PyrΔTE: an AI-based pyrite tarnish probability generator

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Abstract

PyrΔTE is the result of a pilot study conducted to determine whether artificial intelligence (AI) can be used to help identify change in museum specimens. To simplify this proof of concept, numerical colour data were collected from hundreds of pyrite specimens from Oxford University Natural History Museum, National Museum Cardiff, and National Museums Liverpool. Over a dozen volunteers helped to collect thousands of colour data points. They and the collections' curators also assessed whether each specimen was either tarnished or untarnished. This data was then fed into two separate Regression AI modules in Python to identify patterns within the dataset. Here, the AI used the colour data to calculate tarnish likelihood and the overall colour difference (ΔE^*_{00}).

Multiple iterations of the calculator have been developed, increasing the size of the training dataset and adding new features with each version. The present version allows the user to input their own CIELAB colour values, either individually or as a series of data points in a .csv file. The user can also select either the default untarnished pyrite colour values or enter their own set of values to use in calculating the ΔE^*_{00}. Whilst this programme is presently limited in scope to colorimetry and pyrite, PyrΔTE demonstrates that, with further development, **similar AI tools can be created to aid identifying and treating visual and material changes to museum objects.**

Facts & Figures

- **10,000+ data points**
  - CIELAB color coordinates
  - 3 tarnish assessments: volunteer, curator, & Kathryn
- **19 volunteers** from Universities of Oxford & Liverpool
- **3 museums**
  - Oxford University Natural History Museum (OUNHM)
  - National Museum Cardiff (NMC)
  - National Museums Liverpool (NML)

Specimen	L*(D65)	a*(D65)	b*(D65)	Tarnish KRS	Tarnish Curator	Tarnish Volunteer	Tarnish T-Score	ΔE*00
OUHNM.MIN.28005	72.7	-0.6	13.91	0	0	0	0	61.78
OUHNM.MIN.28005	70.58	-0.68	13.05	0	0	0	0	59.15
OUHNM.MIN.28005	70.28	-0.72	12.98	0	0	0	0	58.79
OUHNM.MIN.28005	71.93	-0.75	12.84	0	0	0	0	60.74
OUHNM.MIN.28005	72.56	-0.6	13.98	0	0	0	0	61.61
OUHNM.MIN.28005	71.36	-0.28	14.74	0	0	0	0	60.24
OUHNM.MIN.28005	72.6	-0.6	14.01	0	0	0	0	61.67
OUHNM.MIN.28005	72.92	-0.67	13.48	0	0	0	0	62
OUHNM.MIN.28005	72.98	-0.69	13.41	0	0	0	0	62.07
OUHNM.MIN.28005	73.21	-0.71	13.25	0	0	0	0	62.34
OUHNM.MIN.28005	72.11	-0.63	13.57	0	0	0	0	61.03
OUHNM.MIN.8291	50.53	1.27	12.49	1	1	0	0.67	38.3
OUHNM.MIN.8291	56.06	1.24	18.11	1	1	0	0.67	44.3
OUHNM.MIN.8291	56.39	1.23	17.96	1	1	0	0.67	44.59

Fig. 1: Example of data collected & input into the AI algorithm.

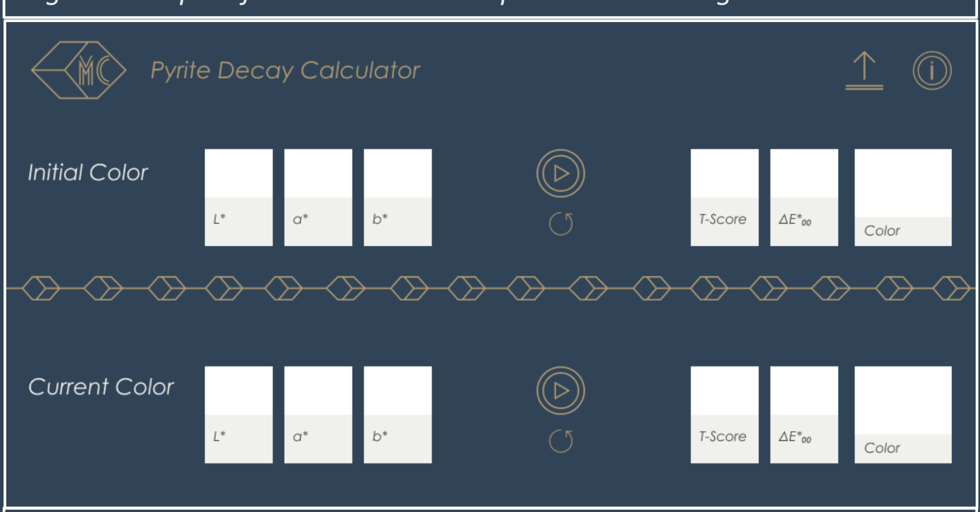

Fig. 2: Screenshot of the PyrΔTE user interface.

Table 1: Number of specimens measured & data points collected per museum.

Museum	Number of Specimens	Number of Data Points
OUNHM	247	8,752
NMC	59	718
NML	33	354
Other	3	699
Grand total	342	10,523

Development & Training

PyrΔTE was made & trained entirely in Python.

- **AI:** TensorFlow package (linear regression model)
  - Keras module: creates neural network layers
- **Graphic user interface** (GUI): TKinter package

- trained AI with 80% of available dataset
- program reviews data multiple times to find pattern
- remaining 20% used to test pattern's accuracy
- process reiterated as training dataset increased

Conclusions & Further Applications

- Successful proof of concept
  - AI able to predict likelihood of an untrained eye to detect tarnish
- Method can be applied more broadly with further development
  - Tarnishing
  - Darkening
  - Yellowing
  - Meteorites
  - Metals
  - Pigments