

## University of Groningen

### Correction to

Morales, David; Talavera, Estefania; Remeseiro, Beatriz

*Published in:*  
Neural Computing and Applications

*DOI:*  
[10.1007/s00521-021-06407-7](https://doi.org/10.1007/s00521-021-06407-7)

**IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.**

*Document Version*  
Publisher's PDF, also known as Version of record

*Publication date:*  
2022

[Link to publication in University of Groningen/UMCG research database](#)

*Citation for published version (APA):*

Morales, D., Talavera, E., & Remeseiro, B. (2022). Correction to: Playing to distraction: towards a robust training of CNN classifiers through visual explanation techniques . *Neural Computing and Applications*, 34(8), 6571-6574. <https://doi.org/10.1007/s00521-021-06407-7>

#### Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

#### Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

*Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.*



## Correction to: Playing to distraction: towards a robust training of CNN classifiers through visual explanation techniques

David Morales<sup>1,2</sup> · Estefania Talavera<sup>3</sup> · Beatriz Remeseiro<sup>4</sup>

Received: 14 August 2021 / Accepted: 14 August 2021 / Published online: 16 September 2021  
© Springer-Verlag London Ltd., part of Springer Nature 2021

### Correction to: Neural Computing and Applications

<https://doi.org/10.1007/s00521-021-06282-2>

Unfortunately, the article was published with some errors in Tables 1, 3, 5, and 7 and in the captions of Figures 1, 2, and 3 in the online version of the article.

The correct tables and figures are given (Tables 1, 3, 5, and 7 and Figs. 1, 2, and 3).

---

The original article can be found online at <https://doi.org/10.1007/s00521-021-06282-2>.

---

✉ David Morales  
david.morales@hattec.de

Estefania Talavera  
e.talavera.martinez@rug.nl

Beatriz Remeseiro  
bremeseiro@uniovi.es

<sup>1</sup> University of Granada, 18071 Granada, Spain

<sup>2</sup> HAT.tec GmbH. c/o Universität der Bundeswehr, Werner-Heisenberg-Weg 39, 85579 Neubiberg, Germany

<sup>3</sup> Department of Computer Science, University of Groningen, Nijenborgh 9, 9747 AG Groningen, The Netherlands

<sup>4</sup> Department of Computer Science, Universidad de Oviedo, Campus de Gijón s/n, 33203 Gijón, Spain

**Table 1** Classification performance, averaged across five runs, of the different approaches on the Stanford cars [11] and FGVC-Aircraft [12] datasets

	FT-ResNet50	0-occlusion	R-occlusion	1-occlusion
Stanford cars				
Accuracy	0.849 ± 0.009	<b>0.871 ± 0.007</b>	0.860 ± 0.009	0.869 ± 0.008
Precision	0.855 ± 0.007	<b>0.876 ± 0.007</b>	0.866 ± 0.008	0.873 ± 0.008
Recall	0.849 ± 0.009	<b>0.870 ± 0.008</b>	0.860 ± 0.009	0.868 ± 0.009
F1	0.848 ± 0.009	<b>0.870 ± 0.008</b>	0.859 ± 0.009	0.867 ± 0.009
FGVC-Aircraft				
Accuracy	0.731 ± 0.013	<b>0.749 ± 0.005</b>	0.739 ± 0.012	0.743 ± 0.005
Precision	0.746 ± 0.011	<b>0.762 ± 0.005</b>	0.755 ± 0.010	0.759 ± 0.004
Recall	0.731 ± 0.013	<b>0.749 ± 0.005</b>	0.739 ± 0.012	0.743 ± 0.005
F1	0.731 ± 0.014	<b>0.748 ± 0.005</b>	0.739 ± 0.012	0.743 ± 0.005

Best results are in bold

**Table 3** Classification performance, averaged across five runs, making use of different backbones on the Stanford cars [11] and FGVC-Aircraft [12] datasets

	FT-InceptionV3	0-occlusion-InceptionV3	FT-DenseNet	0-occlusion-DenseNet
Stanford cars				
Accuracy	0.778 ± 0.023	<b>0.791 ± 0.020</b>	0.883 ± 0.010	<b>0.894 ± 0.011</b>
Precision	0.788 ± 0.021	<b>0.798 ± 0.020</b>	0.888 ± 0.009	<b>0.898 ± 0.011</b>
Recall	0.777 ± 0.023	<b>0.791 ± 0.020</b>	0.882 ± 0.010	<b>0.893 ± 0.012</b>
F1	0.776 ± 0.023	<b>0.790 ± 0.021</b>	0.882 ± 0.010	<b>0.893 ± 0.012</b>
FGVC-Aircraft				
Accuracy	0.618 ± 0.029	<b>0.633 ± 0.026</b>	0.767 ± 0.026	<b>0.780 ± 0.025</b>
Precision	0.630 ± 0.030	<b>0.641 ± 0.029</b>	0.786 ± 0.024	<b>0.794 ± 0.023</b>
Recall	0.618 ± 0.028	<b>0.633 ± 0.026</b>	0.767 ± 0.026	<b>0.780 ± 0.025</b>
F1	0.616 ± 0.029	<b>0.630 ± 0.026</b>	0.768 ± 0.026	<b>0.780 ± 0.025</b>

Best results per backbone architecture are in bold

**Table 5** Classification performance, averaged across five runs, of the different approaches on the EgoFoodPlaces dataset [15]

	Hierarchical approach [15]	FT-ResNet50	0-occlusion
Macro Precision	0.56	<b>0.59 ± 0.03</b>	<b>0.59 ± 0.05</b>
Macro Recall	0.53	<b>0.55 ± 0.03</b>	0.54 ± 0.06
Macro F1	<b>0.53</b>	<b>0.53 ± 0.04</b>	<b>0.53 ± 0.06</b>
Weighted Precision	0.65	0.67 ± 0.02	<b>0.68 ± 0.03</b>
Weighted Recall	<b>0.68</b>	0.67 ± 0.03	<b>0.68 ± 0.04</b>
Weighted F1	0.65	0.64 ± 0.03	<b>0.66 ± 0.04</b>
Accuracy	<b>0.68</b>	0.67 ± 0.03	<b>0.68 ± 0.04</b>

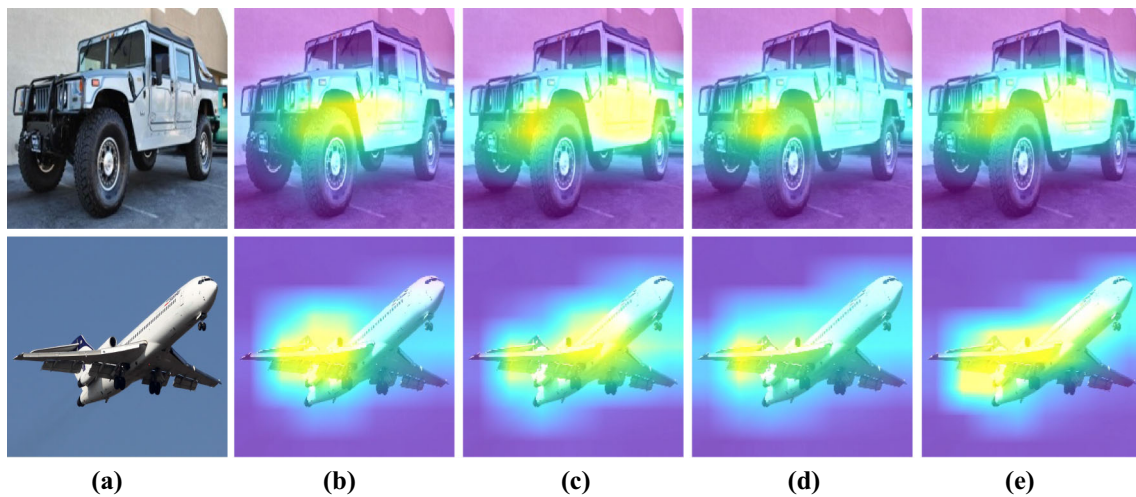
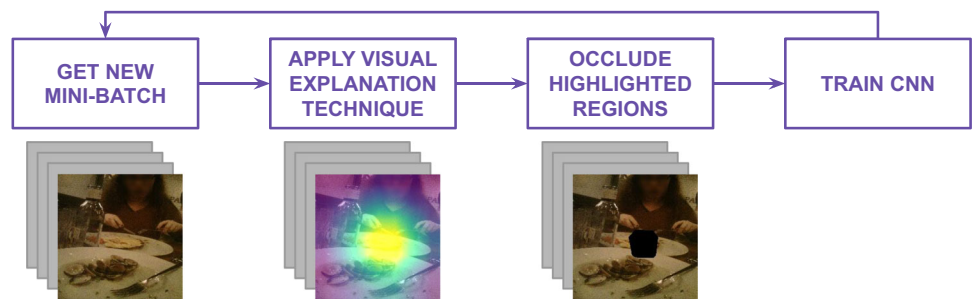
Best results are in bold

**Table 7** Classification performance, averaged across five runs, of the baseline method and the proposed training scheme when we randomly hid some regions on the test images

	FT-ResNet50	0-occlusion
Macro Precision	0.53 ± 0.01	<b>0.54 ± 0.02</b>
Macro Recall	0.47 ± 0.02	<b>0.48 ± 0.03</b>
Macro F1	0.47 ± 0.02	<b>0.48 ± 0.05</b>
Weighted Precision	<b>0.63 ± 0.02</b>	<b>0.63 ± 0.03</b>
Weighted Recall	0.59 ± 0.02	<b>0.65 ± 0.03</b>
Weighted F1	<b>0.59 ± 0.02</b>	<b>0.59 ± 0.02</b>
Accuracy	0.59 ± 0.02	<b>0.60 ± 0.02</b>

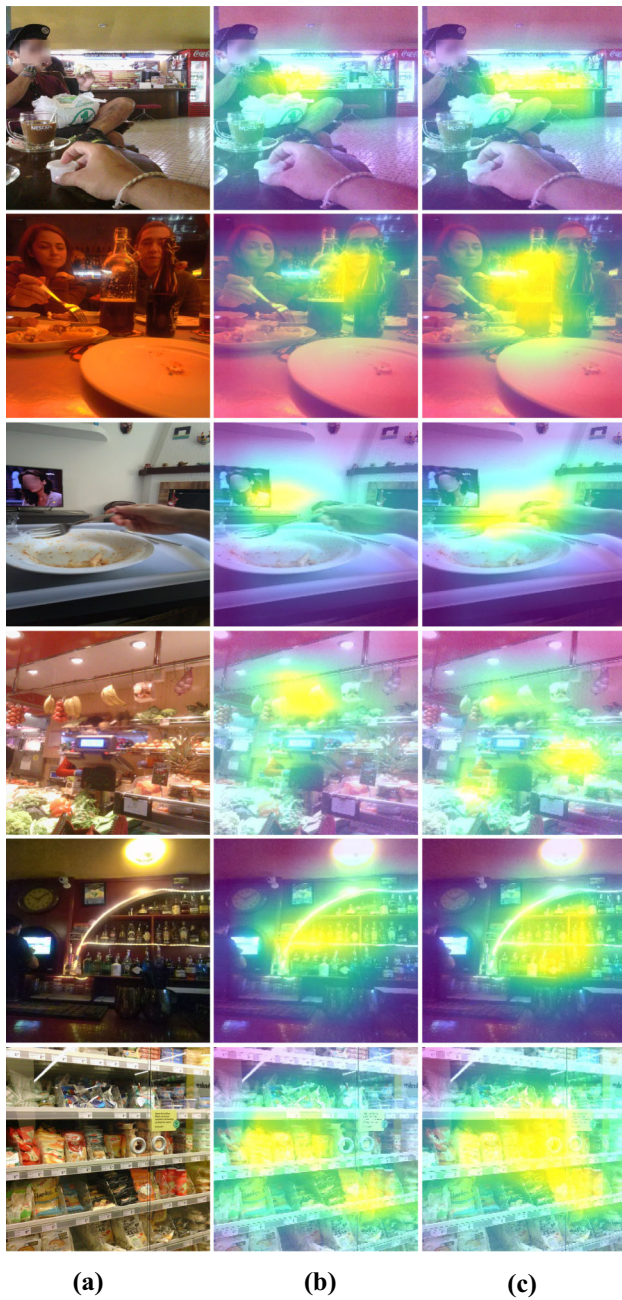
Best results are in bold

**Fig. 1** Workflow of our alternative training scheme, which **1** gets a new mini-batch of input images, **2** applies a visual explanation technique to generate the heat maps, **3** occludes the regions highlighted in the previous step, and **4** trains the CNN classifier



**Fig. 2 a** Input images from the Stanford cars (top) and FGVC-Aircraft (bottom) datasets, **b** heat maps generated by Grad-CAM for the baseline FT-ResNet50, and heat maps generated by Grad-CAM

for the model trained with the proposed training scheme using **c** 0-occlusion, **d** R-occlusion, and **e** 1-occlusion



**Fig. 3** **a** Input images, **b** heat maps generated by Grad-CAM for the baseline FT-ResNet50, and **c** heat maps generated by Grad-CAM for the model trained with the proposed training scheme (0-occlusion)

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.