Chapter 4
Convolutional Neural Networks and Deep Learning Techniques for Glass Surface Defect Inspection

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ABSTRACT

Convolutional neural networks and their variants have revolutionized the field of image processing, allowing to find solutions to various types of problems in automatic visual inspection, such as, for instance, the detection and classification of surface defects in different types of industrial applications. In this chapter, a comparative study of different deep learning models aimed at solving the problem of classifying defects in images from a publicly available glass surface dataset is presented. Ten experiments were designed that allowed testing with several variants of the dataset, convolutional neural network architectures, residual learning-based networks, transfer learning, data augmentation, and (hyper)parameter tuning. The results show that the problem is difficult to solve due to both the nature of the defects and the ambiguity of the original class labels. All the experiments were analyzed in terms of different metrics for the sake of a better illustration and understanding of the compared alternatives.

DOI: 10.4018/978-1-6684-4991-2.ch004

INTRODUCTION

Seeking for defects in surfaces such as glass sheets is a task that can be performed from different approaches, among which deep learning (DL) stands out as an alternative that offers good results when applied in its different variants such as convolutional neural networks (CNN), deep networks and residual learning (RL)-based networks (Zhou et al., 2019), which can be complemented by using techniques such as data augmentation (DA) (Shorten and Khoshgoftaar, 2019) and transfer learning (TL) (Hafemann et al., 2015). The number of model configuration alternatives might become a combinatorial problem, making difficult for the practitioner to design a system that fulfills both performance requirements and practical constraints. Therefore, the objective of this chapter is to present a comparative study of different models that, based on DL, address the problem of classifying thirteen categories of defects that appear in images from a public glass inspection (GI) surface. The GI dataset seems to be difficult to classify due to its heterogeneity and the potential ambiguities in the original labeling; moreover, to the best of the authors' knowledge, the GI dataset has not been used before in other studies since the authors did not find citations to it.

The comparative study consists in ten experiments with several variants of the dataset, CNN architectures, RL-based networks, TL, DA, and (hyper)parameter tuning including combinations of various configuration alternatives. The evaluation was made according to global metrics such as accuracy (reporting its minimum, maximum and average values) and the micro and average measures of precision, recall and F1-score; other more specific performance measures were also considered, including the confusion matrix and the classification report by class, which were complemented with learning-validation curves and predictive classification graphs.

Regarding the design of the classification system, two neural network architectures were adopted, namely: i) a CNN and ii) a RL that makes use of TL by incorporating a previously trained Inception ResNet (Deng et al., 2009). The chosen networks were combined with DA techniques that were applied either in a previous phase or at training time. The best solution was obtained with a model using RL-based networks and DA, reporting an average accuracy of 0.8365, which the authors have considered good given the challenging nature of the problem.

The remaining part of the chapter is organized as follows. Essential concepts of visual inspection techniques, DL, neural networks, RL-based network, TL, and DA are described in section Background and related work. The subsequent section presents the Method for the comparative study, describing the different variants of the datasets, the CNN models, and the configuration of the experiments. Afterwards, the Experimental results and discussions achieved are presented and finally, the Conclusion is given.