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A Deep Learning Approach to MRI Scanner Manufacturer and Model Identification

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Abstract

Forensics research has developed several techniques to identify the model and manufacturer of a digital image or videos source camera. However, to the best of our knowledge, no work has been performed to identify the manufacturer and model of the scanner that captured an MRI image. MRI source identification can have several important applications ranging from scientific fraud discovery, exposing issues around anonymity and privacy of medical records, protecting against malicious tampering of medical images, and validating AI-based diagnostic techniques whose performance varies on different MRI scanners. In this paper, we propose a new CNN-based approach to learn forensic traces left by an MRI scanner and use these traces to identify the manufacturer and model of the scanner that captured an MRI image. Additionally, we identify an issue called weight divergence that can occur when training CNNs using a constrained convolutional layer and propose three new correction functions to protect against this. Our experimental results show we can identify an MRI scanners manufacturer with 97.88% accuracy and its model with 91.07% accuracy. Additionally, we show that our proposed correction functions can noticeably improve our CNNs accuracy when performing scanner model identification.

Introduction

Identifying the source of digital images is a critical issue for the forensics community [1, 2]. Source identification techniques are important for many scenarios such as evidence verification, criminal investigation, intellectual property protection, forgery detection in social networks, etc. Many approaches to identify the source of digital images have been developed through significant effort from many researchers within the forensics community. Traditionally, researchers developed several algorithms based on specific forensics traces introduced by the image acquisition pipeline such as CFA demosaicing features [3, 4, 5, 6, 7], sensor noise [8, 9, 10, 11], and prediction residuals [12] or rich model features [13, 14]. In recent years, convolutional neural networks have been widely used by the forensics community due to their ability to automatically learn forensics traces directly from data [15, 16, 17, 18, 19]. Several forensic algorithms have been developed to perform camera model identification using convolutional neural networks and deep learning [20, 21, 22, 23]. These algorithms have achieved an improvement in the accuracy of source identification, led to the development of video source identification algorithms [24, 25], and enabled open set approaches to camera identification [26, 27, 28, 22, 29, 30], as well as led to the development of new anti-forensic attacks [31, 32, 33].

However, while most forensics research has focused on images and videos from standard digital cameras, to the best of our knowledge no work has focused on identifying the source of medical images, and specifically, magnetic resonance imaging (MRI) images [34]. While MRI scanners use a different physical and algorithmic data process pipeline than standard digital cameras, these machines still likely leave behind traces that can be linked to an MRI images source. For example, MRI images may contain imaging noise or other artifacts that some radiologists have anecdotally speculated may differ between MRI manufacturers and models.

Considering the development of the demands of MRI devices from society, identifying the source of an MRI scan has several potential but important implications for both the medical and information forensics communities. First, researchers may be able to identifying scientific fraud such like falsified MRI scans that do not come from a consistent source or contain cut-and-paste forgery. Second, researchers may protect patients anonymity and privacy such like by identifying the source of leaked MRI scan data. Lastly, researchers may also be able to protect against malicious manipulation of medical records via checking the source of different part of the same MRI scan.

In this paper, we propose a new CNN-based approach to learn the forensic traces left by an MRI scanner and use these traces to identity the manufacturer and model of the scanner that captured and MRI image. Our approach builds upon the CNN architecture proposed by Bayar and Stamm [17] as our baseline architecture. Additionally, we identify an issue called weight divergence during training and overcome it with propose new "correction function" according to the data characteristics of MRI scan. Through a series of experiments, our results show that we can identify the source of an MRI scan with 91.07% accuracy. Furthermore, our proposed correction functions can achieve a significant improvement in the system's accuracy, corresponding to a 27.10% relative error reduction over our baseline CNN.

Problem Formulation

We investigate the problem of identifying the manufacturer as well as their particular model of an MRI scanner. An MRI scan often contains a series of continues 2-dimensional images slices that form a 3-dimensional data with calibration. We demonstrate that such imaging process will leave some specific traces in 2-D level regarding to different sensors and algorithm the devices implemented. Therefore, we can separate an MRI scan into a series of 2-D images and we can use a CNN to extract the low-level information just like other work in camera model source identification.

Meanwhile, MRI scanners have different physical and digital data process from camera models. While camera model is designed to capture the photon that enter a sensor through lens, MRI

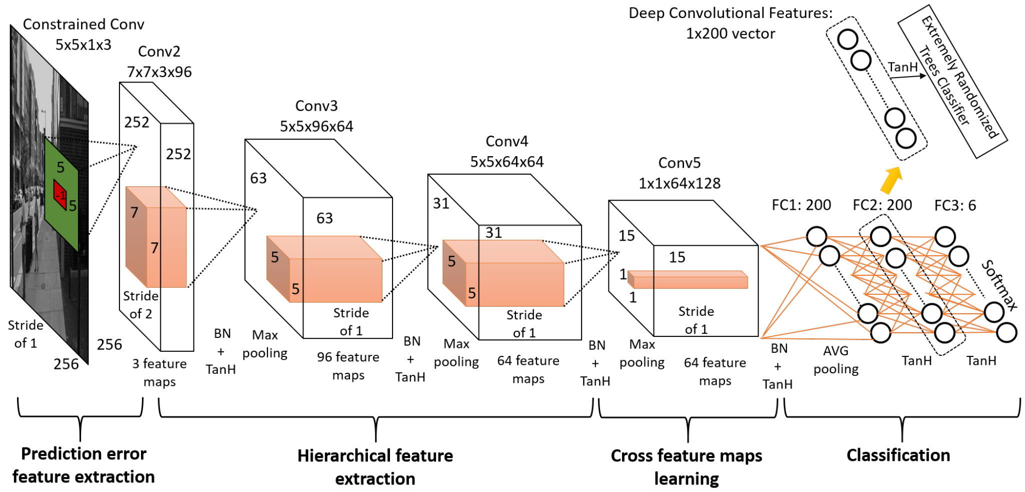

Figure 1: The MISLnet CNN Architecture used for MRI scanner model and manufacturer identification.

scanner usually use a series of coil to detect the radio frequency emitted by excited atoms. In addition, 2-D MRI scans often undertake some calibration algorithm to form 3-D scans, and MRI pixels value range is usually [0, 65535], while camera-captured image pixels is [0, 255]. Therefore, though both devices images 2-D pictures, their data process pipeline are still entirely different, which causes different structure and scale of forensics traces left by the devices. Based such difference, we train our CNN from scratch instead of transferring from pretrained models based on camera model data.

Additionally, we also demonstrate that by adding a new correction function into the constrained convolutional layer in our forensic CNN, we can prevent a weight divergence in constrained filters. Weight divergence is an issue that occurs during training - the magnitude of some entries in the filters in the constrained convolutional layer might gradually increase into a very large scale and then contaminate the whole CNN by outputting artificially large activations. To protect against this problem, we propose three new correction functions that prevent weight divergence from occurring. We evaluate the effect of these correction functions when performing MRI manufacturer identification and model identification. We found that all 3 correction functions significantly increases the classification accuracy, resulting in a Relative Error Reduction (RER) of 27.10% over the baseline approach when performing MRI model identification.

Proposed Method

We propose identifying the manufacturer and model of a medical images source MRI machine by using a forensic convolutional neural network.

To accomplish this, we extract a 128x128 pixel patch from an image in an MRI record, then feed it into our CNN trained to identify the manufacturer and/or model of its source MRI machine. This CNN is trained from scratch to learn MRI manufacturer/model identification features. We do not fine tune a forensic CNN pre-trained to perform camera model identification because the traces left by an MRI scanner are likely different in nature than those left by a digital camera (due to physical differences in the image/scan formation pipeline).

CNN Achitecture

In this work, we use the MISLnet CNN architecture proposed by Bayar and Stamm [17] as our baseline architecture. This CNN begins with a constrained convolutional layer in which each filter is constrained to learn a prediction filter (center value = -1, remaining filter values sum to 1). The design of constrained layer is inspired by [13], in which a high-pass filter is used to extract the pixel-level noise information of a digital picture. This layer is followed by three convolutional blocks, where each block consists of several convolutional filters, batch normalization, tanh activation, and max pooling. These convolutional blocks is designed to extract the high-level information based on the low-level noise information output by constrained layer. The combination of constrained layer and several convolutional blocks is treated as a learned forensics feature extractor. After that, the convolutional blocks are followed by two fully connected layers containing 200 neurons each, then finally an output layer with softmax activation where each neuron corresponds to a single class. The fully-connected layers is our classifier.

A key reason we used the MISLnet architecture as our baseline is that its constrained convolutional layers are designed to suppress the content of an image and learn on forensic traces. This should help the CNN ignore anatomical features within a scan and focus solely on MRI traces.

Using this architecture, we train CNNs to perform (1) MRI manufacturer identification as well as (2) MRI model identification.

New Correction Functions

In early experiments, we noticed that sometimes the filters in the constrained convolutional layer would diverge from their constraint. Specifically, the learned filter would develop one or more very large positive values along with very large negative values that effectively cancel each other out. When this occurred, the filter would effectively diverge from the constraint to learn predictive filters even though it did not violate the mathematical constraint. This could cause divergent filters to output extremely large values than that dominate other filters outputs and contaminate the network as a whole.

To avoid this situation, we developed three new *correction functions* to the constrained layer to force all filter entries to take a maximum magnitude of 1. We applied the correction functions after each update during training in order to force the model learn constrained filters in a balanced fashion. Pseudocode outlining our training procedure with correction functions is given in Algorithm 1. Our proposed correction functions are described below:

Let a filter coefficient be w and y(w) be the correction function applied to w.

1) **Clipping function** - The first is a simple value clip function. If the magnitude of a particular entry becomes larger than 1, we clip it into [-1, 1]. That is to say:

$$y(w) = \begin{cases} 1, & \text{if } \ w > 1 \\ w, & \text{if } \ -1 < w < 1 \\ -1, & \text{if } \ w < -1 \end{cases} \tag{1}$$

2) **Sigmoid scaling** - Each filter entry is independently scaled into [-1,1] by passing it through a sigmoid function. We first normalize the weights of constrained filter according to its standard update procedure, then feed the weights into the sigmoid function. That is to say:

$$y(w) = \frac{1}{1+e^{-w}}. \tag{2}$$

The sigmoid function makes the change of weights in constrained layer smoother.

3) $\mathbf{L_\infty}$ **norm normalization** (Max absolute value normalization) - In this approach, we divide all weights by the largest magnitude weight in the constrained filter. That is to say:

$$y(w) = \frac{w}{\|\mathbf{w}\|_\infty} \tag{3}$$

where $\mathbf{w}$ represents the vector of all the weights in a filter, and $\|\cdot\|_\infty$ indicates the L_∞ norm, i.e. taking the maximum value over all indices of a filter in the constrained layer.

Experimental Results

In this section, we present our experimental setup and the results of manufacturer identification and model identification of MRI devices. We create a dataset based on MRI scans and evaluate our classifiers with the accuracy based on testing set of our dataset. Our experiments showed that the MRI scanner do leave behind traces that can be detected and the forensic CNN model can be implemented to identify the source of MRI images. Besides we also demonstrate that our new "Correction Function" significant increased the accuracy in manufacturer identification and model identification of MRI images.

Data Collection

To evaluate our proposed approach, we created a dataset of MRI images captured from different models and manufacturer. Each MRI model data are from variety of machines from at least two different hospitals. Each model was used to collect several different cases, where each case corresponds to multiple scans of a patient. Each scan was de-identified to provide patient anonymity. For each case, several scans were collected corresponding to different parts of the anatomy, for example, neck, foot, abdomen, etc. Each scan consists of a group of anatomical MRI images showing the 3-D structure of a specific part of the human body.

Algorithm 1 Training Algorithm for Correction Functions

Initialize w_k's using randomly drawn weights
i = 1
while $i \le max\_iter$ **do**
  Do feedforward pass
  Update filter weights through stochastic gradient decent and backpropagate errors
  Set $w_k(0,0)^{(1)}$ = 0 for all K filters
  Normalize $w_k^{(1)}$'s such that $\sum_{l,m\neq 0} w_k^{(1)}(l,m) = 1$
  Set $w_k(0,0)^{(1)}$ = -1 for all K filters
  Update $w_k^{(1)}$ for all K filters by selected correction function
  i = i + 1
  if *training accuracy converges* **then**
    exit
  end if
end while

MRI scans were collected using four different MRI models made by two different manufacturers General Electric Healthcare (GE) and Siemens Magnetom (SM) with enough quantity of data as well as variety of devices for training. The MRI scanner models used were the GE Optima, GE Discovery, SM Espree, and SM Skyra. Using these MRI images, we formed a set of 26,000 128x128 pixel patches for each model, resulting in a dataset of 104,000 patches in total. From each MRI models set of 26,000 patches, we randomly selected 20,000 for training, 1,000 for validation, and 5,000 for testing. This resulted in a training set of 80,000 total patches, a validation set of 4,000 patches, and a testing set of 20,000 patches

Training Procedure

In both manufacturer and model identification task, We trained our CNN with 80,000 MRI patches as training set in total, for 200 epochs on batches of 64 patches. We used Adam optimization algorithm with 0.0001 as beginning learning rate, then updated the learning rate into 0.00001 for one time when the accuracy of validation set begin to fluctuate. For each model we train implement early stop before validation accuracy goes down. All our training were executed on NVIDIA GTX 1080Ti GPU.

MRI Manufacturer Identification

For MRI manufacturer identification, we compare the overall accuracy of the trained CNN with corrections functions to baseline CNN. The table 1 shows the comparison between baseline CNN and CNNs with correction functions. The relative error reduction (RER) measures the error reduction achieved divided by the total error reduction possible. It is defined as:

$$RER = \frac{Acc2\ -\ Acc1}{100\ -\ Acc1} \tag{4}$$

where Acc1 is the percent accuracy of the baseline approach (in this case the standard constrained conv layer) and Acc2 is the accuracy achieved by the improved approach (i.e. when using the correction function).

Table 1: Manufacturer Identification Accuracy Comparison

Correction Function	Accuracy	RER
None	96.67%	0.00%
Clipping Function	**97.88%**	**36.34%**
Sigmoid Scaling	96.35%	-9.61%
L-Infinity Norm Normalization	97.26%	17.72%

The highest manufacturer identification accuracy of 97.88% was achieved when our CNN used the clipping correction function. All four CNNs have strong ability to distinguish the source manufacturer. These results show that our CNN is capable of very accurately distinguishing between the different MRI manufacturers in our database.

We note that for MRI manufacturer identification, we can achieve high accuracy despite without correction function. However, the clipping functions still provided 36.34% improvement in relative error reduction(RER). Our detail results for this task are shown in table 2 , which contains confusion matrices obtained for our CNN using each correction function.

Table 2: Confusion Matrices of Manufacturer Identification

(a) Standard constrained layer

True \Prediction	GE	SM
GE	**93.74%**	6.26%
SM	0.39%	**99.61%**

(b) Clipping Function

True \Prediction	GE	SM
GE	**97.40%**	2.60%
SM	1.65%	**98.35%**

(c) Sigmoid Scaling

True \Prediction	GE	SM
GE	**94.39%**	5.61%
SM	1.68%	**98.32%**

(d) L-Infinity Norm Normalization

True \Prediction	GE	SM
GE	**95.45%**	4.55%
SM	0.92%	**99.08%**

MRI Model Identification

The comparison of overall accuracy obtained for MRI model identification are also shown in Table 3 and detail results which contains confusion matrices obtained for our CNN using each correction function in Table 4. The highest MRI model identification accuracy of 91.07% was achieved using our clipping correction function. These results shows that our proposed approach can accurately identify the scanner model used to capture an MRI image.

Table 3: Model Identification Accuracy Comparison

Correction Function	Accuracy	RER
None	87.75%	0.00%
Clipping Function	**91.07%**	**27.10%**
Sigmoid Scaling	90.14%	19.51%
L-Infinity Norm Normalization	88.25%	4.08%

Additionally, these results show that our proposed correction functions noticeably increase the performance of our CNN, with the clipping function approach performing the best. As a baseline, the MISLnet CNN using the standard constrained convolutional layer achieves an average accuracy of 87.75%. When using the clipping function, we achieve an average accuracy of 91.07%, which corresponds to a 3.32 percentage point accuracy gain and a relative error reduction (RER) of 27.10%. Our results shows that Clipping function can suppress weight divergence and overfitting and achieve highest performances in both manufacturer and model identification tasks

Table 4: Confusion Matrices of Model Identification

(a) Standard constrained layer

	Optima	Discovery	Espree	Skyra
Optima	**77.92%**	15.34%	5.24%	1.50%
Discovery	1.34%	**96.56%**	2.02%	0.08%
Espree	0.26%	0.50%	**93.22%**	6.02%
Skyra	0.32%	0.32%	16.06%	**83.30%**

(b) Clipping Function

	Optima	Discovery	Espree	Skyra
Optima	**87.14%**	5.86%	4.70%	2.30%
Discovery	4.42%	**93.00%**	2.04%	0.54%
Espree	0.28%	0.08%	**92.74%**	6.90%
Skyra	0.22%	0.08%	8.32%	**91.38%**

(c) Sigmoid Scaling

	Optima	Discovery	Espree	Skyra
Optima	**91.18%**	4.04%	2.74%	2.04%
Discovery	6.02%	**91.92%**	1.32%	0.74%
Espree	2.26%	0.24%	**87.90%**	9.60%
Skyra	2.72%	0.02%	7.70%	**89.56%**

(d) L-Infinity Norm Normalization

	Optima	Discovery	Espree	Skyra
Optima	**80.34%**	3.74%	11.58%	4.34%
Discovery	4.56%	**92.08%**	2.04%	1.32%
Espree	0.14%	0.08%	**87.92%**	11.86%
Skyra	0.10%	0.00%	7.24%	**92.66%**

We note that our other two correction functions also yield performance gains over the standard constrained convolutional layer. When using the sigmoid scaling function, we achieved an average accuracy at 90.14%, which corresponds to a RER of 19.51%. When the max absolute value normalization function was used, we achieved an average accuracy of 88.25%, which corresponds to a RER of 4.08%.

Conclusion

In this paper, We demonstrate that MRI scanners leave behind traces that can be used to identify the source of an MRI image. To the best of our knowledge, no work has been performed on MRI image source identification. This finding can be potentially useful to researchers in the information forensics, security, and medical imaging fields. We also show that a forensic CNN can identify the manufacturer and model of the MRI scanner that captured an MRI image. We evaluate our proposed approach on a new databases of MRI images and our results show that we can identify an MRI scanners manufacturer with 97.88% accuracy and model with 91.07% accuracy. During training process, we identify an issue, which we call weight divergence, that can occur when training a filter in the constrained convolutional layer of a forensic CNN. This issue has not been identified before and can lead to decreased CNN performance. We propose three new correction functions to prevent weight divergence, and experimentally demonstrate that they can noticeably increase the performance of our CNN when performing MRI scanner model identification.

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