C14 Deep Learning With Camera Identification

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After attending this presentation, attendees will better understand the limitations and possibilities of camera identification.

This presentation will impact the forensic science community by providing deep learning techniques that can be used for a variety of databases. It appears that the right clustering was found for only for a few cameras based on the Photo Response Non-Uniformity (PRNU) pattern.

In this presentation, a camera model identification using a deep learning technique is introduced. The PRNU noise pattern, the fingerprint of the camera, is extracted to classify and identify the camera model. Deep learning is a subfield of machine learning, which trains the computer as a human brain to recognize similarities and differences by scanning in order to identify an object. In forensic science, it is important, especially for child pornography cases, to link a photo or a set of photos with a specific camera.

Each different camera has a different noise pattern, the so-called PRNU noise pattern. Each camera has an imaging sensor that converts the light into an electrical signal. Charge-Coupled Device (CCD), Complementary Metal-Oxide Semiconductor (CMOS), Junction Field-Effect Transistor (JFET) and Foveon® X3 are some of the popular imaging sensors, with the CCD being most common.

For the experiments, NVIDIA® DIGITS, an interactive deep learning Graphics Processing Unit (GPU) training system, is used for the implementation of the project. DIGITS applies deep learning to the database that is uploaded, then classified. In the next step, the appropriate network is chosen depending on the size of the dataset. During the second step, the model is trained in order to extract features and find similarities and differences between the categories. There are three given networks: LeNet, AlexNet, and GoogleNet. Furthermore, a graph is provided informing the user of the success of the training. The most important aspects are the accuracy of the trained model and the loss of data during the process of training and validation. In the last step, the user uploads a single image and the program provides the top five predictions.

By modifying the AlexNet, the results improved, providing material for further research. The accuracy rate was high (80%-90%); however, DIGITS was able to successfully identify only 3 camera models out of 17 from the database. Furthermore, individualization of a camera was unsuccessful. In a database containing more than one camera of the same model, the accuracy rate was extremely low. In both cases, the problem was expected to be the imaging sensor. Manufacturers use the same imaging sensors, which result in similar PRNU noise patterns. As a result, DIGITS cannot distinguish the similarities and the differences of the images. It is important for future research to create a much larger database, as the one used contained 200 images per class. A larger database will feed the program with much more information.

Deep Learning, PRNU, Camera Identification