Capstone Proposal

Udacity Machine Learning Nanodegree 2020

Steel Defect Detection

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Domain Background

Steel is used in many areas throughout society; buildings, bridges, cars, ships, wind turbines, etc. Unattended defects in steel structures can cause catastrophic consequences [1]. Traditional methods for detecting defects in steel are time consuming and costly. Current methods include Eddy Current testing [2], Electrical Resistance Testing, Thermographic testing, Ultrasonic testing, Visual testing [3], and others.

Various areas of industry today are looking for technological solutions to maintenance of steel. This can remove the human element of errors and inconsistencies. Providing more efficient production and maintenance of steel.

Problem Statement

The main objective of this project will be to use neural network techniques for localising and classifying steel defects. Defects in steel can grow under stress and effect the performance of the mechanical system. Development of effective identification of these defects will improve the reliability of the equipment or structure in use.

Datasets and Inputs

The problem domain chosen is detecting defects in steel. As provided by the Severstal Kaggle dataset [4].

The dataset contains 1000 images of test and training images, with a csv containing information of the image id, class id (defect types), and encoded pixels.

Solution Statement

The solution is a model that receives an image, and can classify multiple defects (up to 4) and locate which pixels the defect applies. A Convolutional Neural Network will be used to develop the model as they work well in image classification problems. The appropriate model will be verified after testing and experiments with the data.

Benchmark Model

The project is a multiclass classification problem. The mean Dice coefficient result will be above 0.6 and the accuracy for the model classifying defects will be above 0.85.

Evaluation Metrics

The project will be evaluated using mean Dice coefficient. The Dice coefficient compares the pixel-wise agreement between a predicted segmentation and its corresponding ground truth.

$$\frac{2 \times |X \cap Y|}{|X| + |Y|}$$

X is the predicted set of pixels
Y is the ground truth

The Dice coefficient is 1 when both X and Y are empty.

Dice coefficient can also be written:

$$\frac{2TP}{2TP + FP + FN}$$

Using the definition of true positive (TP), false positive (FP), and false negative (FN).

Project Design

Workflow for the project:

- Exploring the Data
  - Study attributes
  - Identify target attributes
  - Visualise data
  - Study correlations
- Data preprocessing
  - Data cleaning
  - Feature selection
  - Feature engineering
  - Training and validation test split
- Evaluate Algorithms
  - Train multiple models
  - Measure and compare performance
  - Analyse variables and errors
  - Select top performing models
- Fine Tune Model
  - Fine-tune hyperparameters
- Solution

References

[1] Shi, Zhanqun, et al. “Quantitative Detection of Cracks in Steel Using Eddy Current Pulsed Thermography.” *Sensors*, vol. 18, no. 4, 2018, p. 1070., doi:10.3390/s18041070.

[2] NDT Product DepartmentZetec, “Metal Crack Testing: Best Methods for Detecting Surface-Breaking Cracks,” *Zetec*, 24-Apr-2019. [Online]. Available: https://www.zetec.com/blog/metal-crack-testing-best-methods-for-detecting-surface-breaking-cracks/.

[3] G. Hands and T. Armitt, “Surface and internal defect detection,” *Handbook of Condition Monitoring*, pp. 102–135, 1998.

[4] “Severstal: Steel Defect Detection,” *Kaggle*. [Online]. Available: https://www.kaggle.com/c/severstal-steel-defect-detection/overview.