Packages

In [1]:
```
import numpy as np
import scipy.io
import numpy as np
import matplotlib.pyplot as plt
```

Neural Networks as Universal Function Approximators

Functions

In [2]:
```
def initialize_weights(input_size, output_size):
    """
    Initialize weights parameters randomly and biases to zeros.

    Args:
    - input_size: Number of input units to the layer.
    - output_size: Number of output units from the layer.

    Returns:
    - weights: Initialized weights with shape (input_size, output_size).
    - biases: Initialized biases with shape (output_size,).
    """
    weights = np.random.randn(input_size, output_size) * 0.01
    biases = np.zeros(output_size)

    return weights, biases
```

In [3]:
```
def linear_forward(x, weights, biases):
    """
    Perform the forward pass through a linear layer.

    Args:
    - x: Input to the linear layer.
    - weights: Weights of the linear layer.
    - biases: Biases of the linear layer.

    Returns:
    - output: Output of the linear layer after applying the linear transforr
    """
    output = np.dot(x, weights) + biases
    return output
```

In [4]:
```
def linear_backward(grad_output, weights, x):
    """
    Perform the backward pass for a linear layer.

    Args:
    - grad_output: The gradient of the loss with respect to the output of tl
    - weights: The weights of the linear layer.
    - input: The input to the linear layer (from the previous layer or the (
    - learning_rate: The learning rate for the update.

    Returns:
    - grad_input: The gradient of the loss with respect to the input of the
    - weights_grad: The gradient of the loss with respect to the weights of
    - biases_grad: The gradient of the loss with respect to the biases of tl
    """
```

```
    # Compute gradients
    weights_grad = np.dot(x.T, grad_output)  # Gradient of loss w.r.t. weigh
    biases_grad = np.sum(grad_output, axis=0)    # Gradient of loss w.r.t. b
    grad_input = np.dot(grad_output, weights.T)  # Gradient of loss w.r.t. i

    return grad_input, weights_grad, biases_grad
```

In [5]:
```
def sigmoid_forward(x):
    """
    Perform the forward pass through a sigmoid activation layer.

    Args:
    - x: Input to the sigmoid activation layer.

    Returns:
    - output: Output of the sigmoid activation layer after applying the sigm
    """
    output = 1 / (1 + np.exp(-x))
    return output
```

In [6]:
```
def sigmoid_backward(grad_output, output):
    """
    Perform the backward pass for a sigmoid activation layer.

    Args:
    - grad_output: The gradient of the loss with respect to the output of th
    - output: The output from the forward pass of the sigmoid layer.

    Returns:
    - grad_input: The gradient of the loss with respect to the input of the
    """
    # The derivative of the sigmoid function is output * (1 - output)
    sigmoid_derivative = output * (1 - output)

    # The gradient of the loss with respect to the input of the sigmoid laye
    # is the chain rule application: grad_output * sigmoid_derivative
    grad_input = grad_output * sigmoid_derivative

    return grad_input
```

In [7]:
```
def mse_loss_forward(predictions, labels):
    """
    Calculate the Mean Squared Error loss.

    Args:
    - predictions: numpy array, predicted outputs from the neural network
    - targets: numpy array, actual target values

    Returns:
    - loss: a single float value representing the loss
    """
    # Calculate the difference between the predictions and the targets
    differences = predictions - labels

    # Square the differences and compute the mean (average)
    loss = np.mean(differences ** 2)

    return loss
```

In [8]:
```
def mse_loss_backward(predictions, labels):
    """
    Calculate the gradient of the MSE loss with respect to the predictions.
```

```
    Args:
    - y_pred: Predicted values, numpy array of any shape
    - y_true: True values, numpy array with the same shape as y_pred

    Returns:
    - grad: Gradient of the MSE loss with respect to y_pred
    """
    n = labels.shape[0]
    grad = (2/n) * (predictions - labels)
    return grad
```

In [9]:
```
def initialize_adam(parameters):
    """
    Initialize m_i, v_i, which are zero vectors with same shape as weights W
    """
    adam_params = []

    for (weights, biases) in parameters:
        m_w = np.zeros_like(weights)
        v_w = np.zeros_like(weights)
        m_b = np.zeros_like(biases)
        v_b = np.zeros_like(biases)

        adam_params.append({'m_w': m_w, 'v_w': v_w, 'm_b': m_b, 'v_b': v_b})

    return adam_params
```

In [10]:
```
def update_with_adam(parameters, grads, adam_params, t, learning_rate, beta1
    new_parameters = []

    for i, ((w, b), (dw, db), param) in enumerate(zip(parameters, grads, ada

        m_w, v_w = param['m_w'], param['v_w']
        m_b, v_b = param['m_b'], param['v_b']

        # Update the moving averages of the gradients
        m_w = beta1 * m_w + (1 - beta1) * dw
        m_b = beta1 * m_b + (1 - beta1) * db

        # Update the moving averages of the squared gradients
        v_w = beta2 * v_w + (1 - beta2) * (dw ** 2)
        v_b = beta2 * v_b + (1 - beta2) * (db ** 2)

        # Compute bias-corrected first and second moments
        m_w_hat = m_w / (1 - beta1 ** t)
        m_b_hat = m_b / (1 - beta1 ** t)
        v_w_hat = v_w / (1 - beta2 ** t)
        v_b_hat = v_b / (1 - beta2 ** t)

        # Update parameters
        w = w - learning_rate * m_w_hat / (np.sqrt(v_w_hat) + epsilon)
        b = b - learning_rate * m_b_hat / (np.sqrt(v_b_hat) + epsilon)

        new_parameters.append((w, b))
        adam_params[i]['m_w'], adam_params[i]['v_w'] = m_w, v_w
        adam_params[i]['m_b'], adam_params[i]['v_b'] = m_b, v_b

    return new_parameters, adam_params
```

In [11]:
```
# Function to make predictions with the neural network
def predict_neural_network(X, parameters):
    activations = [X]
```

```
    for i, (weights, biases) in enumerate(parameters):
        z = linear_forward(activations[-1], weights, biases)
        a = sigmoid_forward(z) if i < len(parameters) - 1 else z  # No sigmo
        activations.append(a)
    return activations[-1]
```

In [12]:
```
# Function to get mini-batches
def get_mini_batches(X, Y, batch_size):
    indices = np.random.choice(len(X), batch_size, replace=False)
    return X[indices], Y[indices]
```

In [36]:
```
# Modify the train_neural_network function to use mini-batches
def train_neural_network(X, Y, layers, learning_rate, epochs, batch_size):
    # Initialize the weights and biases for all layers
    parameters = [initialize_weights(layers[i], layers[i+1]) for i in range(
    adam_params = initialize_adam(parameters)
    t = 1
    tolerance = 1e-5  # Set a tolerance for early stopping
    prev_loss = np.inf

    for epoch in range(epochs):
        # Get mini-batches
        X_mini, Y_mini = get_mini_batches(X, Y, batch_size)

        # Forward propagation
        activations = [X_mini]
        for i, (weights, biases) in enumerate(parameters):
            z = linear_forward(activations[-1], weights, biases)
            a = sigmoid_forward(z) if i < len(parameters) - 1 else z  # No s
            activations.append(a)

        # Compute loss for the mini-batch
        loss = mse_loss_forward(activations[-1], Y_mini)

        # Loss reporting and early stopping check can stay outside the mini-
        if epoch % 50 == 0:
            print(f"Epoch {epoch}, Loss: {loss}")

        # Backward propagation
        grads = []

        grad_loss = mse_loss_backward(activations[-1], Y_mini)

        # Backpropagate through the last layer (which does not have a sigmoi
        last_layer_weights, last_layer_biases = parameters[-1]
        grad_last_layer = linear_backward(grad_loss, last_layer_weights, act
        grads.append((grad_last_layer[1], grad_last_layer[2]))  # Append gra

        # Propagate gradients through the rest of the layers
        grad_next_layer = grad_last_layer[0]

        for i in reversed(range(len(parameters) - 1)):
            # Backpropagate through the sigmoid
            grad_sigmoid = sigmoid_backward(grad_next_layer, activations[i+1

            # Backpropagate through the linear layer
            weights, biases = parameters[i]
            grad_linear = linear_backward(grad_sigmoid, weights, activations

            # Store the gradients
            grads.append((grad_linear[1], grad_linear[2]))  # Append gradien

            # Update the gradient for the next layer
```

```
                grad_next_layer = grad_linear[0]

            # Reverse the gradients list so it's in the same order as the parame
            grads = grads[::-1]

            # Update the weights and biases with the gradients
            parameters, adam_params = update_with_adam(parameters, grads, adam_p

            # Increment the timestep for Adam
            t += 1

            #if abs(prev_loss - loss) < tolerance:
                #print(f"Stopping early at epoch {epoch} due to small change in
                #break

            #prev_loss = loss

    return parameters
```

Checking the Neural Network with Synthetic Data

Quadratic function

In [14]:

```
# Generate synthetic training data
def generate_data(num_samples):
    np.random.seed(42)
    X = np.random.rand(num_samples, 1) * 10 - 5  # Generate random values be
    y = 0.5 * X**2 - 3*X + 2 + np.random.randn(num_samples, 1)  # Quadratic
    return X, y

# Generate data
X_train, y_train = generate_data(100)

# Normalize the input data for better performance
x_mean, x_std = X_train.mean(), X_train.std()
y_mean, y_std = y_train.mean(), y_train.std()

x_train_normalized = (X_train - x_mean) / x_std
y_train_normalized = (y_train - y_mean) / y_std
```

In [15]:

```
# Generate synthetic testing data
def generate_data(num_samples):
    np.random.seed(40)
    X = np.random.rand(num_samples, 1) * 10 - 5  # Generate random values be
    y = 0.5 * X**2 - 3*X + 2 + np.random.randn(num_samples, 1)  # Quadratic
    return X, y

# Generate data
X_test, y_test = generate_data(100)

# Normalize the input data for better performance
x_mean, x_std = X_test.mean(), X_test.std()
y_mean, y_std = y_test.mean(), y_test.std()

x_test_normalized = (X_test - x_mean) / x_std
y_test_normalized = (y_test - y_mean) / y_std
```

In [16]:

```
learning_rate = 1E-2
batch_size = 50
epochs = 200
```

```
# Define network architecture
layers = [1, 448, 391, 1]  # Input size, hidden layer sizes, output size

# Train the neural network
parameters_model = train_neural_network(x_train_normalized, y_train_normali
```

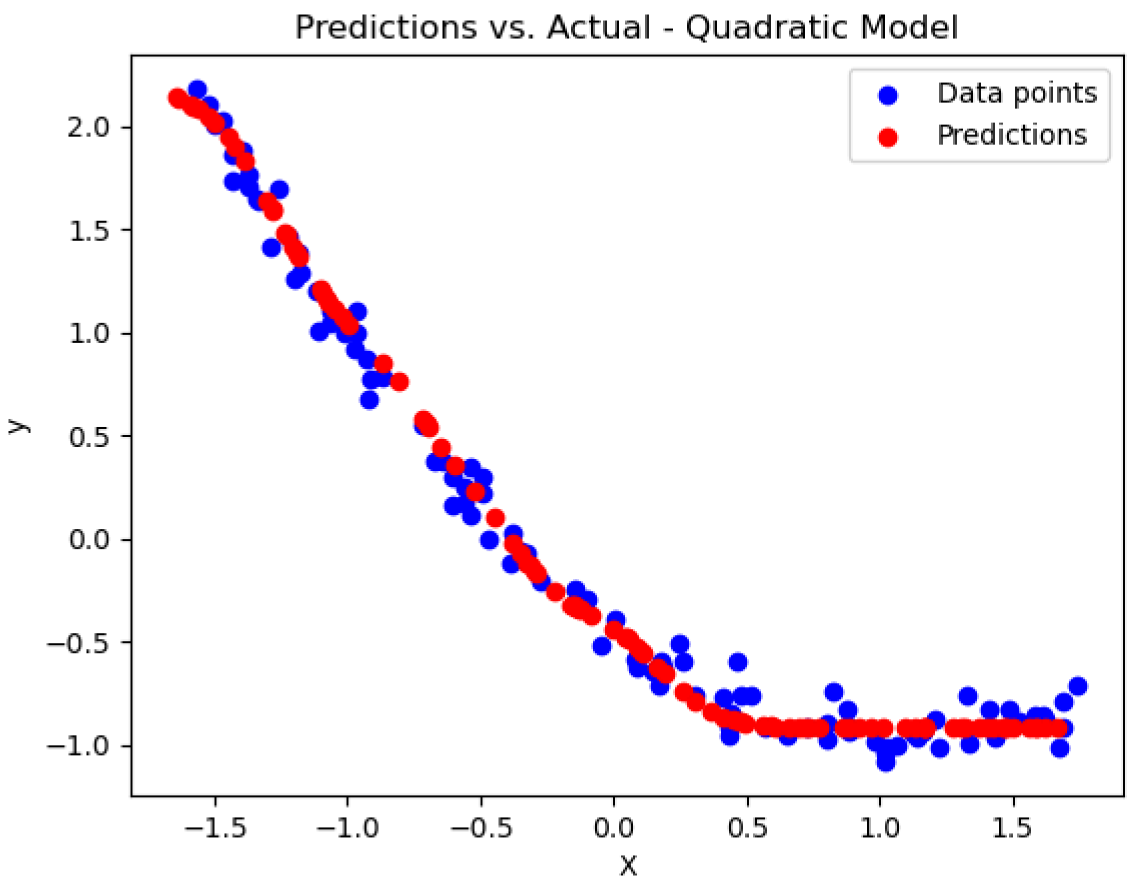
```
Epoch 0, Loss: 1.0325280533907033
Epoch 50, Loss: 1.1077711207943264
Epoch 100, Loss: 0.9771348898279135
Epoch 150, Loss: 0.02862408487496236
```

In [17]:

```
# Function to perform forward pass through the trained network
def predict(X, parameters):
    activations = [X]
    for i, (weights, biases) in enumerate(parameters):
        z = linear_forward(activations[-1], weights, biases)
        a = sigmoid_forward(z) if i < len(parameters) - 1 else z
        activations.append(a)
    return activations[-1]
```

In [18]:

```
# Make predictions
predictions = predict(x_test_normalized, parameters_model)

# Visualize the predictions
plt.scatter(x_train_normalized, y_train_normalized, color='blue', label='Da
plt.scatter(x_test_normalized, predictions, color='red', label='Predictions
plt.xlabel('X')
plt.ylabel('y')
plt.title('Predictions vs. Actual - Quadratic Model')
plt.legend()
plt.show()
```



Cubic Function

In [19]:
```
# Generate synthetic training data for a cubic function
def generate_data(num_samples):
    np.random.seed(42)
    X = np.random.rand(num_samples, 1) * 10 - 5  # Generate random values be
    y = 0.5 * X**3 - 3*X**2 + 2*X + np.random.randn(num_samples, 1)  # Cubic
    return X, y

# Generate synthetic training data
X_train_cubic, y_train_cubic = generate_data(100)

# Normalize the input data for better performance
x_mean_cubic, x_std_cubic = X_train_cubic.mean(), X_train_cubic.std()
y_mean_cubic, y_std_cubic = y_train_cubic.mean(), y_train_cubic.std()

x_train_normalized_cubic = (X_train_cubic - x_mean_cubic) / x_std_cubic
y_train_normalized_cubic = (y_train_cubic - y_mean_cubic) / y_std_cubic
```

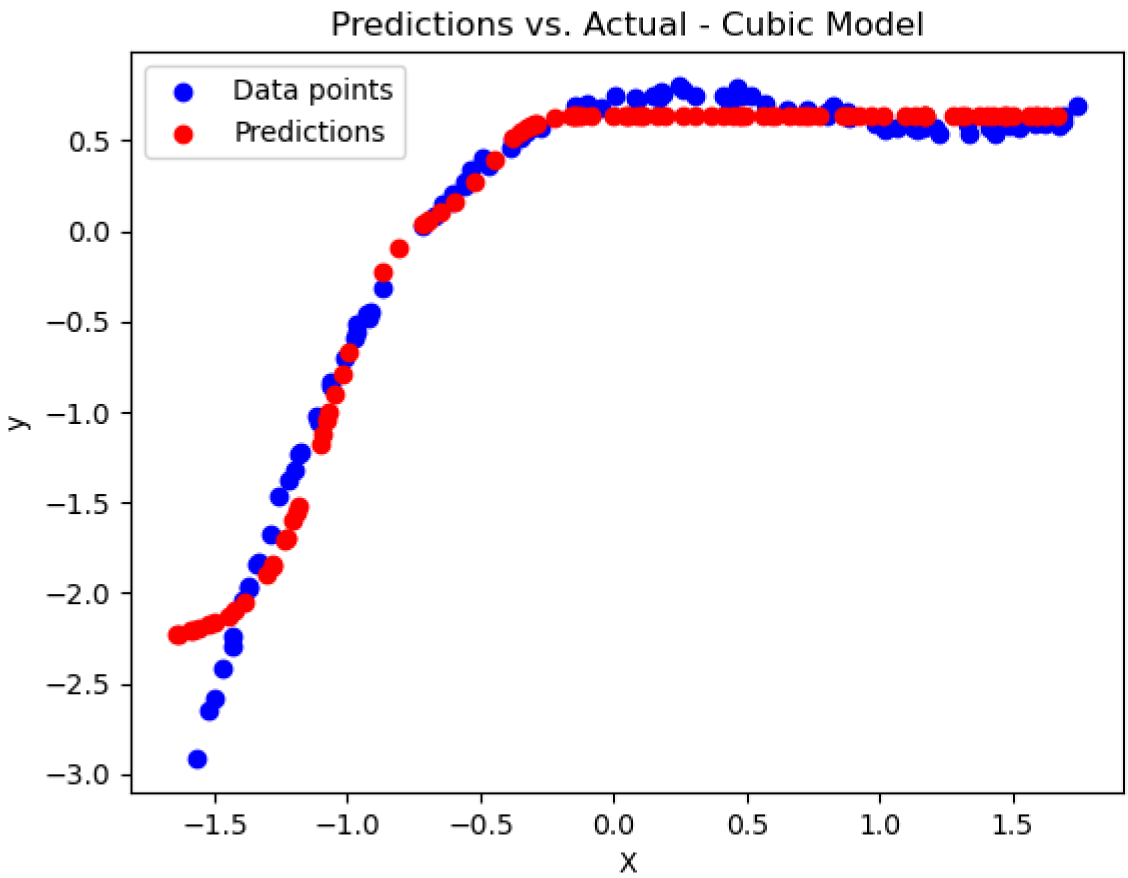
In [20]:
```
def generate_data(num_samples):
    np.random.seed(40)
    X = np.random.rand(num_samples, 1) * 10 - 5  # Generate random values be
    y = 0.5 * X**3 - 3*X**2 + 2*X + np.random.randn(num_samples, 1)  # Cubic
    return X, y

# Generate synthetic testing data
X_test_cubic, y_test_cubic = generate_data(100)

# Normalize the input data for better performance
x_mean_cubic, x_std_cubic = X_test_cubic.mean(), X_test_cubic.std()
y_mean_cubic, y_std_cubic = y_test_cubic.mean(), y_test_cubic.std()

x_test_normalized_cubic = (X_test_cubic - x_mean_cubic) / x_std_cubic
y_test_normalized_cubic = (y_test_cubic - y_mean_cubic) / y_std_cubic
```

In [21]:
```
learning_rate = 1E-2
epochs = 500
# Define network architecture
layers = [1, 448, 391, 1]  # Input size, hidden layer sizes, output size

# Train the neural network
parameters_model_cubic = train_neural_network(x_train_normalized_cubic, y_t
```

```
Epoch 0, Loss: 0.910268178128963
Epoch 50, Loss: 1.295172740617556
Epoch 100, Loss: 0.9789473238811998
Epoch 150, Loss: 0.4333154605380154
Epoch 200, Loss: 0.3111497634000977
Epoch 250, Loss: 0.20309512115496567
Epoch 300, Loss: 0.13671496631712873
Epoch 350, Loss: 0.0683231516069031
Epoch 400, Loss: 0.06032304440198521
Epoch 450, Loss: 0.03800497093361399
```

In [22]:
```
# Make predictions
predictions_cubic = predict(x_test_normalized_cubic, parameters_model_cubic

# Visualize the predictions
plt.scatter(x_train_normalized_cubic, y_train_normalized_cubic, color='blue
plt.scatter(x_test_normalized_cubic, predictions_cubic, color='red', label=
plt.xlabel('X')
plt.ylabel('y')
plt.title('Predictions vs. Actual - Cubic Model')
```

```
plt.legend()
plt.show()
```



Images

In [23]:
```
path = '/Users/anouckrietveld/Documents/Columbia/ML for DS/Homework 2/nn_dat
data = scipy.io.loadmat(path)
data
```

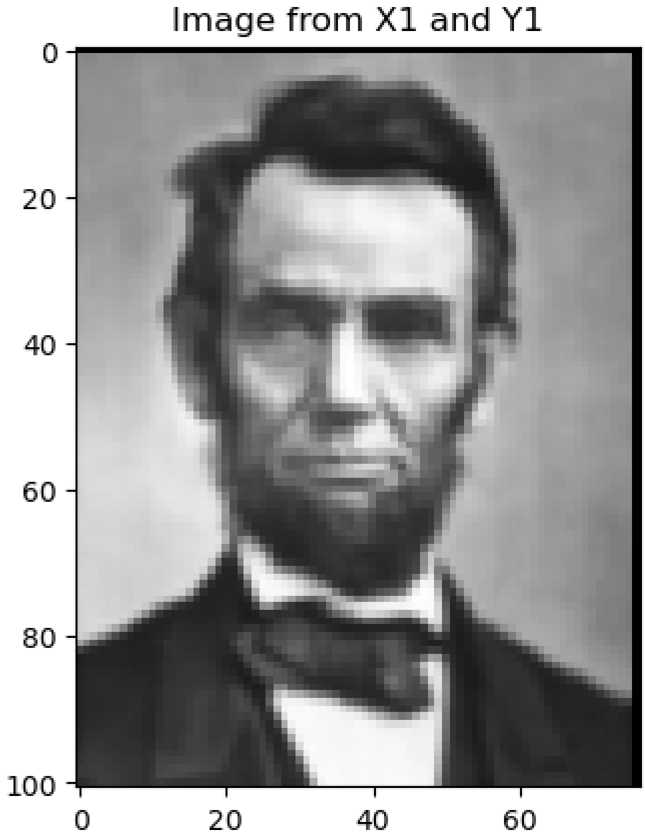
Out[23]:
```
{'__header__': b'MATLAB 5.0 MAT-file, Platform: PCWIN64, Created on: Sat Se
p  3 23:17:48 2022',
 '__version__': '1.0',
 '__globals__': [],
 'X1': array([[  1.,   1.],
        [  1.,   2.],
        [  1.,   3.],
        ...,
        [100.,  74.],
        [100.,  75.],
        [100.,  76.]], dtype=float32),
 'X2': array([[  1.,   1.],
        [  1.,   2.],
        [  1.,   3.],
        ...,
        [133., 138.],
        [133., 139.],
        [133., 140.]], dtype=float32),
 'Y1': array([[138.],
        [140.],
        [144.],
        ...,
        [ 52.],
        [ 46.],
        [ 42.]], dtype=float32),
 'Y2': array([[0., 0., 0.],
        [0., 0., 0.],
        [0., 0., 0.],
        ...,
        [0., 0., 0.],
        [0., 0., 0.],
        [0., 0., 0.]], dtype=float32)}
```

Image 1 Reconstruction

In [24]:
```python
# Since we need to infer the dimensions of the images, let's start with the
# We'll use the unique coordinates in X1 to determine the image dimensions.
unique_x1 = np.unique(data['X1'], axis=0)
dim_y1_x = len(np.unique(unique_x1[:, 0]))
dim_y1_y = len(np.unique(unique_x1[:, 1]))

unique_x2 = np.unique(data['X2'], axis=0)
dim_y2_x = len(np.unique(unique_x2[:, 0]))
dim_y2_y = len(np.unique(unique_x2[:, 1]))
```

In [25]:
```python
X1 = data['X1']
Y1 = data['Y1']

# Find the maximum values in X1 to determine the size of the image
max_x = np.max(X1[:, 0])  # Max value in the first column (x-coordinates)
max_y = np.max(X1[:, 1])  # Max value in the second column (y-coordinates)

# Initialize an empty image array with the determined dimensions
image_height, image_width = int(max_y) + 1, int(max_x) + 1
image = np.zeros((image_height, image_width))

# Populate the image array with Y1 values at the coordinates specified by X1
for i in range(len(X1)):
    x_coord, y_coord = int(X1[i, 0]), int(X1[i, 1])
    image[y_coord, x_coord] = Y1[i]

# Rotate the image array 90 degrees clockwise
rotated_image = np.rot90(image, k=-1)
```

```
# Visualize the rotated image
plt.imshow(rotated_image, cmap='gray')
plt.title('Image from X1 and Y1')
plt.show()
```



In [26]:
```
# Normalize the input data for better performance
X1_mean, X1_std = X1.mean(), X1.std()
Y1_mean, Y1_std = Y1.mean(), Y1.std()

X1_normalized = (X1 - X1_mean) / X1_std
Y1_normalized = (Y1 - Y1_mean) / Y1_std
```

Image 1 - Baseline

In [38]:
```
layers_image1 = [2, 250, 350, 1]
learning_rate = 1E-2
epochs = 9000
batch_size = 100

# Train the neural network
parameters_image1 = train_neural_network(X1_normalized, Y1_normalized, laye
```

```
Epoch 0, Loss: 1.0850143030215489
Epoch 50, Loss: 0.9974399597467906
Epoch 100, Loss: 0.8698120022849609
Epoch 150, Loss: 1.1153192249424237
Epoch 200, Loss: 0.8098259690848922
Epoch 250, Loss: 0.8193096173988752
Epoch 300, Loss: 0.8815173703047776
Epoch 350, Loss: 1.0103826215361957
Epoch 400, Loss: 0.9761963054555792
Epoch 450, Loss: 1.0303003965435222
Epoch 500, Loss: 0.8243757190476346
Epoch 550, Loss: 0.9166520238896857
Epoch 600, Loss: 0.8173526430105871
Epoch 650, Loss: 0.9977867170637696
Epoch 700, Loss: 0.8070611918473037
Epoch 750, Loss: 1.0082659953775432
Epoch 800, Loss: 0.8795036220601345
Epoch 850, Loss: 0.8661138999389368
Epoch 900, Loss: 1.1223198199447362
Epoch 950, Loss: 0.8531578015401174
Epoch 1000, Loss: 0.8359990259838839
Epoch 1050, Loss: 0.7800247732446784
Epoch 1100, Loss: 0.7971493577033881
Epoch 1150, Loss: 0.6392243136216953
Epoch 1200, Loss: 0.7350515879497671
Epoch 1250, Loss: 0.5437547544222003
Epoch 1300, Loss: 0.5930673755466919
Epoch 1350, Loss: 0.6317582374656986
Epoch 1400, Loss: 0.7441840220304488
Epoch 1450, Loss: 0.6948302414675769
Epoch 1500, Loss: 0.7069899657290848
Epoch 1550, Loss: 0.4545040253103389
Epoch 1600, Loss: 0.5690257029736664
Epoch 1650, Loss: 0.5787660247243699
Epoch 1700, Loss: 0.5138330024486083
Epoch 1750, Loss: 0.6667466393688859
Epoch 1800, Loss: 0.5065853981343325
Epoch 1850, Loss: 0.6564539816315373
Epoch 1900, Loss: 0.4759088308072428
Epoch 1950, Loss: 0.5029742544788963
Epoch 2000, Loss: 0.6395355081737477
Epoch 2050, Loss: 0.4890728296650588
Epoch 2100, Loss: 0.6691839681183214
Epoch 2150, Loss: 0.538173832368296
Epoch 2200, Loss: 0.38752877087107956
Epoch 2250, Loss: 0.5758204790796293
Epoch 2300, Loss: 0.5615942293280387
Epoch 2350, Loss: 0.453917836872579
Epoch 2400, Loss: 0.5219844881833668
Epoch 2450, Loss: 0.5968951843729644
Epoch 2500, Loss: 0.4335320509210508
Epoch 2550, Loss: 0.6330707030339332
Epoch 2600, Loss: 0.5268604690263067
Epoch 2650, Loss: 0.5510114089515781
Epoch 2700, Loss: 0.3585043569967471
Epoch 2750, Loss: 0.522862674758481
Epoch 2800, Loss: 0.5698735242095055
Epoch 2850, Loss: 0.5144234827084196
Epoch 2900, Loss: 0.5305646739535933
Epoch 2950, Loss: 0.5085272370313706
Epoch 3000, Loss: 0.3231032763167628
Epoch 3050, Loss: 0.37134391456566923
Epoch 3100, Loss: 0.448542239133055
Epoch 3150, Loss: 0.6200503362211588
```

```
Epoch 3200, Loss: 0.5385779467351453
Epoch 3250, Loss: 0.47006588546819705
Epoch 3300, Loss: 0.40432537931346135
Epoch 3350, Loss: 0.45235878771813576
Epoch 3400, Loss: 0.35864595748628497
Epoch 3450, Loss: 0.4924424222297569
Epoch 3500, Loss: 0.4390389066919889
Epoch 3550, Loss: 0.4220896334764413
Epoch 3600, Loss: 0.5262535106790891
Epoch 3650, Loss: 0.433200258497324
Epoch 3700, Loss: 0.44030592676646974
Epoch 3750, Loss: 0.5648216604511301
Epoch 3800, Loss: 0.5072055901541356
Epoch 3850, Loss: 0.47578300612643504
Epoch 3900, Loss: 0.5054771992021584
Epoch 3950, Loss: 0.4593506828396567
Epoch 4000, Loss: 0.5427943038756661
Epoch 4050, Loss: 0.47328012286133614
Epoch 4100, Loss: 0.45056444402056145
Epoch 4150, Loss: 0.5497183315698577
Epoch 4200, Loss: 0.3550004209430599
Epoch 4250, Loss: 0.4563129147918247
Epoch 4300, Loss: 0.4145589396285809
Epoch 4350, Loss: 0.38646823611853337
Epoch 4400, Loss: 0.26376743645781436
Epoch 4450, Loss: 0.37702065191943285
Epoch 4500, Loss: 0.39845202767072174
Epoch 4550, Loss: 0.4589929344634824
Epoch 4600, Loss: 0.46296923498975856
Epoch 4650, Loss: 0.28639509628931686
Epoch 4700, Loss: 0.40171705894700943
Epoch 4750, Loss: 0.4309564321692168
Epoch 4800, Loss: 0.43960602489085543
Epoch 4850, Loss: 0.29762865982819026
Epoch 4900, Loss: 0.3677014017185518
Epoch 4950, Loss: 0.29889243222165174
Epoch 5000, Loss: 0.40806149102542105
Epoch 5050, Loss: 0.27412885045507634
Epoch 5100, Loss: 0.29260649510733855
Epoch 5150, Loss: 0.2498154813864091
Epoch 5200, Loss: 0.3785653122087976
Epoch 5250, Loss: 0.3192920813395279
Epoch 5300, Loss: 0.3660938840985598
Epoch 5350, Loss: 0.2973754446419709
Epoch 5400, Loss: 0.27708603782506275
Epoch 5450, Loss: 0.384169034305182
Epoch 5500, Loss: 0.2654992630172771
Epoch 5550, Loss: 0.3876626467922648
Epoch 5600, Loss: 0.2286860146330522
Epoch 5650, Loss: 0.3693862384503076
Epoch 5700, Loss: 0.2837580062215055
Epoch 5750, Loss: 0.27841444284627337
Epoch 5800, Loss: 0.26499484477306745
Epoch 5850, Loss: 0.2659725284171822
Epoch 5900, Loss: 0.34911891534214434
Epoch 5950, Loss: 0.24758449874605395
Epoch 6000, Loss: 0.24214654021570767
Epoch 6050, Loss: 0.27242094411333634
Epoch 6100, Loss: 0.24235942278538591
Epoch 6150, Loss: 0.2878619369676553
Epoch 6200, Loss: 0.22981869661436527
Epoch 6250, Loss: 0.41788985363678527
Epoch 6300, Loss: 0.2295496241916329
Epoch 6350, Loss: 0.26396374194697503
```

```
Epoch 6400, Loss: 0.28201483641034947
Epoch 6450, Loss: 0.23583932246503814
Epoch 6500, Loss: 0.23275469414072744
Epoch 6550, Loss: 0.24755700834448294
Epoch 6600, Loss: 0.23342378830830707
Epoch 6650, Loss: 0.23154625553610675
Epoch 6700, Loss: 0.2791959531725172
Epoch 6750, Loss: 0.22602742281482083
Epoch 6800, Loss: 0.12762351096595365
Epoch 6850, Loss: 0.23531103607069773
Epoch 6900, Loss: 0.1726342983152488
Epoch 6950, Loss: 0.3466067750441564
Epoch 7000, Loss: 0.15606141096367387
Epoch 7050, Loss: 0.22328455372134992
Epoch 7100, Loss: 0.21038503476564116
Epoch 7150, Loss: 0.26616716917761846
Epoch 7200, Loss: 0.1687617400412512
Epoch 7250, Loss: 0.20205440770966301
Epoch 7300, Loss: 0.18957711668502153
Epoch 7350, Loss: 0.27414161707934814
Epoch 7400, Loss: 0.18500454983053113
Epoch 7450, Loss: 0.22586600681400226
Epoch 7500, Loss: 0.2085593036631965
Epoch 7550, Loss: 0.1685243687541001
Epoch 7600, Loss: 0.19414118610156408
Epoch 7650, Loss: 0.19290148480443275
Epoch 7700, Loss: 0.25034771854709487
Epoch 7750, Loss: 0.23735560435554123
Epoch 7800, Loss: 0.20088834994614013
Epoch 7850, Loss: 0.33481131497306704
Epoch 7900, Loss: 0.17237724627388026
Epoch 7950, Loss: 0.1780955414943015
Epoch 8000, Loss: 0.20792321266590016
Epoch 8050, Loss: 0.16414166193612986
Epoch 8100, Loss: 0.24404845836802802
Epoch 8150, Loss: 0.22068804546757448
Epoch 8200, Loss: 0.1564982364965555
Epoch 8250, Loss: 0.18973827565614715
Epoch 8300, Loss: 0.28656508139966785
Epoch 8350, Loss: 0.2117809937885518
Epoch 8400, Loss: 0.23273235386376961
Epoch 8450, Loss: 0.2516387107239366
Epoch 8500, Loss: 0.20207167424812827
Epoch 8550, Loss: 0.2268353318543875
Epoch 8600, Loss: 0.1609835362539445
Epoch 8650, Loss: 0.1514172141855182
Epoch 8700, Loss: 0.18175568954920845
Epoch 8750, Loss: 0.17811936672306147
Epoch 8800, Loss: 0.2248132795683453
Epoch 8850, Loss: 0.22346833956476583
Epoch 8900, Loss: 0.1898743648313692
Epoch 8950, Loss: 0.24908466634258772
```

In [39]:

```python
# Generate predictions for the first dataset
Y1_pred_normalized = predict_neural_network(X1_normalized, parameters_image1

# Assuming Y1_pred_normalized contains the normalized predictions
min_Y1 = np.min(Y1)
max_Y1 = np.max(Y1)

# Denormalize the predictions
Y1_pred = Y1_pred_normalized * (max_Y1 - min_Y1) + min_Y1

# Reshape the predictions to match the image dimensions
```

```
Y1_pred_reshaped = Y1_pred.reshape((dim_y1_x, dim_y1_y))

# Visualize the generated image from predictions
plt.figure(figsize=(8, 6))
plt.imshow(Y1_pred_reshaped, cmap='gray')
plt.title('Generated Image 1')
plt.axis()
plt.show()
```

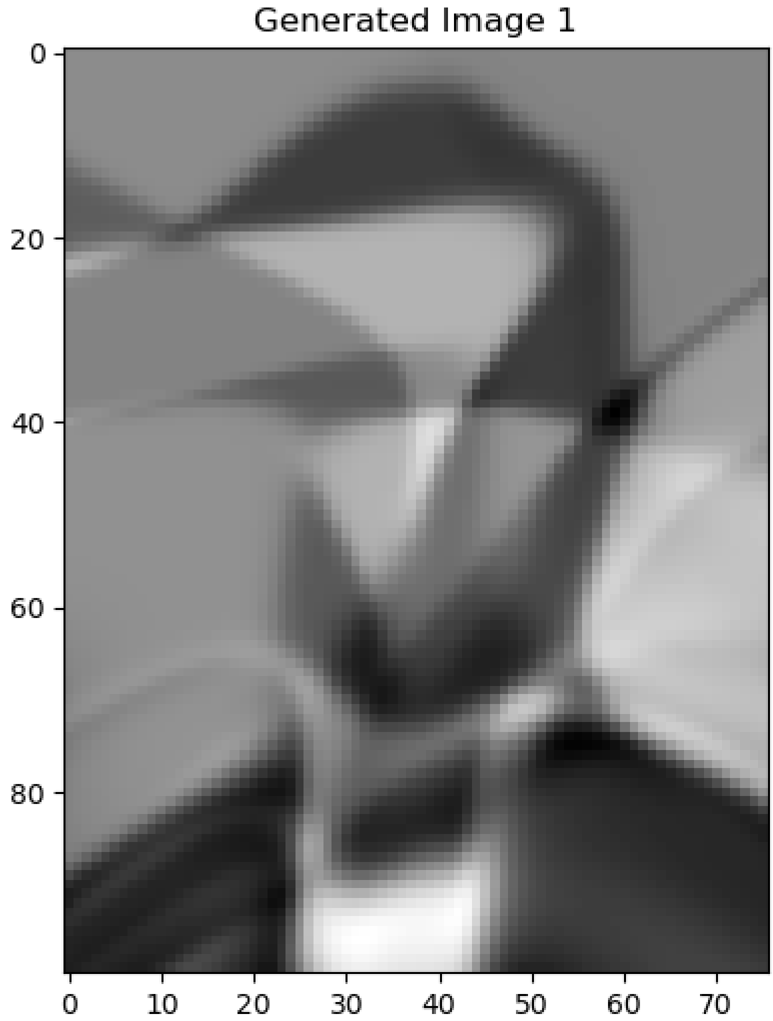


Image 1 - Number of Hidden Layers

In [40]:
```
# Higher Number of Hidden Layers
layers_image1 = [2, 30, 100, 50, 60, 1]
learning_rate = 1E-2
epochs = 9000
batch_size = 100

# Train the neural network
parameters_image1 = train_neural_network(X1_normalized, Y1_normalized, laye
```

```
Epoch 0, Loss: 0.9736488945765701
Epoch 50, Loss: 0.9465882014750276
Epoch 100, Loss: 0.999759365689102
Epoch 150, Loss: 0.9887366298711542
Epoch 200, Loss: 1.1043977312015387
Epoch 250, Loss: 1.0642681314995488
Epoch 300, Loss: 1.0617892553261437
Epoch 350, Loss: 1.0978470396501618
Epoch 400, Loss: 0.9822014981015892
Epoch 450, Loss: 0.9238813651430682
Epoch 500, Loss: 0.9555512145896609
Epoch 550, Loss: 0.9805578938652866
Epoch 600, Loss: 0.947146339275704
Epoch 650, Loss: 1.1115899926171258
Epoch 700, Loss: 0.9589059621680452
Epoch 750, Loss: 0.9730600314319178
Epoch 800, Loss: 0.9293676066914128
Epoch 850, Loss: 1.1004380502010698
Epoch 900, Loss: 1.0748809382679099
Epoch 950, Loss: 1.01916972635468
Epoch 1000, Loss: 1.0607793254739835
Epoch 1050, Loss: 0.8198927995954176
Epoch 1100, Loss: 1.011292387130896
Epoch 1150, Loss: 1.0399577949750478
Epoch 1200, Loss: 0.8980667175392775
Epoch 1250, Loss: 0.9740632861398076
Epoch 1300, Loss: 0.8567529451424747
Epoch 1350, Loss: 1.1489963406423496
Epoch 1400, Loss: 0.9175380904619371
Epoch 1450, Loss: 0.8428578672750895
Epoch 1500, Loss: 0.9803551212631401
Epoch 1550, Loss: 0.9133588341444238
Epoch 1600, Loss: 0.7898699091768662
Epoch 1650, Loss: 0.7861563862028739
Epoch 1700, Loss: 0.7115607649351141
Epoch 1750, Loss: 0.8968960471593402
Epoch 1800, Loss: 0.6617449880632588
Epoch 1850, Loss: 0.8858022297799907
Epoch 1900, Loss: 0.8723925347686935
Epoch 1950, Loss: 1.0368128853875773
Epoch 2000, Loss: 1.1764679277139714
Epoch 2050, Loss: 0.930490413442489
Epoch 2100, Loss: 0.7694342310039586
Epoch 2150, Loss: 1.0759748681936907
Epoch 2200, Loss: 0.7148710345944788
Epoch 2250, Loss: 0.9492761653752685
Epoch 2300, Loss: 0.9692589262253395
Epoch 2350, Loss: 0.8982130315138437
Epoch 2400, Loss: 0.7608258749955799
Epoch 2450, Loss: 0.6792728660349695
Epoch 2500, Loss: 0.9131864241881534
Epoch 2550, Loss: 0.8298586042118282
Epoch 2600, Loss: 0.7597997171632146
Epoch 2650, Loss: 0.9536867612494927
Epoch 2700, Loss: 0.6624848808689292
Epoch 2750, Loss: 0.620747296528837
Epoch 2800, Loss: 0.7732469440237896
Epoch 2850, Loss: 0.8054297971553414
Epoch 2900, Loss: 0.74624810231113
Epoch 2950, Loss: 0.6504127055546945
Epoch 3000, Loss: 0.8417867535082477
Epoch 3050, Loss: 0.5732831665576448
Epoch 3100, Loss: 0.6224646908958883
Epoch 3150, Loss: 0.9979752745847974
```

```
Epoch 3200, Loss: 1.0375092143021798
Epoch 3250, Loss: 0.9867075194985838
Epoch 3300, Loss: 0.8088409424161997
Epoch 3350, Loss: 0.6035352643986575
Epoch 3400, Loss: 0.9333356756214144
Epoch 3450, Loss: 0.7577355982740237
Epoch 3500, Loss: 0.8532302132449172
Epoch 3550, Loss: 0.7430037205695409
Epoch 3600, Loss: 0.7207948364655208
Epoch 3650, Loss: 0.771332770008421
Epoch 3700, Loss: 0.9261714930528993
Epoch 3750, Loss: 0.5122293715597854
Epoch 3800, Loss: 0.8637574787572503
Epoch 3850, Loss: 0.8292120300636543
Epoch 3900, Loss: 0.8754974076078806
Epoch 3950, Loss: 0.8139025613131159
Epoch 4000, Loss: 0.8542981444245593
Epoch 4050, Loss: 0.7297591325775906
Epoch 4100, Loss: 0.9710474064921951
Epoch 4150, Loss: 0.6082382154893955
Epoch 4200, Loss: 0.6748823325342371
Epoch 4250, Loss: 0.5937258372345645
Epoch 4300, Loss: 1.0834342246974211
Epoch 4350, Loss: 0.8732709167030019
Epoch 4400, Loss: 0.7453140968174943
Epoch 4450, Loss: 0.7681836797543484
Epoch 4500, Loss: 0.9716927021051011
Epoch 4550, Loss: 0.9803739047294832
Epoch 4600, Loss: 1.0000389041945252
Epoch 4650, Loss: 0.8411048930373473
Epoch 4700, Loss: 0.8607584143527479
Epoch 4750, Loss: 0.6862134797407258
Epoch 4800, Loss: 0.8209996750689649
Epoch 4850, Loss: 0.9040942800769094
Epoch 4900, Loss: 0.6459677154866658
Epoch 4950, Loss: 0.9102207363529635
Epoch 5000, Loss: 0.8874982628446639
Epoch 5050, Loss: 0.7618915404006943
Epoch 5100, Loss: 0.7226483704550436
Epoch 5150, Loss: 0.8403057390476043
Epoch 5200, Loss: 0.7292391118289152
Epoch 5250, Loss: 0.7673246350800725
Epoch 5300, Loss: 0.6772641346387661
Epoch 5350, Loss: 0.9986942146563651
Epoch 5400, Loss: 0.748959702317779
Epoch 5450, Loss: 0.7693574929133152
Epoch 5500, Loss: 0.721446776660444
Epoch 5550, Loss: 0.7594878776981175
Epoch 5600, Loss: 0.6304667719068978
Epoch 5650, Loss: 0.7634645368462707
Epoch 5700, Loss: 0.8470321677844891
Epoch 5750, Loss: 0.9488495034380112
Epoch 5800, Loss: 0.6736023899169244
Epoch 5850, Loss: 0.8265905216714965
Epoch 5900, Loss: 0.7264142017300707
Epoch 5950, Loss: 0.7668564459361868
Epoch 6000, Loss: 0.7292729165199415
Epoch 6050, Loss: 1.0635837144338043
Epoch 6100, Loss: 0.5966378553122762
Epoch 6150, Loss: 0.7639279527457894
Epoch 6200, Loss: 0.7961235086567021
Epoch 6250, Loss: 0.8330772447665982
Epoch 6300, Loss: 0.8004498656874545
Epoch 6350, Loss: 0.8753512507169916
```

```
Epoch 6400, Loss: 0.8367790088187875
Epoch 6450, Loss: 0.8271934874286765
Epoch 6500, Loss: 0.7734327794473543
Epoch 6550, Loss: 0.8178200427528246
Epoch 6600, Loss: 1.0733713498829622
Epoch 6650, Loss: 0.618567172057475
Epoch 6700, Loss: 0.7289999992361237
Epoch 6750, Loss: 0.8303989067753481
Epoch 6800, Loss: 0.9090876975380229
Epoch 6850, Loss: 0.7399973688471184
Epoch 6900, Loss: 0.8907743211546416
Epoch 6950, Loss: 0.8224471618317822
Epoch 7000, Loss: 0.7762879597431733
Epoch 7050, Loss: 0.6618332237784951
Epoch 7100, Loss: 0.8136099420093362
Epoch 7150, Loss: 0.8569444471098623
Epoch 7200, Loss: 1.0613317783530742
Epoch 7250, Loss: 0.8491288774500095
Epoch 7300, Loss: 0.6225192241571579
Epoch 7350, Loss: 0.64877760199609
Epoch 7400, Loss: 0.8270287378423287
Epoch 7450, Loss: 0.8067614431168901
Epoch 7500, Loss: 0.743095781436956
Epoch 7550, Loss: 0.910778754812945
Epoch 7600, Loss: 0.8941365649947421
Epoch 7650, Loss: 0.942339175996475
Epoch 7700, Loss: 1.0049759067156714
Epoch 7750, Loss: 0.6806312977306703
Epoch 7800, Loss: 0.8219642741628955
Epoch 7850, Loss: 0.7391645714336152
Epoch 7900, Loss: 0.9389898523522848
Epoch 7950, Loss: 0.8393470749613904
Epoch 8000, Loss: 0.5734466657015608
Epoch 8050, Loss: 0.894680382207427 8
Epoch 8100, Loss: 1.0411990086256537
Epoch 8150, Loss: 0.6182665154897221
Epoch 8200, Loss: 0.7992222213252329
Epoch 8250, Loss: 0.7098853910392623
Epoch 8300, Loss: 0.8654500936691837
Epoch 8350, Loss: 0.9389574276258448
Epoch 8400, Loss: 0.7378629712782008
Epoch 8450, Loss: 0.8048321766483454
Epoch 8500, Loss: 0.9724179689548497
Epoch 8550, Loss: 0.8229884569962017
Epoch 8600, Loss: 0.725482039396673 9
Epoch 8650, Loss: 0.6553355669397987
Epoch 8700, Loss: 1.0761629374496706
Epoch 8750, Loss: 0.8355155039382577
Epoch 8800, Loss: 0.8538297254014324
Epoch 8850, Loss: 0.7362210829028852
Epoch 8900, Loss: 1.0192035705360343
Epoch 8950, Loss: 0.9362870633972326
```

In [42]:

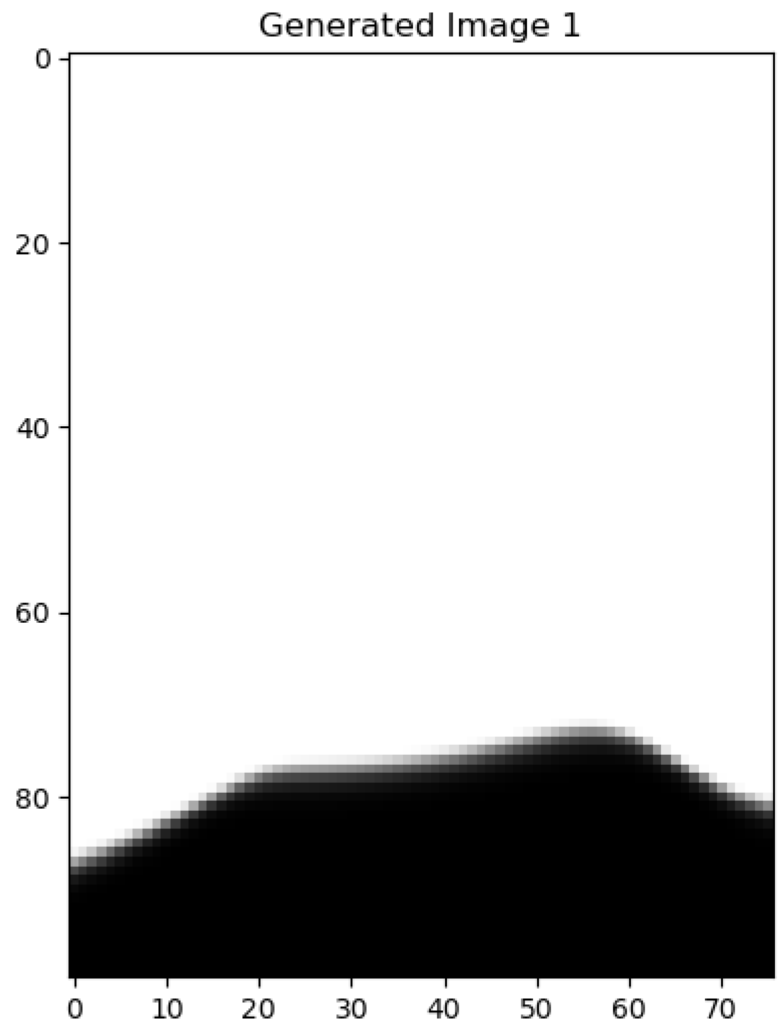
```
# Generate predictions for the first dataset
Y1_pred_normalized = predict_neural_network(X1_normalized, parameters_image1

min_Y1 = np.min(Y1)
max_Y1 = np.max(Y1)

# Denormalize the predictions
Y1_pred = Y1_pred_normalized * (max_Y1 - min_Y1) + min_Y1

# Reshape the predictions to match the image dimensions
Y1_pred_reshaped = Y1_pred.reshape((dim_y1_x, dim_y1_y))
```

```
# Visualize the generated image from predictions
plt.figure(figsize=(8, 6))
plt.imshow(Y1_pred_reshaped, cmap='gray')
plt.title('Generated Image 1')
plt.axis()
plt.show()
```



In [44]:
```
# Lower Number of Hidden Layers
layers_image1 = [2, 400, 1]
learning_rate = 1E-2
epochs = 10000
batch_size = 100

# Train the neural network
parameters_image1 = train_neural_network(X1_normalized, Y1_normalized, laye
```

```
Epoch 0, Loss: 0.9242371300328734
Epoch 50, Loss: 0.8373276606591376
Epoch 100, Loss: 0.7929047458172654
Epoch 150, Loss: 0.9493640859938733
Epoch 200, Loss: 0.8767913296138565
Epoch 250, Loss: 1.0008380813369484
Epoch 300, Loss: 1.2245877064558746
Epoch 350, Loss: 0.7373768477039695
Epoch 400, Loss: 1.1351023164297964
Epoch 450, Loss: 1.083931637719686
Epoch 500, Loss: 1.0467705997464505
Epoch 550, Loss: 0.9673799297807996
Epoch 600, Loss: 1.003345785506205
Epoch 650, Loss: 1.5304708017499289
Epoch 700, Loss: 0.9745357525732353
Epoch 750, Loss: 1.2780737448398716
Epoch 800, Loss: 0.9435607655554574
Epoch 850, Loss: 0.969789901136774
Epoch 900, Loss: 0.9878097766925624
Epoch 950, Loss: 0.8520568244261645
Epoch 1000, Loss: 1.1030895370957252
Epoch 1050, Loss: 0.9243514602303149
Epoch 1100, Loss: 0.8124307914196551
Epoch 1150, Loss: 1.0102273183610462
Epoch 1200, Loss: 0.8239557822388073
Epoch 1250, Loss: 0.700940674571083
Epoch 1300, Loss: 0.6355827115550311
Epoch 1350, Loss: 0.7127950216425483
Epoch 1400, Loss: 0.7500178083542782
Epoch 1450, Loss: 0.8241974031036152
Epoch 1500, Loss: 0.8429913980936934
Epoch 1550, Loss: 0.7608312029096841
Epoch 1600, Loss: 0.999029986359522
Epoch 1650, Loss: 0.6709103736497889
Epoch 1700, Loss: 0.6725145719243897
Epoch 1750, Loss: 1.094166733282282
Epoch 1800, Loss: 0.9015961326536427
Epoch 1850, Loss: 0.8287180435476589
Epoch 1900, Loss: 0.8664551344657309
Epoch 1950, Loss: 0.7410652268154663
Epoch 2000, Loss: 0.7472190819359915
Epoch 2050, Loss: 0.763137633530914
Epoch 2100, Loss: 0.766370290133224
Epoch 2150, Loss: 0.6329082722139718
Epoch 2200, Loss: 0.9212559915567529
Epoch 2250, Loss: 0.9032958929656688
Epoch 2300, Loss: 0.6556003595821625
Epoch 2350, Loss: 0.7186975019526717
Epoch 2400, Loss: 0.7935775098908198
Epoch 2450, Loss: 0.653392089595297
Epoch 2500, Loss: 0.7064569768608471
Epoch 2550, Loss: 0.6414908335264486
Epoch 2600, Loss: 0.5826002515350979
Epoch 2650, Loss: 0.5218945288169164
Epoch 2700, Loss: 0.6656348922204092
Epoch 2750, Loss: 0.559702905609589
Epoch 2800, Loss: 0.6190886133319321
Epoch 2850, Loss: 0.5997538845209812
Epoch 2900, Loss: 0.4216507562936598
Epoch 2950, Loss: 0.5335883537272144
Epoch 3000, Loss: 0.5565817462225856
Epoch 3050, Loss: 0.5873404279959642
Epoch 3100, Loss: 0.6032322420092127
Epoch 3150, Loss: 0.5299200779799823
```

```
Epoch 3200, Loss: 0.48071366620379935
Epoch 3250, Loss: 0.4489560136360263
Epoch 3300, Loss: 0.3584861136328275
Epoch 3350, Loss: 0.4677984783212598
Epoch 3400, Loss: 0.44823795217289075
Epoch 3450, Loss: 0.5932126111662598
Epoch 3500, Loss: 0.5840013244865774
Epoch 3550, Loss: 0.56544270265043
Epoch 3600, Loss: 0.5950980124272987
Epoch 3650, Loss: 0.5200106102927347
Epoch 3700, Loss: 0.5219395949210167
Epoch 3750, Loss: 0.5252188182049666
Epoch 3800, Loss: 0.5850602447348404
Epoch 3850, Loss: 0.4428332370284877
Epoch 3900, Loss: 0.5805279440792067
Epoch 3950, Loss: 0.48012337986369125
Epoch 4000, Loss: 0.4100631606447447
Epoch 4050, Loss: 0.638100669210249
Epoch 4100, Loss: 0.6898602968929103
Epoch 4150, Loss: 0.4754684154346107
Epoch 4200, Loss: 0.47289973616865993
Epoch 4250, Loss: 0.5700894956772417
Epoch 4300, Loss: 0.39927001260809186
Epoch 4350, Loss: 0.5976208020800401
Epoch 4400, Loss: 0.42887187450661474
Epoch 4450, Loss: 0.606496850422173
Epoch 4500, Loss: 0.5127157373456118
Epoch 4550, Loss: 0.41491477874803484
Epoch 4600, Loss: 0.4163709928206956
Epoch 4650, Loss: 0.4741251914256712
Epoch 4700, Loss: 0.4670888296844052
Epoch 4750, Loss: 0.6158361376632739
Epoch 4800, Loss: 0.6630637868434774
Epoch 4850, Loss: 0.6606096189593859
Epoch 4900, Loss: 0.42641965256701225
Epoch 4950, Loss: 0.39213583473553565
Epoch 5000, Loss: 0.515949133024939
Epoch 5050, Loss: 0.44637513942203794
Epoch 5100, Loss: 0.4394273580535779
Epoch 5150, Loss: 0.5335324853820245
Epoch 5200, Loss: 0.6080479489864604
Epoch 5250, Loss: 0.5099699988413348
Epoch 5300, Loss: 0.3667156250198178
Epoch 5350, Loss: 0.535185063282587
Epoch 5400, Loss: 0.4405727776756545
Epoch 5450, Loss: 0.5219060882242901
Epoch 5500, Loss: 0.3875312324210416
Epoch 5550, Loss: 0.5723618083479586
Epoch 5600, Loss: 0.5598654093486879
Epoch 5650, Loss: 0.5124077269463909
Epoch 5700, Loss: 0.37276840275068074
Epoch 5750, Loss: 0.386312297746259
Epoch 5800, Loss: 0.49963915226055333
Epoch 5850, Loss: 0.5169019921427976
Epoch 5900, Loss: 0.42230720222424906
Epoch 5950, Loss: 0.6176865911302823
Epoch 6000, Loss: 0.3377683921402352
Epoch 6050, Loss: 0.43905680639193906
Epoch 6100, Loss: 0.36542441110023133
Epoch 6150, Loss: 0.5072774314763273
Epoch 6200, Loss: 0.40165289047004166
Epoch 6250, Loss: 0.49010112167454234
Epoch 6300, Loss: 0.4116099390642792
Epoch 6350, Loss: 0.4499063901265462
```

```
Epoch 6400, Loss: 0.46038935314496404
Epoch 6450, Loss: 0.5426381270806958
Epoch 6500, Loss: 0.4898302951565619
Epoch 6550, Loss: 0.4480566071157338
Epoch 6600, Loss: 0.6506580192838228
Epoch 6650, Loss: 0.3833943995606211
Epoch 6700, Loss: 0.39402370620901017
Epoch 6750, Loss: 0.38275485729303216
Epoch 6800, Loss: 0.4222263282256666
Epoch 6850, Loss: 0.4329814061361259
Epoch 6900, Loss: 0.38504363072103454
Epoch 6950, Loss: 0.5131760919872455
Epoch 7000, Loss: 0.5612334242010253
Epoch 7050, Loss: 0.42297839307836893
Epoch 7100, Loss: 0.3233438333669525
Epoch 7150, Loss: 0.34574543090105764
Epoch 7200, Loss: 0.4727233035936726
Epoch 7250, Loss: 0.3684462788829951
Epoch 7300, Loss: 0.4595287487515989
Epoch 7350, Loss: 0.46636448363041233
Epoch 7400, Loss: 0.48259139592374106
Epoch 7450, Loss: 0.3693356578243677
Epoch 7500, Loss: 0.36557996374445834
Epoch 7550, Loss: 0.4104771518697132
Epoch 7600, Loss: 0.331020783359857
Epoch 7650, Loss: 0.30493296366791645
Epoch 7700, Loss: 0.5285317487930733
Epoch 7750, Loss: 0.4471027643869323
Epoch 7800, Loss: 0.2703764439865066
Epoch 7850, Loss: 0.4446182523588935
Epoch 7900, Loss: 0.5067190174478223
Epoch 7950, Loss: 0.40228964067585093
Epoch 8000, Loss: 0.3109127254855599
Epoch 8050, Loss: 0.44914146727567683
Epoch 8100, Loss: 0.330286536749271
Epoch 8150, Loss: 0.3635989580305315
Epoch 8200, Loss: 0.23550680603236607
Epoch 8250, Loss: 0.4167145416159614
Epoch 8300, Loss: 0.4351214870671628
Epoch 8350, Loss: 0.419573295666778
Epoch 8400, Loss: 0.32999721016612754
Epoch 8450, Loss: 0.47609718444728905
Epoch 8500, Loss: 0.44890124003713266
Epoch 8550, Loss: 0.3054168904486812
Epoch 8600, Loss: 0.40526270220601274
Epoch 8650, Loss: 0.3393467135319819
Epoch 8700, Loss: 0.478602007467762
Epoch 8750, Loss: 0.42554124887218864
Epoch 8800, Loss: 0.39826230981151345
Epoch 8850, Loss: 0.33644900874609535
Epoch 8900, Loss: 0.3814256870414138
Epoch 8950, Loss: 0.41545834679511645
Epoch 9000, Loss: 0.40617714063008237
Epoch 9050, Loss: 0.3591256638275962
Epoch 9100, Loss: 0.30654872838685276
Epoch 9150, Loss: 0.38844388914259737
Epoch 9200, Loss: 0.35984332254987483
Epoch 9250, Loss: 0.34048295905840037
Epoch 9300, Loss: 0.3823022297627551
Epoch 9350, Loss: 0.328572333772837
Epoch 9400, Loss: 0.3787812501435328
Epoch 9450, Loss: 0.3358259353253906
Epoch 9500, Loss: 0.3139783866664512
Epoch 9550, Loss: 0.3343590504481485
```

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Epoch 9600, Loss: 0.35107587626685266
Epoch 9650, Loss: 0.36605916378420905
Epoch 9700, Loss: 0.4809464820477416
Epoch 9750, Loss: 0.35850537695586016
Epoch 9800, Loss: 0.3456792606760493
Epoch 9850, Loss: 0.34970355565054684
Epoch 9900, Loss: 0.3079591836148465
Epoch 9950, Loss: 0.4083611285851165
```

In [45]:

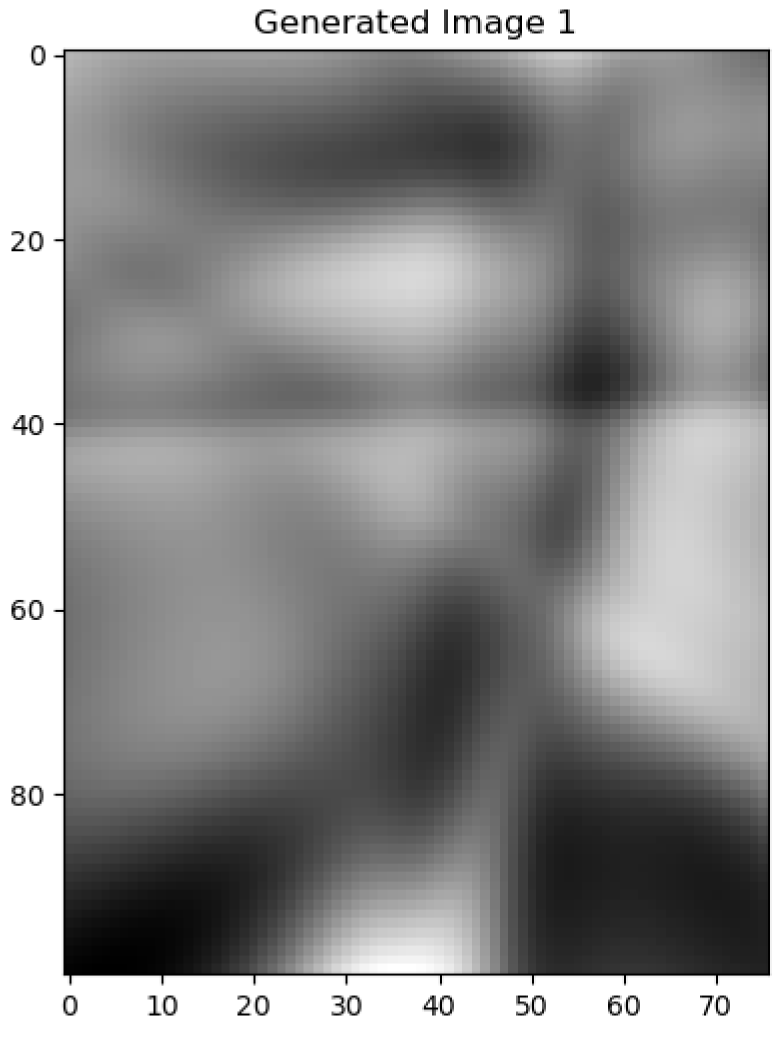
```python
# Generate predictions for the first dataset
Y1_pred_normalized = predict_neural_network(X1_normalized, parameters_image1

min_Y1 = np.min(Y1)
max_Y1 = np.max(Y1)

# Denormalize the predictions
Y1_pred = Y1_pred_normalized * (max_Y1 - min_Y1) + min_Y1

# Reshape the predictions to match the image dimensions
Y1_pred_reshaped = Y1_pred.reshape((dim_y1_x, dim_y1_y))

# Visualize the generated image from predictions
plt.figure(figsize=(8, 6))
plt.imshow(Y1_pred_reshaped, cmap='gray')
plt.title('Generated Image 1')
plt.axis()
plt.show()
```



Size of Hidden Layers

In [55]:
```
# Lower Size of Hidden Layers
layers_image1 = [2, 100, 150, 1]
learning_rate = 1E-2
epochs = 25000
batch_size = 100

# Train the neural network
parameters_image1 = train_neural_network(X1_normalized, Y1_normalized, layer
```

```
Epoch 0, Loss: 1.0071054835397502
Epoch 50, Loss: 0.8150249933218038
Epoch 100, Loss: 1.004926712635904
Epoch 150, Loss: 1.0778534780238416
Epoch 200, Loss: 0.9325769013774058
Epoch 250, Loss: 0.9977133318934235
Epoch 300, Loss: 0.7976360533077748
Epoch 350, Loss: 1.0088038127070533
Epoch 400, Loss: 1.0449111375268183
Epoch 450, Loss: 0.7734595765291682
Epoch 500, Loss: 0.8352134286939388
Epoch 550, Loss: 1.0189372248478998
Epoch 600, Loss: 0.7942453824435379
Epoch 650, Loss: 1.0391422389426332
Epoch 700, Loss: 0.7473273054628968
Epoch 750, Loss: 0.8227184929740875
Epoch 800, Loss: 0.7605686970008085
Epoch 850, Loss: 0.8438486441938429
Epoch 900, Loss: 0.5416235289637942
Epoch 950, Loss: 0.4931804122161626
Epoch 1000, Loss: 0.6495966387839617
Epoch 1050, Loss: 0.64023356501951
Epoch 1100, Loss: 0.5986116444538191
Epoch 1150, Loss: 0.7124712408241249
Epoch 1200, Loss: 0.5551671277533344
Epoch 1250, Loss: 0.7405499439222123
Epoch 1300, Loss: 0.7008122728397969
Epoch 1350, Loss: 0.523043879363716
Epoch 1400, Loss: 0.5877941790455852
Epoch 1450, Loss: 0.7536312879164556
Epoch 1500, Loss: 0.47209841914468226
Epoch 1550, Loss: 0.45589054611579477
Epoch 1600, Loss: 0.5759257101941548
Epoch 1650, Loss: 0.604105202419002
Epoch 1700, Loss: 0.4996346999015685
Epoch 1750, Loss: 0.4918324819721209
Epoch 1800, Loss: 0.6700719132314623
Epoch 1850, Loss: 0.7206834639559295
Epoch 1900, Loss: 0.5028349613503837
Epoch 1950, Loss: 0.5399976949724361
Epoch 2000, Loss: 0.44140151470234457
Epoch 2050, Loss: 0.5495782189253177
Epoch 2100, Loss: 0.49493280342453905
Epoch 2150, Loss: 0.34499787616954797
Epoch 2200, Loss: 0.42171508494926363
Epoch 2250, Loss: 0.44494700138103627
Epoch 2300, Loss: 0.29167030948686523
Epoch 2350, Loss: 0.7561052582864325
Epoch 2400, Loss: 0.39120248663730195
Epoch 2450, Loss: 0.30976713741690864
Epoch 2500, Loss: 0.5920973953696439
Epoch 2550, Loss: 0.5967797048203239
Epoch 2600, Loss: 0.5107537572014161
Epoch 2650, Loss: 0.2949188600021353
Epoch 2700, Loss: 0.5861494057301274
Epoch 2750, Loss: 0.34461737862995956
Epoch 2800, Loss: 0.3438365649784692
Epoch 2850, Loss: 0.29911769716712217
Epoch 2900, Loss: 0.34326417436634743
Epoch 2950, Loss: 0.3915542689844385
Epoch 3000, Loss: 0.4361241643298996
Epoch 3050, Loss: 0.48515224140851065
Epoch 3100, Loss: 0.5900834974715898
Epoch 3150, Loss: 0.4038860373874996
```

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Epoch 3200, Loss: 0.4312183169218163
Epoch 3250, Loss: 0.47263019855487426
Epoch 3300, Loss: 0.35704895228940614
Epoch 3350, Loss: 0.2981681547480811
Epoch 3400, Loss: 0.43508448205135003
Epoch 3450, Loss: 0.4588719961654108
Epoch 3500, Loss: 0.4350929993998181
Epoch 3550, Loss: 0.393157516935381
Epoch 3600, Loss: 0.4621829836458327
Epoch 3650, Loss: 0.47244086668457747
Epoch 3700, Loss: 0.37744951980498975
Epoch 3750, Loss: 0.35089445272437386
Epoch 3800, Loss: 0.5829503154559741
Epoch 3850, Loss: 0.3306413063125255
Epoch 3900, Loss: 0.3835704534539414
Epoch 3950, Loss: 0.4534400891265541
Epoch 4000, Loss: 0.42403435609498197
Epoch 4050, Loss: 0.3468269782705286
Epoch 4100, Loss: 0.3512677138063674
Epoch 4150, Loss: 0.39018755047616965
Epoch 4200, Loss: 0.503228745413285
Epoch 4250, Loss: 0.3725228532506643
Epoch 4300, Loss: 0.4826340028438747
Epoch 4350, Loss: 0.3226255349271371
Epoch 4400, Loss: 0.35223648503015587
Epoch 4450, Loss: 0.4766623240709805
Epoch 4500, Loss: 0.41650949989714703
Epoch 4550, Loss: 0.3035264122603119
Epoch 4600, Loss: 0.34924693513131133
Epoch 4650, Loss: 0.27090174991258364
Epoch 4700, Loss: 0.21512466205506742
Epoch 4750, Loss: 0.3540265198439985
Epoch 4800, Loss: 0.24931726802934326
Epoch 4850, Loss: 0.3103475698710772
Epoch 4900, Loss: 0.3195440659591269
Epoch 4950, Loss: 0.31168814155796193
Epoch 5000, Loss: 0.39386657341028036
Epoch 5050, Loss: 0.3778714597655972
Epoch 5100, Loss: 0.21287770151864874
Epoch 5150, Loss: 0.3057937661030133
Epoch 5200, Loss: 0.34626738630470166
Epoch 5250, Loss: 0.30802020851617873
Epoch 5300, Loss: 0.29873073682928075
Epoch 5350, Loss: 0.2988808677151279
Epoch 5400, Loss: 0.3735343388371018
Epoch 5450, Loss: 0.20690743805040207
Epoch 5500, Loss: 0.33600121688486395
Epoch 5550, Loss: 0.2631974555085408
Epoch 5600, Loss: 0.23553437092887397
Epoch 5650, Loss: 0.2539479032686425
Epoch 5700, Loss: 0.3020960995085728
Epoch 5750, Loss: 0.2683652767463025
Epoch 5800, Loss: 0.23248468559813204
Epoch 5850, Loss: 0.30817968583839855
Epoch 5900, Loss: 0.22763659968337255
Epoch 5950, Loss: 0.29270583826465973
Epoch 6000, Loss: 0.22898497941985668
Epoch 6050, Loss: 0.2118175023949001
Epoch 6100, Loss: 0.2936315187792566
Epoch 6150, Loss: 0.20040177867618109
Epoch 6200, Loss: 0.44133232722107474
Epoch 6250, Loss: 0.23326687218000342
Epoch 6300, Loss: 0.33720271706947785
Epoch 6350, Loss: 0.2886030850871091
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Epoch 6400, Loss: 0.3402515121297843
Epoch 6450, Loss: 0.25216272687467195
Epoch 6500, Loss: 0.26288944375009526
Epoch 6550, Loss: 0.1987577605826657
Epoch 6600, Loss: 0.2918914437524796
Epoch 6650, Loss: 0.25750593621934015
Epoch 6700, Loss: 0.2470231596033279
Epoch 6750, Loss: 0.3639954109896661
Epoch 6800, Loss: 0.32872939879339813
Epoch 6850, Loss: 0.35032954589333193
Epoch 6900, Loss: 0.2549620589978968
Epoch 6950, Loss: 0.207216121926627 5
Epoch 7000, Loss: 0.32843730607433264
Epoch 7050, Loss: 0.20432995203080956
Epoch 7100, Loss: 0.21395910518369798
Epoch 7150, Loss: 0.2224725898681611
Epoch 7200, Loss: 0.2542508477894944
Epoch 7250, Loss: 0.2518396589163181
Epoch 7300, Loss: 0.22813272567658205
Epoch 7350, Loss: 0.2719132313215154
Epoch 7400, Loss: 0.21199755835728898
Epoch 7450, Loss: 0.34091393997057956
Epoch 7500, Loss: 0.23574266783805695
Epoch 7550, Loss: 0.2556408834437995
Epoch 7600, Loss: 0.20763910068428632
Epoch 7650, Loss: 0.2880039268290326
Epoch 7700, Loss: 0.1292716154631506
Epoch 7750, Loss: 0.1426590585355428
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Epoch 7850, Loss: 0.293503002660611
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Epoch 8350, Loss: 0.1596364816468663
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Epoch 8500, Loss: 0.19838589522321107
Epoch 8550, Loss: 0.191777979141034
Epoch 8600, Loss: 0.16510305855141003
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Epoch 8850, Loss: 0.25228526463282985
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Epoch 9100, Loss: 0.1913170325151119
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Epoch 9500, Loss: 0.17590637767037187
Epoch 9550, Loss: 0.1214867008725969
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Epoch 9600, Loss: 0.18883071619629288
Epoch 9650, Loss: 0.10264371988670916
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Epoch 9750, Loss: 0.16221606448232126
Epoch 9800, Loss: 0.14607810428723972
Epoch 9850, Loss: 0.17556256303291362
Epoch 9900, Loss: 0.1363862656880217
Epoch 9950, Loss: 0.11681549572374006
Epoch 10000, Loss: 0.14142303159380604
Epoch 10050, Loss: 0.2444288989366469
Epoch 10100, Loss: 0.15574536935172767
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Epoch 10200, Loss: 0.14261832661752846
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Epoch 10350, Loss: 0.13900136849761804
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Epoch 10650, Loss: 0.07568823966605713
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Epoch 11050, Loss: 0.0979892848279567
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Epoch 11250, Loss: 0.18566173263136354
Epoch 11300, Loss: 0.1270690522305642
Epoch 11350, Loss: 0.1746455693252995
Epoch 11400, Loss: 0.12466177722841242
Epoch 11450, Loss: 0.11433674784545479
Epoch 11500, Loss: 0.11805327035080979
Epoch 11550, Loss: 0.08422250258624821
Epoch 11600, Loss: 0.10656712260456862
Epoch 11650, Loss: 0.07982841141415369
Epoch 11700, Loss: 0.11610050774324565
Epoch 11750, Loss: 0.13996963816092037
Epoch 11800, Loss: 0.10820636272368662
Epoch 11850, Loss: 0.11459535982460292
Epoch 11900, Loss: 0.10207259820374316
Epoch 11950, Loss: 0.09211862051561524
Epoch 12000, Loss: 0.07839203495505877
Epoch 12050, Loss: 0.13958779820671915
Epoch 12100, Loss: 0.1727566958305049
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Epoch 12200, Loss: 0.12381510298402221
Epoch 12250, Loss: 0.06725471981154492
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Epoch 12350, Loss: 0.05844325784291189
Epoch 12400, Loss: 0.07787214085737633
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Epoch 12550, Loss: 0.10916293956425997
Epoch 12600, Loss: 0.11276018959997453
Epoch 12650, Loss: 0.08921423312625508
Epoch 12700, Loss: 0.08242416689831478
Epoch 12750, Loss: 0.08363562911530886
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Epoch 12800, Loss: 0.08950752498923248
Epoch 12850, Loss: 0.11326625713856185
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Epoch 13000, Loss: 0.08099729679613246
Epoch 13050, Loss: 0.11066048549695605
Epoch 13100, Loss: 0.09967422321555464
Epoch 13150, Loss: 0.11155768728596918
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Epoch 13250, Loss: 0.1314897516906726
Epoch 13300, Loss: 0.10282309151856431
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Epoch 13400, Loss: 0.10203975055382525
Epoch 13450, Loss: 0.07965625064442522
Epoch 13500, Loss: 0.11584063576202991
Epoch 13550, Loss: 0.08236751636726453
Epoch 13600, Loss: 0.09998187165762248
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Epoch 14500, Loss: 0.08263145415253913
Epoch 14550, Loss: 0.07390679760942477
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Epoch 14650, Loss: 0.0937967787836749
Epoch 14700, Loss: 0.09396713070722676
Epoch 14750, Loss: 0.08764472619347233
Epoch 14800, Loss: 0.10736542281644479
Epoch 14850, Loss: 0.12631983140456243
Epoch 14900, Loss: 0.09354636610880358
Epoch 14950, Loss: 0.12273808275289147
Epoch 15000, Loss: 0.10367985779854105
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Epoch 15100, Loss: 0.11472900075559814
Epoch 15150, Loss: 0.06667204252638385
Epoch 15200, Loss: 0.13400495082247355
Epoch 15250, Loss: 0.11399021137649827
Epoch 15300, Loss: 0.08644302627527141
Epoch 15350, Loss: 0.08215289711955423
Epoch 15400, Loss: 0.08473923638025381
Epoch 15450, Loss: 0.053332141307147196
Epoch 15500, Loss: 0.10791875260514593
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Epoch 15650, Loss: 0.13516887149724907
Epoch 15700, Loss: 0.05623303329131185
Epoch 15750, Loss: 0.07938392632198443
Epoch 15800, Loss: 0.07168052230335877
Epoch 15850, Loss: 0.0681692633871957
Epoch 15900, Loss: 0.07331915702941008
Epoch 15950, Loss: 0.0750181987813334
```

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Epoch 16000, Loss: 0.09130786214728763
Epoch 16050, Loss: 0.08156927448946892
Epoch 16100, Loss: 0.07203184161893333
Epoch 16150, Loss: 0.11773599358343341
Epoch 16200, Loss: 0.06988812580245274
Epoch 16250, Loss: 0.06057988376422873
Epoch 16300, Loss: 0.11863028713355829
Epoch 16350, Loss: 0.06514895744926824
Epoch 16400, Loss: 0.054851459803356
Epoch 16450, Loss: 0.052291915090299616
Epoch 16500, Loss: 0.07116963445178645
Epoch 16550, Loss: 0.07901672977645834
Epoch 16600, Loss: 0.07001099562084521
Epoch 16650, Loss: 0.10905255757355867
Epoch 16700, Loss: 0.11598352430412101
Epoch 16750, Loss: 0.10507705672082303
Epoch 16800, Loss: 0.06660932677845494
Epoch 16850, Loss: 0.12393984133490134
Epoch 16900, Loss: 0.09618560384502726
Epoch 16950, Loss: 0.07145873142218626
Epoch 17000, Loss: 0.0856686983805013
Epoch 17050, Loss: 0.10214110478969061
Epoch 17100, Loss: 0.0632003134187247
Epoch 17150, Loss: 0.07400394544379683
Epoch 17200, Loss: 0.09763746314399514
Epoch 17250, Loss: 0.059562223405824025
Epoch 17300, Loss: 0.05606878076187778
Epoch 17350, Loss: 0.06328252053105925
Epoch 17400, Loss: 0.09424836732993956
Epoch 17450, Loss: 0.13735215008762006
Epoch 17500, Loss: 0.09308211583690772
Epoch 17550, Loss: 0.0748752526170431
Epoch 17600, Loss: 0.05761443171685242
Epoch 17650, Loss: 0.07082611822498831
Epoch 17700, Loss: 0.07509047248095342
Epoch 17750, Loss: 0.0662081369631461
Epoch 17800, Loss: 0.04579204079922571
Epoch 17850, Loss: 0.057298702335360475
Epoch 17900, Loss: 0.05557076306703305
Epoch 17950, Loss: 0.0403617652943688
Epoch 18000, Loss: 0.06704973483943977
Epoch 18050, Loss: 0.060227889952171265
Epoch 18100, Loss: 0.09444652110425117
Epoch 18150, Loss: 0.0695750597510081
Epoch 18200, Loss: 0.09843258180391391
Epoch 18250, Loss: 0.05017087695229727
Epoch 18300, Loss: 0.047930948100596955
Epoch 18350, Loss: 0.13727663939223914
Epoch 18400, Loss: 0.07509658648770716
Epoch 18450, Loss: 0.06564243705268216
Epoch 18500, Loss: 0.04866420479215645
Epoch 18550, Loss: 0.06334903110080756
Epoch 18600, Loss: 0.04586845132316489
Epoch 18650, Loss: 0.061714282590902704
Epoch 18700, Loss: 0.08680221590726926
Epoch 18750, Loss: 0.08164790121354061
Epoch 18800, Loss: 0.10077100758174591
Epoch 18850, Loss: 0.1080308845072271
Epoch 18900, Loss: 0.0666028766818421
Epoch 18950, Loss: 0.05179973964163616
Epoch 19000, Loss: 0.07282782332252899
Epoch 19050, Loss: 0.0657417931989019
Epoch 19100, Loss: 0.05376851690893004
Epoch 19150, Loss: 0.11400742813985353
```

```
Epoch 19200, Loss: 0.06257767293182964
Epoch 19250, Loss: 0.052061046437283265
Epoch 19300, Loss: 0.06732565209662252
Epoch 19350, Loss: 0.14392295425729829
Epoch 19400, Loss: 0.08721303631402672
Epoch 19450, Loss: 0.07893634543543768
Epoch 19500, Loss: 0.06705859574797797
Epoch 19550, Loss: 0.04578881129448486
Epoch 19600, Loss: 0.03314902937561678
Epoch 19650, Loss: 0.0690568553703186
Epoch 19700, Loss: 0.06270489101900424
Epoch 19750, Loss: 0.047603615926387975
Epoch 19800, Loss: 0.052290196435091724
Epoch 19850, Loss: 0.06294924490914053
Epoch 19900, Loss: 0.09729790967646408
Epoch 19950, Loss: 0.09892210007849973
Epoch 20000, Loss: 0.04775349263644326
Epoch 20050, Loss: 0.05236296004635374
Epoch 20100, Loss: 0.061686981237987465
Epoch 20150, Loss: 0.040563132067672425
Epoch 20200, Loss: 0.08203439778439037
Epoch 20250, Loss: 0.07193513784912853
Epoch 20300, Loss: 0.060208351021672456
Epoch 20350, Loss: 0.08673190762097721
Epoch 20400, Loss: 0.05338946505560987
Epoch 20450, Loss: 0.05957056651688333
Epoch 20500, Loss: 0.05221962961186702
Epoch 20550, Loss: 0.07800943124369528
Epoch 20600, Loss: 0.06658214761624716
Epoch 20650, Loss: 0.04338871369220503
Epoch 20700, Loss: 0.0652906304840134
Epoch 20750, Loss: 0.08619266805367326
Epoch 20800, Loss: 0.06159538936279845
Epoch 20850, Loss: 0.0747838004309571
Epoch 20900, Loss: 0.0629800276794778
Epoch 20950, Loss: 0.06304614714327103
Epoch 21000, Loss: 0.0338830282068482
Epoch 21050, Loss: 0.0659285411000353
Epoch 21100, Loss: 0.0624317659167517
Epoch 21150, Loss: 0.10449704197402034
Epoch 21200, Loss: 0.0798287579804619
Epoch 21250, Loss: 0.030660272505015018
Epoch 21300, Loss: 0.09889537151823824
Epoch 21350, Loss: 0.05658179901162815
Epoch 21400, Loss: 0.09625097355469421
Epoch 21450, Loss: 0.08690823067887601
Epoch 21500, Loss: 0.07429641538179423
Epoch 21550, Loss: 0.06698895521843608
Epoch 21600, Loss: 0.1162612136279723
Epoch 21650, Loss: 0.047772699700228884
Epoch 21700, Loss: 0.04648289542141733
Epoch 21750, Loss: 0.05100574768083236
Epoch 21800, Loss: 0.03557028195786973
Epoch 21850, Loss: 0.038764109754455475
Epoch 21900, Loss: 0.06218483495695443
Epoch 21950, Loss: 0.08418772035350004
Epoch 22000, Loss: 0.0650572686990193
Epoch 22050, Loss: 0.05459095179813622
Epoch 22100, Loss: 0.09885729851468573
Epoch 22150, Loss: 0.07776884028143645
Epoch 22200, Loss: 0.04140524915049518
Epoch 22250, Loss: 0.055937588395531215
Epoch 22300, Loss: 0.07812688442266927
Epoch 22350, Loss: 0.04504325937379052
```

```
Epoch 22400, Loss: 0.07088139136441085
Epoch 22450, Loss: 0.058437462414732855
Epoch 22500, Loss: 0.05524657658226007
Epoch 22550, Loss: 0.07487777967158789
Epoch 22600, Loss: 0.06439800031209653
Epoch 22650, Loss: 0.12173404549922077
Epoch 22700, Loss: 0.04431568360274725
Epoch 22750, Loss: 0.050845789706851434
Epoch 22800, Loss: 0.06303348780263966
Epoch 22850, Loss: 0.04317161259659159
Epoch 22900, Loss: 0.07527669308553961
Epoch 22950, Loss: 0.10200032283281814
Epoch 23000, Loss: 0.06915582131446774
Epoch 23050, Loss: 0.07066198611674485
Epoch 23100, Loss: 0.03898341898120349
Epoch 23150, Loss: 0.08631153021903304
Epoch 23200, Loss: 0.05137627424324962
Epoch 23250, Loss: 0.056634402645606416
Epoch 23300, Loss: 0.0610433640666129
Epoch 23350, Loss: 0.04238481985824242
Epoch 23400, Loss: 0.05305765869786633
Epoch 23450, Loss: 0.03883866745310778
Epoch 23500, Loss: 0.06530035842996895
Epoch 23550, Loss: 0.0856952124222632
Epoch 23600, Loss: 0.08486405361985516
Epoch 23650, Loss: 0.05776336258306095
Epoch 23700, Loss: 0.04858300003838404
Epoch 23750, Loss: 0.08035560613033443
Epoch 23800, Loss: 0.11381876315403637
Epoch 23850, Loss: 0.061518257556548175
Epoch 23900, Loss: 0.045397560910702975
Epoch 23950, Loss: 0.05618715512186847
Epoch 24000, Loss: 0.041000713711715146
Epoch 24050, Loss: 0.08214918597094614
Epoch 24100, Loss: 0.10720235262059508
Epoch 24150, Loss: 0.0637847195035363
Epoch 24200, Loss: 0.04039050295623325
Epoch 24250, Loss: 0.07662194950177051
Epoch 24300, Loss: 0.061821643581184284
Epoch 24350, Loss: 0.07867952914814529
Epoch 24400, Loss: 0.0583922730409428
Epoch 24450, Loss: 0.05759980544085865
Epoch 24500, Loss: 0.06379104925552967
Epoch 24550, Loss: 0.08284123265787492
Epoch 24600, Loss: 0.060417688609766554
Epoch 24650, Loss: 0.05337830868271982
Epoch 24700, Loss: 0.05739687996080468
Epoch 24750, Loss: 0.058021036877339845
Epoch 24800, Loss: 0.05284859456071354
Epoch 24850, Loss: 0.05822270400190286
Epoch 24900, Loss: 0.03569510681049825
Epoch 24950, Loss: 0.0446670824572761
```

In [57]:

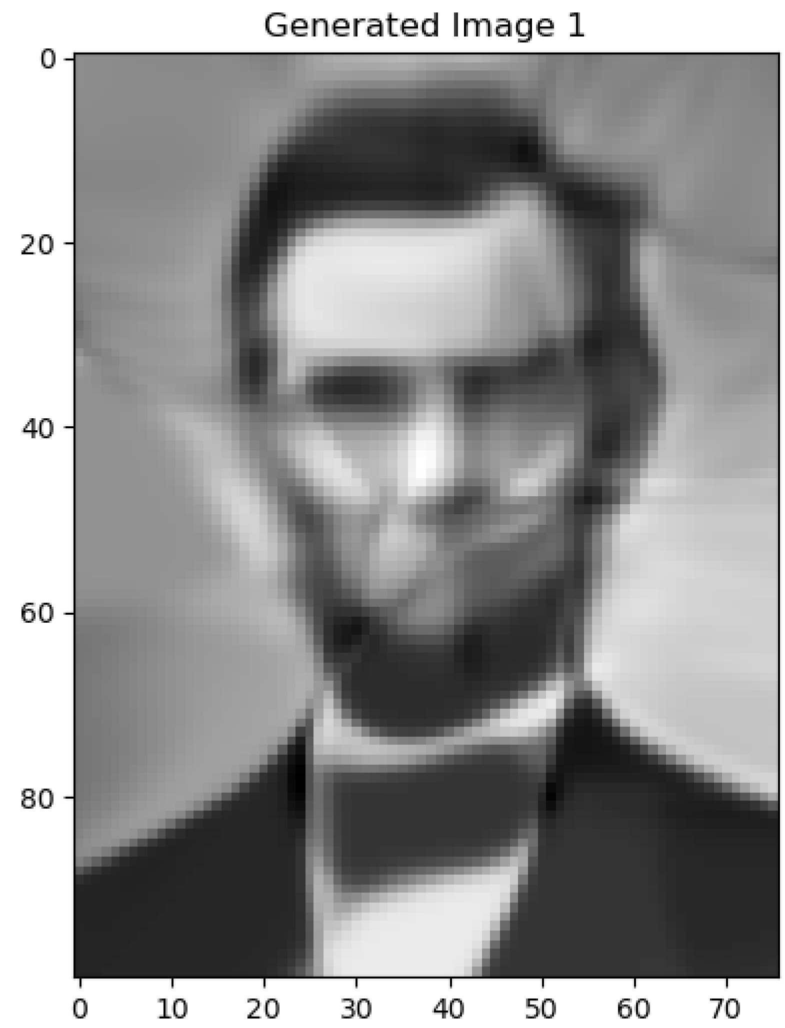
```
# Generate predictions for the first dataset
Y1_pred_normalized = predict_neural_network(X1_normalized, parameters_image1

min_Y1 = np.min(Y1)
max_Y1 = np.max(Y1)

# Denormalize the predictions
Y1_pred = Y1_pred_normalized * (max_Y1 - min_Y1) + min_Y1

# Reshape the predictions to match the image dimensions
Y1_pred_reshaped = Y1_pred.reshape((dim_y1_x, dim_y1_y))
```

```python
# Visualize the generated image from predictions
plt.figure(figsize=(8, 6))
plt.imshow(Y1_pred_reshaped, cmap='gray')
plt.title('Generated Image 1')
plt.axis()
plt.show()
```



In [58]:
```python
# Higher Size of Hidden Layers
layers_image1 = [2, 1000, 1000, 1]
learning_rate = 1E-2
epochs = 9000
batch_size = 100

# Train the neural network
parameters_image1 = train_neural_network(X1_normalized, Y1_normalized, laye
```

```
Epoch 0, Loss: 1.0053087849953393
Epoch 50, Loss: 0.8665330445707068
Epoch 100, Loss: 0.9467829510627399
Epoch 150, Loss: 0.8808036340787649
Epoch 200, Loss: 0.9351487926026762
Epoch 250, Loss: 1.025387002915079
Epoch 300, Loss: 0.936630955660974
Epoch 350, Loss: 1.020372388388965
Epoch 400, Loss: 1.080002117406507
Epoch 450, Loss: 0.9755646841341435
Epoch 500, Loss: 0.9014126417893071
Epoch 550, Loss: 0.9497781829722922
Epoch 600, Loss: 1.083387604781258
Epoch 650, Loss: 1.0980307492345296
Epoch 700, Loss: 1.1006009839181576
Epoch 750, Loss: 1.0881316091111268
Epoch 800, Loss: 1.0137588082900044
Epoch 850, Loss: 0.9463166244892298
Epoch 900, Loss: 1.0686900591794248
Epoch 950, Loss: 0.9003335258184392
Epoch 1000, Loss: 1.1725183609941048
Epoch 1050, Loss: 1.1573058491894919
Epoch 1100, Loss: 0.9510992588950897
Epoch 1150, Loss: 0.919975828654639
Epoch 1200, Loss: 0.9297747270778056
Epoch 1250, Loss: 0.9784758687921301
Epoch 1300, Loss: 1.0750797389721838
Epoch 1350, Loss: 1.0679221548589837
Epoch 1400, Loss: 1.0894149547113328
Epoch 1450, Loss: 1.050691504935824
Epoch 1500, Loss: 1.0795785402387539
Epoch 1550, Loss: 1.0259637658096157
Epoch 1600, Loss: 1.006808782996889
Epoch 1650, Loss: 1.0812559970411497
Epoch 1700, Loss: 0.9455725241608031
Epoch 1750, Loss: 0.9954693413512671
Epoch 1800, Loss: 0.8720919113340632
Epoch 1850, Loss: 1.0863647391262168
Epoch 1900, Loss: 0.899931109518375
Epoch 1950, Loss: 0.9423948753711049
Epoch 2000, Loss: 1.0156136487796208
Epoch 2050, Loss: 1.1252663159271707
Epoch 2100, Loss: 1.0899015362580406
Epoch 2150, Loss: 0.9695310274401708
Epoch 2200, Loss: 1.054002162821398
Epoch 2250, Loss: 1.0606233892009937
Epoch 2300, Loss: 1.0871912359074118
Epoch 2350, Loss: 1.0816698274838228
Epoch 2400, Loss: 1.0137522568220747
Epoch 2450, Loss: 1.034062464409252
Epoch 2500, Loss: 1.2461943570000662
Epoch 2550, Loss: 0.897400597926709
Epoch 2600, Loss: 0.9978605004953863
Epoch 2650, Loss: 1.0181631549283525
Epoch 2700, Loss: 0.9339871160536068
Epoch 2750, Loss: 1.1316653776512655
Epoch 2800, Loss: 0.8817732611973714
Epoch 2850, Loss: 1.0449467547148545
Epoch 2900, Loss: 0.9653060421568999
Epoch 2950, Loss: 0.9078452692358034
Epoch 3000, Loss: 1.0421676466613723
Epoch 3050, Loss: 0.897385787480477
Epoch 3100, Loss: 0.978341711249149
Epoch 3150, Loss: 1.040668823754242
```

```
Epoch 3200, Loss: 1.1278727745250452
Epoch 3250, Loss: 1.0098010202494143
Epoch 3300, Loss: 1.2473347619317945
Epoch 3350, Loss: 0.9612355203118397
Epoch 3400, Loss: 1.1467482069309116
Epoch 3450, Loss: 0.8956679382734972
Epoch 3500, Loss: 0.831964388114683
Epoch 3550, Loss: 0.8641687199036302
Epoch 3600, Loss: 0.9694832179439327
Epoch 3650, Loss: 1.0526320077219518
Epoch 3700, Loss: 1.0520254419856123
Epoch 3750, Loss: 1.1519487397407038
Epoch 3800, Loss: 0.9569067844277229
Epoch 3850, Loss: 0.9699411438605432
Epoch 3900, Loss: 1.1185465064942908
Epoch 3950, Loss: 1.0868758305886332
Epoch 4000, Loss: 0.9446686243747503
Epoch 4050, Loss: 0.9827531549536138
Epoch 4100, Loss: 0.9895128005875108
Epoch 4150, Loss: 0.8200897975855962
Epoch 4200, Loss: 0.9957741767820025
Epoch 4250, Loss: 1.0643264627541267
Epoch 4300, Loss: 1.0135416247418114
Epoch 4350, Loss: 0.9093775048927688
Epoch 4400, Loss: 1.0391401602180295
Epoch 4450, Loss: 0.9766930357252329
Epoch 4500, Loss: 0.9890220805816458
Epoch 4550, Loss: 0.8602912324260454
Epoch 4600, Loss: 0.9965168458727989
Epoch 4650, Loss: 0.9092793349177585
Epoch 4700, Loss: 0.8040932236264487
Epoch 4750, Loss: 0.8521391531470179
Epoch 4800, Loss: 0.7237924196954956
Epoch 4850, Loss: 0.9538028512755387
Epoch 4900, Loss: 0.7928626527501867
Epoch 4950, Loss: 0.6471528806546235
Epoch 5000, Loss: 0.9431025182102253
Epoch 5050, Loss: 0.7107162478049642
Epoch 5100, Loss: 0.7873783370748266
Epoch 5150, Loss: 0.677394078592225
Epoch 5200, Loss: 0.7564249765546829
Epoch 5250, Loss: 0.775272475042939
Epoch 5300, Loss: 0.723976526533962
Epoch 5350, Loss: 0.6739620219111149
Epoch 5400, Loss: 0.6994644354993562
Epoch 5450, Loss: 0.4737877264445995
Epoch 5500, Loss: 0.6025982562413538
Epoch 5550, Loss: 0.7157970621358869
Epoch 5600, Loss: 0.6466229004140216
Epoch 5650, Loss: 0.6607895455327889
Epoch 5700, Loss: 0.6003251925845919
Epoch 5750, Loss: 0.532618248180001
Epoch 5800, Loss: 0.526611486769541
Epoch 5850, Loss: 0.7407557866926322
Epoch 5900, Loss: 0.8589415712381191
Epoch 5950, Loss: 0.5767504584884654
Epoch 6000, Loss: 0.7259348136599327
Epoch 6050, Loss: 0.7257018375779769
Epoch 6100, Loss: 0.5768289617674293
Epoch 6150, Loss: 0.6501522352774394
Epoch 6200, Loss: 0.7127363614765198
Epoch 6250, Loss: 0.6204980535942678
Epoch 6300, Loss: 0.6906835192911674
Epoch 6350, Loss: 0.9149515376975883
```

```
Epoch 6400, Loss: 0.8181551415556184
Epoch 6450, Loss: 0.4998051747648215
Epoch 6500, Loss: 0.6724556841504707
Epoch 6550, Loss: 0.5241652129559505
Epoch 6600, Loss: 0.7154219722517642
Epoch 6650, Loss: 0.606447839036471
Epoch 6700, Loss: 0.42288811992146874
Epoch 6750, Loss: 0.654460068496792
Epoch 6800, Loss: 0.4319734846002743
Epoch 6850, Loss: 0.6899165354078933
Epoch 6900, Loss: 0.4434596698624213
Epoch 6950, Loss: 0.4108448500062822
Epoch 7000, Loss: 0.5965220521252109
Epoch 7050, Loss: 0.5685302496449443
Epoch 7100, Loss: 0.4270830007960464
```

```
/var/folders/t9/3_j1j0w50mv74c18b6096qsh0000gn/T/ipykernel_13245/354248453
0.py:11: RuntimeWarning: overflow encountered in exp
  output = 1 / (1 + np.exp(-x))
```

```
Epoch 7150, Loss: 0.48065463769225253
Epoch 7200, Loss: 0.32606075705406906
Epoch 7250, Loss: 0.49130355386149616
Epoch 7300, Loss: 0.6919231801223102
Epoch 7350, Loss: 0.4989388609424832
Epoch 7400, Loss: 0.5800194059627523
Epoch 7450, Loss: 0.33196538546100773
Epoch 7500, Loss: 0.41304025243390435
Epoch 7550, Loss: 0.5230438321710299
Epoch 7600, Loss: 0.5659095871083918
Epoch 7650, Loss: 0.5394072530136348
Epoch 7700, Loss: 0.37047631317429575
Epoch 7750, Loss: 0.410052234971672
Epoch 7800, Loss: 0.47801744764622506
Epoch 7850, Loss: 0.5769028697457089
Epoch 7900, Loss: 0.4998258208301843
Epoch 7950, Loss: 0.3803911340391912
Epoch 8000, Loss: 0.6911558018842032
Epoch 8050, Loss: 0.5372910308555151
Epoch 8100, Loss: 0.32948707071270833
Epoch 8150, Loss: 0.43294708137224197
Epoch 8200, Loss: 0.31511671105497724
Epoch 8250, Loss: 0.39597421458019477
Epoch 8300, Loss: 0.4172105167494495
Epoch 8350, Loss: 0.5320531649630758
Epoch 8400, Loss: 0.43954335193976996
Epoch 8450, Loss: 0.46111056706457193
Epoch 8500, Loss: 0.42962745249925793
Epoch 8550, Loss: 0.3546743456318355
Epoch 8600, Loss: 0.42977703386849114
Epoch 8650, Loss: 0.43834594107572256
Epoch 8700, Loss: 0.3535319378804894
Epoch 8750, Loss: 0.417419399741261
Epoch 8800, Loss: 0.5152946613692175
Epoch 8850, Loss: 0.3568594061186351
Epoch 8900, Loss: 0.399416805210761
Epoch 8950, Loss: 0.2883660677284986
```

In [62]:
```
# Generate predictions for the first dataset
Y1_pred_normalized = predict_neural_network(X1_normalized, parameters_image1

min_Y1 = np.min(Y1)
max_Y1 = np.max(Y1)

# Denormalize the predictions
Y1_pred = Y1_pred_normalized * (max_Y1 - min_Y1) + min_Y1
```

```
# Reshape the predictions to match the image dimensions
Y1_pred_reshaped = Y1_pred.reshape((dim_y1_x, dim_y1_y))

# Visualize the generated image from predictions
plt.figure(figsize=(8, 6))
plt.imshow(Y1_pred_reshaped, cmap='gray')
plt.title('Generated Image 1')
plt.axis()
plt.show()
```

```
/var/folders/t9/3_j1j0w50mv74c18b6096qsh0000gn/T/ipykernel_13245/354248453
0.py:11: RuntimeWarning: overflow encountered in exp
  output = 1 / (1 + np.exp(-x))
```

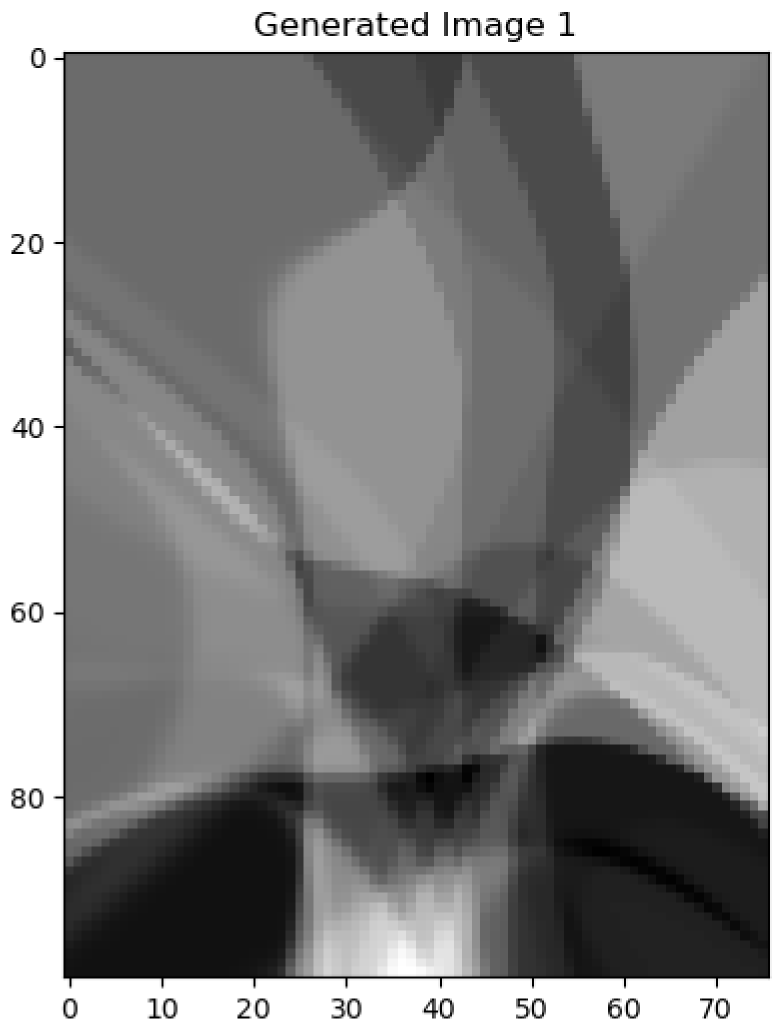


Image 2

In [63]:
```
X2 = data['X2']
Y2 = data['Y2']

# Inspect the maximum values of X2 to ensure we have the correct dimensions
max_x2 = np.max(X2[:, 0])  # Max value in the first column (x-coordinates)
max_y2 = np.max(X2[:, 1])  # Max value in the second column (y-coordinates)

# Correct the dimensions of the image array based on the max coordinates fro
image2_corrected = np.zeros((int(max_y2) + 1, int(max_x2) + 1, 3))

# Populate the image array with Y2 values at the coordinates specified by X2
for i in range(len(X2)):
    x_coord, y_coord = int(X2[i, 0]), int(X2[i, 1])
```

```
    image2_corrected[y_coord, x_coord, :] = Y2[i]

# Visualize the corrected second image
plt.imshow(image2_corrected.astype(np.uint8))
plt.title('Image from X2 and Y2 ')
plt.axis()
plt.show()
```

In [64]:
```
# Normalize the input data for better performance
X2_mean, X2_std = X2.mean(), X2.std()
Y2_mean, Y2_std = Y2.mean(), Y2.std()

X2_normalized = (X2 - X1_mean) / X2_std
Y2_normalized = (Y2 - Y1_mean) / Y2_std
```

Generated Image 2

Image 2 - Baseline

In [65]:
```
layers_image2 = [2, 350, 390, 3]
epochs = 10000
learning_rate = learning_rate = 1E-2
batch_size = 100

# Train the neural network
parameters_image2 = train_neural_network(X2_normalized, Y2_normalized, laye
```

```
Epoch 0, Loss: 1.0176108043128376
Epoch 50, Loss: 0.9427608429225521
Epoch 100, Loss: 1.041042158488625
Epoch 150, Loss: 1.047333243371814
Epoch 200, Loss: 0.9826212247401563
Epoch 250, Loss: 0.9685582985052086
Epoch 300, Loss: 0.8915741860102165
Epoch 350, Loss: 0.9765089185186205
Epoch 400, Loss: 0.9702991595271618
Epoch 450, Loss: 0.9639798033313868
Epoch 500, Loss: 1.0793377724742144
Epoch 550, Loss: 1.067436544876927
Epoch 600, Loss: 1.0586323598086846
Epoch 650, Loss: 0.9556382467473299
Epoch 700, Loss: 0.9535355590504654
Epoch 750, Loss: 0.9966053208703473
Epoch 800, Loss: 1.04272936198416
Epoch 850, Loss: 1.0356608112725
Epoch 900, Loss: 1.0237957888014082
Epoch 950, Loss: 0.9690556185854482
Epoch 1000, Loss: 0.9856740133211808
Epoch 1050, Loss: 0.9878323754373703
Epoch 1100, Loss: 0.9953542829551899
Epoch 1150, Loss: 1.0421956296449817
Epoch 1200, Loss: 1.035328728096337
Epoch 1250, Loss: 1.0528848738889145
Epoch 1300, Loss: 1.0054919301233474
Epoch 1350, Loss: 0.8815893490624437
Epoch 1400, Loss: 1.0638881173883294
Epoch 1450, Loss: 1.0241556771260583
Epoch 1500, Loss: 0.9432498710724463
Epoch 1550, Loss: 0.9640240757284095
Epoch 1600, Loss: 0.8970021519463713
Epoch 1650, Loss: 1.0581280670535516
Epoch 1700, Loss: 1.0233898130681276
Epoch 1750, Loss: 1.0047276105231
Epoch 1800, Loss: 0.945686818192911
Epoch 1850, Loss: 1.0081446649864896
Epoch 1900, Loss: 1.0191550304167352
Epoch 1950, Loss: 0.9584968181757099
Epoch 2000, Loss: 0.9990757872266885
Epoch 2050, Loss: 0.9911306975385382
Epoch 2100, Loss: 1.0684316822525248
Epoch 2150, Loss: 0.9844674273478901
Epoch 2200, Loss: 1.0124197741950536
Epoch 2250, Loss: 0.9913449453713385
Epoch 2300, Loss: 1.0789434399430078
Epoch 2350, Loss: 1.030282252962834
Epoch 2400, Loss: 0.9763111832307264
Epoch 2450, Loss: 0.916700982502416
Epoch 2500, Loss: 0.9422082381152244
Epoch 2550, Loss: 1.043110156974443
Epoch 2600, Loss: 1.0666464246655831
Epoch 2650, Loss: 0.9926709112447808
Epoch 2700, Loss: 0.9172768300589179
Epoch 2750, Loss: 1.0592701179305541
Epoch 2800, Loss: 0.9386798429113088
Epoch 2850, Loss: 1.1496867775284279
Epoch 2900, Loss: 0.9735230099209654
Epoch 2950, Loss: 1.0295367263502204
Epoch 3000, Loss: 1.0410614554308988
Epoch 3050, Loss: 1.029852380433185
Epoch 3100, Loss: 0.9825954877624774
Epoch 3150, Loss: 0.9849342121686101
```

```
Epoch 3200, Loss: 0.9917715606394002
Epoch 3250, Loss: 0.9308503053917544
Epoch 3300, Loss: 1.050780953072895
Epoch 3350, Loss: 0.8961759356568102
Epoch 3400, Loss: 0.44693429309421245
Epoch 3450, Loss: 0.4233155906446922
Epoch 3500, Loss: 0.2874438364400774
Epoch 3550, Loss: 0.19787658381107798
Epoch 3600, Loss: 0.26983754261905235
Epoch 3650, Loss: 0.21248282343894873
Epoch 3700, Loss: 0.15516783399973252
Epoch 3750, Loss: 0.1451065421361097
Epoch 3800, Loss: 0.19220003133086627
Epoch 3850, Loss: 0.28566869242508736
Epoch 3900, Loss: 0.21658435480536742
Epoch 3950, Loss: 0.19834002158138478
Epoch 4000, Loss: 0.18060144401012873
Epoch 4050, Loss: 0.15924557487797034
Epoch 4100, Loss: 0.15117988388974604
Epoch 4150, Loss: 0.1341160095460092
Epoch 4200, Loss: 0.18524427937707885
Epoch 4250, Loss: 0.1632097907664612
Epoch 4300, Loss: 0.1590497898834479
Epoch 4350, Loss: 0.1687127088887382
Epoch 4400, Loss: 0.2189607459648238
Epoch 4450, Loss: 0.1774036359470239
Epoch 4500, Loss: 0.07148818688499738
Epoch 4550, Loss: 0.1831700170435551
Epoch 4600, Loss: 0.10724887981155198
Epoch 4650, Loss: 0.15506611686389932
Epoch 4700, Loss: 0.14678633889138393
Epoch 4750, Loss: 0.18469549368157723
Epoch 4800, Loss: 0.13138605316938864
Epoch 4850, Loss: 0.13810177365361573
Epoch 4900, Loss: 0.1747056314818905
Epoch 4950, Loss: 0.1467226675215937
Epoch 5000, Loss: 0.1093383691171243
Epoch 5050, Loss: 0.11982246930621426
Epoch 5100, Loss: 0.2078199798816043
Epoch 5150, Loss: 0.11393154989400299
Epoch 5200, Loss: 0.20706071863284284
Epoch 5250, Loss: 0.09938338697816765
Epoch 5300, Loss: 0.11542421876338485
Epoch 5350, Loss: 0.14209164548702025
Epoch 5400, Loss: 0.11265897393827283
Epoch 5450, Loss: 0.1676547935953773
Epoch 5500, Loss: 0.1780318309342099
Epoch 5550, Loss: 0.17548408777016009
Epoch 5600, Loss: 0.22092878775952787
Epoch 5650, Loss: 0.17105052568326207
Epoch 5700, Loss: 0.20317433460228468
Epoch 5750, Loss: 0.12102836968803649
Epoch 5800, Loss: 0.10926360850607937
Epoch 5850, Loss: 0.11648744522086393
Epoch 5900, Loss: 0.10319687312208894
Epoch 5950, Loss: 0.10218513160370399
Epoch 6000, Loss: 0.10736545436176231
Epoch 6050, Loss: 0.11178301832654279
Epoch 6100, Loss: 0.11227078803269228
Epoch 6150, Loss: 0.11654201167298986
Epoch 6200, Loss: 0.18753540410525588
Epoch 6250, Loss: 0.1435645220197935
Epoch 6300, Loss: 0.09025220217053893
Epoch 6350, Loss: 0.13619854320867722
```

```
Epoch 6400, Loss: 0.14519884090968543
Epoch 6450, Loss: 0.20009039345370452
Epoch 6500, Loss: 0.1008435508786717
Epoch 6550, Loss: 0.22418951040377474
Epoch 6600, Loss: 0.16920667241151885
Epoch 6650, Loss: 0.1643417286708572
Epoch 6700, Loss: 0.1648810185815408
Epoch 6750, Loss: 0.1152073448844571
Epoch 6800, Loss: 0.17123282631929196
Epoch 6850, Loss: 0.15272695529420127
Epoch 6900, Loss: 0.13676373636228628
Epoch 6950, Loss: 0.12200092640395245
Epoch 7000, Loss: 0.11200220528610463
Epoch 7050, Loss: 0.13471075952998235
Epoch 7100, Loss: 0.13735546604268922
Epoch 7150, Loss: 0.1313238368267912
Epoch 7200, Loss: 0.13971834597796803
Epoch 7250, Loss: 0.11914866136233956
Epoch 7300, Loss: 0.13759383285229768
Epoch 7350, Loss: 0.11372545529600003
Epoch 7400, Loss: 0.12274322343481738
Epoch 7450, Loss: 0.08897281728973708
Epoch 7500, Loss: 0.22177407151559114
Epoch 7550, Loss: 0.2117093204539228
Epoch 7600, Loss: 0.16999894170173901
Epoch 7650, Loss: 0.21138053131947196
Epoch 7700, Loss: 0.10185810715853579
Epoch 7750, Loss: 0.11566301184371346
Epoch 7800, Loss: 0.11801319513481966
Epoch 7850, Loss: 0.12379973475980392
Epoch 7900, Loss: 0.15642351029757015
Epoch 7950, Loss: 0.19343623896730028
Epoch 8000, Loss: 0.1038503061954798
Epoch 8050, Loss: 0.18526910156953852
Epoch 8100, Loss: 0.14304171959549083
Epoch 8150, Loss: 0.14078694060054223
Epoch 8200, Loss: 0.13997478142170688
Epoch 8250, Loss: 0.16148061938243927
Epoch 8300, Loss: 0.15251341371061902
Epoch 8350, Loss: 0.11354777773747356
Epoch 8400, Loss: 0.18413995515885667
Epoch 8450, Loss: 0.16634117432186435
Epoch 8500, Loss: 0.12227877328608258
Epoch 8550, Loss: 0.08538894747590609
Epoch 8600, Loss: 0.11444048926677487
Epoch 8650, Loss: 0.11175471829687021
Epoch 8700, Loss: 0.14776864218173996
Epoch 8750, Loss: 0.22442218604396444
Epoch 8800, Loss: 0.13857977425076073
Epoch 8850, Loss: 0.15144273923345763
Epoch 8900, Loss: 0.1378939378578763
Epoch 8950, Loss: 0.1403509316185695
Epoch 9000, Loss: 0.11995679852367246
Epoch 9050, Loss: 0.1885123124293886
Epoch 9100, Loss: 0.16966630548994058
Epoch 9150, Loss: 0.13508341888318567
Epoch 9200, Loss: 0.17540468562093622
Epoch 9250, Loss: 0.15472745756242742
Epoch 9300, Loss: 0.20384354361093288
Epoch 9350, Loss: 0.1563996460954185
Epoch 9400, Loss: 0.14038163208417057
Epoch 9450, Loss: 0.1347342661043995
Epoch 9500, Loss: 0.13823384105651895
Epoch 9550, Loss: 0.14382697666829733
```

```
Epoch 9600, Loss: 0.14616762945046355
Epoch 9650, Loss: 0.24023069302089994
Epoch 9700, Loss: 0.11781004769585894
Epoch 9750, Loss: 0.20636204709100647
Epoch 9800, Loss: 0.12032428155721292
Epoch 9850, Loss: 0.19473024814618747
Epoch 9900, Loss: 0.13859703037364612
Epoch 9950, Loss: 0.09523455099818941
```

In [67]:

```
# Generate predictions
Y2_pred_normalized = predict_neural_network(X2_normalized, parameters_image2

min_Y2 = np.min(Y2)
max_Y2 = np.max(Y2)

# Denormalize the predictions
Y2_pred = Y2_pred_normalized * (max_Y2 - min_Y2) + min_Y2

# Reshape the predictions to match the image dimensions
Y2_pred_reshaped = Y2_pred.reshape((dim_y2_x, dim_y2_y, 3))

# Visualize the generated color image from predictions
plt.figure(figsize=(8, 6))
plt.imshow(np.clip(Y2_pred_reshaped, 0, 255).astype('uint8'))
plt.title('Generated Image 2')
plt.axis()
plt.show()
```

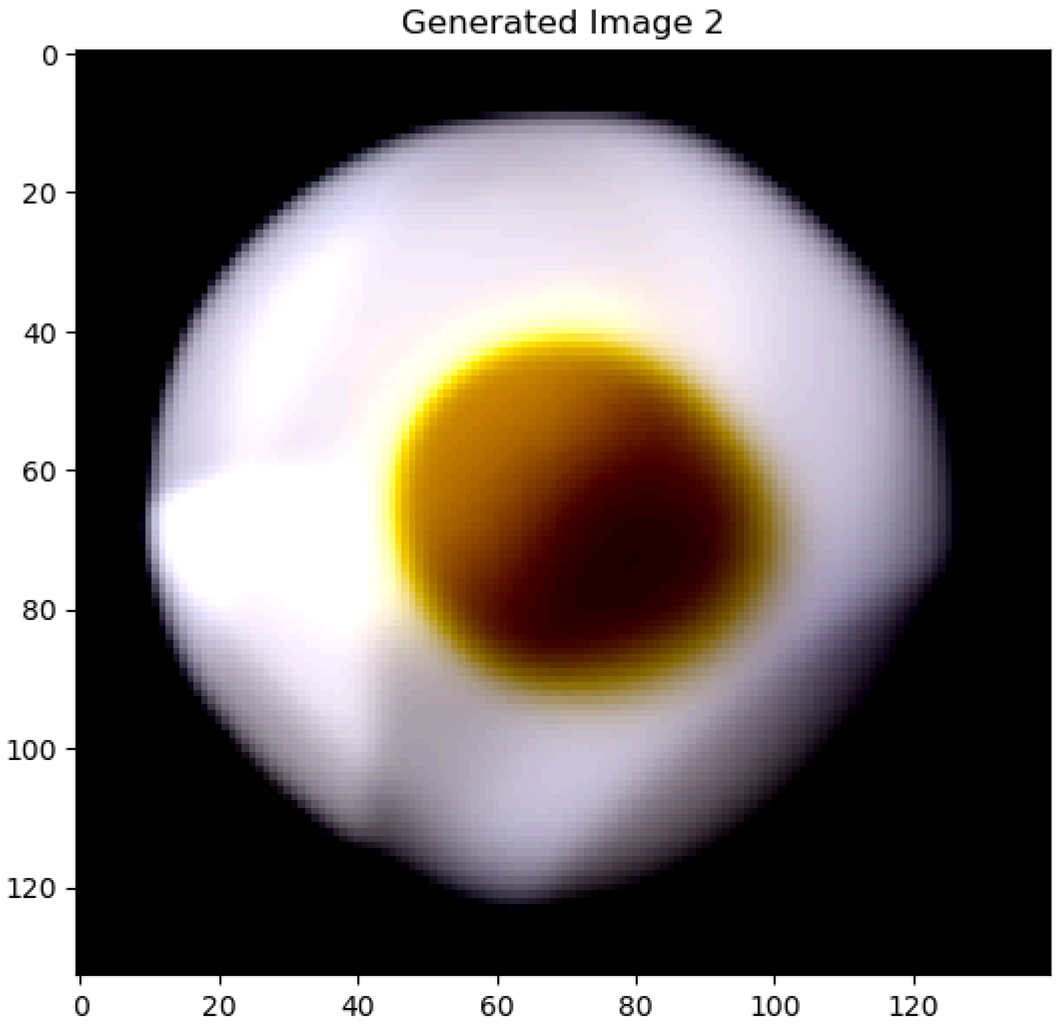


Image 2 - Number of Layers

In [68]:
```
layers_image2 = [2, 100, 100, 50, 3]
epochs = 9000
batch_size = 100

# Train the neural network
parameters_image2 = train_neural_network(X2_normalized, Y2_normalized, layer
```

```
Epoch 0, Loss: 1.1199535206147437
Epoch 50, Loss: 0.9993218651672137
Epoch 100, Loss: 0.8792303931897626
Epoch 150, Loss: 0.9430202241011553
Epoch 200, Loss: 0.8058095068003099
Epoch 250, Loss: 0.855152097793518
Epoch 300, Loss: 0.7854092134125976
Epoch 350, Loss: 0.7158163394065697
Epoch 400, Loss: 0.7055957241831753
Epoch 450, Loss: 0.6902962756926524
Epoch 500, Loss: 0.7253545105015489
Epoch 550, Loss: 0.675392877508217
Epoch 600, Loss: 0.7488350688931583
Epoch 650, Loss: 0.71112793824452
Epoch 700, Loss: 0.5714161363140127
Epoch 750, Loss: 0.7007113786736191
Epoch 800, Loss: 0.6298864461229524
Epoch 850, Loss: 0.7377331747012178
Epoch 900, Loss: 0.7068617291459536
Epoch 950, Loss: 0.6549315983417365
Epoch 1000, Loss: 0.766397940981559
Epoch 1050, Loss: 0.7591707235974949
Epoch 1100, Loss: 0.6536229002285476
Epoch 1150, Loss: 0.6790398911080573
Epoch 1200, Loss: 0.7523798840916944
Epoch 1250, Loss: 0.7187587973447092
Epoch 1300, Loss: 0.7015041196874507
Epoch 1350, Loss: 0.6047251445321338
Epoch 1400, Loss: 0.6559780940778721
Epoch 1450, Loss: 0.6846528544533177
Epoch 1500, Loss: 0.8957108862927928
Epoch 1550, Loss: 0.6350226450118096
Epoch 1600, Loss: 0.7215101836253771
Epoch 1650, Loss: 0.747308170247256
Epoch 1700, Loss: 0.556411702003842
Epoch 1750, Loss: 0.5784331504567324
Epoch 1800, Loss: 0.6326986107165932
Epoch 1850, Loss: 0.8277738070891317
Epoch 1900, Loss: 0.7929957388764526
Epoch 1950, Loss: 0.5681940261280367
Epoch 2000, Loss: 0.7002617588864359
Epoch 2050, Loss: 0.8439011005592003
Epoch 2100, Loss: 0.7535799565453051
Epoch 2150, Loss: 0.6879697863926427
Epoch 2200, Loss: 0.8398865028301581
Epoch 2250, Loss: 0.6122729823856038
Epoch 2300, Loss: 0.7647933656898225
Epoch 2350, Loss: 0.6336272158449985
Epoch 2400, Loss: 0.667726146477638
Epoch 2450, Loss: 0.7045240554390749
Epoch 2500, Loss: 0.568411860108253
Epoch 2550, Loss: 0.547629643387351
Epoch 2600, Loss: 0.6187162931303491
Epoch 2650, Loss: 0.6253479040641319
Epoch 2700, Loss: 0.5286036725900791
Epoch 2750, Loss: 0.3894533487147738
Epoch 2800, Loss: 0.27391926877148565
Epoch 2850, Loss: 0.18211094932555588
Epoch 2900, Loss: 0.24048664813837925
Epoch 2950, Loss: 0.17984969491787295
Epoch 3000, Loss: 0.17077939776413212
Epoch 3050, Loss: 0.23536670715198052
Epoch 3100, Loss: 0.3418200424060127
Epoch 3150, Loss: 0.3144257231298686
```

```
Epoch 3200, Loss: 0.18574734082658229
Epoch 3250, Loss: 0.1990150540498523
Epoch 3300, Loss: 0.2232566895544009
Epoch 3350, Loss: 0.14078448095395857
Epoch 3400, Loss: 0.17211189969023774
Epoch 3450, Loss: 0.14572703686202967
Epoch 3500, Loss: 0.2901232828121902
Epoch 3550, Loss: 0.18985170306106586
Epoch 3600, Loss: 0.21671986328876433
Epoch 3650, Loss: 0.11685708983907452
Epoch 3700, Loss: 0.1567719359596122
Epoch 3750, Loss: 0.15989671016799512
Epoch 3800, Loss: 0.09648141468115608
Epoch 3850, Loss: 0.1716421167324831
Epoch 3900, Loss: 0.19605903517522413
Epoch 3950, Loss: 0.19132650670037313
Epoch 4000, Loss: 0.1657904693945882
Epoch 4050, Loss: 0.116195695927233
Epoch 4100, Loss: 0.10683445094766
Epoch 4150, Loss: 0.13679639511833325
Epoch 4200, Loss: 0.1132421067092939
Epoch 4250, Loss: 0.14452873346558762
Epoch 4300, Loss: 0.22412248076875604
Epoch 4350, Loss: 0.15271340453924215
Epoch 4400, Loss: 0.18338313360131708
Epoch 4450, Loss: 0.1758936652401774
Epoch 4500, Loss: 0.25284926557428744
Epoch 4550, Loss: 0.17073787581823235
Epoch 4600, Loss: 0.16456590385129102
Epoch 4650, Loss: 0.14255056449192988
Epoch 4700, Loss: 0.20903979905913658
Epoch 4750, Loss: 0.12350459493132641
Epoch 4800, Loss: 0.1890690617364135
Epoch 4850, Loss: 0.178959682712784
Epoch 4900, Loss: 0.19132471082816396
Epoch 4950, Loss: 0.11894205321622209
Epoch 5000, Loss: 0.14346604145931405
Epoch 5050, Loss: 0.1204083647097904
Epoch 5100, Loss: 0.16739556519201032
Epoch 5150, Loss: 0.16518491321455425
Epoch 5200, Loss: 0.10654668747214285
Epoch 5250, Loss: 0.16901813082926898
Epoch 5300, Loss: 0.21353300636613387
Epoch 5350, Loss: 0.1246739632070661
Epoch 5400, Loss: 0.14875120068781914
Epoch 5450, Loss: 0.17625812492645726
Epoch 5500, Loss: 0.1744616688327506
Epoch 5550, Loss: 0.09543182804807282
Epoch 5600, Loss: 0.11880741056609923
Epoch 5650, Loss: 0.17571614812992342
Epoch 5700, Loss: 0.1291071327989808
Epoch 5750, Loss: 0.10952536745552663
Epoch 5800, Loss: 0.15395930088027382
Epoch 5850, Loss: 0.12239919853719772
Epoch 5900, Loss: 0.12202638494677283
Epoch 5950, Loss: 0.17462227956609447
Epoch 6000, Loss: 0.14265408431414084
Epoch 6050, Loss: 0.1319008633321559
Epoch 6100, Loss: 0.0921495598042547
Epoch 6150, Loss: 0.16293297019385677
Epoch 6200, Loss: 0.38268359977438027
Epoch 6250, Loss: 0.22211506138871234
Epoch 6300, Loss: 0.12752236134783113
Epoch 6350, Loss: 0.11937915494669042
```

```
Epoch 6400, Loss: 0.13577449024076255
Epoch 6450, Loss: 0.2588695318940625
Epoch 6500, Loss: 0.15752601517882206
Epoch 6550, Loss: 0.10306041677245813
Epoch 6600, Loss: 0.17578830461590922
Epoch 6650, Loss: 0.12834854376886076
Epoch 6700, Loss: 0.14989632439679962
Epoch 6750, Loss: 0.13481016911650906
Epoch 6800, Loss: 0.2241090388654656
Epoch 6850, Loss: 0.10316074463034837
Epoch 6900, Loss: 0.14331333300607307
Epoch 6950, Loss: 0.15405681313778022
Epoch 7000, Loss: 0.16949703592409637
Epoch 7050, Loss: 0.12678767139721847
Epoch 7100, Loss: 0.15044557941943515
Epoch 7150, Loss: 0.0863932407457759
Epoch 7200, Loss: 0.13608506898632985
Epoch 7250, Loss: 0.15063590483735098
Epoch 7300, Loss: 0.20630152737537652
Epoch 7350, Loss: 0.11803404082120977
Epoch 7400, Loss: 0.10076506786829542
Epoch 7450, Loss: 0.1491936475743839
Epoch 7500, Loss: 0.15347823598709406
Epoch 7550, Loss: 0.0660532510749611
Epoch 7600, Loss: 0.22249427395618496
Epoch 7650, Loss: 0.15171768172172795
Epoch 7700, Loss: 0.11368936680423765
Epoch 7750, Loss: 0.08363176338498238
Epoch 7800, Loss: 0.23234692441043572
Epoch 7850, Loss: 0.2317206729893752
Epoch 7900, Loss: 0.14746680831296996
Epoch 7950, Loss: 0.2895725057549091
Epoch 8000, Loss: 0.1998594882835839
Epoch 8050, Loss: 0.15407502617338475
Epoch 8100, Loss: 0.08680379013908641
Epoch 8150, Loss: 0.1332451554245052
Epoch 8200, Loss: 0.09480495190312214
Epoch 8250, Loss: 0.17919886672389873
Epoch 8300, Loss: 0.18781843920270422
Epoch 8350, Loss: 0.15417954055038138
Epoch 8400, Loss: 0.16501685419910278
Epoch 8450, Loss: 0.162850304049337
Epoch 8500, Loss: 0.14341192943179099
Epoch 8550, Loss: 0.11806869421036092
Epoch 8600, Loss: 0.13663980298809225
Epoch 8650, Loss: 0.16958341487588088
Epoch 8700, Loss: 0.13804769973253522
Epoch 8750, Loss: 0.14212427390941423
Epoch 8800, Loss: 0.16348873654328125
Epoch 8850, Loss: 0.19592625123818333
Epoch 8900, Loss: 0.15029955170883422
Epoch 8950, Loss: 0.21450980672554015
```

In [69]:

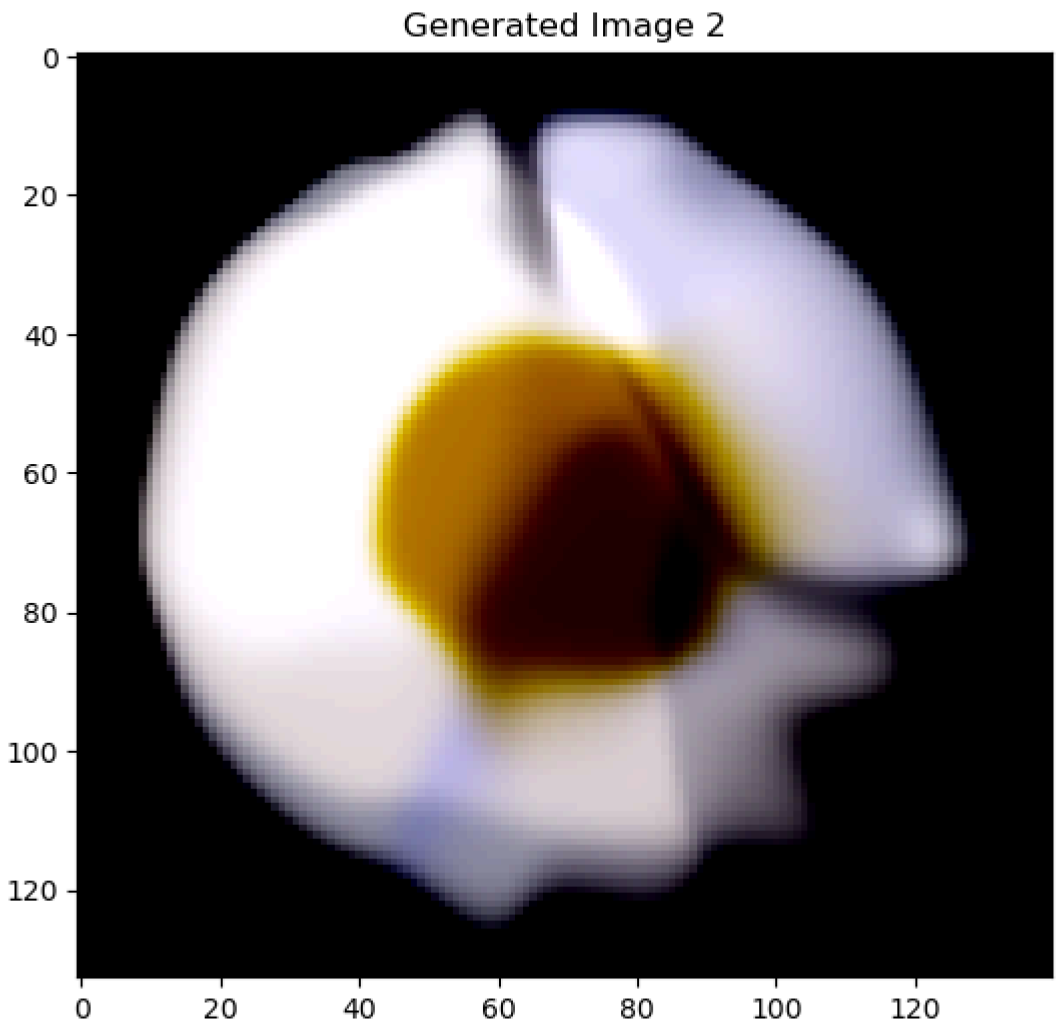
```
# Generate predictions
Y2_pred_normalized = predict_neural_network(X2_normalized, parameters_image2

min_Y2 = np.min(Y2)
max_Y2 = np.max(Y2)

# Denormalize the predictions
Y2_pred = Y2_pred_normalized * (max_Y2 - min_Y2) + min_Y2

# Reshape the predictions to match the image dimensions
Y2_pred_reshaped = Y2_pred.reshape((dim_y2_x, dim_y2_y, 3))
```

```
# Visualize the generated color image from predictions
plt.figure(figsize=(8, 6))
plt.imshow(np.clip(Y2_pred_reshaped, 0, 255).astype('uint8'))
plt.title('Generated Image 2')
plt.axis()
plt.show()
```



Version 3 - Size of Hidden Layers

In [70]:
```
# Small size of hidden layers
layers_image2 = [2, 50, 50, 3]
epochs = 9000
batch_size = 100

# Train the neural network
parameters_image2 = train_neural_network(X2_normalized, Y2_normalized, laye
```

```
Epoch 0, Loss: 1.0595961670152567
Epoch 50, Loss: 1.0247067419539644
Epoch 100, Loss: 0.8859784455225796
Epoch 150, Loss: 0.874892499453172
Epoch 200, Loss: 0.9069540250413176
Epoch 250, Loss: 0.9400131616997042
Epoch 300, Loss: 0.9023149708632499
Epoch 350, Loss: 0.9061003582720798
Epoch 400, Loss: 0.8852377173440376
Epoch 450, Loss: 0.8956283214990856
Epoch 500, Loss: 0.8138644673275383
Epoch 550, Loss: 0.885427267887463
Epoch 600, Loss: 0.8360810140411565
Epoch 650, Loss: 0.9560234760328096
Epoch 700, Loss: 0.922705223373756
Epoch 750, Loss: 0.8894620306818907
Epoch 800, Loss: 0.8142075787406897
Epoch 850, Loss: 0.8760446788778231
Epoch 900, Loss: 0.9660161656136896
Epoch 950, Loss: 0.8206528455652431
Epoch 1000, Loss: 0.8309697427646507
Epoch 1050, Loss: 0.8968114394273594
Epoch 1100, Loss: 0.8163975444967368
Epoch 1150, Loss: 0.7894555608337442
Epoch 1200, Loss: 0.9145103344427798
Epoch 1250, Loss: 0.8467451189919323
Epoch 1300, Loss: 0.8555036697515707
Epoch 1350, Loss: 0.7001991533334125
Epoch 1400, Loss: 0.7309819077664435
Epoch 1450, Loss: 0.7030665099496146
Epoch 1500, Loss: 0.7116408150437663
Epoch 1550, Loss: 0.7425740446115772
Epoch 1600, Loss: 0.6167623664669774
Epoch 1650, Loss: 0.7502238106467616
Epoch 1700, Loss: 0.7031687100510016
Epoch 1750, Loss: 0.5785284215855948
Epoch 1800, Loss: 0.6106919091816001
Epoch 1850, Loss: 0.5363020001980007
Epoch 1900, Loss: 0.513400222890745
Epoch 1950, Loss: 0.34444257262187933
Epoch 2000, Loss: 0.4597347801620262
Epoch 2050, Loss: 0.3644272053848809
Epoch 2100, Loss: 0.37297307365138344
Epoch 2150, Loss: 0.33598028172024064
Epoch 2200, Loss: 0.35431497066325673
Epoch 2250, Loss: 0.41137809187116486
Epoch 2300, Loss: 0.3342971337106835
Epoch 2350, Loss: 0.28964584335302723
Epoch 2400, Loss: 0.30361075134171983
Epoch 2450, Loss: 0.2866103643292887
Epoch 2500, Loss: 0.2595234239060448
Epoch 2550, Loss: 0.2780659641492125
Epoch 2600, Loss: 0.2099402198171946
Epoch 2650, Loss: 0.24299047724720027
Epoch 2700, Loss: 0.3384267134528966
Epoch 2750, Loss: 0.25535362123826905
Epoch 2800, Loss: 0.21425587324973663
Epoch 2850, Loss: 0.24384958214841027
Epoch 2900, Loss: 0.24510689640298877
Epoch 2950, Loss: 0.22848359022173317
Epoch 3000, Loss: 0.2092740462254241
Epoch 3050, Loss: 0.2211799391414816
Epoch 3100, Loss: 0.234391164887911
Epoch 3150, Loss: 0.2356580280770755
```

```
Epoch 3200, Loss: 0.16131288698412122
Epoch 3250, Loss: 0.1889916393783835
Epoch 3300, Loss: 0.19281917943630694
Epoch 3350, Loss: 0.2705388894866579
Epoch 3400, Loss: 0.2007217590134652
Epoch 3450, Loss: 0.21698146968263898
Epoch 3500, Loss: 0.20439585294576668
Epoch 3550, Loss: 0.15013569762426876
Epoch 3600, Loss: 0.26452163602514644
Epoch 3650, Loss: 0.12464477453554414
Epoch 3700, Loss: 0.21780216765196292
Epoch 3750, Loss: 0.12995594680379732
Epoch 3800, Loss: 0.19058954958530083
Epoch 3850, Loss: 0.23109149345108695
Epoch 3900, Loss: 0.1509375613390157
Epoch 3950, Loss: 0.17183520907187963
Epoch 4000, Loss: 0.1768062202109481
Epoch 4050, Loss: 0.2207604861309164
Epoch 4100, Loss: 0.24653412490180415
Epoch 4150, Loss: 0.2834995446951861
Epoch 4200, Loss: 0.23009326643792283
Epoch 4250, Loss: 0.17491686275229518
Epoch 4300, Loss: 0.14811190900169316
Epoch 4350, Loss: 0.22400442633978468
Epoch 4400, Loss: 0.14928956872299787
Epoch 4450, Loss: 0.16786466509531375
Epoch 4500, Loss: 0.13716015240290014
Epoch 4550, Loss: 0.1376835327430584
Epoch 4600, Loss: 0.16442694812710154
Epoch 4650, Loss: 0.16062278715790185
Epoch 4700, Loss: 0.21154395901499087
Epoch 4750, Loss: 0.14664168755333556
Epoch 4800, Loss: 0.10287316194134084
Epoch 4850, Loss: 0.14368805182866196
Epoch 4900, Loss: 0.14325091464045128
Epoch 4950, Loss: 0.11267077157096272
Epoch 5000, Loss: 0.14204599550504393
Epoch 5050, Loss: 0.1840945489457839
Epoch 5100, Loss: 0.1512829412847422
Epoch 5150, Loss: 0.10884979077688607
Epoch 5200, Loss: 0.1424383057924584
Epoch 5250, Loss: 0.23641744429948655
Epoch 5300, Loss: 0.18845418289155402
Epoch 5350, Loss: 0.19178349136918144
Epoch 5400, Loss: 0.16190033391469463
Epoch 5450, Loss: 0.1871219518354724
Epoch 5500, Loss: 0.127671166005244
Epoch 5550, Loss: 0.15494599047695146
Epoch 5600, Loss: 0.2117618327250949
Epoch 5650, Loss: 0.17595646902702933
Epoch 5700, Loss: 0.1603601290129229
Epoch 5750, Loss: 0.14009687403225426
Epoch 5800, Loss: 0.09350119533894485
Epoch 5850, Loss: 0.17205731334623672
Epoch 5900, Loss: 0.2052643136900239
Epoch 5950, Loss: 0.18698428249218654
Epoch 6000, Loss: 0.21907232604657878
Epoch 6050, Loss: 0.2214189847939945
Epoch 6100, Loss: 0.14520135239505397
Epoch 6150, Loss: 0.13377680764787628
Epoch 6200, Loss: 0.18891936960391376
Epoch 6250, Loss: 0.11962595597295926
Epoch 6300, Loss: 0.2004261043621868
Epoch 6350, Loss: 0.1641685405631233
```

```
Epoch 6400, Loss: 0.18403334075302472
Epoch 6450, Loss: 0.19066908898531884
Epoch 6500, Loss: 0.12333677144716217
Epoch 6550, Loss: 0.13404551881146787
Epoch 6600, Loss: 0.2025021564455283
Epoch 6650, Loss: 0.2056478199014982
Epoch 6700, Loss: 0.1115411482109117
Epoch 6750, Loss: 0.1511012721850053
Epoch 6800, Loss: 0.14628430141956347
Epoch 6850, Loss: 0.23272644057994726
Epoch 6900, Loss: 0.15053300303518594
Epoch 6950, Loss: 0.12589490013646
Epoch 7000, Loss: 0.15607077274206949
Epoch 7050, Loss: 0.1623197080558828
Epoch 7100, Loss: 0.10279006171919329
Epoch 7150, Loss: 0.18832161019306815
Epoch 7200, Loss: 0.15048315493904363
Epoch 7250, Loss: 0.12438818410967784
Epoch 7300, Loss: 0.1377642746488911
Epoch 7350, Loss: 0.1130163240052363
Epoch 7400, Loss: 0.11497211357414888
Epoch 7450, Loss: 0.1496804256185247
Epoch 7500, Loss: 0.1497143082876308
Epoch 7550, Loss: 0.09410078703791584
Epoch 7600, Loss: 0.2832309177063812
Epoch 7650, Loss: 0.14265982508564137
Epoch 7700, Loss: 0.16724937283561758
Epoch 7750, Loss: 0.13861764076595592
Epoch 7800, Loss: 0.13649495596697286
Epoch 7850, Loss: 0.12099555839908703
Epoch 7900, Loss: 0.15133240105225237
Epoch 7950, Loss: 0.10508528289987654
Epoch 8000, Loss: 0.15148668167015714
Epoch 8050, Loss: 0.1080959359715025
Epoch 8100, Loss: 0.16136599385341754
Epoch 8150, Loss: 0.18518877940350228
Epoch 8200, Loss: 0.1801850557479007
Epoch 8250, Loss: 0.17137092056428488
Epoch 8300, Loss: 0.15243744090509806
Epoch 8350, Loss: 0.23374529457213772
Epoch 8400, Loss: 0.13601460190346004
Epoch 8450, Loss: 0.1253715199291014
Epoch 8500, Loss: 0.20999225976349062
Epoch 8550, Loss: 0.20105739277233384
Epoch 8600, Loss: 0.21870546944771585
Epoch 8650, Loss: 0.13986650583804167
Epoch 8700, Loss: 0.20416923350275698
Epoch 8750, Loss: 0.12888701374069883
Epoch 8800, Loss: 0.09500170100996096
Epoch 8850, Loss: 0.14083231509029004
Epoch 8900, Loss: 0.1539163069438201
Epoch 8950, Loss: 0.20262539876946187
```

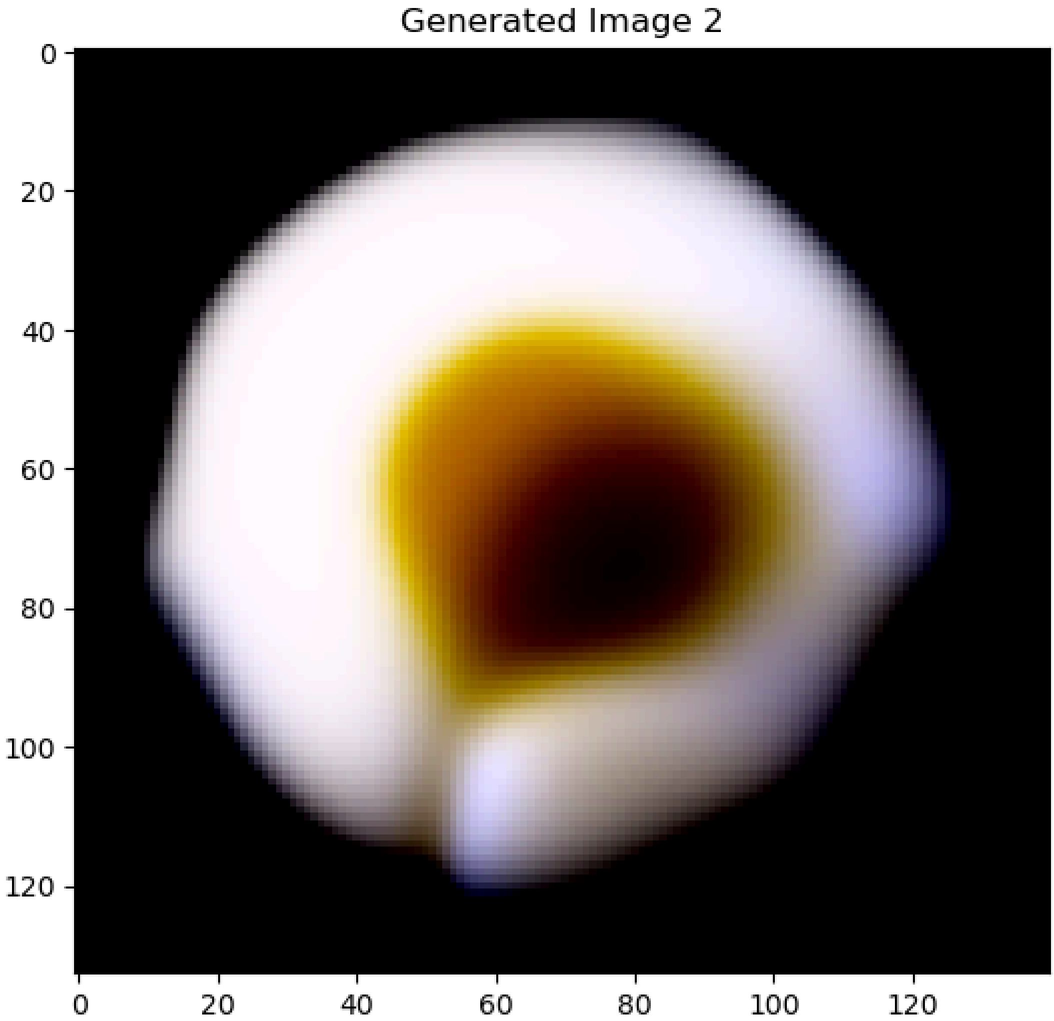
In [71]:
```
# Generate predictions
Y2_pred_normalized = predict_neural_network(X2_normalized, parameters_image2

min_Y2 = np.min(Y2)
max_Y2 = np.max(Y2)

# Denormalize the predictions
Y2_pred = Y2_pred_normalized * (max_Y2 - min_Y2) + min_Y2

# Reshape the predictions to match the image dimensions
Y2_pred_reshaped = Y2_pred.reshape((dim_y2_x, dim_y2_y, 3))
```

```
# Visualize the generated color image from predictions
plt.figure(figsize=(8, 6))
plt.imshow(np.clip(Y2_pred_reshaped, 0, 255).astype('uint8'))
plt.title('Generated Image 2')
plt.axis()
plt.show()
```



In [77]:
```
# High size of hidden layers
layers_image2 = [2, 500, 400, 3]
epochs = 9000
batch_size = 100

# Train the neural network
parameters_image2 = train_neural_network(X2_normalized, Y2_normalized, laye
```

```
Epoch 0, Loss: 1.061182473957971
Epoch 50, Loss: 1.0832297388698278
Epoch 100, Loss: 1.049902759179962
Epoch 150, Loss: 0.939966299881349
Epoch 200, Loss: 1.0142682177432343
Epoch 250, Loss: 1.0147591763448651
Epoch 300, Loss: 0.8431300243413054
Epoch 350, Loss: 1.0670724530099533
Epoch 400, Loss: 1.116067325395139
Epoch 450, Loss: 0.951234944394757
Epoch 500, Loss: 0.9129942517713151
Epoch 550, Loss: 0.938063676824133
Epoch 600, Loss: 1.0607683423887022
Epoch 650, Loss: 0.9792188483168353
Epoch 700, Loss: 1.024120136334613
Epoch 750, Loss: 0.9640838915230165
Epoch 800, Loss: 1.0287311950610967
Epoch 850, Loss: 1.016038219855265
Epoch 900, Loss: 0.9492498099754001
Epoch 950, Loss: 1.075116511555787
Epoch 1000, Loss: 0.9971754856683145
Epoch 1050, Loss: 1.0299233743200777
Epoch 1100, Loss: 1.031443547239619
Epoch 1150, Loss: 1.0573199756449398
Epoch 1200, Loss: 0.9497492948136562
Epoch 1250, Loss: 1.0533750866980347
Epoch 1300, Loss: 0.9987796640317949
Epoch 1350, Loss: 1.0379445268194634
Epoch 1400, Loss: 1.0239983129802757
Epoch 1450, Loss: 1.0240962994258789
Epoch 1500, Loss: 0.885087331359869
Epoch 1550, Loss: 0.9757564570162254
Epoch 1600, Loss: 0.903846662245464
Epoch 1650, Loss: 1.0399707965070206
Epoch 1700, Loss: 0.9607661274916275
Epoch 1750, Loss: 1.0443162822070653
Epoch 1800, Loss: 1.0360067894186324
Epoch 1850, Loss: 1.0358174478226132
Epoch 1900, Loss: 0.9642674540422187
Epoch 1950, Loss: 0.9929368682679304
Epoch 2000, Loss: 1.006506151814266
Epoch 2050, Loss: 0.9850684502332642
Epoch 2100, Loss: 0.9984567061089801
Epoch 2150, Loss: 1.0499650060448675
Epoch 2200, Loss: 1.0926773693238911
Epoch 2250, Loss: 1.0128744097088167
Epoch 2300, Loss: 0.9035662612645505
Epoch 2350, Loss: 1.0463629201968163
Epoch 2400, Loss: 0.9610176583600508
Epoch 2450, Loss: 0.9910524466110197
Epoch 2500, Loss: 0.9765680397808055
Epoch 2550, Loss: 0.9317134968021736
Epoch 2600, Loss: 0.8838861671110535
Epoch 2650, Loss: 1.067120561726709
Epoch 2700, Loss: 1.0760478858516531
Epoch 2750, Loss: 0.9836606100842169
Epoch 2800, Loss: 0.997340877951623
Epoch 2850, Loss: 1.000736258310463
Epoch 2900, Loss: 0.9622600992313898
Epoch 2950, Loss: 1.0676227375348546
Epoch 3000, Loss: 1.026895190466766
Epoch 3050, Loss: 0.9873157295417836
Epoch 3100, Loss: 0.9713604755454651
Epoch 3150, Loss: 0.9901165445027885
```

```
Epoch 3200, Loss: 0.990831142527533
Epoch 3250, Loss: 1.0262859800010358
Epoch 3300, Loss: 1.010795512152498
Epoch 3350, Loss: 1.0479265564374054
Epoch 3400, Loss: 1.0227480064972754
Epoch 3450, Loss: 1.0289039107975486
Epoch 3500, Loss: 1.0545175239429876
Epoch 3550, Loss: 1.0832933365533812
Epoch 3600, Loss: 0.9986771783832539
Epoch 3650, Loss: 0.9571574881838057
Epoch 3700, Loss: 1.0963082871216974
Epoch 3750, Loss: 1.012542946990887
Epoch 3800, Loss: 1.0359676210818376
Epoch 3850, Loss: 0.9206370405157043
Epoch 3900, Loss: 1.0180068116814913
Epoch 3950, Loss: 1.0661002727317999
Epoch 4000, Loss: 1.019690622311562
Epoch 4050, Loss: 1.0403845188471252
Epoch 4100, Loss: 1.0060963514797785
Epoch 4150, Loss: 0.9312652573680154
Epoch 4200, Loss: 1.0233742958091512
Epoch 4250, Loss: 1.0253043568279927
Epoch 4300, Loss: 1.0469081906534818
Epoch 4350, Loss: 0.9645651205142911
Epoch 4400, Loss: 1.021390182954135
Epoch 4450, Loss: 0.9189914966946948
Epoch 4500, Loss: 0.9372994376776698
Epoch 4550, Loss: 0.9520803923335588
Epoch 4600, Loss: 1.0215162364031058
Epoch 4650, Loss: 0.9883238826531348
Epoch 4700, Loss: 0.9638378792307754
Epoch 4750, Loss: 0.9021237295219526
Epoch 4800, Loss: 0.8281187073776419
Epoch 4850, Loss: 1.044959345715832
Epoch 4900, Loss: 0.9983922377157682
Epoch 4950, Loss: 1.0567163389877507
Epoch 5000, Loss: 0.9436845692701813
Epoch 5050, Loss: 1.0003232536331907
Epoch 5100, Loss: 0.9615526089890775
Epoch 5150, Loss: 0.9826978998926548
Epoch 5200, Loss: 0.8898977240079984
Epoch 5250, Loss: 0.9948925534640224
Epoch 5300, Loss: 1.0145809373723325
Epoch 5350, Loss: 1.0718764129977119
Epoch 5400, Loss: 0.9915306282354959
Epoch 5450, Loss: 0.9596584473937427
Epoch 5500, Loss: 0.9402505906724236
Epoch 5550, Loss: 0.991736440425365
Epoch 5600, Loss: 0.9983804138882677
Epoch 5650, Loss: 0.9860664598438098
Epoch 5700, Loss: 0.9624454929933371
Epoch 5750, Loss: 1.0122412130904446
Epoch 5800, Loss: 0.989574107464939
Epoch 5850, Loss: 1.047318354253561
Epoch 5900, Loss: 0.9919133473507803
Epoch 5950, Loss: 1.0291722554044052
Epoch 6000, Loss: 0.9717539689123046
Epoch 6050, Loss: 1.0093663788837937
Epoch 6100, Loss: 1.0414159116547996
Epoch 6150, Loss: 0.9516536395516751
Epoch 6200, Loss: 0.9240463941893688
Epoch 6250, Loss: 1.010299184499574
Epoch 6300, Loss: 0.9905878435658716
Epoch 6350, Loss: 1.036002219886182
```

```
Epoch 6400, Loss: 1.0211814743844918
Epoch 6450, Loss: 1.0036394107022688
Epoch 6500, Loss: 1.041099825703806
Epoch 6550, Loss: 0.9521368933744553
Epoch 6600, Loss: 1.0152913990157348
Epoch 6650, Loss: 1.0602551262572062
Epoch 6700, Loss: 0.9400497706160958
Epoch 6750, Loss: 0.7958272705321824
Epoch 6800, Loss: 0.9733447986723166
Epoch 6850, Loss: 1.0125198925734091
Epoch 6900, Loss: 0.9688344731507103
Epoch 6950, Loss: 1.0110856122490668
Epoch 7000, Loss: 0.9794338480223125
Epoch 7050, Loss: 0.9655925102939564
Epoch 7100, Loss: 0.87764388686083
Epoch 7150, Loss: 1.008656349384372
Epoch 7200, Loss: 0.9474839738833568
Epoch 7250, Loss: 1.0054391091194002
Epoch 7300, Loss: 0.9738293555677512
Epoch 7350, Loss: 0.9595132703432565
Epoch 7400, Loss: 0.9292157076552894
Epoch 7450, Loss: 0.9948348384436155
Epoch 7500, Loss: 0.9731494942482671
Epoch 7550, Loss: 1.0112070899179746
Epoch 7600, Loss: 0.9754281438279339
Epoch 7650, Loss: 1.0889409531726233
Epoch 7700, Loss: 1.0155942877061177
Epoch 7750, Loss: 0.9598730735548667
Epoch 7800, Loss: 1.017758826746893
Epoch 7850, Loss: 1.032657818823822
Epoch 7900, Loss: 0.9755918655161421
Epoch 7950, Loss: 0.9853394180064403
Epoch 8000, Loss: 0.9869727101034518
Epoch 8050, Loss: 1.0603919601102008
Epoch 8100, Loss: 0.8871152134894711
Epoch 8150, Loss: 0.9456255962119231
Epoch 8200, Loss: 1.0005783434685946
Epoch 8250, Loss: 1.0380190498120543
Epoch 8300, Loss: 0.9813795699244607
Epoch 8350, Loss: 0.9642932002787512
Epoch 8400, Loss: 0.9854992839159664
Epoch 8450, Loss: 1.0144587665684188
Epoch 8500, Loss: 1.0860406770581708
Epoch 8550, Loss: 1.0280563354549117
Epoch 8600, Loss: 1.015334064999497
Epoch 8650, Loss: 0.9566840668059026
Epoch 8700, Loss: 0.9176463305442669
Epoch 8750, Loss: 1.0532827582016737
Epoch 8800, Loss: 1.0513870573282662
Epoch 8850, Loss: 0.9971738408925717
Epoch 8900, Loss: 0.9990544476066818
Epoch 8950, Loss: 0.9868016295057621
```

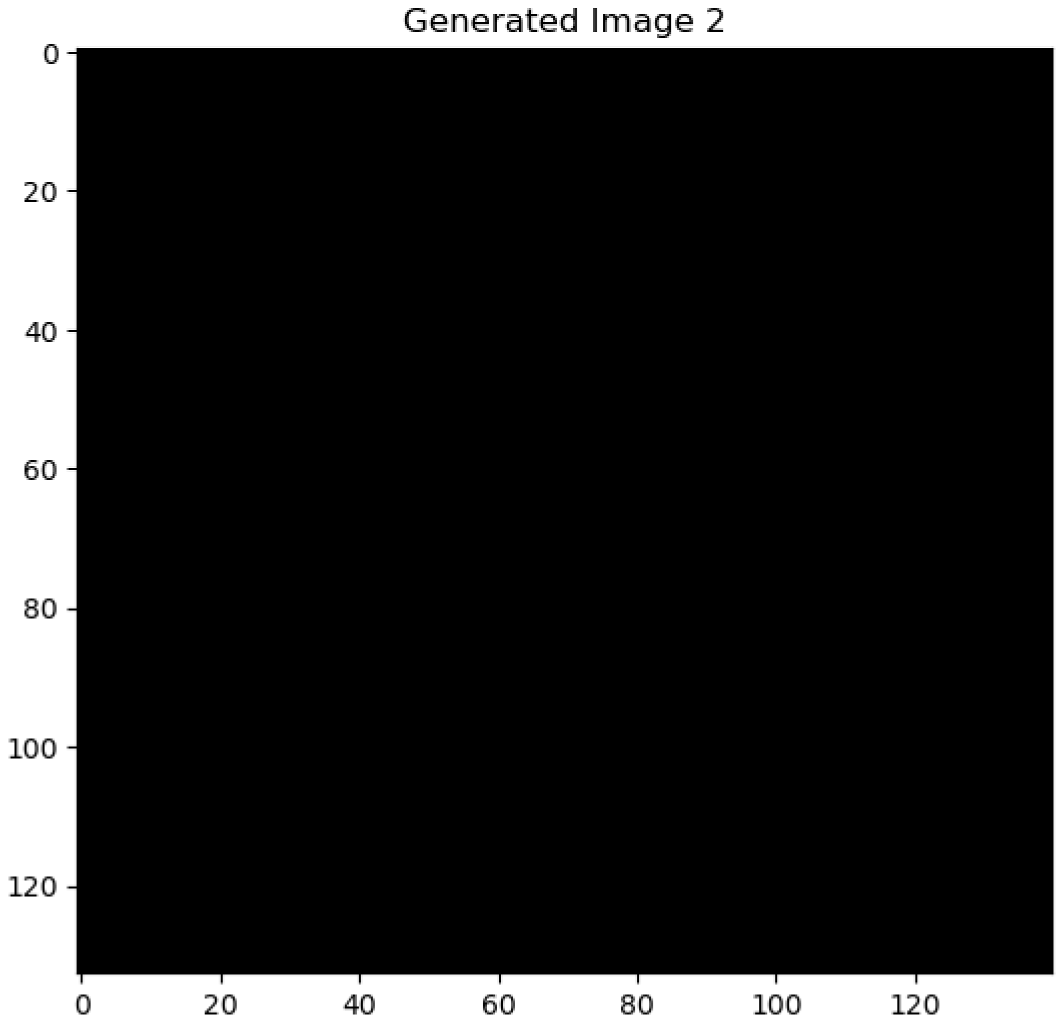
In [78]:
```python
# Generate predictions
Y2_pred_normalized = predict_neural_network(X2_normalized, parameters_image2

min_Y2 = np.min(Y2)
max_Y2 = np.max(Y2)

# Denormalize the predictions
Y2_pred = Y2_pred_normalized * (max_Y2 - min_Y2) + min_Y2

# Reshape the predictions to match the image dimensions
Y2_pred_reshaped = Y2_pred.reshape((dim_y2_x, dim_y2_y, 3))
```

```python
# Visualize the generated color image from predictions
plt.figure(figsize=(8, 6))
plt.imshow(np.clip(Y2_pred_reshaped, 0, 255).astype('uint8'))
plt.title('Generated Image 2')
plt.axis()
plt.show()
```



Data is not normalized

In [74]:
```python
layers_image2 = [2, 350, 390, 3]
epochs = 15000
learning_rate = learning_rate = 1E-2
batch_size = 100

# Train the neural network
parameters_image2 = train_neural_network(X2, Y2, layers_image2, learning_ra
```

```
Epoch 0, Loss: 16933.686017986976
Epoch 50, Loss: 9927.400476086066
Epoch 100, Loss: 9283.906193847368
Epoch 150, Loss: 9692.64488747742
Epoch 200, Loss: 9452.840592777013
Epoch 250, Loss: 9457.390464699769
Epoch 300, Loss: 9478.219202905626
Epoch 350, Loss: 8812.680376002472
Epoch 400, Loss: 8777.397946462985
Epoch 450, Loss: 9039.660668348059
Epoch 500, Loss: 9683.800652063206
Epoch 550, Loss: 9153.857664886998
Epoch 600, Loss: 9603.157541241111
Epoch 650, Loss: 9427.192087194328
Epoch 700, Loss: 9386.273909085356
Epoch 750, Loss: 9488.05581256026
Epoch 800, Loss: 9119.63153142653
Epoch 850, Loss: 8967.272203582146
Epoch 900, Loss: 9703.118222539142
Epoch 950, Loss: 9261.068439563758
Epoch 1000, Loss: 9138.096227308917
Epoch 1050, Loss: 8696.075267596609
Epoch 1100, Loss: 8687.218562174778
Epoch 1150, Loss: 9661.205795805801
Epoch 1200, Loss: 9096.875269409575
Epoch 1250, Loss: 9273.612573134338
Epoch 1300, Loss: 9035.24853998354
Epoch 1350, Loss: 8321.857864896658
Epoch 1400, Loss: 9333.039366389858
Epoch 1450, Loss: 9277.79970111547
Epoch 1500, Loss: 9477.393368701314
Epoch 1550, Loss: 8636.41370057134
Epoch 1600, Loss: 9060.817418577522
Epoch 1650, Loss: 8893.896875947443
Epoch 1700, Loss: 9548.690015196202
Epoch 1750, Loss: 8060.632043540779
Epoch 1800, Loss: 9372.652373316663
Epoch 1850, Loss: 9244.998927932058
Epoch 1900, Loss: 9572.171692907126
Epoch 1950, Loss: 9496.630230662877
Epoch 2000, Loss: 8718.316391920222
Epoch 2050, Loss: 9334.758300043915
Epoch 2100, Loss: 9335.763401963786
Epoch 2150, Loss: 8685.313745314264
Epoch 2200, Loss: 9071.178321209745
Epoch 2250, Loss: 10682.327559790723
Epoch 2300, Loss: 9153.999303488989
Epoch 2350, Loss: 8929.625531227359
Epoch 2400, Loss: 9314.876229641332
Epoch 2450, Loss: 8546.396805856457
Epoch 2500, Loss: 9272.874445098681
Epoch 2550, Loss: 8749.630344743338
Epoch 2600, Loss: 8234.20754049508
Epoch 2650, Loss: 8229.830996576597
Epoch 2700, Loss: 8464.707337507878
Epoch 2750, Loss: 7605.4560383818825
Epoch 2800, Loss: 7502.9512481562015
Epoch 2850, Loss: 6190.962176301991
Epoch 2900, Loss: 5814.536805751673
Epoch 2950, Loss: 6407.071443480785
Epoch 3000, Loss: 8169.513118664192
Epoch 3050, Loss: 7285.274869429941
Epoch 3100, Loss: 5703.181774627365
Epoch 3150, Loss: 5684.96693766491
```

```
Epoch 3200, Loss: 5090.254750340772
Epoch 3250, Loss: 6518.747705291814
Epoch 3300, Loss: 6579.758294135037
Epoch 3350, Loss: 5860.919042386096
Epoch 3400, Loss: 6241.439560500931
Epoch 3450, Loss: 5277.185207455159
Epoch 3500, Loss: 6691.088272044365
Epoch 3550, Loss: 6301.495172273373
Epoch 3600, Loss: 5988.289836224305
Epoch 3650, Loss: 4933.284651835166
Epoch 3700, Loss: 5248.59578205693
Epoch 3750, Loss: 4744.77123813207
Epoch 3800, Loss: 5433.334337339415
Epoch 3850, Loss: 4834.17659999353
Epoch 3900, Loss: 3362.9036774098618
Epoch 3950, Loss: 4200.516029446294
Epoch 4000, Loss: 4361.94515612027
Epoch 4050, Loss: 4646.671772342982
Epoch 4100, Loss: 4204.995789801809
Epoch 4150, Loss: 3121.0310296635816
Epoch 4200, Loss: 3466.399047335376
Epoch 4250, Loss: 3485.684756694297
Epoch 4300, Loss: 3535.4759107294417
Epoch 4350, Loss: 2505.7827112249324
Epoch 4400, Loss: 2997.8799582580596
Epoch 4450, Loss: 2348.086052286961
Epoch 4500, Loss: 2972.8731913820693
Epoch 4550, Loss: 2940.44355338154
Epoch 4600, Loss: 3196.303570843919
Epoch 4650, Loss: 2354.115143882681
Epoch 4700, Loss: 3667.96091158056
Epoch 4750, Loss: 3101.1393385103006
Epoch 4800, Loss: 2342.3314328190086
Epoch 4850, Loss: 2386.0788067639287
Epoch 4900, Loss: 3246.506422537424
Epoch 4950, Loss: 3587.17822081462
Epoch 5000, Loss: 3660.981071373539
Epoch 5050, Loss: 1824.8358647940497
Epoch 5100, Loss: 3101.0514755249696
Epoch 5150, Loss: 2659.0736737627726
Epoch 5200, Loss: 3638.1784395990185
Epoch 5250, Loss: 2871.5292926014417
Epoch 5300, Loss: 2417.530357368919
Epoch 5350, Loss: 2133.216319839104
Epoch 5400, Loss: 2280.2662328841707
Epoch 5450, Loss: 3266.89293888939
Epoch 5500, Loss: 2459.853148827947
Epoch 5550, Loss: 1705.376571834667
Epoch 5600, Loss: 3287.0132100084074
Epoch 5650, Loss: 2199.8747189965443
Epoch 5700, Loss: 2019.078636244929
Epoch 5750, Loss: 1947.0596953194945
Epoch 5800, Loss: 2264.296222270739
Epoch 5850, Loss: 2038.6592388491674
Epoch 5900, Loss: 2635.930851792656
Epoch 5950, Loss: 1629.6295548360404
Epoch 6000, Loss: 1960.9832164586394
Epoch 6050, Loss: 2126.086408147348
Epoch 6100, Loss: 2074.264130482446
Epoch 6150, Loss: 1636.8590669644354
Epoch 6200, Loss: 2103.1134434485034
Epoch 6250, Loss: 2883.5972770613057
Epoch 6300, Loss: 2031.528045554163
Epoch 6350, Loss: 1842.604315073047
```

```
Epoch 6400, Loss: 2844.8407459978303
Epoch 6450, Loss: 1930.7624010780535
Epoch 6500, Loss: 1886.1338498160294
Epoch 6550, Loss: 2680.1796184985324
Epoch 6600, Loss: 2370.2223530133433
Epoch 6650, Loss: 4601.727260353456
Epoch 6700, Loss: 2107.4676258077247
Epoch 6750, Loss: 2134.9510165309525
Epoch 6800, Loss: 2280.7072064710314
Epoch 6850, Loss: 2109.377641559933
Epoch 6900, Loss: 2329.035358322188
Epoch 6950, Loss: 2084.53843408281
Epoch 7000, Loss: 1742.44401454268
Epoch 7050, Loss: 2598.4144762587803
Epoch 7100, Loss: 1820.7431102631754
Epoch 7150, Loss: 2331.7215344627116
Epoch 7200, Loss: 2107.0220328324053
Epoch 7250, Loss: 1233.2801451330417
Epoch 7300, Loss: 1579.029023768733
Epoch 7350, Loss: 1883.0868785666278
Epoch 7400, Loss: 3053.598341304241
Epoch 7450, Loss: 2224.2789254806967
Epoch 7500, Loss: 2260.8871105674407
Epoch 7550, Loss: 1858.2630827689734
Epoch 7600, Loss: 2279.6125272097484
Epoch 7650, Loss: 1398.1933383079574
Epoch 7700, Loss: 2570.9911050710725
Epoch 7750, Loss: 1608.7358492028811
Epoch 7800, Loss: 2189.417469527632
Epoch 7850, Loss: 2143.9196846432365
Epoch 7900, Loss: 1891.543050102839
Epoch 7950, Loss: 1654.2270394710324
Epoch 8000, Loss: 2076.514800331124
Epoch 8050, Loss: 1971.8000979165708
Epoch 8100, Loss: 2392.2257102291055
Epoch 8150, Loss: 1955.5860550824414
Epoch 8200, Loss: 2663.4788902963396
Epoch 8250, Loss: 1728.1832502108869
Epoch 8300, Loss: 1554.8064860534225
Epoch 8350, Loss: 3243.3550176393446
Epoch 8400, Loss: 1551.4603939247356
Epoch 8450, Loss: 2408.682154571812
Epoch 8500, Loss: 2299.234410279602
Epoch 8550, Loss: 1934.2440334939429
Epoch 8600, Loss: 2042.0734843657592
Epoch 8650, Loss: 1768.6120562641338
Epoch 8700, Loss: 2539.0916789564208
Epoch 8750, Loss: 2008.4805111761127
Epoch 8800, Loss: 1127.1134713167332
Epoch 8850, Loss: 1966.005255804115
Epoch 8900, Loss: 3263.586335511345
Epoch 8950, Loss: 1512.7618767561535
Epoch 9000, Loss: 2591.3266127497104
Epoch 9050, Loss: 1825.51551507276
Epoch 9100, Loss: 2228.018648365352
Epoch 9150, Loss: 3311.9725713028392
Epoch 9200, Loss: 1496.572170280822
Epoch 9250, Loss: 2501.46361284904
Epoch 9300, Loss: 1283.9392012394437
Epoch 9350, Loss: 1852.0786211596312
Epoch 9400, Loss: 1421.2285975247325
Epoch 9450, Loss: 2208.032399615941
Epoch 9500, Loss: 2163.913535163385
Epoch 9550, Loss: 1420.780887448233
```

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Epoch 9600, Loss: 1816.2898326330414
Epoch 9650, Loss: 1849.6465957548783
Epoch 9700, Loss: 1665.1623063617824
Epoch 9750, Loss: 1686.1300646459254
Epoch 9800, Loss: 1732.8327825869283
Epoch 9850, Loss: 1352.2253384458413
Epoch 9900, Loss: 1929.0801247792233
Epoch 9950, Loss: 1831.8467630722207
Epoch 10000, Loss: 1817.9398723632637
Epoch 10050, Loss: 1633.6662474069255
Epoch 10100, Loss: 2753.5572617061257
Epoch 10150, Loss: 1407.3260140675175
Epoch 10200, Loss: 1592.8017255147004
Epoch 10250, Loss: 2931.2746480098162
Epoch 10300, Loss: 1315.8289917081497
Epoch 10350, Loss: 1625.6470003442416
Epoch 10400, Loss: 948.8168444634168
Epoch 10450, Loss: 1896.5982466323744
Epoch 10500, Loss: 1933.8243904618876
Epoch 10550, Loss: 2630.999637336753
Epoch 10600, Loss: 1502.642195125649
Epoch 10650, Loss: 1828.46878652387
Epoch 10700, Loss: 2954.9111030461154
Epoch 10750, Loss: 1767.1855708368932
Epoch 10800, Loss: 1343.1581759397066
Epoch 10850, Loss: 1573.6403848095003
Epoch 10900, Loss: 1535.7353533314351
Epoch 10950, Loss: 2041.7229910201913
Epoch 11000, Loss: 1916.2466742371973
Epoch 11050, Loss: 2583.58127788226
Epoch 11100, Loss: 1647.376204399696
Epoch 11150, Loss: 2059.2722970041614
Epoch 11200, Loss: 1753.3436257190258
Epoch 11250, Loss: 2039.721834225492
Epoch 11300, Loss: 2848.3678409149957
Epoch 11350, Loss: 2821.398729190351
Epoch 11400, Loss: 1799.4337342937904
Epoch 11450, Loss: 2204.5098723358933
Epoch 11500, Loss: 1613.0715206231514
Epoch 11550, Loss: 3306.8194382140864
Epoch 11600, Loss: 1694.6718025324487
Epoch 11650, Loss: 1692.9905832104328
Epoch 11700, Loss: 2233.0682511794453
Epoch 11750, Loss: 2241.334751501646
Epoch 11800, Loss: 1547.020798429518
Epoch 11850, Loss: 1638.0925830886151
Epoch 11900, Loss: 2309.8693557018523
Epoch 11950, Loss: 1802.1404979264448
Epoch 12000, Loss: 1715.3694978129581
Epoch 12050, Loss: 2357.284614746468
Epoch 12100, Loss: 1176.098648246983
Epoch 12150, Loss: 1961.6652222026
Epoch 12200, Loss: 1705.6672194914304
Epoch 12250, Loss: 1489.6851201435873
Epoch 12300, Loss: 1919.3057844884747
Epoch 12350, Loss: 1271.6009754405372
Epoch 12400, Loss: 1618.372193075185
Epoch 12450, Loss: 1976.741811181278
Epoch 12500, Loss: 2802.218691083743
Epoch 12550, Loss: 2497.9103026327725
Epoch 12600, Loss: 2408.8479202997164
Epoch 12650, Loss: 1829.5446172625063
Epoch 12700, Loss: 2398.782983049699
Epoch 12750, Loss: 1527.0161443097059
```

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Epoch 12800, Loss: 1275.3545103062213
Epoch 12850, Loss: 2075.373196323872
Epoch 12900, Loss: 2235.6403758248252
Epoch 12950, Loss: 2293.1257837796384
Epoch 13000, Loss: 2310.980923340991
Epoch 13050, Loss: 1446.518350345591
Epoch 13100, Loss: 1883.715782605312
Epoch 13150, Loss: 1911.368369895951
Epoch 13200, Loss: 2550.529331086567
Epoch 13250, Loss: 1669.9613228925532
Epoch 13300, Loss: 1784.344665147759
Epoch 13350, Loss: 1549.9186707967447
Epoch 13400, Loss: 2393.747448366816
Epoch 13450, Loss: 1828.3845863068857
Epoch 13500, Loss: 1576.6027956298487
Epoch 13550, Loss: 1322.133528664225
Epoch 13600, Loss: 2107.1131581495324
Epoch 13650, Loss: 2142.8502595828863
Epoch 13700, Loss: 1770.9943142074137
Epoch 13750, Loss: 2175.62057725322
Epoch 13800, Loss: 1506.4859961053198
Epoch 13850, Loss: 1258.6475216403596
Epoch 13900, Loss: 1430.945896124198
Epoch 13950, Loss: 1637.3888366810963
Epoch 14000, Loss: 1884.1952354701248
Epoch 14050, Loss: 2000.0295457721013
Epoch 14100, Loss: 1138.729654599662
Epoch 14150, Loss: 1411.384350058204
Epoch 14200, Loss: 2597.193851107085
Epoch 14250, Loss: 1943.0955188971463
Epoch 14300, Loss: 2189.460644750053
Epoch 14350, Loss: 1868.0039705344936
Epoch 14400, Loss: 1980.1494679207774
Epoch 14450, Loss: 2266.2278313130732
Epoch 14500, Loss: 1441.6957214088384
Epoch 14550, Loss: 1956.784677359341
Epoch 14600, Loss: 1120.405669983355
Epoch 14650, Loss: 1733.717468734942
Epoch 14700, Loss: 1953.1380692299754
Epoch 14750, Loss: 1923.8504725112377
Epoch 14800, Loss: 2142.041405585192
Epoch 14850, Loss: 1360.6352801750506
Epoch 14900, Loss: 1794.1722568022499
Epoch 14950, Loss: 1736.3952521342912
```
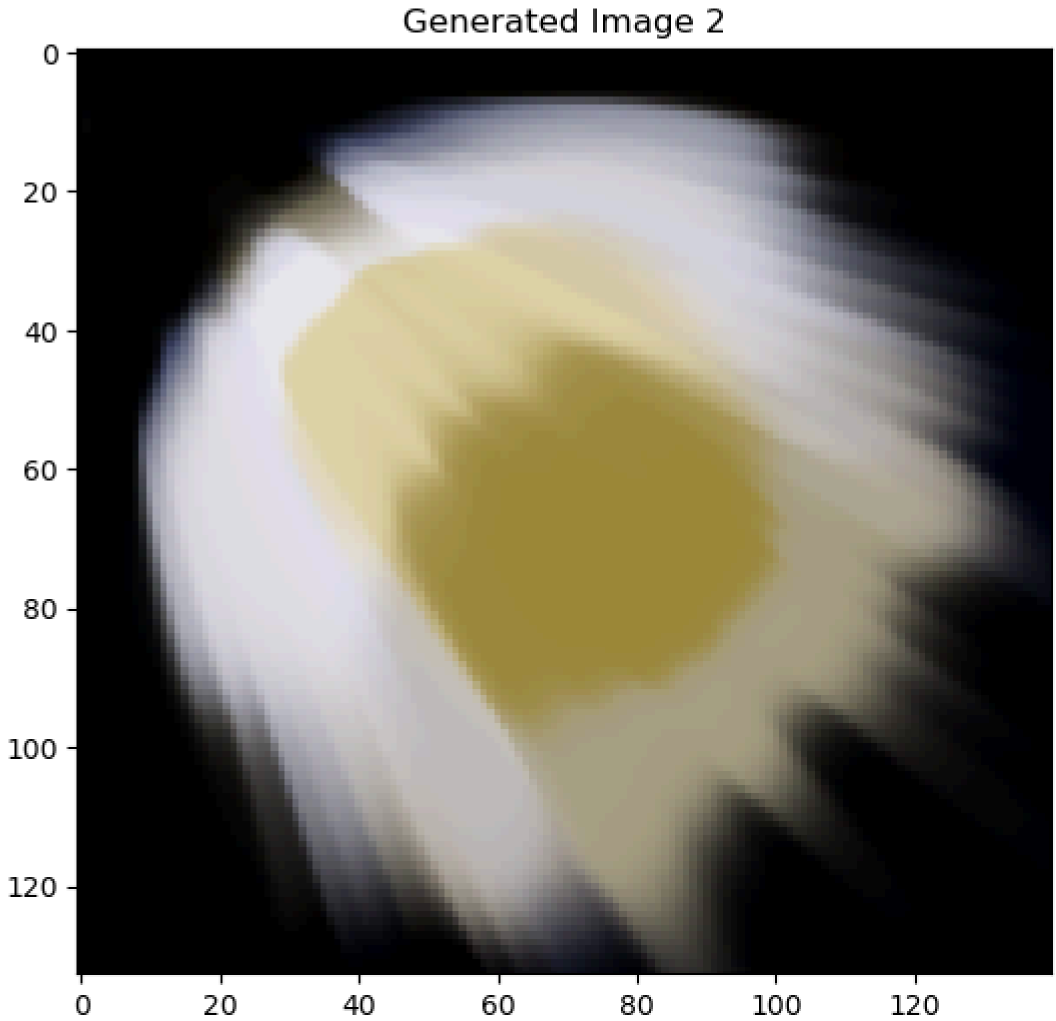

In [76]:

```python
# Generate predictions
Y2_pred = predict_neural_network(X2, parameters_image2)

# Reshape the predictions to match the image dimensions
Y2_pred_reshaped = Y2_pred.reshape((dim_y2_x, dim_y2_y, 3))

# Visualize the generated color image from predictions
plt.figure(figsize=(8, 6))
plt.imshow(np.clip(Y2_pred_reshaped, 0, 255).astype('uint8'))
plt.title('Generated Image 2')
plt.axis()
plt.show()
```




```
In [ ]:
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