```
import kagglehub
gunavenkatdoddi_eye_diseases_classification_path = kagglehub.dataset_download('gunavenkat
print(PATH)
→ Using Colab cache for faster access to the 'eye-diseases-classification' dataset.
     /kaggle/input/eye-diseases-classification/dataset
# Install libraries for PyTorch
!pip install torch-summary
!pip install torchmetrics
→ Collecting torch-summary
       Downloading torch_summary-1.4.5-py3-none-any.whl.metadata (18 kB)
     Downloading torch_summary-1.4.5-py3-none-any.whl (16 kB)
     Installing collected packages: torch-summary
     Successfully installed torch-summary-1.4.5
     Collecting torchmetrics
       Downloading torchmetrics-1.8.2-py3-none-any.whl.metadata (22 kB)
     Requirement already satisfied: numpy>1.20.0 in /usr/local/lib/python3.12/dist-package
     Requirement already satisfied: packaging>17.1 in /usr/local/lib/python3.12/dist-packa
     Requirement already satisfied: torch>=2.0.0 in /usr/local/lib/python3.12/dist-package
     Collecting lightning-utilities>=0.8.0 (from torchmetrics)
       Downloading lightning utilities-0.15.2-py3-none-any.whl.metadata (5.7 kB)
     Requirement already satisfied: setuptools in /usr/local/lib/python3.12/dist-packages
     Requirement already satisfied: typing_extensions in /usr/local/lib/python3.12/dist-pa
     Requirement already satisfied: filelock in /usr/local/lib/python3.12/dist-packages (f
     Requirement already satisfied: sympy>=1.13.3 in /usr/local/lib/python3.12/dist-packag
     Requirement already satisfied: networkx in /usr/local/lib/python3.12/dist-packages (f
     Requirement already satisfied: jinja2 in /usr/local/lib/python3.12/dist-packages (fro
     Requirement already satisfied: fsspec in /usr/local/lib/python3.12/dist-packages (fro
     Requirement already satisfied: nvidia-cuda-nvrtc-cu12==12.6.77 in /usr/local/lib/pyth
     Requirement already satisfied: nvidia-cuda-runtime-cu12==12.6.77 in /usr/local/lib/py
     Requirement already satisfied: nvidia-cuda-cupti-cu12==12.6.80 in /usr/local/lib/pyth
     Requirement already satisfied: nvidia-cudnn-cu12==9.10.2.21 in /usr/local/lib/python3
     Requirement already satisfied: nvidia-cublas-cu12==12.6.4.1 in /usr/local/lib/python3
     Requirement already satisfied: nvidia-cufft-cu12==11.3.0.4 in /usr/local/lib/python3.
     Requirement already satisfied: nvidia-curand-cu12==10.3.7.77 in /usr/local/lib/python
     Requirement already satisfied: nvidia-cusolver-cu12==11.7.1.2 in /usr/local/lib/pytho
     Requirement already satisfied: nvidia-cusparse-cu12==12.5.4.2 in /usr/local/lib/pytho
     Requirement already satisfied: nvidia-cusparselt-cu12==0.7.1 in /usr/local/lib/python
     Requirement already satisfied: nvidia-nccl-cu12==2.27.3 in /usr/local/lib/python3.12/
     Requirement already satisfied: nvidia-nvtx-cu12==12.6.77 in /usr/local/lib/python3.12
     Requirement already satisfied: nvidia-nvjitlink-cu12==12.6.85 in /usr/local/lib/pytho
     Requirement already satisfied: nvidia-cufile-cu12==1.11.1.6 in /usr/local/lib/python3
     Requirement already satisfied: triton==3.4.0 in /usr/local/lib/python3.12/dist-packag
     Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.12/dist-p
     Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.12/dist-pack
     Downloading torchmetrics-1.8.2-py3-none-any.whl (983 kB)
                                               - 983.2/983.2 kB 9.6 MB/s eta 0:00:00
```

Downloading lightning utilities-0.15.2-py3-none-any.whl (29 kB)

```
# Import libraries for data workings and setting compute source
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sea
import os
from tqdm.notebook import tqdm
import cv2 as op
import torch
from torchsummary import summary
import torchmetrics
plt.style.use('seaborn-v0_8')
np.__version__
device = 'cuda' if torch.cuda.is_available() else 'cpu'
device
ヹ゛'cpu'
```

Loading the data

```
PATH = '/kaggle/input/eye-diseases-classification/dataset'
label2id = {}
for i, label in enumerate(os.listdir(PATH)):
    label2id[label] = i
id2label = {key : value for (value, key) in label2id.items()}
filenames, outcome = [], []
for label in tqdm(os.listdir(PATH)):
    for img in os.listdir(os.path.join(PATH, label)):
        filenames.append(os.path.join(PATH, label, img))
        outcome.append(label2id[label])
df = pd.DataFrame({
    "filename" : filenames,
    "outcome" : outcome
})
df = df.sample(frac = 1)
df.head()
```

	filename	outcome	
3776	/kaggle/input/eye-diseases-classification/data	3	ıl.
3646	/kaggle/input/eye-diseases-classification/data	3	
3823	/kaggle/input/eye-diseases-classification/data	3	
1841	/kaggle/input/eye-diseases-classification/data	1	
199	/kaggle/input/eye-diseases-classification/data	0	

Next steps: (Generate code with df

View recommended plots

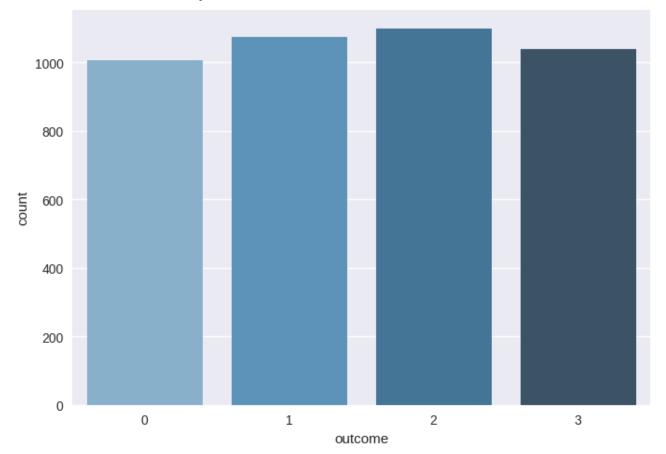
New interactive sheet

Dataset distribution
sea.countplot(x = 'outcome', data = df, palette = 'Blues_d')

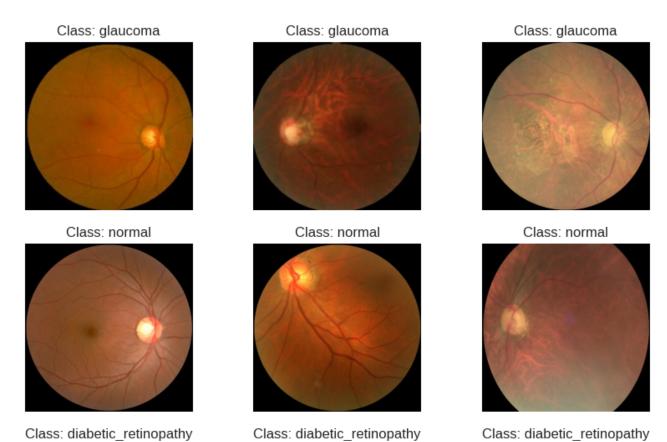
/tmp/ipython-input-1478327885.py:2: FutureWarning:

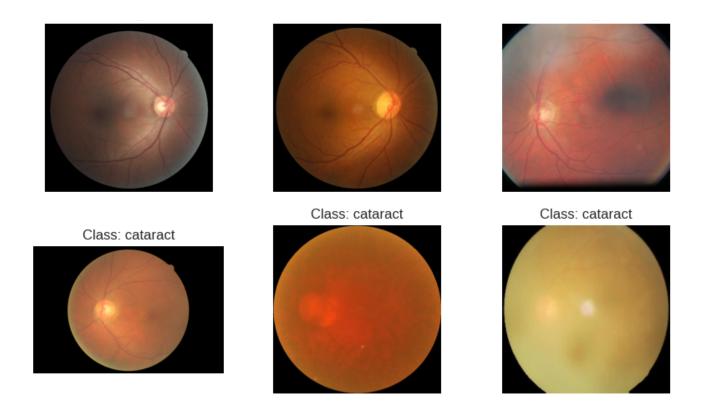
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.

sea.countplot(x = 'outcome', data = df, palette = 'Blues_d')
<Axes: xlabel='outcome', ylabel='count'>



```
display(id2label)
     {0: 'glaucoma', 1: 'normal', 2: 'diabetic_retinopathy', 3: 'cataract'}
# Normalize image using min-max scale method range (0,1) due to image pixel differences
def load_image(path):
    img = plt.imread(path)
    img = (img - img.min())/img.max()
   return img
counter = 0
plt.figure(figsize = (10, 12))
for i in range(4):
    for path in df[df['outcome'] == i].sample(n = 3)['filename']:
        plt.subplot(4, 3, counter + 1)
        img = load_image(path)
        plt.imshow(img)
        plt.axis('off')
        plt.title('Class:' + " " + id2label[i])
        counter += 1
plt.show()
```





```
# Import torch utilities for dataset loading followed by transformations (Random Horizont
import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader
import torchvision
from torchvision import transforms, models
import torch.nn.functional as f
train_transform = transforms.Compose([
   transforms.ToTensor(),
   transforms.Resize(size = (224, 224)),
   transforms.RandomHorizontalFlip(p = 0.5),
   transforms.RandomVerticalFlip(p = 0.5)
])
val_transform = transforms.Compose([
   transforms.ToTensor(),
   transforms.Resize(size = (224, 224))
])
      F....D-+---+ (D-+---+).
```

```
class Eyevataset(vataset):
    def init (self, df, n classes, transform = None):
        self.df = df
        self.n samples = len(self.df)
        self.n classes = n classes
        self.transform = transform
   def __len__(self):
        return self.n_samples
   def __getitem__(self, index):
        img = plt.imread(self.df.iloc[index, 0])
        label = self.df.iloc[index, 1]
        img = (img - img.min())/img.max()
        if self.transform:
            img = self.transform(img)
        return img.to(torch.float32), label
# 85/15 (training/valid) split
from sklearn.model_selection import train_test_split
df_train, df_val = train_test_split(df, test_size = 0.15, random_state = 28)
df_train.shape, df_val.shape
     ((3584, 2), (633, 2))
NUM CLASSES = 4
BATCH_SIZE = 128
train_dataset = EyeDataset(df_train, NUM_CLASSES, train_transform)
val_dataset = EyeDataset(df_val, NUM_CLASSES, val_transform)
train_loader = DataLoader(train_dataset, batch_size = BATCH_SIZE, shuffle = True)
val_loader = DataLoader(val_dataset, batch_size = BATCH_SIZE, shuffle = False)
a, b = next(iter(train_loader))
print(a.shape, b.shape)
del(a)
del(b)
    torch.Size([128, 3, 224, 224]) torch.Size([128])
#Bookset 10 monutes make and the model and /themseton locations
```

```
#wesiner-10 liental lienmork bise-frallen monet neen (frallet. Teat.HTM8)
from math import ceil
class Net(nn.Module):
   def __init__(self):
        super().__init__()
        self.base = torchvision.models.resnet18(pretrained = True)
# Last 15 layers are left trainable while earlier layers are frozen
        for param in list(self.base.parameters())[:-15]:
            param.requires_grad = False
        self.block = nn.Sequential(
            nn.Linear(512, 128),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Linear(128, 4),
        )
        self.base.classifier = nn.Sequential()
        self.base.fc = nn.Sequential()
#Adam optimizer and setting learning rates
    def get optimizer(self):
        return torch.optim.AdamW([
            {'params' : self.base.parameters(), 'lr': 3e-5},
            {'params' : self.block.parameters(), 'lr': 8e-4}
        ])
   def forward(self, x):
       x = self.base(x)
        x = self.block(x)
        return x
#Now Eye Disease Classification
class Trainer(nn.Module):
    def __init__(self, train_loader, val_loader, device):
        super(). init ()
        self.train_loader = train_loader
        self.val loader= val loader
        self.device = device
        self.model = Net().to(self.device)
        self.optimizer = self.model.get_optimizer()
        self.loss fxn = nn.CrossEntropyLoss()
        self.accuracy = torchmetrics.Accuracy(task = "multiclass", num_classes = NUM_CLAS
        self.history = {'train_loss' : [], 'val_loss': [], 'train_acc': [], 'val_acc': []
   def training_step(self, x, y):
```

```
pred = self.model(x)
        loss = self.loss fxn(pred, y)
        acc = self.accuracy(pred, y)
        self.optimizer.zero grad()
        loss.backward()
        self.optimizer.step()
        return loss, acc
   def val_step(self, x, y):
        with torch.no grad():
            pred = self.model(x)
            loss = self.loss fxn(pred, y)
            acc = self.accuracy(pred, y)
        return loss, acc
    def step_fxn(self, loader, step):
       loss, acc = 0, 0
        for X, y in tqdm(loader):
            X, y = X.to(self.device), y.to(self.device)
            1, a = step(X, y)
            loss, acc = loss + l.item(), acc + a.item()
        return loss/len(loader), acc/len(loader)
   def train(self, epochs):
        for epoch in tqdm(range(epochs)):
            train_loss, train_acc = self.step_fxn(self.train_loader, self.training_step)
            val_loss, val_acc = self.step_fxn(self.val_loader, self.val_step)
            for item, value in zip(self.history.keys(), list([train_loss, val_loss, train
                self.history[item].append(value)
            print("[Epoch: {}] Train: [loss: {:.3f} acc: {:.3f}] Val: [loss: {:.3f} acc:{
trainer = Trainer(train loader, val loader, device)
     /usr/local/lib/python3.12/dist-packages/torchvision/models/_utils.py:208: UserWarning
       warnings.warn(
     /usr/local/lib/python3.12/dist-packages/torchvision/models/_utils.py:223: UserWarning
       warnings.warn(msg)
     Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /root/.ca
     100% | 44.7M/44.7M [00:00<00:00, 103MB/s]
```

yer (type:depth-idx) ========	Output Shape	Param #
======================================	[-1, 64, 112, 112]	(9,408)
BatchNorm2d: 1-2	[-1, 64, 112, 112]	(128)
ReLU: 1-3	[-1, 64, 112, 112]	
MaxPool2d: 1-4	[-1, 64, 56, 56]	
Sequential: 1-5	[-1, 64, 56, 56]	
└─BasicBlock: 2-1	[-1, 64, 56, 56]	
└─Conv2d: 3-1	[-1, 64, 56, 56]	(36,864)
└─BatchNorm2d: 3-2	[-1, 64, 56, 56]	(128)
∟ReLU: 3-3	[-1, 64, 56, 56]	
└─Conv2d: 3-4	[-1, 64, 56, 56]	(36,864)
☐BatchNorm2d: 3-5	[-1, 64, 56, 56]	(128)
⊢ReLU: 3-6	[-1, 64, 56, 56]	
└─BasicBlock: 2-2	[-1, 64, 56, 56]	
	[-1, 64, 56, 56]	(36,864)
∟BatchNorm2d: 3-8	[-1, 64, 56, 56]	(128)
	[-1, 64, 56, 56]	
└─Conv2d: 3-10	[-1, 64, 56, 56]	(36,864)
∟BatchNorm2d: 3-11	[-1, 64, 56, 56]	(128)
	[-1, 64, 56, 56]	
Sequential: 1-6	[-1, 128, 28, 28]	
└─BasicBlock: 2-3	[-1, 128, 28, 28]	
	[-1, 128, 28, 28]	(73,728)
· · · · · · · · · · · · · · · · · · ·	[-1, 128, 28, 28]	(256)
LReLU: 3-15	[-1, 128, 28, 28]	(230)
Conv2d: 3-16	[-1, 128, 28, 28]	(147,456)
LBatchNorm2d: 3-17	[-1, 128, 28, 28]	(256)
Sequential: 3-18		(8,448)
LReLU: 3-19	[-1, 128, 28, 28]	(0,440)
BasicBlock: 2-4	[-1, 128, 28, 28]	
Conv2d: 3-20	[-1, 128, 28, 28]	(147,456)
BatchNorm2d: 3-21	[-1, 128, 28, 28]	(256)
	[-1, 128, 28, 28]	(230)
Conv2d: 3-23	[-1, 128, 28, 28]	(147,456)
BatchNorm2d: 3-24	[-1, 128, 28, 28]	(256)
ReLU: 3-25	[-1, 128, 28, 28]	(230)
Sequential: 1-7	[-1, 256, 14, 14]	
∟BasicBlock: 2-5	[-1, 256, 14, 14]	
	[-1, 256, 14, 14]	(294,912)
BatchNorm2d: 3-27	[-1, 256, 14, 14]	(512)
ReLU: 3-28	[-1, 256, 14, 14]	(312)
Conv2d: 3-29	[-1, 256, 14, 14]	(589,824)
	[-1, 256, 14, 14]	(512)
Sequential: 3-31	[-1, 256, 14, 14] [-1, 256, 14, 14]	(33,280)
ReLU: 3-32	[-1, 256, 14, 14] [-1, 256, 14, 14]	(33,200)
BasicBlock: 2-6	- · · · · · · -	
—BasicBlock: 2-6 —Conv2d: 3-33	[-1, 256, 14, 14]	(EQO 024)
•	[-1, 256, 14, 14] [-1, 256, 14, 14]	(589,824) (512)
│ └─BatchNorm2d: 3-34	1 2 3 6 6 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7	15111

```
└─Conv2d: 3-36
                                        [-1, 256, 14, 14]
                                                                  (589,824)
         └─BatchNorm2d: 3-37
                                        [-1, 256, 14, 14]
                                                                  (512)
         └─ReLU: 3-38
                                        [-1, 256, 14, 14]
├─Sequential: 1-8
                                        [-1, 512, 7, 7]
                                                                  --
                                        [-1, 512, 7, 7]
    └─BasicBlock: 2-7
         └─Conv2d: 3-39
                                       [-1, 512, 7, 7]
                                                                  (1,179,648)
         └BatchNorm2d: 3-40
                                        [-1, 512, 7, 7]
                                                                  (1,024)
```

Model Training

```
trainer.train(epochs = 2)
```

```
#Accuracy and loss line chart (accuracy goes up after second epoch and loss goes down aft
plt.figure(figsize = (15, 4))

plt.subplot(1,2,1)
plt.title('Loss')
plt.plot(trainer.history['train_loss'], label = 'Training')
plt.plot(trainer.history['val_loss'], label = 'Validation')
plt.legend()

plt.subplot(1,2,2)
plt.title('Accuracy')
plt.plot(trainer.history['train_acc'], label = 'Training')
plt.plot(trainer.history['val_acc'], label = 'Validation')
plt.legend()
```

```
# Model Predictions
preds, true = [], []

with torch.no_grad():
    for x, y in tqdm(val_loader):
        pred = torch.argmax(trainer.model(x.to(device)), axis = 1).detach().cpu().numpy()
        preds.extend(pred)
        true.extend(y)

len(preds), len(true)

from sklearn.metrics import confusion_matrix

cm = confusion_matrix(true, preds)
sea.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=True)

plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
```

from sklearn.metrics import classification_report
print(classification_report(true, preds, target_names = label2id.keys()))

	precision	recall	f1-score	support
glaucoma	0.89	0.80	0.84	168
normal	0.84	0.89	0.86	154
diabetic_retinopathy	0.96	0.97	0.96	161
cataract	0.90	0.93	0.91	150
accuracy			0.89	633
macro avg	0.89	0.90	0.89	633
weighted avg	0.89	0.89	0.89	633