Comprehensive Quantitative Quality Assessment of Thermal Cut Sheet Edges using Convolutional Neural Networks

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Abstract

In this study, we present a novel holistic approach to assess the quality of thermal cut edges using images of the cut edges. Applying deep learning techniques, we estimate quality criteria such as roughness, edge slope tolerance, groove tracking, and burr height. Our results show that a comprehensive, accurate, and fast prediction of edge quality can be effectively achieved by implementing a simple image acquisition system combined with a convolutional neural network (CNN).

Introduction

Edge quality in sheet metal production is crucial to product performance. Ensuring consistently high quality results is challenging given the variation in material properties and the complexity of the cutting process, such as focus shift [1]. Efficient and fast methods for evaluating the quality of thermal cut edges are needed. Our paper presents a CNN-based method for fast, accurate and comprehensive evaluation using criteria such as roughness depth, edge slope tolerance, groove tracking and burr height. We have chosen a simple image acquisition system that is cost effective to ensure high quality production.

State of the Art

Traditional quality assessment of sheet metal relies on expert human inspection or complex analytical measurements. With deep learning's rise [2] image-based edge evaluations became feasible, automating feature engineering and outperforming rule-based systems. Stahl and Jauch [3] highlighted the use of images for edge roughness assessment. Tatzel et al. [4] enhanced this, predicting several roughness values per edge. Stahl et al. [5] evaluated edge slope tolerance and burr height, taking into account the effect of illumination on the prediction. De Mitri et al. [6] focused on edge segmentation to assess image sharpness for quality evaluation. Our method includes groove tracking assessment for a comprehensive evaluation of cut edges.

Methodology

Creation of the Dataset

The data generation process involved the production of 785 square stainless steel samples, resulting in 3,140 cut edges. During production, various parameters were varied, including feed rate, gas pressure, nozzle-to-sheet distance and adjustment value. After production, the edges were measured using a Keyence VR3200 to obtain depth data from which criteria such as average roughness depth, edge slope tolerance, groove tracking and burr height were calculated.

Image Acquisition and Image Preprocessing

An industrial colour camera with a 35 mm MeVis-C lens and coaxial illumination is used to capture the images that highlight the surface topography. Transmitted light images are captured and binarised to be used as a mask to remove irrelevant image areas. Since CNN architectures are designed for square images, the rectangular images of the cut edges are divided in ten disjoint segments (see Figure 1), increasing the number of data points by a factor of ten. To avoid data leakage, these segments are assigned to either the training, validation or test groups. The predictions of the segments of an edge are averaged for each criterion to obtain a single prediction per criterion for an edge.

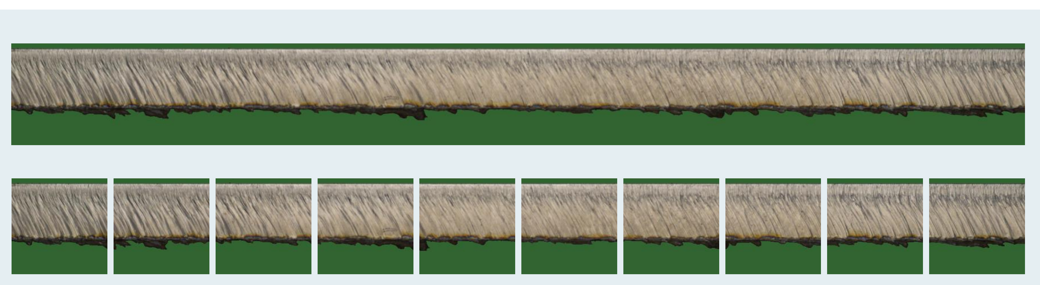

Figure 1: Example of preprocessed images. Using both transmitted and incident illumination allows for simultaneous segmentation, filtering out image regions that are not relevant for quality assessment.

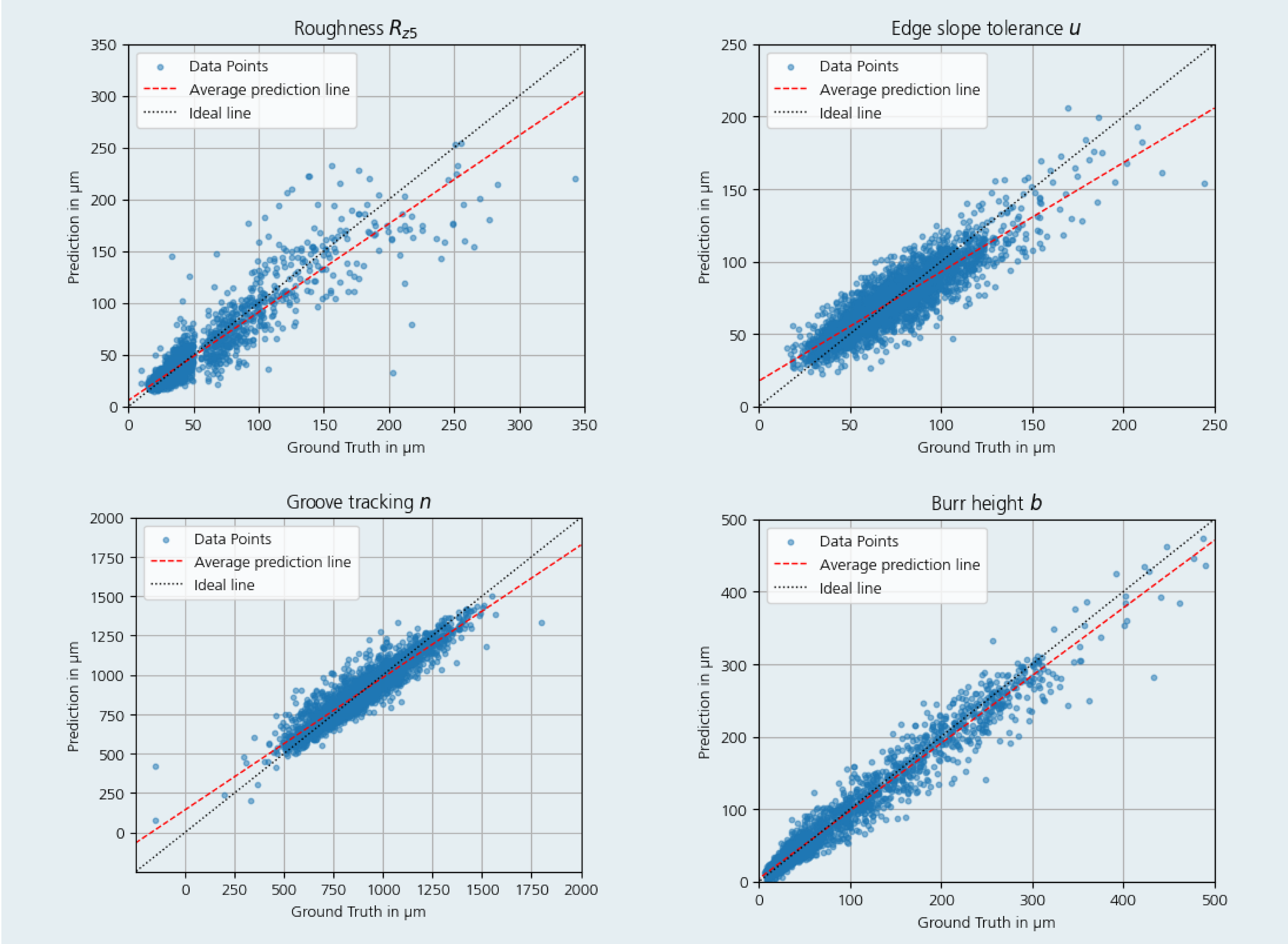

Figure 2: The accumulated predictions of the quality criteria in the test sets of the k-fold-cross validation using the Xception architecture without data augmentation.

Model Training

Examined architectures: VGG16 [7] and Xception [8] were modified to the present regression problem using four output neurons to predict continuous values for each evaluation metric.

- **Data augmentation:** Three different types of image augmentation were investigated: none, moderate (brightness change only) and strong augmentation (includes brightness, height and width shifts as well as horizontal flips and rotations).
- **Transfer learning:** Due to a small data set, models pre-trained on ImageNet were used.
- **Normalization & Hyperparameter tuning:** Min-max normalization for balanced output values and hyperband optimization for optimal hyperparameters was performed.
- **Training procedure:** Early stopping and 10-fold cross-validation were implemented with mean square error as the loss function and Adam as the optimizer.

Results

The results are displayed in Table 1. The Xception model led with an average prediction accuracy of 87.2% without data augmentation. Moderate augmentation of brightness variation improved the prediction of the VGG16 model to an R^2 of 86.9%. While moderate augmentation benefited VGG16, it slightly impaired Xception. Despite having fewer parameters, Xception is preferred due to its better performance.

Table 1: The accumulated prediction quality of the k-fold cross-validation is presented as the coefficient of determination R^2 for each criterion.

	Aug.	R^2 (R_{z5})	R^2 (u)	R^2 (n)	R^2 (b)	R^2 (avg.)
VGG16	no	85.6 %	77.1 %	87.3 %	96.0 %	86.5 %
VGG16	mod.	86.1 %	77.4 %	87.9 %	96.3 %	86.9 %
VGG16	strong	84.6 %	74.8 %	85.4 %	95.1 %	85.0 %
Xception	**no**	**85.8 %**	**79.2 %**	**87.7 %**	**96.2 %**	**87.2 %**
Xception	mod.	85.8 %	78.9 %	87.7 %	96.1 %	87.1 %
Xception	strong	85.2 %	77.4 %	87.2 %	95.7 %	86.4 %

Discussion

Excessive image augmentation during training can reduce prediction quality, possibly due to data set discrepancies or significant semantic image changes. The scatter plots in Figure 2 display the models bias towards the data center, often underestimating highs and overestimating lows. Despite this data distribution, which introduces epistemic uncertainty, the model still achieves a coefficient of determination of 87.2% in predicting edge quality.

Conclusion

Images of cutting edges can be useful for quality assessment. However, curating balanced datasets, especially for roughness and burr, is difficult due to the potential risk of damages of the cutting unit. Further, outliers in the roughness predictions could be due to measurement errors resulting in false ground truth. Improved sampling or alternative measurements could improve accuracy. Future models could refine cutting procedures and set quality benchmarks, with a universal model for the metal industry being the ultimate goal. This research lays the foundation for a holistic assessment of thermal cutting edge quality.

References

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