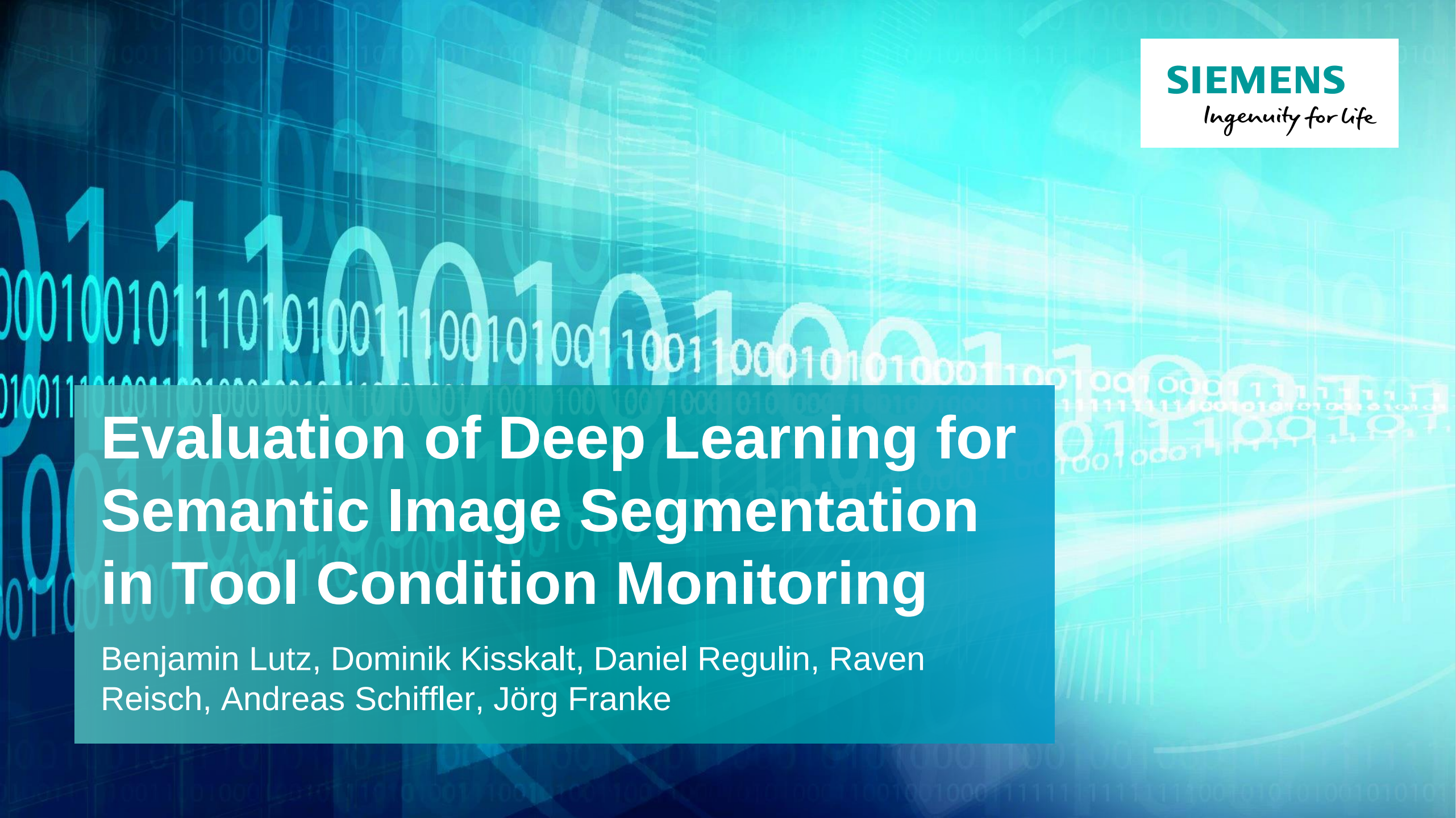

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Evaluation of Deep Learning for Semantic Image Segmentation in Tool Condition Monitoring

Benjamin Lutz, Dominik Kisskalt, Daniel Regulin, Raven Reisch, Andreas Schiffler, Jörg Franke

In tool condition monitoring, vision sensors enable enhanced insight into the state of the cutting tool.

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Approaches for tool condition monitoring

- Indirect observation:
  - Vibration [1, 2]
  - Acoustics [3, 4]
  - Power [4]
  - Current [1, 5]
  - Torque [6]
- Direct observation
  - Laser scanner [7]
  - Vision [8-13]

Microscope

Relevant types of tool wear

a) Flank wear
b) Groove
c) Build-up-edge
[10]

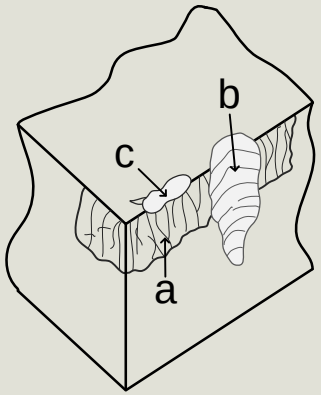
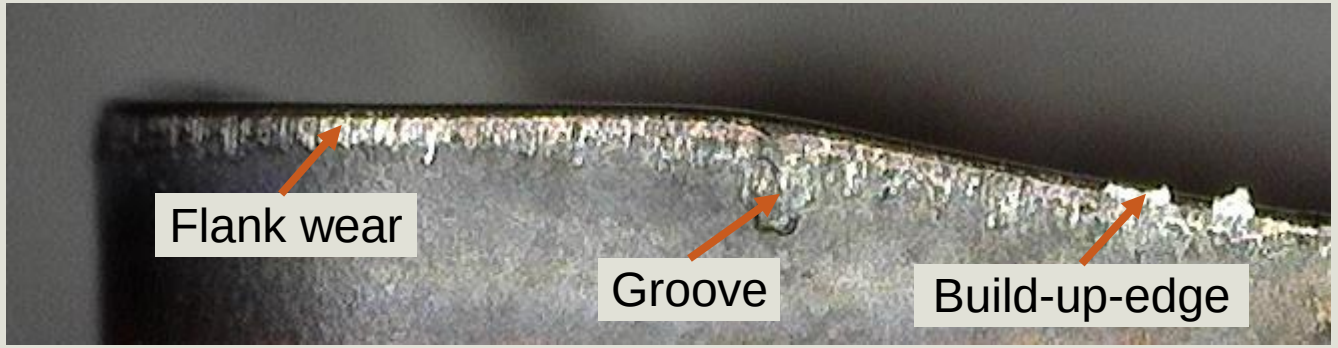


Image of cutting tool insert



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Deep Learning appears to be a promising method for solving the defined goals.

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Goals

- Assistance system for machine operator
  - Automated detection of different wear regions
  - Calculation of relevant metrics such as flank wear width or area of groove
- Robustness against different illumination situations
- Adaptability for different types of cutting tool inserts

Semantic Image Segmentation using Deep Learning

Examples from other fields:

- Robot-assisted surgery [14]
- Tumor detection in ultrasound data [15]
- Analysis of RMI scans [16]
- Detection of human cells [17]

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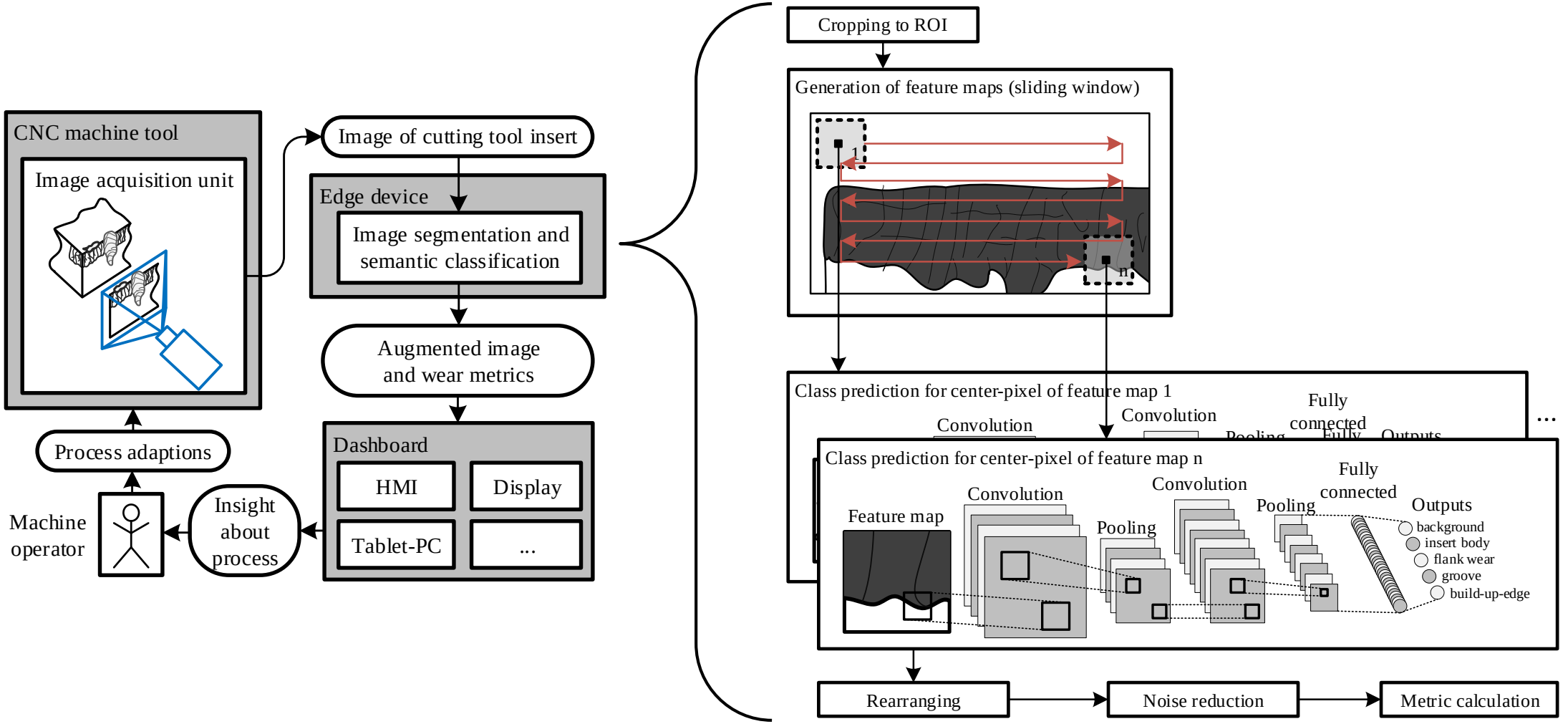
In the presented solution, a sliding window approach using CNNs is used to provide wear information to the worker.



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For every raw image a mask is created indicating whether a pixel depicts background, the tool or a type of wear defect.

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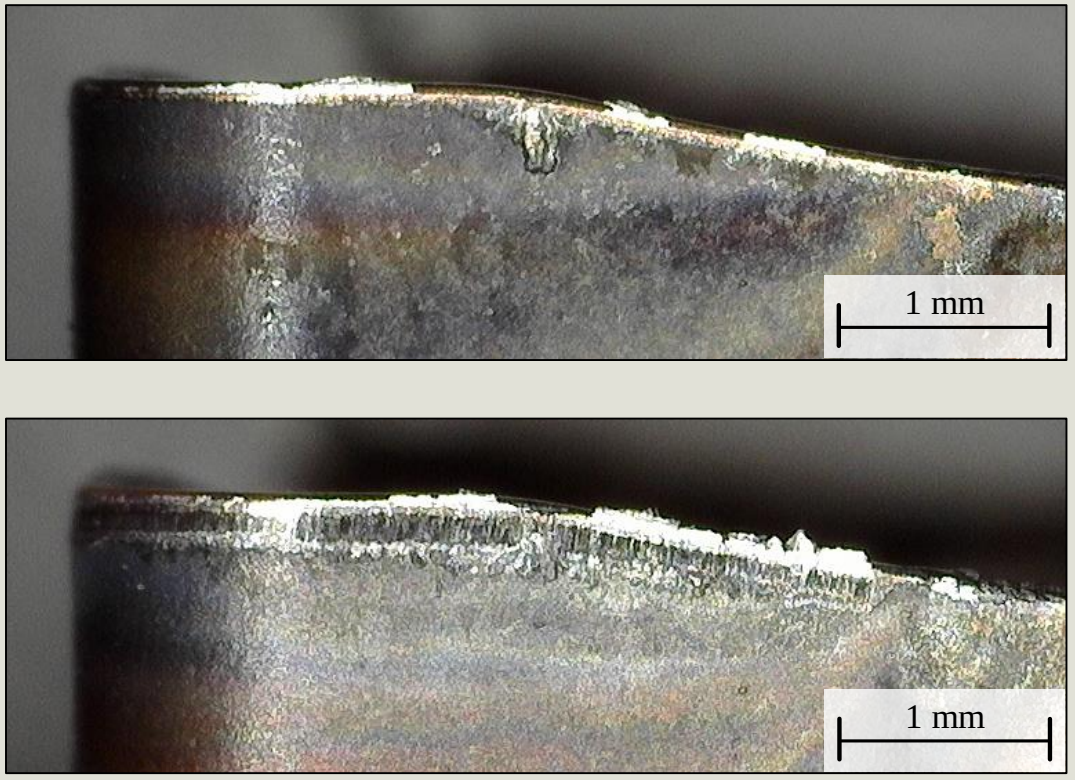
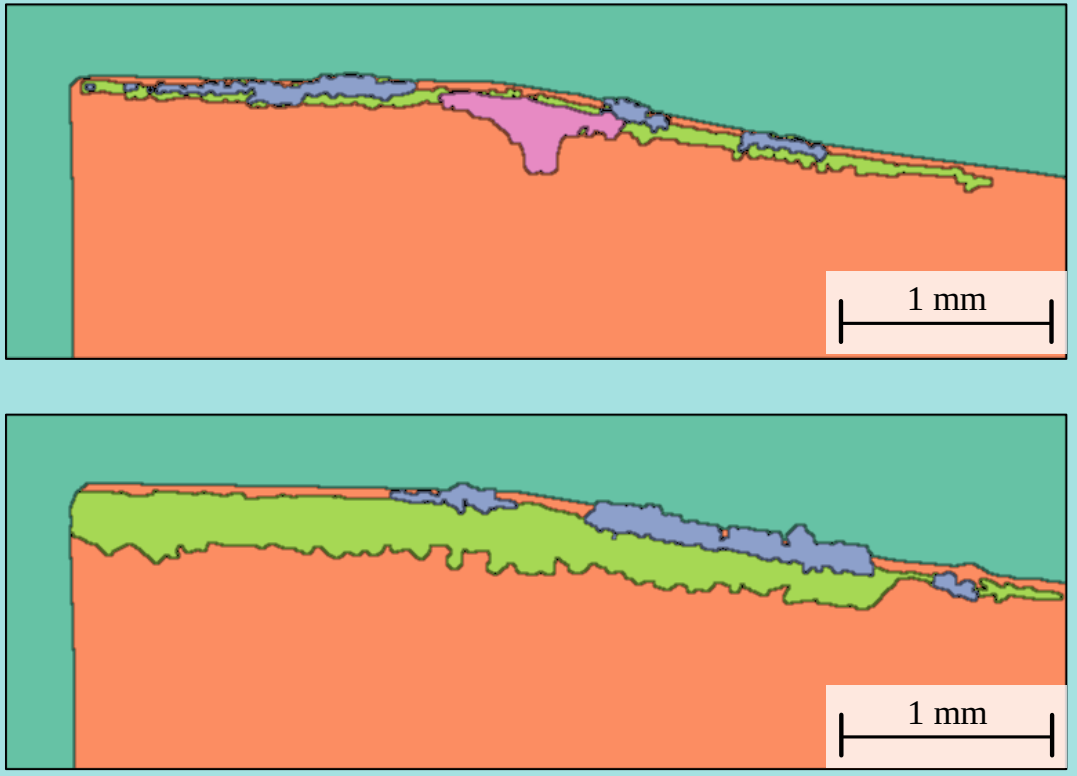
Raw image data



Masked images



Background
Undamaged insert body
Flank wear
Groove
BUE

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Some of the classes seem to be easy separable whereas others look similar to the human eye.

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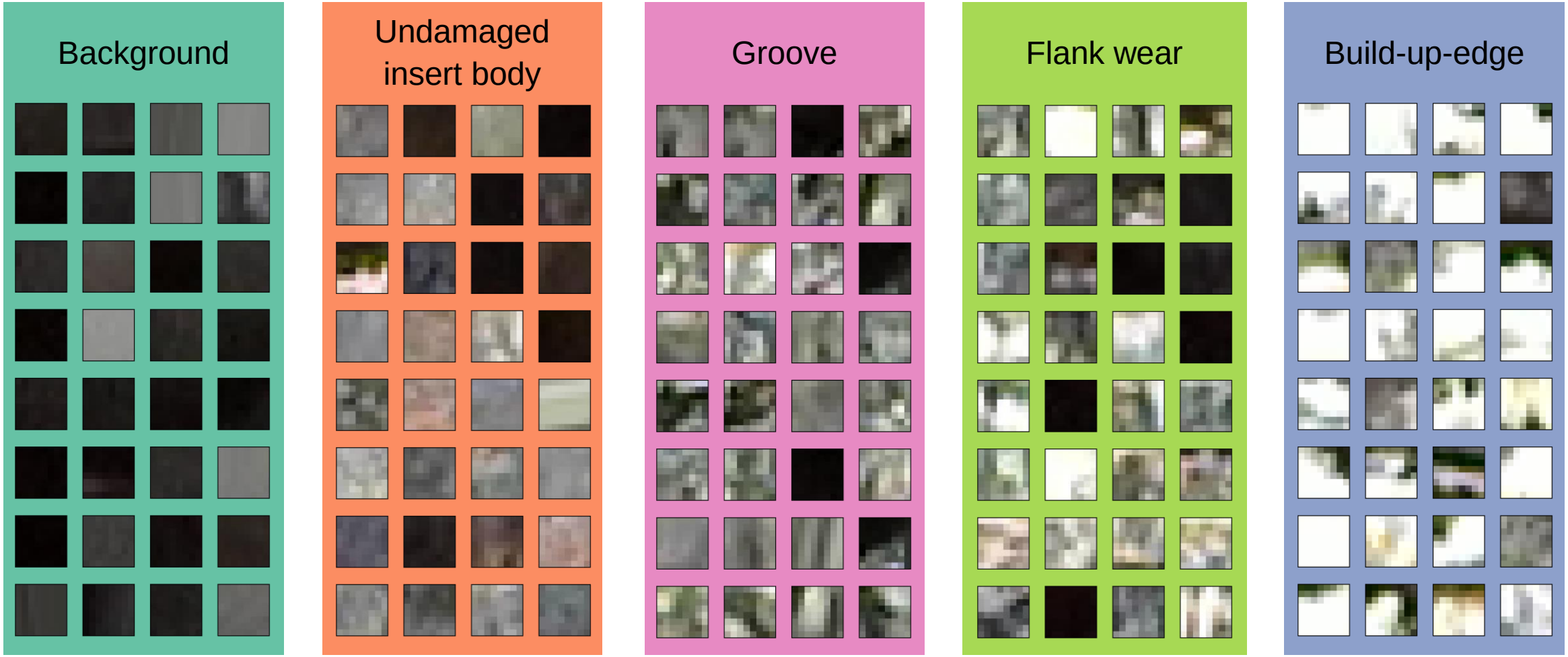

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After hyperparameter optimization, the model reaches a prediction accuracy of 91.5 %.

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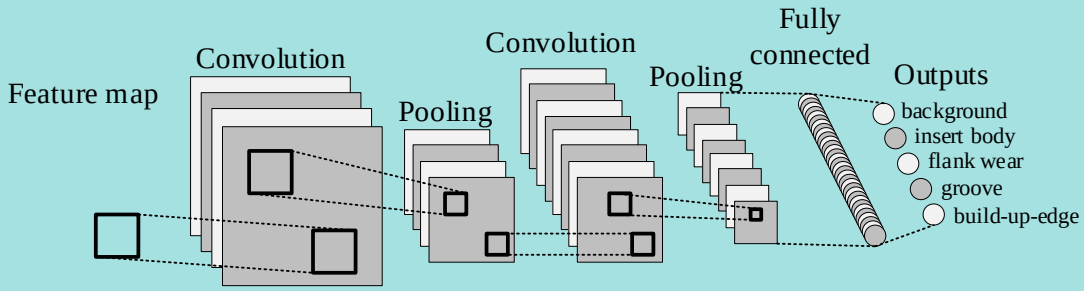
Pre-Processing

- Slicing into windows of size 48x48 pixels
- For training: Balancing of data due to uneven distribution

Class	Share
Background	39.2 %
Undamaged insert body	54.0 %
Flank wear	5.5 %
Groove	0.8 %
Build-up-edge	0.5 %

Machine Learning Model



- Architecture:
  - 5 CNN layers
  - 16, 32, 64, 128, 256 kernels respectively
  - 32 neurons in fully connected hidden layer
  - ReLu activation functions
- Training:
  - Adam optimizer [18]
  - 200 epochs & 0.001 learning rate

Prediction accuracy: 91.5 %

Post-Processing

- Rearrangement of predicted classes to shape of raw data
- Noise removal using morphological operations

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The proposed solution enables additional process insight, automated wear metric calculation and improved accuracy.

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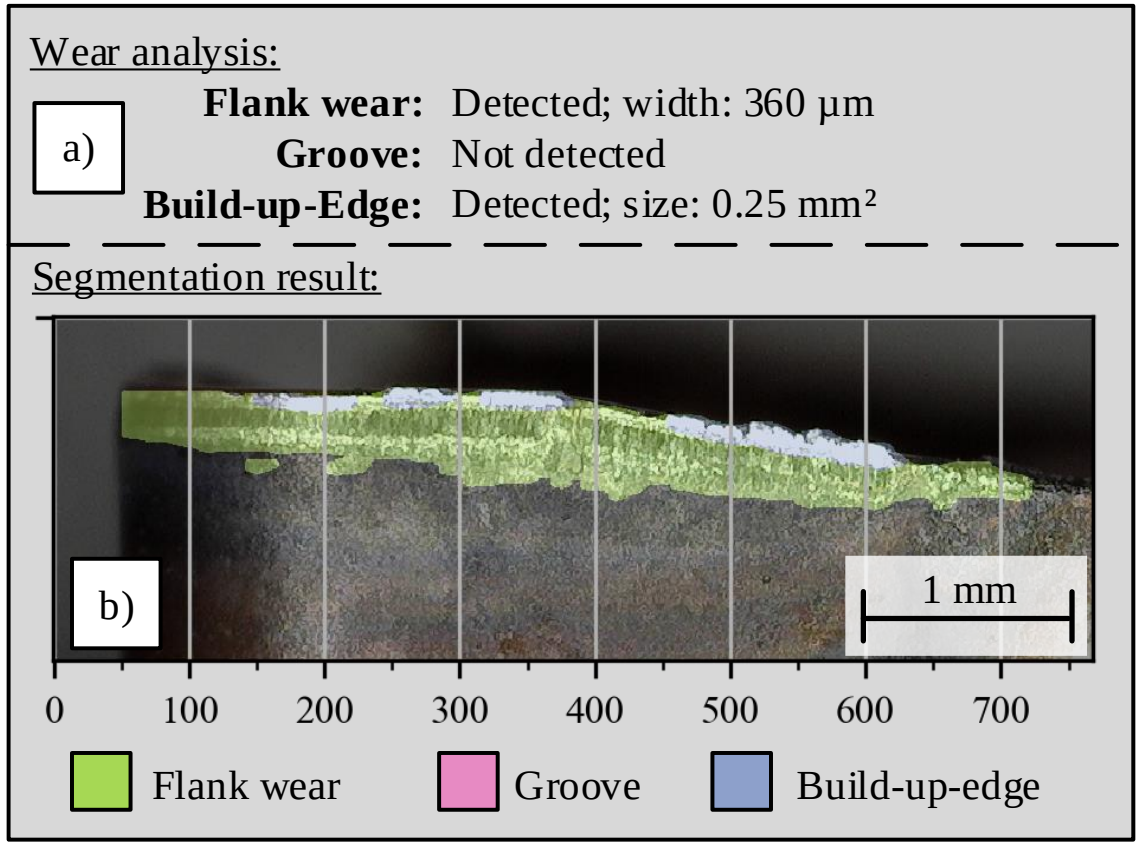
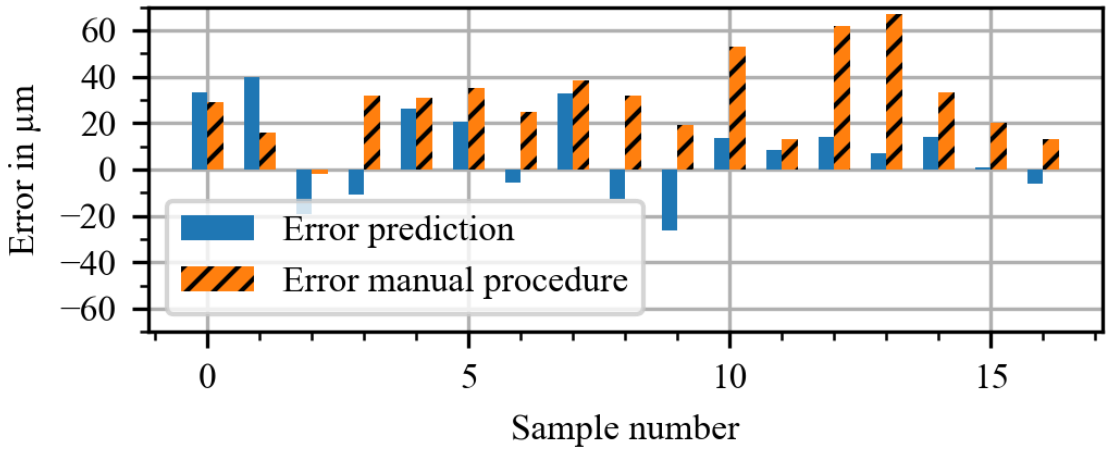
Resulting worker information system:



Flank wear width calculation:

Comparison of proposed solution to manual assessment:

- Average error manual procedure: 30.6 µm
- Average error proposed procedure: 17.1 µm
- For most samples, the proposed solution outperforms the manual assessment



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The study showed, that deep learning is a promising tool for image segmentation in tool condition monitoring.

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Summary

- Deep Learning through CNN can be used for automated semantic segmentation of images for cutting tools
- It is possible to detect and differentiate defects such as flank wear, grooves and build-up-edges
- The developed algorithm outperforms the manual approach in comfort and accuracy

Future research

- Increase of dataset for accuracy improvement
- Investigation of transfer learning strategies for incorporating new type of cutting tool inserts

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Thank you!

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