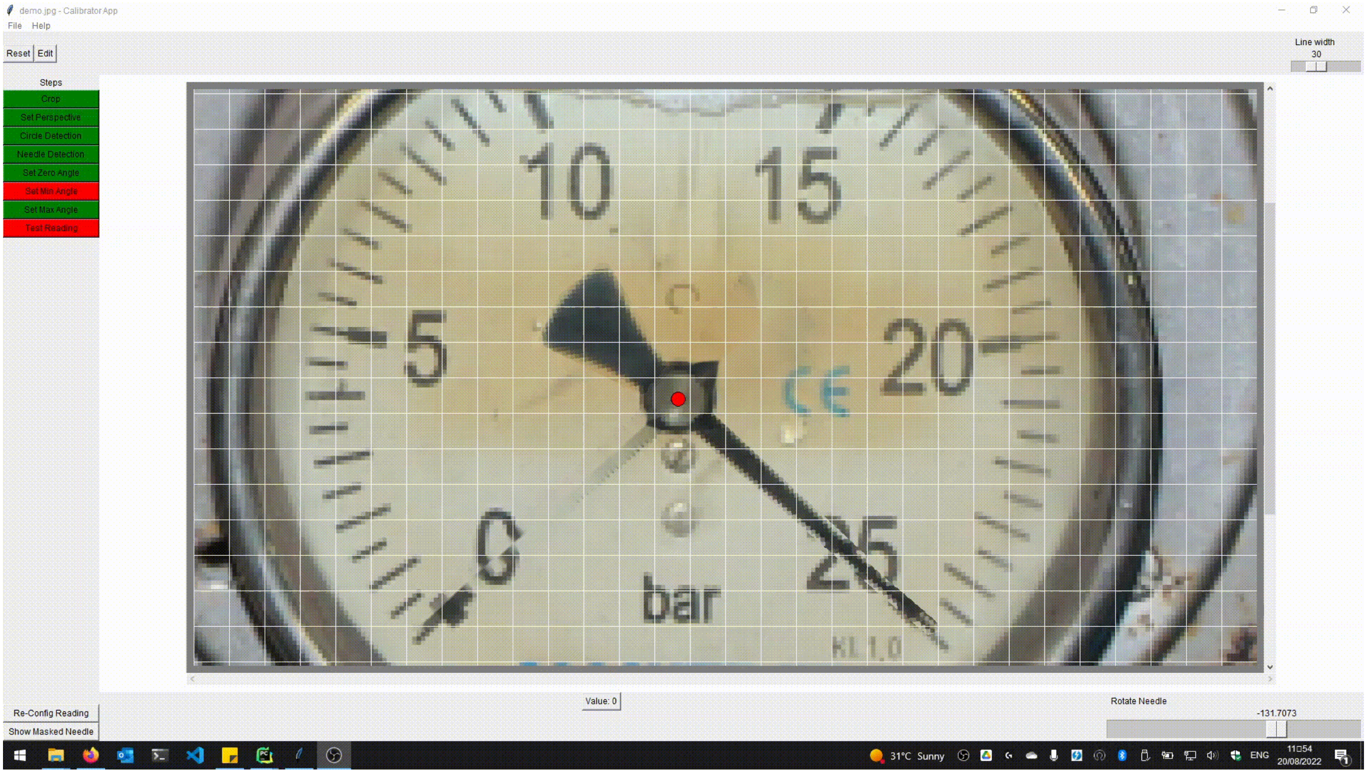
Set Zero Angle

Rotate the gauge to the center angle and mark it. this will change slightly from gauge to gauge and is used for calculating the reading the gauge later.



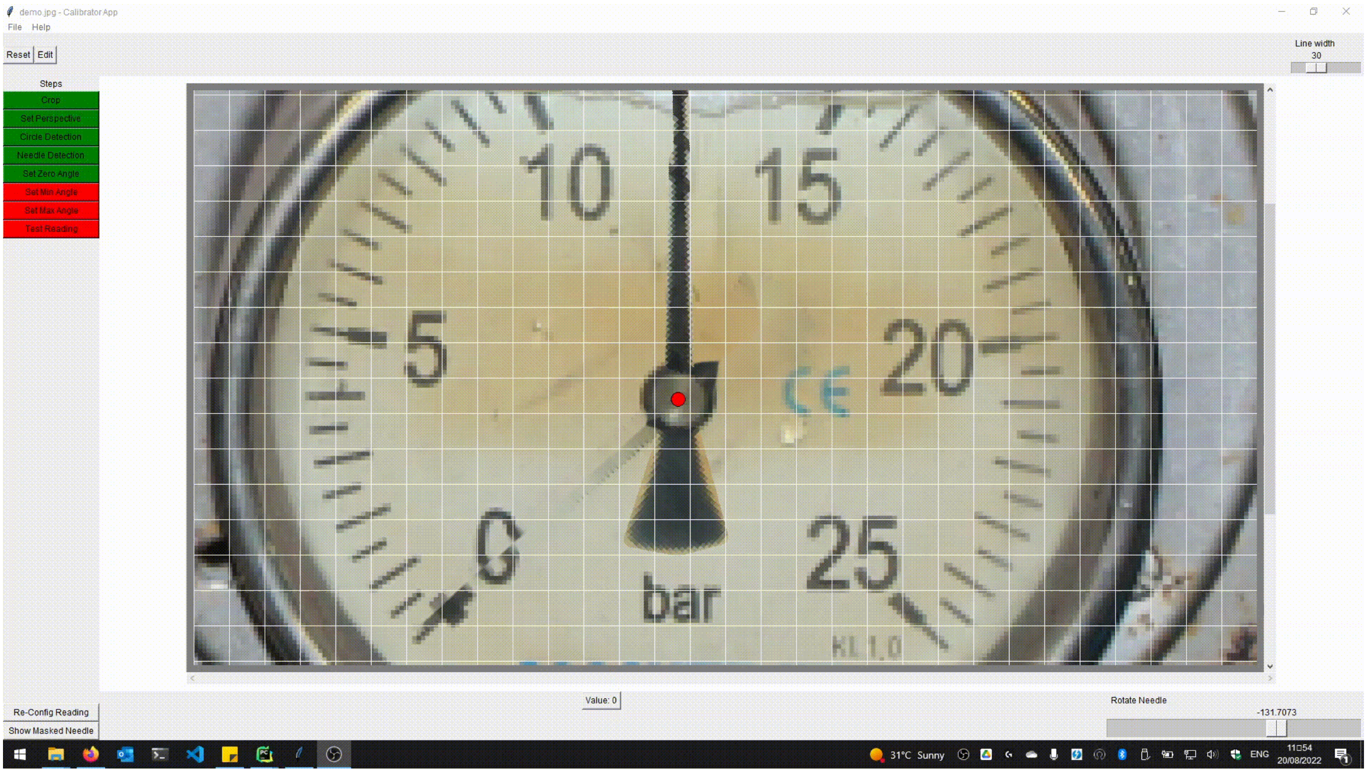
Set Min Angle

Rotate the gauge to the minimal angle and mark it.



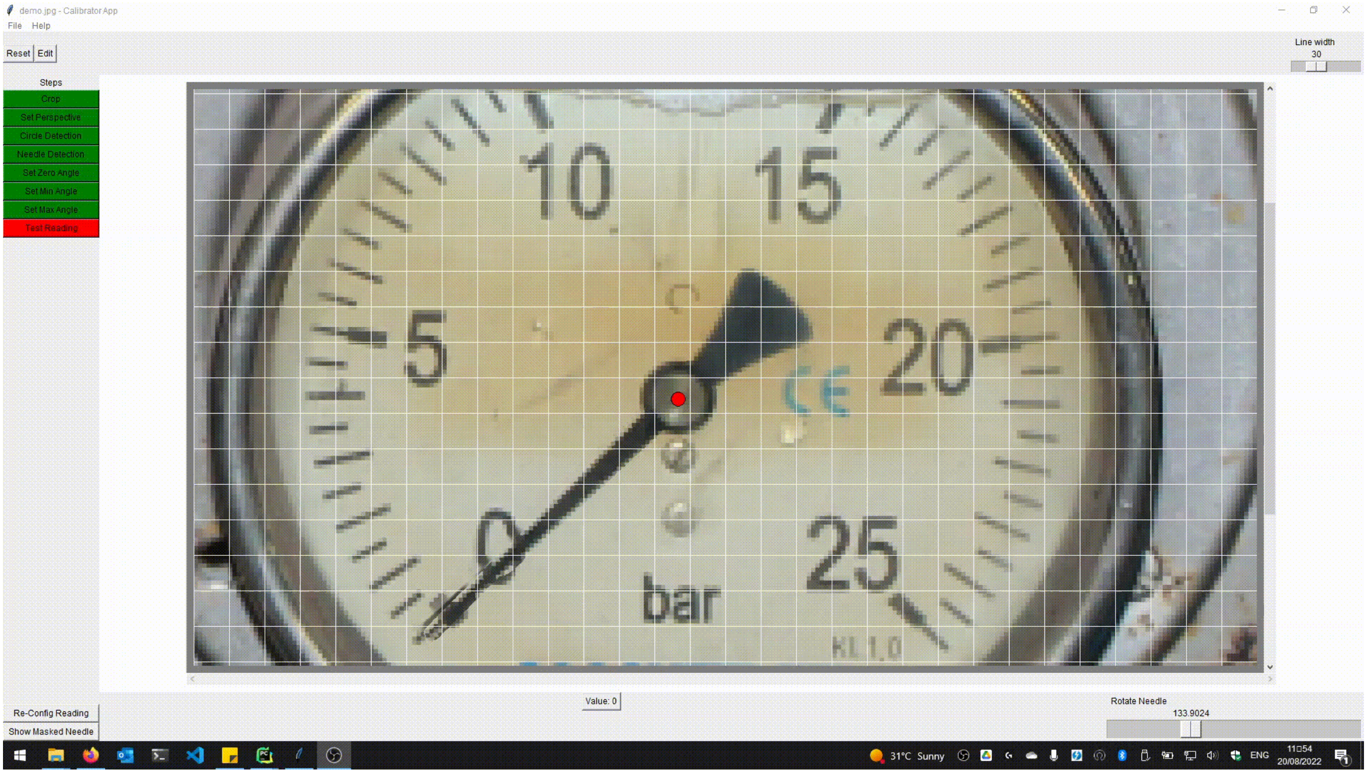
Set Max Angle

Rotate the gauge to the max angle and mark it.



Test Reading

Test the reading from the angles. The reading will be displayed in the bottom bar. Visually examine the reading to make sure the calibration is correct.



> ***NOTE:*** If reading is not correct, it usually indicates that the perspective is not correct. Try to reset and re-calibrate the gauge.

Synthetic Data

Synthetic data will be created automatically for the gauge. The synthetic data is created using the calibration data and will be split into three sets:

- Training set
- Validation set
- Test set

The default split is determined by the batch size, and the default train size is 3 times the batch size. The validation and test sets are each at the same size as the batch size.

The synthetic data can be found in the auto-generated `data/camera_{}/gauge_{}/` folder. where the `{}` represents indexes that are generated automatically when calibrating the gauge.

Training, Validation and Testing

After calibration, the app will start training the model (when using the `full_demo.py` script). this can be also called manually as follows:

```
import src.gauges.gauge as g

calibration = g.AnalogGauge.calibrate()
analog_gauge = g.AnalogGauge(calibration) # calibration is a dictionary with the calibration data. can also be loaded from a file
analog_gauge.start() # start the training, validation and testing process for the gauge
```

The training process will take some time to complete. The app will display the progress in the terminal. Each epoch will display the loss for train and validation data.

Auto Add Epochs

The loss threshold is used to determine when to add more epochs to the model. If the loss is below the threshold. The default is 0.002. This can be disabled or edited in the project's settings file.

Training and Validation Report, Gauge Directory

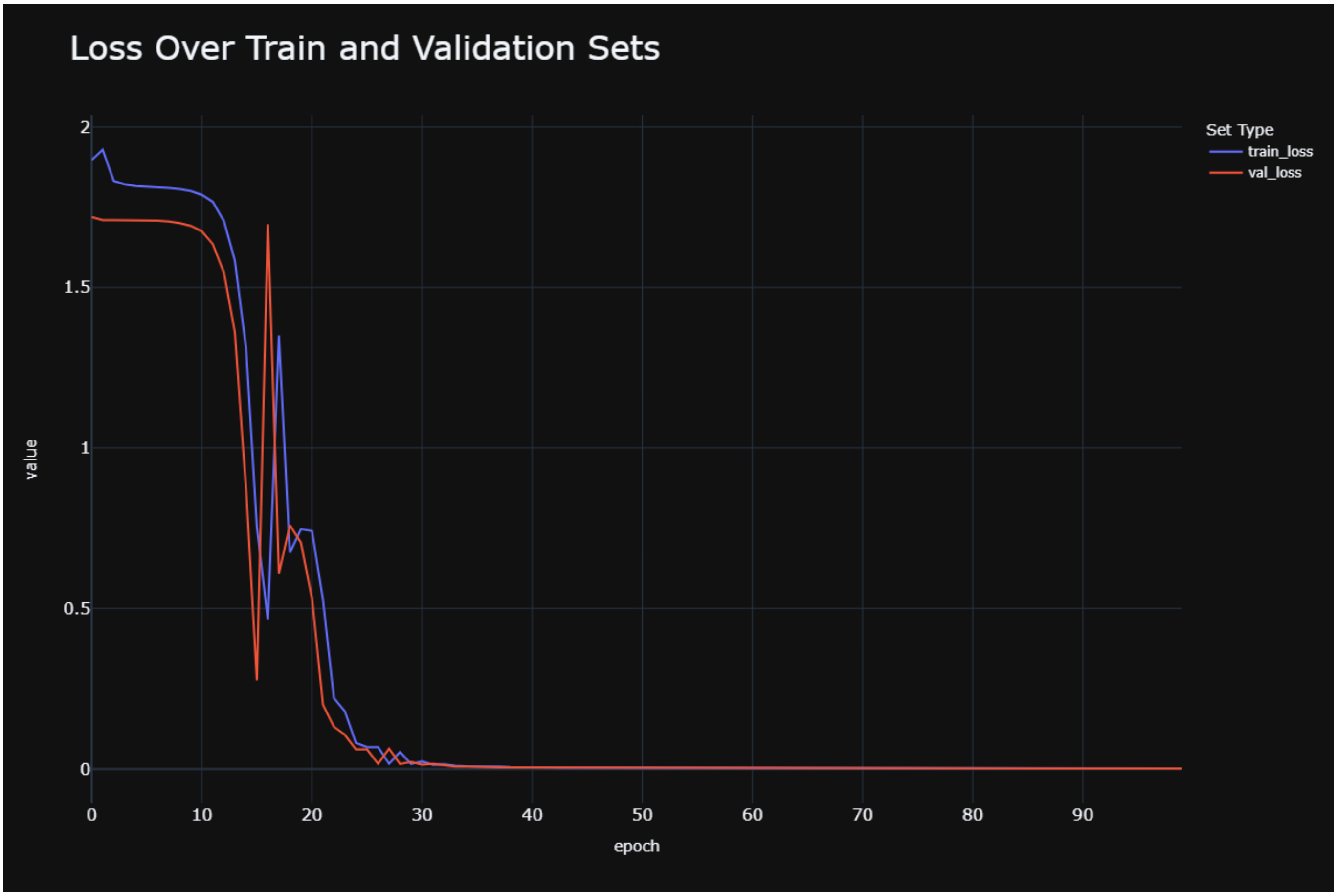
When the training process is complete, a testing process will be performed. The testing process will test the performance of the model on the test set and save a visual report of the results in the gauge's directory.

The gauge directory will contain the following files:

- `train validation test` - the training, validation and test sets containing the data for the model
- `gauge_net_v1.0_best.pt` - the trained model's weights specific to the gauge - best performing model
- `gauge_net_v1.0_last.pt` - the trained model's weights specific to the gauge - last epoch model
- `needle_image.png` - the needle image used for the gauge
- `train_image.png` - the image used for the training set generation
- `train_report.csv` - the training report detailing loss for each epoch of the training set
- `val_report.csv` - the validation report detailing loss for each epoch of the validation set
- `test_report.csv` - the test report detailing loss for each epoch of the test set
- `test_report.png` - a visual reference of the test set results, showing the reading for different angles
- `training_plots.png` - shows the loss for each epoch of the training set and the validation set
- Additional CSV files - containing the summary for each image used in each set, it's real angle in radians and angles, and whether the image was augmented or not.

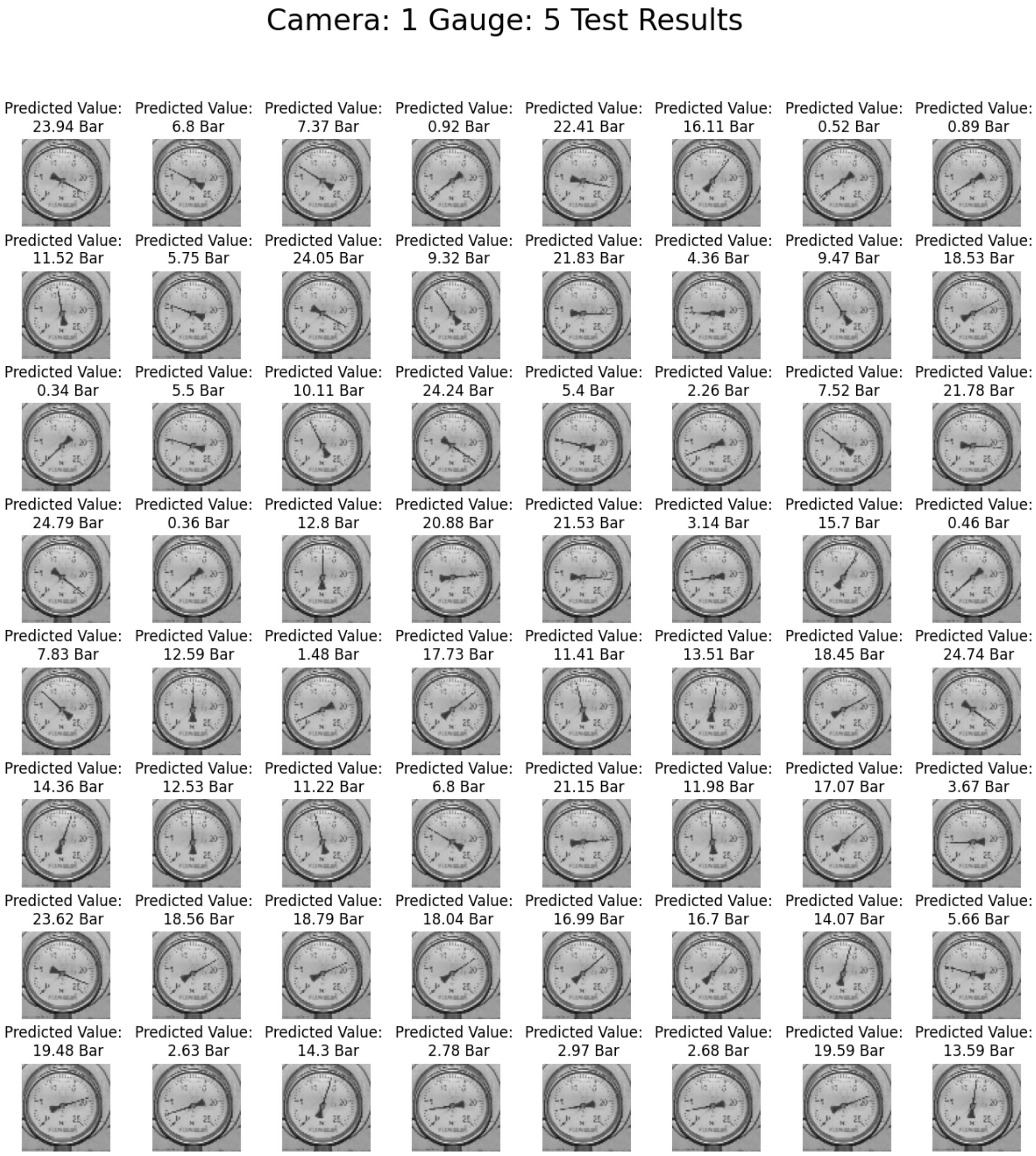
Training and Validation Report

The plot should show a converging trend for the loss. The loss should decrease as the epochs increase.



Test Visual Report

The plot should show the reading for each angle in the test set.



Getting a Reading for a Calibrated Gauge

Finally, in order to get a reading for a calibrated gauge, all that is needed is the calibration's XML file. This allows the app to recreate the preprocessing needed for the model to get its readings quicly, and uses the trained model to get the reading.

```
import src.gauges.gauge as g

analog_gauge =
g.AnalogGauge('camera_{}_analog_gauge_{}.xml').get_reading('image.png')
```

Report

In this part I will dive into the principals and ideas behind the app. This will serve as my submission final report.

Abstract

In order to solve the problem of realtime gauge reading, I used a neural network to predict the angle of a needle in an analog gauge. The neural network is trained to predict the angle of a needle based on synthetic data generated after a quick user guided calibration using a "Calibrator App". The offered CNN supplies an elegant, easy to deploy solution that is also very flexible. This allows fast deployment in a production environment and better results when compared to out of the box classic computer vision solutions such as OpenCV.

Introduction

Ships are a complex system of multiple components. As years go by, less available trained personnel are available and the level of complexity rises. In order to operate a ship today, many hours are wasted on in person approach to reading and storing analog gauges. The app is designed to reduce this waste by automating the process.

Traditionally, CNNs are used in classification or object detection problems. I chose to use a neural network in a regression task for the purpose of this project. This allows me to generate a high performance model and also allows me to use the Pytorch framework, to use GPU in order to accelerate training and much more.

At the first steps of this project, I actually researched for a solution that does not include a neural network, rather using OpenCV and classic computer vision approach. This turned out to be a very difficult task, since the automatic circle and contour detection were not very accurate and also demanded a very hard calibration process. I also found a few Python 2.7 implementations using OpenCV - but when I tried to use them, they were not able to get the results for our use case, and mostly unable to detect correctly the gauge and needles.

Define the Problem

Main Problem:

> Get a reading from an analog gauge remotely, constantly and with minimal human presence

Secondary Problem:

> It is near impossible to generate consistent and extensive training data for an installed analog gauge

Define the Solution

When approaching this problem, one might think that the simplest solution is to install a digital sensor near the gauge that will upload the reading constantly. While this is very possible - it takes time, the equipment is expensive and implementation is difficult - it is not the best solution for existing system. Furthermore, many marine companies don't allow the owner to perform changes to the mechanical systems due to warranty and service issues.

A camera on the other hand costs ~ 100$, it's easy to install and connect. Even better - most ships already have extensive amounts of cameras installed (CCTV).

Since that an installed gauge is impossible to dial into all the available angles, synthetic data is used to train the model.

Implementation

Since I have created this project for the Captain-Eye company, the framework for receiving the video feed, image frames and storing data is already available. I had to think of a way to implement a light network that will be deployed into the existing system.

The offered solution:

- A native calibration app
- Built in training process generating:
    - Synthetic data
    - Trained model
    - Validation and testing reports
- Built in reading process using the trained model

See below the implementation of the app structure:

Chosen Framework and Libraries

While researching the problem, I found that the Pytorch framework is the most efficient and flexible for the problem.

Calibrator App

The app was built entirely using Python TKinter. The app is designed to be used in a desktop environment. The app works on both Windows and Linux. It has built in error handling. The whole calibration process takes around 2 minutes and has top be done only once. Furthermore, the calibration can be later edited simply by editing the XML file.

I used different technics in order to make the process fast and extensible, and also implemented a few smart computer vision techniques.

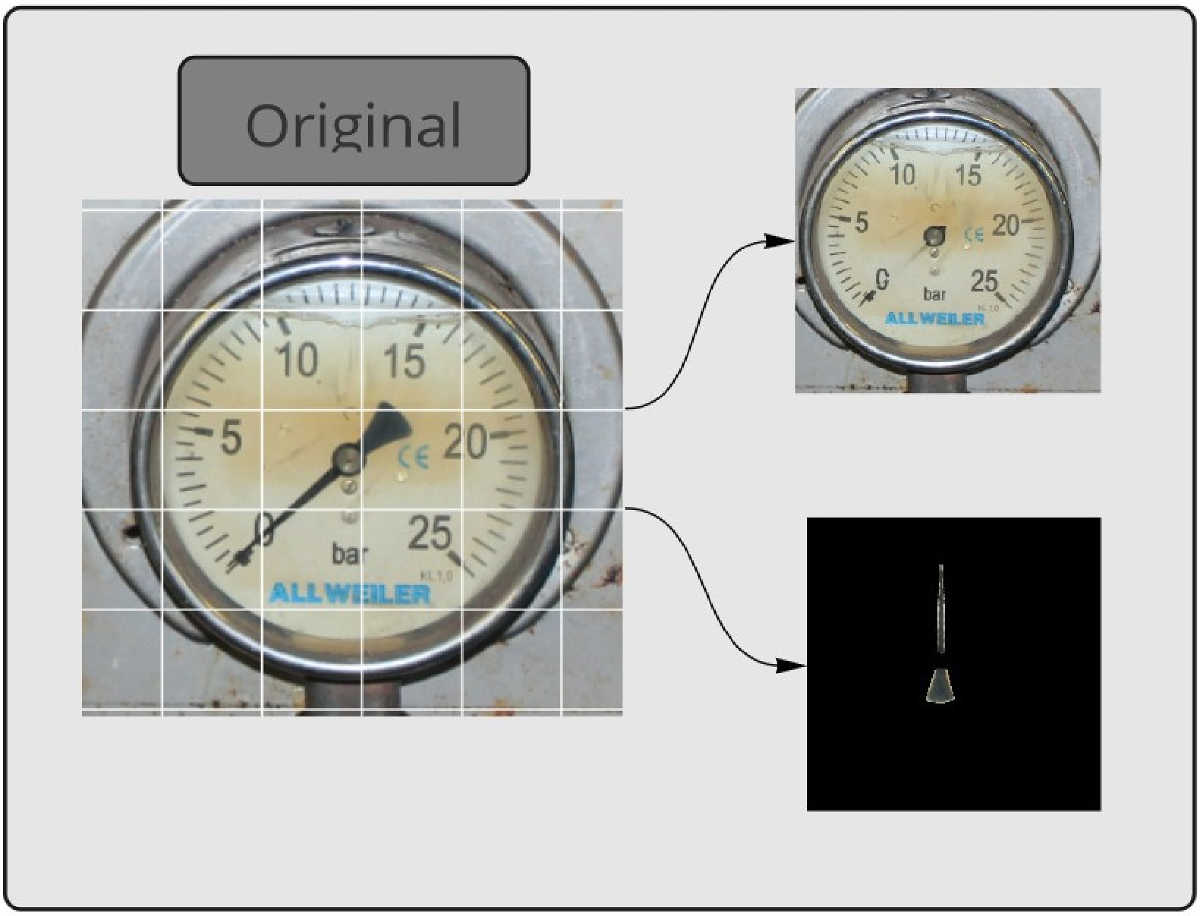
Image manipulation

The app uses OpenCV to manipulate images. The available tools are available from within the app as a part of the calibration process:

- Image cropping
- Image rotation
- Perspective Transformation
- Automatic circle detection

All of the above were implemented using the OpenCV library.

In addition to that, I have implemented a way to automatically mask the needle image from the gauge image. This allows me to later rotate the needle image and use it to generate synthetic data.



Synthetic Data Generation

The synthetic data is created using the following steps:

```
flowchart LR
A[Calculate linear space between min and max angles] --> B[Randomly select angles]
--> C[Split into training, validation and test sets]
```

This is implemented using numpy `linspace` function.

The image writing to files is all done using OpenCV.

Model Architecture

The main consideration for building this model was keeping it as light as possible. The model's architecture was built using Pytorch. In order to design the CNN layers I read several articles and books and gathered the following principals for a regression problem:

- Keeping the input image size as small as possible with good results
- Adding layers until convergence is rather fast
- Calculating the layers inputs and outputs for the chosen image size

> $\frac{\left\lceil N-f+1\ \right\rceil}{s}$

N stands for the input number of dimensions (number of pixels in input image for first layer) and f is the filter size. s is the stride length. In order to calculate the next layer I simply used the equation above replacing N with the previous layer's output size and f with the filter size. for each layer I also had to calculate the activation size, which is simply multiplication of the previous layer's output size and the filter size.

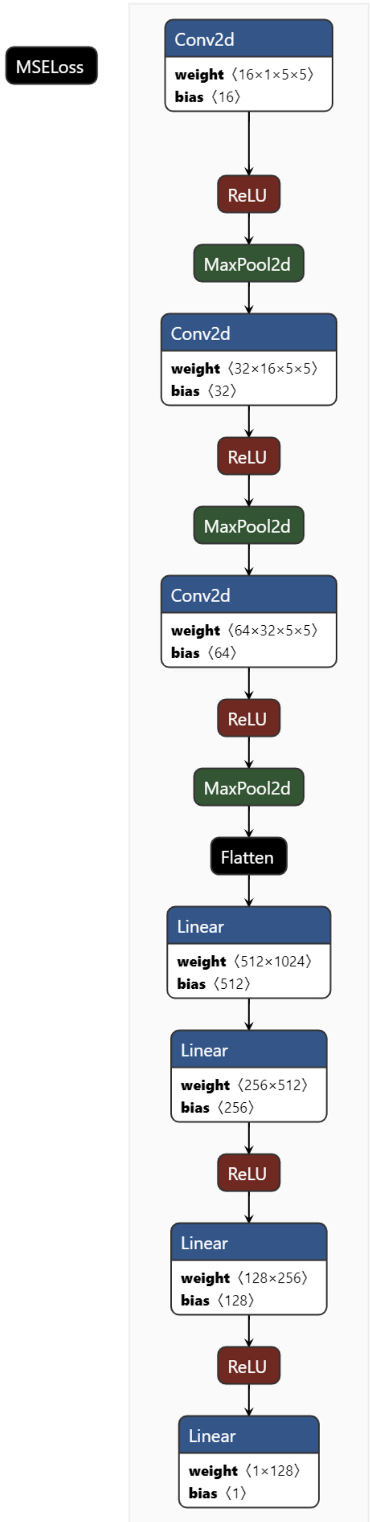
Where N is again the input size and f is the filter size for each layer.

All of the above can be found in the Excel file.

Using this equation I kept adding layers of Conv2D, followed by ReLU and MaxPool. Using Netron to show the structure:

Performance Metrics

In order to calculate loss I chose to use MSE loss. The MSE loss is a good choice for regression problems. It is implemented in Pytorch and is available in the `torch.nn` library. The loss is calculated over the projected angle in radians vs the actual angle in radians.



The chosen optimizer is Adam. Adam is also good choice for regression problems and is implemented in Pytorch as well.

Results

As shown on the loss graph above, the model is able to predict the angle of the needle accurately. The results are good after around 50 epochs of training. After some trial and error, I found that a learning rate of 0.001 is a good choice and around 100 epochs minimize the loss quite well for different gauges.

The model was tested on ~10 different gauges and the results are all very good with accurate readings. All gauges were tested with a train set of 64×3 images. If some gauges show poor results, it is very easy to enlarge the train set and tweak the learning rate or number of epochs to achieve better results.

While I was able to find a few projects dealing with reading analog gauges, I found that the best results were achieved using my solution. I was able to find one similar implementation using Keras, but their implementation did not include the calibration process - images had to be manually cropped and seperated into a masked gauge and needle. See their paper here.

Conclusions and Next Steps

The main and secondary problems are solved. The solution is implemented and ready to be deployed, and actually shows some demand within customers. The learning in this scenario is well proven to be possible, the model is light and can actually run on CPU quite fast. the whole training process takes roughly around 3 minutes for 100 epochs on a standard PC with Intel i7 10th generation processor and 16 GB RAM. On a stronger AWS EC2 instance it's a matter of 0.5 minutes using a GPU.

That said, some work can still be done. Suggested improvements regarding this implementation are:

- Include a testing framework for the code
- Upgrade to Python 3.10.4
- Improve implementation of the UI app - replace Tkinter with PyQt5
- Improve circle detection to shorten the time it takes to process the image
- Add auto unit reading
- Add object detection for the gauge itself

Furthermore, since I used an OOP approach for this whole project, I actually created the classes for a digital gauge reader in the same manner exactly - using the same UI and same network. This might take around 3-4 additional weeks of development to implement, but it is very much mostly straightforward from the current framework.

Additionally, I originally designed a database in order to store the reading values over SQL database. However, I found that this is not necessary and the data will be handled by the company's backend developers.

Final Notes

Coding Standards

I have taken a big effort to try and withstand the following:

- PEP8
- OOP principles
- Documentation
- Simplicity
- Minimal code duplication using inheritance and composition
- Version control is done using Git.

References

- Stevens, E., Antiga, L., & Viehmann, T. (2020). Deep Learning With PyTorch. Manning Publications.
- ayseceyda/analog-meter-reading-openCV - OpenCV implementation of the analog meter reading app.
- Analog Gauge Reader Using OpenCV in Python - Intel article on how to use OpenCV to read analog gauge readings.
- Linear regression with PyTorch - A blog post on how to use Pytorch to implement linear regression.
- Machine Learning in Practice: Using Artificial Intelligence to Read Analog Gauges