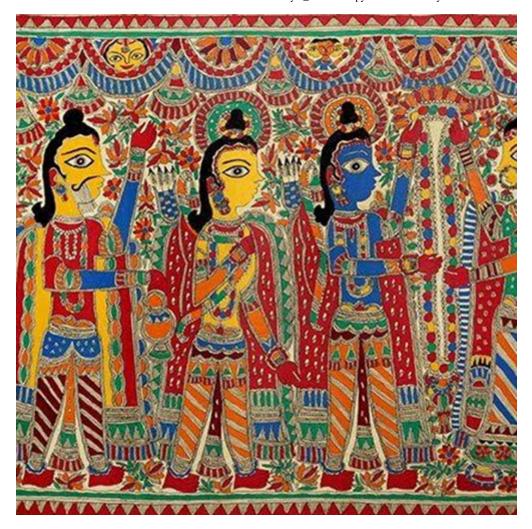
## → 2- Neural Style Transfer with 'Madhubani' Painting Style

```
import numpy as np
from PIL import Image
import requests
from io import BytesIO
from keras import backend
from keras.models import Model
from keras.applications.vgg16 import VGG16
from scipy.optimize import fmin 1 bfgs b
    Using TensorFlow backend.
ITERATIONS = 10
CHANNELS = 3
IMAGE SIZE = 500
IMAGE WIDTH = IMAGE SIZE
IMAGE HEIGHT = IMAGE SIZE
IMAGENET MEAN RGB VALUES = [123.68, 116.779, 103.939]
CONTENT WEIGHT = 0.02
STYLE WEIGHT = 4.5
TOTAL VARIATION WEIGHT = 0.995
TOTAL VARIATION LOSS FACTOR = 1.25
input image path = "input.png"
style image path = "style.png"
output image path = "output.png"
#Input visualization - Content
input image = Image.open("/content/Csueastbay1.jpg")
input image = input image.resize((IMAGE WIDTH, IMAGE HEIGHT))
input image.save(input image path)
input image
Гэ
```



```
# Style visualization - Style
style_image = Image.open("/content/36.jpg")
style_image = style_image.resize((IMAGE_WIDTH, IMAGE_HEIGHT))
style_image.save(style_image_path)
style_image
```

С→



```
# Data normalization and reshaping from RGB to BGR
   input_image_array = np.asarray(input_image, dtype="float32")
   input_image_array = np.expand_dims(input_image_array, axis=0)
   input image array[:, :, :, 0] -= IMAGENET MEAN RGB VALUES[2]
   input image array[:, :, :, 1] -= IMAGENET MEAN RGB VALUES[1]
   input_image_array[:, :, :, 2] -= IMAGENET_MEAN_RGB_VALUES[0]
   input image array = input image array[:, :, ::-1]
   style image array = np.asarray(style image, dtype="float32")
   style image array = np.expand dims(style image array, axis=0)
   style image array[:, :, :, 0] -= IMAGENET MEAN RGB VALUES[2]
   style image array[:, :, :, 1] -= IMAGENET MEAN RGB VALUES[1]
   style_image_array[:, :, :, 2] -= IMAGENET_MEAN_RGB_VALUES[0]
   style image array = style image array[:, :, ::-1]
   # Model
   input image = backend.variable(input image array)
   style image = backend.variable(style image array)
   combination image = backend.placeholder((1, IMAGE HEIGHT, IMAGE SIZE, 3))
   input tensor = backend.concatenate([input image, style image, combination image], axis=
   model = VGG16(input tensor=input tensor, include top=False)
https://colab.research.google.com/drive/11X4z7qUFjIPTcGBTZGSh7hq16-3VcmP1\#scrollTo=OxkC29pSOrpY\&printMode=true
```

□ Downloading data from <a href="https://github.com/fchollet/deep-learning-models/releases/">https://github.com/fchollet/deep-learning-models/releases/</a> def content loss(content, combination): return backend.sum(backend.square(combination - content)) layers = dict([(layer.name, layer.output) for layer in model.layers]) content layer = 'block2 conv2' layer features = layers[content\_layer] content image features = layer features[0, :, :, :] combination\_features = layer\_features[2, :, :, :] loss = backend.variable(0.) loss =loss+ CONTENT WEIGHT \* content loss(content image features, combination features) def gram\_matrix(x): features = backend.batch flatten(backend.permute dimensions(x, (2, 0, 1))) gram = backend.dot(features, backend.transpose(features)) return gram def compute style loss(style, combination): style = gram matrix(style) combination = gram matrix(combination) size = IMAGE\_HEIGHT \* IMAGE\_WIDTH return backend.sum(backend.square(style - combination)) / (4. \* (CHANNELS \*\* 2) \* style layers = ["block1 conv2", "block2 conv2", "block3 conv3", "block4 conv3", "bloc for layer name in style layers: layer features = layers[layer name] style features = layer features[1, :, :, :] combination features = layer features[2, :, :, :] style loss = compute style loss(style features, combination features) loss =loss+ (STYLE\_WEIGHT / len(style\_layers)) \* style\_loss def total variation loss(x): a = backend.square(x[:, :IMAGE\_HEIGHT-1, :IMAGE\_WIDTH-1, :] - x[:, 1:, :IMAGE\_WID b = backend.square(x[:, :IMAGE HEIGHT-1, :IMAGE WIDTH-1, :] - x[:, :IMAGE HEIGHTreturn backend.sum(backend.pow(a + b, TOTAL VARIATION LOSS FACTOR)) loss =loss+ TOTAL VARIATION WEIGHT \* total variation loss(combination image) outputs = [loss] outputs += backend.gradients(loss, combination\_image) def evaluate loss and gradients(x): x = x.reshape((1, IMAGE HEIGHT, IMAGE WIDTH, CHANNELS))

```
outs = backend.function([combination_image], outputs)([x])
    loss = outs[0]
    gradients = outs[1].flatten().astype("float64")
    return loss, gradients
class Evaluator:
    def loss(self, x):
        loss, gradients = evaluate_loss_and_gradients(x)
        self. gradients = gradients
        return loss
    def gradients(self, x):
        return self. gradients
evaluator = Evaluator()
outputs = [loss]
outputs += backend.gradients(loss, combination image)
def evaluate loss and gradients(x):
    x = x.reshape((1, IMAGE_HEIGHT, IMAGE_WIDTH, CHANNELS))
    outs = backend.function([combination image], outputs)([x])
    loss = outs[0]
    gradients = outs[1].flatten().astype("float64")
    return loss, gradients
class Evaluator:
    def loss(self, x):
        loss, gradients = evaluate loss and gradients(x)
        self. gradients = gradients
        return loss
    def gradients(self, x):
        return self. gradients
evaluator = Evaluator()
x = np.random.uniform(0, 255, (1, IMAGE HEIGHT, IMAGE WIDTH, 3)) - 128.
for i in range(ITERATIONS):
    x, loss, info = fmin 1 bfgs b(evaluator.loss, x.flatten(), fprime=evaluator.gradi
    print("Iteration %d completed with loss %d" % (i, loss))
x = x.reshape((IMAGE_HEIGHT, IMAGE_WIDTH, CHANNELS))
x = x[:, :, ::-1]
x[:, :, 0] += IMAGENET MEAN RGB VALUES[2]
x[:, :, 1] += IMAGENET MEAN RGB VALUES[1]
x[:, :, 2] += IMAGENET MEAN RGB VALUES[0]
x = np.clip(x, 0, 255).astype("uint8")
```

```
output_image = Image.fromarray(x)
output_image.save(output_image_path)
# Output
output_image
```

Iteration 0 completed with loss 149901443072
Iteration 1 completed with loss 93296099328
Iteration 2 completed with loss 74111426560
Iteration 3 completed with loss 66574176256
Iteration 4 completed with loss 62600998912
Iteration 5 completed with loss 60307472384
Iteration 6 completed with loss 59194380288
Iteration 7 completed with loss 58550304768
Iteration 8 completed with loss 58085662720
Iteration 9 completed with loss 57757417472

