Camera Model Anonymisation with Augmented cGANs

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Abstract

The model of camera that was used to capture a particular photographic image (model attribution) can be inferred from model-specific artefacts present within the image. Typically these artefacts are found in high-frequency pixel patterns, rather than image content. Model anonymisation is the process of transforming these artefacts such that the apparent capture model is changed. Improved methods for attribution and anonymisation are important for improving digital forensics, and understanding its limits. Through conditional adversarial training, we present an approach for learning these transformations. Significantly, we augment the objective with the losses from pre-trained auxiliary model attribution classifiers that constrain the generator to not only synthesise discriminative high-frequency artefacts, but also salient image-based artefacts lost during image content suppression. Quantitative comparisons against a recent representative approach demonstrate the efficacy of our framework in a non-interactive black-box setting.

1 Introduction

Geradts et al. (2001) made a seminal discovery: photographic images can be attributed to the specific camera model used for capture. Attribution is facilitated by exploiting model-specific acquisition and processing artefacts encoded within the pixels of images (Figure 1).

Most approaches to attribution operate in noise residual space (Tuama et al., 2015; Marra et al., 2015; Filler et al., 2008; Gloe, 2012; Tuama et al., 2016; Bayar & Stamm, 2017), where a noise residual is defined as the difference between an observed image and an estimate of its ideal noise-free imaging sensor response. Artefacts related to model-specific in-camera processes are typically present within these high-frequency micro-patterns, as opposed to the noiseless sensor response (Marra et al., 2017). Nevertheless, denoising is not an absolute operation (Rosenfeld & Sencar, 2009), and not all artefacts are of a high-frequency nature (Lukáš et al., 2006).

In the field of digital image forensics, such artefacts have been used to verify the origin and integrity of images. Notwithstanding, the ability to trace images back to specific camera models, or even devices, 1 evidently raises concerns about unjustifiable misuse. This is particularly pertinent to individuals such as human rights’ activists, photojournalists, and whistle-blowers, that reserve the right to privacy and anonymity (Dirik et al., 2014).

However, in this work we are not concerned with camera model attribution per se, but the challenging problem of camera model anonymisation (Chen et al., 2018; Mandelli et al., 2017; Karaküçük & Dirik, 2015). Namely, the goal is to learn a mapping that transforms the innate model-specific artefacts of an image to those of a disparate target model. Such a system could then be used to preserve privacy, or conversely for validating the robustness and reliability of attribution methods, particularly when attribution results are admitted as forensic evidence in criminal cases.

Despite broadly falling under the remit of image editing

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(Perarnau et al., 2016; Wang et al., 2018; Zhu et al., 2016), the targeted transformations that we seek should not alter the content of an input. Minimal distortion is easily achieved by formulating the problem as a lossy reconstruction task, however low distortion is often at odds with high perceptual quality (Blau & Michaeli, 2018). For example, a minimal blur may effectively conceal artefacts with low distortion (e.g. small $\ell_2$ norm), but noticeably reduce the perceptual quality. Thus, we additionally propose a conditional adversarial regulariser (Mirza & Osindero, 2014) to concurrently direct the targeted transformation process and encourage the transformed images to appear photo-realistic.

A distinguishing feature of this work is the enforced synthesis of salient, discriminative model-specific artefacts. Succinctly, we augment the adversarial and lossy reconstruction losses with the classification losses from pre-trained local noise residual-based camera model attribution classifiers, as well as an image-based classifier. The former ensure that the minute high-frequency model-specific details are synthesised, whereas the latter attends to lower-frequency characteristics discarded in noise residual space.\(^2\) This is unlike recent camera model anonymisation works, which wholly focus on attenuating (Mandelli et al., 2017; Bonettini et al., 2018) or transforming high-frequency artefacts (Chen et al., 2018). Significantly, these local classifiers act as proxies in place of unknown non-interactive black-box target classifiers, i.e. camera model attribution classifiers that we have no knowledge and cannot query, but wish to deceive.

The combination of these losses yields our full objective for targeted camera model anonymisation. We successfully anonymise images derived from the Dresden database of natural images (Gloe & Böhme, 2010), demonstrating that anonymisation necessitates the transformation of both low- and high-frequency artefacts. This is highlighted through an ablation analysis, which includes a comparison against a recent representative approach that entirely centres on the anonymisation of high-frequency noise residual-based artefacts (Chen et al., 2018; 2019). Quantitative results underscore the efficacy of our framework when attacking a variety of non-interactive black-box target classifiers.

### 1.1 Related Work

**Camera Model Attribution.** Classical approaches to camera model attribution typically construct parametric models of particular physical or algorithmic in-camera processes (Choi et al., 2006b; Filler et al., 2008; Choi et al., 2006a; Chen & Stamm, 2015; Bayram et al., 2005; Tuama et al., 2015). Others operate blindly, viewing attribution as a texture classification problem, and derive a set of heuristically designed features irrespective of their physical meaning (Marra et al., 2017; Kharrazi et al., 2004; Gloe, 2012; Xu & Shi, 2012). Recent methods based on deep learning take a data-driven approach, obviating the need for explicit prior domain knowledge (Bayar & Stamm, 2018; Kuzin et al., 2018; Bondi et al., 2016; Tuama et al., 2016; Bayar & Stamm, 2017). Notably, since artefacts related to acquisition processes are contained in the image micro-patterns and not the image content, most classical and contemporary approaches suppress the latter (Tuama et al., 2015; Marra et al., 2015; Filler et al., 2008; Gloe, 2012; Tuama et al., 2016; Bayar & Stamm, 2017). Here we focus on deceiving convolutional neural network (ConvNet) attribution classifiers, which can be considered state-of-the-art. In particular, two noise residual-based classifiers and an image-based classifier.

**Camera Model Anonymisation.** The photo-response non-uniformity (PRNU) of a camera is at root caused by slight variations in the sensitivity of individual pixel sensors (Fridrich, 2009). These variations are random across the sensor array, and different for each device. The effects of these variations propagates non-linearly through the processing steps that result in the final image and thus end up also depending on model-specific aspects such as colour interpolation, on-sensor signal transfer, sensor design, and compression. As a result, camera model (and device) anonymisation methods have mostly focused on attenuating or misaligning this fingerprint. Methods include flat-fielding (Gloe et al., 2007; Böhme & Kirchner, 2013), PRNU estimation and subtraction (Karaküçük & Dirik, 2015; Dirik & Karaküçük, 2014; Bonettini et al., 2018), irreversible forced seam-carving (Dirik et al., 2014), image patch replacement (Entrieri & Kirchner, 2016), and image inpainting (Mandelli et al., 2017). However, a principal issue with the aforementioned approaches is the detectable absence of model-specific artefacts within the anonymised images (Bonettini et al., 2019). In contrast, we focus on transforming the underlying model-specific artefacts of images rather than removing them.

**Generative Adversarial Nets.** Generative adversarial nets (GANs) (Goodfellow et al., 2014) offer a viable framework for training generative models, and are increasingly being used for tasks such as image generation (Karras et al., 2017), image editing (Zhu et al., 2016), and representation learning (Mathieu et al., 2016). Extending this framework to conditional image generation applications, conditional GANs (cGANs) (Mirza & Osindero, 2014) have been successfully applied to image-to-image translation (Zhu et al., 2017a; Isola et al., 2017; Zhu et al., 2017b) and modifying image attributes (Perarnau et al., 2016; Yang et al., 2018). We adopt a conditional adversarial loss with additional terms that force the generator to synthesise targeted, discriminative...
model-specific artefacts used by camera model attribution classifiers. Significantly, *augmenting* the adversarial game has been shown to improve performance on the original task (Odena et al., 2017; Wang et al., 2018; Li et al., 2019).

**GANs for Camera Model Anonymisation.** The most related approach to ours comes from Chen et al. (2018), who perform a *white-box* attack against a camera model attribution classifier, i.e. the gradient from the target classifier to be attacked is used during adversarial training. For each target camera model, a separate generator-discriminator pairing is trained. Notably, through prediction error filtering, the discriminator and classifier both suppress the image content, thereby constraining the generator to synthesise high-frequency artefacts. This method was later applied in an *interactive black-box* setting (Chen et al., 2019), i.e. given an input only the predicted label from the target classifier is observable. Unlike these works, we employ a single camera model anonymising cGAN and operate in a non-interactive black-box setting, where we have no knowledge of a target classifier and cannot submit queries. Moreover, we constrain our generator to not only synthesise high-frequency noise residual-based artefacts, but also image-based artefacts.

### 2 Preliminaries

Consider a camera model attribution task with images $x \in \mathbb{R}^{h \times w \times c}$ and ground-truth source capture camera model labels $s \in \{1, \ldots, C\}$ sampled from a distribution $p_{\text{data}}$. Suppose that $f(\cdot)$ is a ConvNet trained over input-output tuples $(x, s) \sim p_{\text{data}}(x, s)$. Given $x$, $f(\cdot)$ outputs a prediction vector of class probabilities $f(x) \in [0, 1]^C$. The objective function used to train the classifier is the negative log-likelihood (NLL):

$$-E_{x, s \sim p_{\text{data}}(x, s)} \log f(x)_s,$$

where $f(x)_s \in [0, 1]$ represents the probability that $x$ corresponds to the label $s$.

**Desiderata of Targeted Anonymisation.** For some unknown target classifier, denoted $f^*(\cdot)$, and tuple $(x, t)$, where $t \neq s$ is a target label different from the ground-truth label of $x$, our goal is to learn a function $g(\cdot, \cdot)$ that outputs an image $g(x, t) \approx x$, without visual artefacts, whose maximum probability satisfies $\arg\max_i f^*(g(x, t))_i = t$. In other words, $g(x, t)$ must have low distortion (high perceptual similarity) and deceive $f^*(\cdot)$ into thinking that it belongs to class $t$.

**Assumptions.** In this work, we operate in a *non-interactive black-box setting*: we do not assume to have knowledge of a target classifier’s parameters, architecture or training randomness, nor can we interact with it. We do, however, *reasonably* assume that target classifiers function either in

image space or noise residual space.\(^3\) Furthermore, for simplicity, we assume that target classifiers are trained as described above. Finally, we assume that we can sample from the distribution $p_{\text{data}}$; however, we must emphasise that the images drawn are captured by a disjoint set of devices (not models) to those used to train a target classifier $f^*(\cdot)$.

**Notation.** We use $f^*(\cdot)$ to refer to an unknown non-interactive black-box target classifier, and $f(\cdot)$ to refer to a *local* classifier available to our anonymisation framework.

### 3 Method

Formally, we assume that we are given a dataset of examples $\{(x^{(i)}, s^{(i)})\}_{i=1}^n$ sampled from $p_{\text{data}}$.\(^4\) The main idea behind our camera model anonymising augmented cGAN framework is illustrated in Figure 2. Under this class conditional adversarial framework, the generator $g(\cdot, \cdot)$ and the discriminator $d(\cdot, \cdot)$ compete in a two-player zero-sum game: $d(\cdot, \cdot)$ is tasked with correctly classifying whether any given image-label input tuple is real or fake; whilst $g(\cdot, \cdot)$ aims to synthesise, for any target label $t \neq s$, a version of an image $x$ whose class label corresponds to $t$ which looks real to the discriminator. To encourage the synthesised samples to lie within their respective target classes, we propose to pre-train local auxiliary camera model attribution classifiers to act as *proxies* in place of unknown target classifiers. By incorporating the classification losses from these fixed (with respect to their learnt parameters) local classifiers, $g(\cdot, \cdot)$ is forced to update its parameters such that it can better synthesise the salient, target model-specific artefacts used by a classifier for discrimination.

\(^3\)This assumption is reasonable in the sense that we are simply following previous approaches to camera model attribution (Section 1.1).

\(^4\)More often than not we omit the superscript $(i)$ for simplicity.
Our objective contains three types of terms: an adversarial loss for matching the distribution of generated images to the data distribution; a content loss to incentivise the preservation of an input image’s original scene; and local auxiliary camera model attribution classification losses to encourage the synthesis of target model-specific artefacts.

3.1 Adversarial Loss

To generate plausible photo-realistic images, we apply an adversarial loss to $g(\cdot, \cdot)$. For $g(\cdot, \cdot)$ and $d(\cdot, \cdot)$, the training process alternates between $g(\cdot, \cdot)$ minimising

$$
\mathcal{L}_{adv} = \mathbb{E}_{x \sim p_{data}(x)} \left[ (d(g(x, t), t) - 1)^2 \right],
$$

(2)

and $d(\cdot, \cdot)$ minimising

$$
\mathcal{L}_{dis} = \mathbb{E}_{x, s \sim p_{data}(x, s)} \left[ (d(x, s) - 1)^2 \right] + \mathbb{E}_{x \sim p_{data}(x)} \left[ (d(g(x, t), t))^2 \right].
$$

(3)

Note that this is the least squares formulation of the generative adversarial objective (Mao et al., 2017), which offers increased learning stability and generates higher quality results.  

3.2 Content Loss

Although $d(\cdot, \cdot)$ constrains $g(\cdot, \cdot)$ to synthesise realistic images, it does not ensure that the original image content of $x$ is preserved in $g(x, t)$. To incentivise this, we incorporate a simple pixel-wise $\ell_1$ norm loss between $g(x, t)$ and $x$:

$$
\mathcal{L}_{cnt} = \mathbb{E}_{x \sim \mathcal{D}(x) \sim p_{data}(x)} \left[ \| x - g(x, t) \|_1 \right].
$$

(4)

The addition of this loss tasks $g(\cdot, \cdot)$ with synthesising images that are close to the ground-truth input image, i.e. $g(x, t) \approx x$. We prefer an $\ell_1$ norm loss over an $\ell_2$ norm loss since it encourages less blurring (Zhu et al., 2017a).

3.3 Local Auxiliary Attribution Classification Losses

Ideally, given an input tuple $(x, t)$, $g(\cdot, \cdot)$ should encode all relevant target model-specific artefacts that are the result of in-camera processes. However, the previously introduced adversarial and content losses give no guarantees as to whether $g(x, t)$ lies in class $t$ according to an attribution classifier. In particular, as $g(\cdot, \cdot)$ is guided by $d(\cdot, \cdot)$, if $d(\cdot, \cdot)$ picks out, for example, abnormal interpolation patterns within $g(x, t)$, then the adversarial game may fixate on discovering and fixing such peculiarities (Arandjelović & Zisserman, 2019). This could result in a failure to transform the discriminative model-specific artefacts used by an attribution classifier. Therefore, we propose to incorporate the losses from two pre-trained noise residual-based camera model attribution classifiers, as well as a pre-trained image-based camera model attribution classifier. The former ensure that the minute high-frequency model-specific details are attended to, whereas the latter attends to lower-frequency characteristics (e.g. possible vignetting), as well as high-frequency traces (e.g. elements of demosaicing) that may have been lost due to the imprecise nature of image denoising.

3.3.1 Noise Residual Space

The in-camera processing pipeline in digital cameras is complex in nature and can vary greatly between camera models. To capture the common elements of in-camera processing, Chen et al. (2008) proposed the following simplified imaging sensor output model: $x = x_0 + x_0 \rho + \eta$, where $x_0$ is the ideal noise-free sensor response, $x_0 \rho$ is the PRNU term, and $\eta$ is a combination of various other noise sources. Many attribution methods suppress $x_0$, as a preprocessing step, since it contains no information related to in-camera processes. However, the noiseless response $x_0$ must be estimated from the observable image $x$. Let $h(\cdot)$ denote a denoising function:

$$
w = x - h(x)
= x_0 + x_0 - h(x) + (x_0 - x) \rho + \eta
= x_0 + \Xi
$$

(5)

where $\Xi$ is the sum of $\eta$ and two additional terms introduced by $h(\cdot)$. Patently, this process magnifies the high-frequency model-specific noise artefacts $x_0 \rho + \eta \approx x \rho + \Xi$, due to the suppression of the image content $x_0$. We therefore consider two popular approaches to attribution that operate in noise residual space: the first utilises a predetermined fixed hand-crafted filter, whereas the second learns a set of filters.

Wavelet-Based Wiener Denoising Filtering (WDF). The first method (Lukáš et al., 2006) employs a wavelet-based Wiener denoising filter, $h_{wdf}(\cdot)$, to obtain noise residuals.\footnote{We refer the reader to Fridrich (2009) for details on this denoising filter.} Suppose that $f_{wdf}(\cdot) = q_{wdf}(h_{wdf}(\cdot))$ is an attribution ConvNet classifier, trained over $(x, s) \sim p_{data}(x, s)$. The subnetwork $h_{wdf}(\cdot)$, which approximates $h_{wdf}(\cdot)$, maps an image to an estimate of its noise residual, i.e. $x \mapsto w$. The subnetwork $q_{wdf}(\cdot)$ maps said estimate to a prediction vector of probabilities, i.e. $w \mapsto [0, 1]$. Here $q_{wdf}(\cdot)$ and $h_{wdf}(\cdot)$ are pre-trained independently, where $q_{wdf}(\cdot)$ is trained on ground-truth noise residuals $w$ to minimise Equation (1); and $h_{wdf}(\cdot)$ is trained to to minimise an $\ell_2$ norm loss:

$$
\mathbb{E}_{x \sim p_{data}(x)} \left[ \| w - h_{wdf}(x) \|^2 \right].
$$

(6)
We refer the reader to the supplementary material for full implementation details regarding the dataset, network architectures, and training procedures. The PyTorch code, models, and results can be found online.8

4.1 Dataset
The Dresden image database (Gloe & Böhme, 2010) of JPEG colour images was used to evaluate anonymisation. We used a subset of images from 12 camera models, which we centrally cropped to a common resolution of $512 \times 512$. The images were then partitioned into three disjoint sets, denoted Set-A, -B, and -C. The sets are disjoint with respect to the specific devices used to capture the images. Each model within Set-A and -B has two unique capture devices, whereas each model in -C has a single device. For Set-A and -B, we extracted $64 \times 64$ non-overlapping patches from each $512 \times 512$ image. Images in Set-A, -B, and -C were used for target classifier training, camera model anonymising augmented cGAN training, and evaluating the cGAN’s ability to anonymise $512 \times 512$ images from in-distribution and out-of-distribution camera models, respectively. See Table 1 for a full itemisation.

### Table 1. Dataset itemisation. Shown are the number of images per class within each set. Images in Set-A and -B correspond to $64 \times 64$ image patches, whereas images in -C correspond to $512 \times 512$ images.

| Set   | Camera Model              | A  | B  | C  |
|-------|---------------------------|----|----|----|
| Indo. | 1 Kodak M1063             | 48960 | 48640 | 100 |
|       | 2 Casio EX-Z150           | 21440 | 20736 | 100 |
|       | 3 Nikon CoolPixS710       | 21120 | 22528 | 100 |
|       | 4 Praktica DCZ5.9         | 22912 | 22080 | 100 |
|       | 5 Olympus mju-1050SW      | 24256 | 23936 | 100 |
|       | 6 Ricoh GX100             | 18944 | 22592 | 100 |
| Out-of-dist. | 7 Rolleif P3-735XS | – | – | 100 |
|       | 8 Panasonic DMC-FZ50       | – | – | 100 |
|       | 9 Samsung NV15            | – | – | 100 |
|       | 10 Samsung L74wide        | – | – | 100 |
|       | 11 Fujifilm FinePixJ50    | – | – | 100 |
|       | 12 Canon Ixus70           | – | – | 100 |
| Total | 157632                   | 160512 | 1200 |
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classifiers in total.

**Augmented cGAN.** The generative network is also adapted from Johnson et al. (2016) and contains two residual blocks. In \( g(\cdot, \cdot), x \in \mathbb{R}^{64 \times 64 \times 3} \) and \( t \in \{1, \ldots, 6\} \) are always concatenated in the channel dimension at the input level (Perarnau et al., 2016), where \( t \mapsto \{0, 1\}^{64 \times 64 \times 6} \) such that the \( t \)-th channel is filled with ones whilst the remaining channels are filled with zeros. The discriminator is a matching-aware (Reed et al., 2016) 34 × 34 PatchGAN adapted from Isola et al. (2017), which classifies 34 × 34 overlapping patches as real or fake. In this work, the first layer of \( d(\cdot, \cdot) \) is always a constrained convolutional layer (Section 3.3.1), and is padded such that its output retains the spatial size of its input. Label conditions \( t \mapsto \{0, 1\}^{32 \times 32 \times 6} \) are then concatenated in the filter dimension of the output of the first unconstrained convolutional layer (Perarnau et al., 2016). Finally, regarding the local auxiliary classifiers, the subnetwork \( \hat{h}_{wdf}(\cdot) \) contains two residual blocks (Johnson et al., 2016). We utilised a ResNet-18 (He et al., 2016) architecture for \( q_{wdf}(\cdot), f_{pet}(\cdot) \), and \( f_{img}(\cdot) \).

### 4.3 Training Details

For training, Set-A and -B were both split into training (90%) and validation (10%) partitions such that the patches in each partition came from different 512 × 512 images. The training partition patches were augmented using on-the-fly mirroring and rotations; specifically, transformations belonging to the dihedral group \( D_4 \). We also employed class weighted sampling when selecting batch elements to address the issue of class imbalance.

**Target Classifiers.** The subnetwork \( \hat{h}_{wdf}^*(\cdot) \) was trained for 30 epochs using Adam (Kingma & Ba, 2014) with default parameters, a fixed learning rate of \( 1 \times 10^{-4} \), weight decay \( 5 \times 10^{-4} \), and a batch size of 128. Target classifiers with ResNet- and DenseNet-based architectures were trained for 30 and 90 epochs, respectively. Their respective batch sizes were 128 and 64. We used stochastic gradient descent with momentum 0.9 and weight decay \( 5 \times 10^{-4} \). The initial learning rate was 0.1 and was divided by 10 at 60 %, 77 % and 90 % of the total number of epochs.

**Augmented cGAN.** The subnetwork \( \hat{h}_{wdf}(\cdot) \) was pre-trained in the same manner as \( \hat{h}_{wdf}^*(\cdot) \), whereas the local auxiliary classifiers were pre-trained in the same manner as the ResNet-based target classifiers. The parameters of these networks were then fixed. For augmented cGAN training, we empirically set \( \lambda_{adv} = 0.01 \), \( \lambda_{aux} = 0.01 \) and \( \lambda_{cnt} = 1 \) in Equation (7). The model was optimised from scratch for 200 epochs using the Adam solver with a fixed learning rate of \( 2 \times 10^{-4} \), momentum parameter \( \beta_1 = 0.5 \), and a batch size of 32.

## 5 Results and Discussion

In this section we evaluate our augmented cGAN’s ability to anonymise the true source capture model of an image, perform ablation studies, and compare with a representative recent approach. As all networks are fully-convolutional, we can both classify and anonymise images of arbitrary size. Evaluation is performed on 512 × 512 images from Set-C.

**Non-Anonymised Absolute Performance.** The minimum classification accuracy attained on non-anonymised in-distribution images from Set-C for target classifiers \( f_{wdf}^*(\cdot), f_{pet}^*(\cdot) \), and \( f_{img}^*(\cdot) \) was 99.8 %, 99.8 % and 99.7 %, respectively. These results substantiate the utility of these methods for accurate camera model attribution, irrespective of the chosen network architecture, i.e. across the ResNet- and DenseNet-based architectures.

**Evaluation Metrics.** Our desiderata (Section 2) for the successful anonymisation of an image’s true source capture camera model are assessed based on distortion and the attack success rate. To quantify the distortion introduced by the anonymisation procedure, we use the learnt perceptual image patch similarity (LPIPS) (Zhang et al., 2018).\(^{11}\) The success of an attack can be quantified in
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Figure 4. The top left image corresponds to a non-anonymised image with ground-truth camera model label \( s = 6 \). Top row, columns 2–6 correspond to anonymised versions of the non-anonymised image, where \( s \mapsto 1, s \mapsto 2, \ldots, s \mapsto 5 \). The bottom row shows the \( \ell_2 \) difference images between the anonymised images and the original non-anonymised image. The differences were amplified, by clamping the values to be within one standard deviation of the mean, so as to highlight the otherwise imperceptible transformations.

two ways: first, the targeted attack success rate (TASR) which corresponds to the fraction of \( g(x, t) \) that satisfy \( \arg \max_i f^*(g(x, t))_i = t \); and second, the untargeted ASR (UASR) which corresponds to the fraction of \( g(x, t) \) that satisfy \( \arg \max_i f^*(g(x, t))_i \neq s \).

Baseline Method. As a baseline, we adapted the method of Chen et al. (2018; 2019)—previously described in Section 1.1—to a cGAN framework. The cGAN is augmented with the noise residual-based local auxiliary classifier \( f_{pef}(\cdot) \), and utilises a constrained discriminator. Differently, the generative network employs a preprocessor termed a synthetic colour filter array (sCFA), which serves to remove an input image’s original demosaicing traces and forces the generator to redemosaic its input with respect to the target camera model condition. We refer to this method as MISLGAN.

Absolute Anonymisation Performance. Figure 3 shows random examples of our augmented cGAN’s ability to transform images to a disparate target camera model class. On superficial inspection the transformed images appear identical to their corresponding non-anonymised versions. However, well correlated with human opinion scores of perceptual similarity. LPIPS does not suffer from the perception-distortion trade-off to the same extent as metrics such as PSNR and SSIM (Blau & Michaeli, 2018).

In preliminary experiments, we found no significant difference between training multiple unconditioned GANs, i.e. a generator-discriminator pairing for each camera model to falsified, and a single cGAN. We therefore adapted their method such that it used a single cGAN.

The sCFA array projects an RGB image to a CFA mosaic pattern and then back to a demosaiced RGB image. The Bayer ‘RGGB’ pattern is used for this. The resulting output is then fed to the generator at train and test time.

Figure 4 underscores the evident variation in colour, texture and location of the cGAN’s targeted transformation given an input and a target label. On the majority of in-distribution and out-of-distribution images, our augmented cGAN is able to successfully perform targeted transformations, achieving a TASR of \( 94 \pm 2 \% \) and \( 98 \pm 1 \% \), respectively, averaged across all 15 target classifiers. In contrast, MISLGAN achieves a TASR of \( 75 \pm 25 \% \) and \( 81 \pm 25 \% \). With respect to the in-distribution UASR, we attain \( 98 \pm 2 \% \) compared to MISLGAN’s \( 81 \pm 26 \% \). This supports our hypothesis that exclusively centring a generative network on the transformation of high-frequency model-specific artefacts results in suboptimal anonymisation, due to the loss of salient information during image content suppression.

Ablation Studies and Discussion. Tables 2 and 3 show various combinations of the local auxiliary classifiers proposed to augment learning (detailed in Section 3.3), and encourage the synthesis of discriminative, targeted model-specific traces into an input image. Notably, there is little difference in the distortion, as measured by LPIPS, when training a cGAN on this anonymisation task, i.e. regardless of the additional classification terms added or removed.

With respect to augmenting the objective exclusively with either noise residual-based classifier, it is apparent that the generator does not effectively remove and synthesise the necessary target model-specific demosaicing traces without the sCFA preprocessing module. Although the sCFA increases the ASR against image space classifiers, the forced synthesis of demosaicing artefacts seemingly does not account for all traces lost during image content suppression, as evidenced by the ASRs when attacking image-based classifiers. Notably, during preliminary experimentation, the sCFA preprocessor only aided anonymisation when a cGAN
was solely augmented with a noise residual-based classifier. We posit that when the generator additionally receives feedback from a constrained discriminator, this impedes the transformation process despite the generator facts germane to a particular camera model are mostly independent of an image’s scene, and their obfuscation clearly impedes the transformation process despite the generator receiving feedback from a constrained discriminator. This result demonstrates two things: image space classifiers latch onto weaker, pronounced lower-frequency artefacts; and the discriminator’s signal is insufficient to compel the generator to transform all of the necessary minute high-frequency details.

As hypothesised, it is imprudent to exclusively centre the anonymisation process on the transformation of high-frequency noise residual-based artefacts. The combination of a noise residual- and an image-based classification loss significantly improves a cGAN’s ability to anonymise images when attacking image-based classifiers. However, this comes at the expense of degraded anonymisation performance on in-distribution images when attacking noise residual-based target classifiers. Nevertheless, the mean performance when anonymising in-distribution images across the various types of target classifier are roughly commensurate with cGANs augmented solely with noise residual-based classifiers.

Our proposed method in full which utilises the classification losses from all three local classifiers achieves the best mean TASR and UASR result overall. Anonymisation methods that are capable of transforming artefacts of a low- and high-frequency nature are better able to deceive unknown non-interactive black-box target classifiers of varying types. This is particularly useful, since we do not know a priori in which space a target classifier operates. Therefore, it is advisable to attend to a range of artefacts, anonymising the image in its entirety, rather than merely concentrating on the most salient artefacts present within the high-frequency micro-patterns.

### 6 Conclusion

The method proposed in this paper, camera model anonymisation with augmented cGANs, offers a way to preserve privacy. Obversely, while such an application is evidently beneficial to certain vulnerable individuals, anonymisation could equally be open to misuse (Chesney & Citron, 2018). As society is at present afflicted by the deliberate dissemination of personal information, it is imperative to adopt such techniques.
tion of misinformation, we require more robust and reliable digital forensic methods for authenticating the origin and integrity of images. In particular, when faced with fabricated images, which mimic the underlying imperceptible fingerprints of disparate target camera models, such as those generated by our method.

We have shown that targeted camera model anonymisation, beyond attenuation or misalignment of model-specific artefacts, necessitates the transformation of both low- and high-frequency traces. Our approach shows promising results on both in-distribution and out-of-distribution images, with a significant performance increase over a recent representative approach—regardless of a non-interactive black-box target classifier’s architecture.

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