1 LEM3 LABORATOIRE D'ÉTUDE DES MICROSTRUCTURES ET DE MÉCANIQUE DES MATÉRIAUX

2 IRT M2P Institut de Recherche Technologique Matériaux Métallurgie et Procédés

3 ArcelorMittal

Industeel ArcelorMittal

JOURNEES GN-MEBA 2023 (ROUEN)

Convolutional Neural Networks applied to EBSD maps to improve phase discriminations in steels

M. Lavrskyi[1,2]

Under the supervision of

N. Gey[1] and L. Germain[1]

In collaboration with

Ph. Charobert[3], N. Loukachenko[3], A. Couturier[3] and N. Kohout[2]

S. Breumier[1,2] and T. Martinez Ostormujof[1]

UNIVERSITÉ DE LORRAINE

Outline

I. Context and Motivation

II. Semantic Segmentation with U-NET

III. Results

- 1st results on the DP steel
- Results on multiphase steels

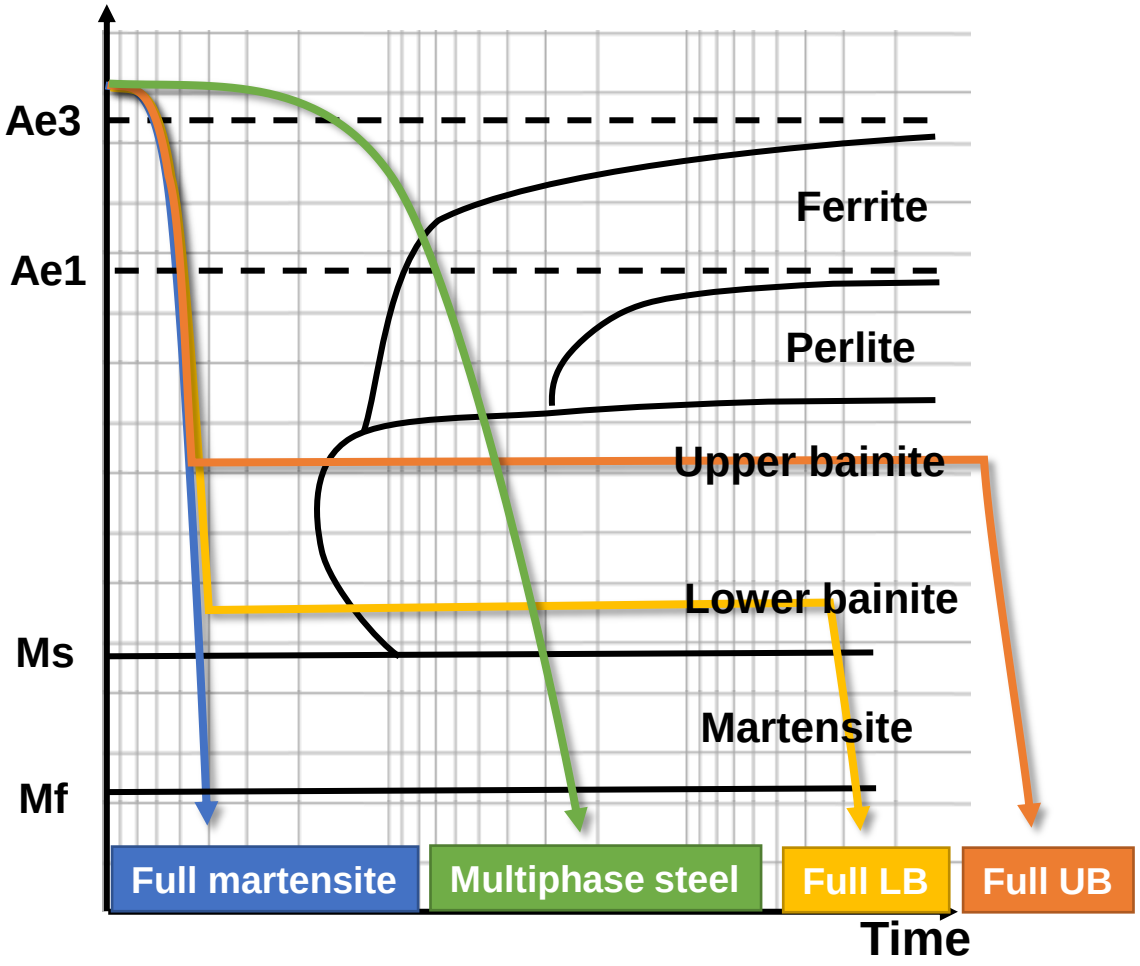
IV. Generalized model

V. Conclusions

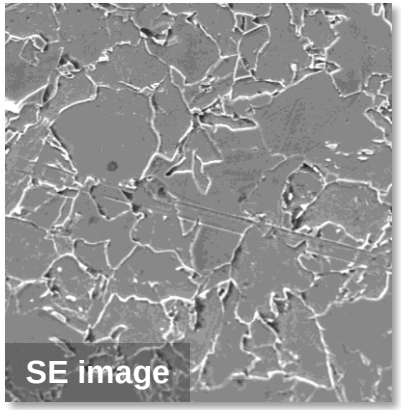
I. Context and Motivation

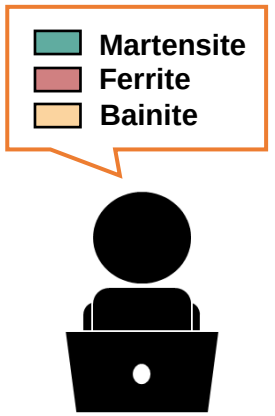
Ferrite – Bainite – Martensite discrimination in low carbon steels

Phase discrimination and quantification of steels is key to better control their properties



Manual classification after chemical etching





Very laborious task

Subjective result

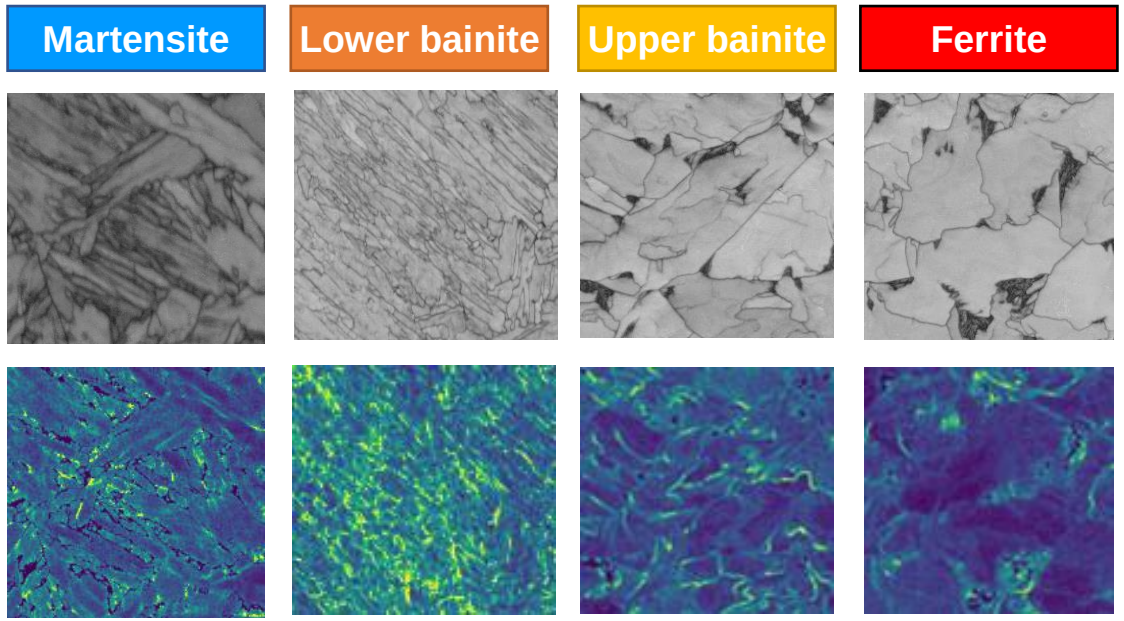
⇨ **Artificial intelligence automation**

Chemical etching does not reveal all relevant information

⇨ **EBSD-based data**

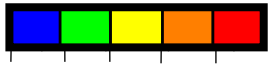
I. Context and Motivation

Benefits of EBSD-based data to distinguish the phases

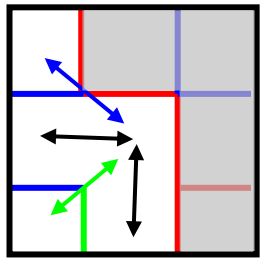


I. Context and Motivation

Calculation of KAM

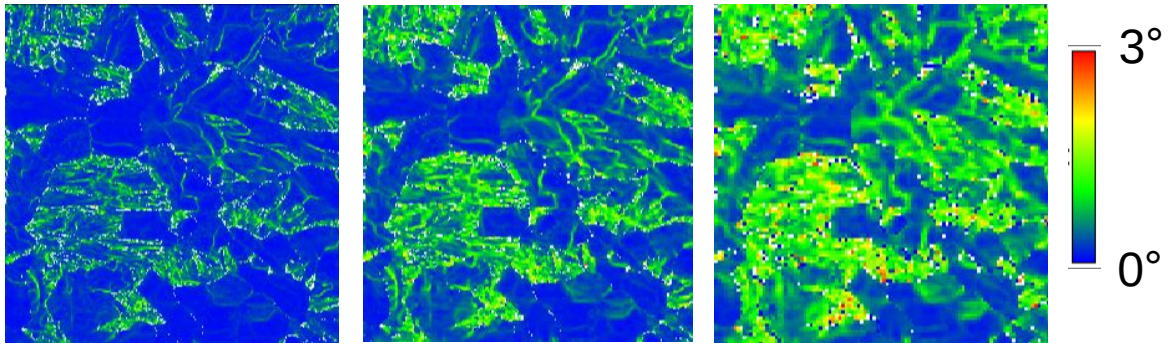


1° 2° 3° 4° 5°



(1+0+2+0)/4 = 0.75°

- The KAM is calculated from the disorientations in a kernel (often 3x3)
- We ignore the pixels that are disoriented beyond a certain threshold (3°) or the pixels in another grain

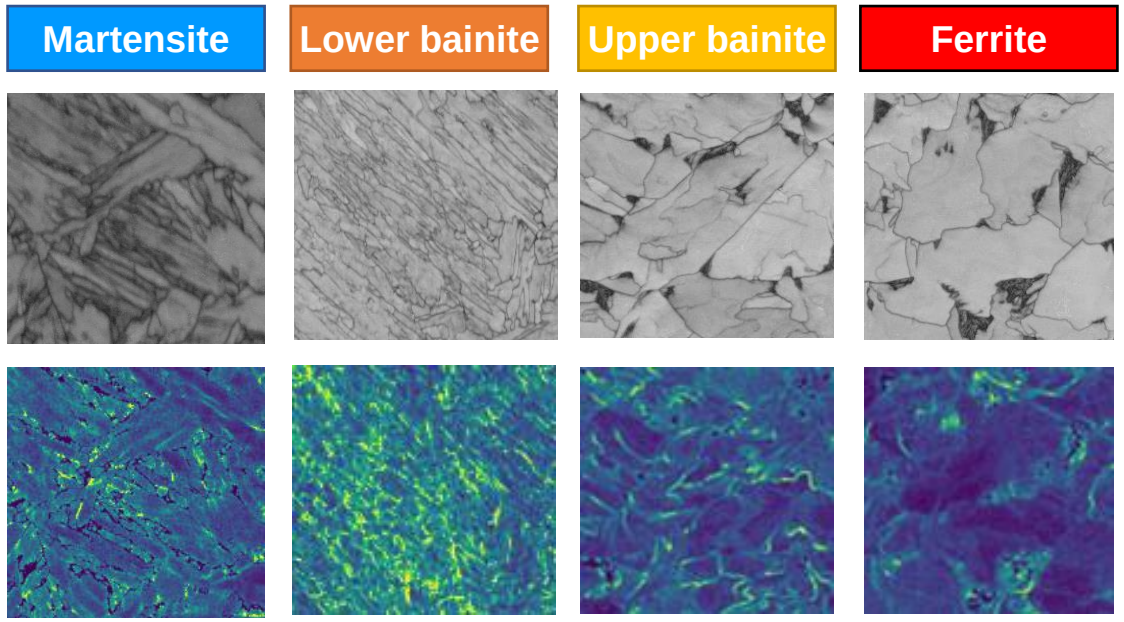


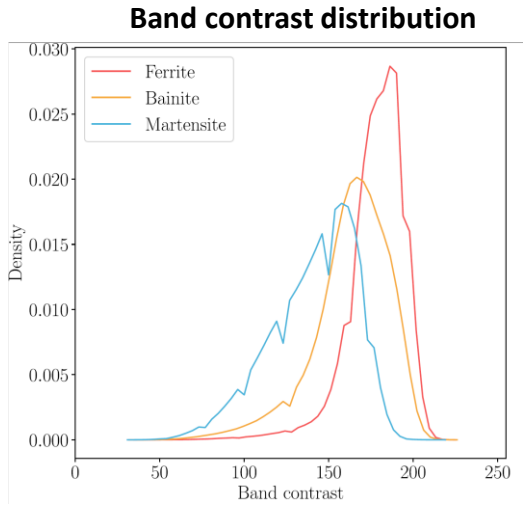
Acquisition step size:

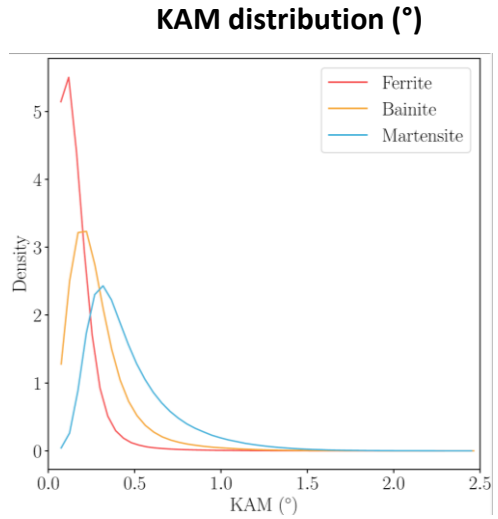
0.1 µm **0.2 µm** **0.4 µm**

I. Context and Motivation

Benefits of EBSD-based data to distinguish the phases







Main goal

Train an AI model based on EBSD data to automatically classify Steel transformation products

Outline

I. Context and Motivation

II. Semantic Segmentation with U-NET

III. Results

- 1st results on the DP steel
- Results on multiphase steels

IV. Generalized model

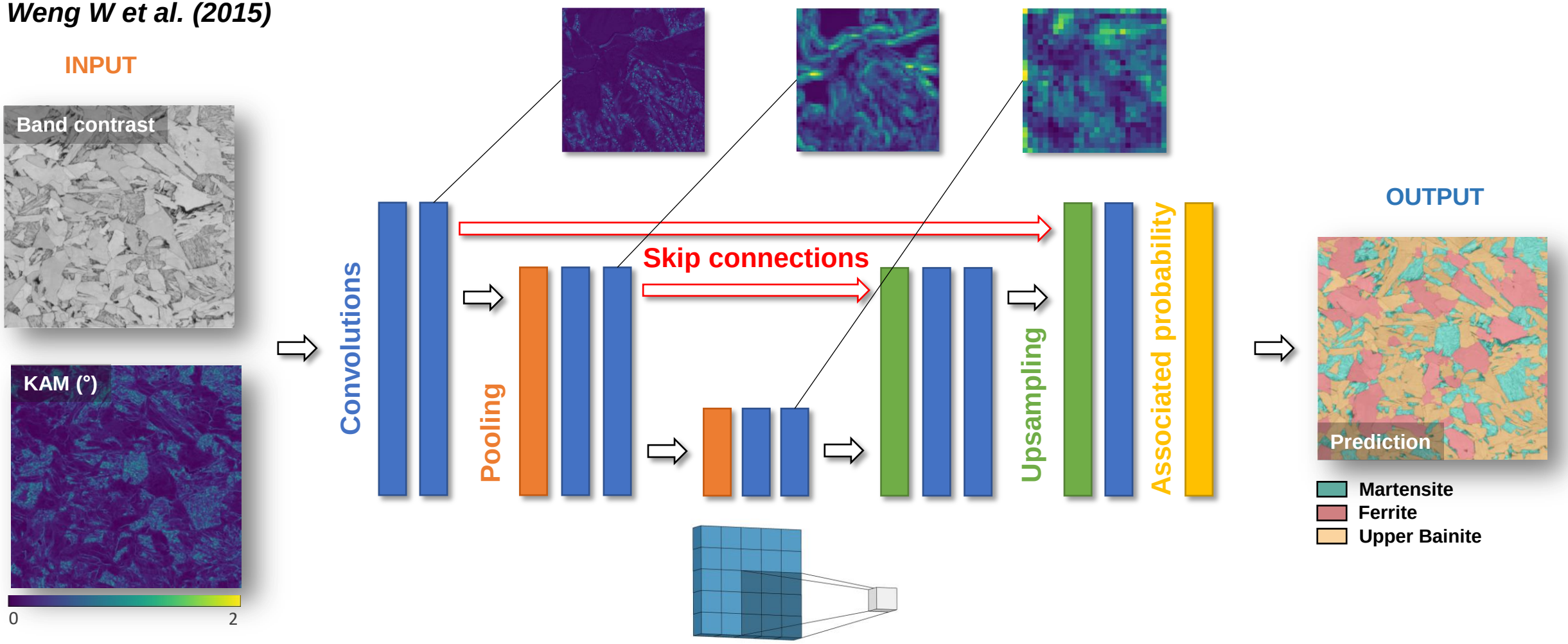
V. Conclusions

II. Semantic Segmentation with U-Net

Working principle

U-Net is a Convolutional Neural Network (CNN) that enables the pixel-wise classification of an image

Weng W et al. (2015)



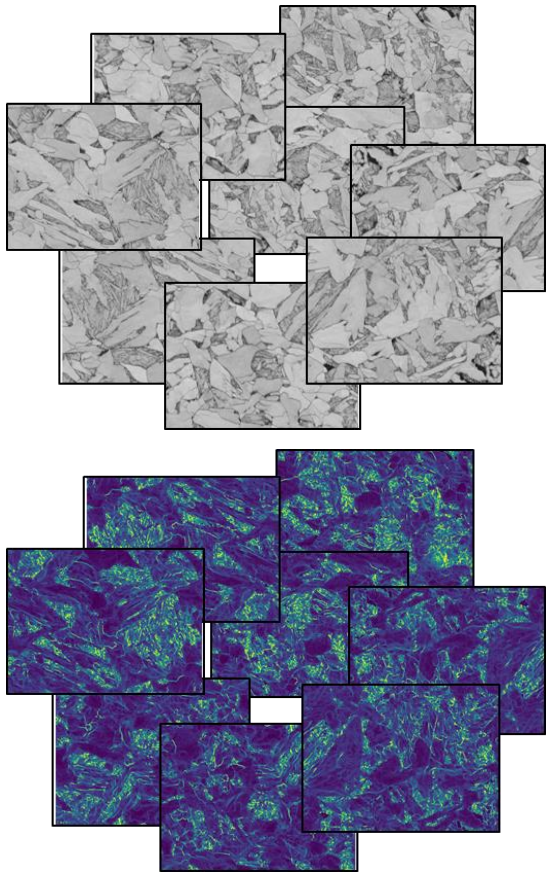
T. Martinez Ostormujof et al., "Deep Learning for automated phase segmentation in EBSD maps. A case study in Dual Phase steel microstructures", Materials characterization, 2022
S. Breumier et al., "Leveraging EBSD data by deep learning for bainite, ferrite and martensite segmentation", Materials characterization, 2022

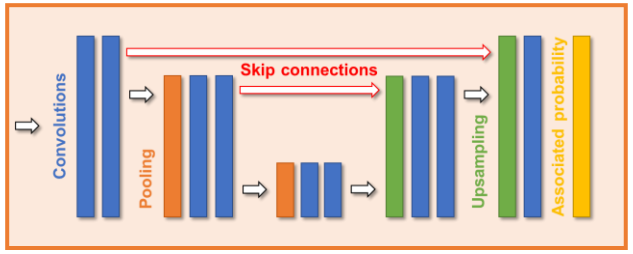
II. Semantic Segmentation with U-Net

Training a segmentation model

Supervised Learning approach: the training images must be provided with their respective labeling

Training dataset

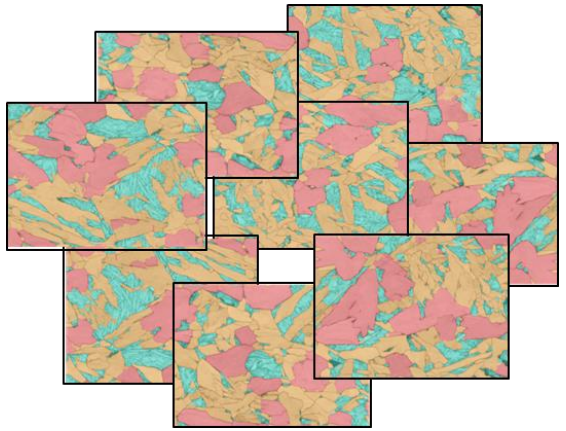




Learning

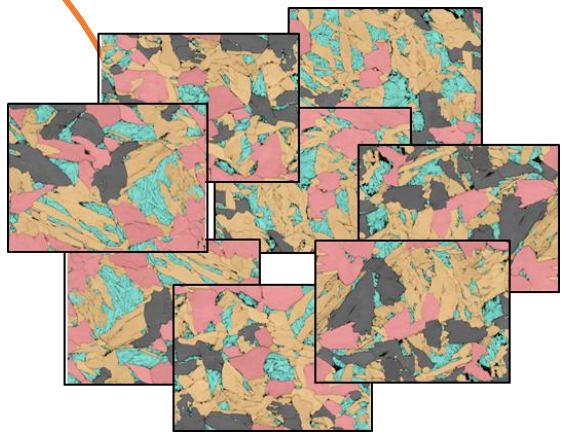
Model saved to predict on unseen maps

Predictions



Laborious and time consuming task

Labeling



Ferrite Upper Bainite Martensite

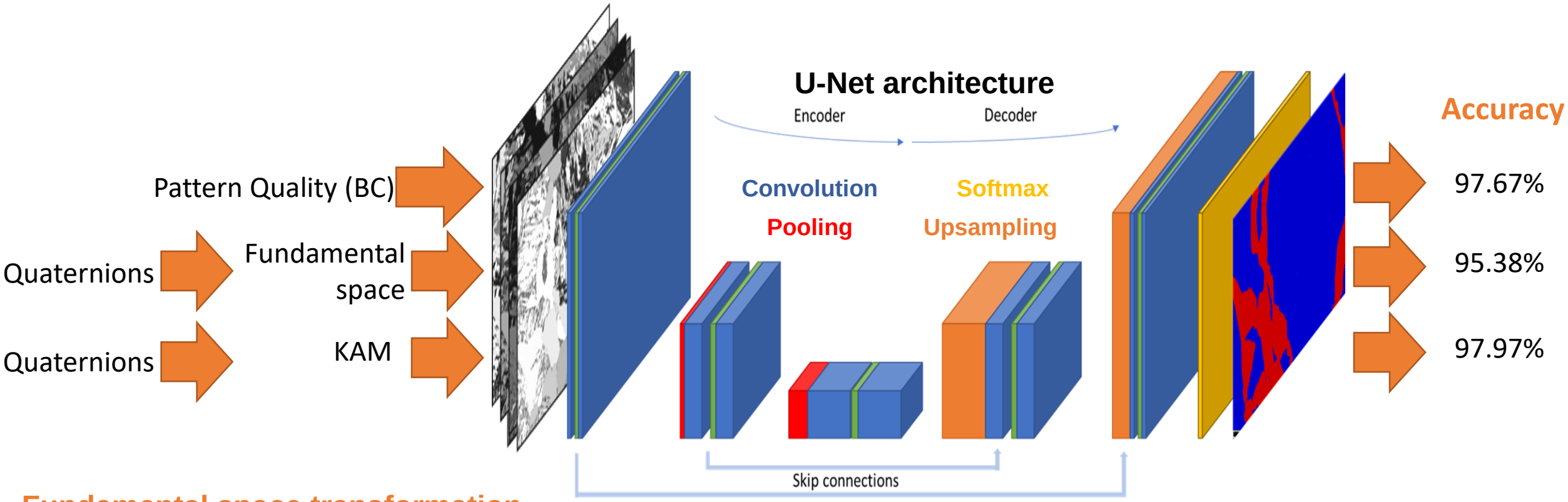
Unknown

Facilitates labeling

Ignored for training

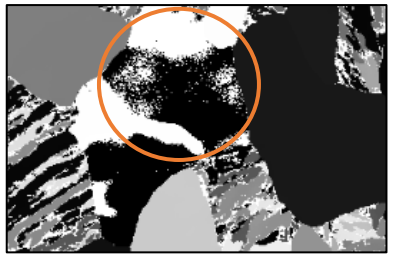
II. Semantic Segmentation with U-Net

Choice of the inputs

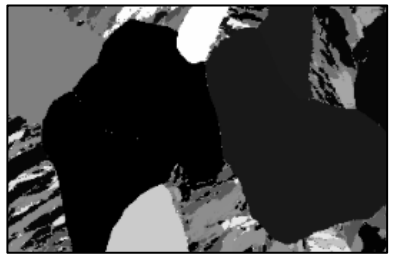


Fundamental space transformation

Raw quaternions



Fundamental space



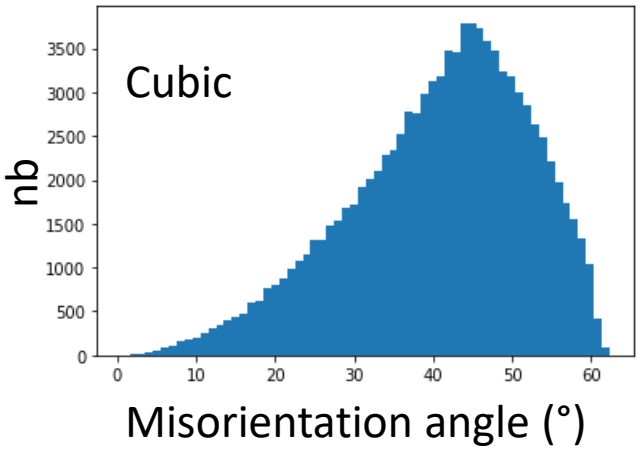
II. Semantic Segmentation with U-Net

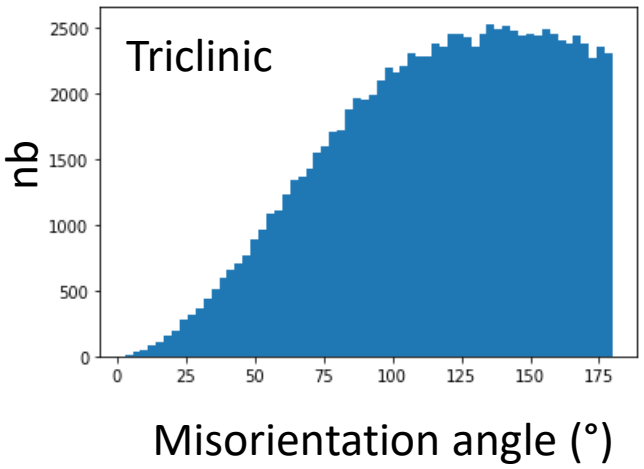
Choice of the input parameters

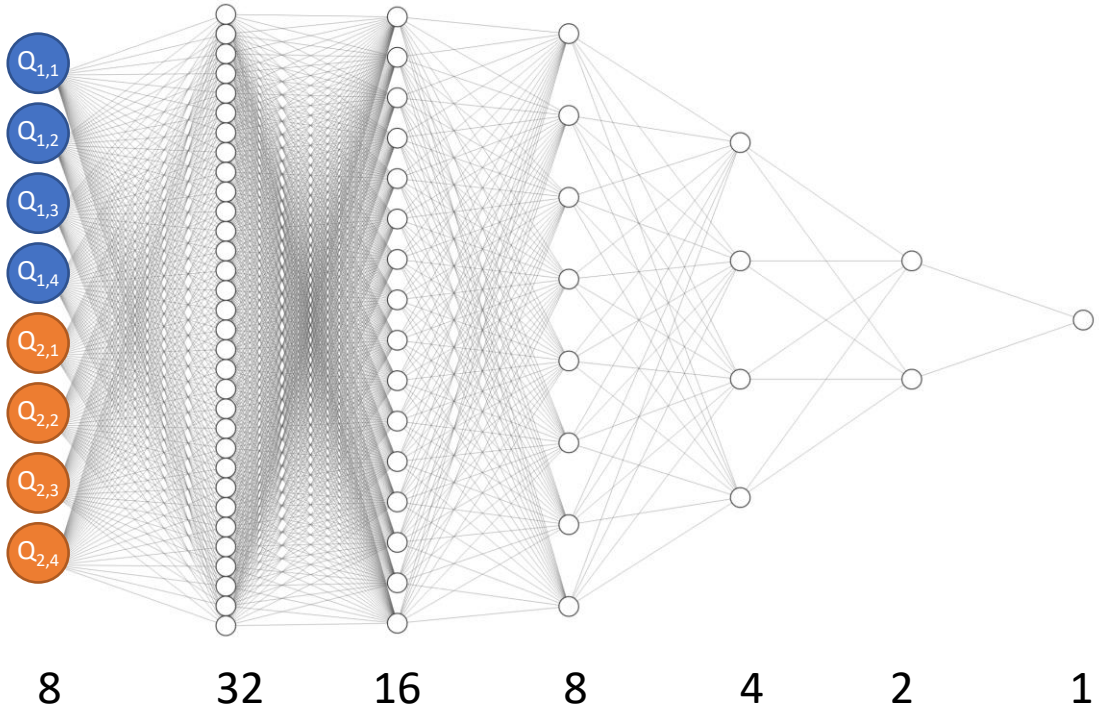
Can a NN understand what misorientation is?

$$mis(Q_1, Q_2) = \min_{i,j}\left(\left(Q_2 \times S_j\right)^{-1} \times Q_1 \times S_i \cdot Q_{ID}\right)$$

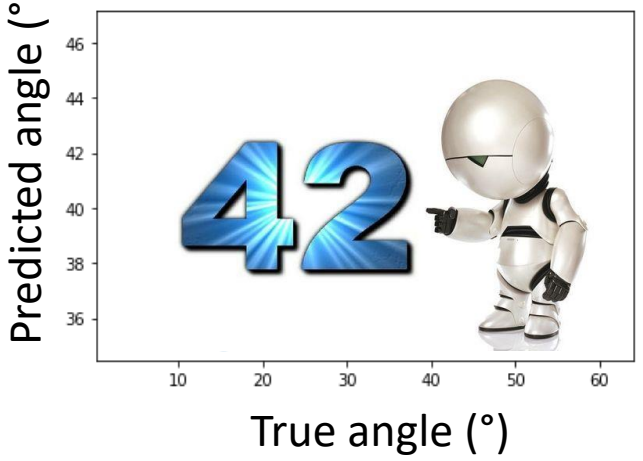
100 000 random couples

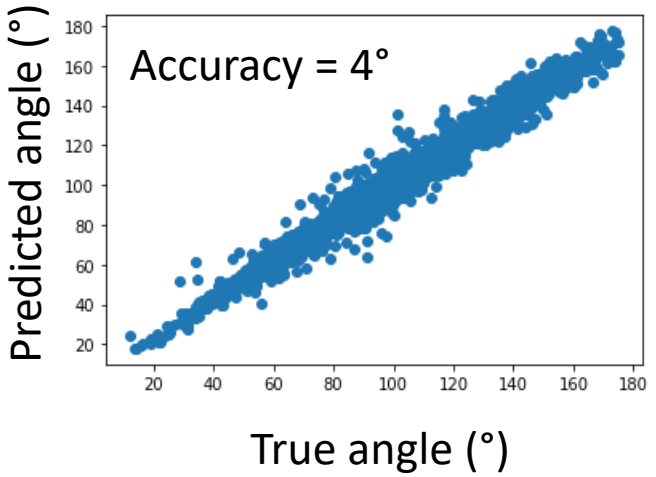






200 epochs – 15min training





D. Adams, "The Hitchhiker's Guide to the Galaxy"

Outline

I. Context and Motivation

II. Semantic Segmentation with U-NET

III. Results

- **1st results on the DP steel**
- **Results on multiphase steels**

IV. Generalized model

V. Conclusions

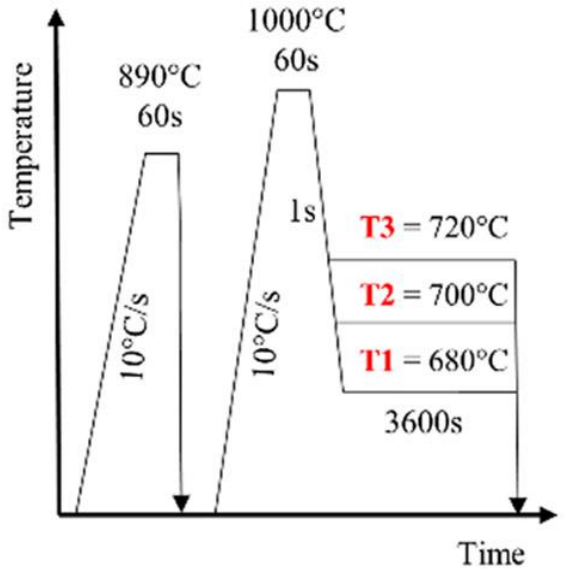
III. Results

Martensite
Ferrite

Studied material

ArcelorMittal

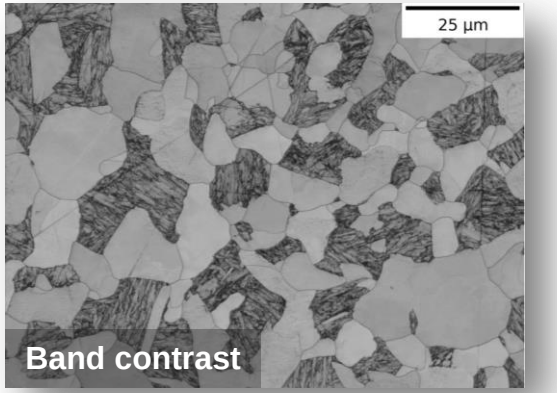
DP steel with composition 0.17%C and 1.5%Mn

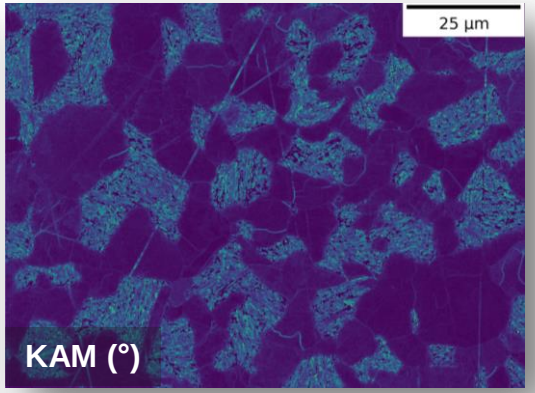


Training dataset

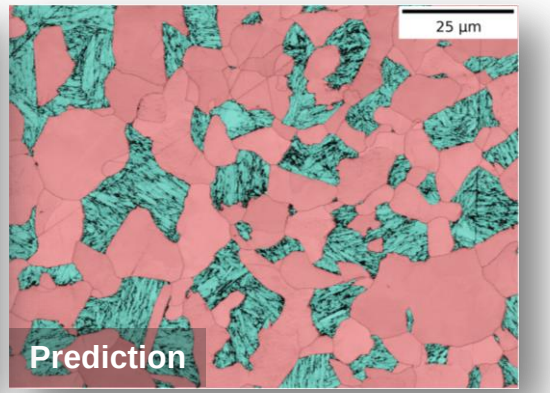
- 6 EBSD maps
- 856x1141 pixels
- Acquisition step size 0.1 µm

T = 680ºC





98% accuracy



Applicable only to dual phase steel, unable to recognize Bainite

~ 98% accuracy

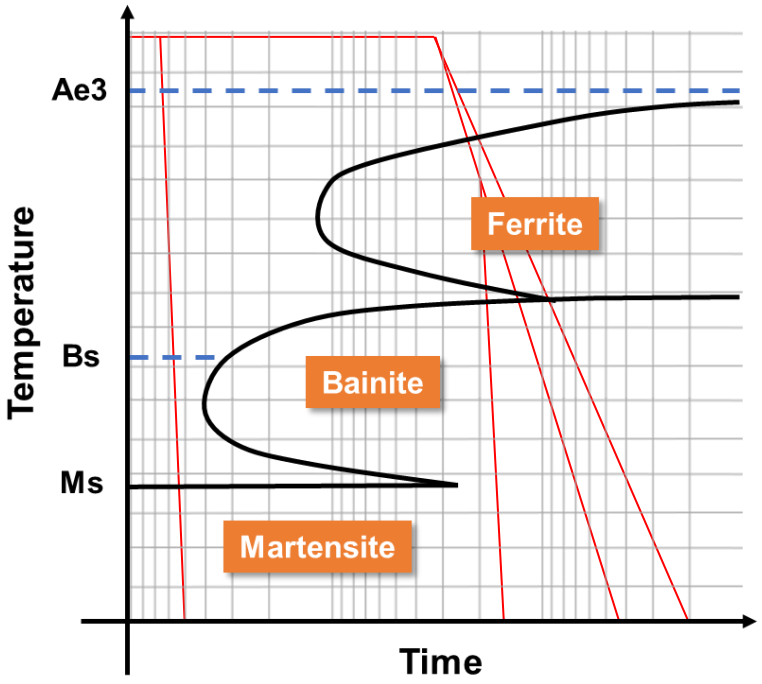
T. Martinez Ostormujof et al., "Deep Learning for automated phase segmentation in EBSD maps. A case study in Dual Phase steel microstructures", Materials characterization, 2022

III. Results

Martensite
Ferrite
Upper Bainite

Studied material

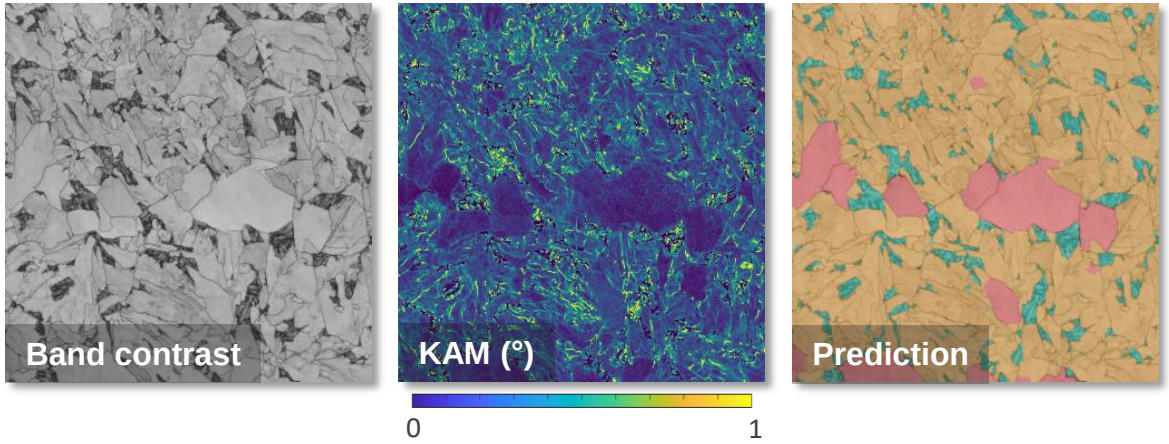
Industeel ArcelorMittal



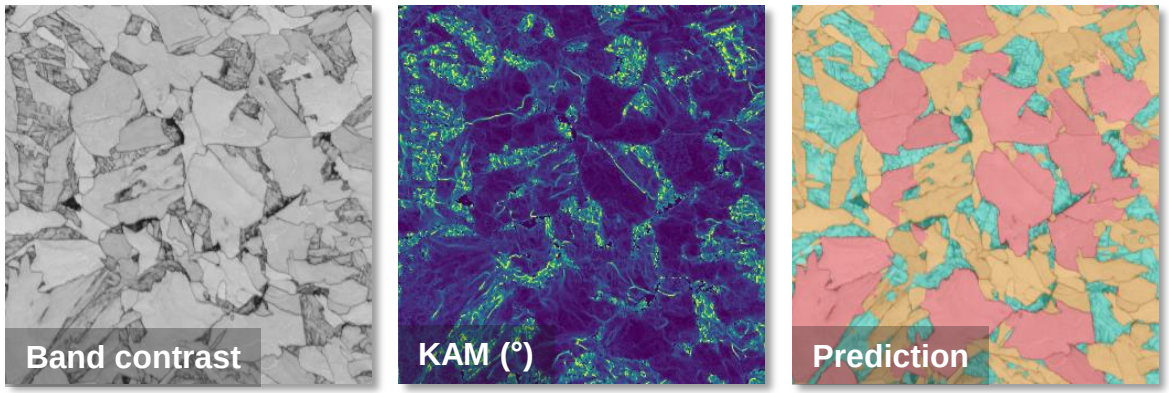
Training dataset

- 4 EBSD maps
- 2520x945 pixels
- Acquisition step size 0.1 µm

F 20% **UB 75%** **M 5%** **94% accuracy**



F 35% **UB 45%** **M 20%** **87% accuracy**



Over 87% accuracy depending on the microstructure complexity

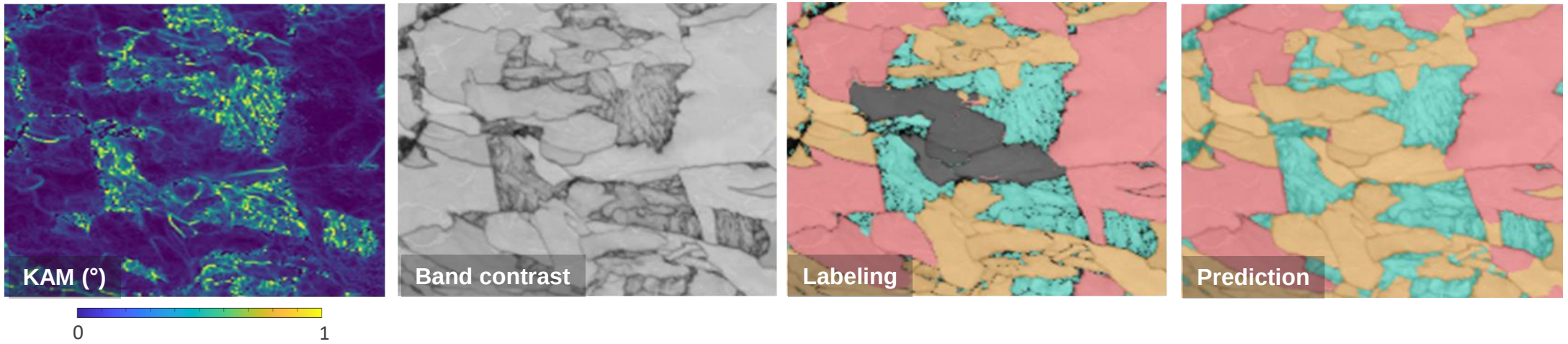
S. Breumier et al., "Leveraging EBSD data by deep learning for bainite, ferrite and martensite segmentation", Materials characterization, 2022

III. Results

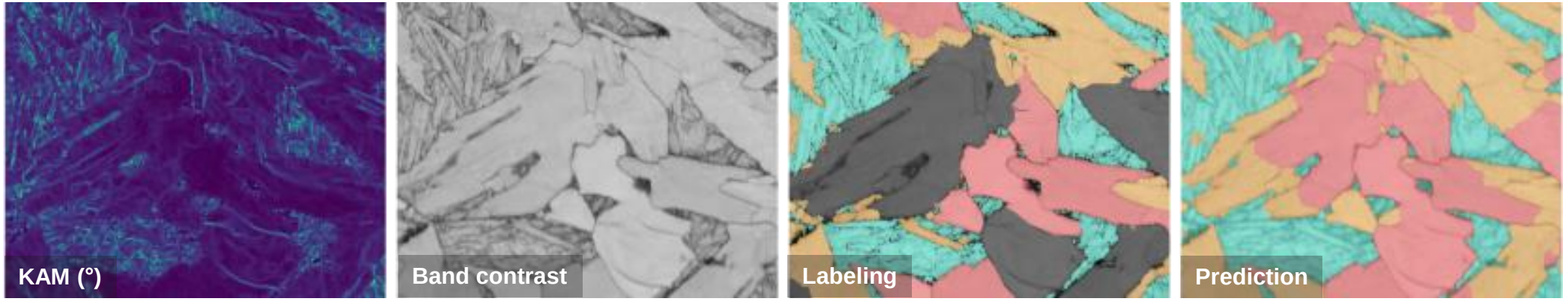
Prediction of unknown class

Martensite
Ferrite
Upper Bainite
Unknown

Case 1: Ambiguous grains ⇨ **Coherent result based on KAM analysis**



Case 2: Ambiguous F-UB boundary ⇨ **Wrong boundary shape** ⇨ **Labeling needed**



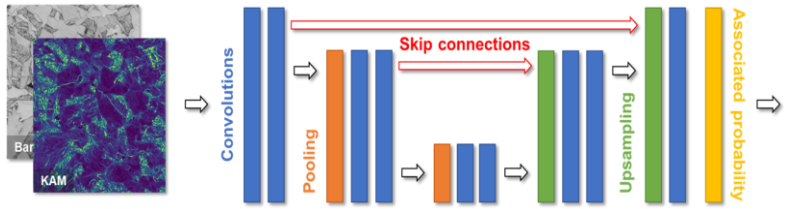
S. Breumier et al., "Leveraging EBSD data by deep learning for bainite, ferrite and martensite segmentation", Materials characterization, 2022

III. Results

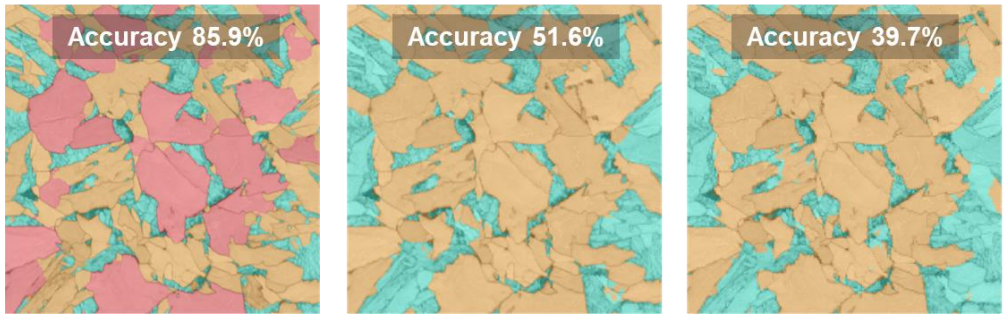
Influence of the acquisition step size

Martensite
Ferrite
Upper Bainite

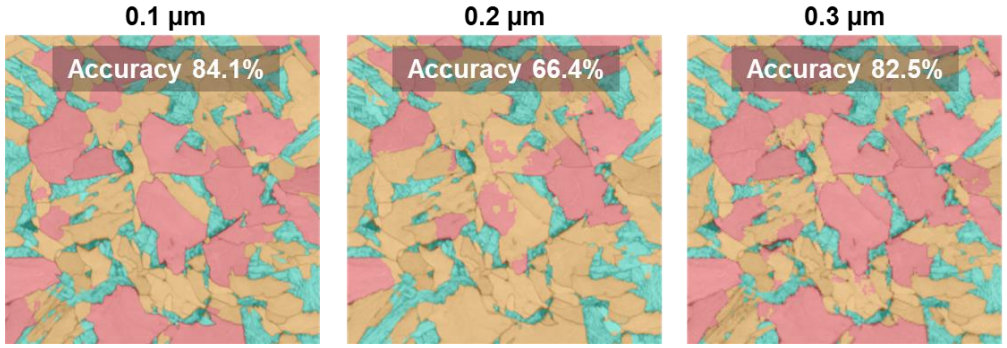
No step size input



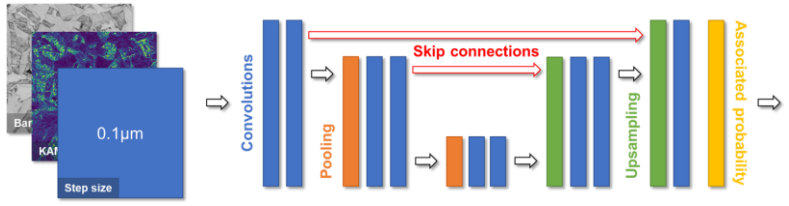
Training with 0.1µm



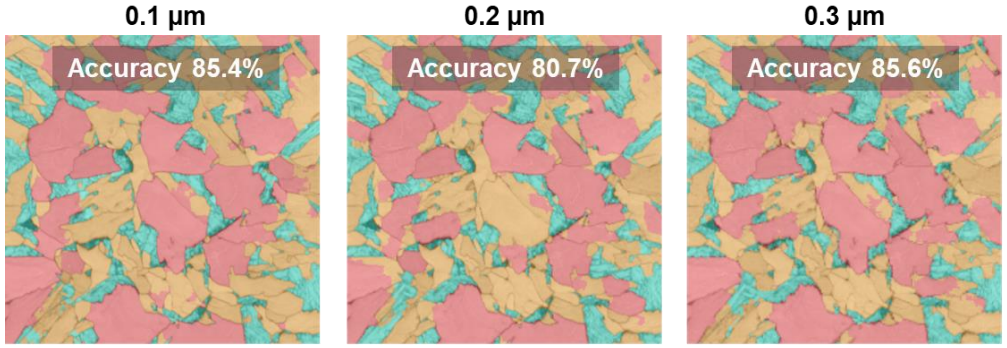
Training with 0.1µm and 0.3µm



Step size input



Training with 0.1µm and 0.3µm



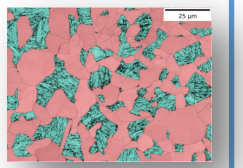
S. Breumier et al., "Leveraging EBSD data by deep learning for bainite, ferrite and martensite segmentation", Materials characterization, 2022

III. Results

Martensite
Ferrite
Upper Bainite

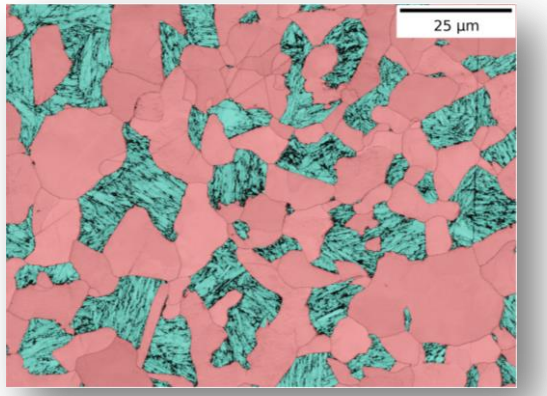
U-Net model for DP steel

6 EBSD maps
856x1141 pixels



>95% accuracy

98% accuracy



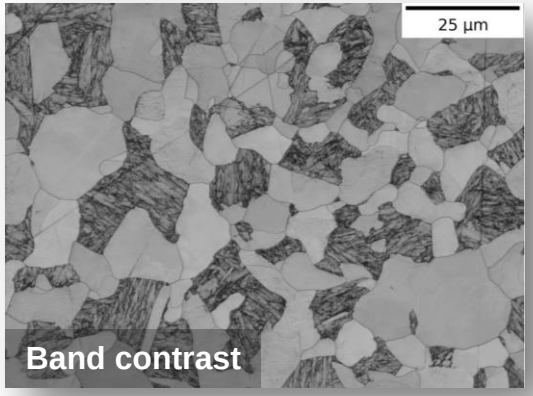
U-Net model for triple phase steel

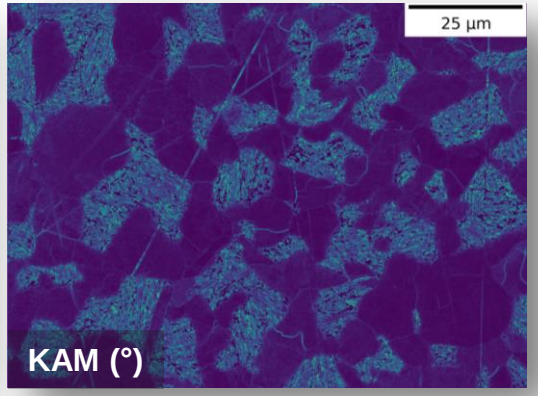
4 EBSD maps
2520x945 pixels

>87% accuracy

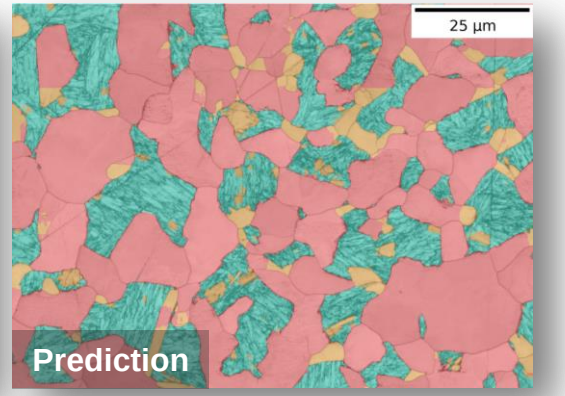
Low performance on DP steel dataset

F 64% UB 9% M 27%





90% accuracy



Outline

I. Context and Motivation

II. Semantic Segmentation with U-NET

III. Results

- 1st results on the DP steel
- Results on multiphase steels

IV. Generalized model

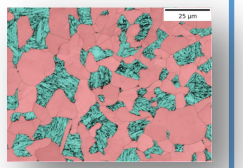
V. Conclusions

IV. Generalized Model

U-Net model for DP steel

6 EBSD maps
856x1141 pixels

~98% accuracy



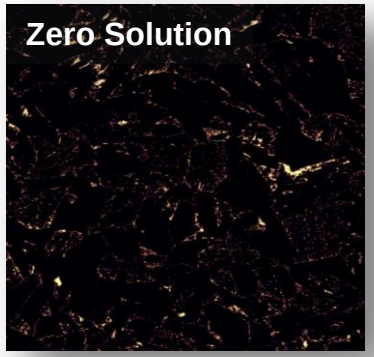
U-Net model for triple phase steel

4 EBSD maps
2520x945 pixels

>87% accuracy

Retained Austenite

New INPUTS



Unified U-Net model for triple phase steel

2 EBSD maps
SA533
API5L
2520x945 pixels

4 EBSD maps for DP steel
856x1141 pixels

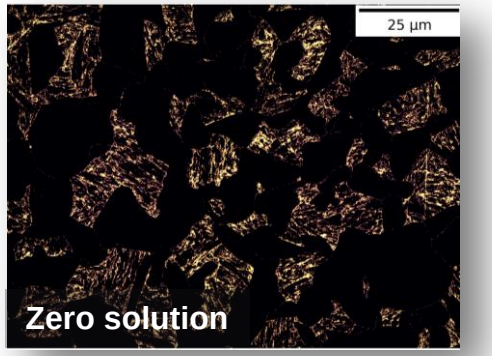
Balanced dataset

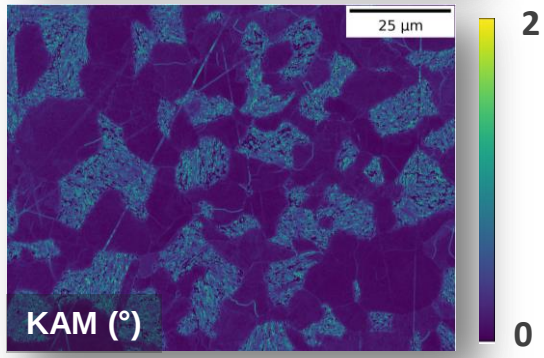
Martensite	Bainite	Ferrite
34.5%	33.0%	32.5%

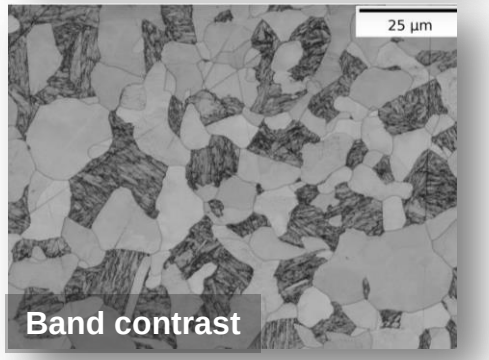
IV. Generalized Model

Model performance on unseen maps

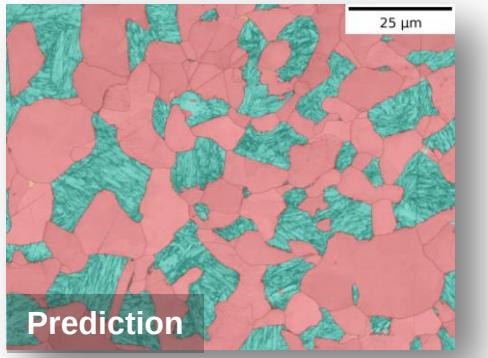
Martensite
Ferrite
Upper Bainite







F 71% UB 0% M 29%



99% accuracy

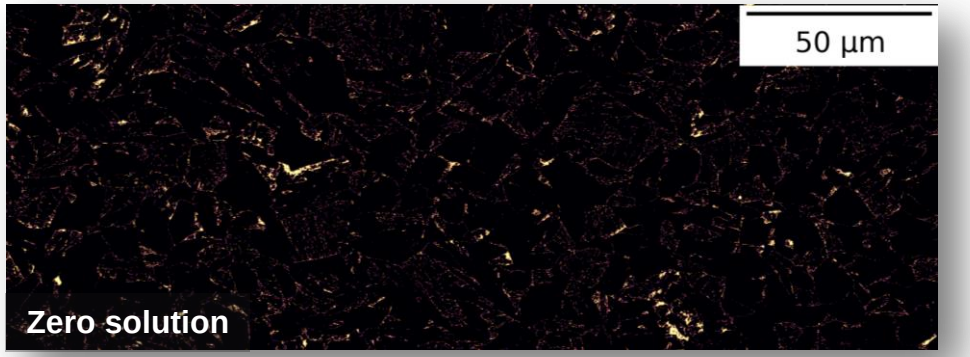
Great discrimination between Ferrite and Martensite

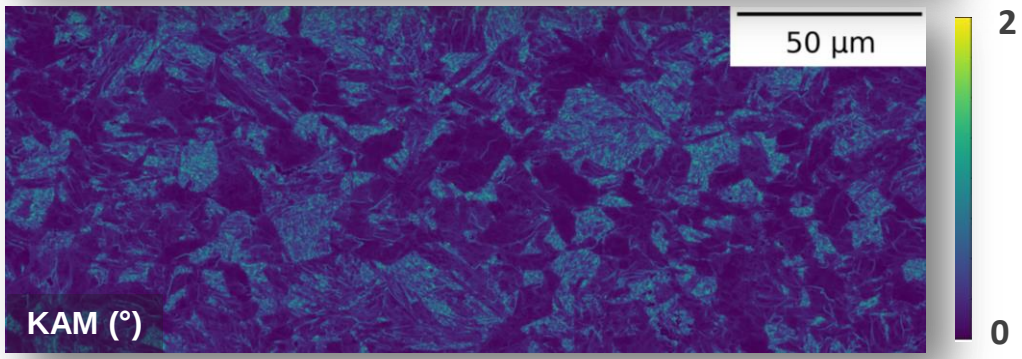
~ 99% on DP steel data

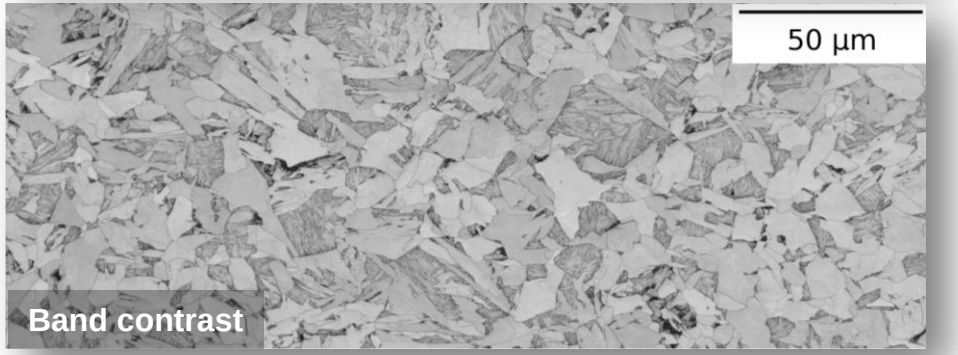
IV. Generalized Model

Model performance on unseen maps

Martensite
Ferrite
Upper Bainite







F 29.5% UB 47.5% M 23%

82% accuracy

Complicated discrimination between Ferrite and Upper Bainite

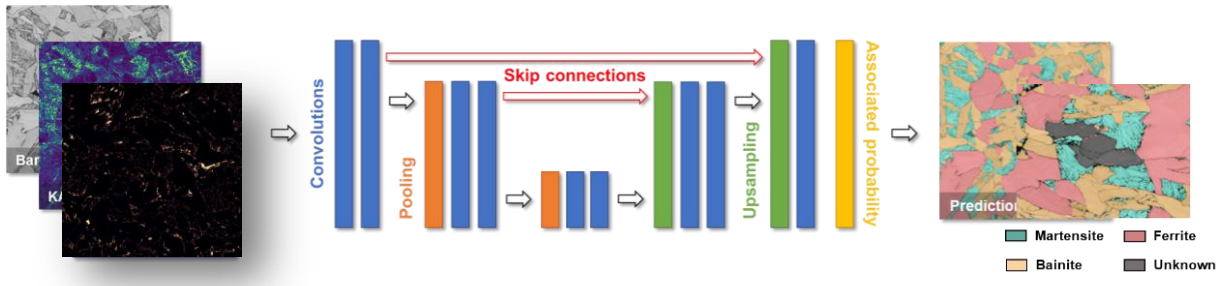
Over 80% accuracy depending on the microstructure complexity

V. Conclusions

Conclusions

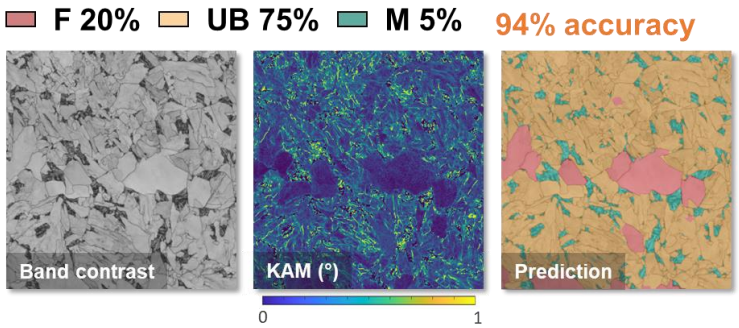
U-Net implementation

- U-Net architecture trained on EBSD maps to automatically segment steel microstructures.
- Independency of the acquisition step size.
- Zero Solution and Retained Austenite pixels were introduced as new input.



Model performance

- Accuracies above 80% depending on the complexity of the particular case.
- Ferrite-Upper Bainite discrimination is complex.
- Generalized for different datasets.
- Result in terms of minutes, faster than conventional approaches.
- Well adapted to perform a repetitive task.



IRT M2P Institut de Recherche Technologique Matériaux Métallurgie et Procédés

LEM3 LABORATOIRE D'ÉTUDE DES MICROSTRUCTURES ET DE MÉCANIQUE DES MATÉRIAUX

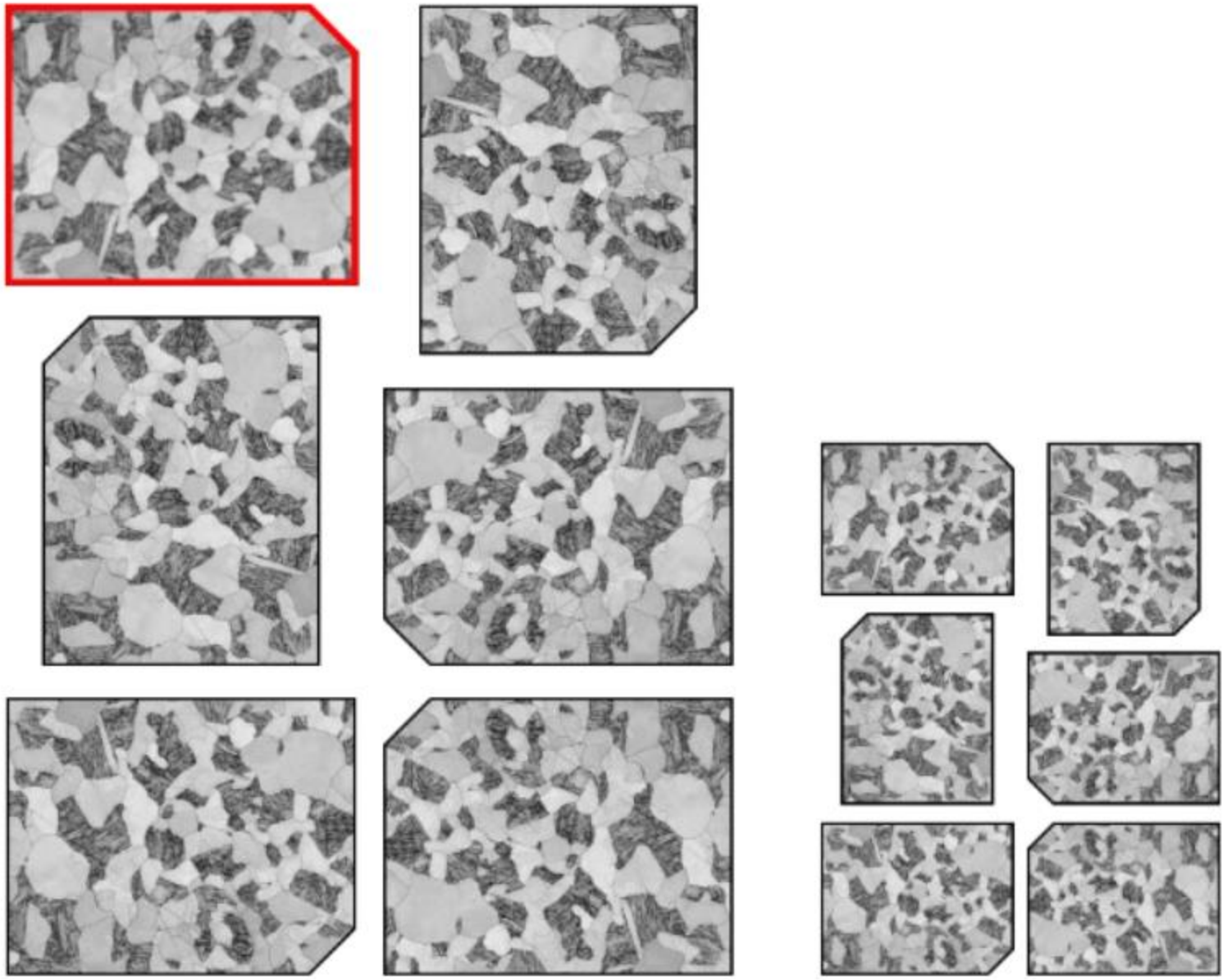
ArcelorMittal

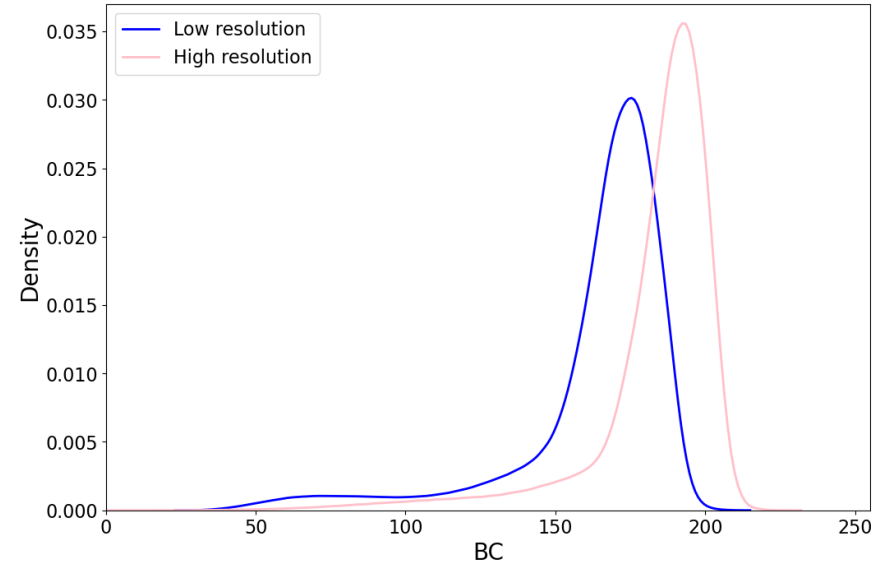
Industeel ArcelorMittal

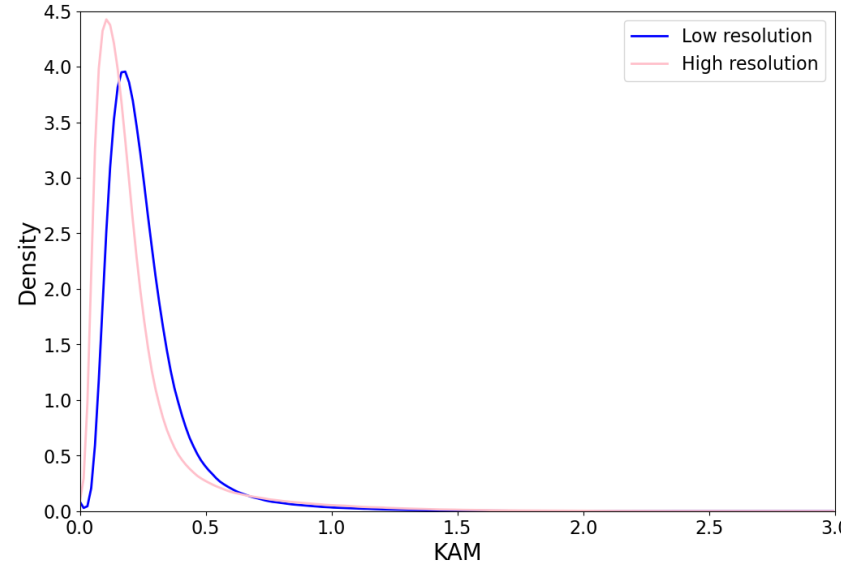
Thank you for your attention

UNIVERSITÉ DE LORRAINE

Augmented data




Low resolution
High resolution
Density
BC
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0
50
100
150
200
250


Low resolution
High resolution
Density
KAM
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5