Anomaly Detection for the Identification of Building Components Defects

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Introduction

- Building inspection is crucial for assessing a building's condition and functionality.
- Automating inspection through anomaly detection could improve accuracy and efficiency.
- This study contributes to developing and approach for defecting detects in roofs and window casings in a real-world dataset.
- The research evaluates the performance of the PatchCore anomaly detection model and provides new insights by employing different backbones and their respective layers, as well as retraining them for various computer vision tasks.

Materials and Methods

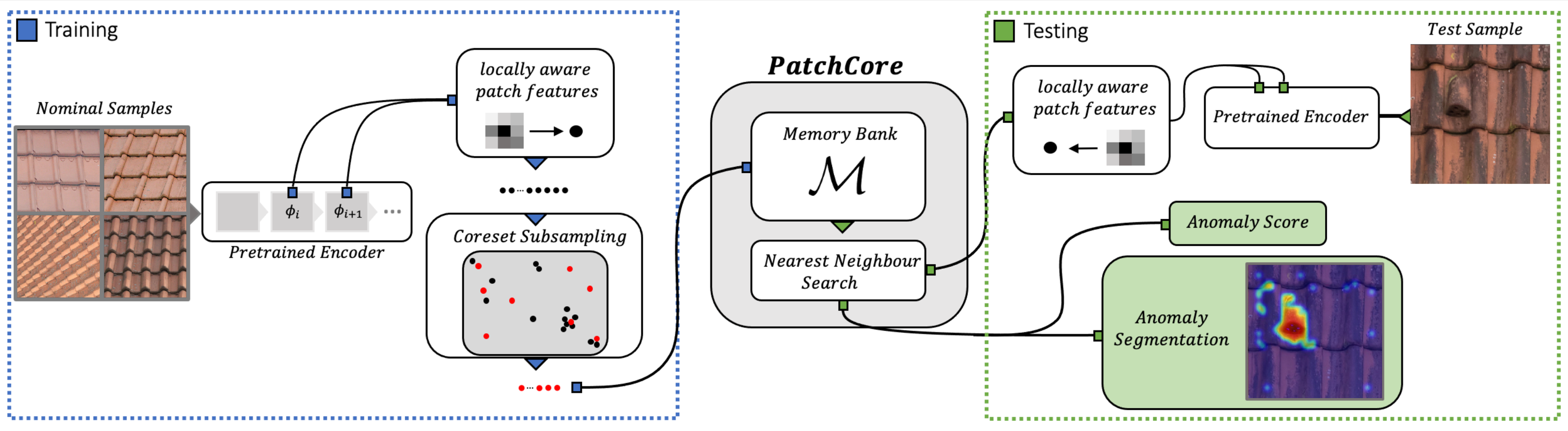


Figure 1. Overview of PatchCore Anomaly Detection model , adopted from [1]

Abstract

This paper focuses on automatic identification of defective roofs and window casings using anomaly detection. A dataset of drone images from the Netherlands is utilized. The PatchCore anomaly detection model as one of the state of the art model was used in this study. We utilized different backbone networks, retrained them with same dataset for classification and segmentation task and different feature extraction layers. WideResNet50 with layers 2 and 3 performs best on the Casings dataset, while the model's performance on the Roof dataset is unsatisfactory. The tiled roof dataset shows improved results and Retrained ResNet50 backbone was the best configuration. The study approved influence of using different setting for the model.

PatchCore Anomaly Detection Model:

- The PatchCore model works by dividing an image into patches and extracting features of normal image by a backbone network from them. We explored alternative backbone networks, retrained them, and leveraged deeper layers of extracted features to improve the performance of the model.

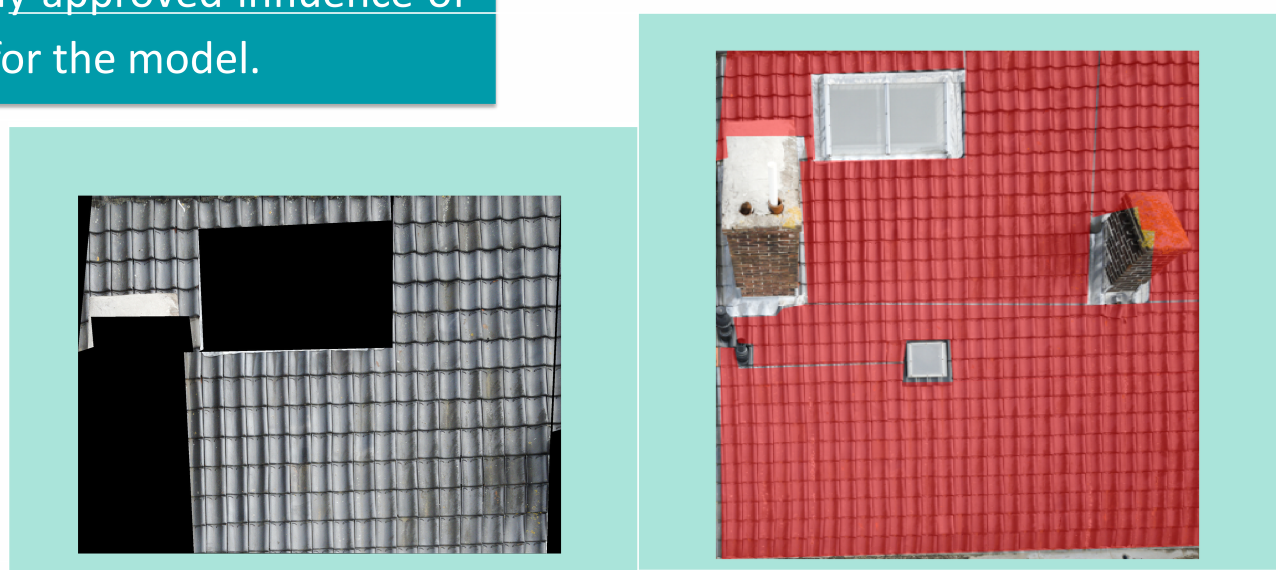
Dataset:

- The images captured by a drone from various buildings and locations in the Netherlands, obtained from an aerial scan company (Aeroscan) and building components and defects annotated by them. Window casings and roof components were cropped from the original images.

An original Image with overlayed masks of components and defects

Cleaned Cropped Casings

Figure 3. An example of preparation for the casings



A Cleaned Cropped roof

An original Image with overlayed masks of components

Figure 2. An example of preparation for the whole roofs

- **Tiled Roof**: To address the wide variety and imbalance between good and defective samples in the whole roof dataset, we divided roof images into tiles of 256 x 256, resulting in a more balanced and homogeneous dataset for roof analysis.

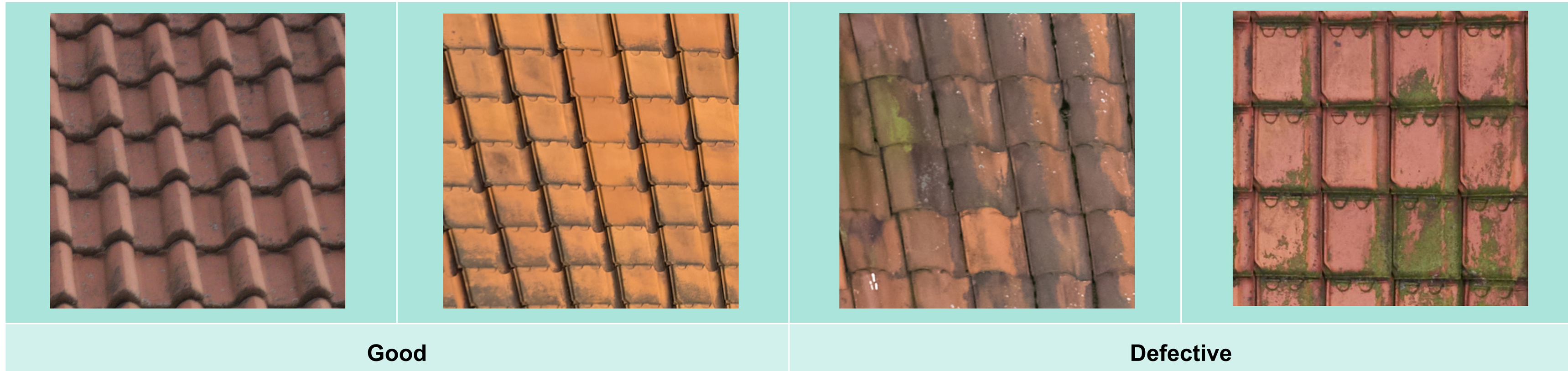


Figure 4. Examples of prepared roof tiles

Experiments and Results

- We employed different backbone networks and experimented with varying layers for feature extraction across the Casing, Roof, and Tiled Roof datasets. Additionally, we explored using default pre-trained weights and re-training the networks on our own data.

Anomaly Detection Results						
Dataset	Backbone Network	Feature Layers	F1-score	AUC	Good Class Accuracy	Defective Class Accuracy
Casing	Pretrained WideResNet50	2, 3	60.4% (0.06)	61.0% (0.06)	65.6% (0.12)	56.3% (0.07)
Roof	Retrained ResNet50 (Classification)	2, 3, 4	55.0% (0.02)	57.6% (0.02)	64.3% (0.1)	50.9% (0.07)
Tiled Roof	Retrained ResNet50 (Classification)	2, 3, 4	82.2% (0.01)	82.2% (0.01)	80.9% (0.03)	83.6% (0.04)

Table 1. Results of the best setting experiment for each dataset; The numbers represent the average and STD of 10 runs for each experiment.

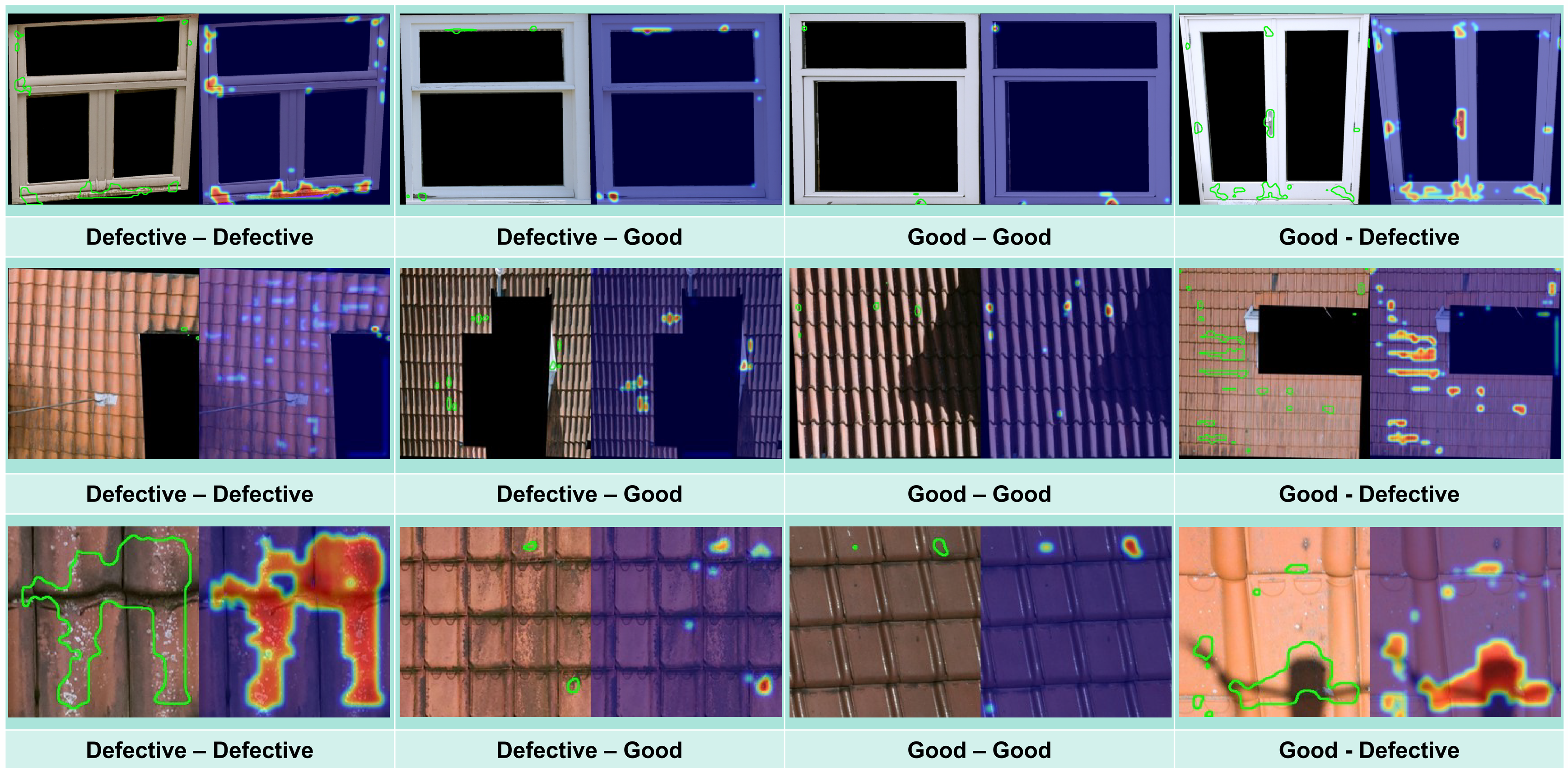


Figure 5. Output of the model for Casing, Roof and Tiled Roof Dataset - Right image depicts heatmap of potential defects on the resized original image, while the left image shows the contour overlay of the heatmap for precise localization of potential defects. In the sub-captions, the left ones are ground truths and right ones are predictions.

- PatchCore anomaly detection technique showed superior performance in identifying defects in casing images using the WideResNet50 backbone with layers 2 and 3.
- The Tiled Roof Dataset significantly improved the model's performance, with the ResNet50 Retrained network with layers 2, 3, and 4 achieving the highest F1-Score and AUC;
- As Figure 5 shows, the model performs well for certain types of defects on casing and tiled roofs. However, there is still room for improvement when it comes to specific types of defects or problem with false positive detection of shadows.

Conclusions

- Utilizing alternative backbone networks, retraining them for the classification task, and leveraging deeper layers of extracted features improved anomaly detection performance.
- Challenges included diverse roof conditions, extensive manual cleaning of annotations, variations in image angles and distances, and object obstructions.
- By utilizing retrained backbones, the low-level features present in deeper layers gain more relevance, leading to potential improvements in the results.
- The PatchCore anomaly detection model incurs high computational costs and memory requirements, but employing a simpler network architecture like ResNet18 reduced costs while small decrease in performance.

Acknowledgements

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References

- [1] Thomas Defard, Aleksandr Setkov, Angelique Loesch, and Romaric Audigier. Padim: a patch distribution modeling framework for anomaly detection and localization. In Pattern Recognition. ICPR International Workshops and Challenges: Virtual Event, January 10–15, 2021, Proceedings, Part IV, pages 475–489. Springer, 2021.