Table of contents

Imports

In [1]:

```
import cv2
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import torch.nn as nn
import torch
import torchvision
import einops
import random
import wandb

from torch import Tensor
from matplotlib import cm
from icecream import ic
from typing import Union, List, Tuple, Literal
```

```python
from tqdm.auto import tqdm, trange
from IPython.display import display, Markdown
from sklearn.model_selection import train_test_split
from torch.utils.data import DataLoader, TensorDataset, Dataset
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix, Conf
from skimage.feature import hog
from skimage import exposure
```

In [ ]:
```python
device = torch.device("cuda" if torch.cuda.is_available() else "mps" if torch.backends.mps.is_available() e
print(f"using {device.type}")
```

```
using mps
```

Loading the model

In [3]:
```python
TRAIN_DATA_PATH = 'data/network visualization'
MODEL_WEIGHTS = 'network_visualization.pth'
MEAN = np.array([0.485, 0.456, 0.406])
STD = np.array([0.229, 0.224, 0.225])
CLASSES = [
    "arctic fox", "corgi", "electric ray", "goldfish", "hammerhead shark", "horse", "hummingbird", "indigo
]
```

In [ ]:
```python
model = torchvision.models.resnet18()
model.fc = nn.Linear(in_features=512, out_features=10, bias=True)
model.load_state_dict(torch.load("./network_visualization.pth", map_location=device))
model.to(device)
```

Out[ ]:
```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
```

```
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
```

```
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=512, out_features=10, bias=True)
)
```

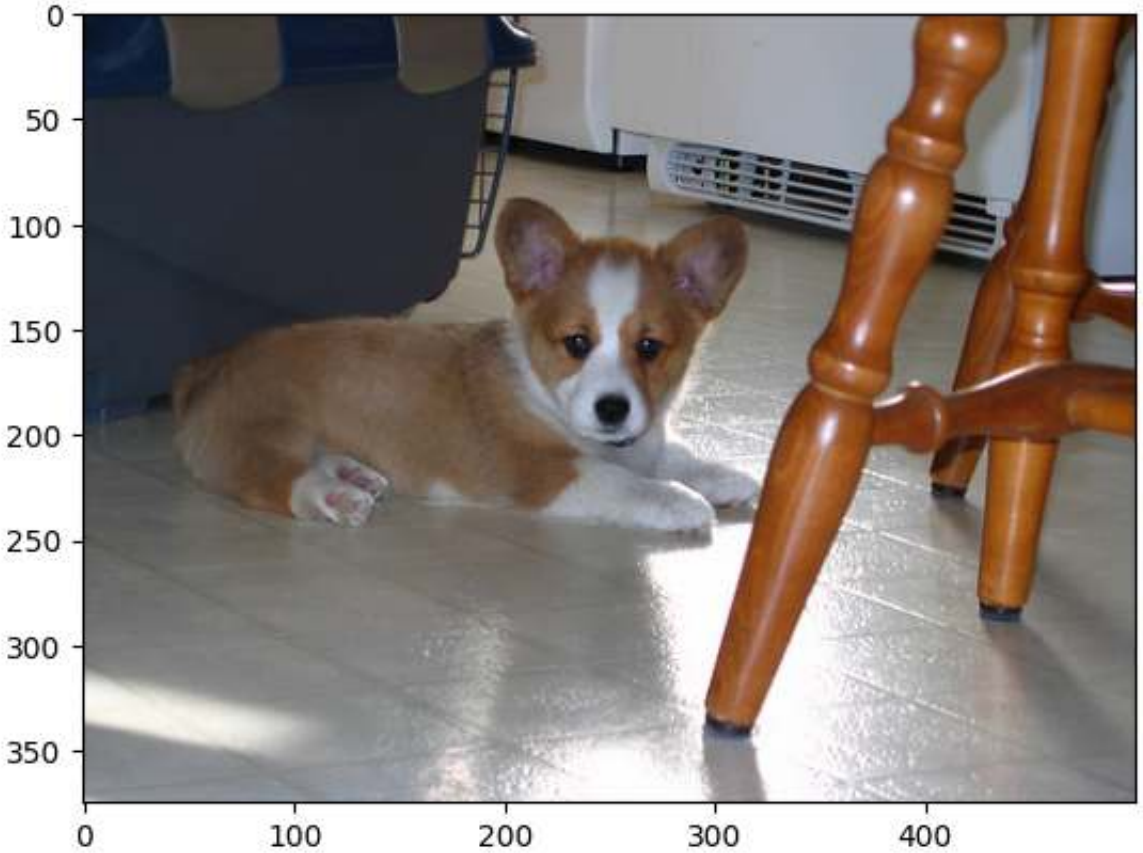
Saliency Maps [15 marks]

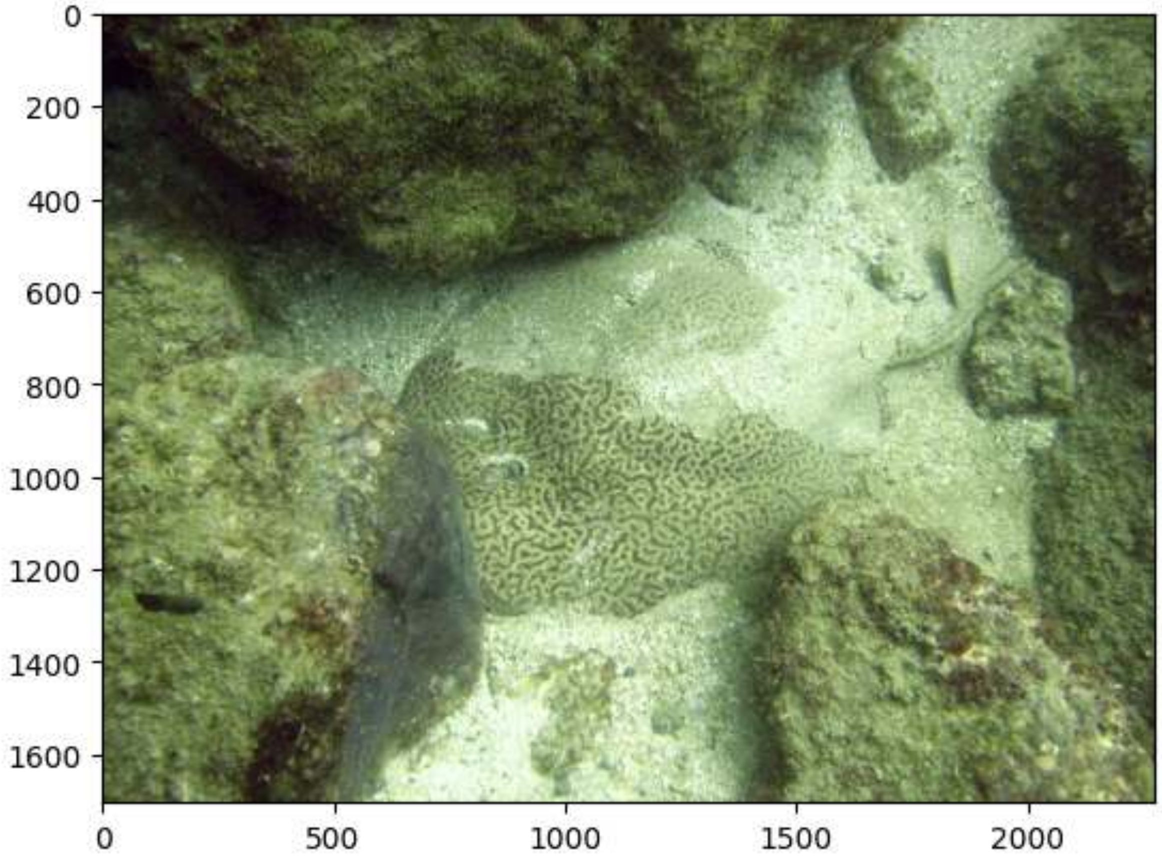
Constructing the dataset

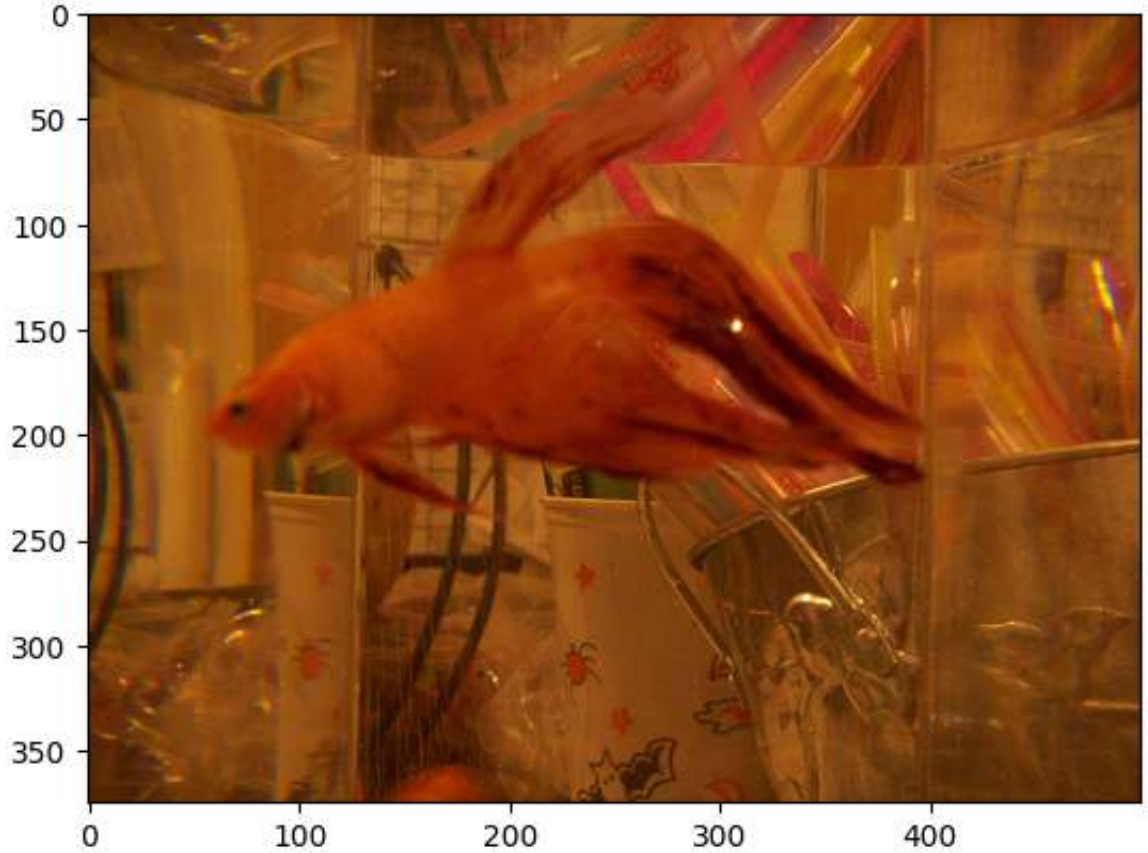
In [5]:
```
img_indices = [random.randint(1, 5) for _ in range(len(CLASSES))]
img_paths = [f"./data/network visualization/{CLASSES[idx]}/{CLASSES[idx]}_{img_num}.JPEG" for idx, img_num
```

In [6]:
```
def visualize_raw_images(img_paths: list):
    for img_path in img_paths:
        plt.imshow(cv2.cvtColor(cv2.imread(img_path), cv2.COLOR_BGR2RGB))
        plt.show()

visualize_raw_images(img_paths)
```

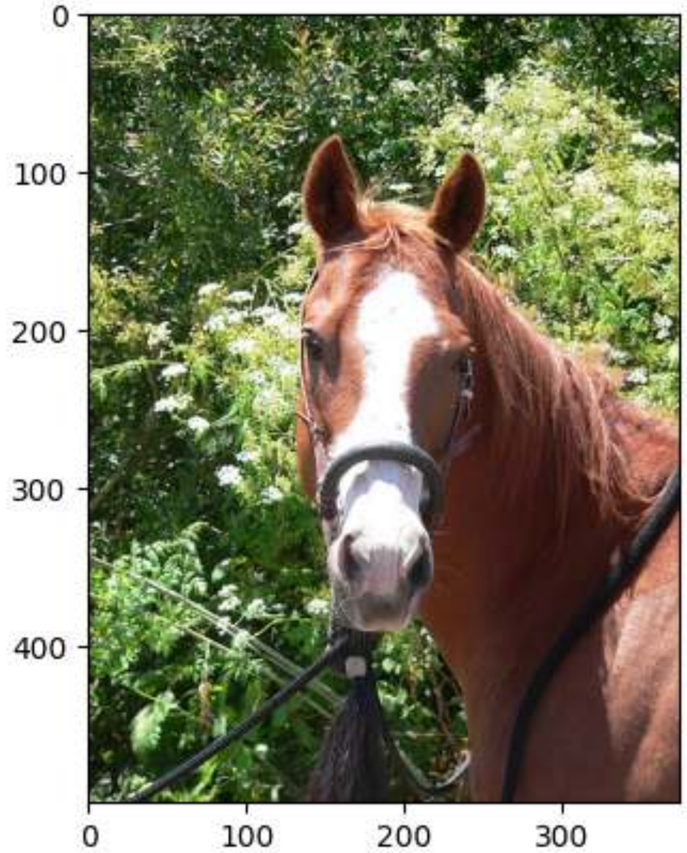

0
50
100
150
200
250
300
0
100
200
300
400


0
50
100
150
200
250
300
350
0
100
200
300
400

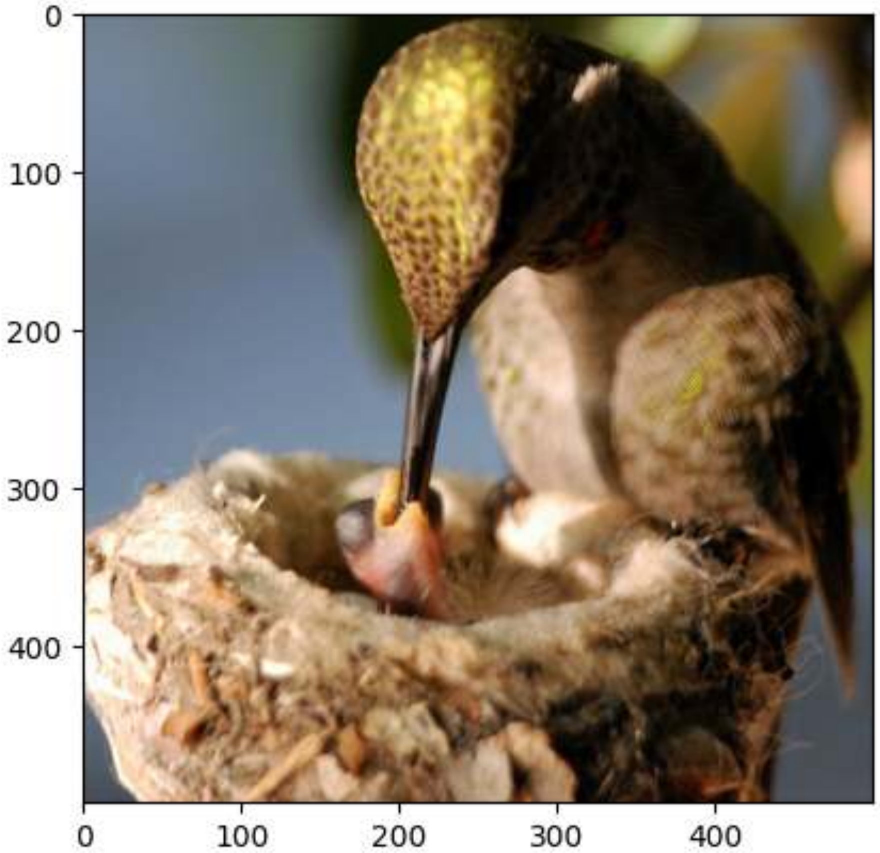

0
200
400
600
800
1000
1200
1400
1600
0
500
1000
1500
2000

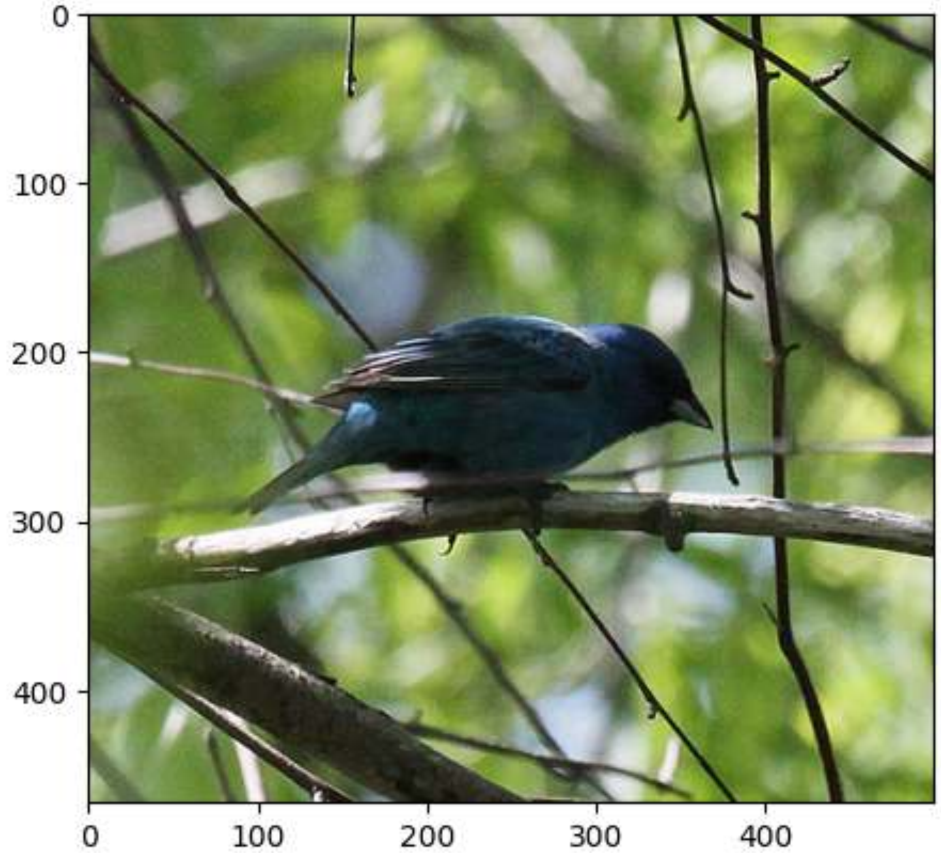

0
50
100
150
200
250
300
350
0
100
200
300
400


0
50
100
150
200
250
300
350
0
100
200
300
400

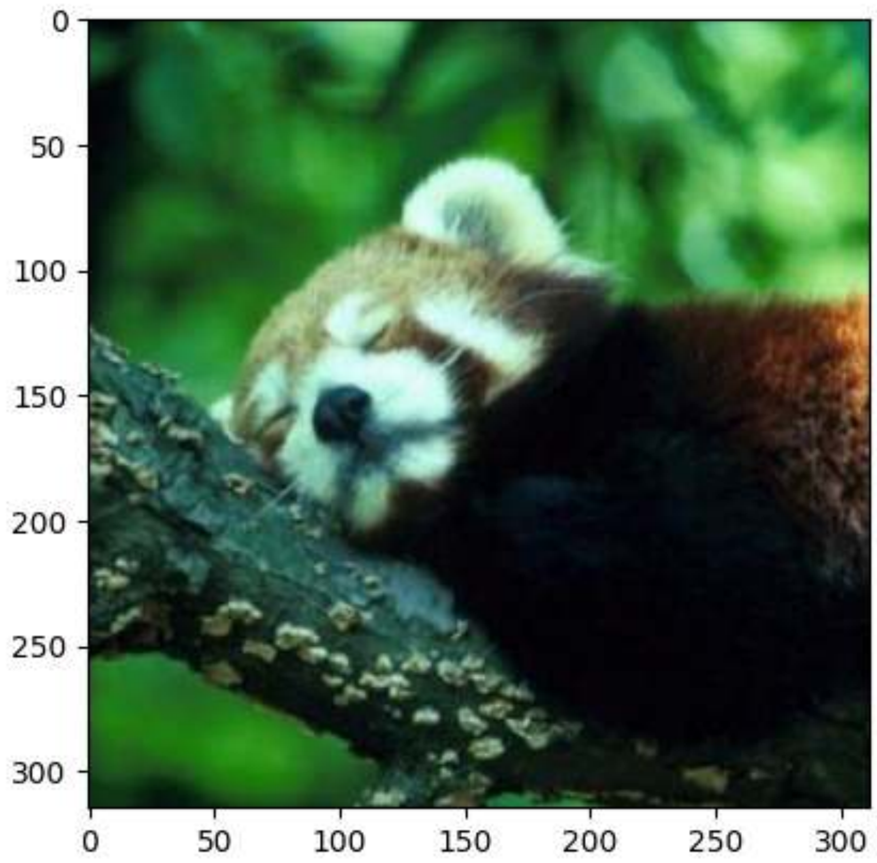


0
100
200
300
400
0
100
200
300


0
100
200
300
400
0
100
200
300
400


0
100
200
300
400
0
100
200
300
400


0
50
100
150
200
250
300
350
0
100
200
300
400



In [7]:
```
class CuteDataset(Dataset):
    def __init__(self, img_paths: list, labels: list, transform=None):
        super().__init__()
        self.data = [cv2.cvtColor(cv2.imread(img_path), cv2.COLOR_BGR2RGB) for img_path in img_paths]
        self.labels = labels
        self.transform = transform

    def __len__(self):
        return len(self.data)

    def __getitem__(self, idx):
        sample = self.data[idx]
```

```python
        label = self.labels[idx]
        if self.transform:
            sample = self.transform(sample)
        return sample, label
```

In [8]:
```python
def preprocess_data(img_paths: list, labels: list, mean: list=MEAN, std: list=STD):
    transformations = torchvision.transforms.Compose([
        torchvision.transforms.ToPILImage(),
        torchvision.transforms.Resize((224, 224)),
        torchvision.transforms.ToTensor(),
        torchvision.transforms.Normalize(mean=mean, std=std),
    ])
    dataset = CuteDataset(img_paths, labels, transformations)
    return dataset
```

In [9]:
```python
cute_dataset = preprocess_data(img_paths, [i for i in range(len(CLASSES))], MEAN, STD)
```

In [ ]:
```python
len(cute_dataset)
```

Out[ ]: 10

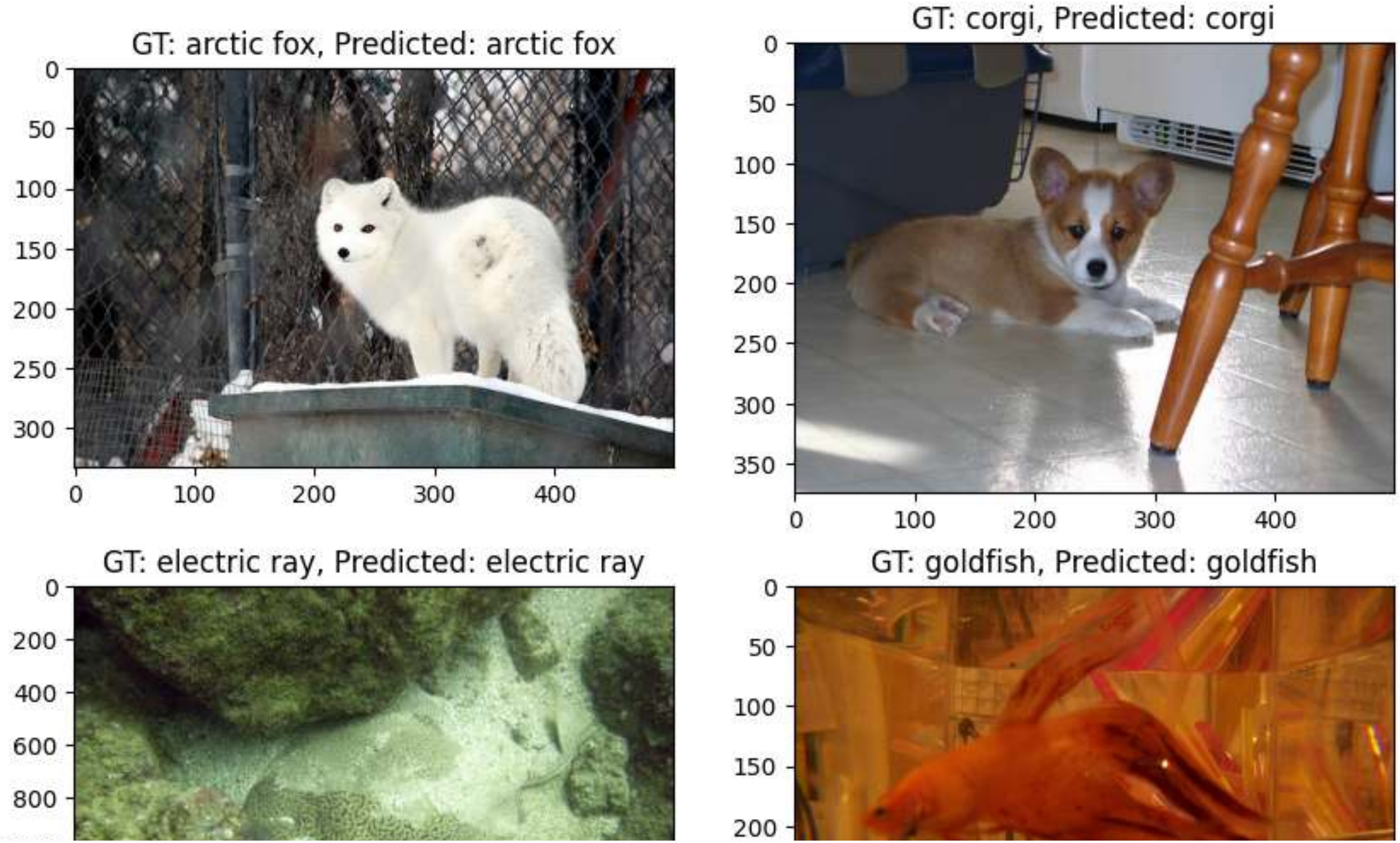
Visualizing model outputs

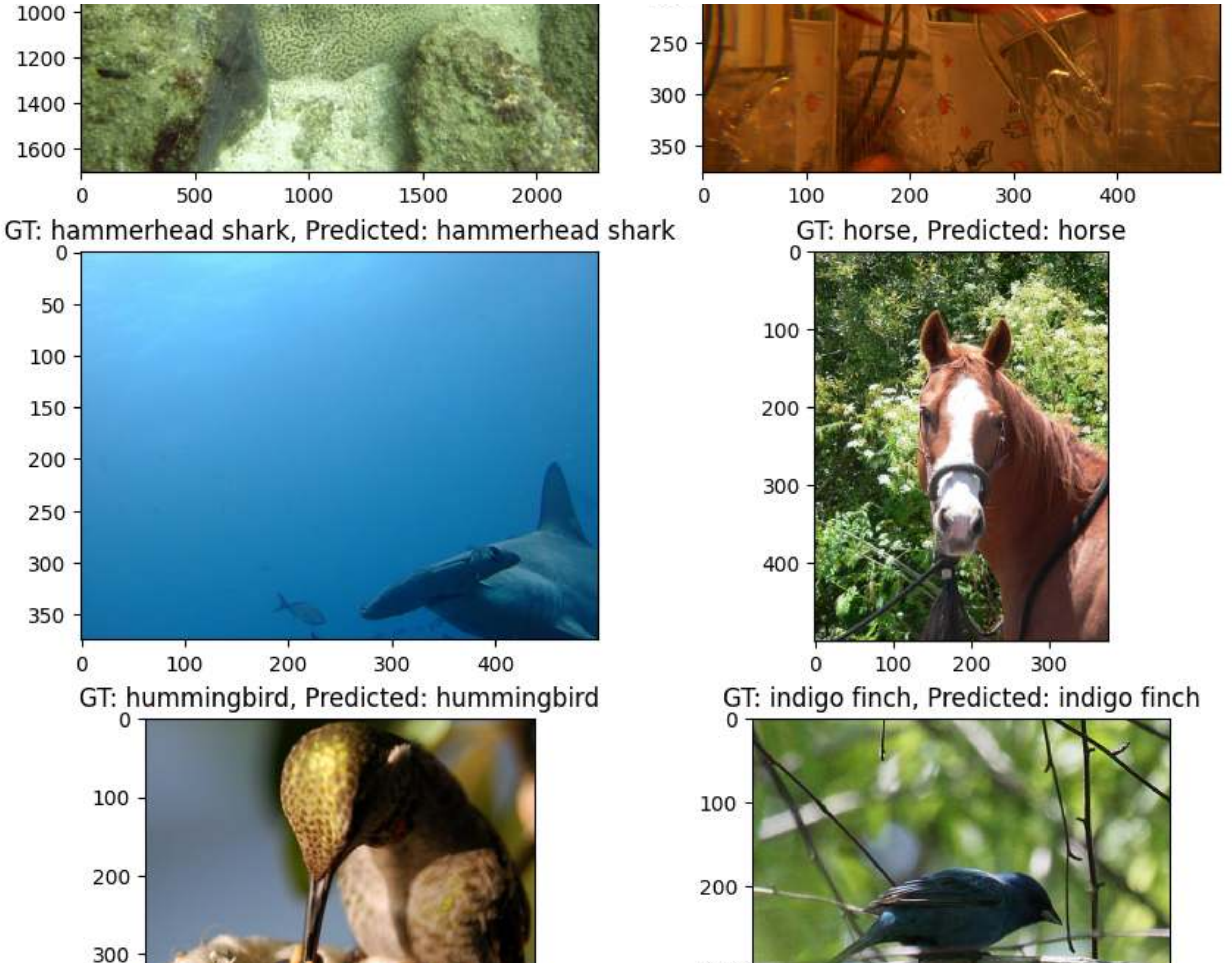
In [11]:
```python
def visualize_model_outputs(dataset: Dataset, model: nn.Module) -> None:
    nsamples = len(dataset)
    nrows = nsamples // 2
    if nsamples % 2:
        nrows += 1
    fig, axs = plt.subplots(nrows, 2, figsize=(10, 20))
    axs = axs.flatten()

    dataloader = DataLoader(cute_dataset, batch_size=1, shuffle=False)
    model.eval()
    with torch.no_grad():
        for idx, (img, label) in enumerate(dataloader):
```

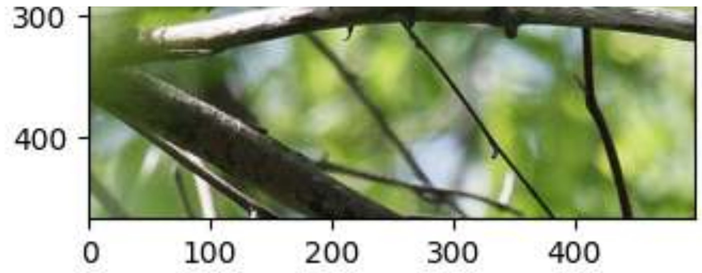
```
            img = img.to(device)
            preds = model(img)
            predicted_class = nn.Softmax(1)(preds).argmax()

            axs[idx].imshow(cv2.cvtColor(cv2.imread(img_paths[idx]), cv2.COLOR_BGR2RGB))
            axs[idx].set_title(f"GT: {CLASSES[label]}, Predicted: {CLASSES[predicted_class]}")
```

In [ ]:

```
visualize_model_outputs(cute_dataset, model)
```

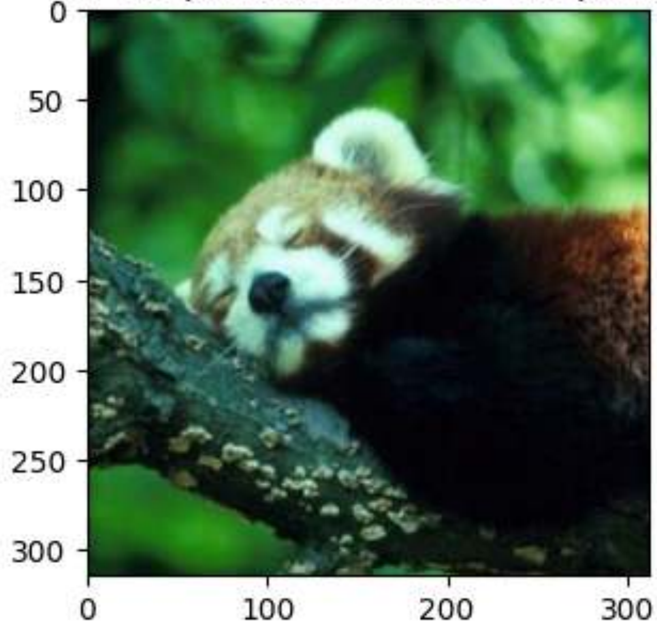



GT: hammerhead shark, Predicted: hammerhead shark
GT: horse, Predicted: horse
GT: hummingbird, Predicted: hummingbird
GT: indigo finch, Predicted: indigo finch



GT: puma, Predicted: puma

GT: red panda, Predicted: red panda



Function to calculate saliency maps

In [ ]:

```
def saliency_map(img: Tensor, label: int, model: nn.Module):
    model.eval()
    img = img.to(device)
    img = einops.rearrange(img, 'h c w -> 1 h c w')
    img.requires_grad_(True)
    criterion = nn.CrossEntropyLoss()
    logits = model(img)
```

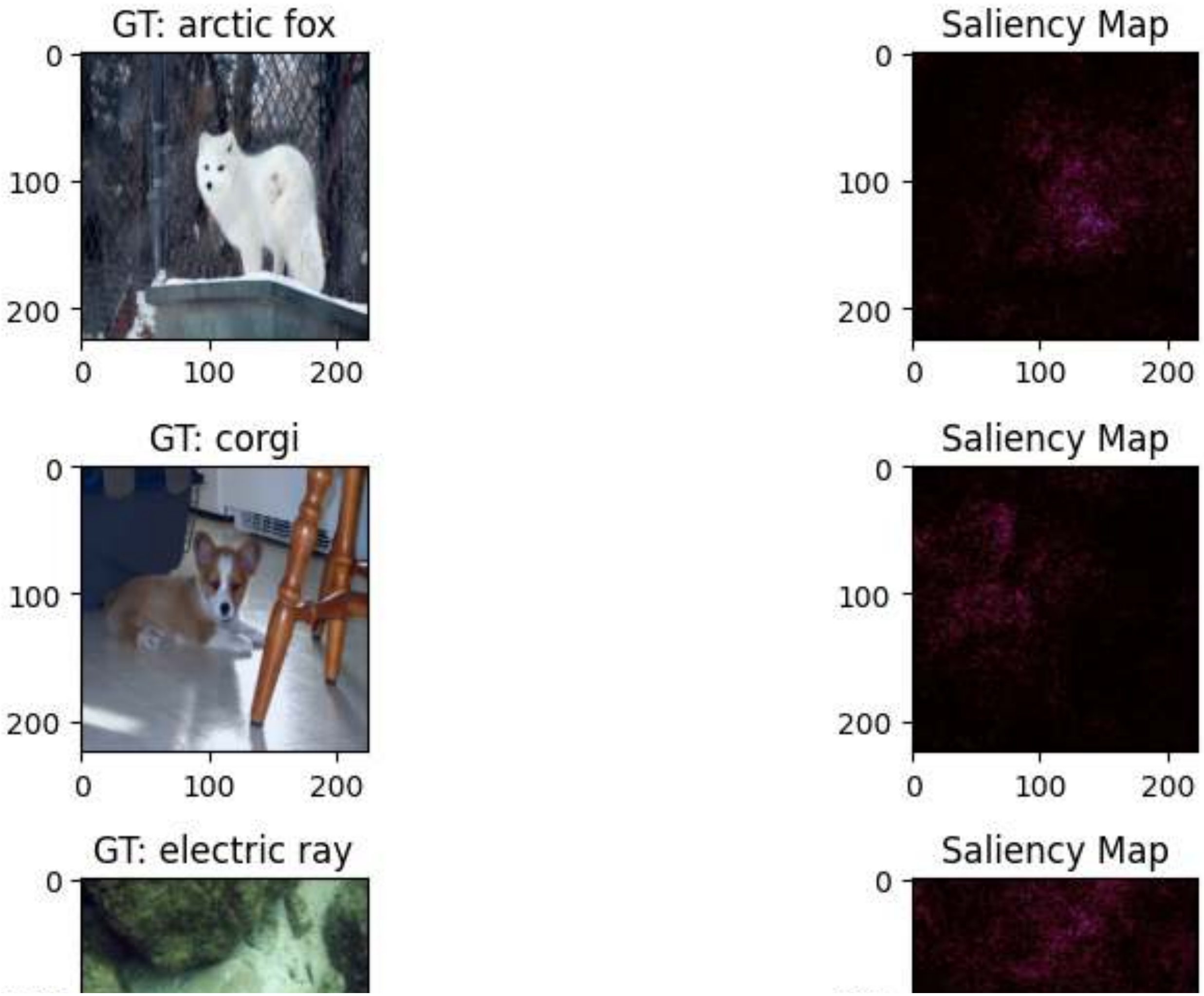
```
    model.zero_grad()
    loss = criterion(logits, torch.tensor([label]).to(device))
    loss.backward()
    saliency = img.grad.abs()
    saliency = einops.rearrange(saliency, '1 c h w -> h w c')
    return saliency
```

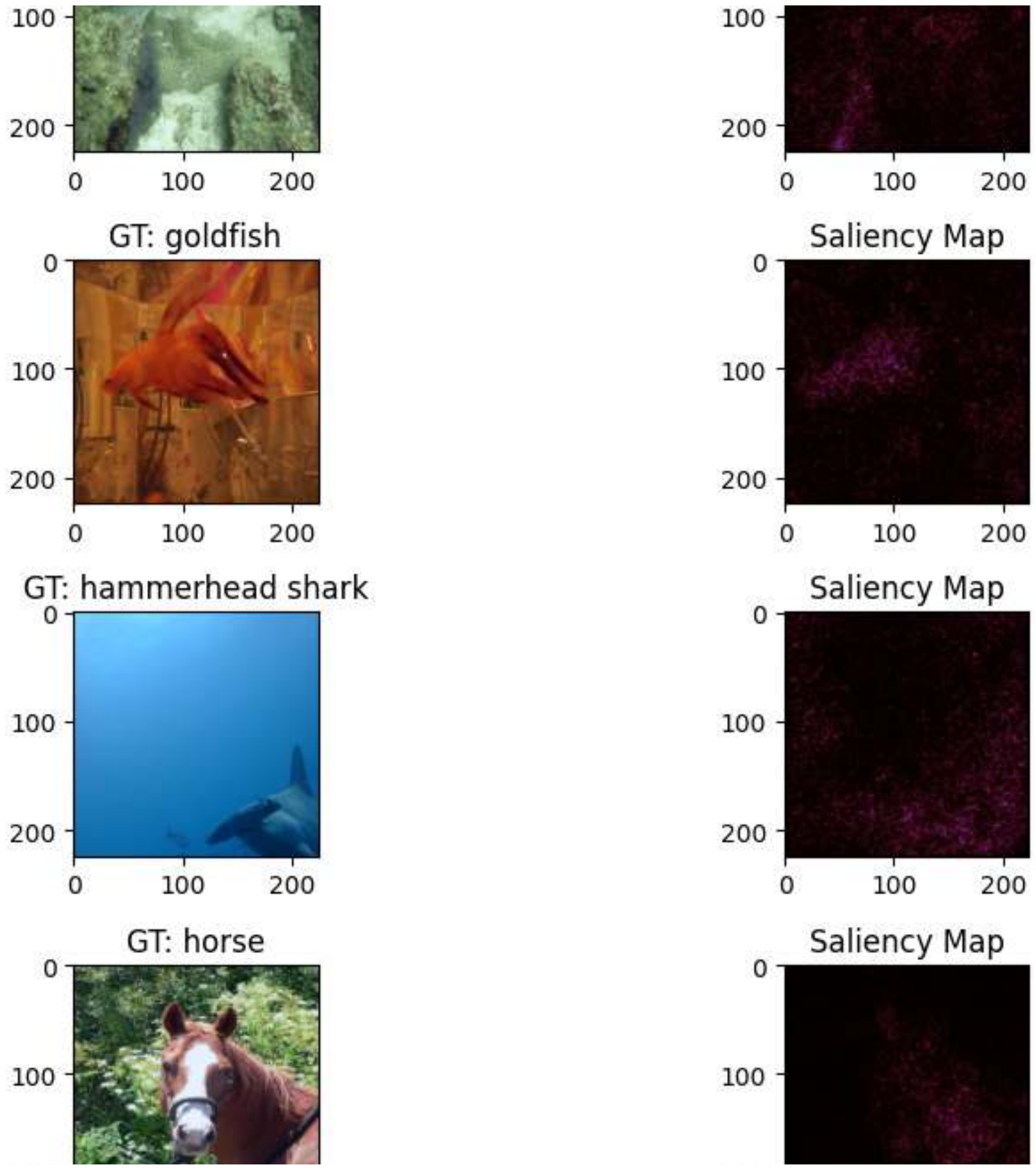
Visualizing saliency maps for the subset

In [14]:
```
def visualize_saliency_maps(model, dataset):
    nsamples = len(dataset)

    fig, axs = plt.subplots(nsamples, 2, figsize=(10, 20))
    axs = axs.flatten()

    dataloader = DataLoader(dataset, batch_size=1, shuffle=False)
    idx = 0
    saliency_maps = []

    for (img, label) in dataloader:
        img = einops.rearrange(img, '1 c h w -> c h w') # saliency map function doesnt expect batch size

        saliency = saliency_map(img, label, model)
        saliency_maps.append(saliency)
        saliency = (saliency - saliency.min()) / (saliency.max() - saliency.min()) * 255
        saliency = saliency.cpu().numpy().astype(np.uint8)
        saliency = cv2.applyColorMap(saliency, cv2.COLORMAP_INFERNO)

        img = einops.rearrange(img, 'c h w -> h w c')
        img = (img - img.min()) / (img.max() - img.min()) * 255
        img = img.cpu().numpy().astype(np.uint8)

        axs[idx].imshow(img)
        axs[idx].set_title(f"GT: {CLASSES[label.item()]}")
        idx += 1
        axs[idx].imshow(saliency)
```

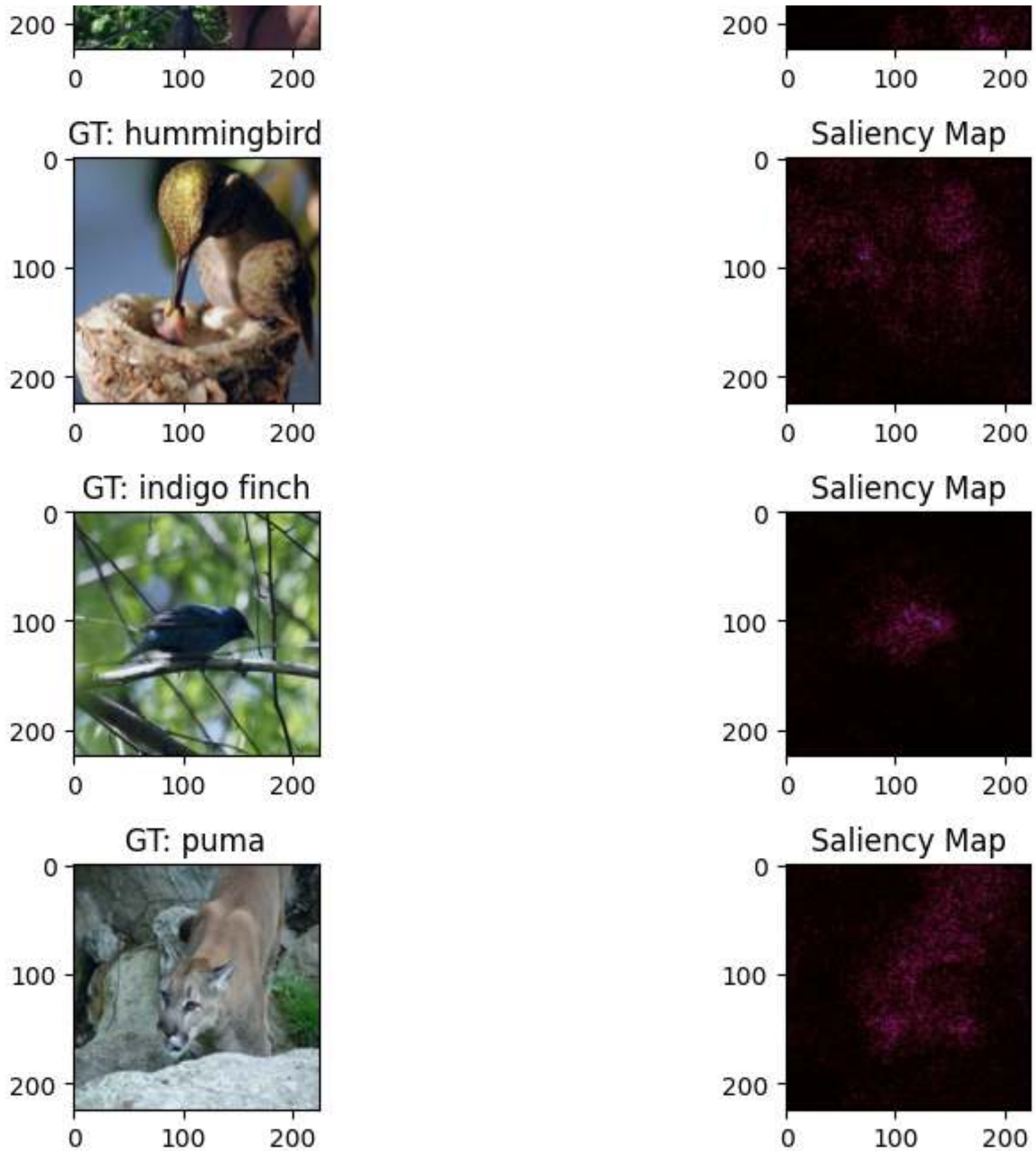
```
        axs[idx].set_title("Saliency Map")
        idx += 1

    plt.tight_layout()
    plt.show()

    return saliency_maps
```

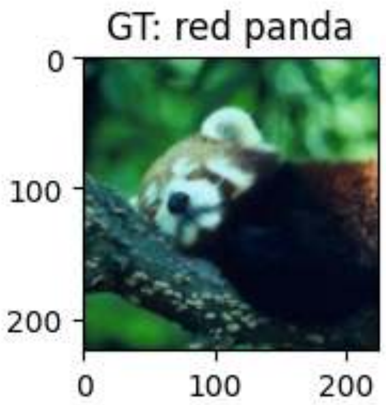
In [ ]:
```
saliency_maps = visualize_saliency_maps(model, cute_dataset)
```

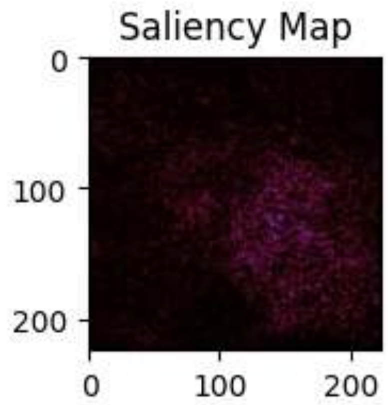




GT: goldfish
Saliency Map
GT: hammerhead shark
Saliency Map
GT: horse
Saliency Map


GT: hummingbird
Saliency Map
GT: indigo finch
Saliency Map
GT: puma
Saliency Map
0
100
200





Masking image using saliency maps

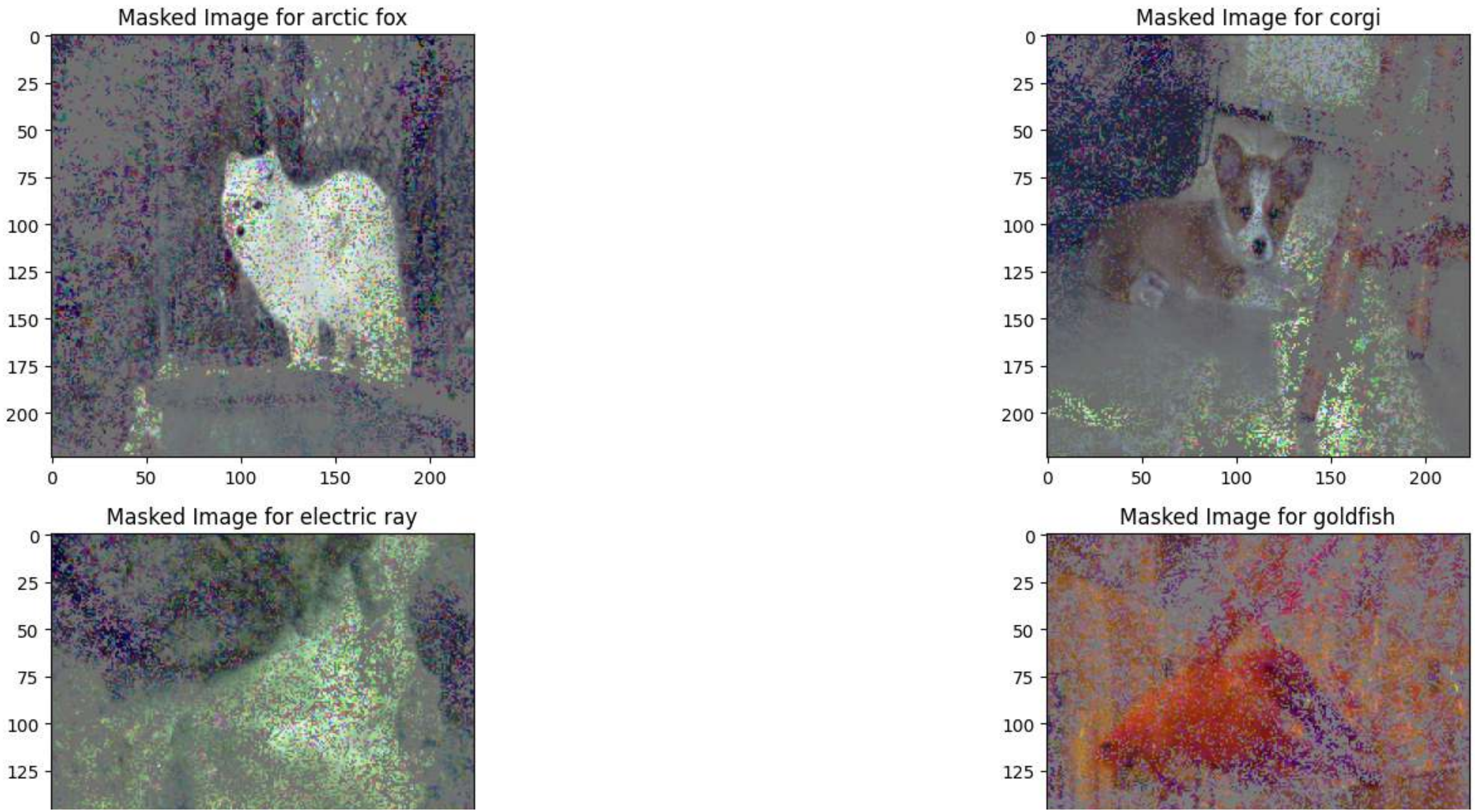
with zero

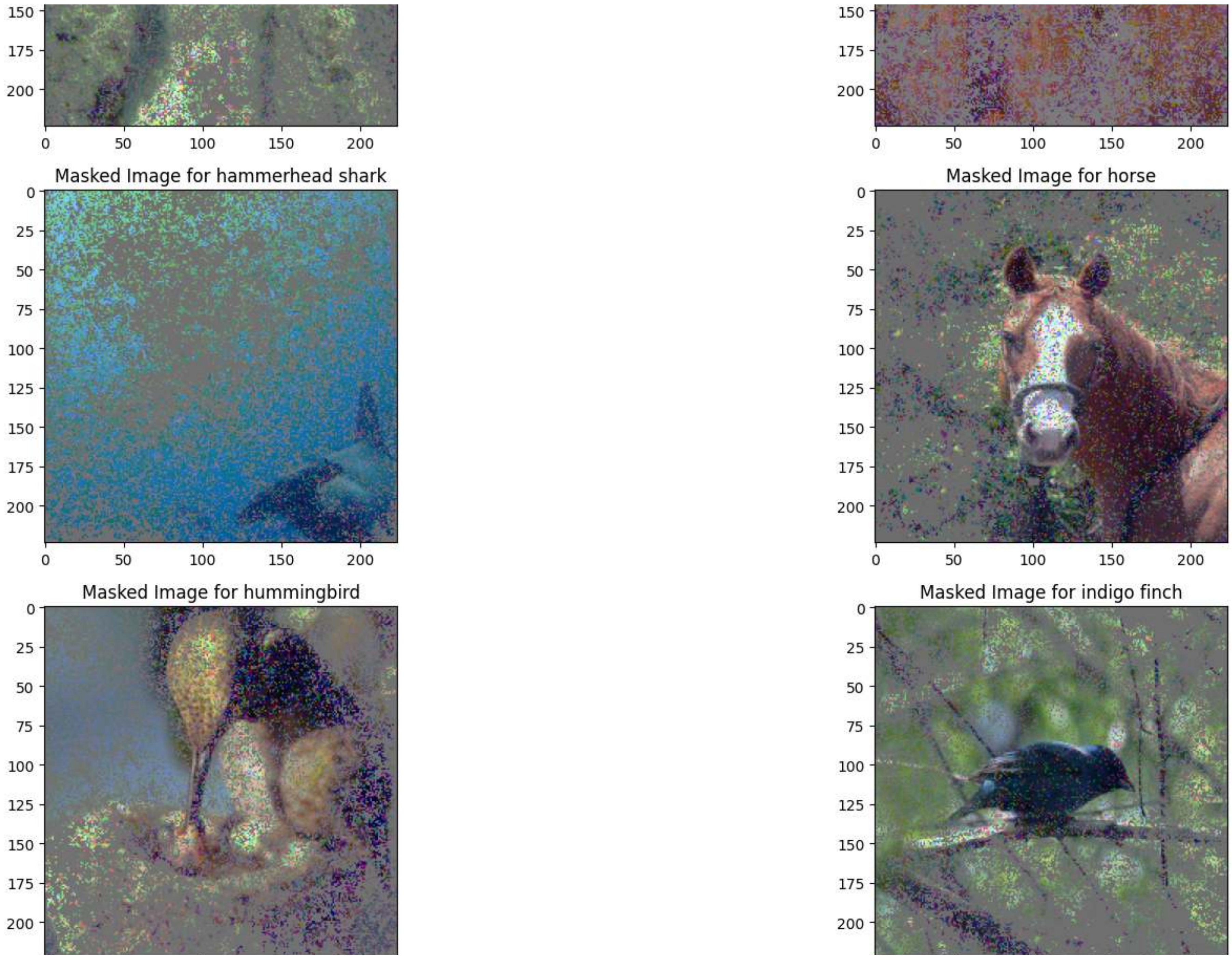
In [16]:
```
def mask_images_constant(saliency_maps: list[Tensor], dataset: Dataset):
    masked_images = []

    for idx, saliency_map in enumerate(saliency_maps):
        flattened = saliency_map.flatten().cpu().numpy()

        q3_threshold = np.percentile(flattened, 60)
        masked_img = torch.where(saliency_map >= q3_threshold, dataset[idx][0].permute(1, 2, 0).to(device),
        masked_images.append(masked_img)

    return masked_images
```

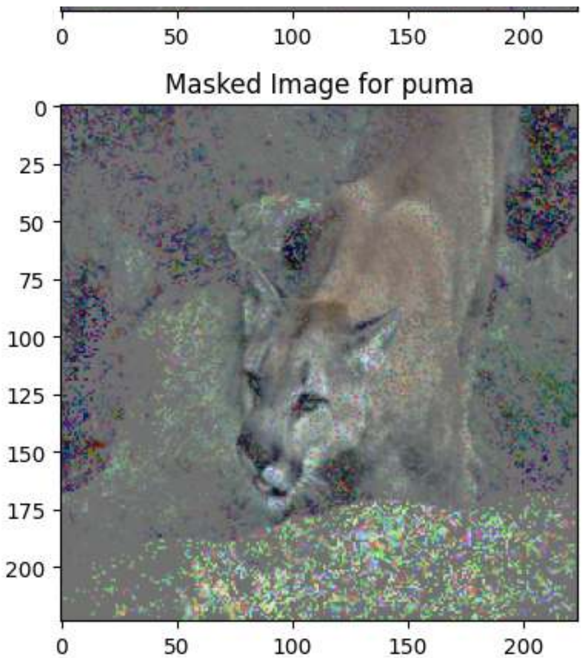
In [17]:
```
def plot_masked_images(saliency_maps):
    fig, axs = plt.subplots(len(saliency_maps) // 2, 2, figsize=(20, 20))
    axs = axs.flatten()

    for idx, masked_img in enumerate(saliency_maps):
        masked_img = (masked_img - masked_img.min()) / (masked_img.max() - masked_img.min()) * 255
```

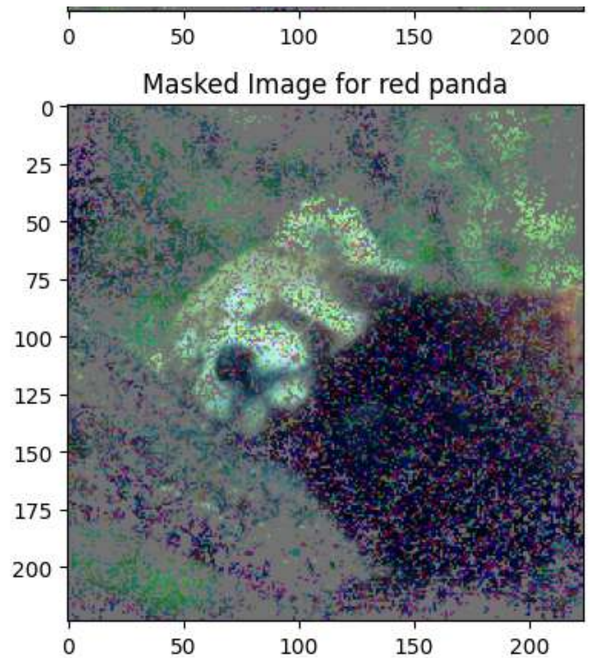
```
        masked_img = masked_img.cpu().numpy().astype(np.uint8)
        axs[idx].imshow(masked_img)
        axs[idx].set_title(f"Masked Image for {CLASSES[idx]}")

    plt.tight_layout()
    plt.show()
```

In [18]:
```
masked_images_const = mask_images_constant(saliency_maps, cute_dataset)

plot_masked_images(masked_images_const)
```




Masked Image for hammerhead shark
Masked Image for horse
Masked Image for hummingbird
Masked Image for indigo finch





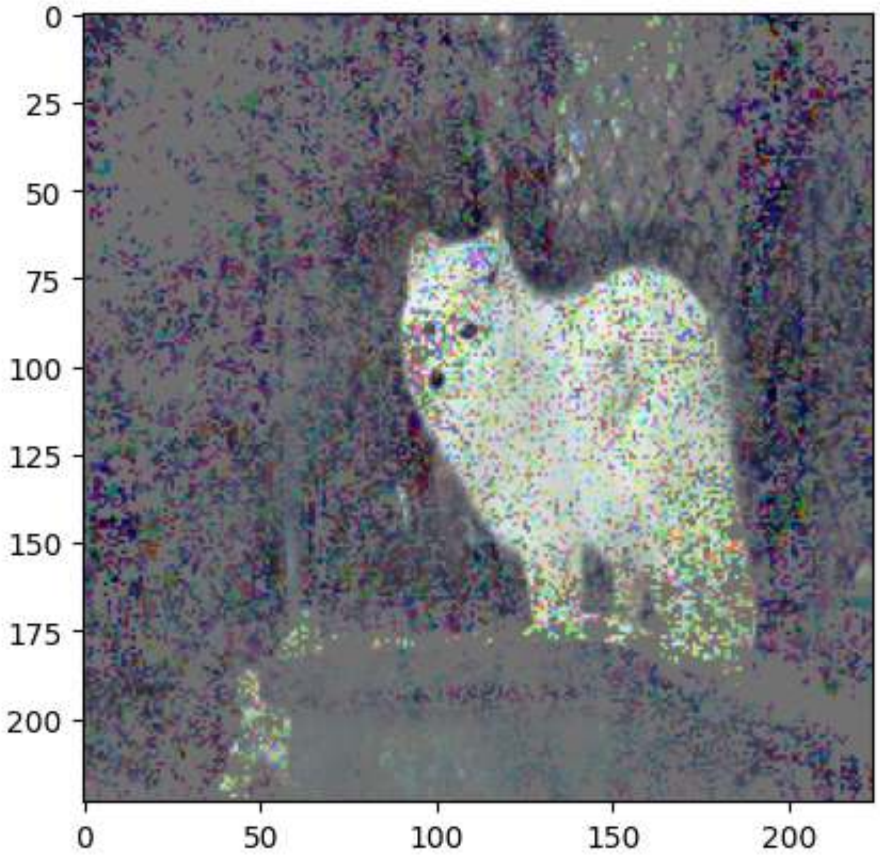
In [19]:

```
def predict_with_masked_imgs(model, masked_imgs):
    model.eval()
    transformations = torchvision.transforms.Compose([
        torchvision.transforms.ToPILImage(),
        torchvision.transforms.Resize((224, 224)),
        torchvision.transforms.ToTensor(),
        torchvision.transforms.Normalize(mean=MEAN, std=STD),
    ])

    with torch.no_grad():
        for idx, masked_img in enumerate(masked_imgs):
            masked_img = einops.rearrange(masked_img, 'h w c -> c h w')
            preds = model(transformations(masked_img).to(device).unsqueeze(0))
            predicted_class = nn.Softmax(1)(preds).argmax()
            print(f"Predicted class: {CLASSES[predicted_class]}, GT: {CLASSES[idx]}")
            masked_img = einops.rearrange(masked_img, 'c h w -> h w c')
            masked_img = (masked_img - masked_img.min()) / (masked_img.max() - masked_img.min()) * 255
            masked_img = masked_img.cpu().numpy().astype(np.uint8)
```

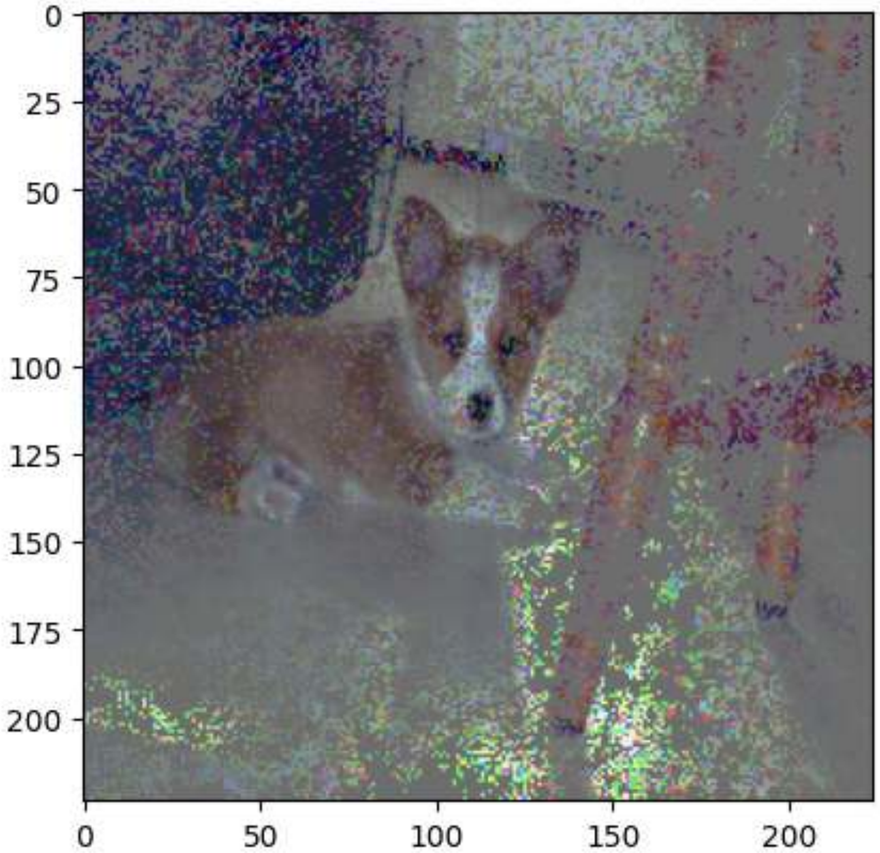
```
            plt.imshow(masked_img)
            plt.show()
```

In [ ]:
```
predict_with_masked_imgs(model, masked_images_const)
```

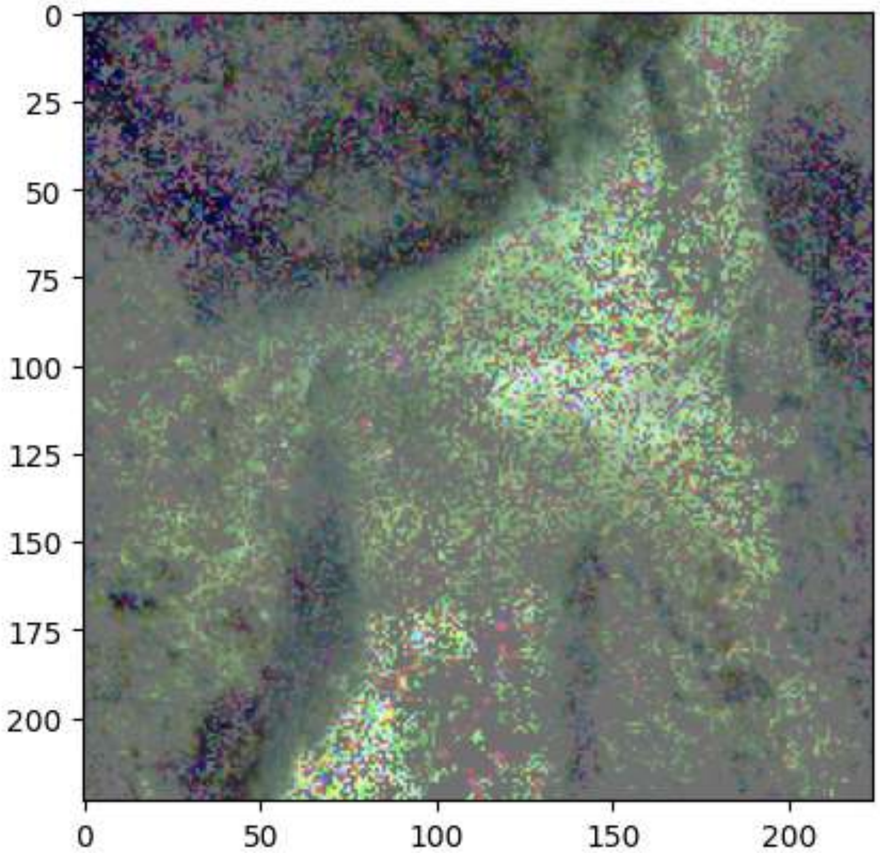
```
Predicted class: hammerhead shark, GT: arctic fox
```



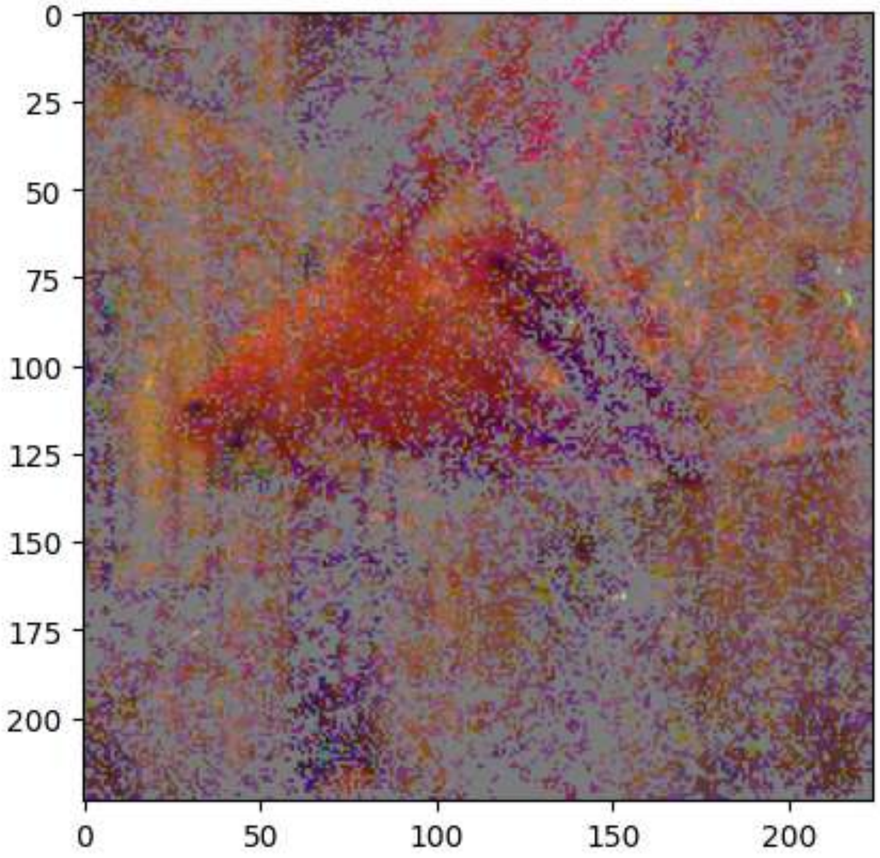

```
Predicted class: hammerhead shark, GT: corgi
```



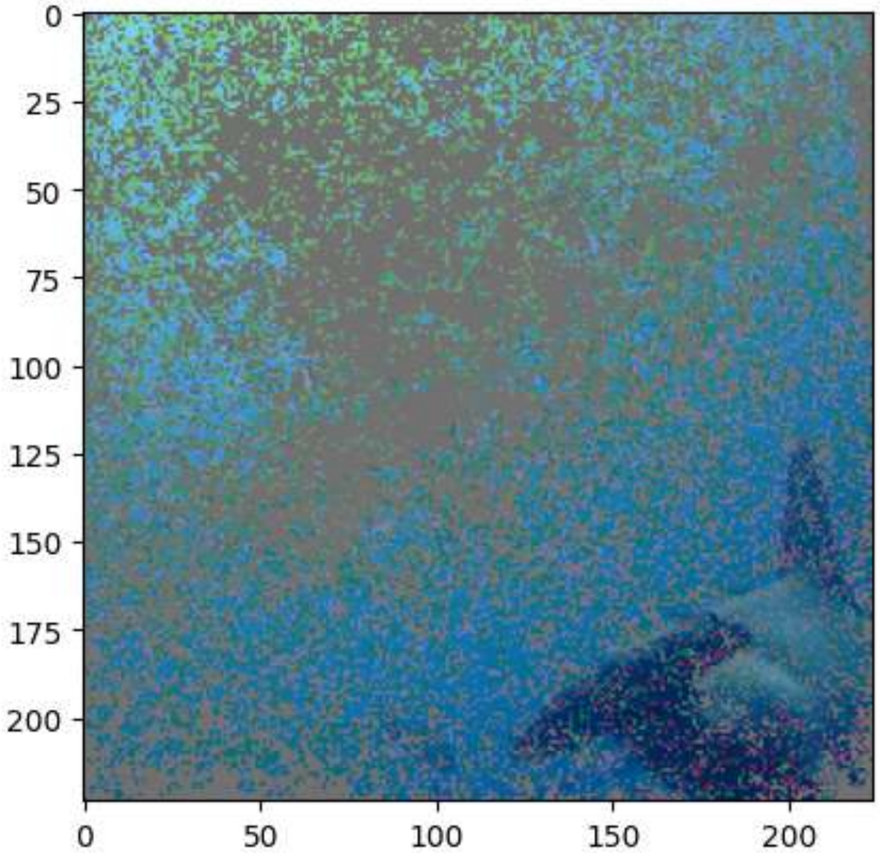
Predicted class: hammerhead shark, GT: electric ray



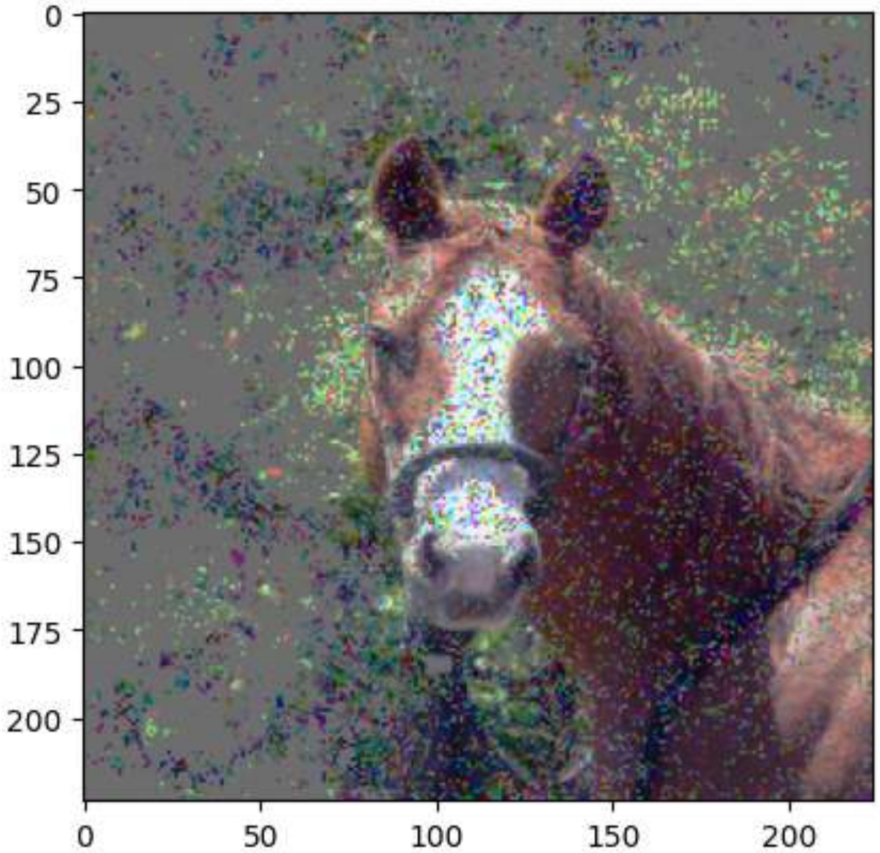
Predicted class: goldfish, GT: goldfish



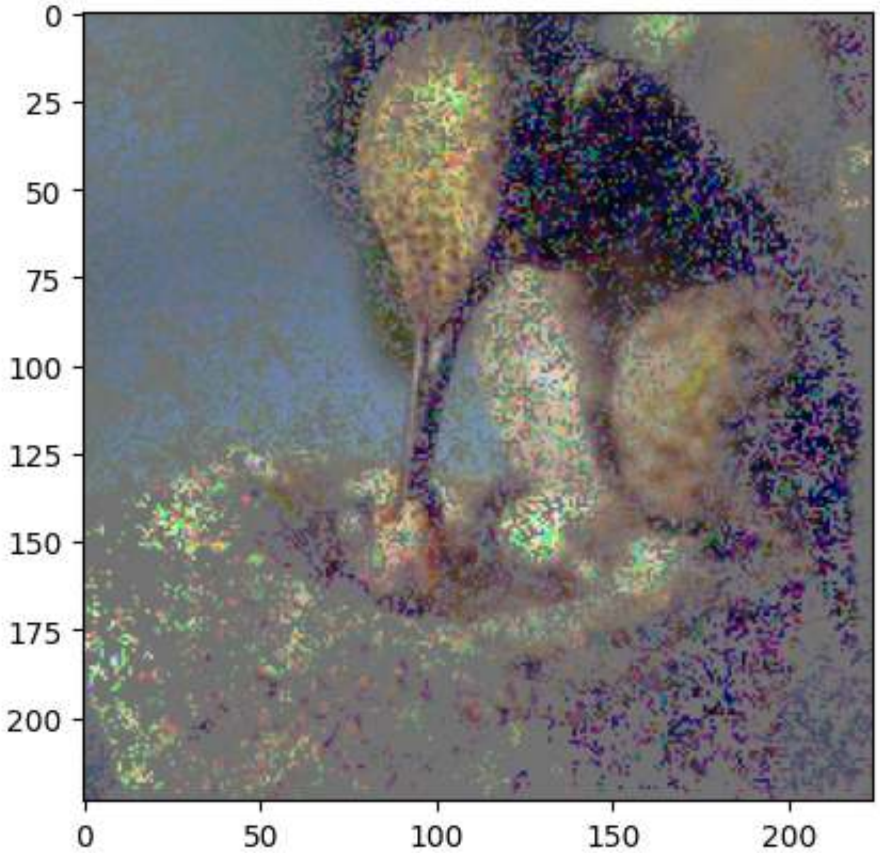
Predicted class: hammerhead shark, GT: hammerhead shark



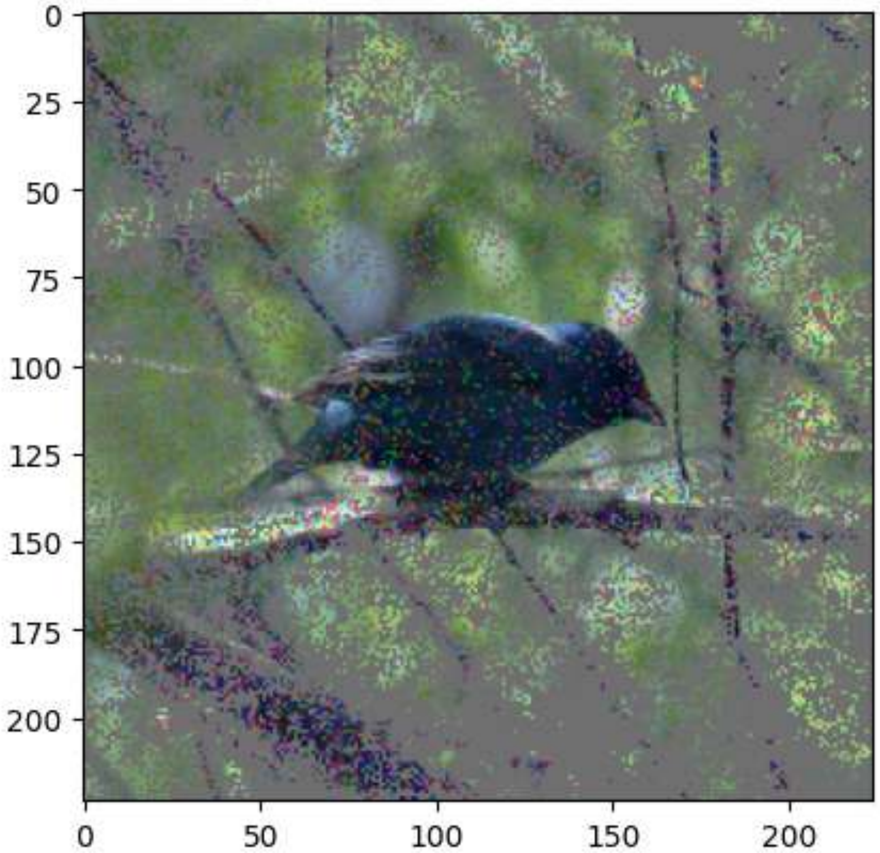
Predicted class: hammerhead shark, GT: horse



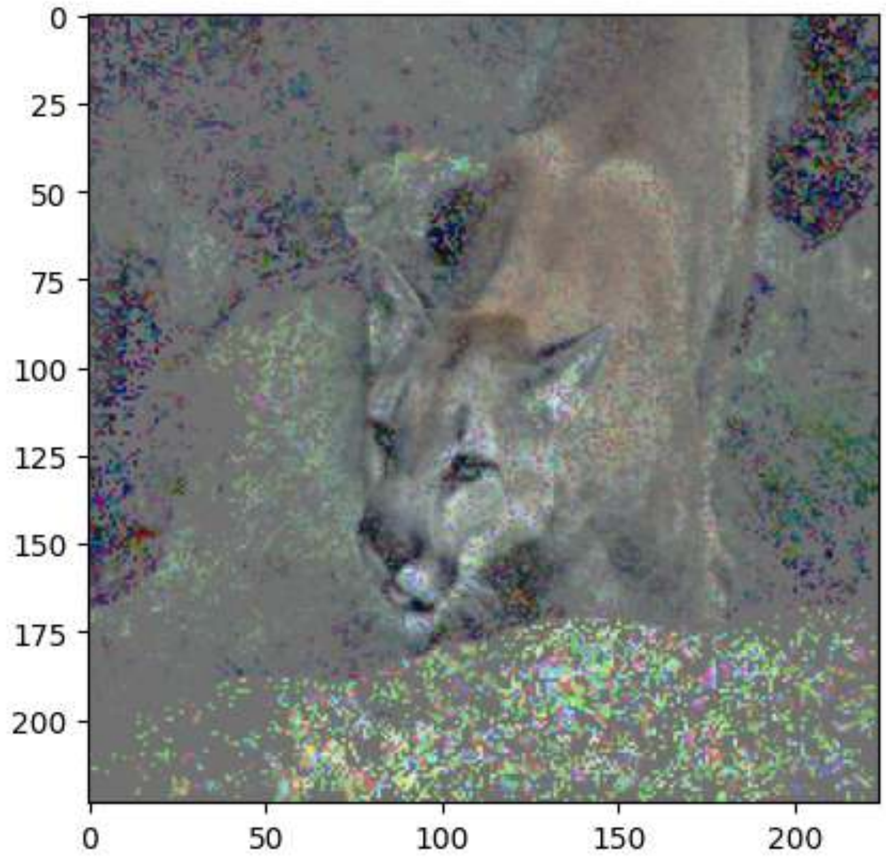
Predicted class: indigo finch, GT: hummingbird



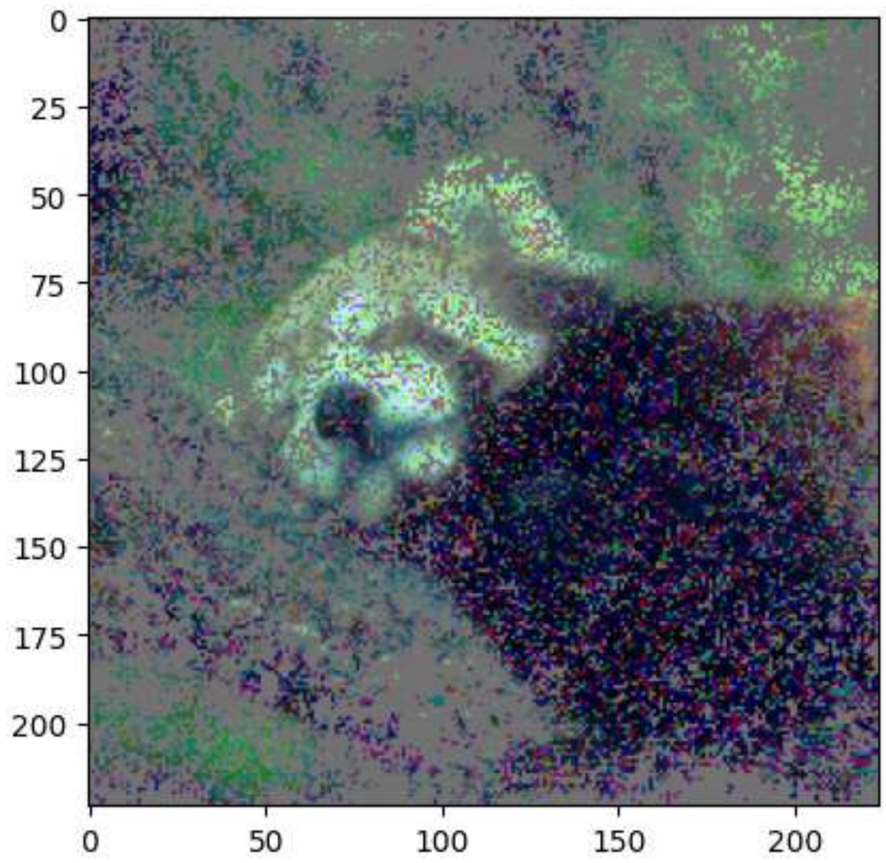
Predicted class: indigo finch, GT: indigo finch



Predicted class: hammerhead shark, GT: puma



Predicted class: hammerhead shark, GT: red panda

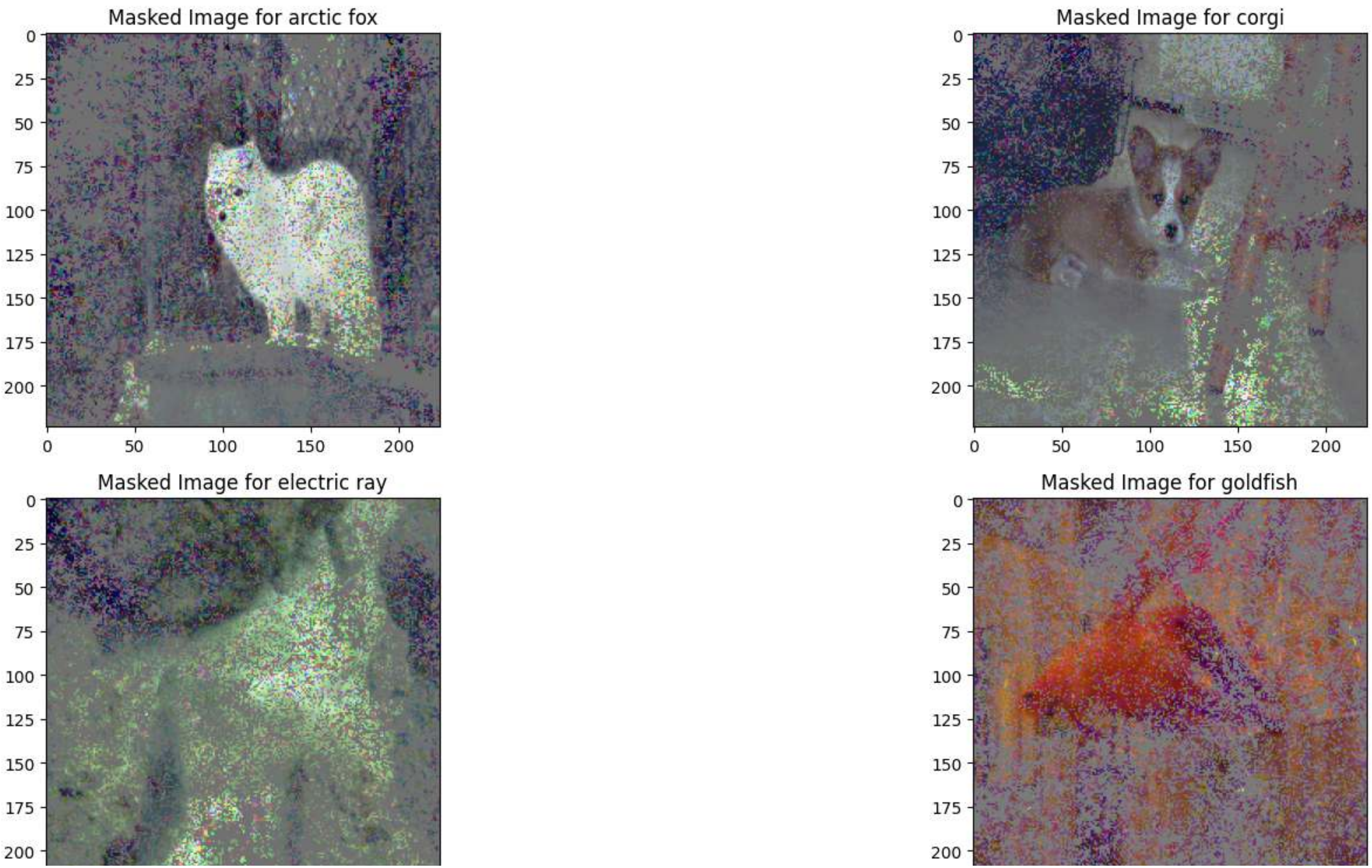


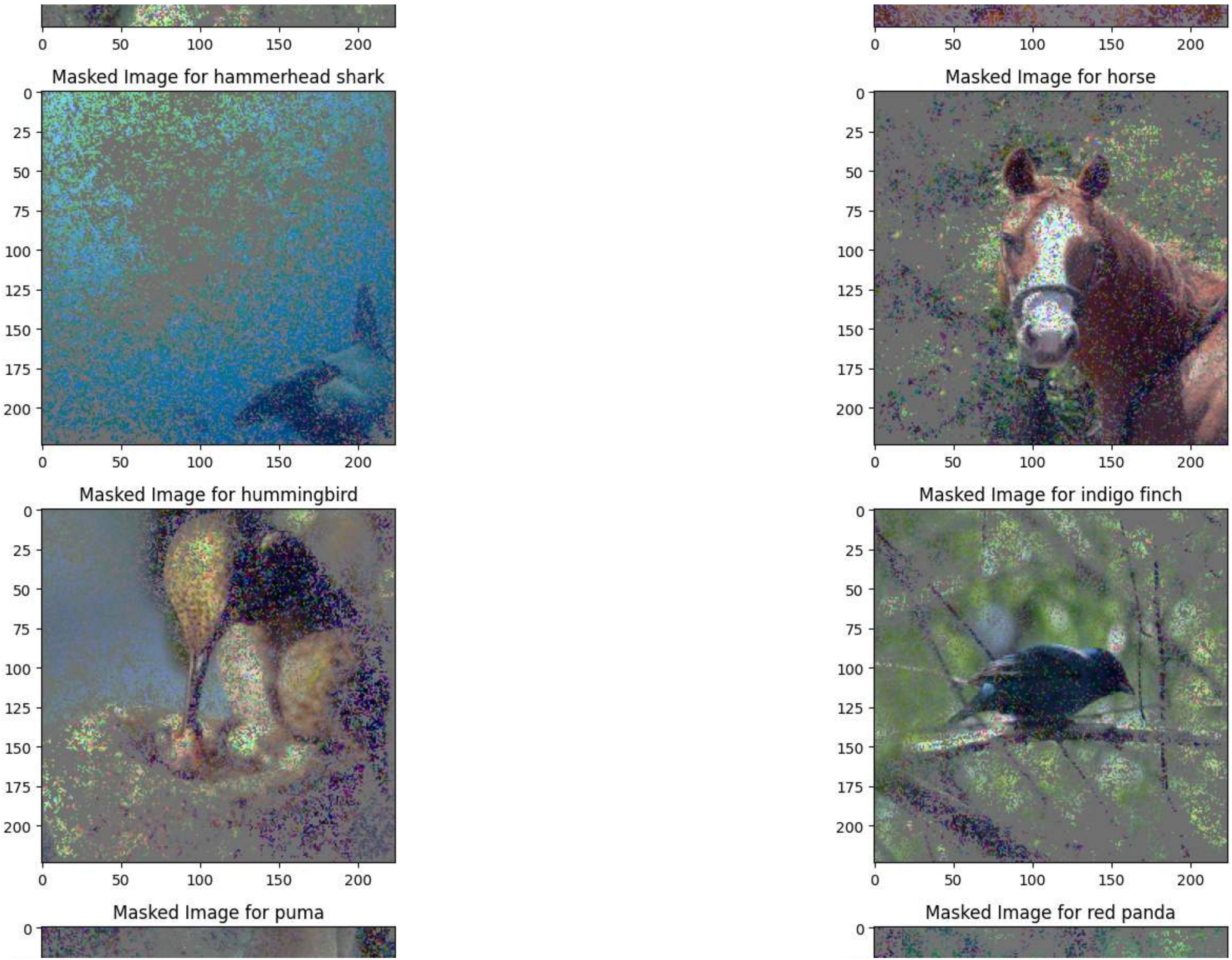
with gaussian noise

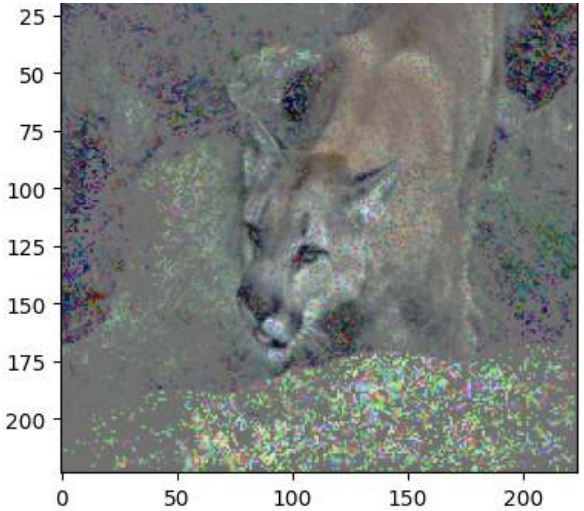
In [21]:
```
def mask_images_gaussian(saliency_maps: list[Tensor], dataset: Dataset):
    masked_images = []

    for idx, saliency_map in enumerate(saliency_maps):
        flattened = saliency_map.flatten().cpu().numpy()

        q3_threshold = np.percentile(flattened, 60)
        std = np.std(flattened)
        masked_img = torch.where(saliency_map >= q3_threshold, dataset[idx][0].permute(1, 2, 0).to(device),
```

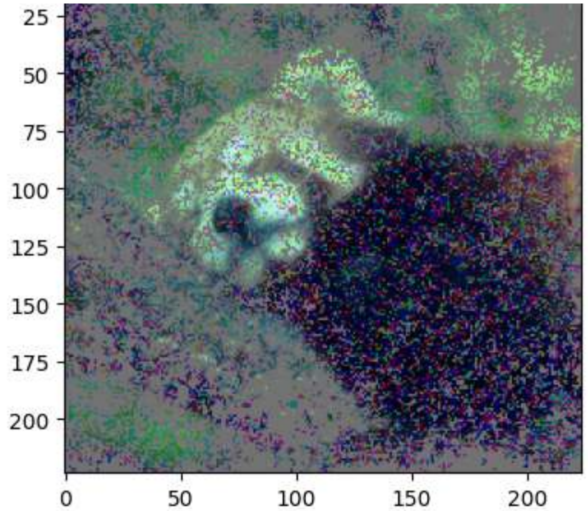
```
        masked_images.append(masked_img)

    return masked_images
```

In [22]:
```
masked_images_gauss = mask_images_gaussian(saliency_maps, cute_dataset)
plot_masked_images(masked_images_gauss)
```



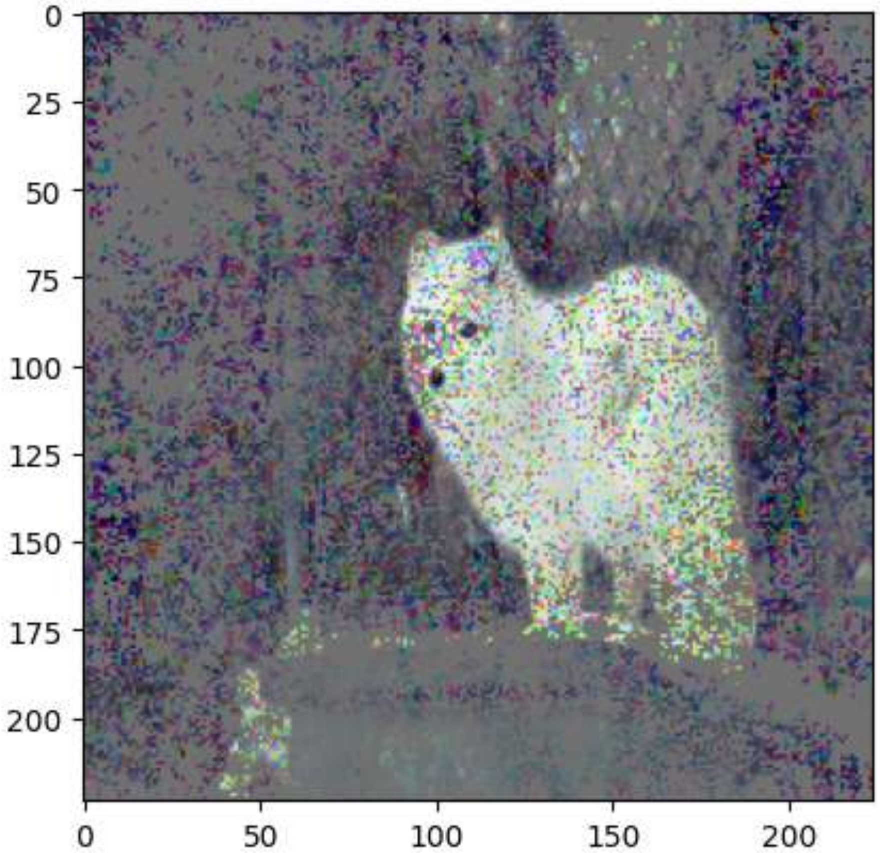

Masked Image for hammerhead shark
Masked Image for horse
Masked Image for hummingbird
Masked Image for indigo finch
Masked Image for puma
Masked Image for red panda



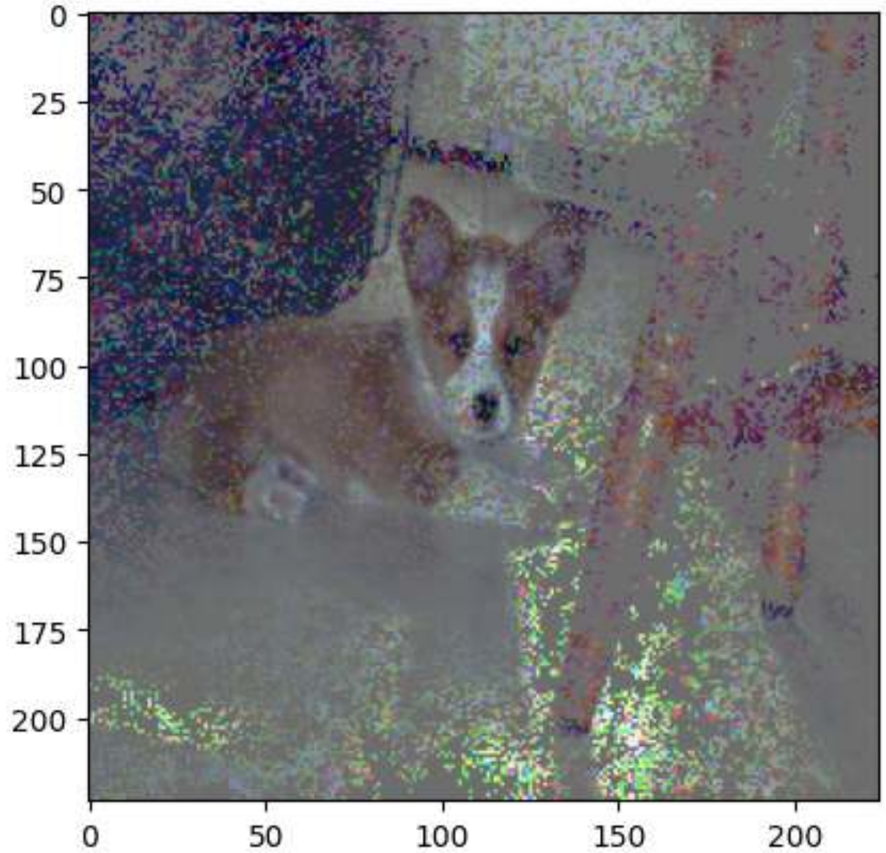


In [ ]:
```
predict_with_masked_imgs(model, masked_images_gauss)
```

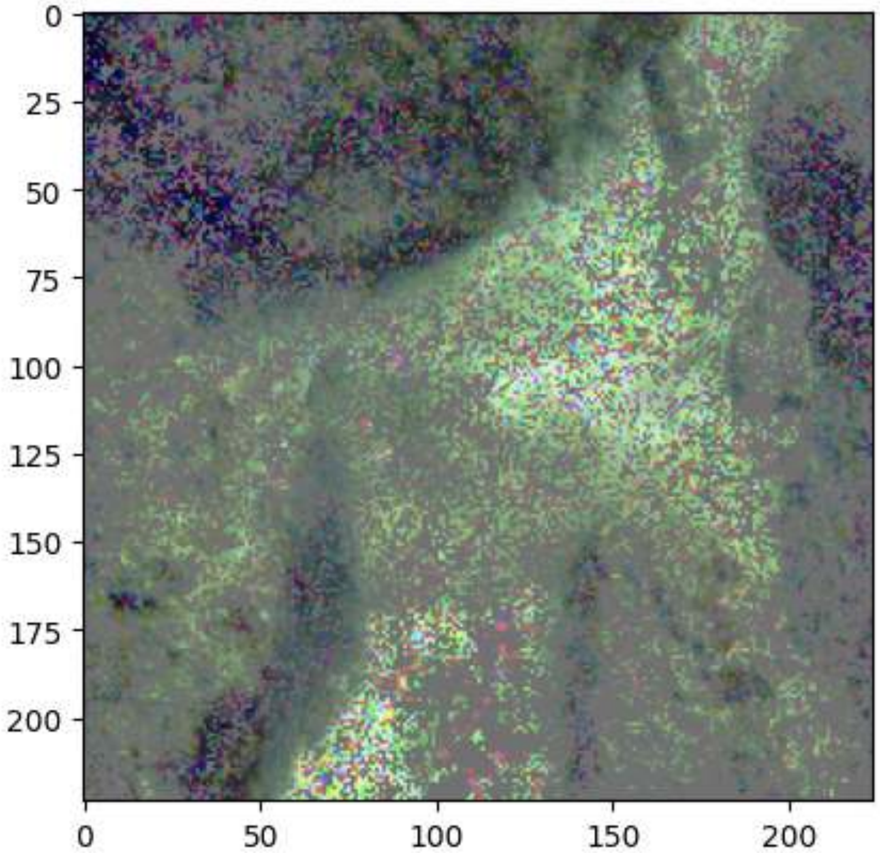
Predicted class: hammerhead shark, GT: arctic fox



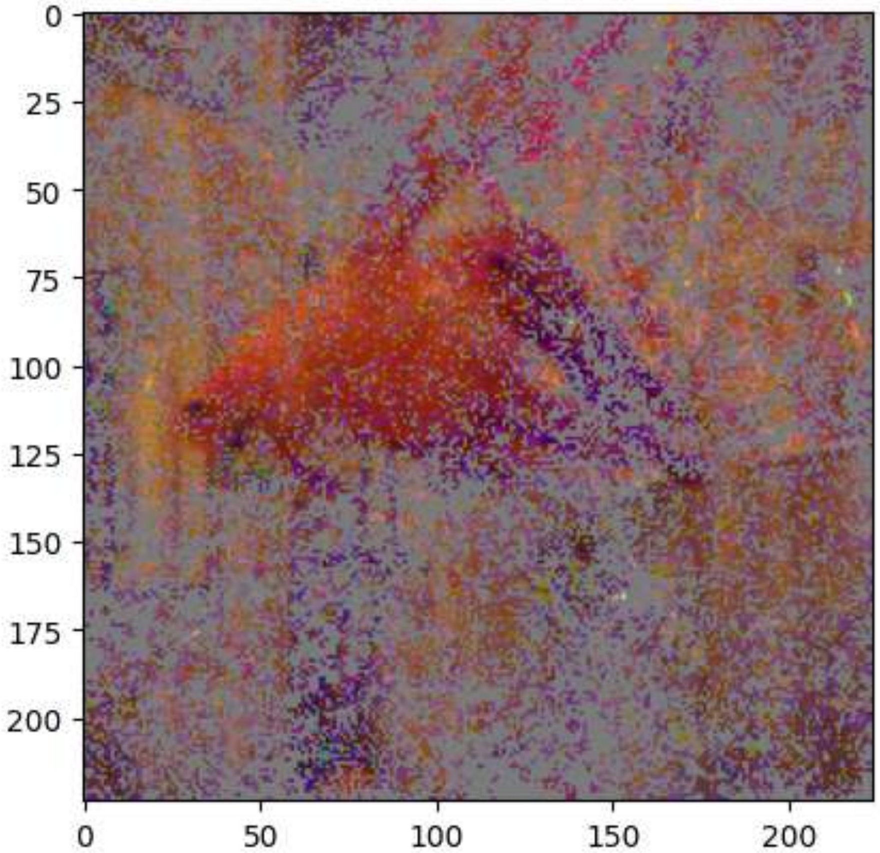
Predicted class: hammerhead shark, GT: corgi



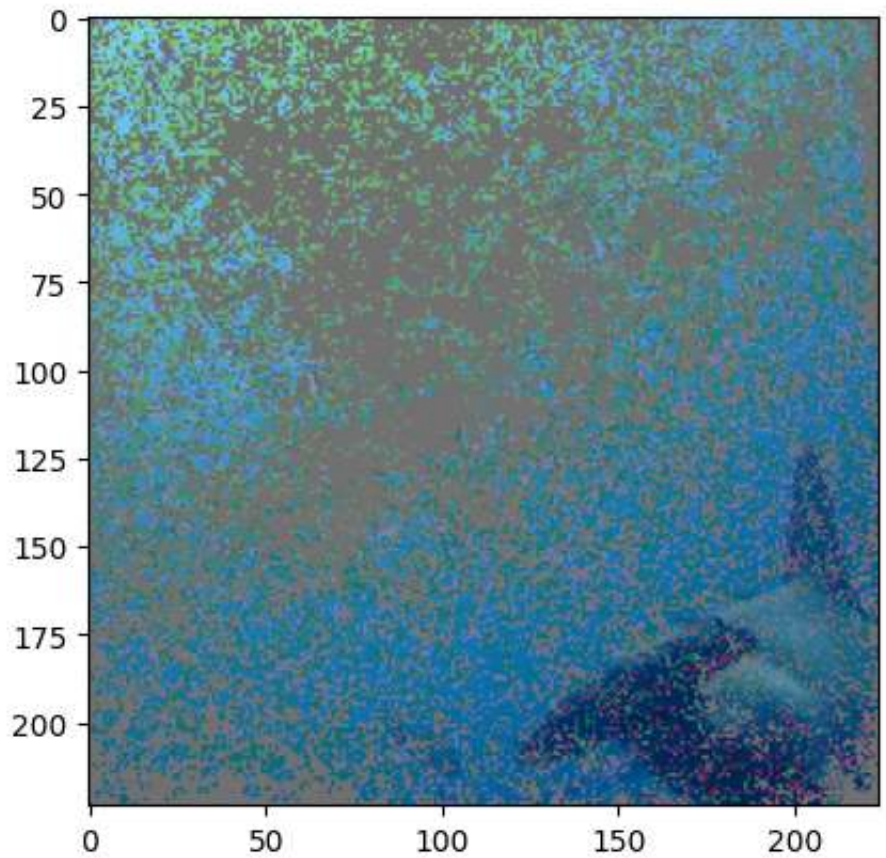
Predicted class: hammerhead shark, GT: electric ray



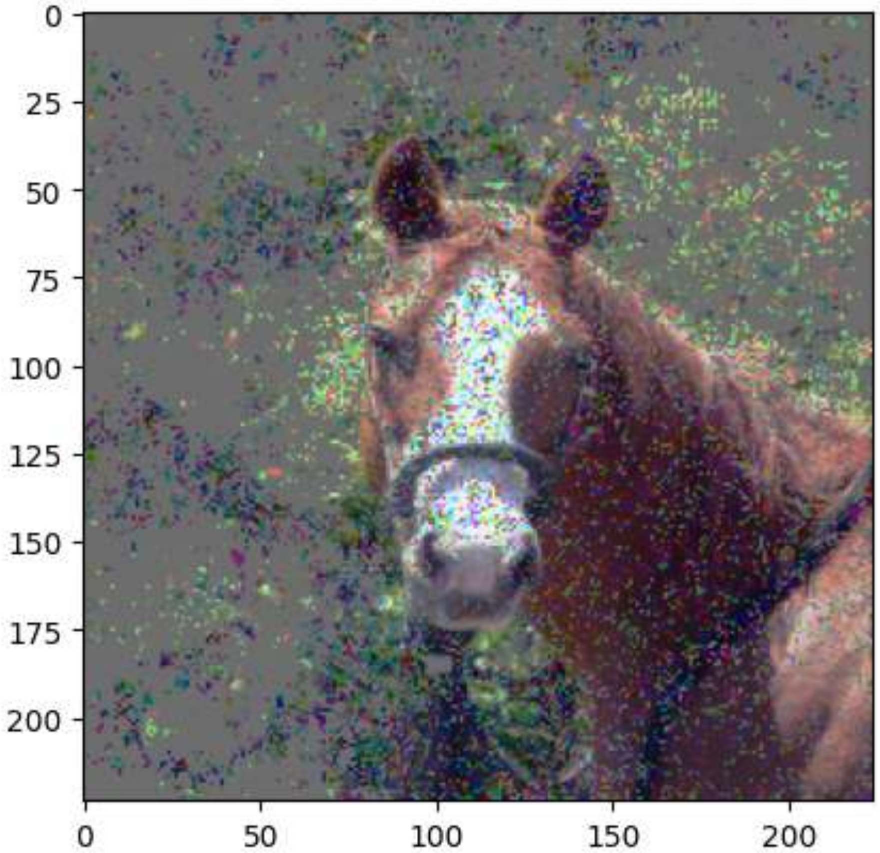
Predicted class: goldfish, GT: goldfish



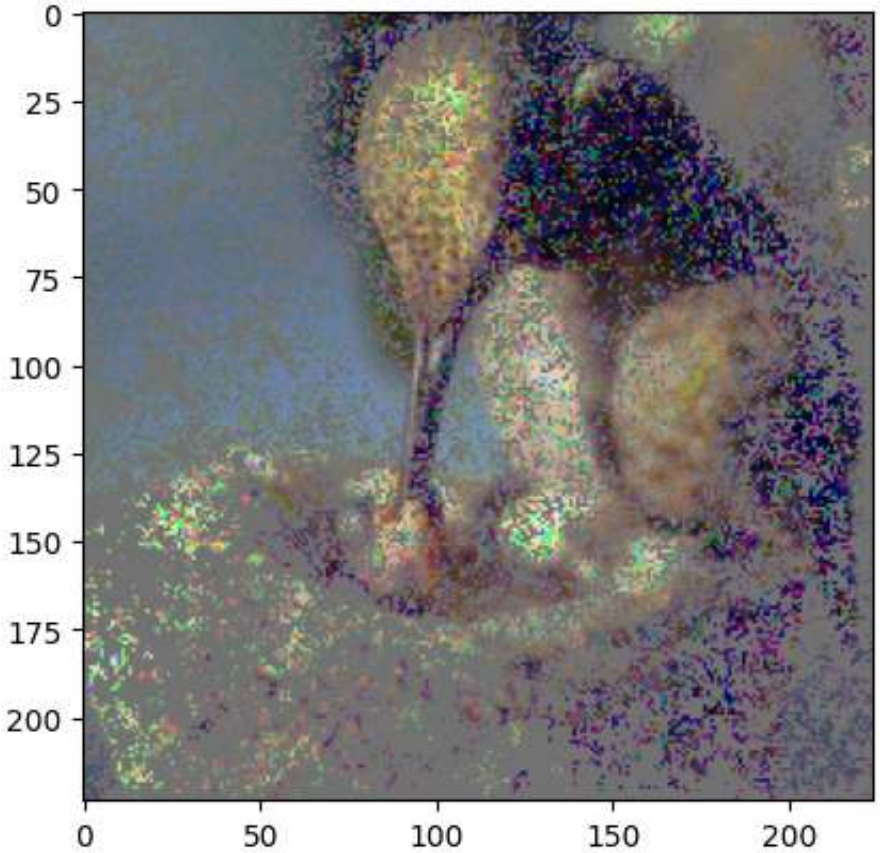
Predicted class: hammerhead shark, GT: hammerhead shark



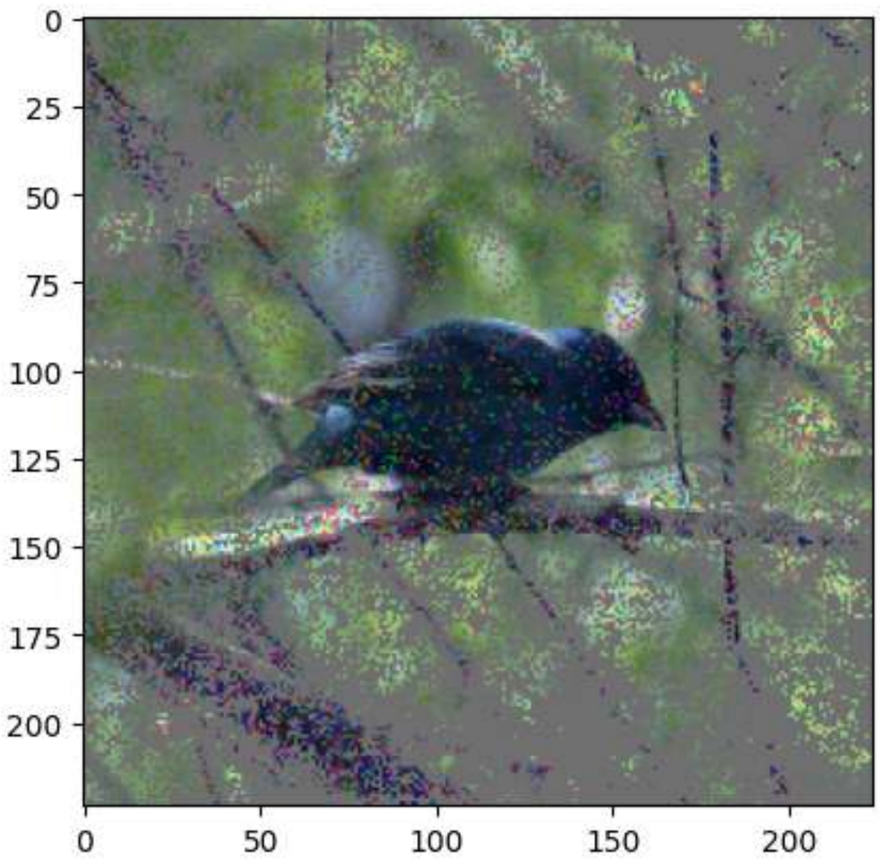
Predicted class: hammerhead shark, GT: horse



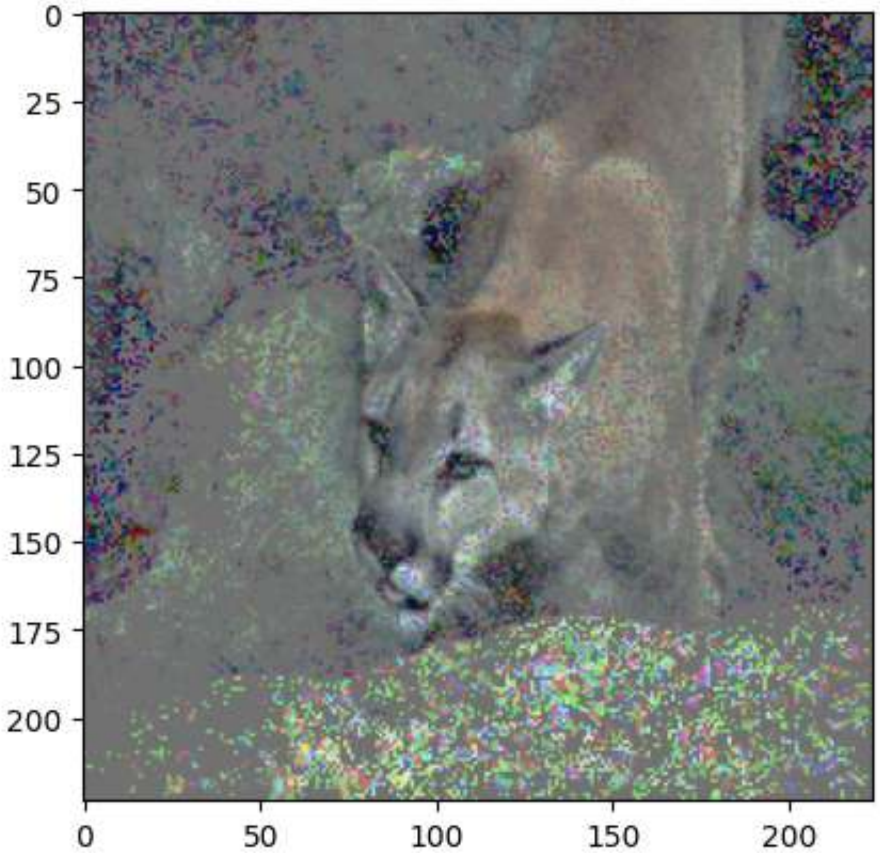
Predicted class: indigo finch, GT: hummingbird



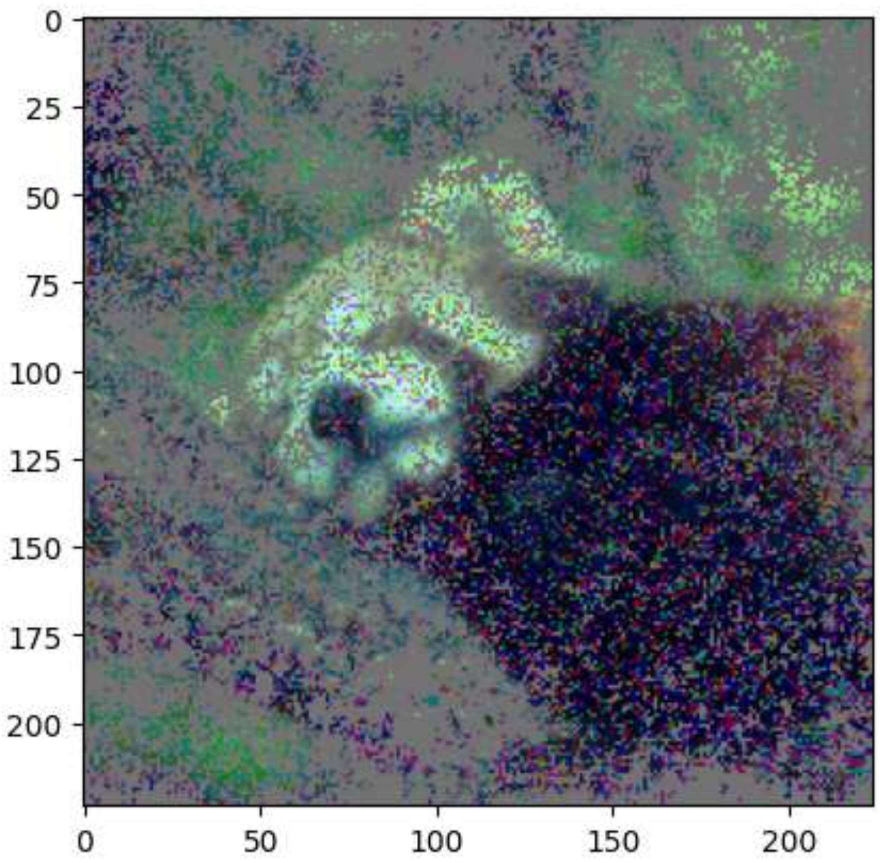
Predicted class: indigo finch, GT: indigo finch



Predicted class: hammerhead shark, GT: puma



Predicted class: hammerhead shark, GT: red panda



Does the model misclassify these images? why or why not?

It misclassifies some of them, depending on the number of pixels masked. When there are very few pixels masked, the performance is basically retained. However, when there are a lot of pixels disturbed, there are some classes that are predicted more than the others, such as hammerhead shark. This can be because for the wrongly predicted classes, the model isnt looking at the foreground as much when deciding the prediction and concludes that the darkness matches the darkness of the hammerhead shark images.

```
In [ ]:
```