Research results for defect detection in Casting products with CNNs

Waleed Akram
*Artifical Intelligence
NU - Fast Universtiy , Peshawar,Pakistan
waleedakram035@gmail.com

***Abstract*—Automation of visual inspection using CNNs for defect detection in casting products.**

I. Introduction

Defects are an unwanted thing in casting industry. For removing this defective product all industry have their quality inspection department. But,the main problem is this inspection process is carried out manually and it is a very time-consuming process and due to human involvement. the results obtained through this method are not 100% accurate. This can because of the rejection of the entire order thus creating a loss for company. This project explores automation of visual inspection with computer vision. A deep learning model called convolutional neural networks (CNN) is created to distinguish images of defective and non-defective castings

II. Data and methods

A. Description of datasets

Our casting product data comprises top-view JPEG images of cast submersible pump impellers, provided by Pilot Technocast. Images were captured with Canon EOS 1300D DSLR camera. Every images are 300×300 pixels in size and already labeled as either def_front (defective castings) or ok_front (non-defective).

The folder train in the input directory contains images that are used for model training/validation. Images located in the test folder are used to test the trained model's performance.

B. Description of analysis pipeline

We are performing a classification predictive modeling which involves assigning a class label (Defective or OK) for a given image of casting product. To prevent the model from making a biased prediction, the dataset must be checked for class imbalance. As shown in the following plot, there is uneven distribution between Defective and OK. However, considering the class imbalance is only by a small amount (6:4), the problem can be treated like a normal classification predictive modeling.

III. Results and discussion

A. These results

An overall classification accuracy of 99.44% is achieved by the trained model .
False negatives (mis-detections), i.e., cases when Defective castings are predicted as OK, must be minimized as it may cause revenue loss for the casting company due to rejection of the whole production order by customer.
On the other hand, false positives (over-detection) may increase waste and production cost, not to mention unnecessary downtime.
The metric recall helps us evaluate model performance when the cost of false negatives is high. Alternatively, when the cost of false positives is high, the metric precision is prioritized.F1-score is an overall measure of a model's accuracy that combines precision and recall.

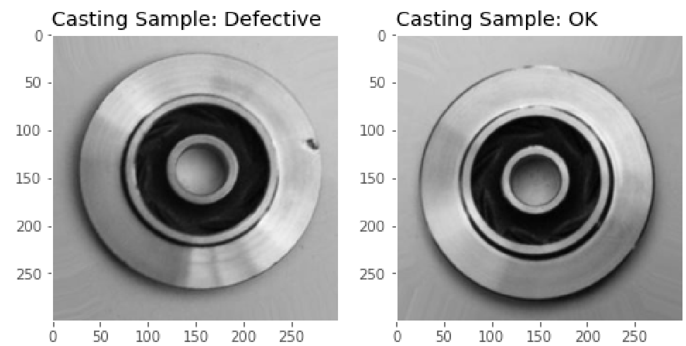

Fig. 1: A sample figure.

B. Comparison with previous work

The trained model is used to predict the class of images that weren't previously included in the training and validation process. The classification will output a probability score between 0-1 and a threshold value of 0.5 is specified to separate the classes. A probability score that is equal to or greater than this threshold is classified as Defective, otherwise OK.

IV. Summary

We will use convolutional neural networks to approach the problem of classifying whether a casting is Defective or OK based on the given image. Almost universally used in computer vision applications, convolutional neural networks (CNN, convnets) is a type of deep-learning model that can look at groups of adjacent pixels in an area of an image and learn to find spatial patterns. CNN is made up of a number of layers: a series of convolutional layers (with activation), pooling layers, and at least one final fully-connected layer that produces a set of class scores for a given image. The convolutional layers of a CNN act as feature extractors; they extract shape and color patterns from the pixel values of training images.

Acknowledgment

A convolutional neural networks model was created to classify images of a casting product as either Defective or OK and achieved a good performance based on F1-score (99.56%). Results of this project suggest viability of deep learning method in automating visual inspection. Incorporation of this method in the production line can provide support for trained inspectors in making better assessments of product quality.