# *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]
j.chatterjee@hull.ac.uk [*]

## Abstract

Wind energy's ability to liberate the world of conventional sources of energy relies on lowering the significant costs associated with the maintenance of wind turbines. Since icing events on turbine rotor blades are a leading cause of operational failures, identifying icing in advance is critical. Some recent studies focus on specific wind parks and fail to generalize to unseen scenarios (e.g. new rotor blade designs). We propose the utilisation of synthetic data augmentation via neural style transfer to improve the generalization of existing ice prediction models. We show that training models with augmented data that captures domain-invariant icing characteristics can help improve predictive performance across multiple wind parks. Through efficient identification of icing, this study can support preventive maintenance of wind energy sources by making them more reliable towards tackling climate change.

## 1 Introduction

With a growing awareness of the pressing need to transition to renewable energy sources globally towards combating climate change, the total global installed wind power capacity has touched over 837 GW in 2022 [1]. Winters are generally considered to be highly promising for wind power generation, owing to higher wind speeds and increased air density accompanied with low prevailing temperatures [2]. However, some countries, particularly in Northern Europe and North America, are highly prone to icing conditions on the wind turbine rotor blades – leading to high stress on the overall structure of the turbines that prohibits their safe operation [3, 4]. Such icing events not only give rise to unexpected downtimes, but also reduce the potential energy yield and shorten the mechanical lifetime of the turbines [5]. Most ice detection sensors mounted on rotor blades at present vary greatly in terms of their quality and are not sufficiently accurate [6, 7]. Additionally, these approaches suffer from several drawbacks [6] – such as inability to provide direct ice measurements. As a potential solution, there has been a rising interest in leveraging colour images (RGB) of turbine rotor blades acquired through cameras installed on the nacelles and applying computer vision techniques for detecting ice accretion on the surface of the blades [8, 9]. A camera generally captures images of the complete rotor blade even under harsh weather conditions (e.g. foggy environments), making this technique more robust than sensor-based approaches [10] and suitable for remote autonomous inspection [11].

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There has been very limited research in applying Artificial Intelligence (AI) techniques for ice detection on rotor blades. Some studies [12, 13, 14, 15, 16] have utilised operational Supervisory Control and Data Acquisition to train conventional machine learning models (e.g. Decision Trees) as well as leveraged Deep Learning (DL) for ice detection. Only a few studies have applied DL for detecting icing based on image data [4, 6]. While the existing studies have achieved near-perfect accuracy [4] with pre-trained Convolutional Neural Networks (CNNs), they are only effective in detecting icing on the rotor blades for the wind park from which the original training images were sourced. However, our experiments show that such models seem to perform poorly in generalizing to different wind parks – thus making them unsuitable for ice detection in new scenarios (e.g. with new rotor blade characteristics). We aim to tackle this challenge by facilitating domain adaptation – our goal is to ensure that a model trained on data from a specific wind park (source domain) is able to make effective predictions in new park locations (target domain). We propose the utilisation of synthetic data augmentation via neural style transfer with CNNs. The proposed method helps in the generation of synthetic images that can capture transferable fine-grained icing representations that are not bound to a specific wind park. By training the domain-specific models with the curated synthetic data, the generalizability of the models is improved towards detecting icing across different wind parks. This can help facilitate adoption of such domain-agnostic models across multiple wind parks in the near future for preventive maintenance of turbines, providing instrumental decision support for making wind turbines more reliable towards tackling climate change.

## 2 Dataset description and pre-processing

For our study, we utilised RGB images recorded by cameras in two real-world wind parks – *wind park A* located in North America and *wind park B* located in Northern Europe. Note that the images acquired from *wind park A* are of significantly higher quality than *wind park B* owing to better camera quality and placement. The images were manually labelled into three classes by two humans (with cross-validation also performed between the labels) – no rotor blade on foreground, rotor blade without icing and rotor blade with icing. We experiment with both scenarios – *wind park A* as source domain and *wind park B* as target domain and vice versa. The training data of the base sets contains 150 background images, 20 rotor blade images plus 50 rotor blade images from the target domain and 70 icing images from the source domain. The rotor blade and ice images are augmented with up to 10% random rotation, reaching 400 images. The test data includes 200 images of each class for *wind park A* and 800 for *wind park B*.

## 3 Proposed Methodology and Learning Models

We intend to utilise existing DL-models which have already achieved success in domain-specific ice detection in past literature as baselines, including MobileNetV2, VGG19 and Xception. We utilised the same dataset types from wind parks used in the past study in our experiments for fair comparison [4]. However in this study, we aim to develop models that are fine-tuned to the domain-specific target using synthetic data for better generalization to other wind parks. As successful training of CNN models for domain-specific applications requires substantial amounts of data, the networks generalize poorly on the face of small, limited datasets with significant class imbalance [17]. As the existing models are domain-specific and bound to distinct wind parks, we apply transfer learning to accomplish generalized ice detection that is independent of characteristics of the wind parks the models have previously been trained on. Consider the RGB images from *wind park A* as the *source* domain, and the images from *wind park B* as the *target* domain (or vice versa). The target domain is significantly different from the source because of the varying rotor blade shape, background of the geographical area, quality of the recorded images etc. However, both domains show some similarities regarding the presence or absence of ice. The goal is to train models which can make more effective predictions for the *target* domain, when trained only with ice images from the *source* domain. Therefore, we chose neural style transfer with CNNs [18, 19] to perform synthetic data augmentation that is utilised to train the standalone ice-prediction models.

The neural style transfer algorithm employs an optimisation technique to transform a *content* image to the style of a reference *style* image – while ensuring that the weighted sum of the *content loss* and *style loss* functions computed across the *content*, *style* and *generated stylised* images are minimised. We also experimented with a more modern approach – a CycleGAN [20]. While the CycleGAN does

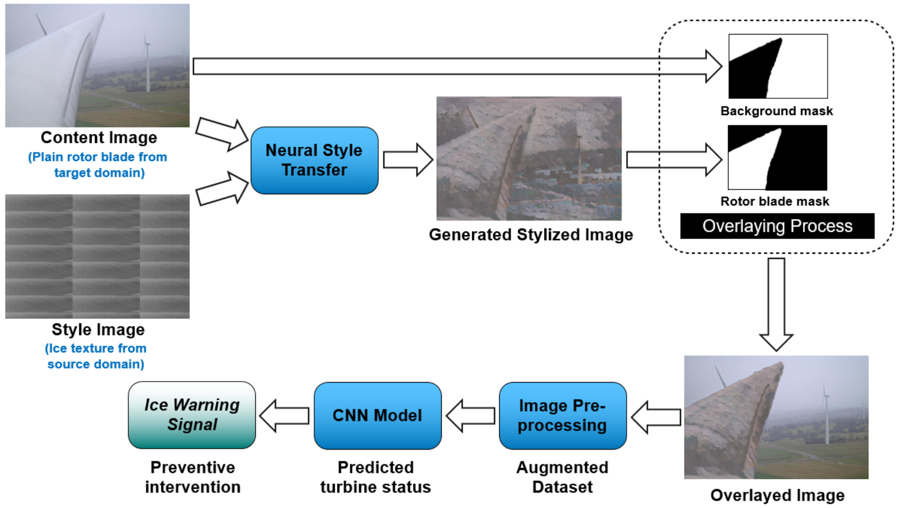


Figure 1: Framework for generalized ice detection with neural style transfer. Plain rotor blades in the target domain are styled with ice from the source domain.

not require a corresponding *style* image to generate stylised images as it directly learns transferable representations from the *content* image, we observed that the CycleGAN generated sub-optimal results for our problem – likely due to the small size and significant class-imbalance in our data set. For our study, we used a combination of two different approaches for synthetic image generation: **(1)** A VGG19 model architecture [21] (originally pre-trained with weights from ImageNet for image classification) **(2)** A pre-trained fast style transfer model (leveraging arbitrary image stylization [22]) (no fine-tuning required). We leverage images from the source domain that represent the ice texture in the rotor blades as *style* images. Note that the icing characteristics in wind turbine rotor blades are domain-invariant irrespective of rotor blade designs in the different wind parks – we aim to reproduce this characteristic in our study. The goal is to modify the plain rotor blade images of the target domain (*content* images) with the icing characteristics of the source domain, to improve the generalizability of the model. To specifically modify the parts of the source image which contain the rotor blade, we followed an overlaying process – wherein, a mask is applied to the *content* image and a reverse mask is applied to the *generated stylised* image. The overlayed images are pre-processed (as discussed in Section 4) and finally utilised for training the CNN models for generalized ice detection. Figure 1 depicts the complete process of the proposed approach.

# 4 Experiments

Three models - MobileNetV2, VGG19 and Xception were trained – as these have achieved the best results in the past study in our domain [4]. Before feeding in the images to the models, the default pre-processing steps (e.g. reshaping the images) were followed. Two distinct strategies were used to train the CNN models – **Strategy 1:** An output layer (dense layer, three classes) was appended to the model and all model layers were trainable. **Strategy 2:** The generic model backbone was frozen and only the output layer (dense layer, three classes) appended to the model was trainable. For both strategies, we used Stochastic Gradient Descent for optimisation with an initial learning rate of 0.0015 and momentum of 0.9, and a learning rate scheduler that decreases the learning rate every 3 epochs by a factor of 0.94. The models were trained for 30 epochs with a batch size of 16.

For neural style transfer, we leveraged the intermediate layers (without the classification head) of the VGG19 model and applied the Adam optimiser with a learning rate of 0.02, *beta_1*=0.99 and *epsilon*=0.1 to train the model for 40 epochs with 100 steps per epoch and modify the *content* with the *style* from our pre-processed images. As the generation of the images at this stage leads to high frequency artifacts and significant variation loss, a denoising process for further optimisation of the images over 40 epochs with 100 steps per epoch and a total variation weight of 30 was used. Default hyperparameters values for the fast style transfer model [22] were applied. 50 rotor blade images of the target domain are style-transferred to generate 200 additional synthetic images for the ice class with the previously described techniques.

Table 1: Results with the training strategies for both wind parks used as target datasets – with synthetic data, the model performance is improved compared to the baselines and the best F1 scores are highlighted in bold.

| Model | Target Data set | Baseline (% Acc - F1) | Training strategy | Synthetic (% Acc - F1) |
|---|---|---|---|---|
| MobileNetV2 | *Wind park A* | 63.3 - 0.528 | Strategy 1 | 68.5 - 0.652 |
| | | | Strategy 2 | 69.6 - 0.664 |
| | *Wind park B* | 39.4 - 0.289 | Strategy 1 | 41.2 - 0.307 |
| | | | Strategy 2 | 46.2 - 0.400 |
| VGG19 | *Wind park A* | 60.2 - 0.488 | Strategy 1 | 66.2 - 0.622 |
| | | | Strategy 2 | 83.6 - **0.831** |
| | *Wind park B* | 39.6 - 0.284 | Strategy 1 | 43.5 - 0.389 |
| | | | Strategy 2 | 45.8 - **0.402** |
| Xception | *Wind park A* | 64.1 - 0.516 | Strategy 1 | 70.9 - 0.666 |
| | | | Strategy 2 | 68.8 - 0.666 |
| | *Wind park B* | 43.1 - 0.332 | Strategy 1 | 42.1 - 0.336 |
| | | | Strategy 2 | 45.0 - 0.394 |

# 5 Results

Table 1 describes the experimental results obtained on training the three different CNN models for generalized ice detection, following the two different training strategies described in Section 4. Note that we also used two distinct target datasets for evaluating the models – *wind park A* and *wind park B*. The baseline models were trained without the synthetic images while using the synthetic data the model makes predictions for the target dataset when only trained with images from the source domain. Based on the F1 score, clearly, the VGG19 model achieves the best performance in generalized ice detection with synthetic images (see Table 1). Additionally, this model achieves an accuracy of up to 83.6% and F1 score of 0.831 for *wind park A* as the target dataset, representing an accuracy gain of 19.5% compared to the best baseline model for *wind park A* (Xception with 64.1% accuracy and F1 score of 0.516). While the prediction results are not as promising when *wind park B* is used as the target dataset (which may primarily be due to the lower quality of images in *wind park B* compared to *wind park A*), the proposed approach still showcases a noticeable performance gain compared to the baseline models. These results highlight that the proposed approach yields improved predictions for the target domain when the models are only trained with images from the source domain.

# 6 Conclusion

The study shows that synthetic data augmentation through neural style transfer improves the generalization of models used for ice detection. To the best of our knowledge, this is the first study to propose generalized detection of ice accretion on rotor blades and can be useful in making more effective icing predictions e.g. in new wind parks that the DL-models have not been previously trained on. This can help improve the reliability of wind turbines, making them a more promising source of renewable energy. Despite its promise, this study has a limitation of only being able to demonstrate high accuracy in generalized ice detection when the target dataset has high quality images, while with lower quality images the performance gain is marginal. Another limitation may be the hand-labelling of data in our study. Although two different humans annotated the datasets, models trained with such data may be affected by the inherent bias of the annotators. Future work aims to automatically create segmentation masks using U-Net, to feed them to paired image-to-image translation models like Pix2Pix towards improving the characteristics of synthetic images. In addition, future research may use regression models for quantifying the ice accumulation.

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