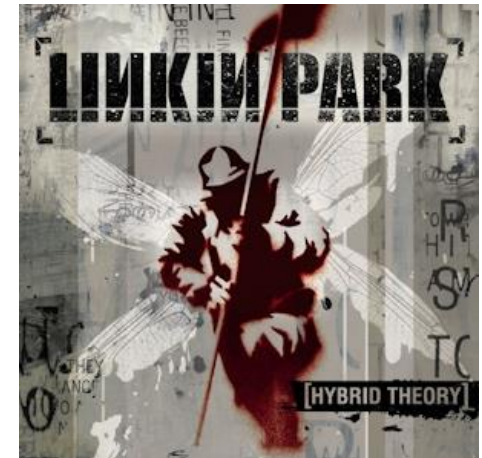


[HYBRID THEORY]

- This project came to mind months ago when I was reading spiderman and listening to music. I thought to myself, what if I could “fuse” my love for comics with heavy metal music?

This project is named after the iconic Nu Metal album, [HYBRID THEORY]. Rest in peace Chester Bennington. Your work continues to inspire millions of people globally.

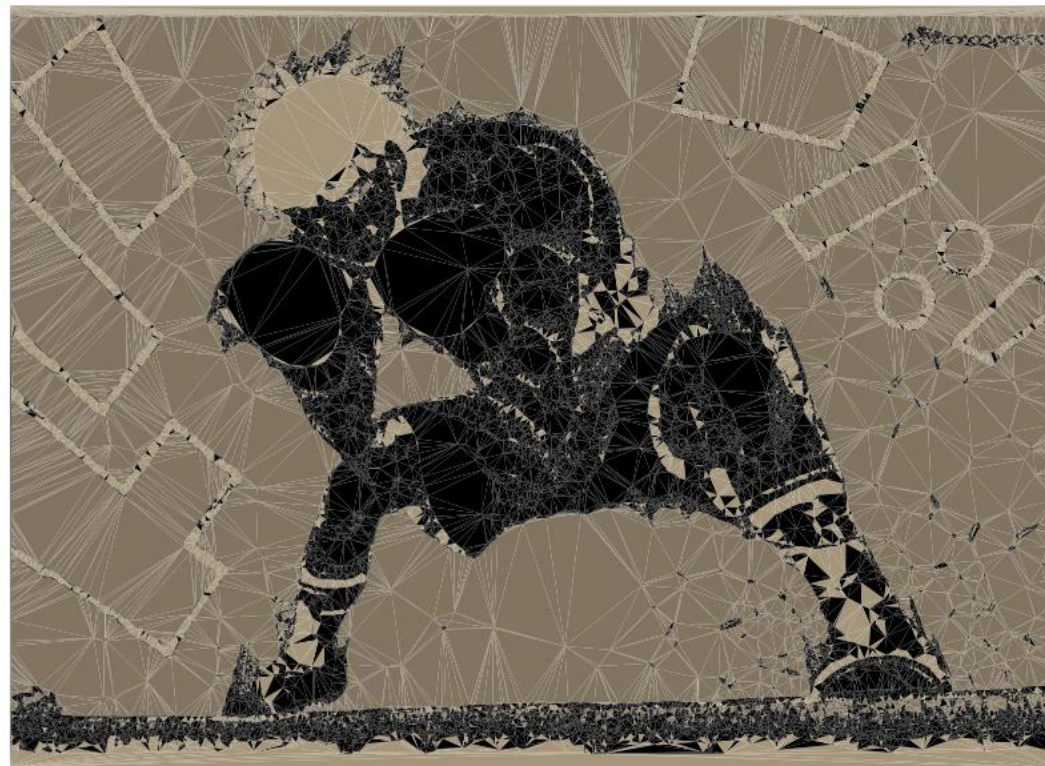




X



=





X

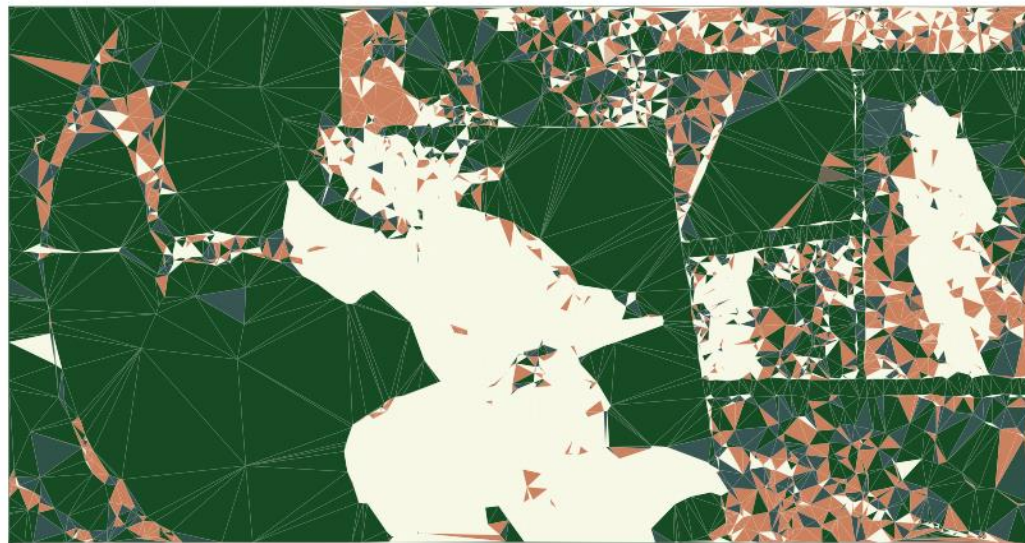
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X



Overview

The system has 2 main colouring methods.

1. A custom made, 256 node, 5 layer Convolutional Neural Network that interprets user feedback and paints a “Template Image” from the colours of a “Palette Image”
2. A standard (x,y) RGB pixel swap coloring

HYBRID THEORY

This system uses neural networks to intelligently map colors from a source image to a target palette when triangulating.

[HYBRID THEORY] Configuration

```
TEMPLATE_IMAGE:    templateImages/spiderman.png
PALETTE_IMAGE:     paletteImages/hybridTheory.jpg
NUM_CLUSTERS:      25
NUM_DISTINCT:      10
DENSITY_REDUCTION: 5
EPOCHS:            1000
FINE_TUNE_EPOCHS:  150
TEMPERATURE:       0.1
```

```
Model Name:        spiderman_hybridTheory
Model Path:        models/spiderman/spiderman_hybridTheory.pth
```

To change images/parameters, edit .env file or set environment variables.
To view TensorBoard go to -> <http://127.0.0.1:6006>

Choose an option:

1. Basic usage (train and apply CNN)
2. Reuse trained model (fast)
3. Plotting & visualization menu
4. Standard coloring (original colors, no CNN)
5. Cleanup orphaned data
- c. Show current configuration
0. Exit

Enter your choice (0-5, c):



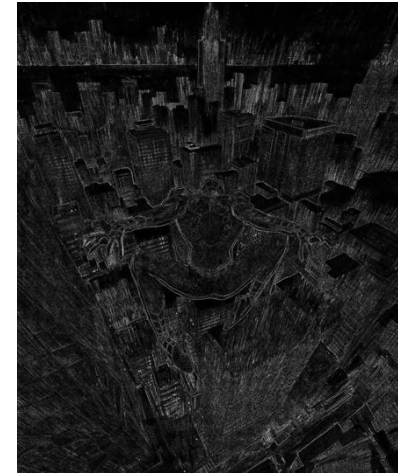
#1



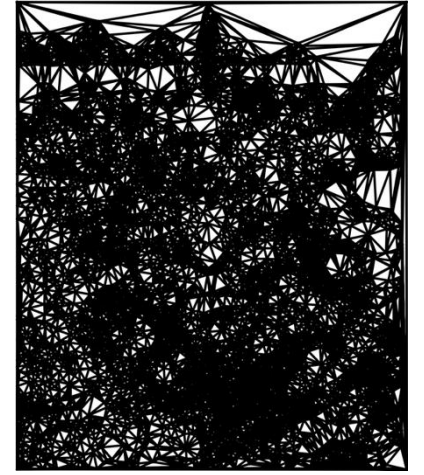
#2



#3



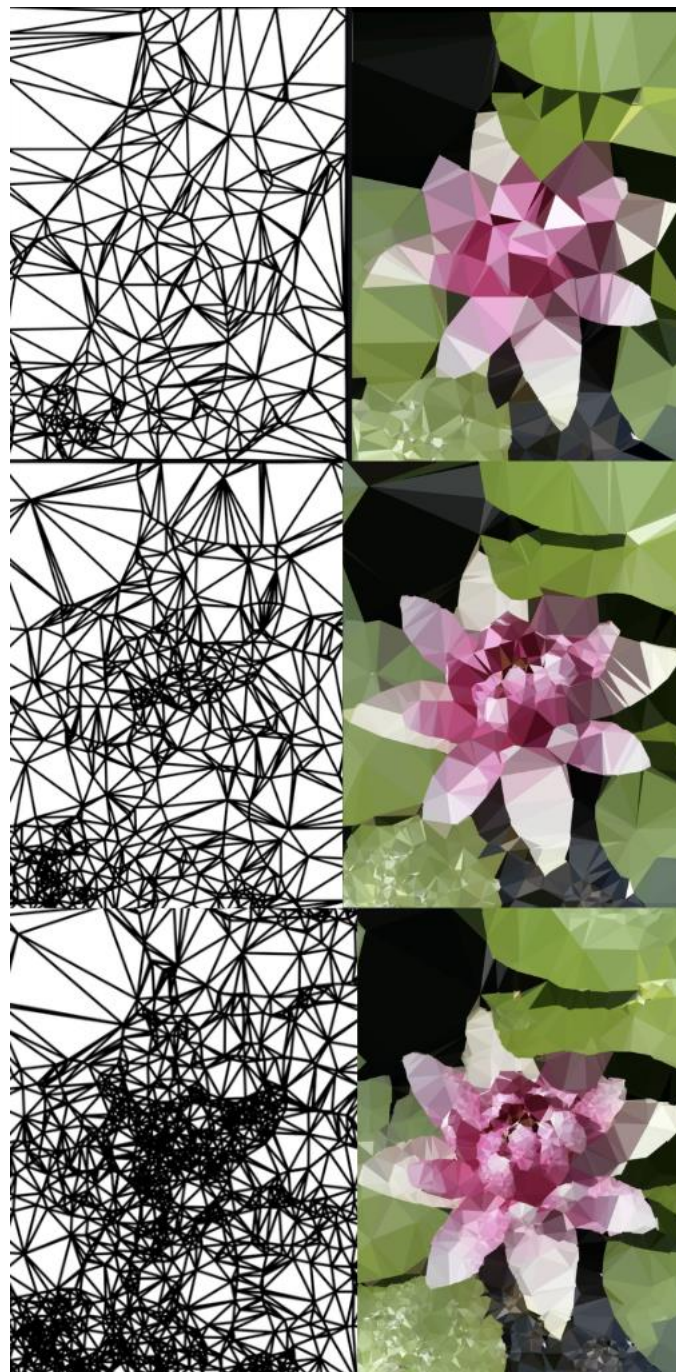
#4



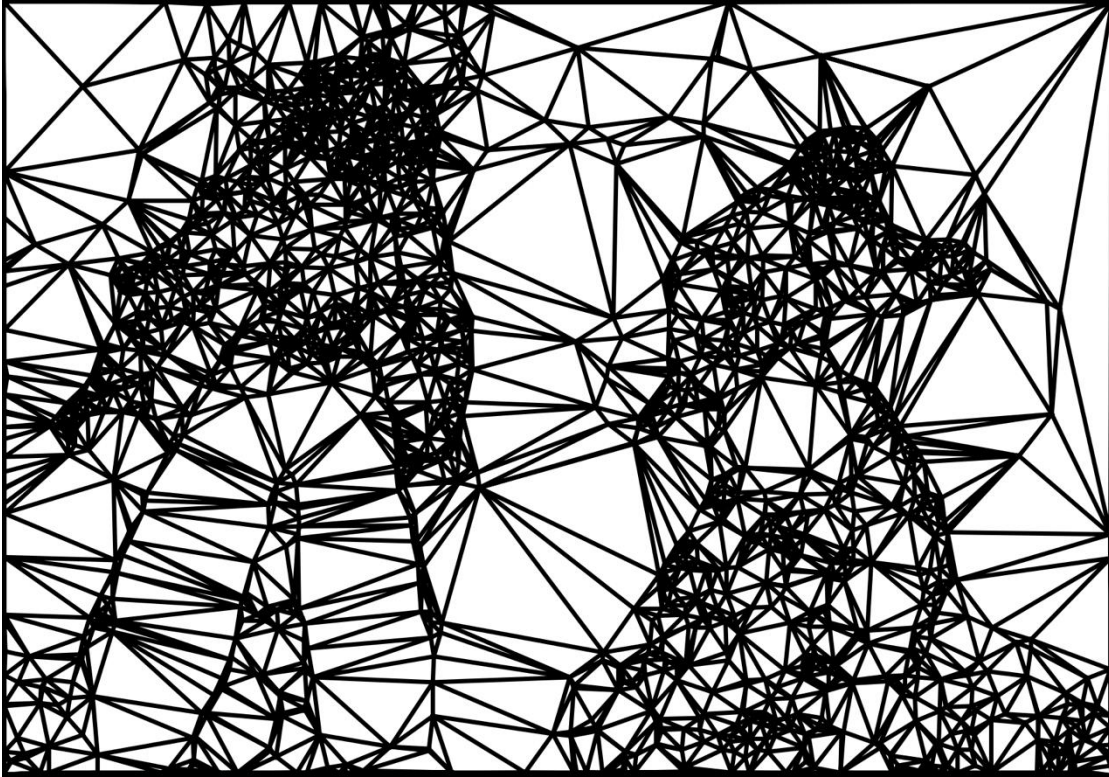
#5

Both methods start the same.

1. Start with a base image
2. Convert to a specific type of greyscale
3. Raise image sharpness
4. Use image Kerneling & Sobel Processing to create a photographic "X-Ray"
5. Compute a Voronoi Diagram of the X-Ray



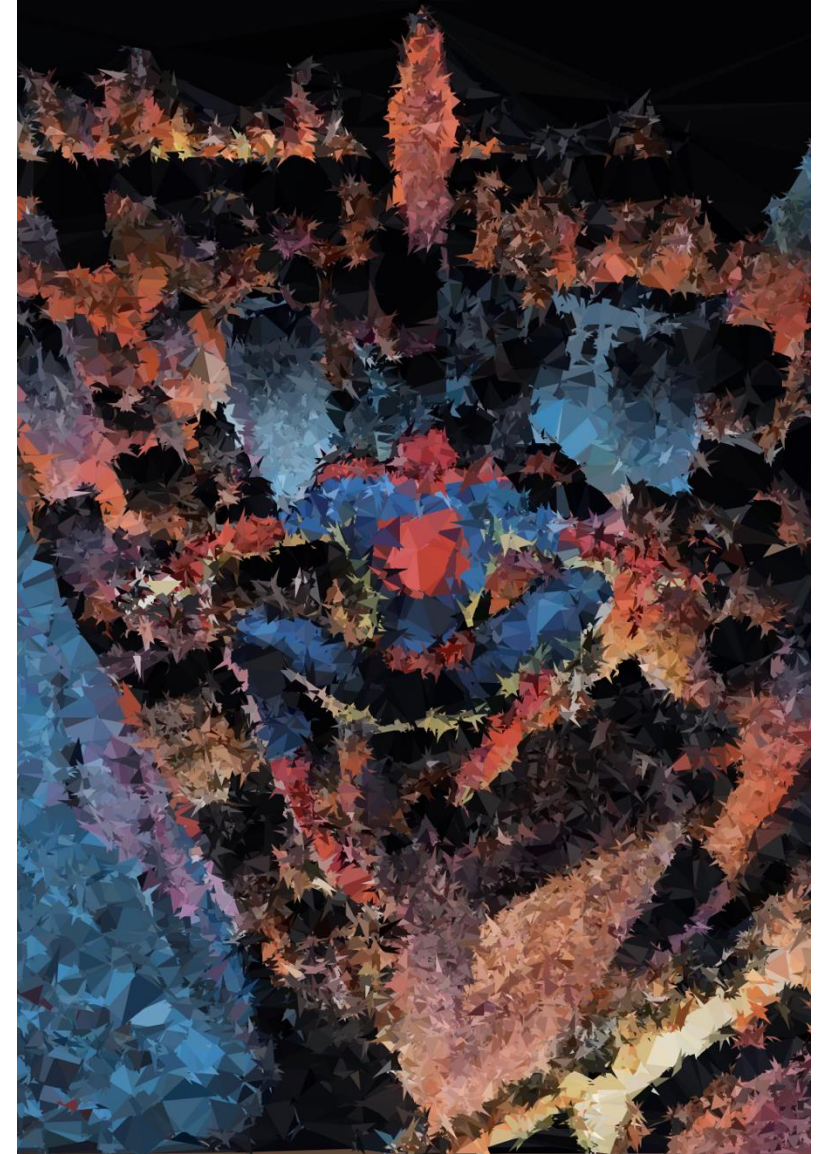
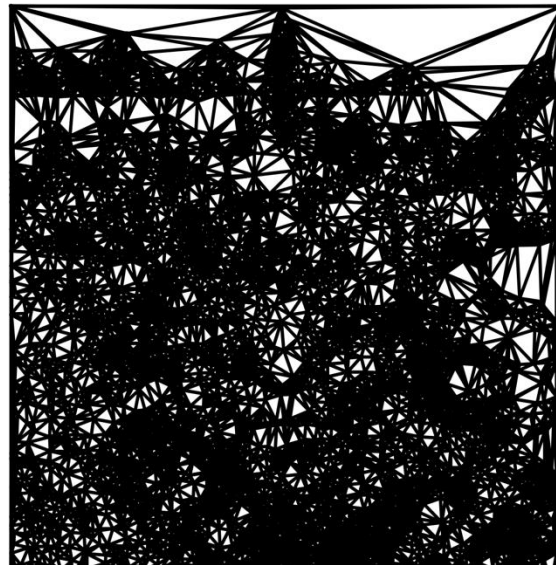
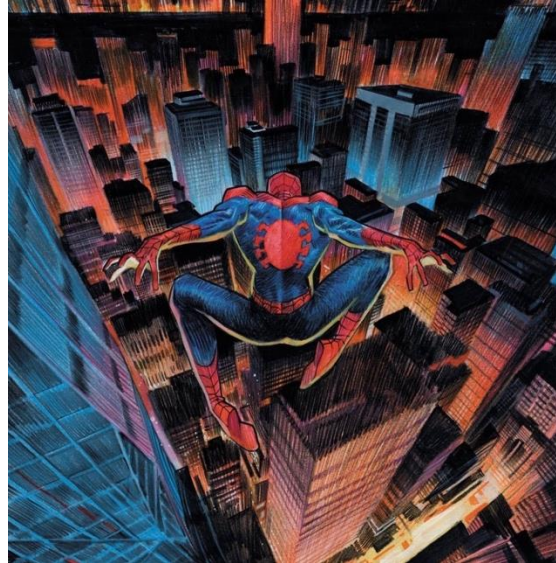
When creating a Voronoi Diagram, each image has its own density function which controls the # of polygons generated. Helping control abstraction and raising levels of creative freedom



When developing the Voronoi diagram, important edge cases to maintain include making sure that the polygons DO NOT overlap, and maintain a similar “structure” to the original image. Otherwise, colouring them back in and maintaining the same “shape” afterwards is impossible

Standard Colouring

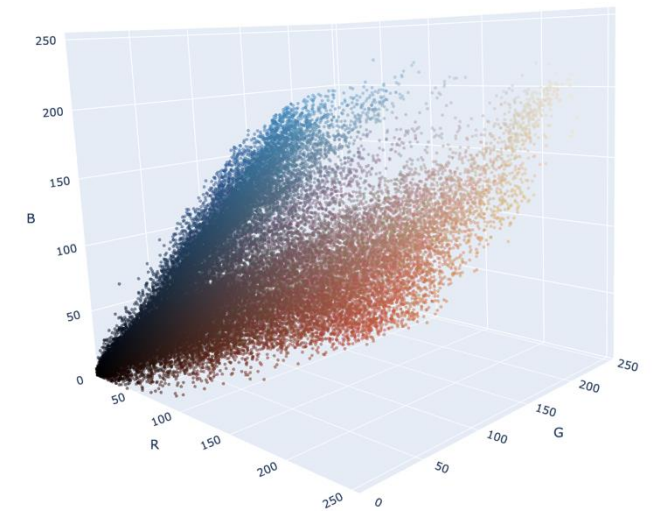
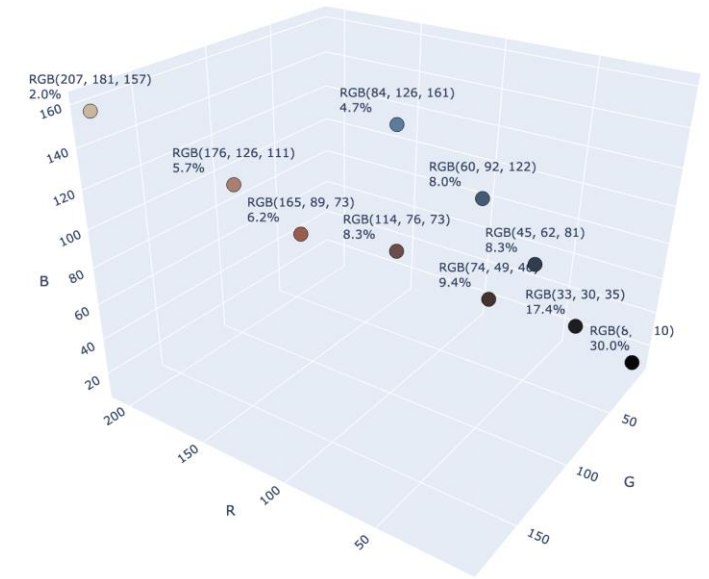
We take a sample pixel inside of each polygon in our Voronoi diagram, found by the (x, y) coordinates of all vertices, and we colour that polygon in, using the RGB value of that exact (x, y) coordinate in the original image.



Custom Colouring

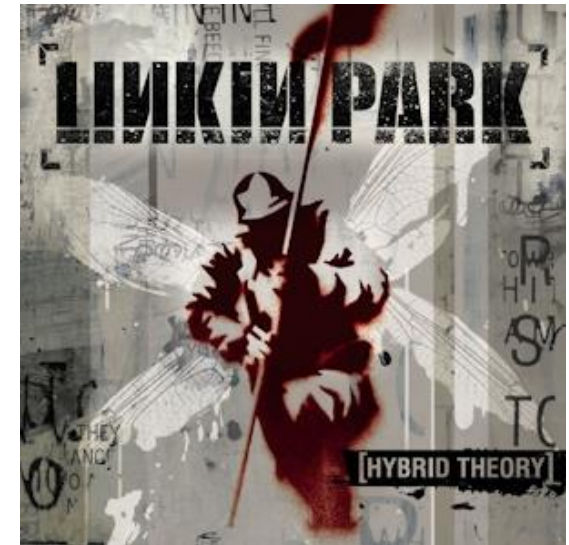
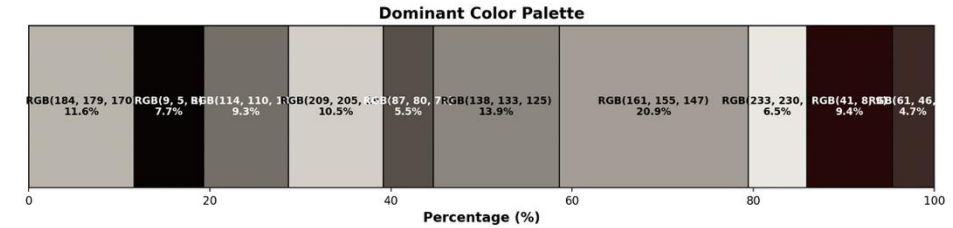
If we want to custom colour our model, then:

1. First we take a sample of 50,000 pixels from our “PalettImage” and plot them in an RGB space.
2. Next we cluster them



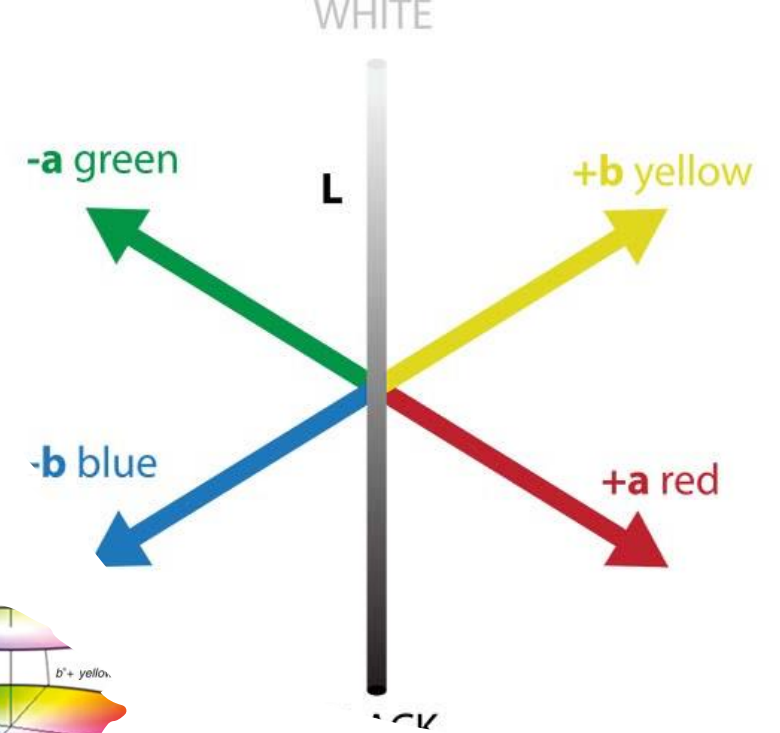
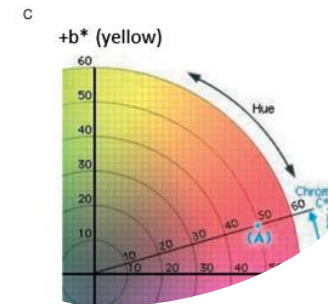
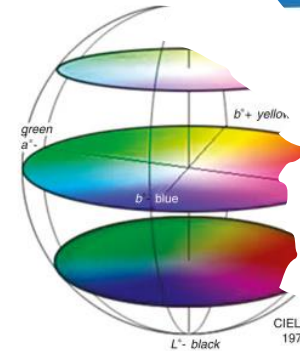
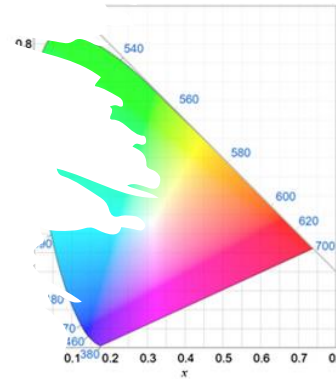
Custom Colouring

- However, this produces an issue. We do not want the colours that show up the most as that would ruin the balance of our weights. The computer recognizes red as the 9th most prominent shade, yet you and I would argue it is the second most prominent colour
- Instead, we need to find the most “distinct” colours. We can define colours as “distinct” if their clusters are far apart in the RGB space.



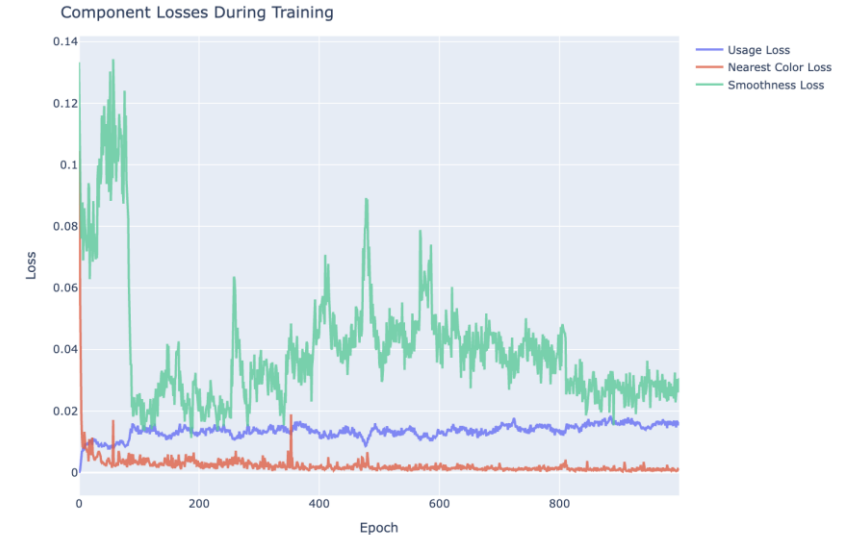
Custom colouring

- By combinatorics, there are 30,240 ways to pick 5 out of 10 objects. This is an INSANE algorithmic bottleneck.
- However, since we know the lightest and darkest colours MUST be distinct (and therefore in our final top 5 colours), we convert RGB to LAB, we use a Numpy array to sort quickly, and then we pull out the first and last colour. Now we only need to pick 3 more colours. Assuming symmetry in our selection, we go from $P(10,5)$ to $(P(8,3))/2 = 168$
- A 90x or %9000 speed increase in our computation

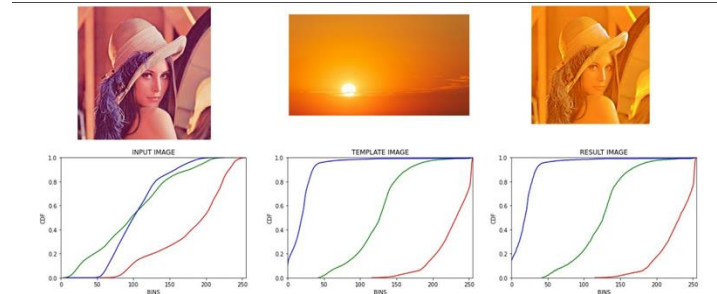


Custom Coloring

- We take those final distinct colours, and we use them in our handmade 256 node, 5 layer Convolutional Neural Network.
- We build a heuristic function made of 4 parts (PaletteUsageLoss, NearestColorDistanceLoss, PaletteEntropyLoss, SmoothnessLoss) to guide us through our CNN using a histogram matching algorithm that identifies how colours should map to each other
- We match probabilities of where each colour belongs with a Wasserstein function
- And we update the weights of each node responsible for each colour, by taking the users feedback in a survey after generating each image.



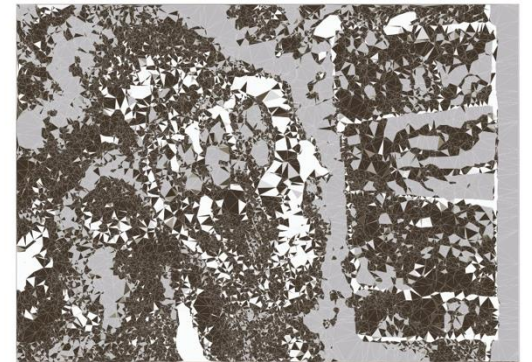
$$\mathcal{W}_p(\mu, \nu) = \left(\int_0^1 |F_\mu^{-1}(z) - F_\nu^{-1}(z)|^p dz \right)^{\frac{1}{p}}$$



Histogram Matching using Python

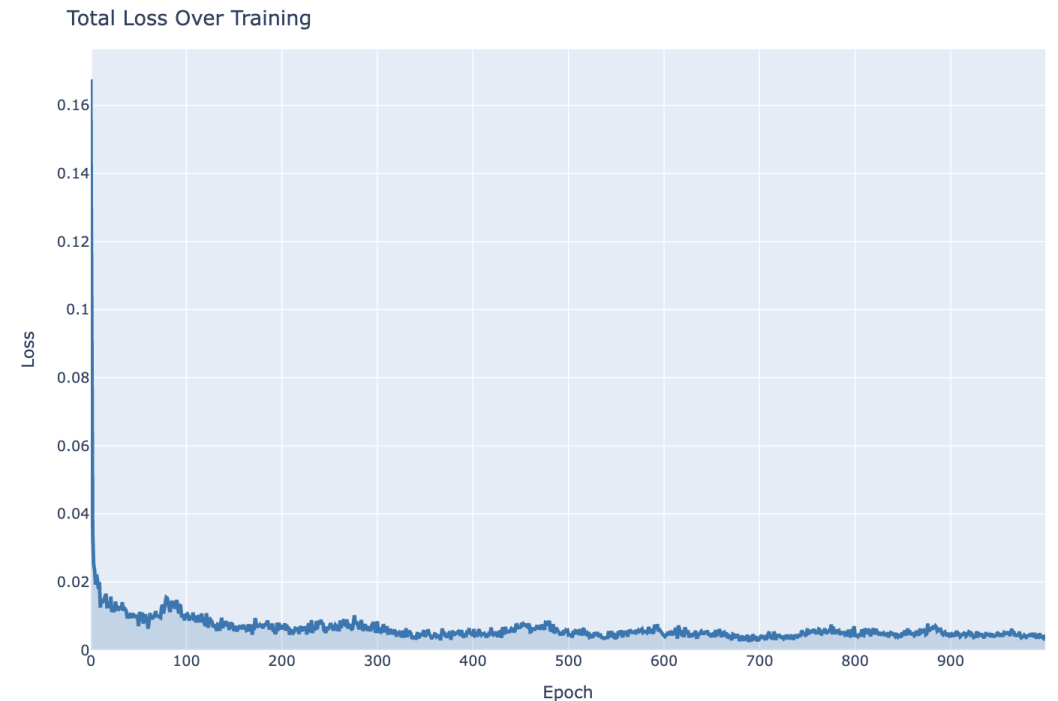
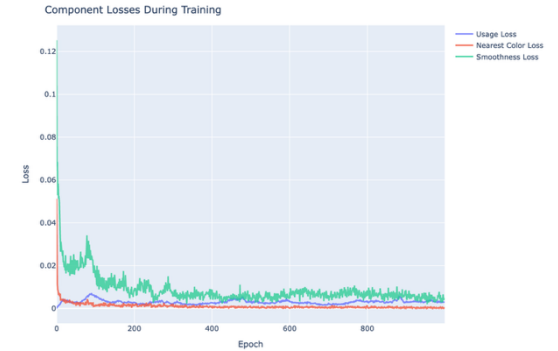
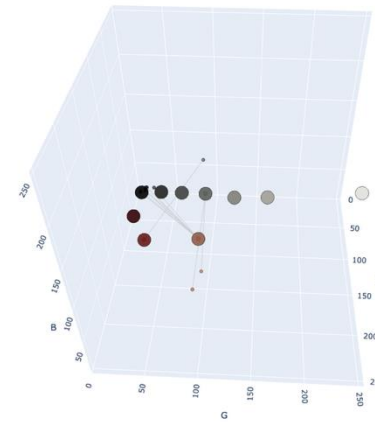
Custom Colouring

- Since a neural network is a statistical machine, over the 100's of thousands of polygons drawn, it produces unique art every time.
- You can mess around with different palettes, density functions (how many triangles), the temperature (how “crazy” of a choice it is for it to choose each colour” etc.



Diagnostics

- Each outcome has its own graphs that are generated in order to help monitor how the system performs. WE can also change the temperature, # of standard Epochs & # of training Epochs of each time we run the CNN in order to alter the outputs in our own favour.



- Additionally, time series evaluations, heatmaps, and many more diagnostic tools exist in your local host when you open TensorBoard.

