Classification of Goossen van der Weyden paintings Consistent with Underdrawing Style

Josephine Wolff, Sina Jafarpour, Maximiliaan Martens, Robert Calderbank and Ingrid Daubechies

Goossen van der Weyden

- Flemish painter of the early 16th century
- Large workshop in Antwerp, with at least 8 apprentices registered each year from 1503 to 1517
- Paintings were often worked on by several different students

Poliptych of St. Dymphna, Antwerp

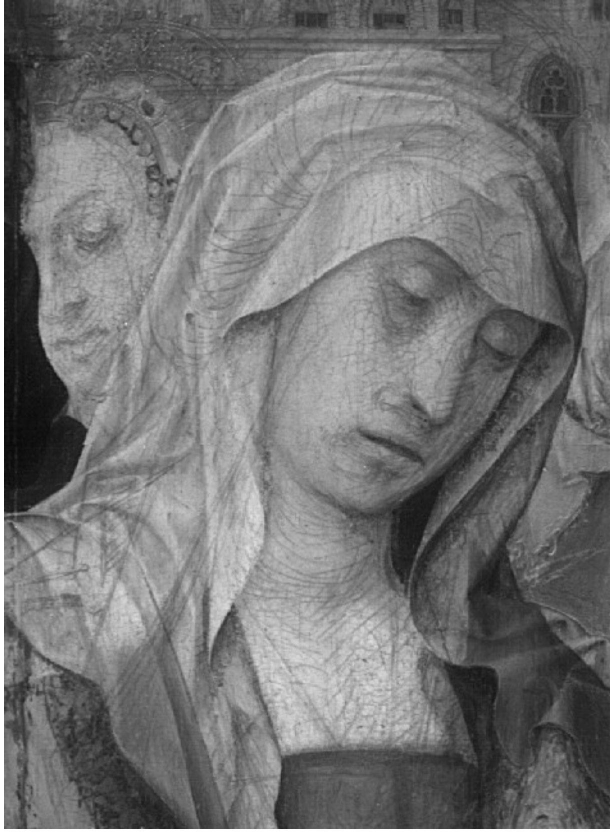
Underdrawings

- An underdrawing is the drawing or sketch done on a canvas before it is painted
- We can visualize these underdrawings using infrared reflectography

Carbon black pigments absorb infrared light

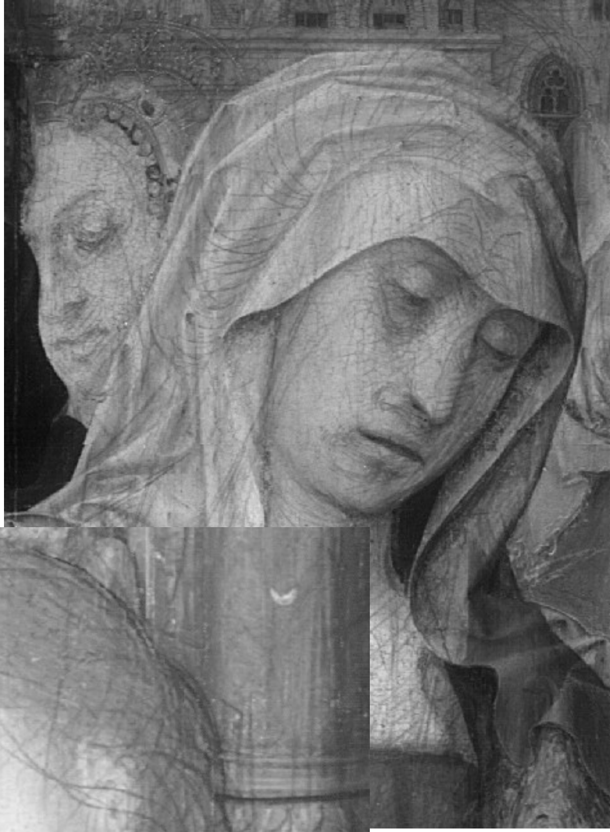
Styles of Underdrawings

- Paintings from van der Weyden’s workshop exhibit several different kinds of underdrawings
- Detail and clarity of underdrawings may correspond to the proficiency of the apprentice(s)



Styles of Underdrawings

- Paintings from van der Weyden’s workshop exhibit several different kinds of underdrawings
- Detail and clarity of underdrawings may correspond to the proficiency of the apprentice(s)

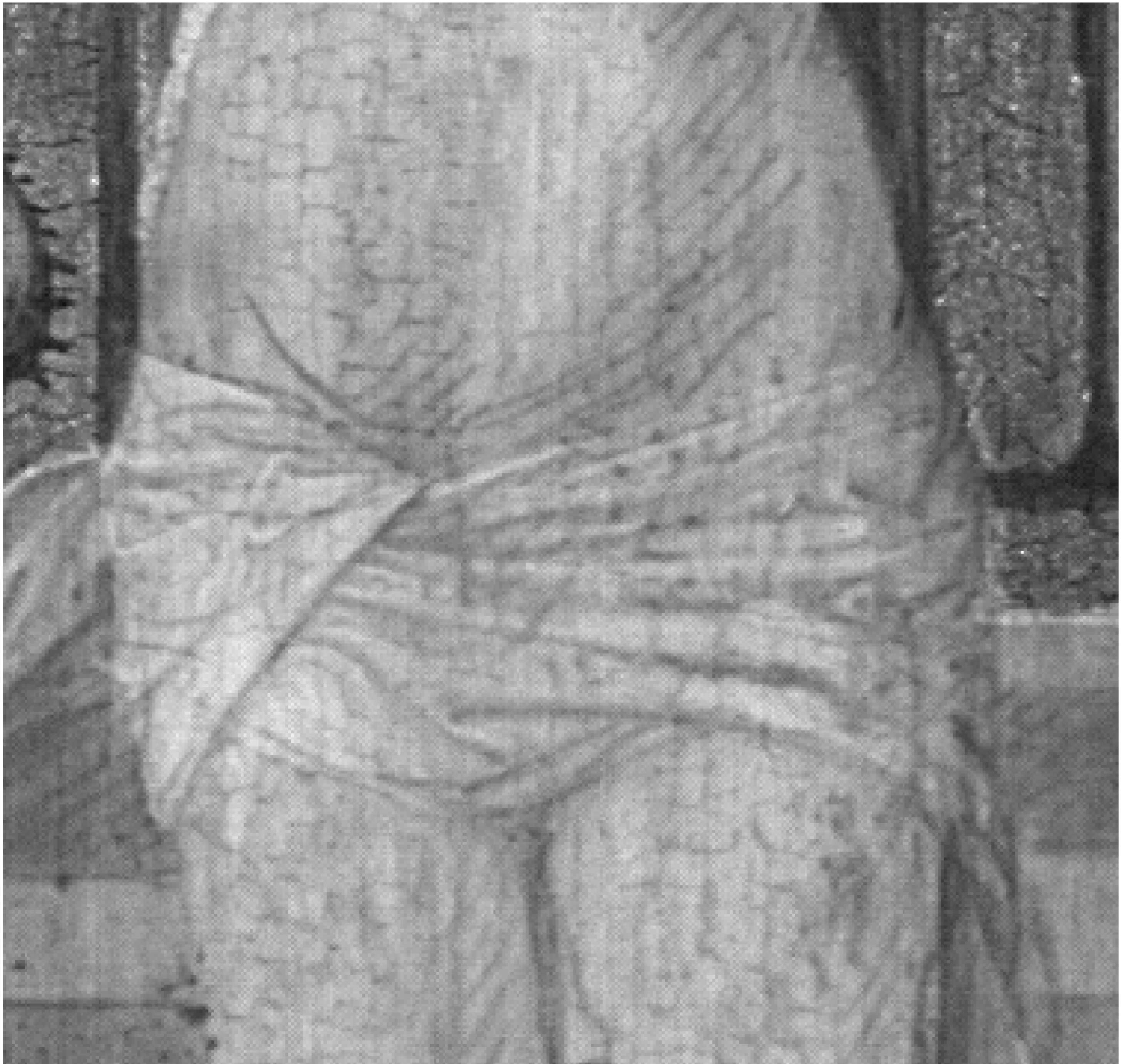


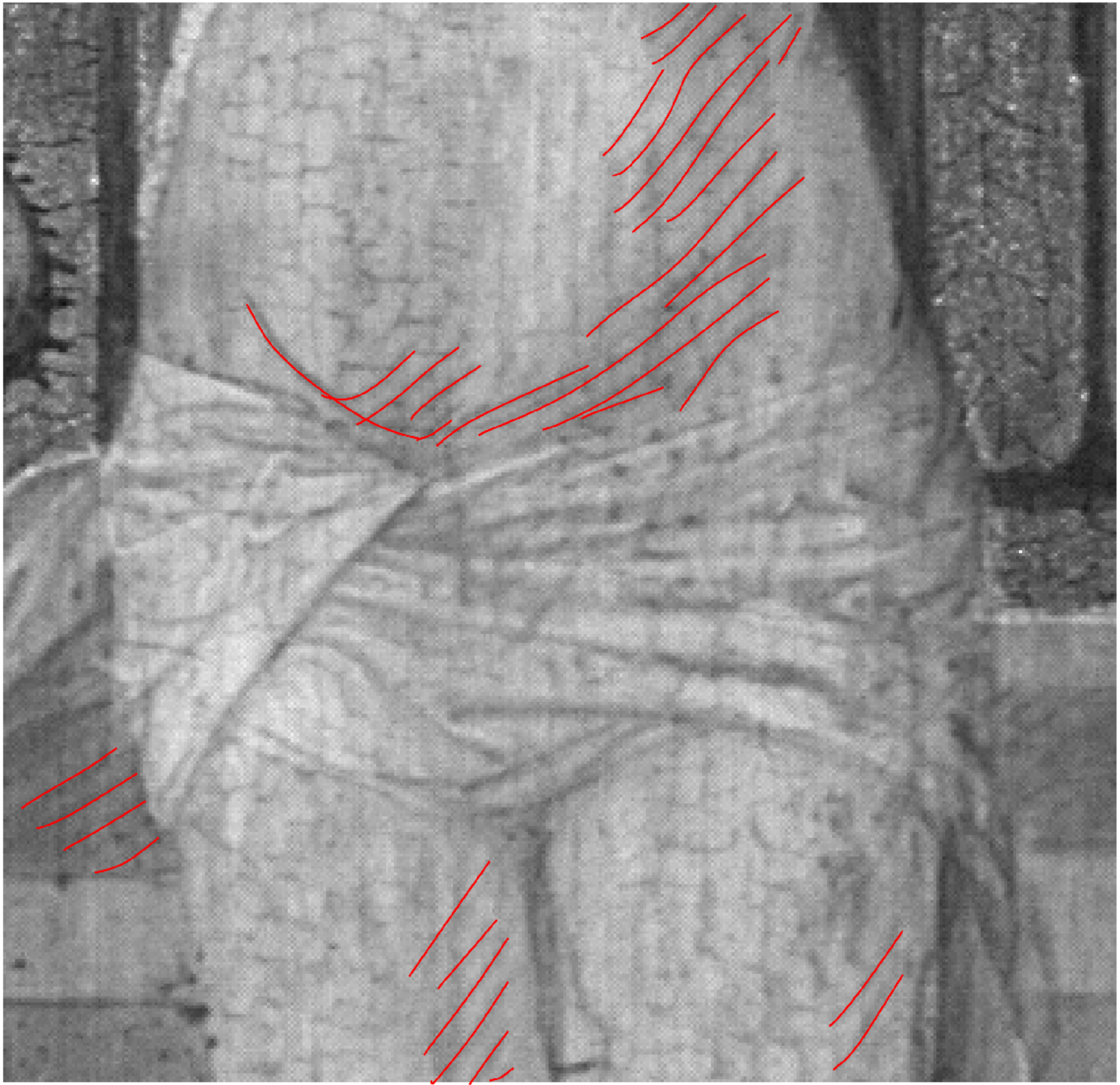
Problem Overview

- Initial data set: 15 details from G. van der Weyden paintings as well as their underdrawings, which were classified into four different categories

Underdrawing Classifications

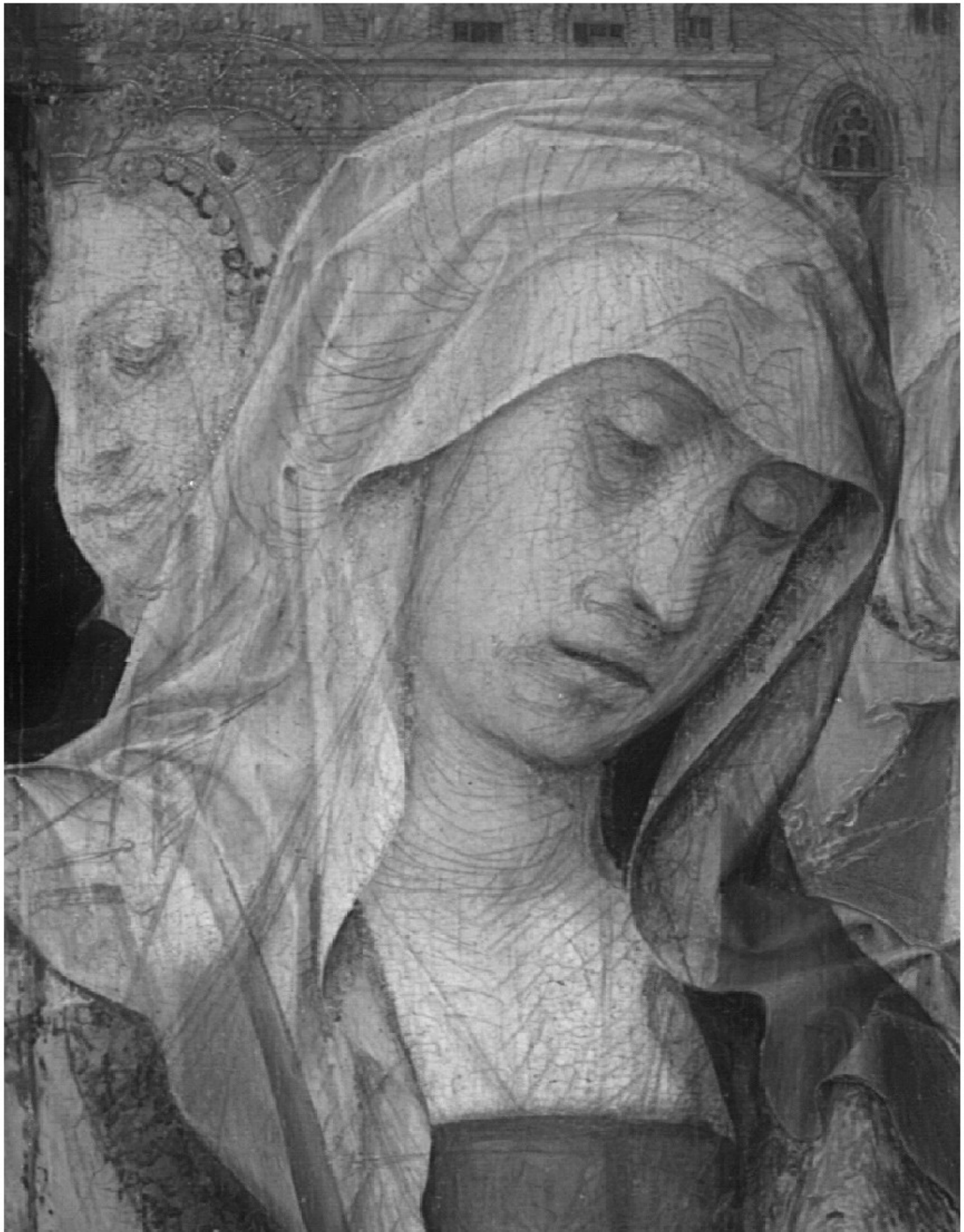
- Class 1: underdrawings done in a dry medium (e.g. fine charcoal) with oblique, parallel lines
-
-
-

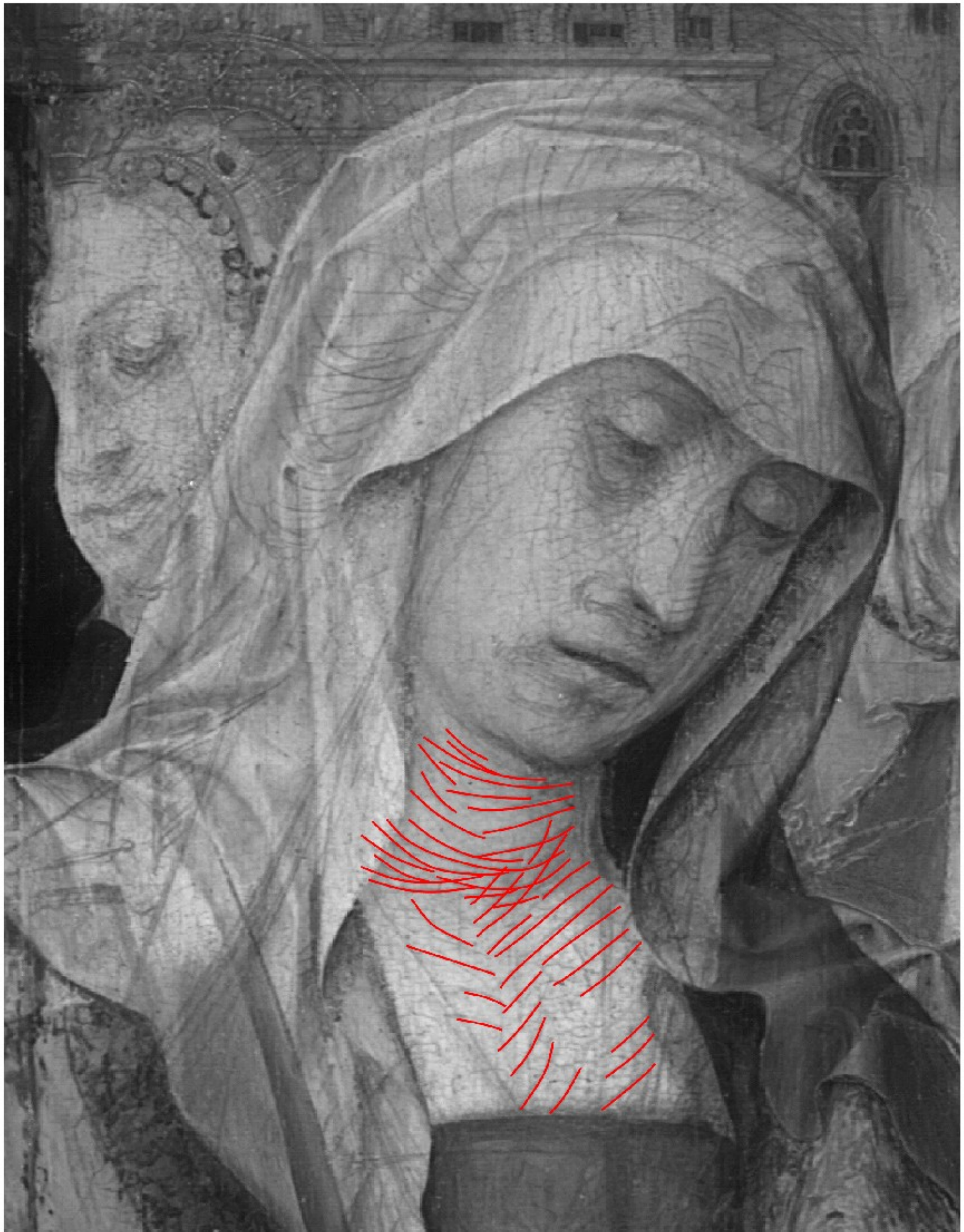




Underdrawing Classifications

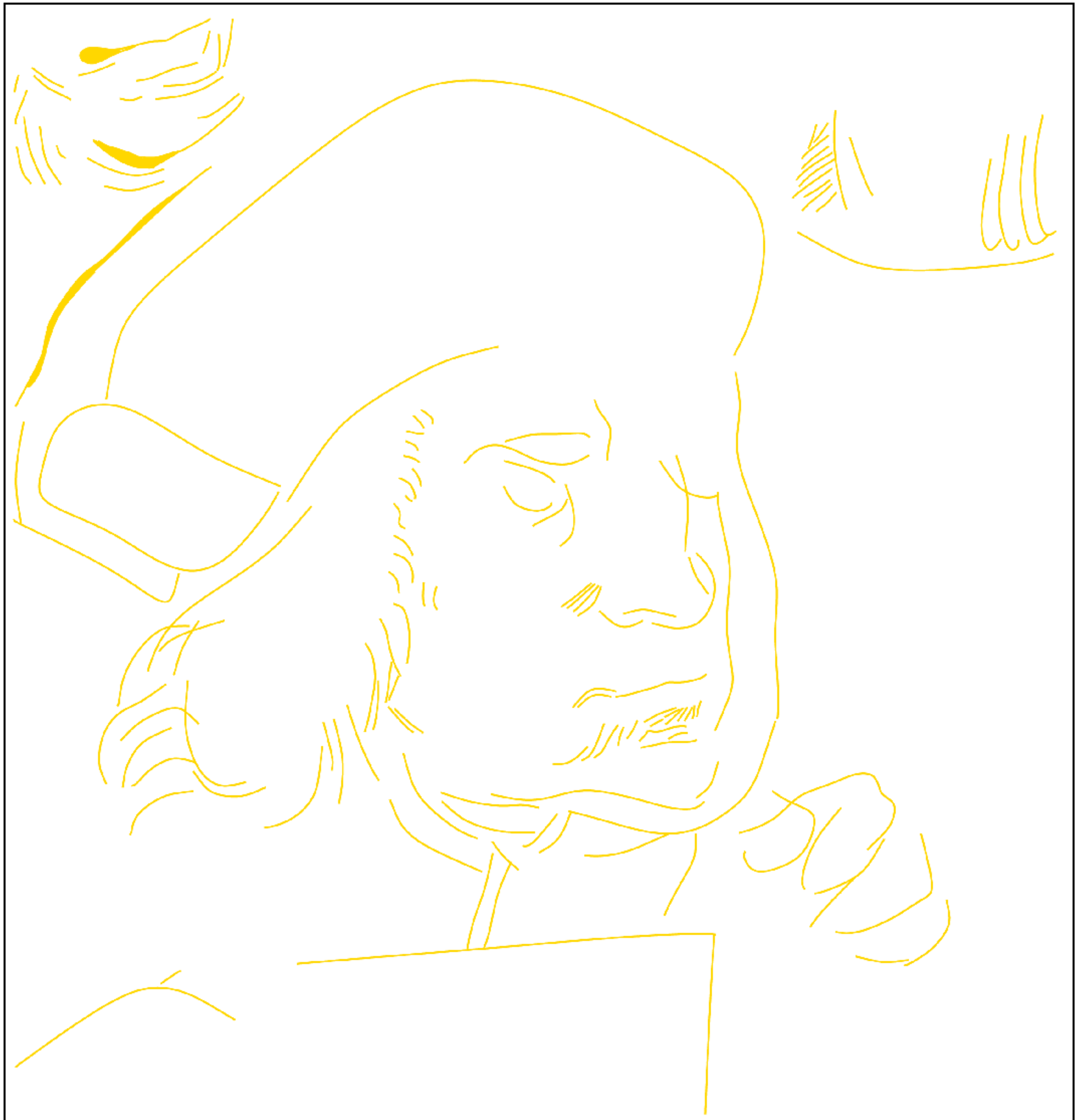
- Class 1: underdrawings done in a dry medium (e.g. fine charcoal) with oblique, parallel lines
- Class 2: underdrawings done with a liquid agent (fine brush) with finer lines that are curved, to indicate volume
-
-





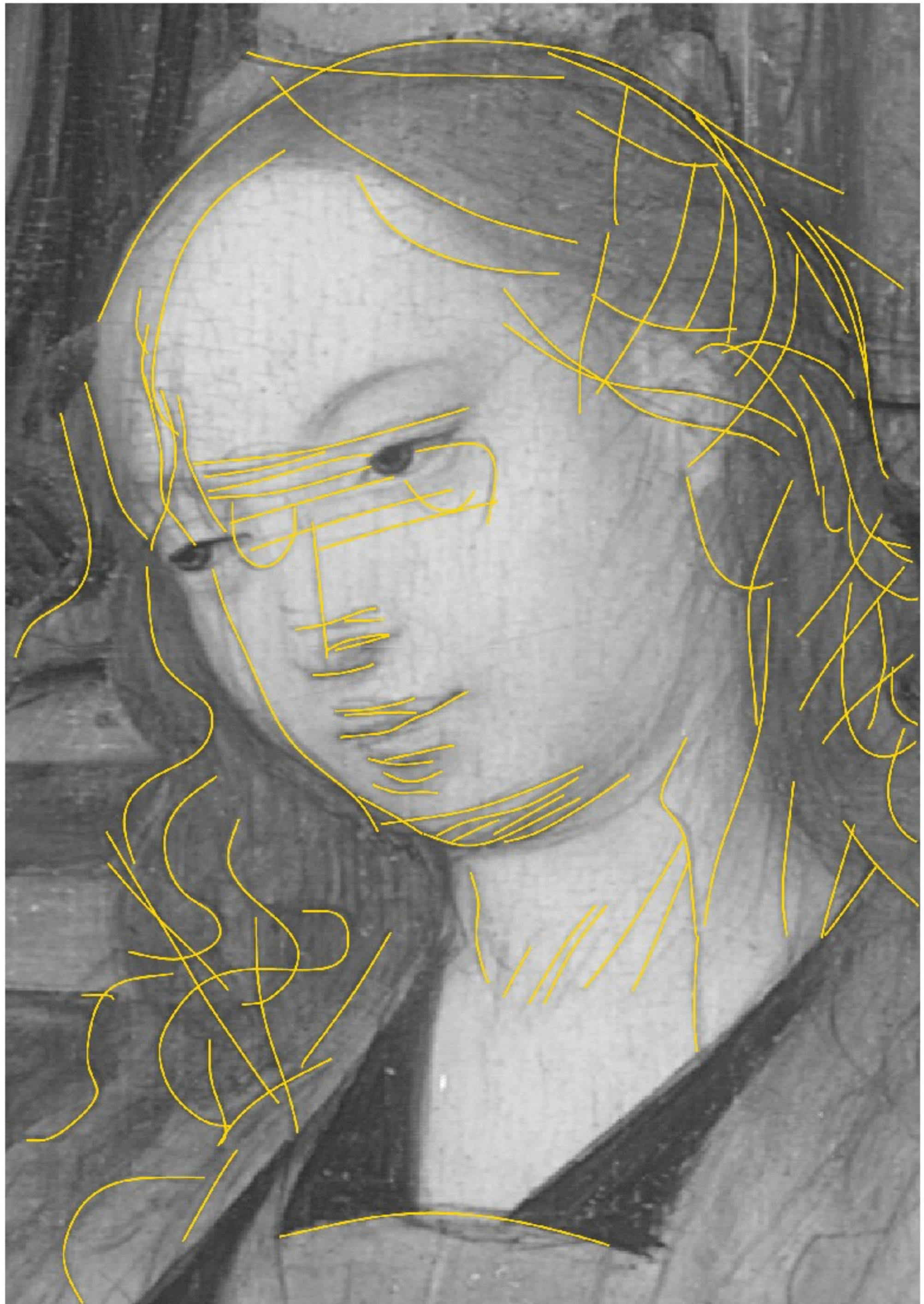
Underdrawing Classifications

- Class 1: underdrawings done in a dry medium (e.g. fine charcoal) with oblique, parallel lines
- Class 2: underdrawings done with a liquid agent (fine brush) with finer lines that are curved, to indicate volume
- Class 3: underdrawings are liquid, sketchy, not precise with no (or very few) parallel lines
-



Underdrawing Classifications

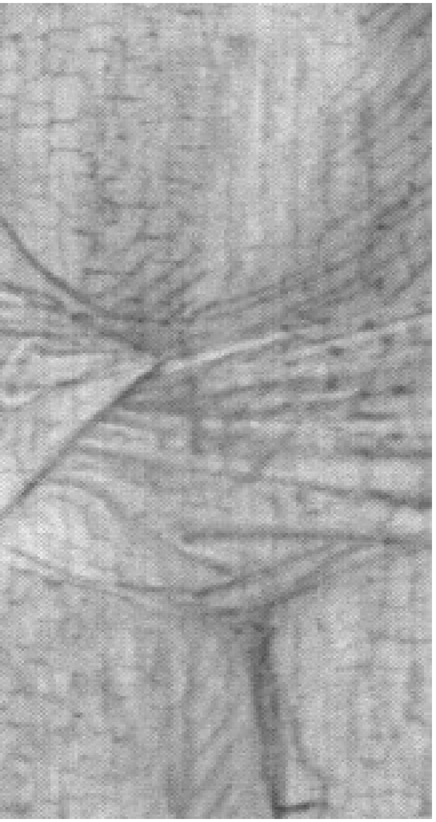
- Class 1: underdrawings done in a dry medium (e.g. fine charcoal) with oblique, parallel lines
- Class 2: underdrawings done with a liquid agent (fine brush) with finer lines that are curved, to indicate volume
- Class 3: underdrawings are liquid, sketchy, not precise with no (or very few) parallel lines
- Class 4: underpaintings done with liquid agent in a very free hand, no precise indication of painting

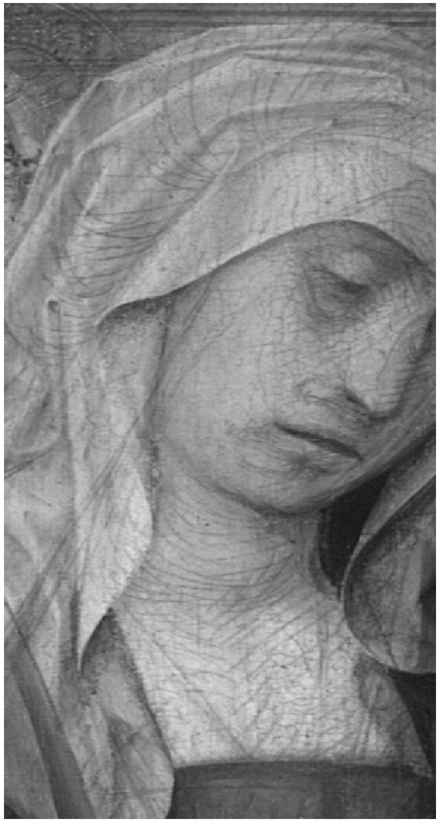


Underdrawing Classifications

- Class 1: underdrawings done in a dry medium (e.g. fine charcoal) with oblique, parallel lines
- Class 2: underdrawings done with a liquid agent (fine brush) with finer lines that are curved, to indicate volume
- Class 3: underdrawings are liquid, sketchy, not precise with no (or very few) parallel lines
- Class 4: underpaintings done with liquid agent in a very free hand, no precise indication of painting

Underdrawing Classifications


CLASS 1


CLASS 2


CLASS 3

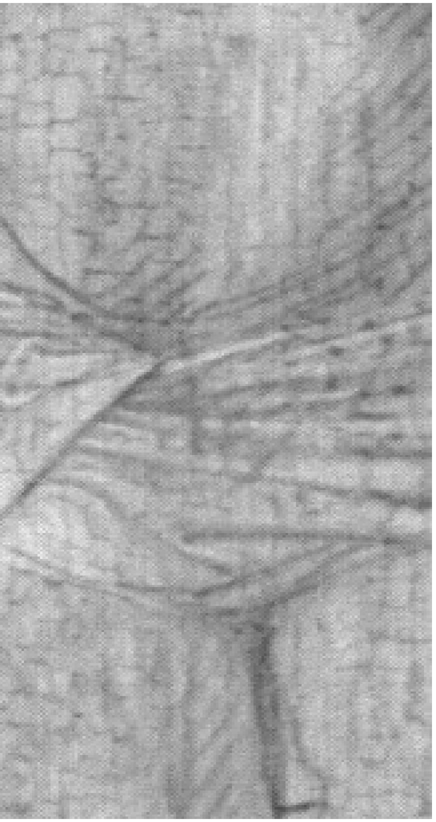

CLASS 4

Problem Overview

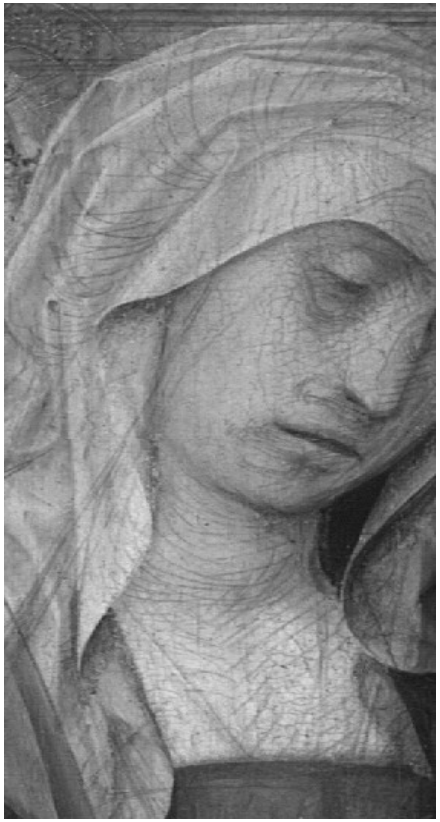
- Initial data set: 15 details from G. van der Weyden paintings as well as their underdrawings, which were classified into four different categories

- Underlying question: Are there distinguishing features of the overlying paintings that allow us to classify them corresponding to the style of their underdrawings?

Underdrawing Classifications



CLASS 1



CLASS 2

CLASS 3

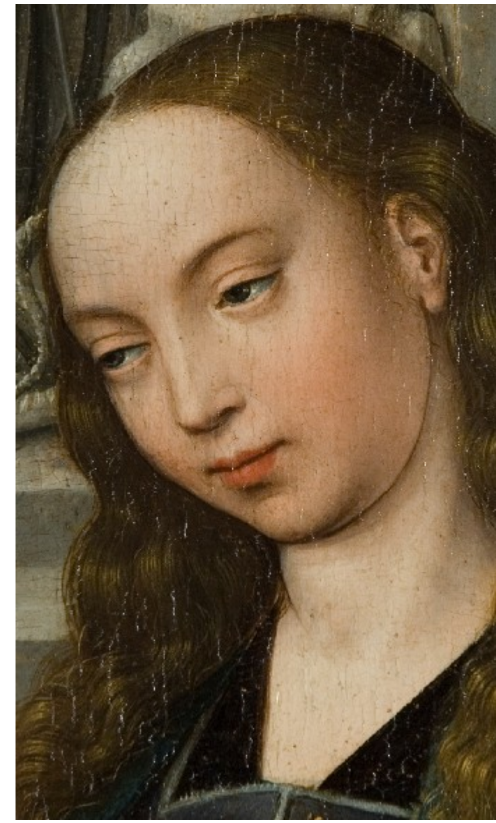
CLASS 4

Underdrawing Classifications

CLASS 1

CLASS 2

CLASS 3



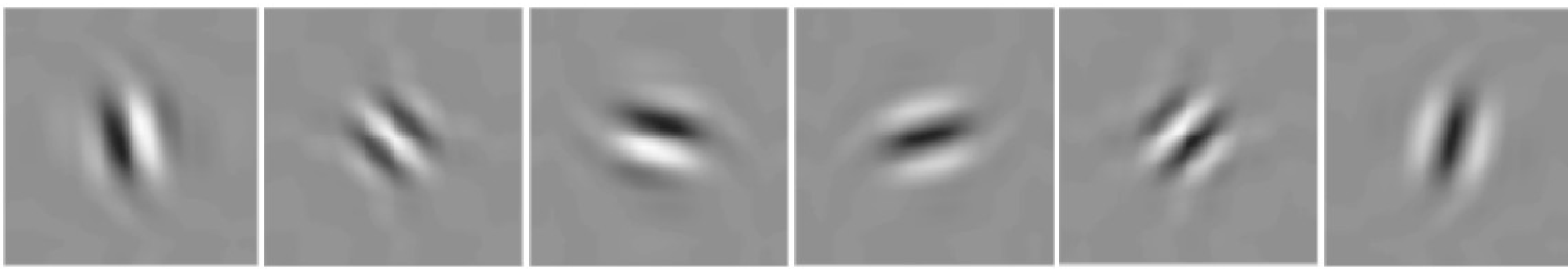
CLASS 4

Wavelet Analysis

- Wavelets allow us to analyze images at different scales and in different directional orientations
- Analyze painting at 8 different scales (from coarsest to finest), store the mean values and differences between neighboring pixels
- Allows for compression and edge detection (edges and ridges are represented by large wavelet coefficients)

Wavelet Analysis: Orientations

Complex wavelet transforms have six directional “subbands” that allow us to store important information on the orientation of the images



-75° -45° -15° 15° 45° 75°

Wavelet Analysis: Key Properties

Locality: localize in space

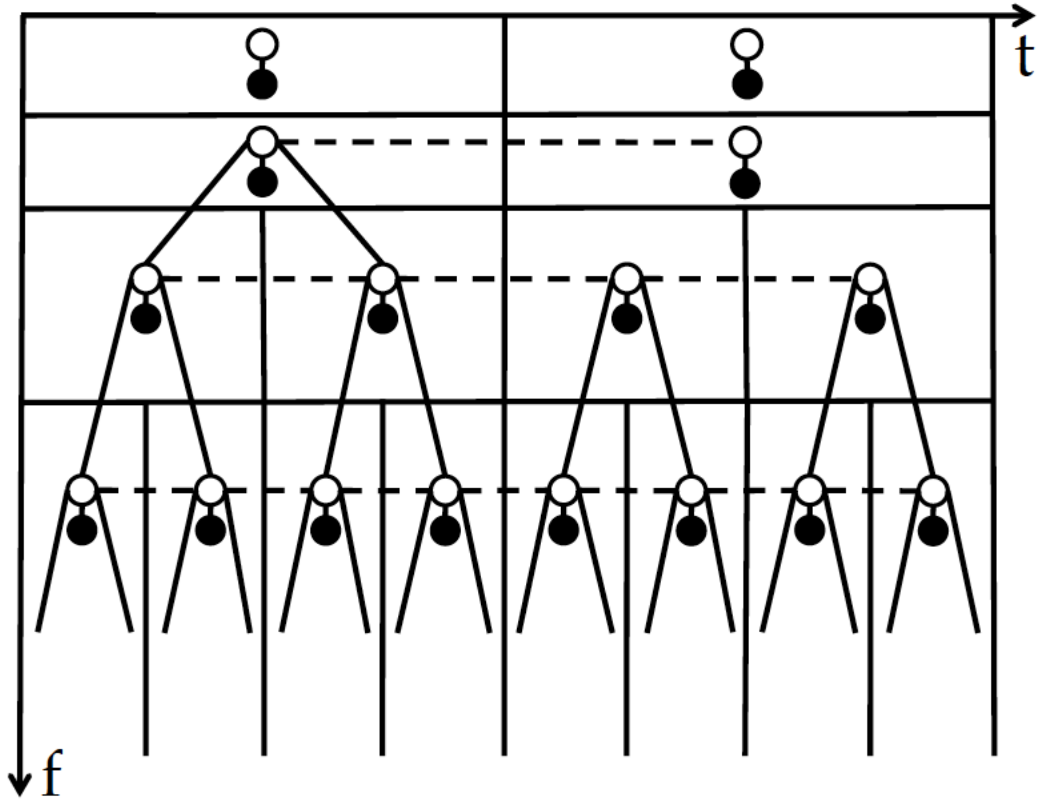
Multi-resolution Representation: capture features at different scales (and localize with resolution appropriate for that scale)

Edge Detection: large coefficients persisting through scales indicate edges

Decorrelation: dependencies between wavelet coefficients are primarily local

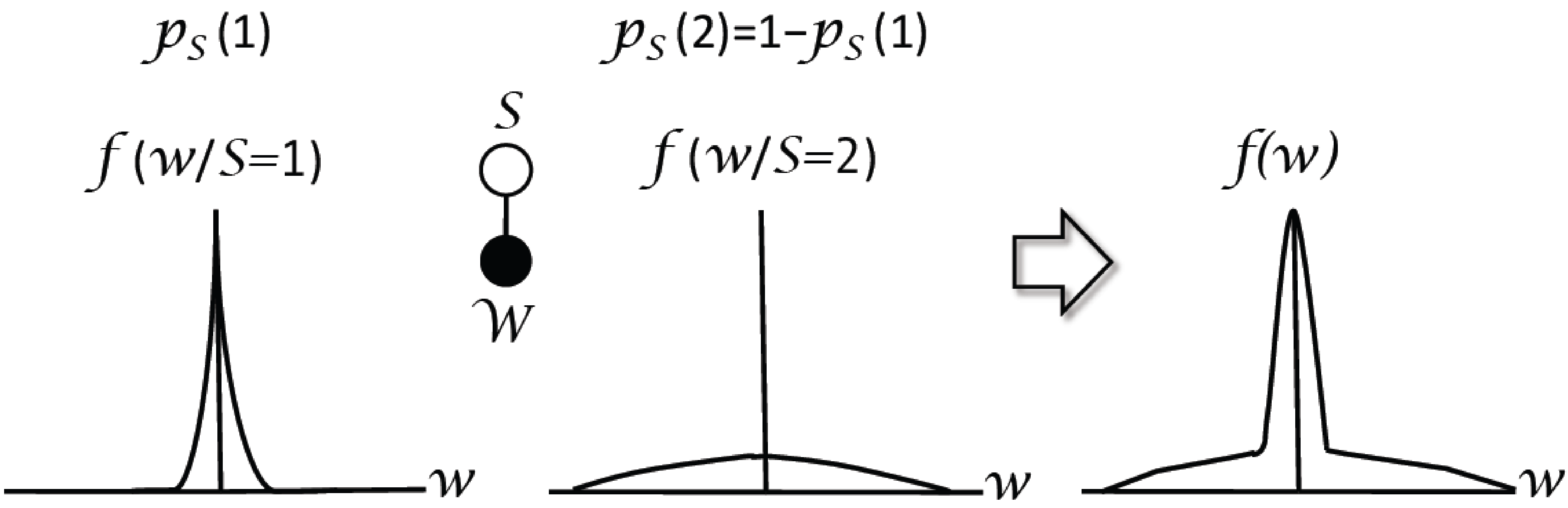
Hidden Markov Models

The local behavior of wavelet coefficients across scales can be modeled well by hidden Markov models (HMMs)



Properties of HMMs

- Probabilistic graphs: Markovian dependencies between the hidden state variables
- Mixture densities: fits the non-Gaussian behavior of the wavelet coefficients



Painting Features

- Each patch (256 x 256 pixels) of each painting now has:
  - A set of sigma variance values for its large and small Gaussian distributions
  - A set of transition probabilities from each state variable to the others

- These values are the features of the paintings that we will use to classify them

Classification

- Our ultimate goal is to classify these paintings into four different groups (corresponding to the style of underdrawing in the training set)

- To figure out which of these many features are most important and useful for classification, we use machine learning algorithms extract patterns and prediction rules from labeled data

Boosting Algorithms

- Combining weak prediction rules (or classifiers) to create a single, strong classifier

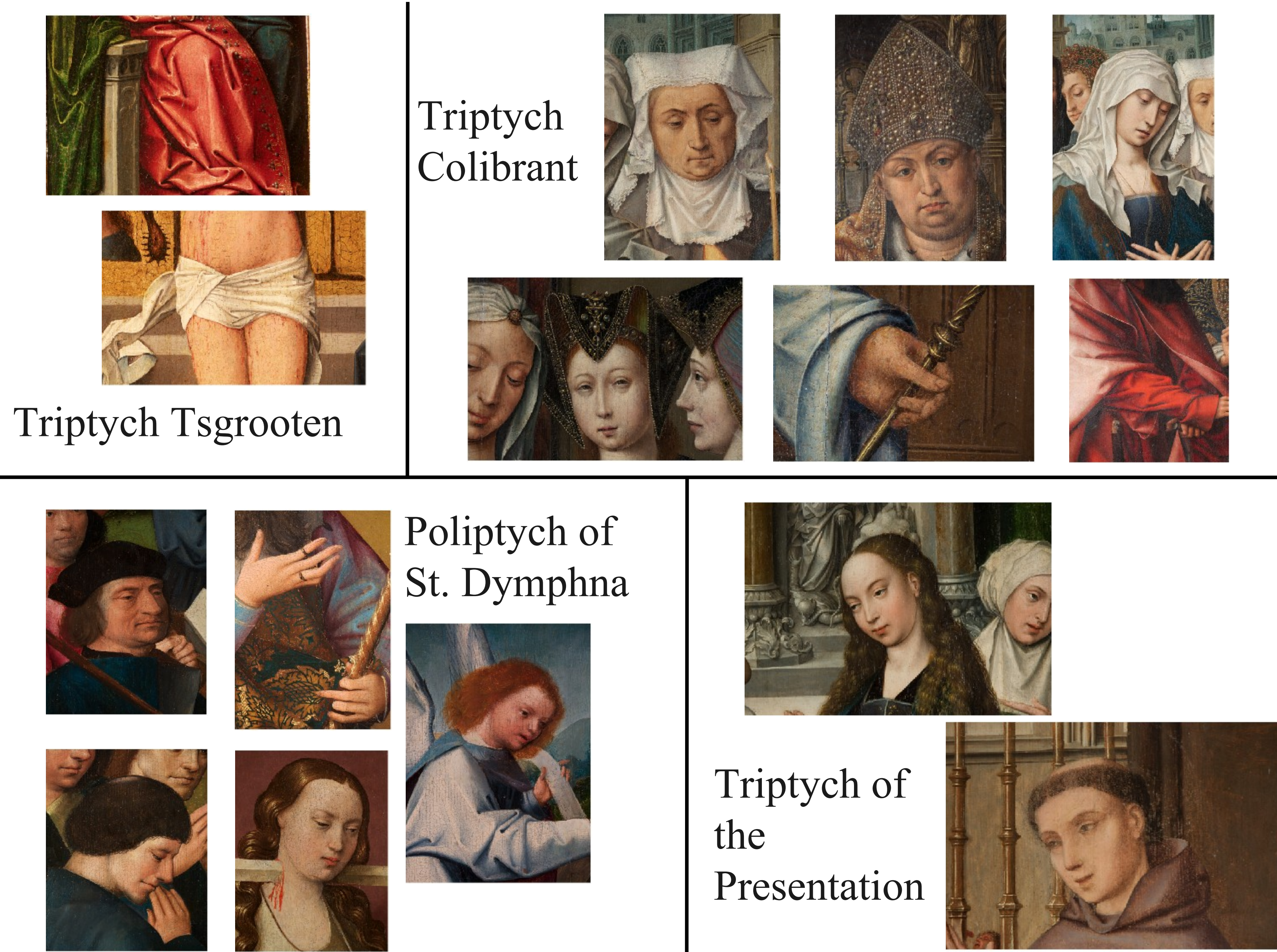
- Boosting algorithms generate multiple weak hypotheses, h_1, h_2, h_3, ..., h_t
  - Data points that are misclassified by a given weak hypothesis h_i are weighted more heavily in the next round
  - Iterative construction of a combined classifier

- Many different algorithms, including AdaBoost and LogitBoost

Results: Four-way Classification

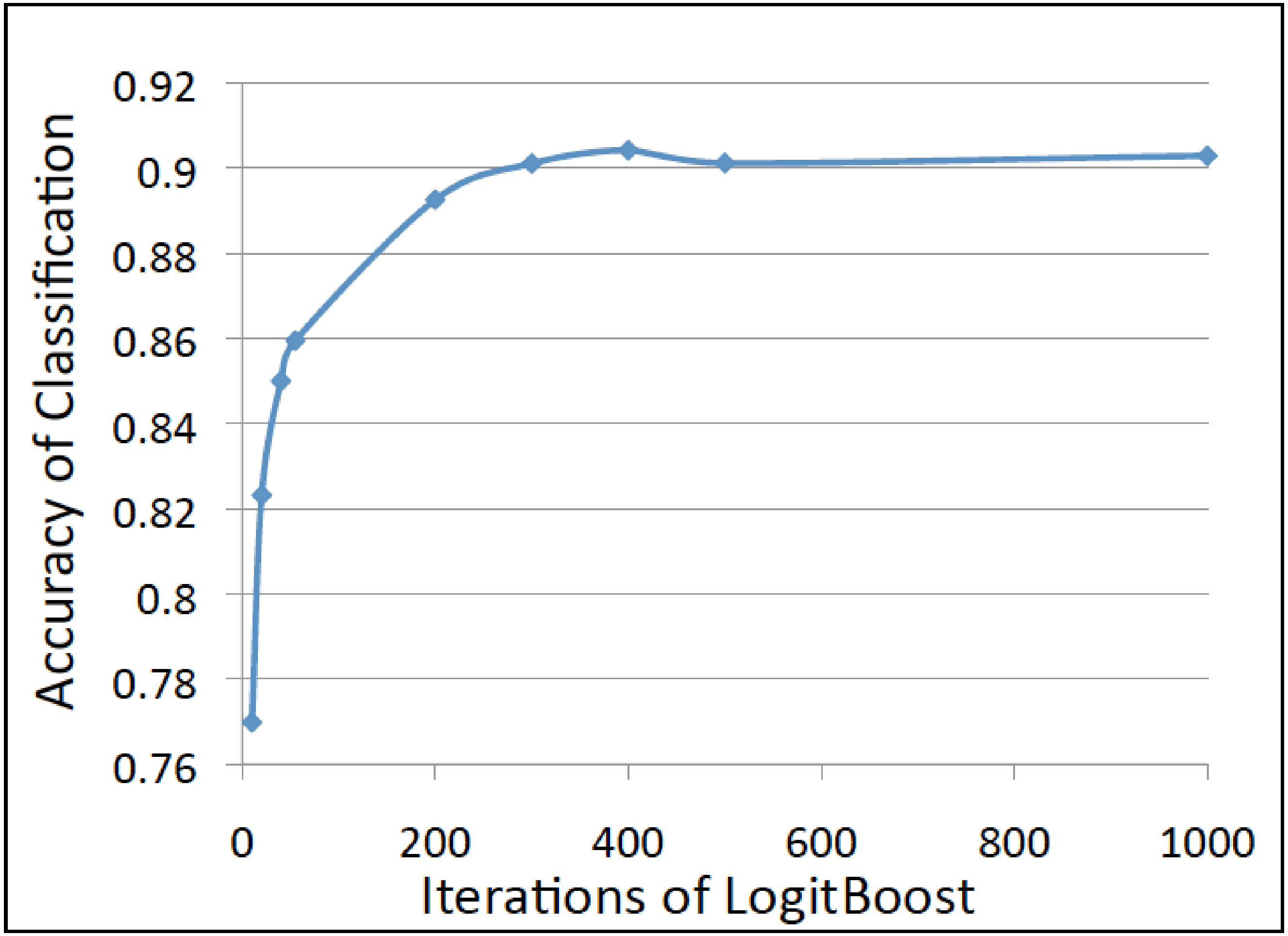
- Subdivided the data set into the original four classes
  - Uneven distribution of data: classes 1 and 4 only had two paintings each

- Consecutive binary classifications showed that there were clear distinctions between the four sets; trickier to classify all in one go, though


Triptych Tsgrooten
Triptych Colibrant
Poliptych of St. Dymphna
Triptych of the Presentation

Results: Four-way Classification

LogitBoost Iterations	Accuracy
10	76.99%
20	82.32%
40	85%
55	85.95%
200	89.26%
300	90.11%
400	90.42%
500	90.12%
1000	90.29%



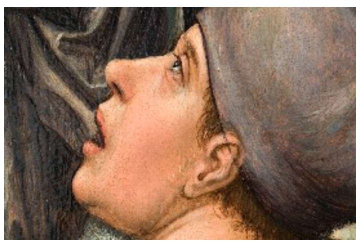
Results: Overfitting & Algorithms

- Overfitting: accuracy begins to decrease after about 400 iterations
  - Learning algorithm adjusts to random features of the training data that are not characteristic of whatever it is aiming to classify

- LogitBoost gives probability of classification for its weak prediction rules, and is less sensitive to outliers than AdaBoost

Results: Blind Data Set

Additional ten unlabeled painting belonging to the same four classes of underdrawings










RESULTS FOR 10 IMAGES OF THE TEST SET

Image number	Probability (in %) that image is of			
	Class 1	Class 2	Class 3	Class 4
1	3	33	50	14
2	0	3	96	1
3	8	31	28	33
4	4	6	82	8
5	2	13	60	25
6	8	18	53	21
7	2	31	28	39
8	1	14	37	48
9	49	21	9	21
10	8	42	49	1

RESULTS FOR 10 IMAGES OF THE TEST SET

Image number	Probability (in %) that image is of Class 1	Class 2	Class 3	Class 4
1	3	33	50	14
2	0	3	96	1
3	8	31	28	33
4	4	6	82	8
5	2	13	60	25
6	8	18	53	21
7	2	31	28	39
8	1	14	37	48
9	49	21	9	21
10	8	42	49	1

RESULTS FOR 10 IMAGES OF THE TEST SET

Image number	Probability (in %) that image is of Class 1	Class 2	Class 3	Class 4
1	3	$\boxed{33}$	50	14
2	0	3	$\boxed{96}$	1
3	8	$\boxed{31}$	28	33
4	4	6	$\boxed{82}$	8
5	2	13	60	$\boxed{25}$
6	$\boxed{8}$	18	53	21
7	2	31	28	$\boxed{39}$
8	1	14	37	$\boxed{48}$
9	49	21	9	$\boxed{21}$
10	8	$\boxed{42}$	49	1

RESULTS FOR 10 IMAGES OF THE TEST SET

Image number	Probability (in %) that image is of Class 1	Class 2	Class 3	Class 4
1	3	33	50	14
2 not GvdW	0	3	96	1
3	8	31	28	33
4	4	6	82	8
5	2	13	60	25
6	8	18	53	21
7	2	31	28	39
8	1	14	37	48
9	49	21	9	21
10	8	42	49	1

RESULTS FOR 10 IMAGES OF THE TEST SET

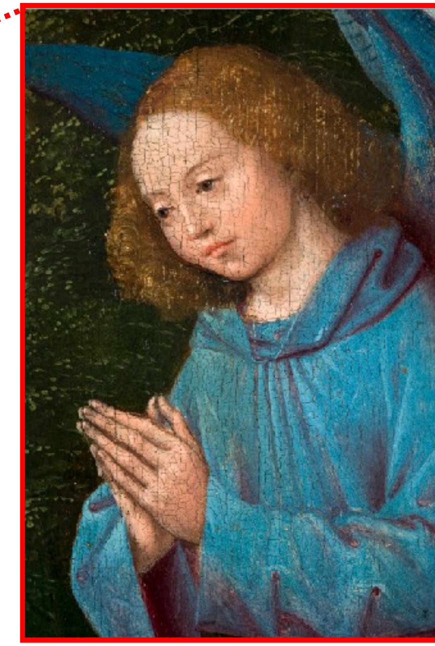
Image number	Probability (in %) that image is of Class 1	Class 2	Class 3	Class 4
2	0	3	$\boxed{96}$	1
3	8	$\boxed{31}$	28	33
4	4	6	$\boxed{82}$	8
5	2	13	60	$\boxed{25}$
6	$\boxed{8}$	18	53	21
8	1	14	37	$\boxed{48}$
10	8	$\boxed{42}$	49	1

RESULTS FOR 10 IMAGES OF THE TEST SET

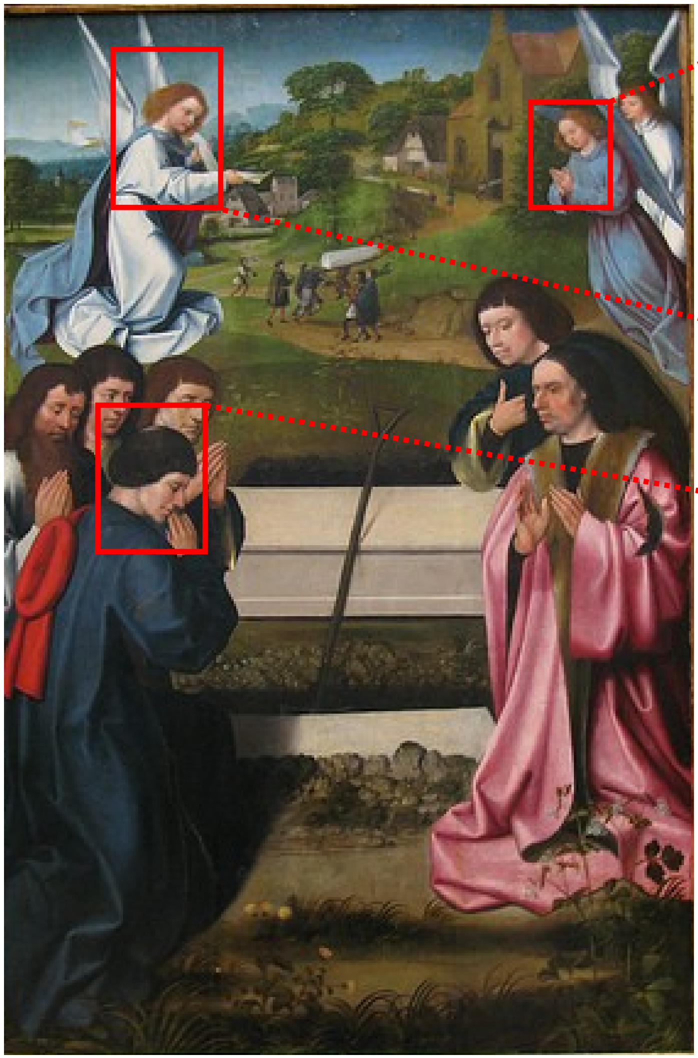
Image number	Probability (in %) that image is of Class 1	Class 2	Class 3	Class 4
2	0	3	$\boxed{96}$	1
3	8	$\boxed{31}$	28	33
4	4	6	$\boxed{82}$	8
5	2	13	60	$\boxed{25}$
6	$\boxed{8}$	18	53	21
8	1	14	37	$\boxed{48}$
10	8	$\boxed{42}$	49	1

Closest Correlation

BLIND



96% of patches classified correctly



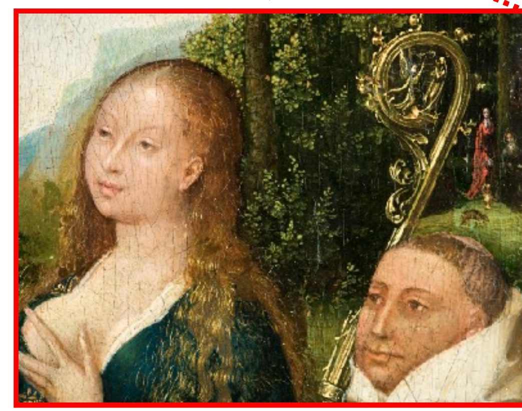
LABELED

Poliptych of St. Dymphna,

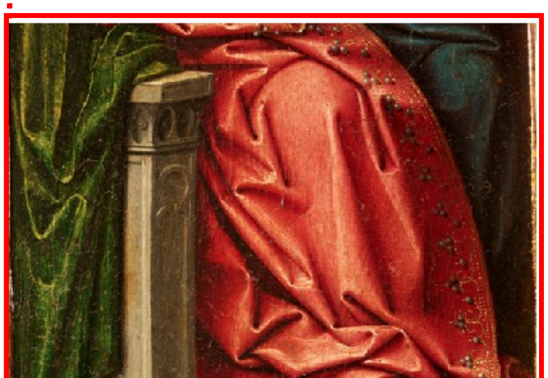
Worst Correlation

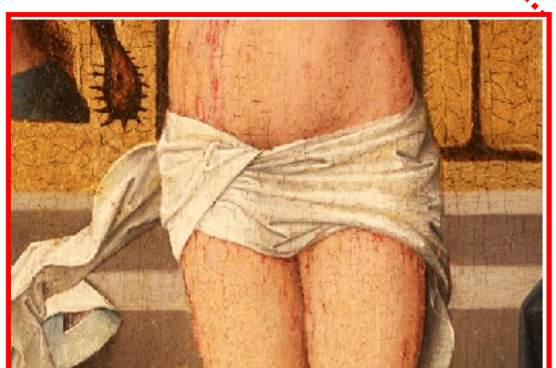
Triptych Tsgrooten

BLIND



LABELED





8% of patches classified correctly

Summary of results

- For the GvdW images in the test set, the algorithm scored the “true class” most likely (3/7) or second most likely (3/7) in all but 1 case out of 7.
- When the algorithm's top class scored over 50 %, it was always correct. (This happened only 2/7, however.)
- The one image where it was COMPLETELY of mark may have been mislabeled (meaning the algorthm may not have been wrong after all).

Conclusion

Promising possibilities in applying wavelet analysis and boosting algorithms to classify paintings, based on their surface painting characteristics, consistent with style of underdrawings.

Further work

- Need to validate: is classification not catching another correlating characteristic (e.g. if all the sketchier underdrawings are features that are painted with more detail, then we might be capturing that aspect, rather than a “different hand”
- Assess classification of underdrawing more locally & do surface classification in more locally resolved way, so as to make “maps”, to compare.
- Extract underdrawing information automatically, and (if successful) do automatic (more gradual?) classification of underdrawing?