Abstract

In recent years, several companies and researchers have started to tackle the problem of damage recognition within the scope of automated inspection of built structures. While companies are neither willing to publish associated data nor models, researchers are facing the problem of data shortage on one hand and inconsistent dataset splitting with the absence of consistent metrics on the other hand. This leads to incomparable results. Therefore, we introduce the building inspection toolkit – bikit – which acts as a simple to use data hub containing relevant open-source datasets in the field of damage recognition. The datasets are enriched with evaluation splits and predefined metrics, suiting the specific task and their data distribution. For the sake of compatibility and to motivate researchers in this domain, we also provide a leaderboard and the possibility to share model weights with the community. As starting point we provide strong baselines for multi-target classification tasks utilizing extensive hyperparameter search using three transfer learning approaches for state-of-the-art algorithms. The toolkit\textsuperscript{1} and the leaderboard\textsuperscript{2} are available online.

1. Introduction

Bridges represent a very important part of the infrastructure worldwide. Their closure, reconstruction or abrupt failure due to poor maintenance leads to economical damage or – even worse – the loss of human lives, what happened in Genoa, Italy in 2018 \[20\]. Therefore, the availability of functioning and safe bridges is crucial. Due to the fact that many bridges are currently reaching ages at which damages occur more often \[7,21\] the assessment intervals must be set more frequently, which increases the pressure on individual inspectors.

Inspectors usually perform a visual assessment from a short distance to the structure taking pictures and notes of every damage, which is very time consuming. Moreover the classification of the damages heavily depends on the inspector’s personal impression. Thereby, the detected damage classifications and recommended consequences in the final reports of different inspectors validating the same building can differ \[19\]. Due to the above mentioned points, an automated damage classification would bring great benefits, like (i) saving time and lowering the costs for the assessment process, (ii) less subjective damage classification, (iii) no need of additional machinery (e.g. mobile under-bridge unit) if UAVs are used to gather the image data, and (iv) the ability to execute routine inspections by less experienced employees.

We want to accelerate the development in the context of damage recognition and therefore introduce bikit. It is designed to be an easy to use platform and consists of three components: (i) datasets with fixed splits, (ii) a public leaderboard with predefined metrics, and (iii) the availability to upload trained models. First, bikit will make all known datasets available with a simple API. Although being a niche area, there is a reasonable number of datasets for reinforced concrete damages (RCD). Most of them are binary classification datasets that examine the presence of cracks \[17,29\] or damages in general \[11\]. Besides that, there are also more detailed and realistic multi-target dataset \[12,18\].

\textsuperscript{1}https://github.com/phiyodr/building-inspection-toolkit
\textsuperscript{2}https://dacl.ai
available. In the current bikit version we provide all open-source datasets. Apart from accessibility, comparability is another crucial feature. Hence, fixed test sets and useful metrics are required. We supply predefined training, validation, and testing splits if missing. On the basis of data distribution, we create individual splits. Moreover, useful metrics are defined for each dataset for performance evaluation. All datasets are provided with a strong baseline using state-of-the-art algorithms. For this purpose, we run an expensive hyperparameter search using three different transfer learning strategies on famous (pre-trained) models and make these available online.

2. Similar Approaches

Data and Model Hubs. Machine learning research is based on the availability of data. In recent years, the number of datasets that are open to the public has continued to grow and the usage has been simplified. Established standard data for various domains is directly accessible via TensorFlow or PyTorch modules. However, specialized hubs have developed as well. For example, datasets [15] is a platform for a large number of NLP datasets from a wide variety of fields. Besides renowned datasets – often cited in research – niche datasets and low-resource languages can also be accessed. OpenML [25] provides metrics and leaderboards in addition to data and helps not only with readily available data but also with results on specific hyperparameter settings. In terms of supply of metrics, the same is true for FAIR’s paperswithcode.com [13]. Moreover, computer vision platforms like timm [27] do not only provide high-quality code for established models but also model weights to simplify usage and accessibility. The above mentioned developments accelerate research and make results more comparable.

Transfer Learning. The most comprehensive work in the area of RCD recognition was executed by Bukhsh et al. [2]. They investigated several concepts of transfer learning for six classification datasets. Transfer learning strategies consist of varying combinations of upstream and downstream datasets using cross-domain and in-domain data. Hence, training from scratch has been evaluated as well. Results show that in-domain and cross-domain perform almost identically well for small datasets, but training on both data types together improves the performance. In their analysis, common CNNs that have been developed before the year 2015, were taken into account. We decided to use more recent architectures for our analysis. Moreover, they only trained the networks’ head. Besides that, we also investigate the gain of updating the whole model.

3. Building Inspection Toolkit

The toolkit consists of three parts, which are elaborated in more detail in the following sections. The first building block are the datasets conceived by other researchers and now harmonized into one module [22]. We also add training, validation and testing data splits, if they do not exist. The second component is the introduction of performance metrics, which fit task type and data distribution. Results are made available via an online leaderboard. As a third part we launch a model hub to make models accessible.

### 3.1. Datasets

Several RCD datasets are publicly available for single-target and multi-target classification (see Tab. 1). To our knowledge no open-source object detection and semantic segmentation datasets exist currently. In this publication we deal with the two multi-target classification datasets MCDS [12] and CODEBRIM [18]. They are more challenging than single-target classification tasks and also more realistic, since several damages can be present on one image at the same time. Moreover, images are taken in a less standardized setting with different camera angles and image resolutions.

In total, there are seven specific damage types, that are currently available in RCD datasets, i.e. cracks, efflorescence, spalling/spallation, exposed bars/reinforcement, rust staining/corrosion strain, scaling, and other/general defects. Other types exist, but are aggregated in meta classes. CDS [11] summarizes graffiti, vegetation, and blistering within the label “unhealthy”. MCDS subordinates graffiti and vegetation to “other damages”. So far MCDS is the most diverse dataset available, whereas the German guideline for uniform acquisition, assessment, recording and evaluation of results of structural inspections [3] currently distinguishes approximately 50 damages in total. To conclude, there is still a lot of work to be done, until machine learning-based systems can reliably support civil engineers.

| Data     | Classes | Types | Size  | Splits |
|----------|---------|-------|-------|--------|
| CDS [11] | 2       | STC   | 1,028 | no     |
| BCD [29] | 2       | STC   | 5,390 | ✓      |
| SDNET2018 [6] | 2 | STC   | 13,620 | no   |
| ICCD [17] | 2       | STC   | 60,010 | ✓    |
| MCDS [12] | 8       | MTC   | 3,607 | no    |
| CODEBRIM [18] | 6 | MTC   | 7,261 | ✓     |

Table 1. Open-source datasets for damage recognition on reinforced concrete bridges. Types are single-target (STC) and multi-target classification (MTC). Splits refer to the presence of fix training, validation and testing splits in the original publication.

3Data is only available upon request.
MCDS. This dataset [12] was created for a three-stage approach where, depending on the results of the first model, a second model may be applied and, depending on that, a third. This dataset was recently transformed into a single-stage approach [2], whereby data acquisition procedure was neglected. The second and third stages determine, whether exposed bars and rust staining is visible. The negative samples have been drawn from stage-one dataset. Hence, only a few images without exposed bars had the label “no exposed bars”. The same applies for “no rust”. We cleaned the dataset and transferred it to an eight-class dataset. Due to the fact that no data splits were provided we introduced fix splits for training (2057 samples), validation (270), and testing (270).

CODEBRIM. This dataset is the second richest in terms of damage categories. It is missing two classes in comparison to MCDS but comes with a much higher number of unique images. The authors also made splits available so that all former research is comparable and no splits need to be created. The numbers for each split are 6013 (training), 616 (validation), and 632 (testing). We use the balanced version for our experiments.

3.2. Metrics

The authors of MCDS decided to provide a huge number of metrics. They show 10 different metrics for all three stages and for all classes, which is exhausting. On the other hand CODEBRIM authors chose to report Exact Match Ratio (EMR) only. Later analysis [2] chose AUROC, accuracy, F1-score, precision, and recall on an aggregated level (not on class level). We go a middle course between one overall metric and 10 metrics for each class. The main metric for multi-target classification in bikit is EMR. Besides that we provide recall by class. We make both metrics accessible in an online leaderboard.

EMR. EMR is a challenging task since all predictions must match. It is, for example, relatively simple to determine cracks in comparison to other classes. Moreover, crack is the class with the highest occurrence (see Tab. 2). From this follows that metrics which weight classes equally or, worse, by occurrence are biased towards easily determinable classes, like cracks. This makes some metrics appear better than they are. While EMR is not a metric created directly for unbalanced data, it is complex enough so that the distribution problem is adequately addressed. Moreover, a side effect is that current values are still not close to perfect fit, which still leaves room for improvement within this research domain.

Recall by class. The previous metric was primarily selected from a machine learning perspective. However, when applied in the real world other metrics are of importance. For civil engineers it is mainly relevant to see how many damages are overlooked. In current approaches, machine learning-based software is made to support and not to replace engineers. Consequently, it is more vital to detect all damages which exist than missing risky damages. Due to that fact, we decided to provide recall measures for all classes, in order to be able to see where current models still fail often.

3.3. Model Hub

Besides providing a data API and performance results on a leaderboard, we also create a model hub to accelerate research. Having pre-trained models available does not only help to reproduce results but also to obviate the need to fine-tune models again and again. This is especially interesting if researchers want to adapt pre-trained classification models for later use in object detectors or for semantic segmentation tasks. We provide strong baseline models for both datasets elaborated in the next chapter.

4. Strong Baselines for Damage Recognition

To fill the model hubs with strong baselines we use three modern CNN architectures and conduct an extensive hyperparameter search with three different transfer learning strategies.

Architectures. The used CNNs are ResNet50 (RN) [8], MobileNetV3-Large (MN) [9], and EfficientNetV1-B0 (EN) [24], which all belong to a set of state-of-the-art models. We initialize the models with weights from ImageNet [5] training. The original heads are removed and replaced by two fully connected layers that have dropout applied before each layer.

Transfer Learning and Hyperparameter Search. In total we want to train and compare three different transfer learning strategies, which are described in detail in Section 4.1. For computational reasons, we only will run the extensive hyperparameter search on the simplest strategy and then transfer knowledge to the other approaches. This is elaborated in Section 4.2.

| Classes          | MCDS  | CODEBRIM |
|------------------|-------|----------|
| No Damage        | 452   | 2,506    |
| Crack            | 787   | 2,507    |
| Efflorescence    | 304   | 833      |
| Spalling         | 422   | 1,898    |
| Exposed Bars     | 221   | 1,507    |
| Rust             | 350   | 1,559    |
| Scaling          | 163   | -        |
| Other damages    | 264   | -        |
| Number of images | 2,597 | 7,261    |
| Avg. number of classes/image | 1.14 | 1.13    |

Table 2. Counts of classes in datasets with additional statistics.


| Hyperparam.       | Hyperparameter space |
|-------------------|----------------------|
| Hidden layer      | 16, 32, 64, 128, 256, 512, 1024 |
| Batch size        | 16, 32 (MCDS); 64, 128, 256, 512 (both) |
| Learning rate     | 1e-4, 5e-4, 1e-3, 5e-3, 1e-2 |
| Scheduler         | Constant (CtW), Cosine (CeW) w/ warmup |
| Dropout           | 0, 0.1, 0.2, 0.3, 0.4 |
| Weight decay      | 1e-7, 1e-6, 1e-5 |

Table 3. Values for the initial parameter search (HO) for MCDS and CODEBRIM. The best hyperparameter settings are displayed in Tab. 4.

#### 4.1. Transfer Learning Strategies

We use one standard approach and two more advanced strategies. The first only updates the head’s weights (HO), the second initially trains the head and then all parameters (HTA), the last applies different learning rates for model head and base (DHB) follows visualization II but with two learning rates.

**Figure 2.** Descriptions of all three transfer learning approaches, where dashed lines indicated trainable weights. *Heads only* (HO) equals the visualization I on the left, *Heads, Then All* (HTA) approach is sequential usage of visualization I and II, and *Different learning rates for Head and Base* (DHB) follows visualization II but with two learning rates.

| Data  | Hyperparameters   | RN  | EN  | MN  |
|-------|-------------------|-----|-----|-----|
| CODEBRIM | Hidden layer   | 128 | 256 | 1024|
|       | Batch size       | 256 | 256 | 64  |
|       | Learning rate    | 1e-5| 1e-7| 1e-6|
|       | Scheduler        | CtW | CeW | CeW |
|       | Dropout          | 0.2 | 0.4 | 0.3 |
|       | Weight decay     | 1e-5| 1e-7| 1e-6|
| MCDS  | Hidden layer     | 32  | 32  | 64  |
|       | Batch size       | 64  | 32  | 64  |
|       | Learning rate    | 5e-3| 5e-3| 5e-3|
|       | Scheduler        | CeW | CtW | CtW |
|       | Dropout          | 0.0 | 0.4 | 0.2 |
|       | Weight decay     | 1e-5| 1e-7| 1e-6|

Table 4. Best hyperparameter results for HO from Bayesian Search for ResNet (RN), EfficientNet (EN), and MobileNet (MN). Possible settings and abbreviations are listed in Tab. 3.

#### 4.2. Hyperparameter Search

We defined a rich set of parameters, which are investigated in our hyperparameter approach for HO. Results are used to reduce the parameter space for two other approaches. All models are trained with comprehensive data augmentation (see Appendix A) and using Adam optimizer with weight decay.

**HO.** Training only the head of a pre-trained model is the most straightforward approach for transfer learning. Hence, we apply the large hyperparameter space to both datasets and all three CNN models. We test different sizes of the hidden layer and various dropout rates. Moreover, we experiment with weight decay for Adam and different batch sizes,
| Data     | Learning rate |
|----------|---------------|
| CODEBRIM |               |
| HTA      | 1e-5          |
| DHB head | 1e-4          |
| DHB base | 1e-5          |
| MCDS     |               |
| HTA      | 1e-7          |
| DHB head | 1e-4          |
| DHB base | 1e-5          |

Table 6. Best learning rate results for HTA and DHB for ResNet (RN), EfficientNet (EN), and MobileNet (MN). Possible learning rate settings are listed in Tab. 5.

We want to share strong baseline models for CODEBRIM as well as MCDS and therefore, went through an expensive evaluation process. We run a hyperparameter search for three state-of-the-art architectures and investigate three different transfer learning strategies. We use EMR as our main metric, but also provide recall per class for a more detailed explanation for applicants. To ensure that our results are reliable, we repeat each final hyperparameter setting five times. This allows us to understand better how trustworthy the outcomes are. Our results are reported in Fig. 3, Fig. 4, and Tab. 7. The best results of the five runs are made available in Tab. 7.

5. Results of Hyperparameter-Tuning and Transfer Learning Analysis

![Figure 3. EMR of five runs with different seeds for CODEBRIM dataset. The used model setups are described in Tab. 4 for HO and in Tab. 5 HTA and DHB.](image)

![Figure 4. EMR of five runs with different seeds for MCDS dataset. The used model setups are described in Tab. 4 for HO and in Tab. 5 HTA and DHB.](image)

HO HTA DHB

Exact Match Ratio

RN MN EN RN MN EN RN MN EN

Figure 4. EMR of five runs with different seeds for MCDS dataset. The used model setups are described in Tab. 4 for HO and in Tab. 5 HTA and DHB.

CODEBRIM. We observe that CODEBRIM results are stable. For the more flexible HTA and DHB approaches, ResNet is the best model with approximately 4 and 1.4 percent margin to the second best model in the respective transfer learning group. Considering HO, ResNet is on a par with MobileNet. The overall best result shows ResNet with HTA, which scores 73.73 percent on EMR. This model outperformed the initially published model slightly by 1.5 percent points [18]. Bukhsh et al. does not provide EMR but AUROC. They score 90 percent⁴, whereas we score 97 percent at AUROC. The recall is the lowest for efflorescence (75.84 percent) and the highest for recognizing exposed bars (88.67 percent). The current best CODEBRIM model still missed 1/4 of efflorescence damages, which is probably related to the small number of images. On the other hand, results for exposed bars are already in a good range.

MCDS. MCDS results are less distinct, as the dispersion for some settings in Fig. 4 indicates. This may be primarily due to the small dataset size. As for CODEBRIM, the more flexible transfer learning approaches perform better. The

⁴They use 10 classes and splits are not published.
best model is MobileNet with HTA transfer learning and it has a 3.5 percentage point lead over the second best model. With a top EMR of 54.44 percent, performance on this dataset is substantially worse than for CODEBRIM, which is again due to the dataset size. Recall is best for efflorescence, where 9 out of 10 damages are detected. The lowest recall is obtained for exposed bars, which have the second smallest number of images in MCDS. Since the original [12] and modified setting [2] are structured differently and no fix splits are provided, we cannot compare results to former research.

Transfer learning. Our results show that not only training of the head but also the base part of the architecture clearly improves transfer learning results. We have included these strategies because RCD images differ a lot from ImageNet objects which were used for the pre-training of our models. There can be no conclusive assessment of which strategy performs better since we only evaluated this on two very specific datasets. This leads to the conclusion that, after the classical HO approach has been conducted, it is reasonable to train all weights. DHB has the advantage of requiring only one pass.

6. Conclusions

The building inspection toolkit simplifies access to datasets and introduces splits in case they are missing. It builds the base for a unified evaluation process by providing metrics from the machine learning and the application perspective. Currently, EMR and recall by class are used. We also provide baseline models trained with three different transfer learning strategies. An online leaderboard finally facilitates comparability between models and accelerates the progress within this application oriented research area. Experiments on the CODEBRIM dataset showed that ResNet works best, whereas MobileNet with HTA is the best model for MCDS. During experiments we found that it is of great importance not only to train parameters in the model's head but also to update the filters in the base model. This is relevant because the pre-trained models were trained with images from a different domain and, therefore, it is beneficial if filters can be adjusted as well.

All parts of the building inspection toolkit will help to speed up research in RCD damage recognition and give it a higher priority and greater visibility. In future work, focus will be on combined occurrences of several damages, like spalling with exposed reinforcement and rust staining. It is planned to (i) extend data augmentation methods, like manipulating color space, injecting noise or mixing images [23], (ii) considering models that can attend to different damages and (iii) label correlations through a graph superimposing framework [26].
References

[1] Lukas Biewald. Experiment tracking with weights and biases, 2020. Software available from wandb.com.

[2] Zaharah A. Bukhsh, Nils Jansen, and Aaqib Saeed. Damage detection using in-domain and cross-domain transfer learning. Neural Computing and Applications, 33, 12 2021.

[3] Bundesanstalt für Straßenwesen. Richtlinie zur einheitlichen Erfassung, Bewertung, Aufzeichnung und Auswertung von Ergebnissen der Bauwerksprüfungen, February 2017.

[4] Ken Chatfield, Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. Return of the devil in the details: Delving deep into convolutional nets. Proceedings of the British Machine Vision Conference, pages 1–11, 2014.

[5] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. ImageNet: A large-scale hierarchical image database. In IEEE Conference on Computer Vision and Pattern Recognition, pages 248–255, 2009.

[6] Sattar Dorafshan, Robert J. Thomas, and Marc Maguire. SDNET2018: An annotated image dataset for non-contact concrete crack detection using deep convolutional neural networks. Data in Brief, 21(November):1664–1668, 2018.

[7] Matthias Hasbeck, Michael A Kraus, and Thomas Braml. Bayesian Reliability Assessment and System Identification for existing Concrete Bridge Structures. Proceedings of the 17th International Probabilistic Workshop, 2019.

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the Conference on Computer Vision and Pattern Recognition, pages 770–778, 2016.

[9] Andrew Howard, Mark Sandler, Bo Chen, Weijun Wang, Mihaelanor, and Li Fei-Fei. ImageNet: A large-scale hierarchical image database. In IEEE Conference on Computer Vision and Pattern Recognition, pages 248–255, 2009.

[10] Jeremy Howard and Sebastian Ruder. Universal language model fine-tuning for text classification. 36th Annual Meeting of the Association for Computational Linguistics, Proceedings of the Conference, 1:328–333, 2019.

[11] Philipp Hüthwohl and Ioannis Brilakis. Detecting healthy concrete surfaces. Advanced Engineering Informatics, 37(April):150–162, 2018.

[12] Philipp Hüthwohl, Ruodan Lu, and Ioannis Brilakis. Multi-classifier for reinforced concrete bridge defects. Automation in Construction, 105, Sep 2019.

[13] Facebook Inc. Papers With Code. https://paperswithcode.com, 2021.

[14] Simon Kornblith, Jonathon Shlens, and Quoc V. Le. Do better imagenet models transfer better? Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2019-June:2656–2666, 2019.

[15] Quentin Lhoest, Albert Villanova del Moral, Yacine Jernite, Abhishek Thakur, Patrick von Platen, Suraj Patil, Julien Chaumond, Mariama Drame, Julien Plu, Lewis Tunstall, Joe Davison, Mario Saško, Gunjan Chhablani, Bhavitvya Malik, Simon Brandeis, Teven Le Scao, Victor Sanh, Canwen Xu, Nicolas Patry, Angelina McMillan-Major, Philipp Schmid, Sylvain Gugger, Clément Delangue, Théo Matussière, Lysandre Debut, Stas Bekman, Pierre Cistac, Thibault Goehring, Victor Mustar, François Lagunas, Alexander M. Rush, and Thomas Wolf. Datasets: A community library for natural language processing, 2021.

[16] Lisha Li, Kevin Jamieson, Giulia DeSalvo, Afshin Rostamizadeh, and Ameet Talwalkar. Hyperband: A novel bandit-based approach to hyperparameter optimization. Journal of Machine Learning Research, 18:1–52, 2018.

[17] Shengyuan Li and Xuefeng Zhao. Image-Based Concrete Crack Detection Using Convolutional Neural Network and Exhaustive Search Technique. Advances in Civil Engineering, 2019.

[18] Martin Mundt, Sagnik Majumder, Sreenivas Murali, Panagiotis Panetos, and Visvanathan Ramesh. Meta-learning convolutional neural architectures for multi-target concrete defect classification with the concrete defect bridge image dataset. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2019.

[19] Brent M. Phares, Glenn A. Washer, Dennis D. Rolander, Benjamin A. Graybeal, and Mark Moore. Routine Highway Bridge Inspection Condition Documentation Accuracy and Reliability. Journal of Bridge Engineering, 9(4):403–413, 2004.

[20] Gaia Pianigiani. Poor Maintenance and Construction Flaws Are Cited in Italy Bridge Collapse. The New York Times, Dec. 2020.

[21] American Road and Transportation Builders Association (ARTBA). 2021 bridge report. 2021-11-09.

[22] Philipp J. Rösch and Johannes Flotzinger. Building inspection toolkit. https://github.com/phiyodr/building-inspection-toolkit, 2022.

[23] Connor Shorten and Taghi M. Khoshgoftaar. A survey on Image Data Augmentation for Deep Learning. Journal of Big Data, 6(1), 2019.

[24] Mingxing Tan and Quoc V. Le. EfficientNet: Rethinking model scaling for convolutional neural networks. 36th International Conference on Machine Learning, ICML 2019, June:10691–10700, 2019.

[25] Joaquin Vanschoren, Jan N. van Rijn, Bernd Bischl, and Luis Torgo. OpenML: Networked Science in Machine Learning. SIGKDD Explorations, 15(2):49–60, 2013.

[26] Ya Wang, Dongliang He, Fu Li, Xiang Long, Zhichao Zhou, Jinwen Ma, and Shilei Wen. Multi-label classification with label graph superimposing. 34th AAAI Conference on Artificial Intelligence, pages 12265–12272, 2020.

[27] Ross Wightman. PyTorch Image Models. https://fastai.github.io/timmdocs/, 2019.

[28] Christopher K Williams and Carl Edward Rasmussen. Gaussian processes for machine learning. MIT press Cambridge, MA, 2006.

[29] Hongyan Xu, Xiu Su, Huaiyuan Xu, and Haotian Li. Automatic bridge crack detection using deep convolutional neural networks. In 3rd International Conference on Computer Engineering, Information Science & Application Technology, pages 274–284. Atlantis Press, 2019.
A. Data Augmentation

The data augmentation process of all training sets follow the subsequent steps:

1. Resizing to 1.1 (≈ 1/0.875) times the input resolution 224 (cropping the central 87.5% is common for testing on ImageNet [14])
2. Center-cropping to a 224 × 224 image
3. Randomly rotating up to 30 degree
4. Flipping horizontally and vertically with 50% probability
5. Normalizing with the mean and standard deviation from ImageNet

The preprocessing of the validation and testing data involved resizing, center-cropping and normalization exclusively.