Device (In)Dependence of Deep Learning-based Image Age Approximation

2022 ICPR Workshop on Artificial Intelligence for Multimedia Forensics and Disinformation Detection

Robert Jöchl and Andreas Uhl

Department of Artificial Intelligence and Human Interfaces
Paris Lodron University of Salzburg

August 21, 2022

Image Age Approximation

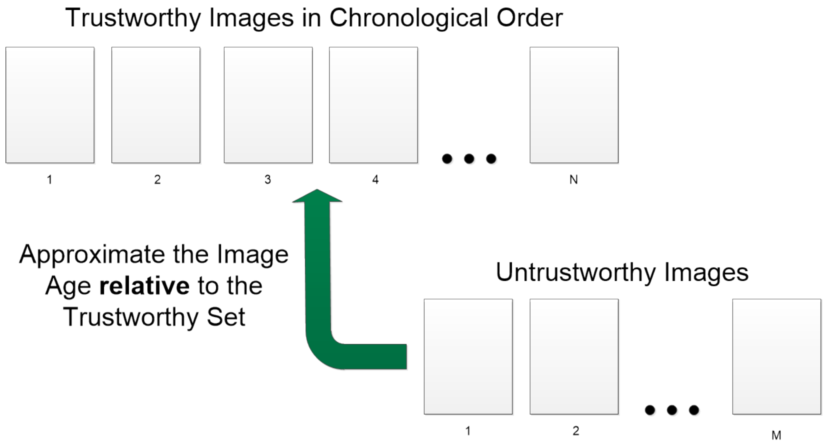

Figure: Overview image age approximation.

In-Field Sensor Defects

In-Field Sensor Defects:

- Develop after the manufacturing process and accumulate over time.
- Are due to cosmic radiation[1].
- Spread to the neighboring pixels because of preprocessing (e.g., demosaicing).

Defect model,

$$F(I) = I + IK + \tau D + c. \tag{1}$$

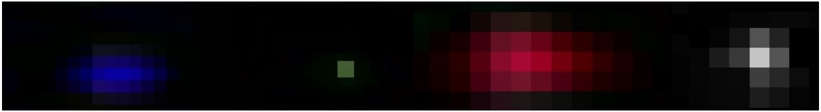

Figure: In-field sensor defects extracted from captured dark-field images.

[1] Albert JP Theuwissen. "Influence of terrestrial cosmic rays on the reliability of CCD image sensors Part 1: Experiments at room temperature". In: *IEEE Transactions on Electron Devices* 54.12 (2007), pp. 3260–3266.

Defect-Based Image Age Approximation

Fridrich et al.[2] propose a maximum likelihood approach, where:

- A defect is considered being noise, and by applying a denoising filter (i.e. a median filter) the defect is filtered out.

We[3] consider image age approximation as a multi-class classification problem, where:

- Traditional machine learning techniques (*i.e.*, a 'Naive Bayes Classifier' and a 'Support Vector Machine') are utilized.

---

[2] Jessica Fridrich and Miroslav Goljan. "Determining approximate age of digital images using sensor defects". In: *Media Watermarking, Security, and Forensics III*. ed. by Nasir D. Memon et al. Vol. 7880. International Society for Optics and Photonics. SPIE, 2011, pp. 49–59.

[3] Robert Joechl and Andreas Uhl. "A Machine Learning Approach to Approximate the Age of a Digital Image". In: *Digital Forensics and Watermarking: 19th International Workshop, IWDW 2020, Melbourne, VIC, Australia, November 25–27, 2020, Revised Selected Papers*. Vol. 12617. Springer LNCS. Springer International Publishing, 2021, pp. 181–195. ISBN: 978-3-030-69448-7. DOI: 10.1007/978-3-030-69449-4_14.

CNN-Based Image Age Approximation

Convolutional Neural Network (CNN) learns the classification features used.

- Ahmed et al.[4] utilize two well-known CNN architectures (*i.e.*, the AlexNet and GoogLeNet) to approximate the age of a digital image.
- The authors reported an accuracyof more than 85% for a five-class classification problem.
- The authors suggest that the features learned are not dependent on a certain image block, since the networks are trained on several non-overlapping image patches.

[4] Farah Ahmed et al. "Temporal Image Forensic Analysis for Picture Dating with Deep Learning". In: *2020 International Conference on Computing, Electronics Communications Engineering (iCCECE)*. 2020, pp. 109–114. DOI: 10.1109/iCCECE49321.2020.9231160.

CNN-Based Image Age Approximation

We[5] systematically investigated the influence of the presence of strong in-field sensor defects on training a CNN.

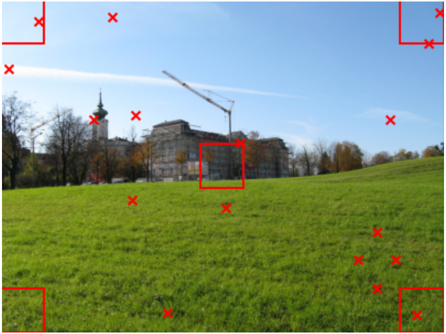

Figure: Five-crop and defect locations.

⇒ **The presence of a strong in-field sensor defect is irrelevant for improving the classification accuracy.**

[5] Robert Joechl and Andreas Uhl. "Apart from In-Field Sensor Defects, are there Additional Age Traces Hidden in a Digital Image?" In: *2021 IEEE International Workshop on Information Forensics and Security (WIFS)*. Montpellier, France, 2021, pp. 1–6. DOI: 10.1109/WIFS53200.2021.9648396.

Steganalysis Residual Network (SRNet)

Analogy to Image Steganalysis $\rightarrow$ detection of a weak signal.

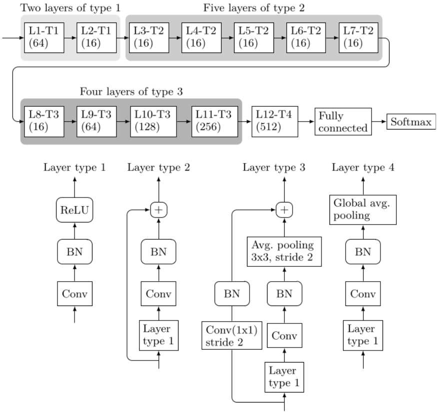

Figure: Overview SRNet[6].

[6] Mehdi Boroumand, Mo Chen, and Jessica Fridrich. "Deep residual network for steganalysis of digital images". In: *IEEE Transactions on Information Forensics and Security* 14.5 (2018), pp. 1181–1193.

Dataset - PLUS Aging Dataset

The PLUS Aging Dataset:

- Our own dataset where we have images from 4 different devices.
- A binary classification problem is considered with a time difference between the classes ranges from 7 to 13 years.

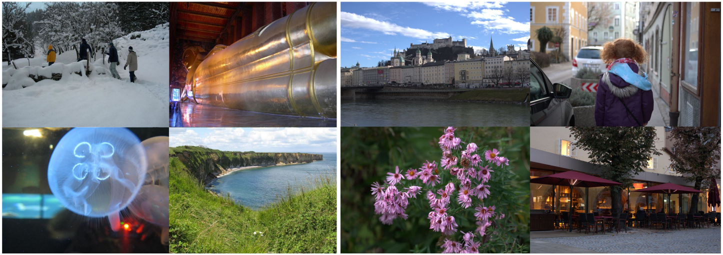

Figure: Random samples of the PLUS Aging Dataset.

Dataset - NTIF

The Northumbria Temporal Image Forensics (NTIF)[7] Database:

- Is a publicly available dataset.
- Consists of images from 10 different devices.
- For each device, approximately 71 timeslots ranging over 94 weeks (between 2014 and 2016) are available.
- A binary classification problem is considered, where timeslot 1-5 is reagerded as first class and timeslot 21-25 as second class (similar as in[8]).

[7] Farah Ahmed et al. "The 'Northumbria Temporal Image Forensics' Database: Description and Analysis". In: *2020 7th International Conference on Control, Decision and Information Technologies (CoDIT)*. vol. 1. 2020, pp. 982–987. DOI: 10.1109/CoDIT49905.2020.9263888.

[8] Ahmed et al., "Temporal Image Forensic Analysis for Picture Dating with Deep Learning".

Cross Device Evaluation

Are the learned features device (in)dependent?

To answer this question, we trained the SRNet (using the 'five-crop fusion' scenario) on image from a specific device and applied the trained model to images from different devices.

Cross Device Evaluation - Results

For 3 out 14 devices the learned age features are basically not device independent.

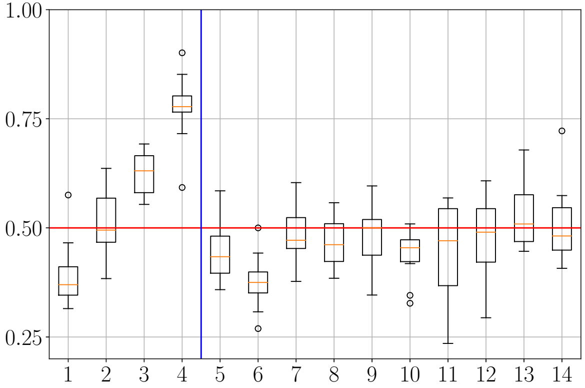

Figure: Boxplot of the resulting prediction accuracy for 10 different runs. The boxes 1-4 (left of the vertical blue line) represent the PLUS devices and the boxes 5-14 represent the NTIF devices. The model is trained on images from device number 4.

Cross Device Evaluation - Results

For 3 out 14 devices the learned age features are basically fully device independent.

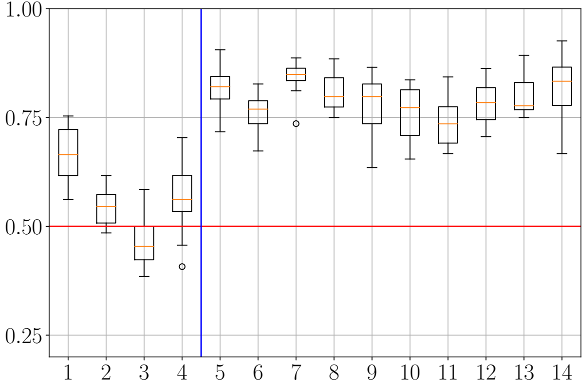

Figure: Boxplot of the resulting prediction accuracy for 10 different runs. The boxes 1-4 (left of the vertical blue line) represent the PLUS devices and the boxes 5-14 represent the NTIF devices. The model is trained on images from device number 8.

Cross Device Evaluation - Results

For 10 of 14 devices the results across the images from NTIF devices are relatively similar.

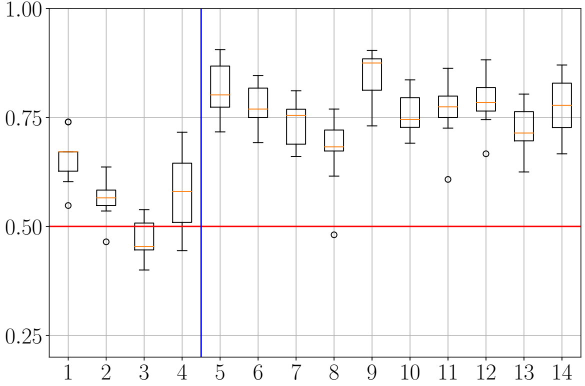

Figure: Boxplot of the resulting prediction accuracy for 10 different runs. The boxes 1-4 (left of the vertical blue line) represent the PLUS devices and the boxes 5-14 represent the NTIF devices. The model is trained on images from device number 9.

Conclusion

No overall trend was observable and the question if the learned features are device (in)dependent can hardly be answered.

Conclusion

⇒ The results suggest that not solely age-related features are exploited by the network!

It is likely that images taken in close temporal proximity (*e.g.*, belonging to the same age class) share some common features. For example:

- Common scene properties (*e.g.*, urban or nature scenes).
- Common weather conditions (*e.g.*, cloudy or blue sky).
- Seasonal commonalities (*e.g.*, light conditions and vegetation).

Thank you for your attention!