

Automated Identification of Blockx Paints through VNIR–XRF Spectral Data Fusion

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INTRODUCTION

Identifying the commercial materials used in an artwork is central to its conservation and art-historical study. Yet, because no single analytical technique captures a paint's full signature, reliable identification means combining several complementary methods, a slow and labour-intensive process. In this work, visible–near-infrared (VNIR) reflectance spectroscopy and macro-X-ray fluorescence (MA-XRF) images were fused to automatically identify paints from five historical Blockx colour charts, using machine-learning methods.

Produced between 1909 and 1976 (with two variants of the 1920 chart), the charts vary in conservation state, support, and preparation layer, providing documented, known-composition swatches and a realistic test of robustness under heterogeneous conditions.

CLASSIFICATION

Pixels from the same swatch are highly redundant. A random split would leak them across train and test and inflate accuracy. To avoid this, we use a "leave-one-chart-out" approach: train on all charts but one, test on the held-out chart, and rotate so each is tested once, which also measures cross-chart transfer. Only paints appearing on ≥ 2 charts are kept, so every validated paint was trained on a different, independently produced chart. Variants of the same base pigment (Cadmiums, Ultramarines...) are merged, giving 23 classes in total. Four models were evaluated: Logistic Regression, Random Forest, MLP, and CNN.

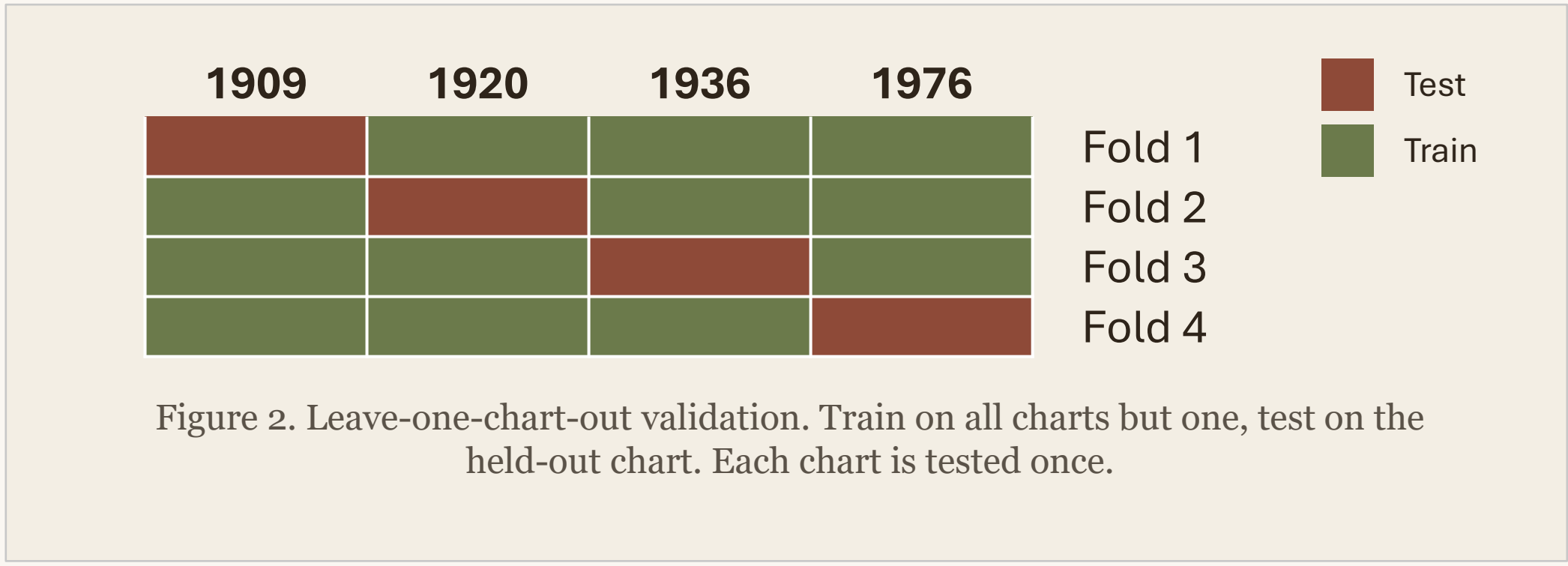


Figure 2. Leave-one-chart-out validation. Train on all charts but one, test on the held-out chart. Each chart is tested once.

RESULTS

Fusing VNIR + MA-XRF beats either modality alone (best model: MLP, 0.826 accuracy / 0.789 macro-recall). Pigments with a unique diagnostic element or distinctive reflectance (cobalts, cadmiums, vermilion, chrome greens, ultramarine,...) classify near-perfectly. The largest remaining confusions concentrate in two chemically coherent groups: the iron-oxide earths and the carbon-based darks, whose flat spectra offer little to tell them apart. Nasturtium Yellow, a Madder Lake-based paint, confuses with Madder Lake and Red Iron Oxide, its actual components, as well as with the similarly hued Cadmium Red. More broadly, a few pigments are poorly represented in the dataset (present on only two or three charts) and tend to fail when one of their distinctive charts is held out, since the model must then identify them from limited and possibly dissimilar examples. Within the iron-oxide classes, finer historical distinctions are not recovered. The reds grouped as Red Iron Oxide, for instance, are all hematite. They differ mainly in trace elements (calcium, potassium, sulfur). Resolving the finer distinctions likely needs additional spectral information.

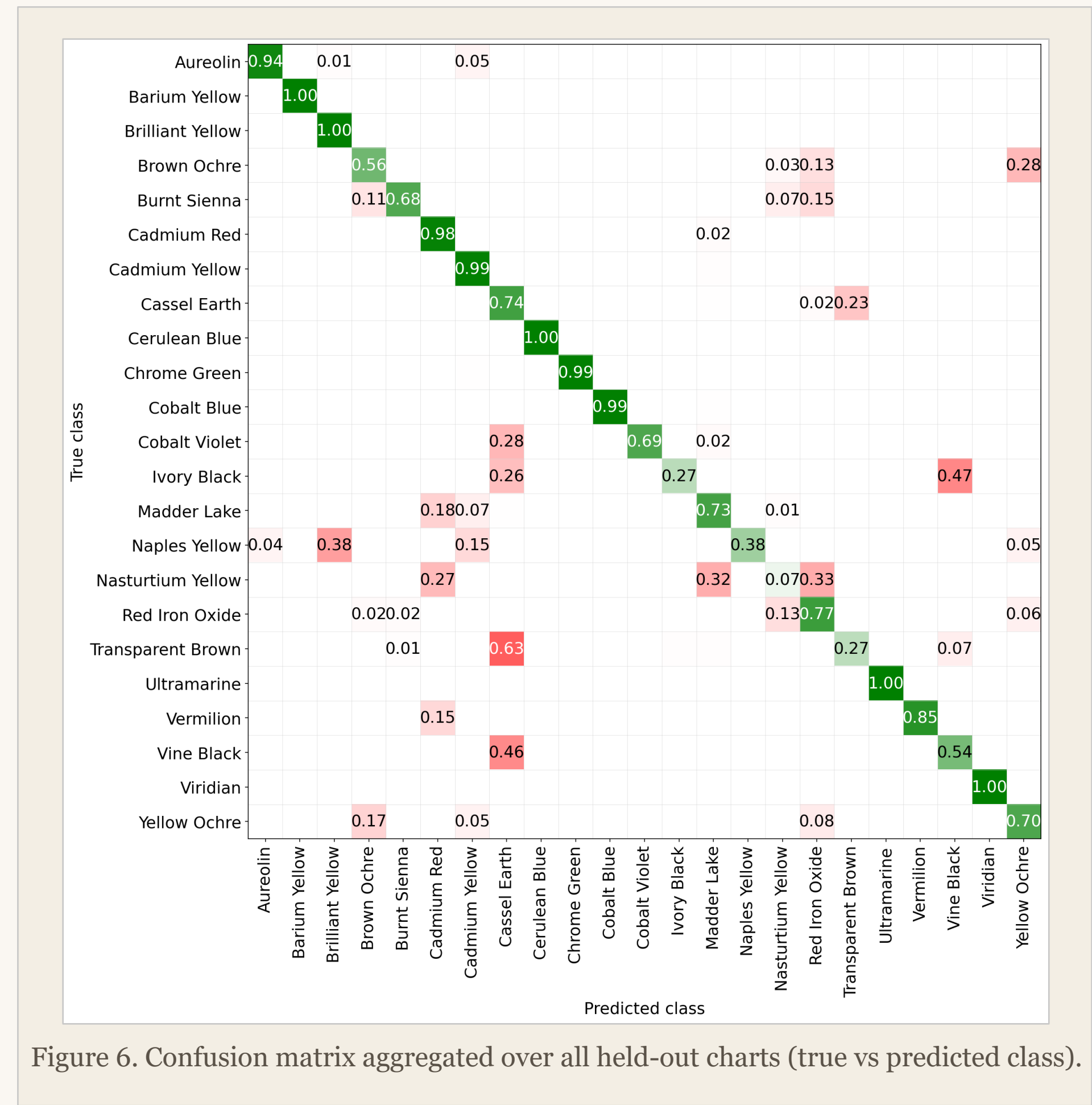


Figure 6. Confusion matrix aggregated over all held-out charts (true vs predicted class).



Figure 1. Historical Blockx colour charts (1909–1976) used in this study, varying in conservation state, base layer and support.

DATA FUSION

VNIR datacubes are stitched into one mosaic using SIFT keypoint matching. MA-XRF maps are then registered to the VNIR's reconstructed RGB by maximising mutual information between the two images, in two stages: a global affine transform (scale, rotation, translation), then a non-rigid B-spline transform for local deformations [1].

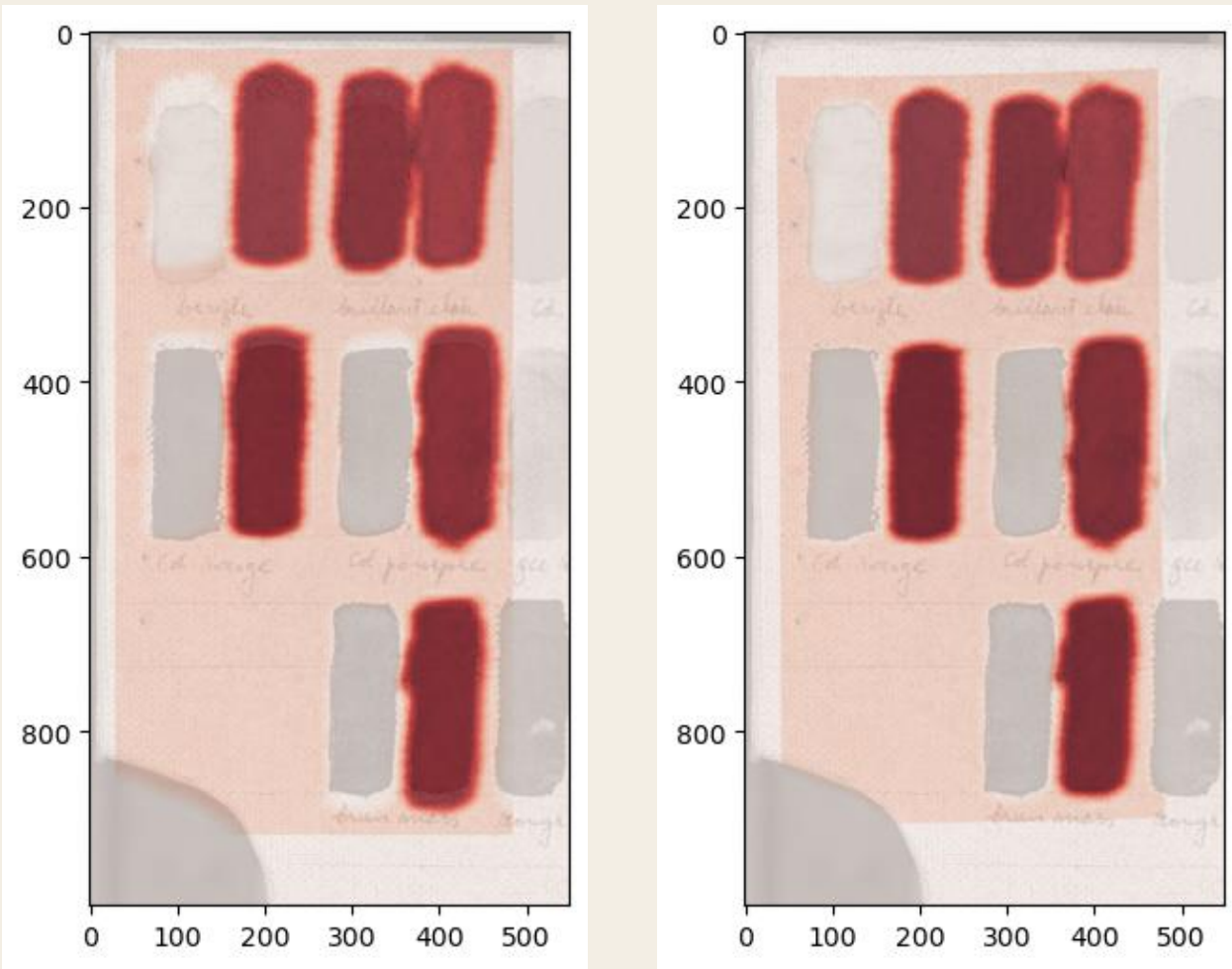


Figure 4. MA-XRF image of Zn K line registered on a grayscale image of the VNIR reconstructed image before registration (left) and after (right).

DISCUSSION

Beyond raw accuracy, the SHAP analysis indicates that the classifier is relying on meaningful spectral and elemental signatures rather than dataset artefacts. The model appears to have learned underlying chemical relationships rather than simply memorizing chart-specific patterns. The fact that most errors recur across multiple charts, rather than clustering within a single chart, further supports this interpretation: the model is capturing genuine similarities between materials, rather than chart-specific quirks. This is essential for reliable transfer to previously unseen artworks.

PERSPECTIVES

The main limiting factor lies in the available information, not in the model. When pigments share the same dominant element, particularly the iron oxides, XRF alone cannot distinguish between them, and their reflectance spectra are largely featureless. Extending the acquisition range into the SWIR (>1000 nm) would add spectral information that could help resolve class confusion that the current range cannot. Enlarging the dataset would also strengthen the model for classes where coverage is currently thin. Ultimately, the aim is to move beyond colour charts and apply the approach to real artworks, where mixtures, layering, and degradation make identification substantially harder.

REFERENCES

[1] Maria Eugenia Villafane, Nathan Daly, Christine Kimbriel, Catherine Higgitt, and Pier Luigi Dragotti. 2023. "Multimodal Image Registration and Mosaicking of Artworks: An Approach Based on Mutual Information." Optics for Arts, Architecture, and Archaeology (O3A) IX, vol. 12620, 21–38. Bellingham, WA: SPIE. https://doi.org/10.1117/12.2673427.