

Animal Classification

This notebook is in association with the Unified Mentor Machine Learning internship project submission.

The task is to develop a system which can recognise 15 different animals. We will fine-tune the `EfficientNet_B0` model by unfreezing top 10 layers.

[Visit Project's Streamlit App](#)

1. Download Dataset & Libraries

In []:

```
!git clone https://github.com/PranayJagtap06/UFM_Animal_Classification.git

import zipfile

# Kaggle
# zip_ref = zipfile.ZipFile("/kaggle/working/UFM_Animal_Classification/animal_classification.zip", 'r')
# zip_ref.extractall("/kaggle/working")

# Colab
zip_ref = zipfile.ZipFile("/content/UFM_Animal_Classification/animal_classification.zip", 'r')
zip_ref.extractall("/content")

zip_ref.close()
```

```
Cloning into 'UFM_Animal_Classification'...
remote: Enumerating objects: 433, done.
remote: Counting objects: 100% (8/8), done.
remote: Compressing objects: 100% (6/6), done.
remote: Total 433 (delta 4), reused 6 (delta 2), pack-reused 425 (from 3)
Receiving objects: 100% (433/433), 45.09 MiB | 11.99 MiB/s, done.
Resolving deltas: 100% (5/5), done.
```

All the images are stored in a single folder. We will create two separate folders for training images and testing/validation images.

In []:

```
import os
import shutil
import random

# Define the dataset folder and the split ratio
# dataset_folder = '/kaggle/working/Animal Classification/dataset' # Kaggle
dataset_folder = '/content/Animal Classification/dataset' # Colab
train_ratio = 0.8

# Create the training and testing folders if they don't exist
train_folder = os.path.join(dataset_folder, 'train')
test_folder = os.path.join(dataset_folder, 'test')

if not os.path.exists(train_folder):
    os.makedirs(train_folder)

if not os.path.exists(test_folder):
    os.makedirs(test_folder)
```

```

# Iterate through each animal folder
for animal_folder in os.listdir(dataset_folder):
    # Skip the train and test folders
    if animal_folder in ['train', 'test']:
        continue

    # Get the path to the animal folder
    animal_folder_path = os.path.join(dataset_folder, animal_folder)

    # Create the training and testing subfolders for the animal
    animal_train_folder = os.path.join(train_folder, animal_folder)
    animal_test_folder = os.path.join(test_folder, animal_folder)

    if not os.path.exists(animal_train_folder):
        os.makedirs(animal_train_folder)

    if not os.path.exists(animal_test_folder):
        os.makedirs(animal_test_folder)

    # Get the list of image files in the animal folder
    image_files = os.listdir(animal_folder_path)

    # Split the image files into training and testing sets
    random.shuffle(image_files)
    train_size = int(len(image_files) * train_ratio)
    train_files = image_files[:train_size]
    test_files = image_files[train_size:]

    # Copy the training and testing images to their respective folders
    for file in train_files:
        shutil.copy2(os.path.join(animal_folder_path, file), animal_train_folder)

    for file in test_files:
        shutil.copy2(os.path.join(animal_folder_path, file), animal_test_folder)

    print(f"Split {animal_folder} into {len(train_files)} training images and {len(test_files)} testing images.")

```

Split Giraffe into 103 training images and 26 testing images.
 Split Horse into 104 training images and 26 testing images.
 Split Zebra into 109 training images and 28 testing images.
 Split Bear into 100 training images and 25 testing images.
 Split Dog into 97 training images and 25 testing images.
 Split Bird into 109 training images and 28 testing images.
 Split Cow into 104 training images and 27 testing images.
 Split Tiger into 103 training images and 26 testing images.
 Split Deer into 101 training images and 26 testing images.
 Split Dolphin into 103 training images and 26 testing images.
 Split Lion into 104 training images and 27 testing images.
 Split Cat into 98 training images and 25 testing images.
 Split Panda into 108 training images and 27 testing images.
 Split Kangaroo into 100 training images and 26 testing images.
 Split Elephant into 106 training images and 27 testing images.

In []:

```

# Installing required libraries
!pip install dagshub mlflow icecream torchmetrics

```

```

Collecting dagshub
  Downloading dagshub-0.4.2-py3-none-any.whl.metadata (11 kB)
Collecting mlflow
  Downloading mlflow-2.19.0-py3-none-any.whl.metadata (30 kB)
Collecting icecream
  Downloading icecream-2.1.3-py2.py3-none-any.whl.metadata (1.4 kB)
Collecting torchmetrics
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Requirement already satisfied: httpx>=0.23.0 in /usr/local/lib/python3.10/dist-packages (from dagshub) (0.28.1)
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Requirement already satisfied: Jinja2<4,>=2.11 in /usr/local/lib/python3.10/dist-packages (from mlflow) (3.1.4)
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Requirement already satisfied: google-auth~=2.0 in /usr/local/lib/python3.10/dist-packages (from databricks-sdk<1,>=0.20.0->mlflow-skinny==2.19.0->mlflow) (2.27.0)
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Downloading mlflow_skinny-2.19.0-py3-none-any.whl (5.9 MB)
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Downloading torchmetrics-1.6.1-py3-none-any.whl (927 kB)
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Downloading alembic-1.14.0-py3-none-any.whl (233 kB)
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Downloading appdirs-1.4.4-py2.py3-none-any.whl (9.6 kB)
Downloading asttokens-3.0.0-py3-none-any.whl (26 kB)
Downloading colorama-0.4.6-py2.py3-none-any.whl (25 kB)
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Downloading dagshub_annotation_converter-0.1.2-py3-none-any.whl (33 kB)
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147.8/147.8 kB 6.8 MB/s eta 0:00:00
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114.9/114.9 kB 7.1 MB/s eta 0:00:00
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Downloading treelib-1.7.0-py3-none-any.whl (18 kB)
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Downloading botocore-1.35.90-py3-none-any.whl (13.3 MB)
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Downloading databricks_sdk-0.40.0-py3-none-any.whl (629 kB)
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Downloading graphql_core-3.2.5-py3-none-any.whl (203 kB)
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Downloading graphql_relay-3.2.0-py3-none-any.whl (16 kB)
Downloading jmespath-1.0.1-py3-none-any.whl (20 kB)
Downloading marshmallow-3.23.2-py3-none-any.whl (49 kB)
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Downloading s3transfer-0.10.4-py3-none-any.whl (83 kB)
83.2/83.2 kB 7.4 MB/s eta 0:00:00
Downloading typing_inspect-0.9.0-py3-none-any.whl (8.8 kB)
Downloading gql-3.5.0-py2.py3-none-any.whl (74 kB)
74.0/74.0 kB 7.8 MB/s eta 0:00:00
Downloading Mako-1.3.8-py3-none-any.whl (78 kB)
78.6/78.6 kB 8.5 MB/s eta 0:00:00
Downloading mypy_extensions-1.0.0-py3-none-any.whl (4.7 kB)
Installing collected packages: appdirs, treelib, pathvalidate, mypy-extensions, marshmallow, Mako, lightning-utilities, jmespath, gunicorn, graphql-core, executing, dacite, colorama, backoff, asttokens, typing-inspect, icecream, graphql-relay, docker, botocore, alembic, torchmetrics, s3transfer, graphene, gql, dataclasses-json, databricks-sdk, dagshub-annotation-converter, boto3, mlflow-skinny, dagshub, mlflow
Successfully installed Mako-1.3.8 alembic-1.14.0 appdirs-1.4.4 asttokens-3.0.0 backoff-2.1 boto3-1.35.90 botocore-1.35.90 colorama-0.4.6 dacite-1.6.0 dagshub-0.4.2 dagshub-annotation-converter-0.1.2 databricks-sdk-0.40.0 dataclasses-json-0.6.7 docker-7.1.0 executing-2.1.0 gql-3.5.0 graphene-3.4.3 graphql-core-3.2.5 graphql-relay-3.2.0 gunicorn-23.0.0 icecream-2.1.3 jmespath-1.0.1 lightning-utilities-0.11.9 marshmallow-3.23.2 mlflow-2.19.0 mlflow-skinny-2.19.0 mypy-extensions-1.0.0 pathvalidate-3.2.1 s3transfer-0.10.4 torchmetrics-1.6.1 treelib-1.7.0 typing-inspect-0.9.0

```

In []:

```

# Importing libraries.
import mlflow
import dagshub
from torchvision import datasets, transforms
from torch.utils.data import Dataset, DataLoader
import torch.nn.functional as F
import torchvision
import torchmetrics
import torch

```

```

import torch.nn as nn
from sklearn.metrics import classification_report, confusion_matrix, precision_recall_curve, roc_curve
from sklearn.model_selection import train_test_split
from sklearn.utils.class_weight import compute_class_weight
from typing import Dict, Any, Optional, List, Tuple
from urllib.parse import urlparse
from icecream import ic
from rich.progress import track
from PIL import Image

import os
import pickle
import plotly
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.io as pio
# pio.templates.default = "seaborn"
pio.renderers.default = "colab"

```

2. Data Loader Script

In []:

```

%%writefile data_loader.py
import os
import torchvision
import torch
import numpy as np
import pandas as pd
import torch.nn as nn
from typing import Dict, List, Optional, Tuple
from dataclasses import dataclass, field
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
from torch.utils.data import WeightedRandomSampler
from torch.utils.data.distributed import DistributedSampler
from sklearn.utils.class_weight import compute_class_weight

NUM_WORKERS = os.cpu_count()

def load_data_objs(
    batch_size: int,
    rank: int,
    world_size: int,
    epochs: int,
    x_train_path: str,
    x_val_path: str,
    gpu: bool,
    gpu_id: int,
    learning_rate: float,
    num_workers: int,
    lr_scheduler: Optional[str] = None,
) -> tuple[DataLoader, DataLoader, nn.Module, nn.CrossEntropyLoss, torch.optim.Optimizer, Optional[torch.optim.lr_scheduler._LRScheduler]]:
    # Loading DEFAULT = best available weights of EfficientNet_B0 model
    weights = torchvision.models.EfficientNet_B0_Weights.DEFAULT

    # Loading transform for transforming the images to be compatible with EfficientNet_B0 model
    auto_transforms = weights.transforms()
    torch.save(auto_transforms, "effnetb0_transform.pt")

    # Loading EfficientNet_B0 model
    model = torchvision.models.efficientnet_b0(weights=weights)

    # Use ImageFolder to create dataset(s)

```

```

train_data = datasets.ImageFolder(x_train_path, transform=auto_transforms)
torch.save(train_data, "train_data.pt")
val_data = datasets.ImageFolder(x_val_path, transform=auto_transforms)
torch.save(val_data, "val_data.pt")

# Get class names
class_names = train_data.classes
torch.save(class_names, "class_names.pt")

# Freeze all base layers in the "features" section of the model (the feature extractor)
# by setting requires_grad=False
for param in model.features.parameters():
    param.requires_grad = False

# Unfreeze the last 10 layers
layers = list(model.named_parameters())
for name, param in layers[-10:]:
    param.requires_grad = True

# Recreate the classifier layer
model.classifier = nn.Sequential(
    nn.Dropout(p=0.2, inplace=True),
    nn.Linear(in_features=model.classifier[1].in_features, out_features=len(class_names), bias=True))

optimizer = torch.optim.Adam(
    params=model.parameters(), lr=learning_rate, weight_decay=1e-4)

criterion = nn.CrossEntropyLoss()

if gpu:
    dist_sampler_train = DistributedSampler(
        train_data, num_replicas=world_size, rank=rank, seed=42)
    train_dtl = DataLoader(train_data, batch_size=batch_size, shuffle=False,
                           pin_memory=True, sampler=dist_sampler_train, num_workers=
num_workers, )

    dist_sampler_val = DistributedSampler(val_data, num_replicas=world_size, rank=rank, seed=42)
    val_dtl = DataLoader(val_data, batch_size=1, shuffle=False, pin_memory=True, sampler=dist_sampler_val, num_workers=num_workers, )

else:
    train_dtl = DataLoader(train_data, batch_size=batch_size,
                           shuffle=True, pin_memory=True, num_workers=num_workers, )

    val_dtl = DataLoader(val_data, batch_size=1, shuffle=False, pin_memory=True, num_workers=num_workers, )

scheduler = None
if lr_scheduler:
    LR_SCHEDULER = {
        # requires to set metric
        "reduce_lr": torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='min', factor=0.5, patience=2),
        "one_cycle_lr": torch.optim.lr_scheduler.OneCycleLR(optimizer, max_lr=0.01, epochs=epochs, steps_per_epoch=len(train_dtl), anneal_strategy='cos')
    }

    if lr_scheduler in LR_SCHEDULER:
        scheduler = LR_SCHEDULER[lr_scheduler]
    else:
        raise ValueError(f"Invalid lr_scheduler value: {lr_scheduler}. Valid options are: {list(LR_SCHEDULER.keys())}")
return train_dtl, val_dtl, model, criterion, optimizer, scheduler

```

Writing data_loader.py

3. PyTorch Engine Script

In []:

```
%%writefile pt_engine.py
from torch.nn.parallel import DistributedDataParallel as DDP
from torch.utils.data import DataLoader
from typing import List, Dict, Optional
from rich.progress import track
from pathlib import Path
from icecream import ic
import torch.distributed as dist
import torch.nn.functional as F
import torch.nn as nn
import numpy as np
import random
import torchmetrics
import torch
import time
import os

def set_seed(seed):
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    if torch.cuda.is_available():
        torch.cuda.manual_seed(seed)
        torch.cuda.manual_seed_all(seed)

def loss_metric_tensor(array: List[Dict[str, np.ndarray]]) -> torch.Tensor:
    all_tensors = [torch.tensor([[array[0][j][k] for k in range(
        len(array[0][j]))]], dtype=torch.float32) for j in array[0].keys()]
    b = torch.cat(all_tensors, dim=0)
    return b.transpose(0, 1)

class CustomTrainer:
    def __init__(
        self,
        model: nn.Module,
        train_data: DataLoader,
        val_data: DataLoader,
        criterion: nn.CrossEntropyLoss,
        optimizer: torch.optim.Optimizer,
        gpu_id: int,
        save_path: str | Path,
        gpu: bool,
        patience: int = 5,
        max_epochs: int = 10,
        world_size: int = 1,
        scheduler: Optional[torch.optim.lr_scheduler._LRScheduler] = None
    ) -> None:
        self.model = model
        self.train_data = train_data
        self.val_data = val_data
        self.criterion = criterion
        self.optimizer = optimizer
        self.gpu_id = gpu_id
        self.save_path = save_path
        self.gpu = gpu
        self.patience = patience
        self.max_epochs = max_epochs
        self.world_size = world_size
        self.scheduler = scheduler

        if self.gpu:
            self.model = DDP(self.model.to(self.gpu_id), device_ids=[self.gpu_id])
            self.train_losses_ = [{f'train_losses{i}': np.array([]) for i in range(self.world_size)}]
            self.val_losses_ = [{f'val_losses{i}': np.array([]) for i in range(self.world_size)}]
            self.train_fls_ = [{f'train_metrics{i}': np.array([]) for i in range(self.world_size)}]
```

```

rld_size)]]
        self.val_fls_ = [{f'val_metrics{i}': np.array([]) for i in range(self.world_
size)]]
        self.train_accuracies_ = [{f'train_metrics{i}': np.array([]) for i in range(
self.world_size)]]
        self.val_accuracies_ = [{f'val_metrics{i}': np.array([]) for i in range(self
.world_size)]]
        self.train_metric_accuracy = torchmetrics.classification.MulticlassAccuracy(
num_classes=15, average="micro", sync_on_compute=False).to(self.gpu_id)
        self.train_metric_flscore = torchmetrics.classification.MulticlassF1Score(nu
m_classes=15, average="macro", sync_on_compute=False).to(self.gpu_id)
        self.val_metric_accuracy = torchmetrics.classification.MulticlassAccuracy(nu
m_classes=15, average="micro", sync_on_compute=False).to(self.gpu_id)
        self.val_metric_flscore = torchmetrics.classification.MulticlassF1Score(num_
classes=15, average="macro", sync_on_compute=False).to(self.gpu_id)
        # self.val_metric_accuracy = torchmetrics.classification.BinaryAccuracy(sync
_on_compute=False).to(self.gpu_id)
        # self.val_metric_flscore = torchmetrics.classification.BinaryF1Score(sync_o
n_compute=False).to(self.gpu_id)
    else:
        self.train_losses_ = [{"losses": np.array([])}]
        self.val_losses_ = [{"losses": np.array([])}]
        self.train_fls_ = [{"metrics": np.array([])}]
        self.val_fls_ = [{"metrics": np.array([])}]
        self.train_accuracies_ = [{"metrics": np.array([])}]
        self.val_accuracies_ = [{"metrics": np.array([])}]
        self.train_metric_accuracy = torchmetrics.classification.MulticlassAccuracy(
num_classes=15, average="micro")
        self.train_metric_flscore = torchmetrics.classification.MulticlassF1Score(nu
m_classes=15, average="macro")
        self.val_metric_accuracy = torchmetrics.classification.MulticlassAccuracy(nu
m_classes=15, average="micro")
        self.val_metric_flscore = torchmetrics.classification.MulticlassF1Score(num_
classes=15, average="macro")
        # self.val_metric_accuracy = torchmetrics.classification.BinaryAccuracy()
        # self.val_metric_flscore = torchmetrics.classification.BinaryF1Score()

    def _run_batch(self, source: torch.Tensor, targets: torch.Tensor, pred_labels: np.nd
array) -> tuple[float]:
        source = source.to(self.gpu_id)
        targets = targets.to(self.gpu_id)

        self.model.train()
        self.optimizer.zero_grad()
        y_logits = self.model(source)
        preds = torch.softmax(y_logits, dim=1)
        preds = torch.argmax(preds, dim=1)
        loss = self.criterion(y_logits, targets)
        loss.backward()
        self.optimizer.step()

        pred_labels[0]['preds'].extend(preds.detach().cpu().numpy().tolist())
        pred_labels[0]['targets'].extend(targets.cpu().numpy().tolist())

        self.train_metric_accuracy.update(preds, targets)
        self.train_metric_flscore.update(preds, targets)

    return loss.item(), pred_labels

    def _run_eval(self, epoch: int) -> tuple[float, float, float]:
        self.model.eval()
        total_samples = len(self.val_data.dataset)
        total_loss = 0
        total_accuracy = 0
        total_flscore = 0
        total_samples_ = 0

        if self.gpu:
            self.val_data.sampler.set_epoch(epoch)
            self.val_metric_accuracy.reset()

```

```

        self.val_metric_f1score.reset()

    pred_labels = np.array([{'targets': [], 'preds': []}])
    with torch.inference_mode():
        for source, targets in track(self.val_data, description=f"Evaluating...", style='red', complete_style='cyan', finished_style='green'):
            source = source.to(self.gpu_id)
            targets = targets.to(self.gpu_id)

            y_logits = self.model(source)
            preds = torch.softmax(y_logits, dim=1)
            preds = torch.argmax(preds, dim=1)
            loss = self.criterion(y_logits, targets)

            batch_size_ = source.size(0)  # Get batch size
            total_samples_ += batch_size_  # Accumulate total samples

            self.val_metric_accuracy.update(preds, targets)
            self.val_metric_f1score.update(preds, targets)
            total_loss += loss.item() * batch_size_

            pred_labels[0]['preds'].extend(preds.detach().cpu().numpy().tolist())
            pred_labels[0]['targets'].extend(targets.cpu().numpy().tolist())

    self.model.train()
    avg_loss = total_loss / total_samples_

    accuracy = self.val_metric_accuracy.compute()
    f1score = self.val_metric_f1score.compute()

    return avg_loss, accuracy.item(), f1score.item(), pred_labels

def _run_epoch(self, epoch: int, total_epochs: int) -> tuple[float, float, float]:
    total_samples = len(self.train_data.dataset)
    num_batches = len(self.train_data)
    total_loss = 0
    total_accuracy = 0
    total_f1score = 0
    total_samples_ = 0

    if self.gpu:
        self.train_data.sampler.set_epoch(epoch)
        self.train_metric_accuracy.reset()
        self.train_metric_f1score.reset()

    pred_labels = np.array([{'targets': [], 'preds': []}])
    for source, targets in track(self.train_data, description=f""{f"[GPU{self.gpu_id}] " if self.gpu else ""}Epoch {epoch + 1}/{total_epochs} | Training: {num_batches} batches...", style='red', complete_style='cyan', finished_style='green'):

        batch_size_ = source.size(0)  # Get batch size
        total_samples_ += batch_size_  # Accumulate total samples

        loss, pred_labels = self._run_batch(source, targets, pred_labels)
        total_loss += loss * batch_size_

    avg_loss = total_loss / total_samples_

    accuracy = self.train_metric_accuracy.compute()
    f1score = self.train_metric_f1score.compute()

    return avg_loss, accuracy.item(), f1score.item(), pred_labels

def _save_checkpoint(self, train_loss: float, val_loss: float, train_accuracy: float, val_accuracy: float, train_f1score: float, val_f1score: float, train_labels: np.ndarray, val_labels: np.ndarray) -> None:
    ckp = self.model.module.state_dict()
    ckppath = f"{self.save_path}/best_model.pt"
    torch.save(ckp, ckppath)

```

```

np.save("loss_train.npy", train_loss, allow_pickle=True)
np.save("accuracy_train.npy", train_accuracy, allow_pickle=True)
np.save("f1score_train.npy", train_f1score, allow_pickle=True)
np.save("train_labels.npy", train_labels, allow_pickle=True)
np.save("loss_val.npy", val_loss, allow_pickle=True)
np.save("accuracy_val.npy", val_accuracy, allow_pickle=True)
np.save("f1score_val.npy", val_f1score, allow_pickle=True)
np.save("val_labels.npy", val_labels, allow_pickle=True)

if self.gpu:
    print(f"\t\tNew best model saved at {ckp_path} from GPU{self.gpu_id}.")
else:
    print(f"\t\tNew best model save at {ckp_path}.")

def gather_tensor(self, t: torch.Tensor) -> torch.Tensor:
    gathered_t = [torch.zeros_like(t) for _ in range(self.world_size)]
    torch.distributed.all_gather(gathered_t, t)
    return torch.cat(gathered_t, dim=0)

def train(self) -> None:
    if self.gpu:
        should_stop = torch.zeros(1).to(self.gpu_id)
        patience_count = torch.zeros(1, dtype=torch.int32).to(self.gpu_id)

        # Gather losses from all GPUs
        train_losses = [torch.zeros(1).to(self.gpu_id)
                        for _ in range(self.world_size)]
        val_losses = [torch.zeros(1).to(self.gpu_id)
                     for _ in range(self.world_size)]
        train_f1s = [torch.zeros(1).to(self.gpu_id)
                    for _ in range(self.world_size)]
        val_f1s = [torch.zeros(1).to(self.gpu_id)
                  for _ in range(self.world_size)]
        train_accuracies = [torch.zeros(1).to(self.gpu_id)
                           for _ in range(self.world_size)]
        val_accuracies = [torch.zeros(1).to(self.gpu_id)
                         for _ in range(self.world_size)]
        val_losses_t = torch.empty(0).to(self.gpu_id)
        val_metrics_t = torch.empty(0).to(self.gpu_id)
    else:
        should_stop = torch.zeros(1)
        patience_count = torch.zeros(1, dtype=torch.int32)
        train_losses = []
        val_losses = []
        train_f1s = []
        val_f1s = []
        train_accuracies = []
        val_accuracies = []
        val_losses_t = []
        val_metrics_t = []

    set_seed(42)
    for epoch in range(self.max_epochs):
        train_loss, train_accuracy, train_f1, train_labels = self._run_epoch(epoch,
self.max_epochs)
        val_loss, val_accuracy, val_f1, val_labels = self._run_eval(epoch)

        print(f"""\t{f"[GPU{self.gpu_id}] | " if self.gpu else ""}Batches: {len(self
.train_data)} per GPU | Val Steps: {len(self.val_data)} | train_loss: {train_loss:.4f} |
val_loss: {val_loss:.4f} | train_accuracy: {train_accuracy:.4f} | val_accuracy: {val_accu
racy:.4f} | train_f1: {train_f1:.4f} | val_f1: {val_f1:.4f} | Learning Rate: {self.optimi
zer.param_groups[0]['lr']:.6f}""")

        if self.scheduler is not None:
            self.scheduler.step(val_loss)

        # ic(pred_labels[0]['targets'][-6:], pred_labels[0]['preds'][-6:])

        # Save losses for all GPUs
        if self.gpu:

```

```

        try:
            torch.distributed.all_gather(
                train_losses, torch.tensor([train_loss]).to(self.gpu_id))
            torch.distributed.all_gather(
                val_losses, torch.tensor([val_loss]).to(self.gpu_id))
            torch.distributed.all_gather(
                train_fls, torch.tensor([train_fl]).to(self.gpu_id))
            torch.distributed.all_gather(
                val_fls, torch.tensor([val_fl]).to(self.gpu_id))
            torch.distributed.all_gather(
                train_accuracies, torch.tensor([train_accuracy]).to(self.gpu_id))
        )

        torch.distributed.all_gather(
            val_accuracies, torch.tensor([val_accuracy]).to(self.gpu_id))
    except RuntimeError as e:
        print(f"Error gathering losses: {e}")
        break

    for i in range(self.world_size):
        self.train_losses[0][f"train_losses{i}"] = np.append(
            self.train_losses[0][f"train_losses{i}"], train_losses[i].item()
        )

        self.val_losses[0][f"val_losses{i}"] = np.append(
            self.val_losses[0][f"val_losses{i}"], val_losses[i].item())
        self.train_fls[0][f"train_metrics{i}"] = np.append(
            self.train_fls[0][f"train_metrics{i}"], train_fls[i].item())
        self.val_fls[0][f"val_metrics{i}"] = np.append(
            self.val_fls[0][f"val_metrics{i}"], val_fls[i].item())
        self.train_accuracies[0][f"train_metrics{i}"] = np.append(
            self.train_accuracies[0][f"train_metrics{i}"], train_accuracies
[i].item())

        self.val_accuracies[0][f"val_metrics{i}"] = np.append(
            self.val_accuracies[0][f"val_metrics{i}"], val_accuracies[i].it
em())

    val_losses_t = loss_metric_tensor(self.val_losses_)
    val_metrics_t = loss_metric_tensor(self.val_fls_)

    val_losses_last_item = np.min(val_losses_t[-1:].squeeze().numpy())
    val_metrics_last_item = np.max(val_metrics_t[-1:].squeeze().numpy())
    bval_loss = np.min(val_losses_t.numpy())
    bval_metric = np.max(val_metrics_t.numpy())

    improved = torch.tensor([False], dtype=torch.bool).to(self.gpu_id)
    else:
        self.val_losses[0]["losses"] = np.append(self.val_losses[0]["losses"],
val_losses)

        self.val_fls[0]["metrics"] = np.append(self.val_fl_s[0]["metrics"], val
_fls)

        self.val_accuracies[0]["metrics"] = np.append(self.val_accuracies[0]["
metrics"], val_accuracies)

        val_losses_last_item = self.val_losses[0]["losses"][-1]
        val_metrics_last_item = self.val_fls[0]["metrics"][-1]
        bval_loss = np.min(self.val_losses_)
        bval_metric = np.max(self.val_fls_)
        improved = torch.tensor([False], dtype=torch.bool)

    if self.gpu:
        if (len(torch.where(val_losses_t == val_losses_last_item)[1]) == 1) and
(
            len(torch.where(val_metrics_t == val_metrics_last_item)[1]) == 1
):
            val_losses_last_gpu = torch.where(
                val_losses_t == val_losses_last_item)[1].item()
            val_metrics_last_gpu = torch.where(
                val_metrics_t == val_metrics_last_item)[1].item()
            val_losses_last_gpu_row = torch.where(
                val_losses_t == val_losses_last_item)[0].item()
            val_metrics_last_gpu_row = torch.where(
                val_metrics_t == val_metrics_last_item)[0].item()

```

```

        val_losses_last_gpu]
        val_metrics_last_loss = val_losses_t[val_metrics_last_gpu_row, val_m
etrics_last_gpu]

        if (val_losses_last_item == bval_loss) and (val_metrics_last_item ==
bval_metric) and (
            val_losses_last_gpu == val_metrics_last_gpu) and (self.gpu_id
== val_losses_last_gpu):
            print(f"""\t\tl1/1:[GPU{self.gpu_id}] val_loss improved to {
val_losses_last_item:.4f} | val_f1score improved to {val_metrics
_last_item:.4f}""")
            self._save_checkpoint(train_loss, train_accuracy, train_f1, val_
loss, val_accuracy, val_f1, train_labels, val_labels)

            improved = torch.tensor([True], dtype=torch.bool).to(self.gpu_id
)

            time.sleep(2)
        elif (val_losses_last_item == bval_loss) and (val_metrics_last_item
== bval_metric) and (
            val_losses_last_gpu != val_metrics_last_gpu) and (self.gpu_id
== val_losses_last_gpu):
            print(f"""\t\tl1/2:[GPU{self.gpu_id}] val_loss improved to {
val_losses_last_item:.4f} | val_f1score: {val_losses_last_metric
:.4f}""")
            self._save_checkpoint(train_loss, train_accuracy, train_f1, val_
loss, val_accuracy, val_f1, train_labels, val_labels)

            improved = torch.tensor([True], dtype=torch.bool).to(self.gpu_id
)

            time.sleep(2)
        elif (val_losses_last_item == bval_loss) and (self.gpu_id == val_lo
ses_last_gpu):
            print(f"""\t\tl1/3:[GPU{self.gpu_id}] val_loss improved to {
val_losses_last_item:.4f} | val_f1score: {val_losses_last_metric
:.4f}""")
            self._save_checkpoint(train_loss, train_accuracy, train_f1, val_
loss, val_accuracy, val_f1, train_labels, val_labels)

            improved = torch.tensor([True], dtype=torch.bool).to(self.gpu_id
)

            time.sleep(2)
        elif (val_metrics_last_item == bval_metric) and (self.gpu_id == val_
metrics_last_gpu):
            print(f"""\t\tl1/4:[GPU{self.gpu_id}] val_loss: {
val_metrics_last_loss:.4f} | val_f1score improved to {val_metric
s_last_item:.4f}""")
            self._save_checkpoint(train_loss, train_accuracy, train_f1, val_
loss, val_accuracy, val_f1, train_labels, val_labels)

            improved = torch.tensor([True], dtype=torch.bool).to(self.gpu_id
)

            time.sleep(2)
        elif (len(torch.where(val_losses_t == val_losses_last_item)[1]) == 1) an
d (
            len(torch.where(val_metrics_t == val_metrics_last_item)[1]) > 1)
:
            val_losses_last_gpu = torch.where(
                val_losses_t == val_losses_last_item)[1].item()
            val_losses_last_gpu_row = torch.where(
                val_losses_t == val_losses_last_item)[0].item()
            val_losses_last_metric = val_metrics_t[val_losses_last_gpu_row, val_
losses_last_gpu]

            if (val_losses_last_item == bval_loss) and (self.gpu_id == val_losse
s_last_gpu):
                print(f"""\t\tl3:[GPU{self.gpu_id}] val_loss improved to {
val_losses_last_item:.4f} | val_f1score: {val_losses_last_metric

```

```

:.4f}""")
        self._save_checkpoint(train_loss, train_accuracy, train_f1, val_
loss, val_accuracy, val_f1, train_labels, val_labels)

        improved = torch.tensor([True], dtype=torch.bool).to(self.gpu_id
)

        time.sleep(2)
    else:
        pass
    else:
        if (val_losses_last_item == bval_loss) and (val_metrics_last_item == bva
l_metric):
            print(f"""\t\t1:val_loss improved to {
val_losses_last_item:.4f} | val_f1score improved to {val_metrics_las
t_item:.4f}""")
            self._save_checkpoint(train_loss, train_accuracy, train_f1, val_loss
, val_accuracy, val_f1, train_labels, val_labels)

            improved = torch.tensor([True], dtype=torch.bool)

            time.sleep(2)
        elif val_losses_last_item == bval_loss:
            print(f"""\t\t2:val_loss improved to {
val_losses_last_item:.4f} | val_f1score: {val_metrics_last_item:.4f}
""")
            self._save_checkpoint(train_loss, train_accuracy, train_f1, val_loss
, val_accuracy, val_f1, train_labels, val_labels)

            improved = torch.tensor([True], dtype=torch.bool)

            time.sleep(2)
        elif val_metrics_last_item == bval_metric:
            print(f"""\t\t3:val_loss: {
val_losses_last_item:.4f} | val_f1score improved to {val_metrics_las
t_item:.4f}""")
            self._save_checkpoint(train_loss, train_accuracy, train_f1, val_loss
, val_accuracy, val_f1, train_labels, val_labels)

            improved = torch.tensor([True], dtype=torch.bool)

            time.sleep(2)
        else:
            pass

    if self.gpu:
        # Synchronize patience count across all GPU
        improved_state = self.gather_tensor(improved)

        # Update patience count
        if self.world_size == 1:
            if improved_state:
                patience_count.zero_()
            else:
                patience_count += 1
        else:
            if (improved_state[0] and improved_state[1]) or (improved_state[0] o
r improved_state[1]):
                patience_count.zero_()
            else:
                patience_count += 1

        # Synchronize patience count across all GPUs
        all_patience_counts = self.gather_tensor(patience_count)
        max_patience_count = torch.max(all_patience_counts).item()
        patience_count.fill_(max_patience_count)

    if max_patience_count >= self.patience:
        print(
            f"""\n[GPU{self.gpu_id}] Patience exceeded. Early stopping...")
        should_stop[0] = 1

```

```

        # Synchronize the should_stop tensor across all GPUs
        should_stop_list = [torch.zeros(1).to(
            self.gpu_id) for _ in range(self.world_size)]
        torch.distributed.all_gather(should_stop_list, should_stop)

        # If any GPU wants to stop, all GPUs should stop
        if any(_stop.item() for _stop in should_stop_list):
            break
    else:
        if improved:
            patience_count.zero_()
        else:
            patience_count += 1

            if patience_count >= self.patience:
                print(f"\nPatience exceeded. Early stopping...")
                break

    time.sleep(2)

if self.gpu:
    # Ensure all GPUs exit the training loop together
    dist.barrier()

    if self.gpu_id == 0:
        np.save("train_losses.npy", self.train_losses_, allow_pickle=True)
        np.save("train_fls.npy", self.train_fls_, allow_pickle=True)
        np.save("train_accuracies.npy", self.train_accuracies_, allow_pickle=True)

        np.save("val_losses.npy", self.val_losses_, allow_pickle=True)
        np.save("val_fls.npy", self.val_fls_, allow_pickle=True)
        np.save("val_accuracies.npy", self.val_accuracies_, allow_pickle=True)
    else:
        np.save("train_losses.npy", self.train_losses_, allow_pickle=True)
        np.save("train_fls.npy", self.train_fls_, allow_pickle=True)
        np.save("train_accuracies.npy", self.train_accuracies_, allow_pickle=True)
        np.save("val_losses.npy", self.val_losses_, allow_pickle=True)
        np.save("val_fls.npy", self.val_fls_, allow_pickle=True)
        np.save("val_accuracies.npy", self.val_accuracies_, allow_pickle=True)

```

Writing pt_engine.py

4. Training Script

In []:

```

%%writefile pt_train.py
from torch.distributed import init_process_group, destroy_process_group
from pt_engine import CustomTrainer
from data_loader import load_data_objs
from typing import Optional
from pathlib import Path
import torch.multiprocessing as mp
import torch.distributed as dist
import numpy as np
import argparse
import random
import torch
import time
import os

NUM_WORKERS = os.cpu_count()

def find_free_port():
    """Finds a free port."""
    import socket
    with socket.socket(socket.AF_INET, socket.SOCK_STREAM) as s:
        s.bind(('', 0)) # Bind to port 0 to get a free port

```



```

        print("Got free port...")
        return s.getsockname()[1]

def ddp_setup(rank: int, world_size: int) -> None:
    """
    Args:
        rank: Unique identifier of each process
        world_size: Total number of processes
    """
    os.environ['MASTER_ADDR'] = 'localhost'
    os.environ['MASTER_PORT'] = '12355'
    print("Init. process group...")
    dist.init_process_group("nccl", rank=rank, world_size=world_size)
    torch.cuda.set_device(rank)

def cleanup():
    dist.destroy_process_group()

def set_seed(seed):
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    if torch.cuda.is_available():
        torch.cuda.manual_seed(seed)
        torch.cuda.manual_seed_all(seed)

def main(rank: Optional[int], world_size: Optional[int], total_epochs: int, patience: int
, batch_size: int, save_path: str | Path, xtrain_path: str, xval_path: str, learning_rate
: float, lr_scheduler: str, gpu: bool) -> None:
    if gpu:
        # if rank == 0:
        print(f"{'>' * 10}AnimalClassifier Model Training{'<' * 10}\n")
        ddp_setup(rank, world_size)
        print("Initializing dataset and model...")
        train_dtl, val_dtl, model, criterion, optimizer, scheduler = load_data_objs(
            batch_size, rank, world_size, total_epochs, xtrain_path, xval_path, gpu, ran
k,
            learning_rate, NUM_WORKERS, lr_scheduler)
        print("Created dataset and initialized model...")
        trainer = CustomTrainer(model=model, train_data=train_dtl, val_data=val_dtl, cri
terion=criterion, optimizer=optimizer, gpu_id=rank, save_path=save_path, gpu=gpu, patien
ce=patience, max_epochs=total_epochs, world_size=world_size, scheduler=scheduler)
        print("Starting model training...")
        trainer.train()
        # destroy_process_group()
        cleanup()
        print(f"\n<{'=' * 10}Training completed & best model saved{'=' * 10}>\nExiting..
.")
    else:
        print(f"{'>' * 10}AnimalClassifier Model Training{'<' * 10}\n")
        train_dtl, val_dtl, model, criterion, optimizer, scheduler = load_data_objs(
            batch_size, rank, world_size, total_epochs, xtrain_path, xval_path, gpu, ran
k,
            learning_rate, NUM_WORKERS, lr_scheduler)
        trainer = CustomTrainer(model=model, train_data=train_dtl, val_data=val_dtl, cri
terion=criterion, optimizer=optimizer, gpu_id=rank, save_path=save_path, gpu=gpu, patien
ce=patience, max_epochs=total_epochs, world_size=world_size, scheduler=scheduler)
        trainer.train()
        print(f"\n<{'=' * 10}Training completed & best model saved{'=' * 10}>\nExiting..
.")

def create_model_path(path_str: str) -> Path | None:
    try:
        model_path = Path(path_str)
        model_path.mkdir(parents=True, exist_ok=True)

        # Check if the directory is writable

```

```

        if not os.access(model_path, os.W_OK):
            raise PermissionError(f"The directory {model_path} is not writable.")

        return model_path

    except PermissionError as e:
        print(f"Permission error: {e}")
        return None

    except OSError as e:
        print(f"OS error occurred when creating directory: {e}")
        return None

    except Exception as e:
        print(f"An unexpected error occurred: {e}")
        return None

def exec_time(st: float, et: float) -> None:
    hour = int(et-st)//3600
    minute = int((et-st)%3600)//60
    second = int(et-st)%60
    print(f'\nexec time => {hour:02d}hr : {minute:02d}min : {second:02d}sec')

if __name__ == "__main__":
    os.environ['NOTEBOOKAPP_IOPUB_MSG_RATE_LIMIT'] = '10000.0'
    os.environ['NOTEBOOKAPP_RATE_LIMIT_WINDOW'] = '10.0'
    os.environ["PYTORCH_CUDA_ALLOC_CONF"] = "expandable_segments:True"
    parser = argparse.ArgumentParser(description='simple distributed training job')
    parser.add_argument('--total_epochs', default=10, type=int,
                        help='Total epochs to train the model (default: 10)')
    parser.add_argument('--patience', default=5, type=int,
                        help='Patience for increasing val_loss (default: 5)')
    parser.add_argument('--batch_size', default=32, type=int,
                        help='Input batch size on each device (default: 32)')
    parser.add_argument('--model_save_path', default='./checkpoints', type=str,
                        help='Path to save the best model (default: ./checkpoints)')
    parser.add_argument('--xtrain_path', default='X_train.npy', type=str,
                        help='Path to X_train pytorch tensor (default: X_train.npy)')
    parser.add_argument('--xval_path', default='X_val.npy', type=str,
                        help='Path to X_val pytorch tensor (default: X_val.npy)')
    parser.add_argument('--learning_rate', default=0.001, type=float,
                        help='Select learning rate (default: 0.001)')
    parser.add_argument('--lr_scheduler', default=None, type=str,
                        help='Select learning rate scheduler (default: None)')
    parser.add_argument('--world_size', default=None, type=int,
                        help='Pass the number of GPUs to be used for training (default: N
one(all))')
    parser.add_argument('--gpu', action='store_true', help='Train on GPU (default)')
    parser.add_argument('--no-gpu', dest='gpu', action='store_false', help='Train on CPU
')
    parser.set_defaults(gpu=True)
    args = parser.parse_args()

    MODEL_PATH = create_model_path(args.model_save_path)

    if MODEL_PATH is None:
        print("Failed to create model path. Exiting program.")
        exit(1)

    if args.gpu:
        if args.world_size == None:
            world_size = torch.cuda.device_count()
        else:
            world_size = args.world_size

        # Set the start method to 'forkserver'
        mp.set_start_method('forkserver', force=True)

        set_seed(42)

```

```

        start_time = time.time()
        mp.spawn(main,
                  args=(world_size, args.total_epochs, args.patience, args.batch_size, MODEL_PATH, args.xtrain_path,
                        args.xval_path, args.learning_rate, args.lr_scheduler, args.gpu),
                  nprocs=world_size, join=True)
        end_time = time.time()
        exec_time(start_time, end_time)
    else:
        start_time = time.time()
        set_seed(42)
        main(None, None, args.total_epochs, args.patience, args.batch_size, MODEL_PATH,
             args.xtrain_path,
             args.xval_path, args.learning_rate, args.lr_scheduler, args.gpu)
        end_time = time.time()
        exec_time(start_time, end_time)

```

Writing pt_train.py

5. Start Training

In []:

```

# Kaggle
# !python pt_train.py --total_epochs 10 --batch_size 64 --gpu --xtrain_path '/kaggle/working/Animal Classification/dataset/train' --xval_path '/kaggle/working/Animal Classification/dataset/test' --learning_rate 0.001 --world_size 1

# Colab
!python pt_train.py --total_epochs 10 --batch_size 64 --gpu --xtrain_path '/content/Animal Classification/dataset/train' --xval_path '/content/Animal Classification/dataset/test' --learning_rate 0.001 --world_size 1

```

>>>>>>>>>AnimalClassifier Model Training<<<<<<<<<<

Init. process group...

[W1229 10:28:47.623564793 CUDAAllocatorConfig.h:28] Warning: expandable_segments not supported on this platform (function operator())

Initializing dataset and model...

Downloading: "https://download.pytorch.org/models/efficientnet_b0_rwightman-7f5810bc.pth" to /root/.cache/torch/hub/checkpoints/efficientnet_b0_rwightman-7f5810bc.pth

100% 20.5M/20.5M [00:00<00:00, 143MB/s]

Created dataset and initialized model...

Starting model training...

[GPU0] Epoch 1/10 | Training: 25 batches... 100%
0:00:19

Evaluating... 100% 0:00:16

[GPU0] | Batches: 25 per GPU | Val Steps: 395 | train_loss: 1.2156 | val_loss: 0.2112 | train_accuracy: 0.7476 | val_accuracy: 0.9494 | train_f1: 0.7471 | val_f1: 0.9494 | Learning Rate: 0.001000

1/1:[GPU0] val_loss improved to 0.2112 | val_f1score improved to 0.9494

New best model saved at checkpoints/best_model.pt from GPU0.

[GPU0] Epoch 2/10 | Training: 25 batches... 100%
0:00:17

Evaluating... 100% 0:00:15

[GPU0] | Batches: 25 per GPU | Val Steps: 395 | train_loss: 0.2113 | val_loss: 0.1287 | train_accuracy: 0.9645 | val_accuracy: 0.9772 | train_f1: 0.9644 | val_f1: 0.9775 | Learning Rate: 0.001000

1/1:[GPU0] val_loss improved to 0.1287 | val_f1score improved to 0.9775

New best model saved at checkpoints/best_model.pt from GPU0.

[GPU0] Epoch 3/10 | Training: 25 batches... 100%
0:00:17

Evaluating... 100% 0:00:15

[GPU0] | Batches: 25 per GPU | Val Steps: 395 | train_loss: 0.0956 | val_loss: 0.0993 | train_accuracy: 0.9813 | val_accuracy: 0.9696 | train_f1: 0.9811 | val_f1: 0.9697 | Learning Rate: 0.001000

1/3:[GPU0] val_loss improved to 0.0993 | val_f1score: 0.9697

New best model saved at checkpoints/best_model.pt from GPU0.

[GPU0] Epoch 4/10 | Training: 25 batches... 100%
0:00:18

Evaluating... 100% 0:00:15

```

Evaluating... 100% 0:00:15
[GPU0] | Batches: 25 per GPU | Val Steps: 395 | train_loss: 0.0587 | val_loss: 0.0846 |
train_accuracy: 0.9871 | val_accuracy: 0.9747 | train_f1: 0.9870 | val_f1: 0.9754 | Learn
ing Rate: 0.001000
1/3:[GPU0] val_loss improved to 0.0846 | val_f1score: 0.9754
New best model saved at checkpoints/best_model.pt from GPU0.
[GPU0] Epoch 5/10 | Training: 25 batches... 100%
0:00:17
Evaluating... 100% 0:00:15
[GPU0] | Batches: 25 per GPU | Val Steps: 395 | train_loss: 0.0421 | val_loss: 0.0735 |
train_accuracy: 0.9923 | val_accuracy: 0.9823 | train_f1: 0.9923 | val_f1: 0.9823 | Learn
ing Rate: 0.001000
1/1:[GPU0] val_loss improved to 0.0735 | val_f1score improved to 0.9823
New best model saved at checkpoints/best_model.pt from GPU0.
[GPU0] Epoch 6/10 | Training: 25 batches... 100%
0:00:17
Evaluating... 100% 0:00:15
[GPU0] | Batches: 25 per GPU | Val Steps: 395 | train_loss: 0.0334 | val_loss: 0.0688 |
train_accuracy: 0.9955 | val_accuracy: 0.9772 | train_f1: 0.9954 | val_f1: 0.9772 | Learn
ing Rate: 0.001000
1/3:[GPU0] val_loss improved to 0.0688 | val_f1score: 0.9772
New best model saved at checkpoints/best_model.pt from GPU0.
[GPU0] Epoch 7/10 | Training: 25 batches... 100%
0:00:17
Evaluating... 100% 0:00:15
[GPU0] | Batches: 25 per GPU | Val Steps: 395 | train_loss: 0.0213 | val_loss: 0.0768 |
train_accuracy: 0.9955 | val_accuracy: 0.9797 | train_f1: 0.9954 | val_f1: 0.9796 | Learn
ing Rate: 0.001000
[GPU0] Epoch 8/10 | Training: 25 batches... 100%
0:00:17
Evaluating... 100% 0:00:15
[GPU0] | Batches: 25 per GPU | Val Steps: 395 | train_loss: 0.0230 | val_loss: 0.0861 |
train_accuracy: 0.9948 | val_accuracy: 0.9722 | train_f1: 0.9948 | val_f1: 0.9723 | Learn
ing Rate: 0.001000
[GPU0] Epoch 9/10 | Training: 25 batches... 100%
0:00:17
Evaluating... 100% 0:00:15
[GPU0] | Batches: 25 per GPU | Val Steps: 395 | train_loss: 0.0228 | val_loss: 0.0758 |
train_accuracy: 0.9974 | val_accuracy: 0.9772 | train_f1: 0.9975 | val_f1: 0.9772 | Learn
ing Rate: 0.001000
[GPU0] Epoch 10/10 | Training: 25 batches... 100%
% 0:00:18
Evaluating... 100% 0:00:14
[GPU0] | Batches: 25 per GPU | Val Steps: 395 | train_loss: 0.0228 | val_loss: 0.0830 |
train_accuracy: 0.9955 | val_accuracy: 0.9772 | train_f1: 0.9955 | val_f1: 0.9773 | Learn
ing Rate: 0.001000

<=====Training completed & best model saved=====>
Exiting...

exec time => 00hr : 06min : 45sec

```

6. Model Evaluation

In []:

```

# Function for saving plotly plots as html to embed them later
with open('html_template.html', 'w') as f:
    f.write("""
<!doctype html>
<html>
<head>
<meta charset="utf-8" />
<meta name="viewport" content="width=device-width, initial-scale=1.0" />
</head>

<body>
<!-- <h3>{{ heading }}</h3> -->
{{ fig }}
</body>

```

```

</head>
""")

# Function to save plotly plots as html
def fig_to_html(fig: plotly.graph_objs._figure.Figure,
                # plot_heading: str,
                output_path: Optional[str]="output.html",
                template_path: Optional[str]="html_template.html") -> None:
    """
    Convert a plotly figure to an HTML.

    """

    # Create output directory if it doesn't exist
    output_dir = "plotly_html"
    os.makedirs(output_dir, exist_ok=True)

    from jinja2 import Template

    # Convert the figure to HTML
    plotly_jinja_data = {
        "fig": fig.to_html(full_html=False, include_plotlyjs="cdn"),
        # "heading": plot_heading
    }

    # Load the template
    with open(os.path.join(output_dir, output_path), "w", encoding="utf-8") as f:
        with open(template_path, "r", encoding="utf-8") as template_file:
            template = Template(template_file.read())
            f.write(template.render(plotly_jinja_data))

```

In []:

```

# Preparing data for plotting epochs vs metrics curve.

tl_data = pd.DataFrame(np.load('train_losses.npy', allow_pickle=True).item())
vl_data = pd.DataFrame(np.load('val_losses.npy', allow_pickle=True).item())
ta_data = pd.DataFrame(np.load('train_accuracies.npy', allow_pickle=True).item())
va_data = pd.DataFrame(np.load('val_accuracies.npy', allow_pickle=True).item())
tfl_data = pd.DataFrame(np.load('train_f1s.npy', allow_pickle=True).item())
vfl_data = pd.DataFrame(np.load('val_f1s.npy', allow_pickle=True).item())

losses_df = pd.concat([tl_data, vl_data], axis=1)
accuracies_df = pd.concat([ta_data, va_data], axis=1)
f1scores_df = pd.concat([tfl_data, vfl_data], axis=1)

losses_df['epochs'] = np.arange(1, len(losses_df)+1)
accuracies_df['epochs'] = np.arange(1, len(accuracies_df)+1)
f1scores_df['epochs'] = np.arange(1, len(f1scores_df)+1)

# Plotting curve.

if len(losses_df.columns) > 3:

    fig1 = px.line(data_frame=losses_df, x='epochs', y=['train_losses0', 'val_losses0'],
height=750, width=750, title='Loss Curves: GPU0')

    fig1.update_xaxes(title_text='Epoch',)

```

```

fig1.update_yaxes(title_text='Loss')

fig_to_html(fig1, 'loss_curve_g0.html')
fig1.show()

fig2 = px.line(data_frame=losses_df, x='epochs', y=['train_losses1', 'val_losses1'],
height=750, width=750, title='Loss Curves: GPU1')

fig2.update_xaxes(title_text='Epoch',)

fig2.update_yaxes(title_text='Loss')

fig_to_html(fig2, 'loss_curve_g1.html')
fig2.show()

fig3 = px.line(data_frame=accuracies_df, x='epochs', y=['train_metrics0', 'val_metri
cs0'], height=750, width=750, title='Accuracy Curves: GPU0')

fig3.update_xaxes(title_text='Epoch',)

fig3.update_yaxes(title_text='Accuracy')

fig_to_html(fig3, 'accuracy_curve_g0.html')
fig3.show()

fig4 = px.line(data_frame=accuracies_df, x='epochs', y=['train_metrics1', 'val_metri
cs1'], height=750, width=750, title='Accuracy Curves: GPU1')

fig4.update_xaxes(title_text='Epoch',)

fig4.update_yaxes(title_text='Accuracy')

fig_to_html(fig4, 'accuracy_curve_g1.html')
fig4.show()

fig5 = px.line(data_frame=f1scores_df, x='epochs', y=['train_metrics0', 'val_metrics
0'], height=750, width=750, title='F1Score Curves: GPU0')

fig5.update_xaxes(title_text='Epoch',)

fig5.update_yaxes(title_text='F1Score')

fig_to_html(fig5, 'f1score_curve_g0.html')
fig5.show()

fig6 = px.line(data_frame=f1scores_df, x='epochs', y=['train_metrics1', 'val_metrics
1'], height=750, width=750, title='F1Score Curves: GPU1')

fig6.update_xaxes(title_text='Epoch',)

fig6.update_yaxes(title_text='F1Score')

fig_to_html(fig6, 'f1score_curve_g1.html')
fig6.show()

# fig1.show(), fig2.show(), fig3.show(), fig4.show(), fig5.show(), fig6.show()
elif len(losses_df.columns == 3) and 'train_losses1' not in losses_df.columns:
    fig1 = px.line(data_frame=losses_df, x='epochs', y=['train_losses0', 'val_losses0'],
height=750, width=750, title='Loss Curves')

    fig1.update_xaxes(title_text='Epoch',)

    fig1.update_yaxes(title_text='Loss')

    fig_to_html(fig1, 'loss_curve.html')

    fig2 = px.line(data_frame=accuracies_df, x='epochs', y=['train_metrics0', 'val_metri
cs0'], height=750, width=750, title='Accuracy Curves')

    fig2.update_xaxes(title_text='Epoch',)

    fig2.update_yaxes(title_text='Accuracy')

```

```

fig_to_html(fig2, 'accuracy_curve.html')

fig3 = px.line(data_frame=f1scores_df, x='epochs', y=['train_metrics0', 'val_metrics0'], height=750, width=750, title='F1Score Curves')

fig3.update_xaxes(title_text='Epoch',)

fig3.update_yaxes(title_text='F1Score')

fig_to_html(fig3, 'f1score_curve.html')

fig1.show(), fig2.show(), fig3.show()
else:

    fig1 = px.line(data_frame=losses_df, x='epochs', y=['train_losses', 'val_losses'], height=750, width=750, title='Loss Curves')

    fig1.update_xaxes(title_text='Epoch',)

    fig1.update_yaxes(title_text='Loss')

    fig_to_html(fig1, 'loss_curve.html')

    fig2 = px.line(data_frame=accuracies_df, x='epochs', y=['train_metrics', 'val_metrics'], height=750, width=750, title='Accuracy Curves')

    fig2.update_xaxes(title_text='Epoch',)

    fig2.update_yaxes(title_text='Accuracy')

    fig_to_html(fig2, 'accuracy_curve.html')

    fig3 = px.line(data_frame=f1scores_df, x='epochs', y=['train_metrics', 'val_metrics'], height=750, width=750, title='F1Score Curves')

    fig3.update_xaxes(title_text='Epoch',)

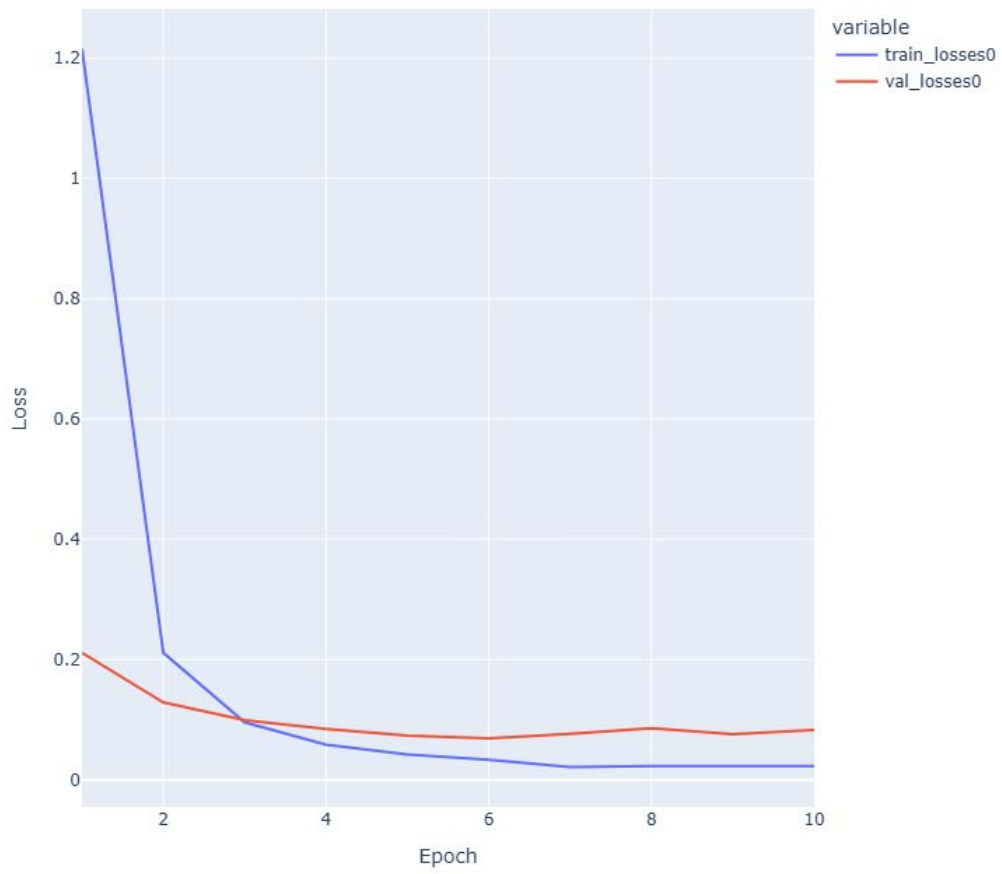
    fig3.update_yaxes(title_text='F1Score')

    fig_to_html(fig3, 'f1score_curve.html')

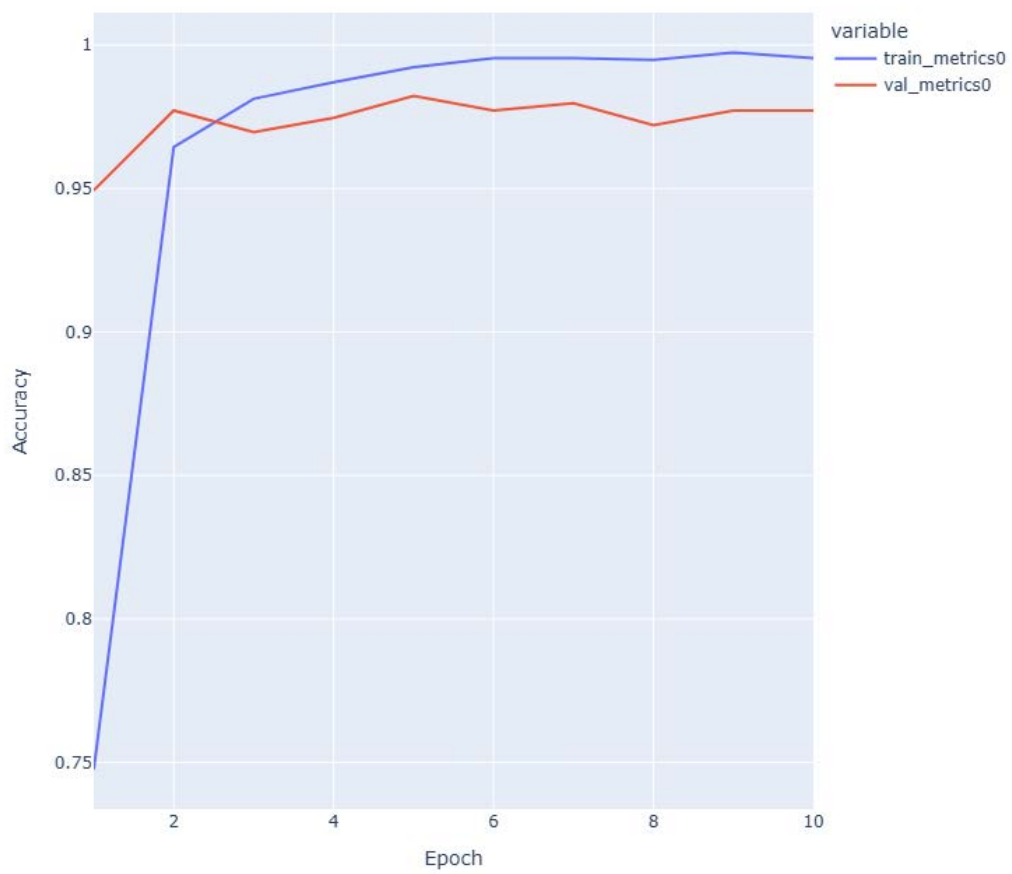
    fig1.show(), fig2.show(), fig3.show()

```

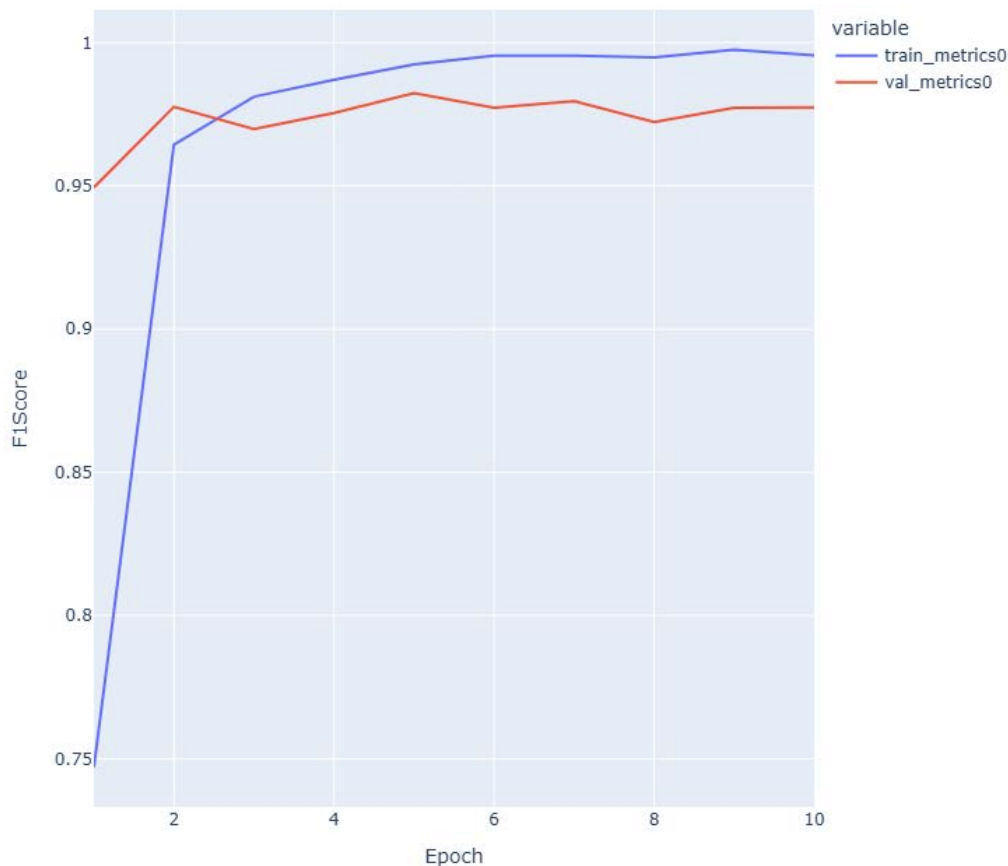
Loss Curves



Accuracy Curves



F1Score Curves



Both accuracy and F1-score curves show very similar patterns, which suggests consistent performance across classes. The model achieves impressive final metrics, with training accuracy/F1-score around 99% and validation accuracy/F1-score around 97%. Let's break down the learning progression:

Initial Learning Phase (Epochs 1-4): The model shows rapid improvement in both metrics, with training performance starting from around 77% and quickly climbing to nearly 99%. This steep learning curve indicates that the model is effectively capturing the distinguishing features of different animal classes during early training.

Convergence Phase (Epochs 4-10): After epoch 4, both metrics stabilize, with training metrics hovering around 99% and validation metrics around 97%. This consistent gap between training and validation performance (about 2%) indicates a small but acceptable level of overfitting.

Initial Loss Reduction: Training loss starts quite high (around 1.2) and drops dramatically in the first two epochs, while validation loss starts lower (around 0.3). This pattern is typical when using transfer learning with a pre-trained model like EfficientNetB0.

Loss Convergence: After epoch 4, both training and validation losses stabilize, with training loss slightly lower than validation loss. The final values (approximately 0.05 for training and 0.1 for validation) indicate good model convergence.

Overall Assessment: The high F1-scores suggest good performance across all animal classes, indicating balanced learning. The model reaches stability relatively quickly (by epoch 4), suggesting efficient learning. The moderate gap between training and validation metrics indicates the model should generalize well to new images.

In []:

```
import builtins
torch.serialization.add_safe_globals([torchvision.transforms._presets.ImageClassification,
torchvision.transforms.functional.InterpolationMode, torchvision.datasets.folder.Image
```

```

Folder, torchvision.datasets.vision.StandardTransform, torchvision.datasets.folder.default_loader, builtins.set])
val_data = torch.load('val_data.pt', weights_only=True)

val_dtl = DataLoader(val_data, batch_size=1, shuffle=False, pin_memory=True)

class_names = torch.load("class_names.pt", weights_only=True)
transform = torch.load("effnetb0_transform.pt", weights_only=True)
model = torchvision.models.efficientnet_b0()
for param in model.features.parameters():
    param.requires_grad = False

# Unfreeze the last 10 layers
layers = list(model.named_parameters())
for name, param in layers[-10:]:
    param.requires_grad = True

# Recreate the classifier layer
model.classifier = nn.Sequential(
    nn.Dropout(p=0.2, inplace=True),
    nn.Linear(in_features=model.classifier[1].in_features, out_features=len(class_names), bias=True))

model.load_state_dict(torch.load('checkpoints/best_model.pt', weights_only=True))
model.to(0)

# Metrics
val_metric_accuracy = torchmetrics.classification.MulticlassAccuracy(num_classes=15, average="micro", sync_on_compute=False).to(0)
val_metric_f1score = torchmetrics.classification.MulticlassF1Score(num_classes=15, average="macro", sync_on_compute=False).to(0)

# Criterion
criterion = nn.CrossEntropyLoss()

model.eval()
total_samples = len(val_dtl.dataset)
total_loss = 0
total_accuracy = 0
total_f1score = 0
total_samples_ = 0

# val_dtl.sampler.set_epoch(epoch)
val_metric_accuracy.reset()
val_metric_f1score.reset()

pred_labels = np.array([{'targets': [], 'preds': []}])
with torch.inference_mode():
    for source, targets in track(val_dtl, description=f"Evaluating...", style='red', complete_style='cyan', finished_style='green'):
        source = source.to(0)
        targets = targets.to(0)

        y_logits = model(source)
        preds = torch.softmax(y_logits, dim=1)
        preds = torch.argmax(preds, dim=1)
        loss = criterion(y_logits, targets)

        batch_size_ = source.size(0) # Get batch size
        total_samples_ += batch_size_ # Accumulate total samples

        val_metric_accuracy.update(preds, targets)
        val_metric_f1score.update(preds, targets)
        total_loss += loss.item() * batch_size_

        pred_labels[0]['preds'].extend(preds.detach().cpu().numpy().tolist())
        pred_labels[0]['targets'].extend(targets.cpu().numpy().tolist())

model.train()
avg_loss = total_loss / total_samples_

accuracy = val_metric_accuracy.compute()

```

```
f1score = val_metric_f1score.compute()

print(f"""\nLoss --> {avg_loss:.4%} | Accuracy --> {accuracy:.4%} | F1Score --> {f1score:.4%}""")
print(f"Classification Report:\n\n{classification_report(np.array(pred_labels[0]['targets']), np.array(pred_labels[0]['preds']), target_names=class_names)}")
```

Loss --> 6.8754% | Accuracy --> 97.7215% | F1Score --> 97.7163%
Classification Report:

	precision	recall	f1-score	support
Bear	1.00	1.00	1.00	25
Bird	0.93	1.00	0.97	28
Cat	0.93	1.00	0.96	25
Cow	0.92	0.89	0.91	27
Deer	1.00	1.00	1.00	26
Dog	1.00	0.96	0.98	25
Dolphin	1.00	1.00	1.00	26
Elephant	0.96	0.96	0.96	27
Giraffe	1.00	1.00	1.00	26
Horse	1.00	0.88	0.94	26
Kangaroo	0.93	0.96	0.94	26
Lion	1.00	1.00	1.00	27
Panda	1.00	1.00	1.00	27
Tiger	1.00	1.00	1.00	26
Zebra	1.00	1.00	1.00	28
accuracy			0.98	395
macro avg	0.98	0.98	0.98	395
weighted avg	0.98	0.98	0.98	395

Overall Performance

- **Accuracy: 97.72%** - This signifies that the model correctly classified nearly 98% of the animals in the validation/test set. This is a very high accuracy, indicating strong overall performance.
- **Macro Average:** This averages the precision, recall, and F1-score across all classes. A macro average of 0.98 is excellent and shows that the model performs well across all animal categories.
- **Weighted Average:** This is similar to macro average, but it weights the scores based on the number of samples in each class. The 0.98 weighted average confirms the model's strong performance, especially considering class imbalances.

Per-Class Performance

Precision: Out of all the animals predicted to be a certain class, what proportion was actually correct?

Recall: Out of all the animals that truly belong to a certain class, what proportion did the model correctly identify?

F1-score: The harmonic mean of precision and recall, providing a balanced measure of the model's performance.

Observations:

High Precision and Recall: Most classes have precision and recall values above 0.90, implying that the model is accurate in identifying each animal and rarely misclassifies them.

Perfect Scores: Some animals (Lion, Panda, Tiger, Zebra, Deer, Bear, Giraffe) achieved perfect or near-perfect scores (1.00 or 0.98+). This highlights the model's exceptional ability to distinguish these animals.

Slight Variations: While most classes performed exceptionally well, a few (Cow, Horse) show slightly lower scores (around 0.90). This suggests there might be some confusion in distinguishing these animals from others, possibly due to visual similarities or fewer training samples.

In []:

```
# Plot Confusion Matrix
```

```
def plot_confusion_matrix(y_test: np.ndarray, y_preds: np.ndarray, plot_name: str, class_names: List[str]) -> None:
    """Plot confusion matrix."""

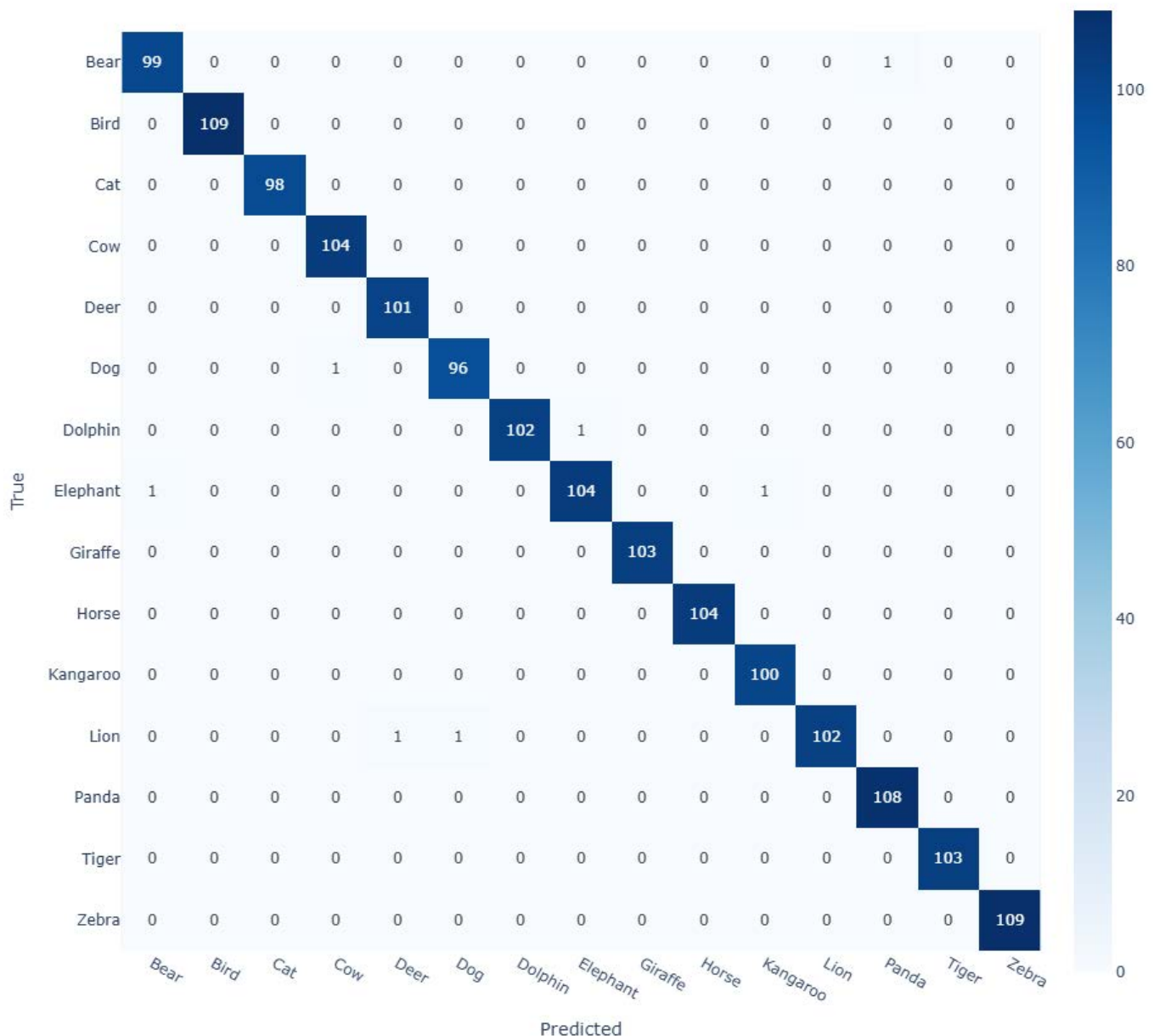
    cm = confusion_matrix(y_test, y_preds)

    fig = px.imshow(
        cm,
        text_auto=True,  # Display values on the heatmap
        labels=dict(x="Predicted", y="True"),  # Set axis labels
        x=class_names,  # Update x-axis labels
        y=class_names,  # Update y-axis labels
        color_continuous_scale="Blues",  # Customize the color scale
        width=920,
        height=920
    )

    fig.update_layout(title=f"Confusion Matrix")  # Set plot title
    fig_to_html(fig, f"{plot_name}")
    fig.show()  # Display plot

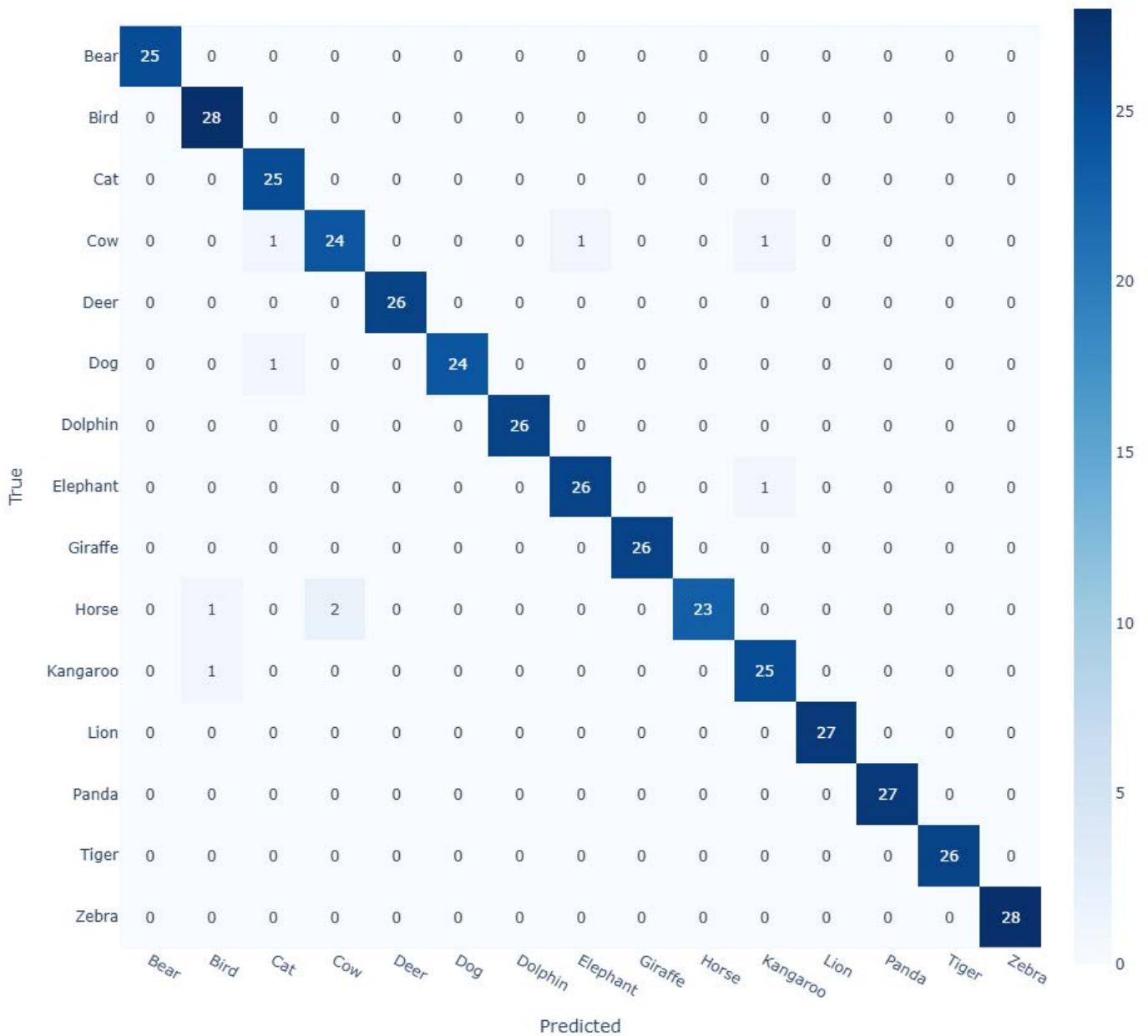
train_labels = np.load('train_labels.npy', allow_pickle=True)
plot_confusion_matrix(np.array(train_labels[0]['targets']), np.array(train_labels[0]['preds']), "confusion matrix train.html")
```

Confusion Matrix



```
plot_confusion_matrix(np.array(pred_labels[0]['targets']), np.array(pred_labels[0]['preds']), "confusion_matrix_val.html")
```

Bear	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bird	0	28	0	0	0	0	0	0	0	0	0	0	0	0	0
Cat	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0
Cow	0	0	1	24	0	0	0	1	0	0	1	0	0	0	0
Deer	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0
Dog	0	0	1	0	0	24	0	0	0	0	0	0	0	0	0
Dolphin	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0
Elephant	0	0	0	0	0	0	0	26	0	0	1	0	0	0	0
Giraffe	0	0	0	0	0	0	0	0	26	0	0	0	0	0	0
Horse	0	1	0	2	0	0	0	0	0	23	0	0	0	0	0
Kangaroo	0	1	0	0	0	0	0	0	0	0	25	0	0	0	0
Lion	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0
Panda	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0
Tiger	0	0	0	0	0	0	0	0	0	0	0	0	0	26	0
Zebra	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28
	Bear	Bird	Cat	Cow	Deer	Dog	Dolphin	Elephant	Giraffe	Horse	Kangaroo	Lion	Panda	Tiger	Zebra
	Predicted														



In []:

```
# Plotting Precision-Recall Curve
def plot_precision_recall_curve(y_test: np.ndarray, y_preds: np.ndarray, plot_name: str,
                                class_names: List=class_names) -> None:
    """Plot precision-recall curve."""

    import plotly.graph_objects as go
    from sklearn.metrics import precision_recall_curve, average_precision_score
    from sklearn.preprocessing import label_binarize

    # Assuming you have 'y_test' (true labels) and 'y_preds' (predicted labels)

    # 1. Binarize the labels
    n_classes = len(class_names) # Get the number of classes
    y_test_bin = label_binarize(y_test, classes=range(n_classes))
    y_preds_bin = label_binarize(y_preds, classes=range(n_classes))

    # 2. Create the Plotly figure
    fig = go.Figure()

    # 3. Calculate and plot precision-recall curves for each class
    for i, cls in enumerate(class_names):
        precision, recall, _ = precision_recall_curve(y_test_bin[:, i], y_preds_bin[:, i])

        avg_precision = average_precision_score(y_test_bin[:, i], y_preds_bin[:, i])

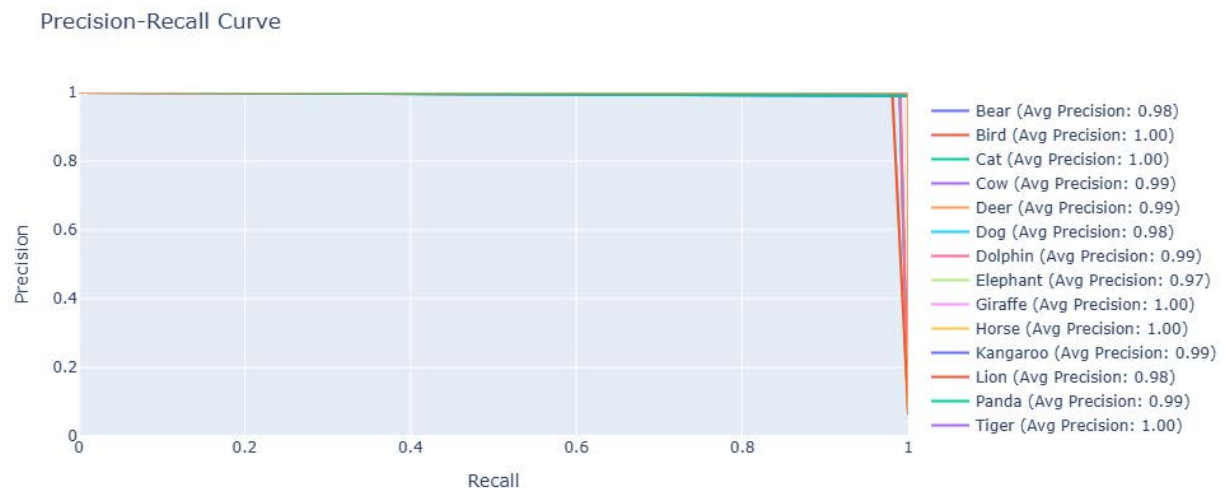
        fig.add_trace(go.Scatter(
            x=recall,
            y=precision,
            mode='lines',
            name=f"{cls} (Avg Precision: {avg_precision:.2f})"
        ))

    # 4. Update layout for better visualization
    fig.update_layout(
        title=f"Precision-Recall Curve",
        xaxis_title="Recall",
        yaxis_title="Precision",
        xaxis_range=[0, 1],
        yaxis_range=[0, 1],
        showlegend=True
    )

    fig_to_html(fig, f"{plot_name}")

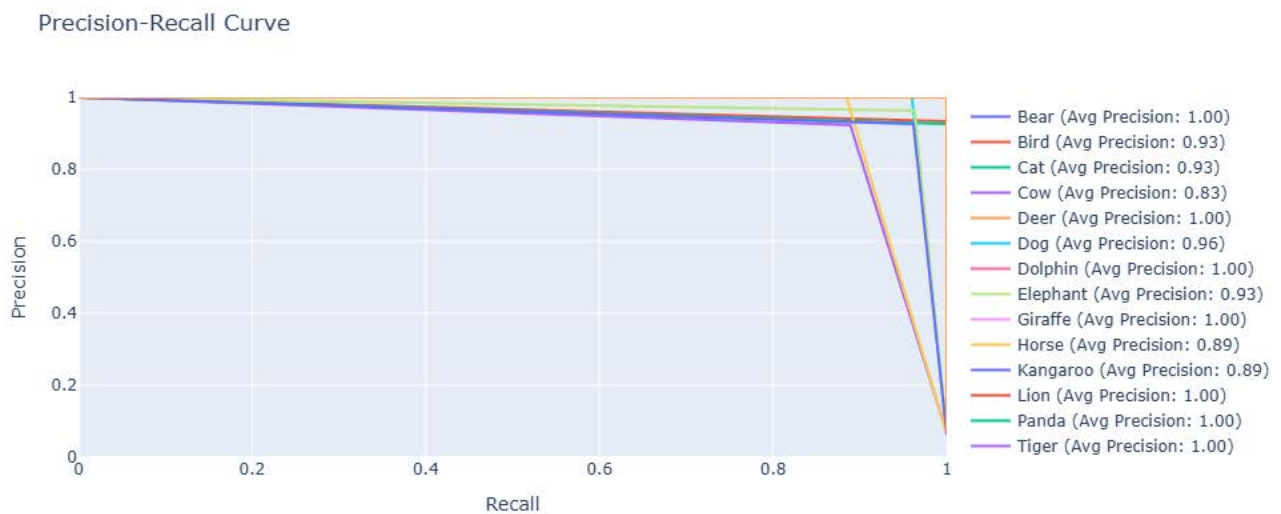
    fig.show() # Display plot

plot_precision_recall_curve(np.array(train_labels[0]['targets']), np.array(train_labels[
0]['preds']), "pr_curve_train.html")
```



In []:

```
plot_precision_recall_curve(np.array(pred_labels[0]['targets']), np.array(pred_labels[0]
['preds']), "pr_curve_val.html")
```



In []:

```
# Plotting ROC Curve
def plot_roc_curve(y_test: np.ndarray, y_preds: np.ndarray, plot_name: str, class_names:
List=class_names) -> None:
    import plotly.graph_objects as go
    from sklearn.metrics import roc_curve, auc, roc_auc_score
    from sklearn.preprocessing import label_binarize
    """Plots the ROC curve."""

    # 1. Binarize the labels.
    n_classes = len(class_names) # Get the number of classes
    y_test_bin = label_binarize(y_test, classes=range(n_classes))
    y_preds_bin = label_binarize(y_preds, classes=range(n_classes))

    # 2. Create the figure.
    fig = go.Figure()

    # 3. Calculate the fpr and tpr.
    for i, cls in enumerate(class_names):
        fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_preds_bin[:, i])
```

```

roc_auc = auc(fpr, tpr)

fig.add_trace(go.Scatter(
    x=fpr,
    y=tpr,
    mode='lines',
    name=f"{cls} (AUC = {roc_auc:.2f})"
))

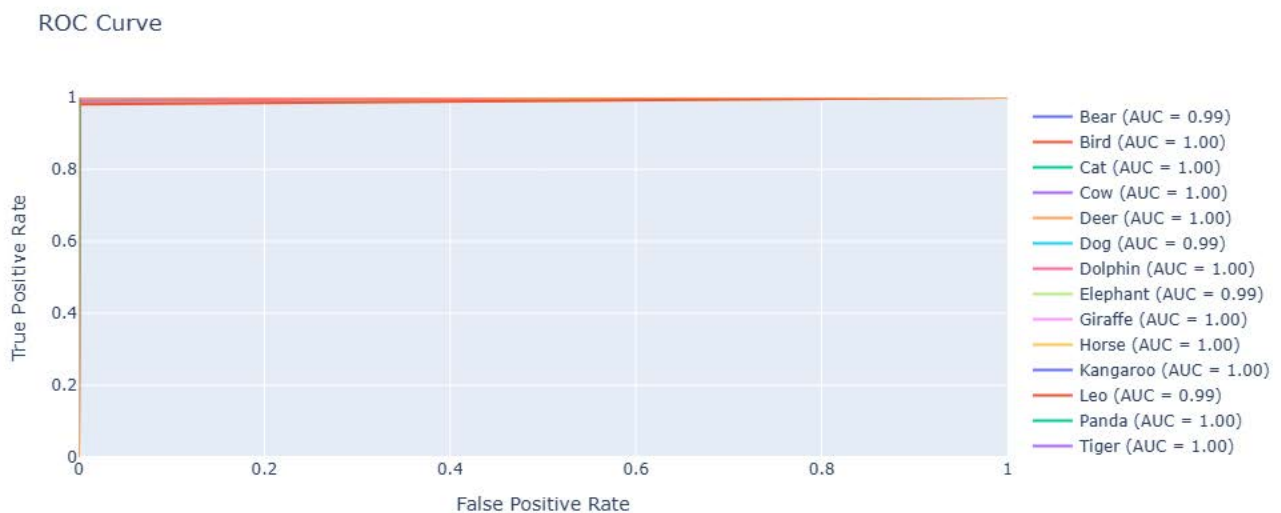
# 4. Update the plot.
fig.update_layout(
    title=f"ROC Curve",
    xaxis_title="False Positive Rate",
    yaxis_title="True Positive Rate",
    xaxis_range=[0, 1],
    yaxis_range=[0, 1],
    showlegend=True
)

fig_to_html(fig, f"{plot_name}")

fig.show() # Display

plot_roc_curve(np.array(train_labels[0]['targets']), np.array(train_labels[0]['preds']),
"roc_curve_train.html")

```



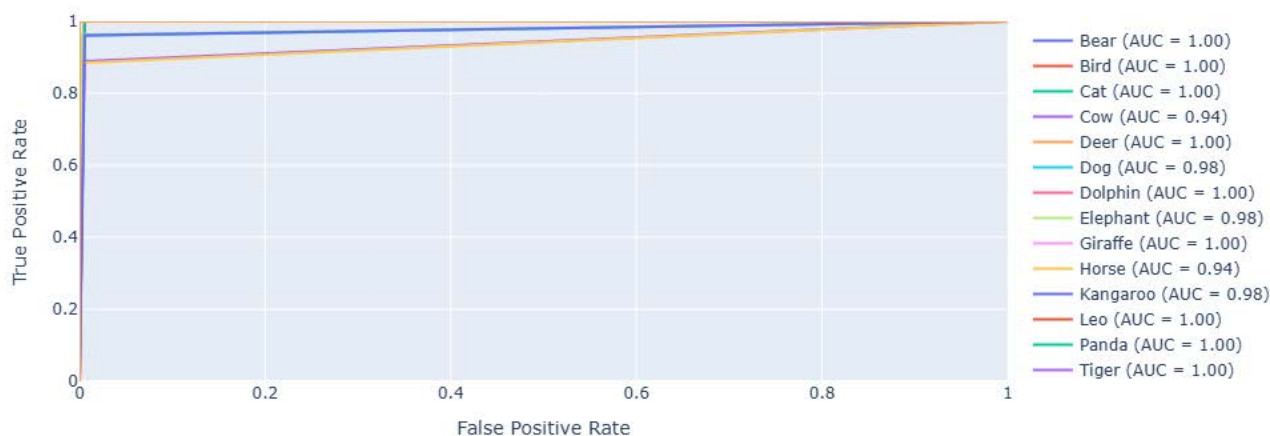
In []:

```

plot_roc_curve(np.array(pred_labels[0]['targets']), np.array(pred_labels[0]['preds']), "
roc_curve_val.html")

```


ROC Curve



7. Logging Model & Artifacts

In [20]:

```
!dagshub login
```

███ AUTHORIZATION REQUIRED ███

Open the following link in your browser to authorize the client:

https://dagshub.com/login/oauth/authorize?state=987b770a-fa8e-4de2-9172-1a068b768cd6&client_id=32b60ba385aa7cecf24046d8195a71c07dd345d9657977863b52e7748e0f0f28&middleman_request_id=216ee3cf52b98d6341693f52133affdc0e9db4dc141210a999740b9ca5c80ee5

⋮ Waiting for authorization

☐ OAuth token added

In [22]:

```
from google.colab import userdata
repo_owner_ = userdata.get('REPO_OWNER')
repo_name_ = userdata.get('REPO_NAME')
tracking_uri = userdata.get('MLFLOW_TRACKING_URI')

# from kaggle_secrets import UserSecretsClient
# repo_owner_ = UserSecretsClient().get_secret("REPO_OWNER")
# repo_name_ = UserSecretsClient().get_secret("REPO_NAME")
# tracking_uri = UserSecretsClient().get_secret("MLFLOW_TRACKING_URI")

os.makedirs('tmp', exist_ok=True)

# Creating function to log experiments to mlflow
def create_experiment(experiment_name: str, run_name: str, run_metrics: Dict[str, Any], model: nn.Module, model_name: Optional[str] = None, artifact_paths: Dict[str, str] = {}, run_params: Optional[Dict[str, Any]] = None, tag_dict: Dict[str, str] = {"tag1": "Binary Classification", "tag2": "Patient Survival Prediction", "tag3": "PyTorch"}):
    try:
        dagshub.init(repo_owner=f"{repo_owner_}", repo_name=f"{repo_name_}", mlflow=True)

    # You can get your MLflow tracking uri from your dagshub repo by opening "Remote" dropdown menu, go to "Experiments" tab and copy the MLflow experiment tracking uri and paste below
```

```

mlflow.set_tracking_uri(f"{tracking_uri}")

mlflow.set_experiment(experiment_name)

with mlflow.start_run(run_name=run_name):

    # log params
    if run_params:
        for param in run_params:
            mlflow.log_param(param, run_params[param])

    # log metrics
    for metric, value in run_metrics.items():
        if isinstance(value, list):

            # If the metric is a list, log each value as a separate step
            for step, v in enumerate(value):
                mlflow.log_metric(metric, v, step=step)
        elif isinstance(value, str):
            value = np.load(value, allow_pickle=True)
            mlflow.log_metric(metric, value)
        else:

            # If it's a single value, log it normally
            mlflow.log_metric(metric, value)

tracking_url_type_store = urlparse(mlflow.get_tracking_uri()).scheme

# log artifacts
for artifact_name, path in artifact_paths.items():
    if path and os.path.exists(path):
        if tracking_url_type_store != "file":
            mlflow.log_artifact(
                path,
                # artifact_name
            )

        elif path:
            print(f"Warning: Artifact file not found: {path}")

# log model
if tracking_url_type_store != "file":
    mlflow.pytorch.log_model(model, "pytorch_model")

mlflow.set_tags(tag_dict)

print(f'Run - {run_name} is logged to Experiment - {experiment_name}')
except Exception as e:
    print(f"An error occurred: {str(e)}")
    import traceback
    traceback.print_exc()

```

In [24]:

```

# Logging Experiment
from datetime import datetime
experiment_name = "animal_clf_pytorch_fttl"
run_name = "run_" + str(datetime.now().strftime("%d-%m-%y_%H:%M:%S"))

run_params = {"epochs": 10, "batch_size": 64, "learning_rate": 0.001, "image_size": 224,
"gpu": True, "lr_scheduler": None}

run_metrics = {"train_accuracy": "accuracy_train.npy", "train_f1score": "f1score_train.n
py", "train_loss": "loss_train.npy", "val_accuracy": "accuracy_val.npy", "val_f1score": "
f1score_val.npy", "val_loss": "loss_val.npy"}

# Kaggle
# kgle = "/kaggle/working"
# plotly_path = "/kaggle/working/plotly_html"

```

```
# Colab
colab = "/content"
plotly_path = "/content/plotly_html"
artifact_paths = {"loss_curve": os.path.join(plotly_path, "loss_curve.html"), "accuracy_
curve": os.path.join(plotly_path, "accuracy_curve.html"), "f1score_curve": os.path.join(
plotly_path, "f1score_curve.html"), "confusion_matrix_train": os.path.join(plotly_path,
"confusion_matrix_train.html"), "pr_curve_train": os.path.join(plotly_path, "pr_curve_tra
in.html"), "roc_curve_train": os.path.join(plotly_path, "roc_curve_train.html"), "confus
ion_matrix_val": os.path.join(plotly_path, "confusion_matrix_val.html"), "pr_curve_val":
os.path.join(plotly_path, "pr_curve_val.html"), "roc_curve_val": os.path.join(plotly_pat
h, "roc_curve_val.html"), "transforms": os.path.join(colab, "effnetb0_transform.pt"), "c
lass_names": os.path.join(colab, "class_names.pt"), "test_data": os.path.join(colab, "va
l_data.pt")}

create_experiment(experiment_name, run_name, run_metrics, model, model_name="pytorch_mode
l_fttl", artifact_paths=artifact_paths, run_params=run_params, tag_dict={"tag1": "Multicl
ass Classification", "tag2": "Animal Classification", "tag3": "PyTorch", "tag4": "Fine T
une Transfer Learning"})
```

Accessing as pranay.makxenia

Initialized MLflow to track repo "pranay.makxenia/ML_Projects"

Repository pranay.makxenia/ML_Projects initialized!

```
2024/12/29 10:46:56 WARNING mlflow.utils.requirements_utils: Found torch version (2.5.1+cu121) contains a local version label (+cu121). MLflow logged a pip requirement for this package as 'torch==2.5.1' without the local version label to make it installable from PyPI. To specify pip requirements containing local version labels, please use `conda_env` or `pip_requirements`.
2024/12/29 10:47:05 WARNING mlflow.utils.requirements_utils: Found torchvision version (0.20.1+cu121) contains a local version label (+cu121). MLflow logged a pip requirement for this package as 'torchvision==0.20.1' without the local version label to make it installable from PyPI. To specify pip requirements containing local version labels, please use `conda_env` or `pip_requirements`.
2024/12/29 10:47:05 WARNING mlflow.models.model: Model logged without a signature and input example. Please set `input_example` parameter when logging the model to auto infer the model signature.
```

□ View run run_29-12-24_10:46:40 at: https://dagshub.com/pranay.makxenia/ML_Projects.mlflow/#/experiments/20/runs/12567e41831b4488a16908e128952e07

□ View experiment at: https://dagshub.com/pranay.makxenia/ML_Projects.mlflow/#/experiments/20

Run - run_29-12-24_10:46:40 is logged to Experiment - animal_clf_pytorch_fttl

8. Identifying Animals

In [25]:

```
# 1. Take in a trained model, class names, image path, image size, a transform and target device
def pred_and_plot_image(model: torch.nn.Module,
                        image_path: str,
                        class_names: List[str],
                        image_size: Tuple[int, int] = (224, 224),
                        transform: torchvision.transforms = None,
                        device: torch.device="cuda:0"):

    # 2. Open image
    img = Image.open(image_path)

    # 3. Create transformation for image (if one doesn't exist)
    if transform is not None:
        image_transform = transform
    else:
        image_transform = transforms.Compose([
            transforms.Resize(image_size),
            transforms.ToTensor(),
```

```

        transforms.Normalize(mean=[0.485, 0.456, 0.406],
                               std=[0.229, 0.224, 0.225]),
    ])

    ### Predict on image ###

    # 4. Make sure the model is on the target device
    model.to(device)

    # 5. Turn on model evaluation mode and inference mode
    model.eval()
    with torch.inference_mode():
        # 6. Transform and add an extra dimension to image (model requires samples in [batch_size, color_channels, height, width])
        transformed_image = image_transform(img).unsqueeze(dim=0)

        # 7. Make a prediction on image with an extra dimension and send it to the target device
        target_image_pred = model(transformed_image.to(device))

        # 8. Convert logits -> prediction probabilities (using torch.softmax() for multi-class classification)
        target_image_pred_probs = torch.softmax(target_image_pred, dim=1)

        # 9. Convert prediction probabilities -> prediction labels
        target_image_pred_label = torch.argmax(target_image_pred_probs, dim=1)

        # 10. Plot image with predicted label and probability
        true_class = image_path.split('/')[0].split('_')[0]
        pred_class = class_names[target_image_pred_label]
        plt.figure()
        plt.imshow(img)
        if true_class == pred_class:
            plt.title(f"True: {true_class} | Pred: {pred_class} | Prob: {target_image_pred_probs.max():.3f}", c='g')
        else:
            plt.title(f"True: {true_class} | Pred: {pred_class} | Prob: {target_image_pred_probs.max():.3f}", c='r')
        plt.axis(False);

```

In [26]:

```

import random
np.random.seed(42)
no_img_pred = 3
test_img_sample = random.sample(val_data.imgs, k=no_img_pred)

for image_path in test_img_sample:
    pred_and_plot_image(model=model,
                        image_path=image_path[0],
                        class_names=class_names,
                        transform=transform,
                        image_size=(224, 224))

```

True: Zebra | Pred: Zebra | Prob: 0.996





True: Lion | Pred: Lion | Prob: 0.843



True: Dolphin | Pred: Dolphin | Prob: 1.000



NEXT

Next we will deploy the trained model on streamlit.