```python
from typing import Optional, Tuple
import torch
from torch import nn
from torch.nn import functional as F
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm
import os
import json
#import imageio
import cv2
import os
os.environ['PYTORCH_CUDA_ALLOC_CONF'] = 'expandable_segments:True'
from PIL import Image

from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly
```

```python
def load_colmap_data():
    r"""
    After using colmap2nerf.py to convert the colmap intrinsics and ex
    read in the transform_colmap.json file

    Expected Returns:
      An array of resized imgs, normalized to [0, 1]
      An array of poses, essentially the transform matrix
      Camera parameters: H, W, focal length

    NOTES:
      We recommend you resize the original images from 800x800 to lowe
      i.e. 200x200 so it's easier for training. Change camera paramete
    """
    ################### YOUR CODE START ###################
```

```
json_path='transforms_colmap.json'
image_dir='./data/data/images'

json_path='/content/drive/MyDrive/ESE 650_HW3_P3/transforms_colmap
image_dir='/content/drive/MyDrive/ESE 650_HW3_P3/data/data/images'
resize_dim=(200, 200)

# Load JSON file
with open(json_path, 'r') as f:
    data = json.load(f)

# Initialize lists to store processed data
imgs = []
poses = []

# Process each frame in the JSON file
for frame in data['frames']:
    # Load and resize image
    img_path = os.path.join(image_dir, frame['file_path'][0])
    img = Image.open(img_path).resize(resize_dim)
    imgs.append(np.array(img) / 255.0)  # Normalize to [0, 1]

    # Process pose
    pose = np.array(frame['transform_matrix'])
    #print (pose)
    poses.append(pose)

# Assuming all images have the same size and focal length
H, W = resize_dim
focal = frame["camera_angle_x"] * W / (2 * np.tan(frame['camera_ar

# Convert lists to numpy arrays
imgs = np.array(imgs)
poses = np.array(poses)

# Camera parameters: Height, Width, Focal length
camera_params = (H, W, focal)

return imgs, poses, camera_params
################### YOUR CODE END ###################
```

```
def get_rays(H, W, focal, c2w,):
    """
    Compute rays passing through each pixel in the world frame.

    Parameters:
    - H: Height of the image.
    - W: Width of the image.
    - focal: Camera intrinsic matrix of shape (3, 3).
    - c2w: Camera-to-world transformation matrix of shape (4, 4).

    Returns:
    - ray_origins: Array of shape (H, W, 3) denoting the origins of ea
    - ray_directions: Array of shape (H, W, 3) denoting the direction
    """
    # Generate mesh grid for pixel coordinates

    # Detect if a GPU is available and choose the device accordingly
    device = torch.device('cuda' if torch.cuda.is_available() else 'cp
    #device = 'cpu' #Due to OOM
    #print(device)

    # Ensure c2w is a torch.Tensor and move it to the chosen device
    if not isinstance(c2w, torch.Tensor):
        c2w = torch.from_numpy(c2w).float()  # Convert from numpy to t
    c2w = c2w.to(device)

    # Generate a grid of (i, j) coordinates
    i, j = torch.meshgrid(torch.linspace(0, W-1, W, device=device), to
    i = i.t().flatten()
    j = j.t().flatten()

    # Normalize pixel coordinates (assuming the image center as origir
    dirs = torch.stack([(i - W * 0.5) / focal, -(j - H * 0.5) / focal,

    # Rotate ray directions from camera frame to the world frame
    rays_d = torch.sum(dirs[..., None, :] * c2w[:3, :3], axis=-1)

    # The origin of all rays is the camera position in the world frame
    rays_o = c2w[:3, -1].expand(rays_d.shape)
```

```
    # Reshape rays_o and rays_d to [H, W, 3]
    rays_o = rays_o.view(H, W, 3)
    rays_d = rays_d.view(H, W, 3)

    return rays_o, rays_d

def sample_points_from_rays(ray_origins, ray_directions, snear, sfar,
    """
    Sample 3D points along rays within the specified near and far bour

    Parameters:
    - ray_origins: Array of shape (H, W, 3) denoting the origins of ea
    - ray_directions: Array of shape (H, W, 3) denoting the direction
    - snear: Scalar or array defining the near clipping distance for e
    - sfar: Scalar or array defining the far clipping distance for eac
    - Nsample: Number of points to sample along each ray.

    Returns:
    - sampled_points: Array of shape (H, W, Nsample, 3) with sampled 3
    - depth_values: Array of shape (H, W, Nsample) with depth values c
    """

    # Make sure snear and sfar are tensors
    H, W, _ = ray_origins.shape
    device = ray_origins.device


    # Compute the depth values for each sample
    depth_values = torch.linspace(snear, sfar, Nsample, device=device)

    depth_values = depth_values.expand(H, W, Nsample)  # Make sure dep

    # Compute the 3D positions of each sample point along the rays
    sampled_points = ray_origins[..., None, :] + depth_values[..., :,

    return sampled_points, depth_values


def positional_encoding(x, max_freq_log2=10, include_input=True):

    """Apply positional encoding to the input. (Section 5.1 of origina
```

```
    Apply positional encoding to the input. (Section 5.1 of origina
    We use positional encoding to map continuous input coordinates int
    higher dimensional space to enable our MLP to more easily approxim
    higher frequency function.

    Expected Returns:
      pos_out: positional encoding of the input tensor.
               (H*W*num_samples, (include_input + 2*freq) * 3)
    """
    frequencies = 2 ** torch.linspace(0, max_freq_log2, steps=max_frec
    # Create a list of frequencies, (sin(2^k * x), cos(2^k * x)) for k
    encodings = [torch.sin(x * freq) for freq in frequencies] + [torch
    # Stack all encodings along the last dimension
    encoded = torch.cat(encodings, dim=-1)

    if include_input:
        # Concatenate the original input with the encoded features
        pos_out = torch.cat([x, encoded], dim=-1)
    else:
        pos_out = encoded

    return pos_out


def volume_rendering(
    radiance_field: torch.Tensor,
    ray_origins: torch.Tensor,
    depth_values: torch.Tensor
) -> Tuple[torch.Tensor]:
    """
    Differentiably renders a radiance field, given the origin of each
    and the sampled depth values along them.

    Args:
      radiance_field: Tensor containing RGB color and volume density a
                      shape (H, W, num_samples, 4).
      ray_origins: Origin of each ray, shape (H, W, 3).
      depth_values: Sampled depth values along each ray, shape (H, W,

    Returns:
      rgb_map: Rendered RGB image, shape (H, W, 3).
```

```
    """
    # Extract sigma (density) and color from the radiance field
    sigma = torch.relu(radiance_field[..., 3])  # Extract volume densi
    rgb = torch.sigmoid(radiance_field[..., :3])  # Extract RGB colors

    # Compute depth intervals
    dists = torch.cat([depth_values[..., 1:] - depth_values[..., :-1],
    alpha = 1.0 - torch.exp(-sigma * dists)
    weights = alpha * torch.cumprod(torch.cat([torch.ones_like(alpha[.

    rgb_map = torch.sum(weights[..., None] * rgb, dim=-2)

    return rgb_map

class TinyNeRF(torch.nn.Module):
    def __init__(self, pos_dim, fc_dim=128):
      r"""Initialize a tiny nerf network, which composed of linear lay
      ReLU activation. More specifically: linear - relu - linear - rel
      - relu -linear. The module is intentionally made small so that w
      achieve reasonable training time

      Args:
        pos_dim: dimension of the positional encoding output
        fc_dim: dimension of the fully connected layer
      """
      super().__init__()

      self.nerf = nn.Sequential(
                    nn.Linear(pos_dim, fc_dim),
                    nn.ReLU(),
                    nn.Linear(fc_dim, fc_dim),
                    nn.ReLU(),
                    nn.Linear(fc_dim, fc_dim),
                    nn.ReLU(),
                    nn.Linear(fc_dim, 4)
                  )

    def forward(self, x):
      r"""Output volume density and RGB color (4 dimensions), given a
      positional encoded points sampled from the rays
      """
```

```
        x = self.nerf(x)
        return x


def get_minibatches(inputs: torch.Tensor, chunksize: Optional[int] = 1
    r"""Takes a huge tensor (ray "bundle") and splits it into a list c
    Each element of the list (except possibly the last) has dimension
    `chunksize`.
    """
    return [inputs[i:i + chunksize] for i in range(0, inputs.shape[0],


def nerf_step_forward(height, width, focal_length, trans_matrix,
                            near_point, far_point, num_depth_samples_p
                            get_minibatches_function, model):
    r"""Perform one iteration of training, which take information of c
    training images, and try to predict its rgb values

    Args:
      height: height of the image
      width: width of the image
      focal_length: focal length of the camera
      trans_matrix: transformation matrix, which is also the camera pc
      near_point: threshhold of nearest point
      far_point: threshold of farthest point
      num_depth_samples_per_ray: number of sampled depth from each ray
      get_minibatches_function: function to cut the ray bundles into s
        to avoid out-of-memory issue

    Expected Returns:
      rgb_predicted: predicted rgb values of the training image
    """
    ################### YOUR CODE START ###################

    # Step 1: Generate rays
    # Assuming an implementation of `get_rays` function that returns r
    ray_origins, ray_directions = get_rays(height, width, focal_lengtł
    # print("ray_origins",ray_origins.shape)
    # print("ray_directions",ray_directions.shape)
    # print(f"ray_origins is stored on: {ray_origins.device}")
    # print(f"ray_directions is stored on: {ray_directions.device}")
```

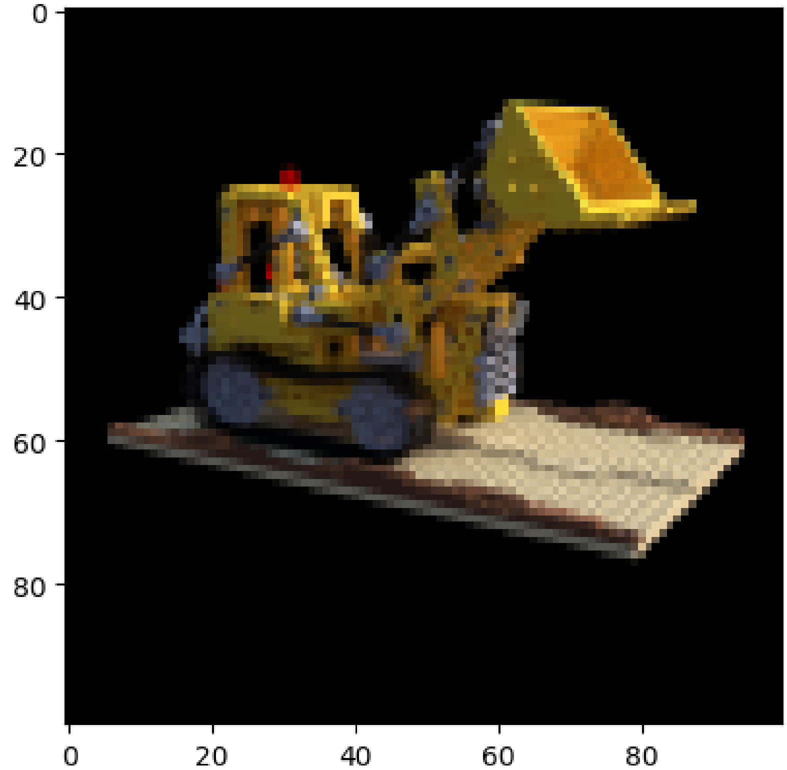
```
# Step 2: Sample points along each ray
# Assuming an implementation of `sample_points_from_rays` that ret
sampled_points, depth_values = sample_points_from_rays(ray_origins
# print("sampled_points",sampled_points.shape)
# print("depth_values",depth_values.shape)
# print(f"sampled_points is stored on: {sampled_points.device}")
# print(f"depth_values is stored on: {depth_values.device}")

# Step 3: Apply positional encoding
# Assuming `positional_encoding` expects a flattened list of point
flattened_sampled_points = sampled_points.reshape(-1, 3)  # Flatte
positional_encoded_points = positional_encoding(flattened_sampled_
# print("positional_encoded_points",positional_encoded_points.shap
# print(f"positional_encoded_points is stored on: {positional_enco


# Step 4: Run the model in batches
# Splitting the points into manageable chunks to avoid OOM
batches = get_minibatches_function(positional_encoded_points, chun
predictions = []
for batch in batches:
    #print(batch.shape)
    predictions.append(model(batch))

radiance_field_flattened = torch.cat(predictions, dim=0)

################### YOUR CODE START ###################

# Step 5: Volume rendering
# Reshape the radiance field to its unflattened shape
radiance_field = radiance_field_flattened.view(height, width, num_
#print(f"radiance_field is stored on: {radiance_field.device}")


# Assuming an implementation of `volume_rendering` that takes the
rgb_predicted = volume_rendering(radiance_field, ray_origins, dept
#print("rgb_predicted",rgb_predicted.shape)


return rgb_predicted
```

```
    return rgb_predicted



def train(images, poses, hwf, near_point,
          far_point, num_depth_samples_per_ray,
          num_iters, model, History,DEVICE="cuda"):
    r"""Training a tiny nerf model

    Args:
      images: all the images extracted from dataset (including train,
      poses: poses of the camera, which are used as transformation mat
      hwf: [height, width, focal_length]
      near_point: threshhold of nearest point
      far_point: threshold of farthest point
      num_depth_samples_per_ray: number of sampled depth from each ray
      num_iters: number of training iterations
      model: predefined tiny NeRF model
    """



    H, W, focal_length = hwf
    H = int(H)
    W = int(W)
    n_train = images.shape[0]
    print(H)

    # Optimizer parameters
    lr = 5e-3
    optimizer = torch.optim.Adam(model.parameters(), lr=lr)

    # Seed RNG, for repeatability
    seed = 9458
    torch.manual_seed(seed)
    np.random.seed(seed)



    for _ in tqdm(range(num_iters)):
      # Randomly pick a training image as the target, get rgb value ar
      train_idx = np.random.randint(n_train)
      train_img_rgb = images[train_idx, ..., :3]
```

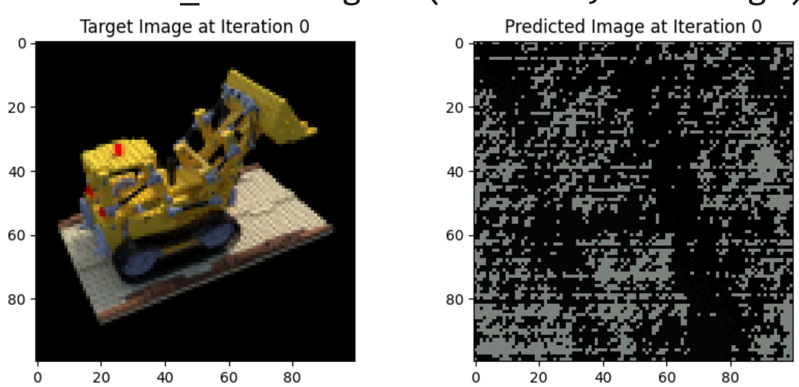
```
    train_pose = poses[train_idx]

    # Run one iteration of TinyNeRF and get the rendered RGB image.
    rgb_predicted = nerf_step_forward(H, W, focal_length,
                                        train_pose, near_point,
                                        far_point, num_depth_sam
                                        get_minibatches, model)



    train_img_rgb_tensor = torch.from_numpy(train_img_rgb)
    train_img_rgb= train_img_rgb_tensor.to(DEVICE).to(dtype=torch.fl


    # Compute mean-squared error between the predicted and target im
    loss = torch.nn.functional.mse_loss(rgb_predicted, train_img_rgb
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
    History.append(loss.cpu().detach().numpy())


    if _ % 200 == 0:
          with torch.no_grad():
              plt.figure(figsize=(10, 4))

              plt.subplot(121)
              plt.imshow(train_img_rgb_tensor.cpu().numpy())
              plt.title(f"Target Image at Iteration {_}")

              plt.subplot(122)
              plt.imshow(rgb_predicted.detach().cpu().numpy())
              plt.title(f"Predicted Image at Iteration {_}")

              plt.show()

              print('Loss at '+str(_)+" iterations: ",loss.cpu().det

  print('Finish training')
```

```
if __name__ == "__main__":
   images, poses, hwf=load_colmap_data()
   #print(type(images[0,:,:,:]))


   #images = data["images"]
   #im_shape = images.shape
   #(num_images, H, W, _) = images.shape
   poses= np.array(data["poses"])
   print (H)
   hwf = np.array([H, W, focal])

   # If plotting or processing images, ensure conversion is safe
   plt.imshow(images[np.random.randint(low=0, high=num_images)])
   plt.show()



   device = torch.device('cuda' if torch.cuda.is_available() else 'cp
   #device = 'cpu' #Due to OOM
   near_point=2.
   far_point=6.
   num_depth_samples_per_ray = 96
   num_iters = 2000
   model = TinyNeRF(69)
   model.to(device)

   History=[]
   train(images, poses, hwf, near_point,
             far_point, num_depth_samples_per_ray,
             num_iters, model, History,DEVICE=device)
```

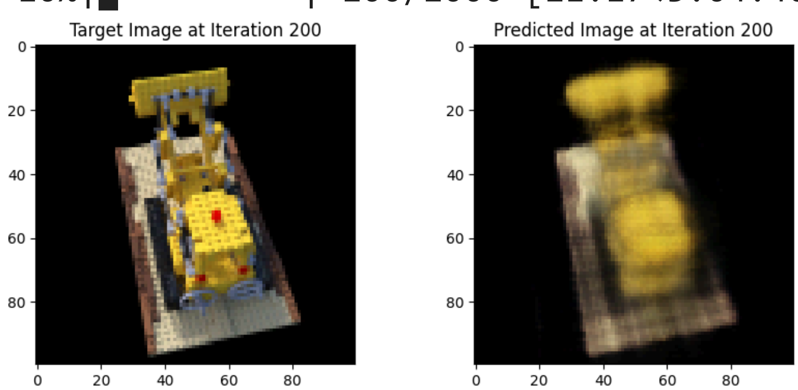
```
100
```



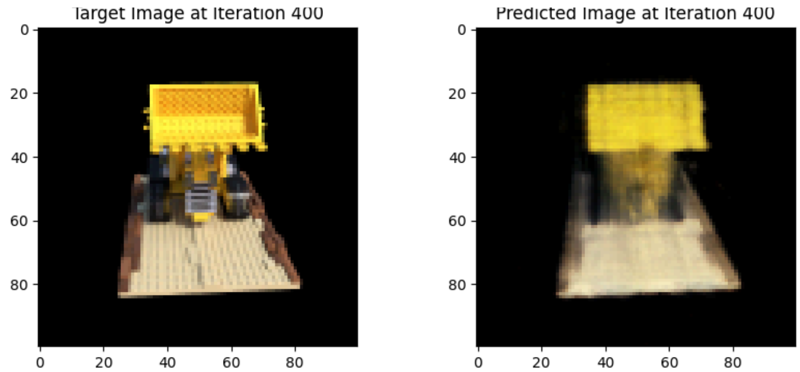
```
100
  0%|          | 0/2000 [00:00<?, ?it/s]
  return _VF.meshgrid(tensors, **kwargs)
```



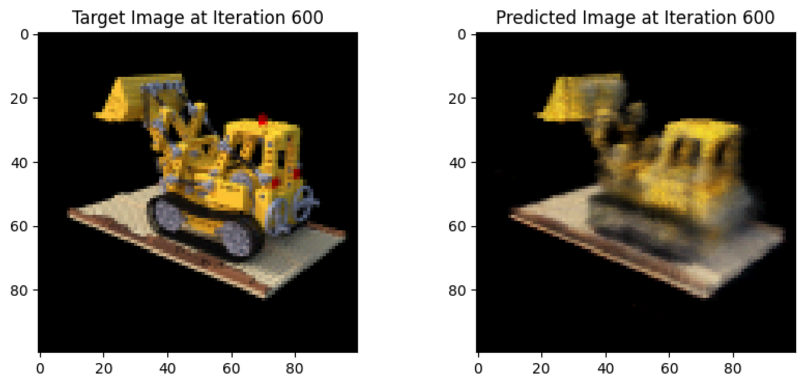

```
  0%|          | 1/2000 [00:08<4:49:22,
 10%|█         | 200/2000 [21:17<3:04:40
```



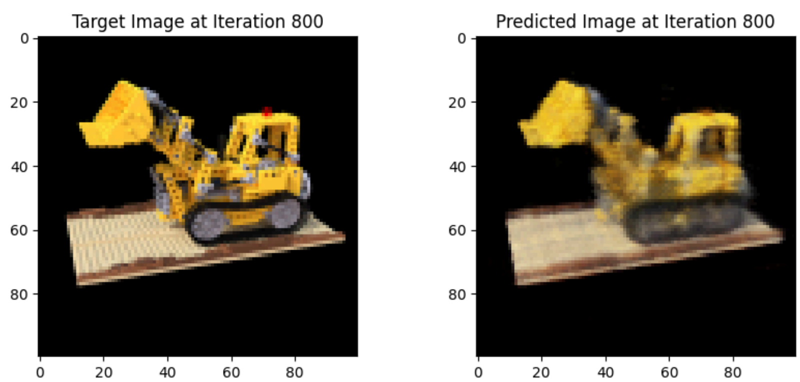

```
 10%|█         | 201/2000 [21:24<3:12:59
 20%|██        | 400/2000 [42:24<3:01:35
```



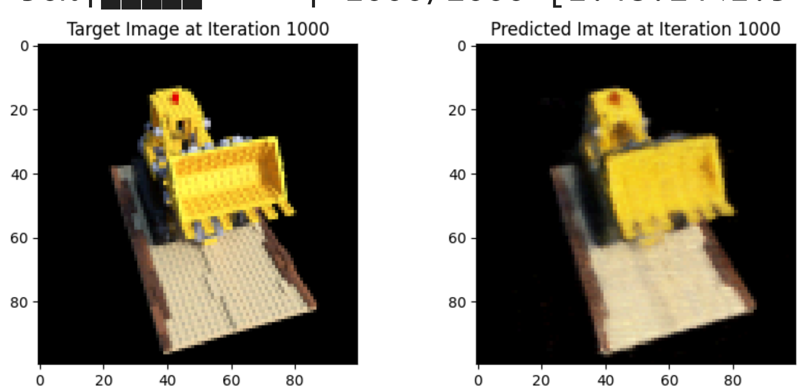

```
20%|██          | 401/2000 [42:30<2:58:43
30%|███         | 600/2000 [1:04:52<2:41:
```



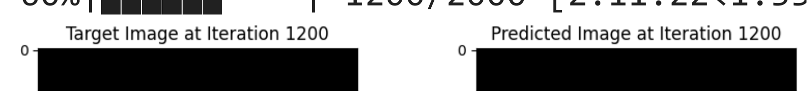

```
30%|███         | 601/2000 [1:04:59<2:41:
40%|████        | 800/2000 [1:26:38<2:07:
```

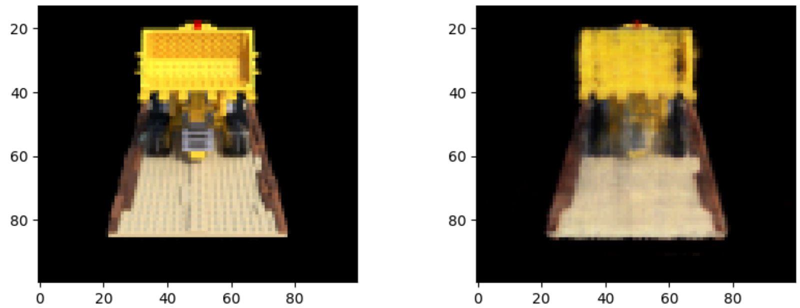



```
40%|████        | 801/2000 [1:26:44<2:06:
50%|█████       | 1000/2000 [1:48:24<1:54
```

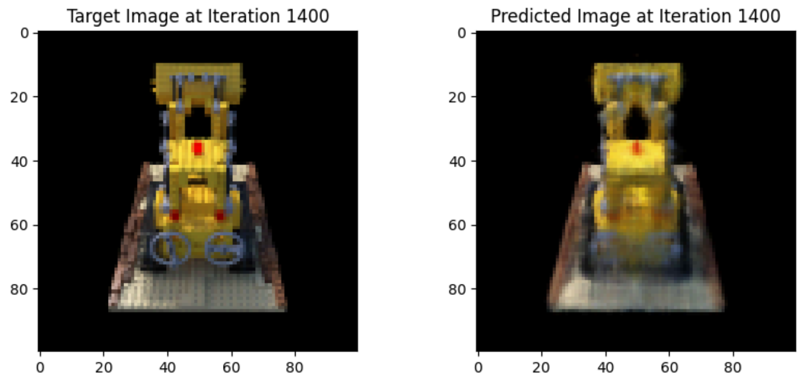



```
50%|█████       | 1001/2000 [1:48:31<1:53
60%|██████      | 1200/2000 [2:11:22<1:33
```

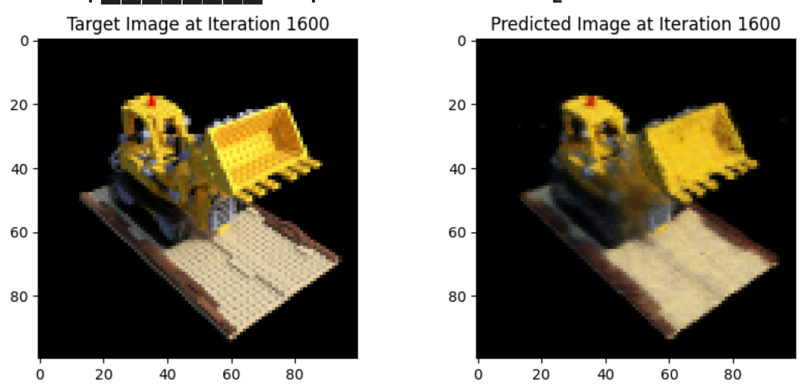




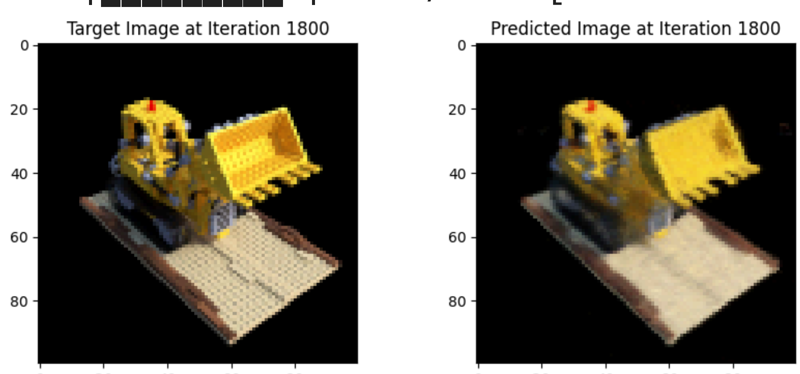

```
 60%|██████    | 1201/2000 [2:11:30<1:34
 70%|███████   | 1400/2000 [2:33:17<1:07
```




```
 70%|███████   | 1401/2000 [2:33:24<1:07
 80%|████████  | 1600/2000 [2:55:18<44:0
```




```
 80%|████████  | 1601/2000 [2:55:24<43:0
 90%|█████████ | 1800/2000 [3:17:38<22:1
```




```
 90%|█████████ | 1801/2000 [3:17:44<21:3
100%|██████████| 2000/2000 [3:40:06<00:0
```

```
plt.plot(History)
```

```
plt.plot(history)
plt.grid()
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("ESE 650 Zhanqian Nerf Training Process")
plt.show()
```