Generalized Ice Detection on Wind Turbine Rotor Blades with Neural Style Transfer

Joyjit Chatterjee[1,2], Maria T. Alvela Nieto[1], Hannes Gelbhardt[1], Nina Dethlefs[2], Jan Ohlendorf[1], Klaus-Dieter Thoben[1]*

University of Bremen, Faculty of Production Engineering, Institute for Integrated Product Development (BIK), 28359, Bremen, Germany[1]

School of Computer Science, University of Hull, Hull, HU6 7RX, United Kingdom[2]

Email: *j.chatterjee@hull.ac.uk[*]*

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Introduction

→ Increasing awareness on the pressing need for transitioning to renewables has led to wind energy reaching a total global installed capacity of 837 GW in 2022

→ In winters, higher wind speeds and air density facilitate a highly promising environment for wind power generation

→ Some parts of the world – particularly in Northern Europe and North America are highly prone to icing on wind turbine rotor blades

→ Such icing events cause unexpected downtimes, loss of potential energy yield and reduced mechanical life of turbine

Our Study

Motivation

→ While sensors mounted on rotor blades can be used for ice-detection, they are mostly not sufficiently accurate and rely on external parameters like temperature/oscillation frequencies

→ There has been rising interest in utilising colour (RGB) images of turbine rotor blades and applying computer vision techniques for detecting icing

→ A camera mounted on rotor blades generally captures complete area of the blade even in harsh weather (e.g. foggy conditions), thus is more robust than sensor-based ice detection

→ Some past studies have used deep learners (e.g. Convolutional Neural Nets – CNNs) for ice detection with RGB images with high accuracy, but are limited to effectively predicting only in source domain wind parks they are originally trained with

→ We aim to facilitate domain adaptation in existing models – to make more effective predictions in new wind park locations (target domain)

Datasets

Two wind park datasets utilised

→ ***Wind park A*** in North America and ***wind park B*** in Northern Europe

→ Quality of images is significantly better for *wind park A* compared to *wind park B*

Description of pre-processing

→ Images were hand-labelled by two humans, with cross-validation performed across the labels

→ **Three classes – background**, **plain rotor blade (no icing)** and **rotor blade with icing**

→ We consider both scenarios – *wind park A* **(source domain)** and *wind park B* **(target domain)** as well as vice versa

→ Training data (base sets) has 150 background, 20 rotor blade + 50 rotor blade images from target domain, and 70 icing images from source domain

→ We augment the rotor blade and ice images (with 10% random rotation) to reach 400 images

→ Test data has 200 images of each class for *wind park A* and 800 for *wind park B*

Proposed Methodology

→ We aim to use existing deep learners that have achieved near-perfect accuracy in past literature as baselines **(MobileNetV2, VGG19 and Xception)**

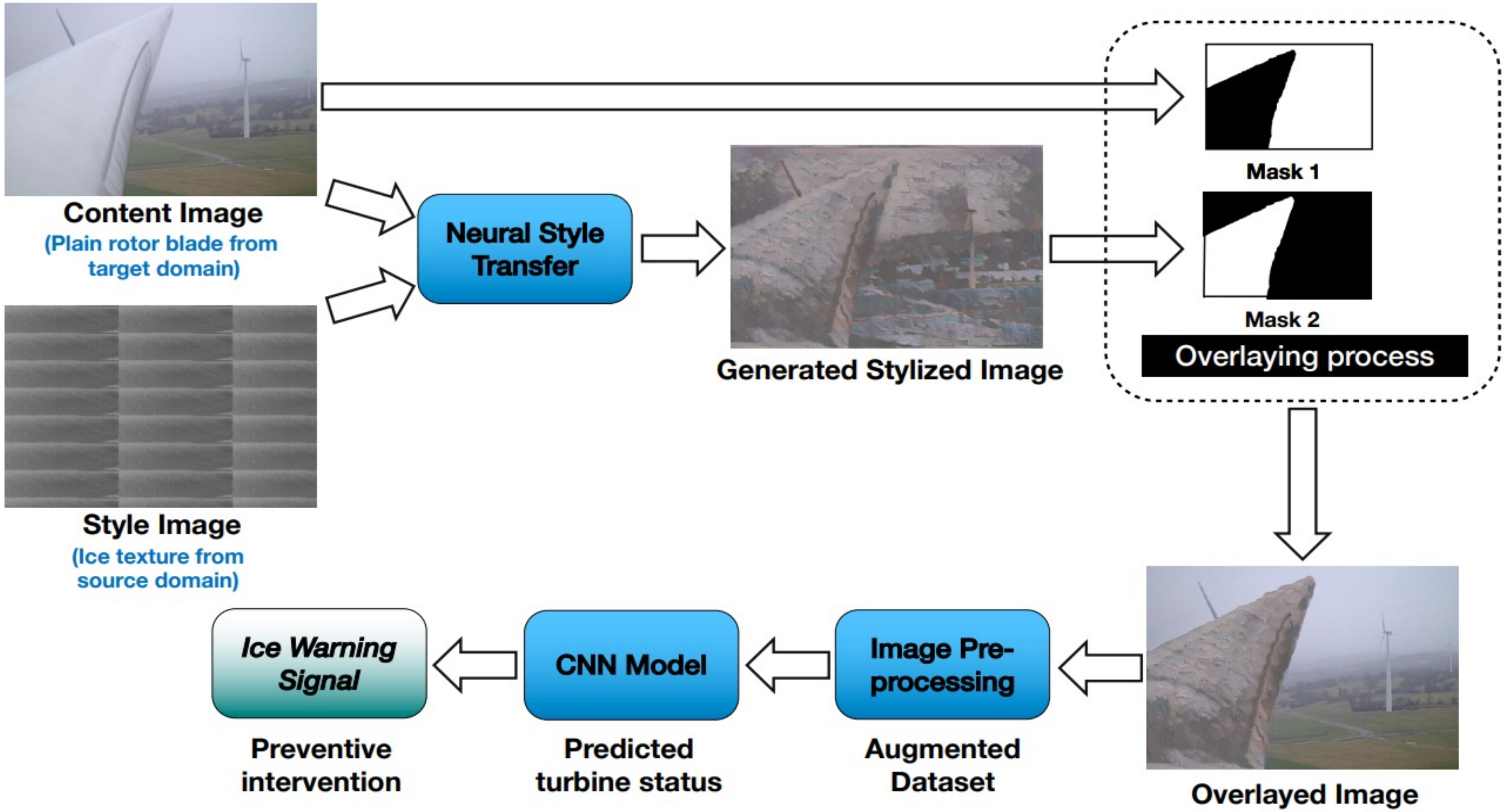
→ Baseline models (domain-specific) were pre-trained from ImageNet and fine-tuned with limited rotor blade images from distinct (standalone) wind parks

→ We propose the generation of synthetic data for improving the generalization of the existing models across other wind parks

→ Transfer learning is proposed to accomplish generalized ice detection independent of characteristics of wind parks the models have previously been trained on

→ We use the **neural style transfer algorithm** to transfer ***content images*** (target domain plain rotor blade images) to the style of reference ***style images*** (source domain rotor blade images with ice texture)

Proposed Methodology



Experiments

→ Three models were trained (MobileNetV2, VGG19 and Xception) – as these have achieved best results in past literature (for ice detection in standalone wind parks)

→ Before the images are fed to the model, we followed the default pre-processing procedures (e.g. reshaping)

→ Two separate strategies were used to train the CNN models:

- **Strategy 1:** An output layer (dense, three classes) was appended to the model and all model layers were trainable
- **Strategy 2:** Generic model backbone was frozen and only the output layer was trainable

→ Models were trained over 30 epochs with batch size of 16

→ For neural style transfer, we used the intermediate layers of VGG19 (without classification head) and trained for 40 epochs

→ We additionally used a pre-trained fast style transfer model (arbitrary image stylisation) for our experiments

→ 50 rotor blade images of target domain are style-transferred to generate 200 additional synthetic images for the ice class with these techniques

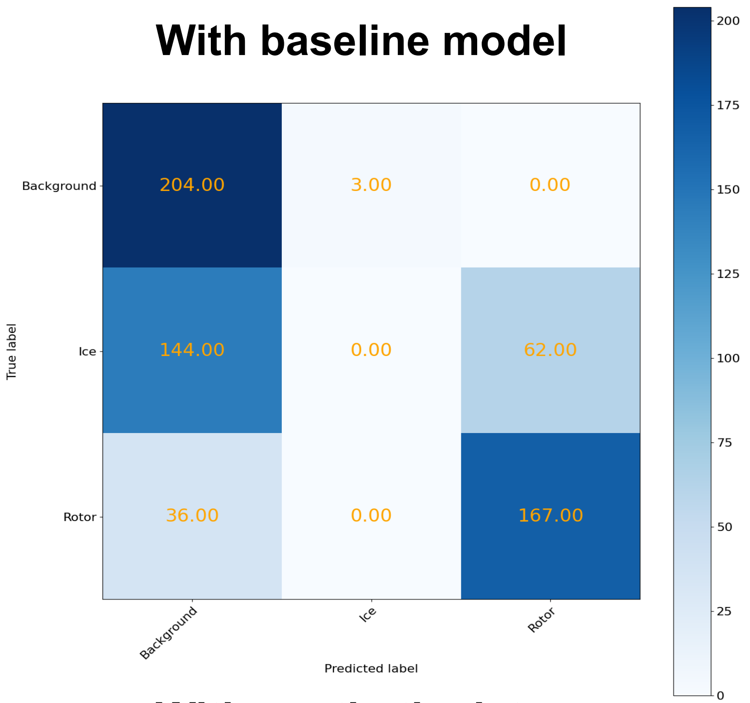
→ Note that we also experimented with a more modern approach (CycleGAN) for unpaired image-to-image yielding poor results, likely due to small size and significant class imbalance in our datasets

Results

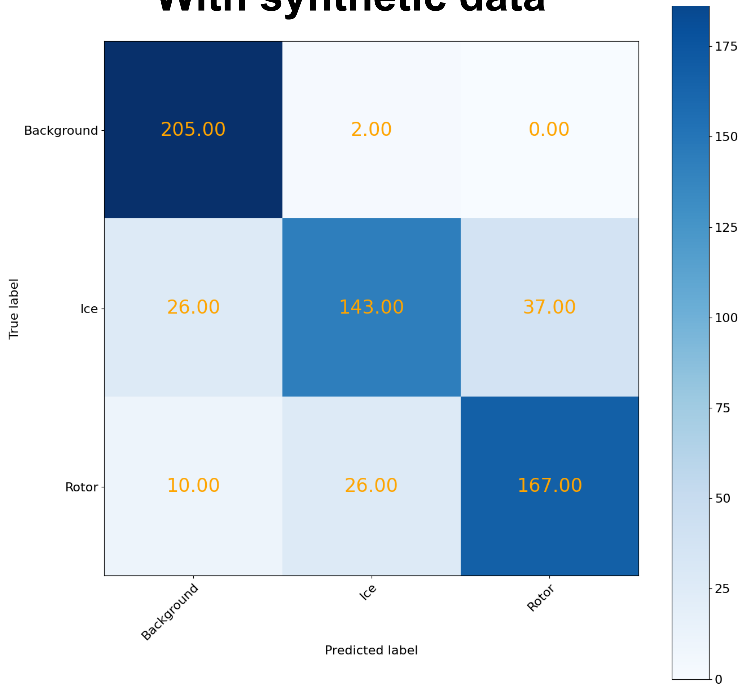
Model	Target Data set	Baseline (Acc - F1)	Training strategy	Synthetic (Acc - F1)
MobileNetV2	*Wind park A*	0.633 - 0.528	Strategy 1	0.685 - 0.652
			Strategy 2	0.696 - 0.664
	Wind park B	0.394 - 0.289	Strategy 1	0.412 - 0.307
			Strategy 2	0.462 - 0.400
VGG19	*Wind park A*	0.602 - 0.488	Strategy 1	0.662 - 0.622
			Strategy 2	0.836 - **0.831**
	Wind park B	0.396 - 0.284	Strategy 1	0.435 - 0.389
			Strategy 2	0.458 - **0.402**
Xception	*Wind park A*	0.641 - 0.516	Strategy 1	0.709 - 0.666
			Strategy 2	0.688 - 0.666
	Wind park B	0.431 - 0.332	Strategy 1	0.421 - 0.336
			Strategy 2	0.450 - 0.394

*Baseline Models: Same models trained without utilising synthetic data from the style transfer

With baseline model



With synthetic data



Conclusions

→ Synthetic data augmentation via neural style transfer helps improve generalizability of standalone deep learners used for ice detection on turbine blades

→ Our study can help generate more effective predictions wherein the deep learners have not been previously trained with data from (e.g. new wind parks)

→ More effective icing predictions can help improve reliability of wind energy

→ Key limitation of the study is that our models are only able to showcase high accuracy for cases with high-quality images in the target dataset

→ Another limitation is in the data annotation of labels – which was done by two humans and can suffer from inherent bias during labelling

→ In future, we aim to automatically create segmentation masks with e.g. U-Net and fine-tune paired image-to-image translation models (like Pix2Pix) for improving characteristics of synthetic images

→ Future research could also focus on extending the classification based ice-detection onto a regression based approach for quantifying the ice accumulation

Universität Bremen

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Thank you!