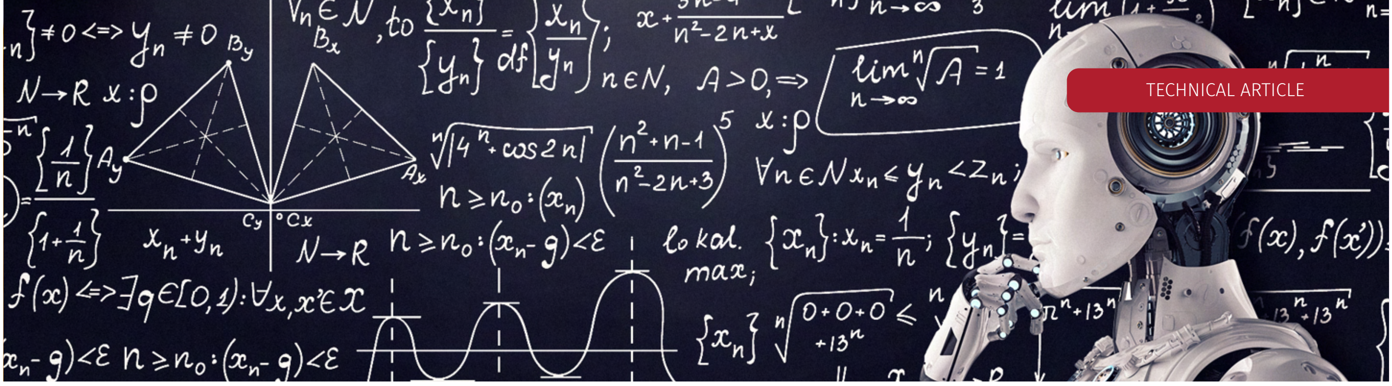

Semi-Supervised Deep Learning Approaches for Classifying Surface Defects

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Quality control is a process for maintaining standards in manufactured products by testing the output samples against the specifications. Surface defects have an adverse effect on quality and performance of industrial products. Surface defects sometimes affect the functions of a component and also spoil the appearance. The responsibility of industry is to reduce the complaints that arise from crashes, scratches etc. So that surface analysis plays an important role in the industrial world. During the surface inspection, the shells of the surfaces are commonly checked manually by the trained workers. Especially, companies that produce products in large numbers are hard to inspect one by one manually. It is obvious that manually classifying something is time consuming, high cost and also less accurate. To overcome this issue, vision based Automatic Surface Inspection (ASI) methods are proposed, as they are fast, highly accurate, and significantly reduce the labour intensity.

Figure 1: *Example image of defected surface*

In ASI, cameras are attached to the production line to capture the surface images. These recordings can be made by a number of cameras from different perspectives. Then captured images will be further analysed for the inspection using applications. Industrial applications will require well-structured data of possible defect types for the analysis. Various systems are proposed for different industrial applications, e.g., steel surface inspection, fabric/texture inspection, tile surface inspection, Aluminium profile surface inspection, and inspection of electronic commutators. However, developing a comprehensive and large data set for the classification is a challenging task as uneven light, strong reflection and also complex materials may appear on the surface.

There are publicly available benchmark datasets for researchers for this domain. In the Northeastern University (NEU) surface defect database [1], six kinds of typical surface defects of the hot-rolled steel strip are collected, i.e., rolled-in scale, patches, crazing, pitted surface, inclusion and scratches. Figure 2 shows some of the example images from each category of this dataset.

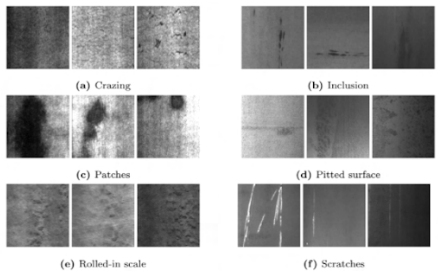

Figure 2: *Example images from NEU dataset*

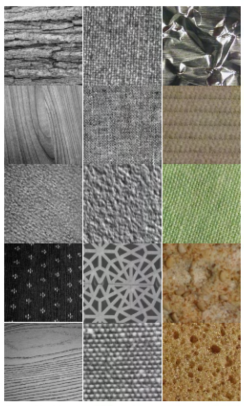

Figure 2: *Example images for surface texture dataset*

Another dataset is Texture dataset [2] which contains 64 classes from three public datasets. Figure 3 shows some of the example images from the surface texture dataset.

In recent years, deep learning in neural networks has achieved tremendous success in analysis of various domains. There are two main classification techniques in machine learning namely supervised learning and unsupervised learning. Supervised learning relies on labelled data, whereas unsupervised learning can handle unlabelled data for the classification. In supervised learning, the model learns from the labelled dataset and then is used to categorise new events. In an unsupervised scenario, the algorithm finds the similarity between different input data. The semi-supervised approach is something in between these two. The semi-supervised learning, using both labelled and unlabelled samples, provides another approach for training.

In the past, many studies have investigated the machine vision techniques for the surface defects classification. These methods mainly focused on traditional image processing and machine learning methods which are based on hand crafted features or shallow learning. Shallow learning techniques generally consist of two independent steps: feature extraction and classification. In the feature extraction step a set of hand-crafted features (e.g. Local Binary Patterns, Histogram of Oriented Gradients) are extracted to describe each image. These features are then used to learn a classifier (e.g. Nearest Neighbour, Support Vector Machines). These approaches have several limitations: As the features are not learned from the data they may not capture the domain-specific characteristics.

In recent years, researchers have begun to use deep learning in Convolutional Neural Network (CNN) which has achieved tremendous success in various domains as they can learn the feature extractor and the classifier together in an end-to-end learning setting. Since the features are learned from the given training data, they can be highly discriminative, and capture domain specific information. However, deep learning requires a large amount of data for training. To overcome this, transfer learning approaches are widely used, where a network trained using a large dataset (e.g. ImageNet) is fine-tuned for a specific domain. Recently, most of the proposed approaches are based on supervised learning. But the problem with supervised learning is it requires a large amount of labelled data. Labelling a large amount of data is time consuming and expensive as it requires expert knowledge to classify them.

Several state-of-the-art approaches have been proposed for this defect classification. Generative Adversarial Network (GAN) based approaches[5] have been used as they can generate new images and provide a way for augmenting the training set. Self-training[6] is another popular approach for semi-supervised learning. Pseudo labelling[3] is a simple and efficient method of semi-supervised learning for deep neural networks. Here, instead of manually labelling the unlabelled data, approximate labels will be given on the basis of the labelled data. Figure 4 depicts the steps involved in semi-supervised learning with Pseudo labelling.

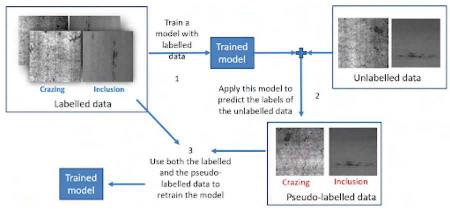

Figure 4: *Steps that involved in [seudo labelling technique*

The semi-supervised learning requires a small amount of labelled data for model training and unlabelled data can be used to improve the performance of the model. Here, the challenge is how to determine whether the predicted labels (pseudo-labels) are true labels or not. There are various weighting schemes [4] proposed to weigh the contribution of the unlabelled samples for the training. These schemes are based on the prediction probabilities and confidence in the prediction of a given unlabelled image. We determine the confidence of prediction of an unlabelled image based on how well an image is classified into one class compared to another class. So, the images with high confidence in prediction should get higher weights and the images with lower confidence in the prediction should get lower weights. In this way, a pseudo label image could be weighted and considered for the training to improve the performance.

There are several other directions that can be focused in this specific domain. Segmenting the defects improves classification accuracy and also contours of defects can be extracted from the image.

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