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Camera Model Identification using CNN

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ABSTRACT: Source camera model identification has consistently been one of the major branches of digital image forensics as it is the basis of resolving a broad set of forensic issues. Various efficacious camera model identification algorithms have evolved for the workable necessity. Although, they are mainly based on conventional machine learning algorithms and depend on refined models and features. As deep learning has made notable advancements in functions of computer vision, remarkable attentiveness has emerged in applying deep learning in image forensics. In this paper, we explore a novel proposal to resolve the camera model identification problem. Precisely, we propose a deep learning technique based on convolutional neural networks, which is trained on the features distinguishing each camera model straight from the obtained images. We alter a convolutional neural networks (CNNs) layout. The identification accuracy on the Kaggle IEEE's Signal database achieves 98.78% over 10 camera models without any other state-of-the-art methods, for example, extra classifier, majority voting, etc. Camera pictures from ten camera models in the IEEE's Signal Processing Society are selected as our test database. Evaluation output express that in ten model's identification, our model can perform the detection with top classification accuracy from 90.39% to 94.88%. Identifying the model of the camera utilized to click a picture allows resolving an extensive series of forensic issues, from copyright violation to ownership characterization. In consequence, the forensic group has brought up a set of source camera model identification techniques that utilize characteristic marks left on images obtained by the refining pipelines certain of every camera model.

KEYWORDS: Camera Model Identification, Convolutional Neural Networks, Deep Learning, Image forensics.

I. INTRODUCTION

On account of the rising accessibility of image accretion tools and multimedia sharing platforms, images are becoming a prevalent role in our everyday life. While downloading, duplicating, plagiarising, and reconstructing digital stuff is becoming effortless throughout the years, some ways of supervision and legitimate validation have become high-priority fundamental. For this purpose, the forensic group has brought up an extensive series of mechanisms to re-implement the past of multimedia items. Amid the issues intercepted by the image forensics group, one that is still thoroughly examined because of its involvement in many applications is camera model identification. When we provide an image to our model, it identifies which camera model and brand has been used to click it. The solution to this problem can support an analyst in pointing out the owner of illegal and disputable stuff (for example, pedo-pornographic pictures, terroristic activity clips, etc.). Furthermore, the research performed on picture patches can be used to reveal splicing forgeries managed between pictures coming from different cameras. Characteristics of an image to a particular camera model in a blind fashion (i.e., not leveraging watermarks initiated at photo inception) is possible utilizing inherent artifacts left at shooting time by the acquisition process. The plan is that each camera model carries out a series of feature complex operations at acquisition time, from directing light rays through lenses to inserting color channels by exclusive demosaicing filters to brightness accommodating, and also others. As these functions are irreversible, they present some distinctive artifacts on the ultimate image. These artifacts a remark that acts as a strength to detect the used camera model. To achieve this, various camera model identification techniques have been presented in the literature. Some of them operate by looking for certain marks on pictures under inspection as a state by a hypothesized analytical model called a priori(e.g., natural image modeling, noise characteristics, imaging model, lens distortion, demosaicing strategies, etc.).Other techniques make uses of characteristics mostly capturing analytical image attributes matched with classifiers of machine learning (for instance-occurrences, local binary patterns, etc.).Although, all the previously stated techniques depend on manually described methods to show traces featuring various camera models.

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II. OVERVIEW

In this paper, we inverse the used model by exploring the possibility of resolving the camera characteristic problem by using data-driven technology. We focus on learning attributes that characterize images taken with different cameras directly from pictures, rather than imposing any model. Our technique is inspired by other victorious deep learning-based algorithms proposed for forensics tasks. Specifically, use a Convolutional Neural Network (CNN)to record camera-specific features in a mechanical way and for classification. The main benefits of using the presented methodology regarding the other state-of-the-art solutions are showed up by our exploratory campaign implemented on more than 14,000images belonging to 10 camera models from a popular dataset. More specifically:

(i)as our method does not depend on any systematic modelling, it is less inclined to errors because of schematic supposition or model simplifications (e.g., linearization, etc.);
(ii) the presented technique can operate on small image marks (i.e.,64×64pixels) with 94%of accuracy, thus terminating the way to approaches such as interfering and splicing localization;
(iii)our presented CNN, trained only once on the IEEE dataset, learns a feature extrication technique that generalizes well on a set of concealed camera models;
(iv) the minimized dimensionality of the extricated feature vectors (128 elements) allows the use of not sophisticated classification tools (linear SVMs).

III. DATASET

Usually, algorithms of camera model identification are assessed on the Dresden Image Dataset. This dataset comprises photos from mainly 70 cameras and about 25+ models with totally non-identical locations for every gadget (e.g., nature, office, etc.). Nevertheless, it needs augmentation and camera pictures from mobiles. Within the current work, we made use of two datasets to assess the performance of our model. The primary one was a dataset that was issued by the Organizers of the IEEE's Signal Processing Society Camera Model Identification Challenge which consisted of 2500 pictures, equivalent to 10 camera models with 250 images respectively. Lens deviation manifested to be a strong attribute within the earlier work. To cease the participants from utilizing it, the competition's organizers cropped central 500x500 elements of the photographs within the testing set. Moreover, half of the photos were augmented by the magnitude of the transformations, Gamma, Resize, Jpeg Compression, or Contrasts and the remaining half were in their raw form. For this dataset, the bottom truth labels were concealed to the participants of this challenge, and analysis was carried out through the Kaggle.com website's LeaderBoard. Within the competition, outside data was permitted to use. Therefore, we had scrapped beyond five hundred GB of images from, Wikipedia Commons, Flickr, Yandex. Fotki and sites of mobile reviews to get pictures for the specified 10 categories. Subsequently, we carried out filtering which had the EXIF property, removing the features which were customized by a LightRoom or PhotoShop code. Afterward, the pictures with the JPEG compression quality were lower than ninety-five, were prohibited. Ultimately, the pictures were filtered out that had the dimensions that were not included in the default record of feasible picture sizes that compatible cameras produced. Following this filtering, we found 78006, not falsified photos. We divided all of them into two sets: The training set and the hundred for the validation set that we used to assess the performance of our model sectionally and to carry out an ablation study.

Camera model	Subset	
	Training	Validation
HTC-1-M7	10156	100
iPhone-6	10053	100
Motorola Droid Maxx	11608	100
Motorola X	1769	100
Samsung GalaxyS4	9351	100
iPhone4S	9383	100
LG Nexus5X	5437	100
Motorola Nexus 6	10950	100
Samsung Galaxy Note3	6025	100
Sony NEX7	3075	100

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IV. IMPLEMENTATION

For this project, we considered the dataset provided by the IEEE Signal Processing Society, which is a publicly available dataset tailored to image source attribution problems. These images are shot with 250 camera instances of 10 different models. For every camera, a varying number of clicks has been taken from diverse spots (e.g., classroom, office, garden, etc.). For each location, a set of different pictures was acquired from different viewpoints (e.g., looking on the right, on the left, etc.). After this, we will refer to a spot as the combination of a specific viewpoint and location. In our approach, we chose only inherent JPEG pictures from various models of the camera having multiple occurrences. This resulted in 10 different camera models and 250 scenes, for a total amount of more than 2500 images. To properly assess algorithms based on deep learning and to make sure an adequately large amount of training data, we had to split the dataset into training, testing, and validation sets as follows:

For every camera model image, I, linked to a particular camera model L, we will extract K non-overlapping patches Pk, $k \in [1, K]$, of the size 64×64 pixels. To circumvent selecting regions that are either overly dark or saturated, we eliminate all patches with saturated pixels and categorize only those whose average value is close to half the image dynamic. Every patch Pk comes into the same label L of the source image. Our current model of Convolutional Neural Network acquires as input patches of only size $64 \times 64 \times 3$, with the pixel values varying from 0 to 255. The training set has the pixel-wise average which is subtracted first to every patch of input. The outcome is then mounted pixels in amplitude by a factor of 0.0125 to reduce its dynamic.

Characteristics about layers of CNN are given in details as follows:

- The first convolutional layer (conv1) with its 32 filters of size 4×4×3 and stride 1 go along with the max-pooling layer (pool1) with the kernel of size 2 and stride 2.
- The second convolutional layer (conv2) with its 48 filters of size 5×5×32 and stride 1 go along with the max-pooling layer (pool2) with a kernel of size 2 and stride 2.
- The third convolutional layer (conv3) with 64 filters of size 5×5×48 and stride 1 goes along with the max-pooling layer (pool3) with the kernel of size 2 and stride 2.
- The fourth convolutional layer (conv4) with 128 filters of size 5×5×64 and stride 1 displays a result vector output of 128 elements.
- An inner product layer (ip1) with 128 output neurons goes along with the ReLU layer (relu1) to generate a 128- dimensional feature vector.
- The last $128 \times N$ inner product layer (ip2), where N is the number of training classes and is followed by the soft-max layer (SoftMax) for computation of the loss.

V. RESULTS AND DISCUSSION

In our work, we have discovered how the accuracy of our model is influenced by the Gamma, JPEG, and image transformations. In the first place, we have assessed the vulnerability of the quality of the model from the size of our training set. We used the dimensions of 25000, 50000, and 62500 respectively. We could not notice the statistical variations for these sizes. We contemplate that this counter instinctive outcome is related to the certainty that for the selected robust architecture with the correlating schedule of training, this task was not challenging enough, which lead to a powerful model with a testing accuracy of 0.73 on the tiniest data point of 25000 images. We have observed that we are required to carry out classification, on more than ten classes like a much bigger number of classes, for example, 100 or substantial classes. The productive association in the size of the training data and accuracy of the model was more salient. Furthermore, we also assessed the outcome of the Gamma, JPEG Compression, and Resize augmentations on the accuracy of validation.

As expected, our model constantly displayed exceptional performance in all the extents of the augmentations used while training the model. After examining the model, it shows that this result provides auxiliary evidence that models of Deep Learning can be made sturdy for a broad span of various transformations only if desired transformations were used as a training time increment. At last, we perceived the consequences of the crop size on the performance of our model. It is regarded as true in the literature that the algorithms that were utilized in it to operate the raw pictures, leave low-level local features that can be useful for the algorithms of camera model identification. We presume that the data that come after this supposition crop size, would not influence the performance of the model for a comprehensive number of crop sizes. Although, the curve may be elucidated as the certainty that not just local, but long-range correlations in pixel values may set out a robust feature.

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Hence, this project contributes to detecting camera models elicited from neural networks and feature extraction.
The algorithm used in our approach incorporates extricating three sets of features. The noise residual is acquired by putting in the wavelet denoising filter. Photos from camera models were used from the database stated and classified by the classifier of CNN.

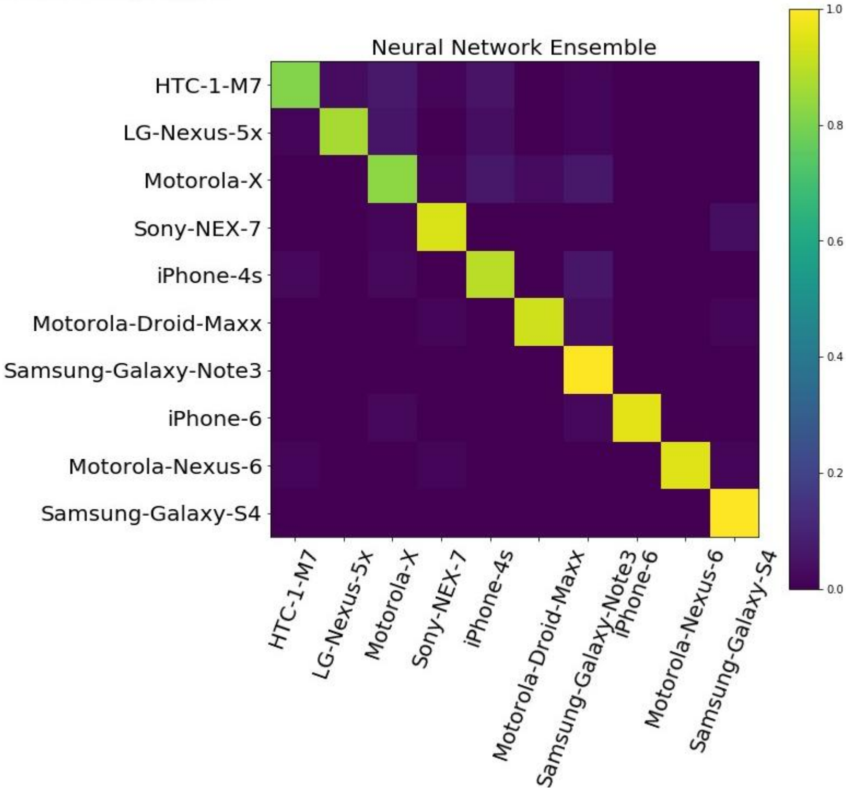

Fig.1. Normalized confusion matrix of our project

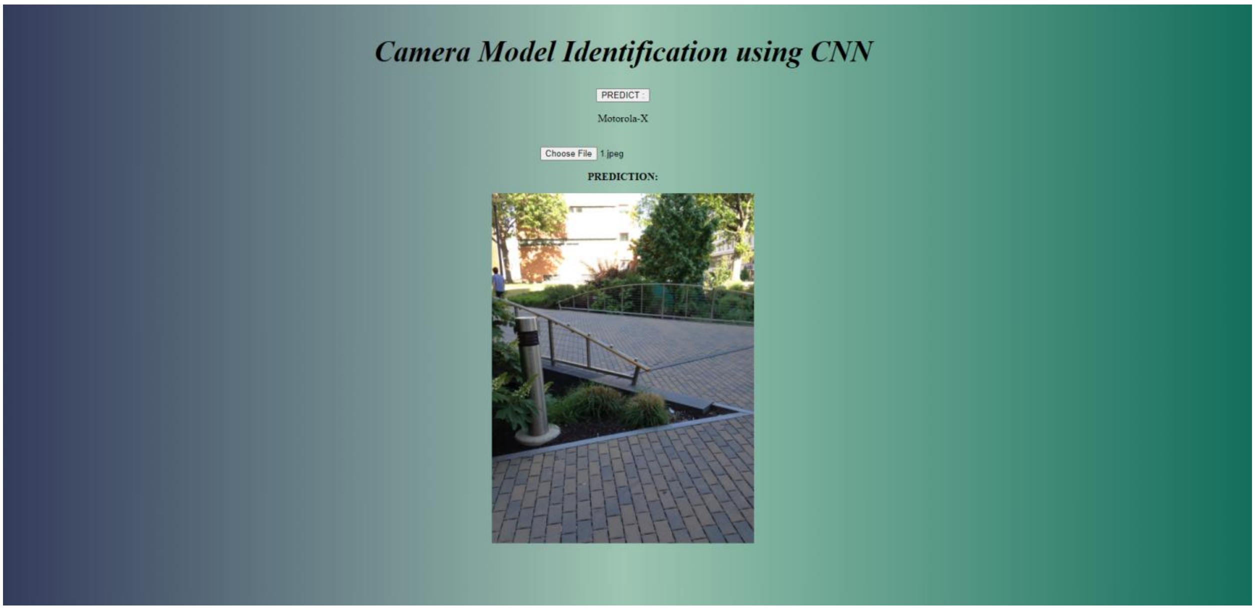

Fig.2.Result of our project

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Weacknowledge the use of imagery from IEEE Signal Processing Society's Dataset provided by Kaggle.

VII. CONCLUSION

Feature-based camera model identification has always usually played a very important part in forensics investigations on images. There are several applications of camera model detection using CNN in image processing. For example, in the field of forensics, it may be pivotal to know whether an image was taken using a Google Pixel or an iPhone or Motorola-X to identify who may be the owner of illicit or incriminating photos or even to determine who is the proper owner of intellectual property or photos which do not respect privacy laws. Now, various learning algorithms are one of the promising research fields for the automated extraction of complex data representations at high levels of abstraction. CNN often produces good results. Nonetheless, we must say that deep learning approaches require high computing resources compared to more traditional machine learning approaches. In our current model, better training of the model will lead to better functionality of the model which gives more accuracy. Therefore, we have successfully understood the efficiency of CNN in source model identification of various camera models.

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