IMAGINE Dataset: Digital Camera Identification Image Benchmarking Dataset

Jarosław Bernacki[a] and Rafał Scherer[b]
Department of Intelligent Computer Systems, Częstochowa University of Technology, al. Armii Krajowej 36, 42-200 Częstochowa, Poland

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Abstract: We present the IMAGINE dataset. The proposed dataset may be used for benchmarking digital camera identification algorithms, which is an important issue in the field of digital forensics. So far, the most common image dataset seems to be the Dresden Image Database, but this dataset contains images from relatively old devices which include charge-coupled device (CCD) imaging sensors. Our dataset contains a number of images coming from modern devices which include mobile devices, compact cameras, and digital single-lens reflex/mirrorless (DSLR/DSLM) with Complementary Metal-Oxide-Semiconductor (CMOS) imaging sensors. Extensive experimental evaluation performed on a set of modern camera identification methods and algorithms confirmed the reliability of the IMAGINE dataset.

1 INTRODUCTION

Digital camera identification based on images has become a very popular task in digital forensics in recent years. In digital forensics, imaging sensor identification is crucial because it can provide valuable information about the origin and authenticity of digital images. Knowing the specific imaging sensor used to capture an image can help forensic analysts to determine whether an image has been altered or manipulated, and to establish the chain of custody of the digital evidence. Therefore, accurate imaging sensor identification is essential for maintaining the integrity of digital forensic investigations. Recognizing a camera based on images is known as "digital fingerprinting" (Goljan, 2008) or a proof of presence. The most common methods for digital camera identification are Photo-Response Non-Uniformity-based (PRNU) methods. Each camera has a unique PRNU pattern, which can be used to identify the source camera that captured an image. The PRNU pattern can be estimated from a large number of images captured by a camera and used as a reference for camera identification. The PRNU-based methods are widely used for camera identification due to their robustness against post-capture processing and compression.

[a] https://orcid.org/0000-0002-4488-3488
[b] https://orcid.org/0000-0001-9592-262X

The most recent family is based on deep learning, usually using Convolutional Neural Networks (CNNs) to extract features from an image and comparing them with the features of known cameras (Bondi et al., 2017; Ding et al., 2019; Kirchner and Johnson, 2020; Li et al., 2018; Lukás et al., 2006; Mandelli et al., 2020; Yao et al., 2018).

Digital camera identification might be realized in two aspects: individual source camera identification (ISCI) and source model camera identification (SCMI). ISCI is able to distinguish a particular camera model among other cameras of the same model. SCMI distinguishes a particular camera model among the different models but does not distinguish a particular copy of camera among other cameras of the same model.

The basis for the effective benchmarking of camera identification algorithms is image datasets. Imaging datasets should be extensive and provide a large number of images coming from multiple modern devices with ground truth labeling, i.e. corresponding camera information, such as the make and model of the camera. One of the most common image datasets is the Dresden Image Database (Gloe and Böhme, 2010). It was presented in 2011 and offers a vast number of images of different devices. However, this dataset is not up to date and this is probably its only disadvantage. It presents images coming from obso-

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lete cameras equipped with CCD (charge-coupled device) imaging sensors. Nowadays, cameras and mobile devices are equipped with CMOS (Complementary Metal-Oxide-Semiconductor) imaging sensors.

In this paper we propose a new dataset called IMAGINE (IMAGIng seNsor idEntification) that may be used for testing digital camera identification algorithms. This dataset is suitable for statistical algorithms, machine learning or deep models including convolutional neural networks (CNN). Our dataset utilizes a number of JPEG images acquired by modern devices enclosing mobile devices (smartphones, tablets), drones, compact cameras, digital single lens reflex/mirrorless (DSLR/DSLM), equipped with CMOS imaging sensors. Therefore, our dataset may be perfect for a reliable examination of digital camera identification algorithms and methods. The dataset is available on the following website:

`https://kisi.pcz.pl/imagine/`

In summary, our main contributions are:

- We propose the IMAGINE dataset for benchmarking individual source camera identification algorithms and methods;
- We benchmark proposed dataset with a set of modern individual source camera identification methods and show that the IMAGINE dataset allows for a reliable testing of such methods; moreover, we experimentally show that proposed dataset may speed up training of convolutional neural networks in the ISCI aspect.

The paper is organized as follows. In the next section we recall existing image datasets. In section 3 we describe in details the proposed IMAGINE dataset. In section 4 we recall state-of-the-art algorithms for individual source camera identification. In section 5, we show the classification results of state-of-the-art algorithms on the proposed dataset. The final section concludes this work.

2 PREVIOUS WORK

One of the most common image databases used in many papers is the Dresden Image Database (Gloe and Böhme, 2010). It contains tens of images coming from (among others) the following cameras: Agfa, Canon, Casio, Kodak, Nikon, Olympus, Praktica, Rollei, Sony and Samsung. Moreover, dataset includes images of the same frame shoot by different copies of the same camera model, which is especially desired for a reliable algorithm evaluation. A drawback of this dataset is that it was introduced in 2011 and contains mostly charge-coupled device (CCD) imaging sensors which are nowadays replaced by modern Complementary Metal-Oxide-Semiconductor (CMOS) sensors.

VISION (Shullani et al., 2017) is a image dataset containing images from 35 modern smartphones of the following manufacturers: Apple (iPad/iPhone), Huawei, Lenovo, LG, Microsoft, OnePlus, Samsung, Sony, Wiko and Xiaomi. VISION comes from 2017 year.

A set of High Dynamic Range (HDR) images that is called UNIFI dataset (Shaya et al., 2018) was published in 2018. This dataset includes smartphones' images of the following brands: Asus, Huawei, iPad/iPhone, OnePlus, Xiaomi and Samsung. It contains a diverse range of scenes captured with multiple exposure settings, and provides high-quality HDR content that is suitable for computer vision and image processing research.

MICHE-I dataset is an iris database that was introduced in 2015 and consist of images taken by three mobile devices: Apple iPhone 5, Samsung Galaxy S4 and Samsung Galaxy Tab 2 (MICHE, 2019; De Marsico et al., 2015). The Biosec Baseline Iris Subcorpus (Fiérrez-Aguilar et al., 2007) and IITD contact lens iris (Kohli et al., 2013) concern iris images. IITD contains 6570 images from Image Analysis and Biometrics Lab of the IIITD. The Notre Dame Iris Cosmetic Contact Lenses is provided by the Computer Vision Research Laboratory (CVRL) (Jr. et al., 2013). The dataset consists of a few thousands images. Although such datasets are dedicated for iris recognition, may also be used for digital camera recognition.

The Forchheim Image Database (Hadwiger and Riess, 2020) was presented in 2020 and consists of images coming from modern smartphones. Although there was used a large number of images (more than 23000), the main weakness seems to be the lack of modern professional cameras, including digital single lens reflex and mirrorless cameras.

Some research is conducted with popular image sharing website Flickr (Flickr, 2023). Note however that many images published on Flickr are manipulated with image processors such as Adobe Lightroom, DxO PhotoLab, Luminar or many others. Therefore, the analysis may not be effective with such images.

3 IMAGINE DATASET DESCRIPTION

Utilized Devices. The proposed dataset utilizes number of different types of 55 imaging devices. In particular, it includes: 12 mobile devices, which are 11 smartphones and one tablet, two drones, 4 compact cameras, 17 digital single lens reflex (DSLR), 18 digital single lens mirrorless (DSLM). The total number of images is 2489.

The devices are equipped with imaging sensors of various physical dimensions. The list of imaging sensor dimensions of used devices is presented in Table 1. The full list of models of devices is listed in Table 2.

Table 1: Sensor dimensions of used devices. **Dim** stands for sensor dimensions (in millimeters), **Diag** denotes sensors' diagonal (in millimeters).

Sensor	Dim	Diag
FF	36.0×24.0	43.27
FX	35.9×24.0	42.18
FE	35.6×23.8	42.74
APS-C[1]	22.3×14.8	26.76
APS-C[2]	23.5×15.7	28.26
APS-C[3]	23.6×15.8	28.40
1"	13.2×8.80	15.86
1/2.55"	6.17×4.55	7.67
1/2.3"	6.16×4.62	7.70
1/3"	4.80×3.60	6.00
1/3.1"	4.40×3.30	5.50
1/4.0"	3.20×2.40	4.00

Note that some devices are used as two copies of the same model (Tab. 2). Also worth mentioning that Samsung Galaxy A40 is equipped with two lenses: standard (wide) and ultrawide – in our dataset we use only standard (wide) images.

Images. The dataset contains JPG images coming directly from cameras – they are not edited in any software in any way. All cameras were set to their default shooting mode with default white balance.

Image Download Script. The images of the IMAGINE dataset may be easily downloaded by using the provided script, written in `BASH`. The script is available on the dataset's webpage and works on Microsoft Windows and Linux operating systems. Detailed instructions, how to run the script on Linux or Microsoft Windows can be found on dataset's web page. Below we present a part of the download script.

```
mkdir Canon_EOS_R5
for ((n=1;n<=42;n++))
do
    wget -O Canon_EOS_R5/$n.jpg https://
    kisi.pcz.pl/imagine/img/Canon_EOS_R5
    /$n.jpg
done
```

4 ALGORITHMS FOR INDIVIDUAL SOURCE CAMERA IDENTIFICATION

In this section we briefly recall the state-of-the-art algorithms for an individual source camera identification that we will benchmark with IMAGINE dataset.

We test algorithms presented by Lukás et al. (Lukás et al., 2006), Bondi et al. (Bondi et al., 2017), Tuama et al. (Tuama et al., 2016), Mandelli et al. (Mandelli et al., 2020) and Kirchner & Johnson (Kirchner and Johnson, 2020). Due to paper limitations, we recall the algorithm presented by Lukás et al., and a shallow conception for CNN-based camera identification based on Bondi—Kirchner & Johnson papers.

Lukás et al.'s Algorithm. The base of the Lukás et al.'s algorithm (Lukás et al., 2006) is the calculation of the noise residual $\mathbf{N}$ which is defined as $\mathbf{N} = \mathbf{I} - F(\mathbf{I})$, where F is a denoising filter, $\mathbf{N}$ denotes a noise residual of one image $\mathbf{I}$. This procedure should be repeated for a certain number of images from a camera (it is suggested to use at least 45 images). The camera's noise residual is eventually calculated as an average of the used number of noise residuals. Images are processed in their original resolution.

Convolutional Neural Networks. The general idea of convolutional neural network-based camera identification of cited papers relies on applying $3-4$ convolutional layers with usually $32-128$ filters of size 4×4 or 5×5 with kernel size 2 and stride also 2 with max-pooling layers. The ReLU is used for activation; for classification are utilized fully connected layers. Other parameters may be found in for instance Bondi's paper (Bondi et al., 2017).

5 EXPERIMENTAL RESULTS – BENCHMARKING THE IMAGINE DATASET

In this section we provide classification experiments with the state-of-the-art algorithms for individual source camera identification (ISCI – mentioned in previous section), trained by images from the IMAGINE dataset. We experimentally check the classification accuracy of the following algorithms: Lukás, Bondi, Tuama, Mandelli and Kirchner & Johnson. We run all listed algorithms in their default (original) parameters with own procedures for classification.

Table 2: Utilized devices. The * symbol denotes that size sensor if not officially given by the manufacturer. However, one may assume that it is similar to 1/4.0”. Resolution stands for image resolution in pixels.

Symbol	Device name	Device type	Released	Resolution	Sensor	# of devices
A01	Acer Liquid Jade S	smartphone	2014	4160×3120	*	1
A02	Apple iPhone 5S	smartphone	2013	3624×2448	1/3”	1
C01	Canon EOS 1D X Mark II	DSLR	2016	5472×3648	FF	1
C02	Canon EOS 5D Mark IV	DSLR	2016	6720×4480	FF	1
C03	Canon EOS 6D Mark II	DSLR	2017	6240×4160	FF	1
C04	Canon EOS 750D	DSLR	2015	6000×4000	APS-C[1]	2
C05	Canon EOS 760D	DSLR	2015	6000×4000	APS-C[1]	2
C06	Canon EOS M3	DSLM	2015	6000×4000	APS-C[1]	2
C07	Canon EOS M5	DSLM	2016	6000×4000	APS-C[1]	2
C08	Canon EOS M50	DSLM	2018	6000×4000	APS-C[1]	2
C09	Canon EOS 90D	DSLR	2019	6940×4640	APS-C[1]	1
C10	Canon EOS M100	DSLM	2017	6000×4000	APS-C[1]	1
C11	Canon EOS M200	DSLM	2019	6000×4000	APS-C[1]	1
C12	Canon EOS R	DSLM	2018	6720×4480	FF	1
C13	Canon EOS R5	DSLM	2020	8192×5464	FF	1
C14	Canon EOS R6	DSLM	2020	5472×3648	FF	1
C15	Canon EOS RP	DSLM	2019	6240×4160	FF	1
C16	Canon PowerShot G9 X Mark II	compact	2017	5472×3648	1”	2
C17	Canon PowerShot SX270 HS	compact	2013	4000×3000	1/2.3	1
D01	DJI Spark	drone	2017	3968×2976	1/2.3	1
F01	Fujifilm X-T200	DSLM	2020	6000×4000	APS-C[2]	1
L01	Lenovo K5 Plus	smartphone	2016	4096×2304	*	1
L02	LG K10	smartphone	2016	4160×2336	*	1
M01	Microsoft Lumia 640	smartphone	2015	3264×1840	1/4.0”	1
N01	Nikon D5	DSLR	2016	5568×3712	FX	1
N02	Nikon D6	DSLR	2020	5568×3712	FX	1
N03	Nikon D500	DSLR	2016	5568×3712	APS-C[3]	1
N04	Nikon D610	DSLR	2013	6016×4016	FX	1
N05	Nikon D750	DSLR	2014	6016×4016	FX	2
N06	Nikon D780	DSLR	2020	6048×4024	FX	1
N07	Nikon D810	DSLR	2014	7360×4912	FX	1
N08	Nikon D850	DSLR	2017	8256×5504	FX	1
N09	Nikon D3100	DSLR	2010	4608×3072	APS-C[3]	2
N10	Nikon D5600	DSLR	2016	6000×4000	APS-C[3]	2
N11	Nikon D7200	DSLR	2015	6000×4000	APS-C[3]	2
N12	Nikon P100	compact	2010	3648×2736	1/2.3”	1
N13	Nikon Z6	DSLM	2018	6048×4024	FX	2
N14	Nikon Z6 II	DSLM	2020	6048×4024	FX	1
N15	Nikon Z7	DSLM	2018	8256×5504	FX	1
N16	Nikon Z7 II	DSLM	2020	8256×5504	FX	1
N17	Nokia 2.2	smartphone	2019	4160×3120	1/3.1”	1
S01	Samsung Galaxy A40	smartphone	2019	4608×3456	1/2.8”	1
S02	Samsung Galaxy Ace 3	smartphone	2013	2560×1920	*	1
S03	Samsung Galaxy S7	smartphone	2016	4032×3024	1/2.55”	2
S04	Samsung Galaxy SIII mini	smartphone	2014	2560×1920	*	1
S05	Samsung Galaxy Tab A 10.1	tablet	2016	3264×1836	*	1
S06	Samsung Galaxy Trend 2 Lite	smartphone	2015	2048×1232	*	1
S07	Samsung Omnia II	smartphone	2009	2560×1920	*	1
S08	Sony A1	DSLM	2021	8640×5760	FE	1
S09	Sony A7R III	DSLM	2017	7952×5304	FE	1
S10	Sony A7S	DSLM	2014	4240×2832	FE	1
S11	Sony A9	DSLM	2017	6000×4000	FE	1
S12	Sony ActionCam AS200V	sport camera	2015	3104×1744	1/2.3”	1
S13	Sony RX100 VI	compact	2018	5472×3648	1”	1
Y01	Yuneec Breeze 4K	drone	2015	4160×3120	1/3”	1

We also compare proposed dataset with well-known in the literature Dresden Image Database (Gloe and Böhme, 2010) (let us in further part of article name it shortly Dresden). As evaluation, we use *accuracy* (ACC) measure, defined as

$$\mathrm{ACC} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}$$

where TP/TN stands for "true positive/true negative"; FP/FN stands for "false positive/false negative". TP denotes number of instances correctly classified to a specific class; TN are cases that are correctly rejected. FP denotes cases incorrectly classified to the specific class; FN are instances incorrectly rejected.

Due to large dimensions, we skip confusion matrices for considered methods. The summary of the average accuracy of each algorithm is presented in Tab. 3.

Table 3: Identification accuracy of the tested algorithms.

Algorithm	Accuracy [%]
Lukás	98.0
Bondi	98.0
Tuama	97.0
Mandelli	98.0
Kirchner & Johnson	93.0

Results clearly indicate very high identification accuracy on the proposed image dataset. The Mandelli et al.'s method obtained the identification accuracy at the level of 98.0%. The other methods achieved similar results of 97.0 – 98.0% accuracy. Only the Kirchner & Johnson algorithm achieved 93.0%. This confirms the usefulness of the proposed IMAGINE dataset.

In Figures 1-2 we present the evaluation results of the IMAGINE dataset. Fig. 1 presents results on training accuracy of considered CNNs for 50 epochs. Results indicate that all CNNs achieve comparable and high training accuracy on IMAGINE dataset. We observe a bit lower results in case of Kirchner & Johnson's CNN, however all networks exceed the training accuracy of 80.0% after passing 30 epochs.

In Fig. 2 we evaluate the training accuracy for Mandelli et al.'s CNN both on the IMAGINE dataset and Dresden Image Database. The analysis shows that the proposed dataset achieves higher training accuracy with a less number of training epochs. Training the CNN for about 20 epochs with the IMAGINE dataset provides accuracy exceeding 80.0% while the Dresden set obtains about 70.0%; learning for at least 30 epochs enables achieving accuracy of about 95.0% for the IMAGINE dataset; the Dresden set requires more than 40 epochs for such result. Similar trend is observed in case of other CNNs presented by Bondi,

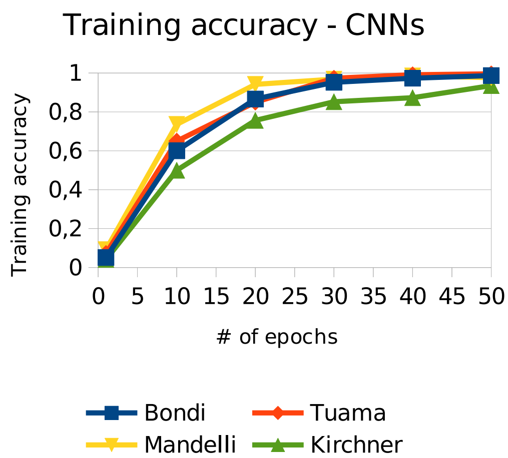

Figure 1: Comparison of training accuracy on selected CNNs on IMAGINE dataset.

Tuama and Kirchner & Johnson (we skip corresponding Figures for clarity). This denotes that the IMAGINE dataset may result in a faster model training than the Dresden Image Database.

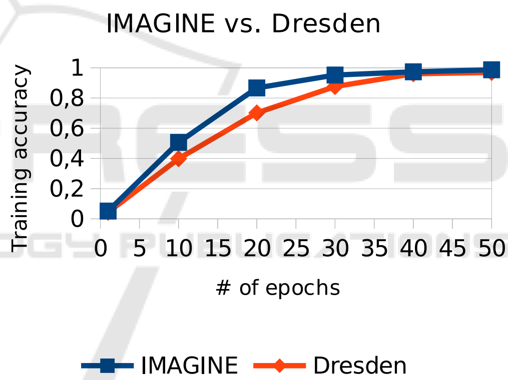

Figure 2: Comparison of training accuracy of Mandelli et al.'s CNN on IMAGINE and Dresden Image Database. Results for CNNs by Bondi, Tuama and Kirchner & Johnson are similar.

We also compare the identification accuracy of Lukás et al.'s algorithm on IMAGINE and Dresden datasets. Similarly as in CNNs, Lukás algorithm obtains a bit higher identification accuracy. Results on the IMAGINE dataset achieve 98.0% of identification accuracy; on the Dresden set it is 96.0%.

To sum up, experiments demonstrated that proposed dataset achieve very high identification accuracy on modern state-of-the-art algorithms in the ISCI aspect. Results indicated also that considered CNNs may be trained with less number of training epochs with the IMAGINE dataset, compared to Dresden Image Database.

6 CONCLUSION

We have proposed an IMAGINE dataset for benchmarking digital camera identification algorithms. Our dataset contains number of images coming from modern CMOS-based devices. This dataset may be used for testing digital camera identification algorithms using different methodologies, including statistical methods, machine learning or deep models with convolutional neural networks (CNN). We have evaluated our dataset on a set of modern state-of-the-art algorithms for individual source camera identification. Results confirmed the reliability of IMAGINE dataset.

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