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DISTINGUISHING DIFFERENT MEDIA TYPES ON SCANNED IMAGES USING MACHINE LEARNING TO AUTOMATE MEDIA SELECTION

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Distinguishing different media types on scanned images using machine learning to automate media selection

ABSTRACT

When using a printer, one of the most frequent operations is to load media onto which the printing will occur.

This operation not only consist in physically loading and placing the media in the paper path for the printer to feed the media, but also consists in providing some media identification to the printer which then will be used to select the proper parameters for optimal printing.

Making a mistake in the identification of the media, something with can occur for new operators or these who do not often use the printer, will lead to a non-optimal printing image quality.

To avoid this, the media loading can be automated to recognize the media correctly using a suitably trained machine learning (ML) algorithm which examines scanned images of the media and then output the correct media category.

The optimal features, along with the fine-tuned classification approach proposed herein, delivers better printer automation, and provides an enhanced experience to the end-user.

ARTICLE

Media type classification is an important problem to automate the printer settings selection and ensure performance.

A supervised classification using Machine Learning methods can be developed to identify common media used in a printer, for instance, Avery, Orajet, 3M, superprint, starflex, mesh, black vinyl, paper, textile, SAV, banner and backlit.

An A4 media sample was cut-out and scanned to obtain a detailed colour image of the media surface. These images were used as training and validation datasets for our machine learning approach. Images may be captured with other methods than digital scanners such as cameras.

The training samples used with the machine learning algorithm consisted in ‘white’ media digitized with scanner at 600 dpi (4960×7015).

While a human operator can distinguish media types of categories easily, recognizing media types within the same category is more difficult. For instance, distinguishing from the 3 different brands of Self-Adhesive Vinyl (or 2 Banners) requires a considerably more experienced operator, a skill not always available to operators, thus these cases are more error prone but could be avoided by an automatic media detection system based on Machine Learning.

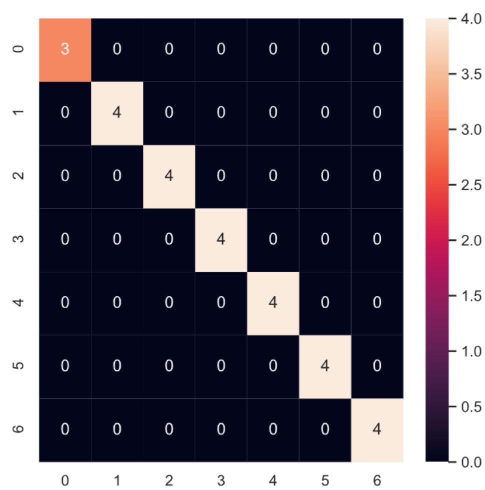
By using statistics and classifier in the inference engine, the Machine Learning algorithms can gain deeper and more fine-grained insights into how exactly our data is structured and based on that structure how we can optimally classify it.

They also allow to explore an entire dataset and compute bias, variance, mean, median and percentile values, among other statistics. Some image features extracted from our scanned images were subdivided into the following classes such as "First order statistics", "Gray level co-occurrence matrix", "Gray level run length matrix" and "Gray level size zone matrix", among others.

To calculate these features, the scanned images were previously cropped to 256×256 overlapped patches. Although the feature extraction can be applied directly to the entire scan, using crops speed up the processing workflow.

Afterwards, the LightGBM classifier was employed to uncover the optimal features (see Figure 1) and classify the unseen media patches (see Figure 3). More specifically, LightGBM is a gradient boosting framework that uses tree-based learning algorithms. It can also handle a large amount of data, needs less memory usage, the training is faster and efficient, and the testing accuracy is usually remarkable.

In fact, in our test the final classification accuracy reached 100% and $\approx$ 96% for 7 and 10 classes, respectively. Although the model outcome is outstanding (see Figure 3), the robustness of the proposed algorithm must be validated with diverse scan settings and media types. Confusion matrices are also shown below.



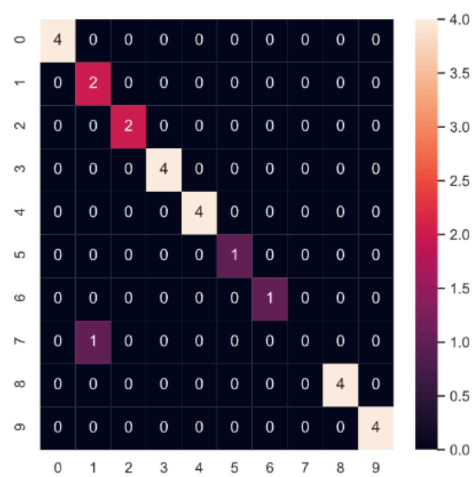


Figure 3. Confusion matrices for both 7 (left) and 10 (right) media type categorization.

To confirm our results, the separability between sets of media is calculated using a principal components analysis (PCA) reduction algorithm over the previous features (see Figure 4). The following 2D (left) / 3D (right) plot shows that the features selected can separate the media with a high margin, which correlates very well with the confusion matrices obtained above.

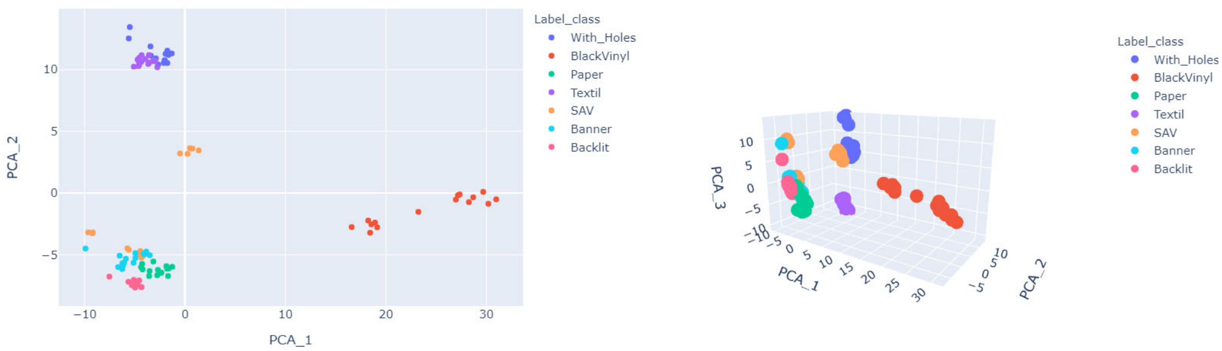


Figure 4. Separability between all medias calculated using PCA and the selected statistical features.

In conclusion, this experiment suggests that unsupervised algorithms along with the selected features can be employed to correctly identify and configure new medias without any user interaction and make the media loading experience more user friendly and less error prone.

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