CSIC5011 Final Project

Art Forgery Detection: Spotting The Real Raphael's Sketches

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Introduction

Art forgery detection by means of physical examination can be extremely delicate and complicated, lest the authentic piece risk irreversible damage. However, a digital approach via statistical analysis has been shown to work just as effectively, if not more.

Figure 1. Portrait of Raphael (presumed)

In this project, we shall attempt to predict whether 7 unlabeled sketch pieces belonged to the prominent Renaissance period Italian painter, Raphael, by training various machine learning models on a set of labeled images of sketch art.

Data

The data consists of 28 labeled scanned images of sketch art, either in JPEG or TIF format.

- **Labels**: 12 Raphael, 9 non-Raphael, and 7 disputed.
- **Size range**: Around 900,000 to 27,000,000 pixels.

Methodology

Models

- **Geometric Tight Frame**: Proposed by Liu et al., this method extracts features by applying 18 pre-selected filters. For classification, we use a simple **outlier detection** method, as well as a **one-hidden-layer neural network**.
- **ResNet-18**: This is a residual neural network first proposed by Microsoft. We apply it by freezing its first convolutional layers for feature extraction, and training its last fully connected layer for classification.

Model Evaluation & Prediction

- **Leave-one-out Cross Validation**: We train our models on all but one sample, and test using the left-out one. We repeat this for all <u>labeled</u> samples in the data set.
- **Prediction**: We train the models on all 21 labeled images, and make predictions on the unlabeled ones.

Geometric Tight Frame (GTF)

Feature Extraction

Given an image, we only look at its greyscale transformation, as colour should be of minimal significance in this case. The algorithm then applies 18 filters; computes 3 statistics for each filtered image; and concatenates these numbers into a 54-dimensional vector. Finally, it puts all these vectors into a matrix X, where each row represents an image (Figure 2).

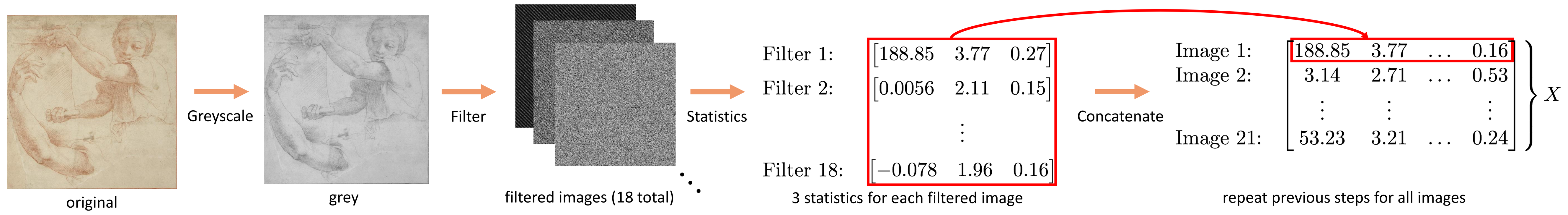

Figure 2. The GTF feature extraction process

Classification Method I: Outlier Detection (OD)

This algorithm assumes that under the 2-norm, Raphael's sketches should be close to each other, while the non-Raphael ones should be outliers. As a rough overview, the algorithm first prunes X by keeping only the most 'useful' columns. Then it computes the 'centre', i.e. the average of the Raphael-rows of the pruned X. Finally, it finds a threshold t such that any rows whose distance from 'centre' is smaller than t are classified as Raphael, and the rest are classified as non-Raphael (Figure 3).

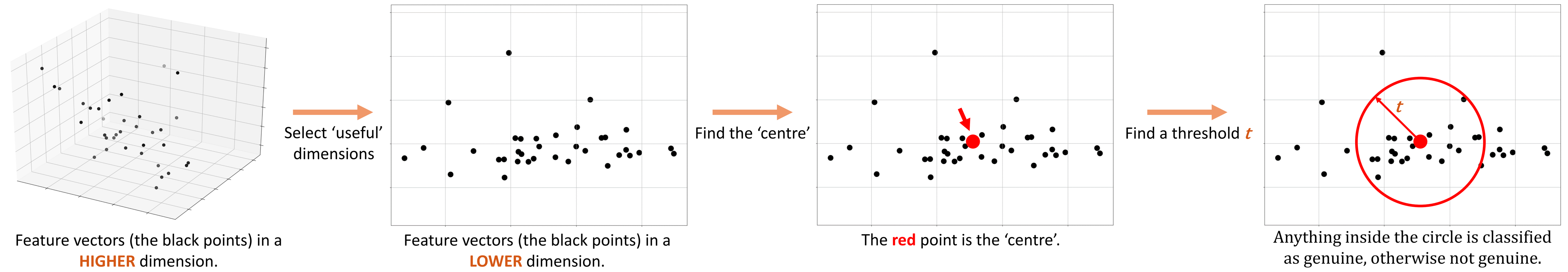

Figure 3. The OD classification process

Classification Method II: Neural Network (NN)

For this method, we simply connect each row of X (not pruned) to a one-hidden-layer neural network (shown in Figure 4), with 6 hidden units and Leaky ReLU activation, and trained by minimising the Cross Entropy Loss.

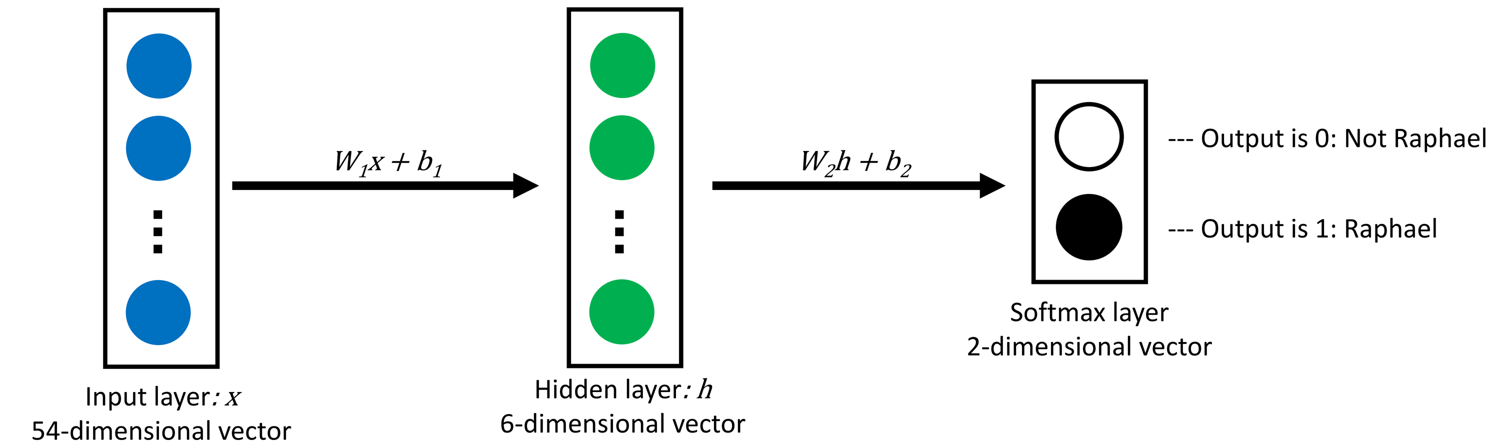

Figure 4. The structure of NN

ResNet-18 (RN18)

Transfer Learning

ResNet-18 means **Res**idual **Net**work with **18** layers, and does both feature extraction and classification by itself. To be able to implement this, we scaled all images down to 512×512, and randomly cut out a 224×224 piece as input. The term 'transfer learning' means we use pre-trained weights for the feature extraction part, and only train the classification part.

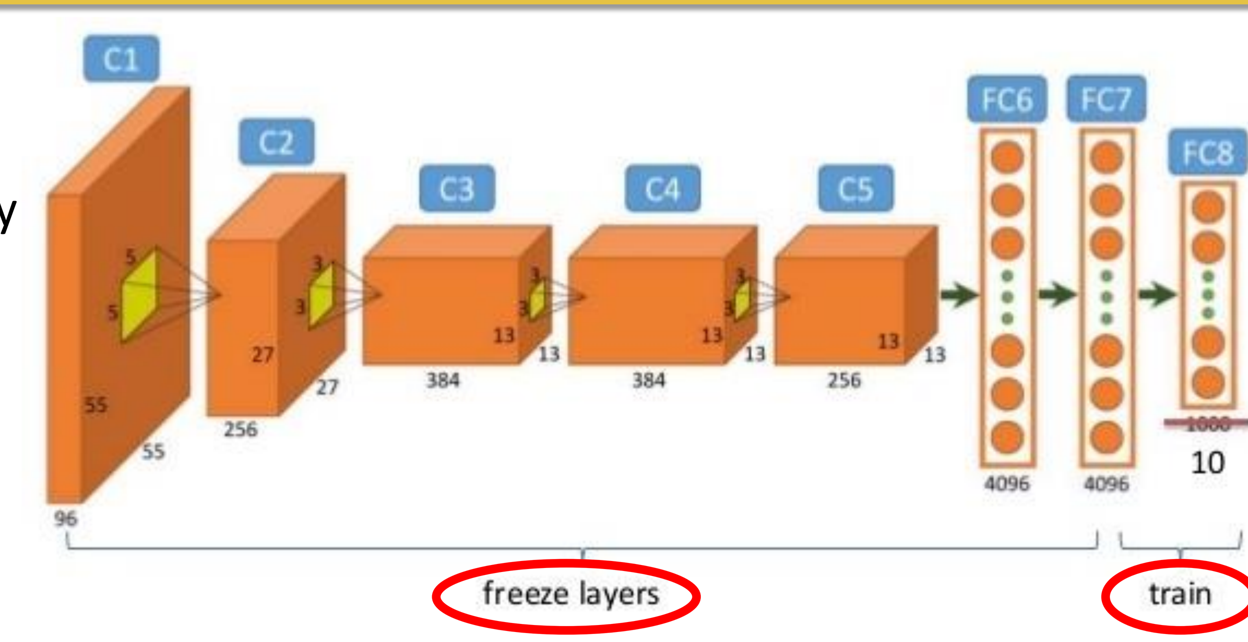

Figure 5. This figure simply illustrates the concept of transfer learning, or more specifically fine-tuning, and does not represent the actual structure of ResNet-18 used in our project. In essence, we keep the first few blocks (the convolutional layers) fixed during training, and only update the fully connected (FC) layers.

Cross Validation (CV)

- The result for OD is obtained by selecting the 4 most frequently used features (columns of X) in the CV process, and doing CV again using just those 4 features.
- The CV results for NN and RN18 are random, we therefore only choose <u>the best one</u>. As a matter of fact, the accuracy of RN18 reached 100% once, but we thought this was not reliable, so we instead chose the second best one, which is shown below in green.

Feature Extraction	Classification	CV Accuracy
GTF	OD	81.0%
	NN	81.0%
RN18	RN18	95.2%

Table 1. Model accuracies

We suspect that the GTF features might not be suitable for capturing the characteristics of Raphael's sketches, and thus giving a rather poor classification accuracy. On the other hand, extracting features directly using RN18 shows drastic improvements (see Table 1).

Predicting the Unlabeled Images

Figure 6. The unlabeled sketches

By training our models on the 21 labeled images, we can now give the predictions for the 7 unlabeled ones (Figure 6) under each of the 3 methods (Table 2). As OD and NN give rather poor CV performance, the predictions of RN18 should be regarded as more credible.

Image ID	OD	NN	RN18
1	✗	✓	✓
7	✗	✗	✗
10	✗	✗	✓
20	✗	✗	✗
23	✗	✗	✗
25	✗	✗	✓
26	✗	✓	✗

Table 2. Predicting the unlabeled images. A tick (✓) means it is classified as Raphael's work, a cross (✗) means it is not.

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References

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