Versions:

- v9: ColorJitter transformation added **[0.896]**
- v10: Changed the dataset to this one with external data. **[0.894]**
- v11: Switched to another dataset which I've created by myself. Also switched from StratifiedKFold to GroupKFold **[0.916]**
- v12: Switched to efficientnet-b1 **[0.919]**
- v13: Using meta featues: sex and age **[0.918]**
- v14: anatom_site_general_challenge meta feature added as one-hot encoded matrix **[0.923]**
- v16: Fixed OOF - now it contains only data from original training dataset, without extarnal data. Also switched back to StratifiedKFold. Added DrawHair augmentation. **[0.909]**
- v18: Too many things were changed at the same time. All experiments should have only one small change each, so it would be easy to understand how changes affect the result. Said that I rolled back everything, keeping only OOF fix, to make sure it work.
- v19: Added 'Hair' augmentation. OOF rework posponed untill the best time, since there is some bug in my code for it. **[0.925]**
- v20: Advanced Hair Augmentation technique used. Read more about it here: https://www.kaggle.com/c/siim-isic-melanoma-classification/discussion/159176 **[0.923]**
- v21: Microscope augmentation added instead of Cutout. Read more here: https://www.kaggle.com/c/siim-isic-melanoma-classification/discussion/159476 **[0.914]**
- v22: Changed the dataset to this one by Chris Deotte. More info here **[0.900]**
- v23: All the same as v22 but effnet-b0 instead of b1 and more epochs per fold. **[0.895]**
- v24: effnet-b01 and more epochs. **[0.9092]**
- v25: Fixed a mistake in a way of filling preds. See this comment. **[0.9016]**
- v26: Fix for another mistake. This time with a way of averaging TTA. See this comment **[0.915]**
- v27: Back to my dataset

In [1]:

```
!pip install efficientnet_pytorch torchtoolbox
```

```
Collecting efficientnet_pytorch
  Downloading efficientnet_pytorch-0.6.3.tar.gz (16 kB)
Collecting torchtoolbox
  Downloading torchtoolbox-0.1.5-py3-none-any.whl (58 kB)
     |████████████████████████████████| 58 kB 261 kB/s
Requirement already satisfied: torch in /opt/conda/lib/python3.7/site-packages (from efficientnet_pyt
orch) (1.5.0)
Requirement already satisfied: pyarrow in /opt/conda/lib/python3.7/site-packages (from torchtoolbox)
(0.16.0)
Collecting lmdb
  Downloading lmdb-0.98.tar.gz (869 kB)
     |████████████████████████████████| 869 kB 501 kB/s
Requirement already satisfied: opencv-python in /opt/conda/lib/python3.7/site-packages (from torchtoo
lbox) (4.2.0.34)
Requirement already satisfied: scipy in /opt/conda/lib/python3.7/site-packages (from torchtoolbox)
(1.4.1)
Requirement already satisfied: scikit-learn in /opt/conda/lib/python3.7/site-packages (from torchtool
box) (0.22.2.post1)
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages (from torchtoolbox) (1.1
4.0)
Requirement already satisfied: tqdm in /opt/conda/lib/python3.7/site-packages (from torchtoolbox) (4.
45.0)
Requirement already satisfied: numpy in /opt/conda/lib/python3.7/site-packages (from torchtoolbox)
(1.18.1)
Requirement already satisfied: future in /opt/conda/lib/python3.7/site-packages (from torch->efficien
tnet_pytorch) (0.18.2)
Requirement already satisfied: joblib>=0.11 in /opt/conda/lib/python3.7/site-packages (from scikit-le
arn->torchtoolbox) (0.14.1)
Building wheels for collected packages: efficientnet-pytorch, lmdb
  Building wheel for efficientnet-pytorch (setup.py) ... - \ done
  Created wheel for efficientnet-pytorch: filename=efficientnet_pytorch-0.6.3-py3-none-any.whl size=1
2419 sha256=d7d71a9bd1febdd0933bbd040bcdf6f6057dec0f5dec116accfd955460888bb3
  Stored in directory: /root/.cache/pip/wheels/90/6b/0c/f0ad36d00310e65390b0d4c9218ae6250ac579c92540c
9097a
  Building wheel for lmdb (setup.py) ... - \ | / - \ done
  Created wheel for lmdb: filename=lmdb-0.98-cp37-cp37m-linux_x86_64.whl size=273154 sha256=24881d080
b5406c4cb01cfb94425ea937c145a55b96f2a633bee6979eb7f6a58
  Stored in directory: /root/.cache/pip/wheels/9e/24/96/783d4dddcf63e3f8cc92db8b3af3c70cf6d76398bff77
f1d5e
Successfully built efficientnet-pytorch lmdb
Installing collected packages: efficientnet-pytorch, lmdb, torchtoolbox
Successfully installed efficientnet-pytorch-0.6.3 lmdb-0.98 torchtoolbox-0.1.5
WARNING: You are using pip version 20.1; however, version 20.2.1 is available.
You should consider upgrading via the '/opt/conda/bin/python3.7 -m pip install --upgrade pip' comman
d.
```

In [2]:

```
import torch
import torchvision
import torch.nn.functional as F
import torch.nn as nn
import torchtoolbox.transform as transforms
from torch.utils.data import Dataset, DataLoader, Subset
from torch.optim.lr_scheduler import ReduceLROnPlateau
from sklearn.metrics import accuracy_score, roc_auc_score
from sklearn.model_selection import StratifiedKFold, GroupKFold, KFold
import pandas as pd
import numpy as np
import gc
import os
import cv2
import time
import datetime
import warnings
import random
import matplotlib.pyplot as plt
import seaborn as sns
from efficientnet_pytorch import EfficientNet
%matplotlib inline
```

In [3]:

```
warnings.simplefilter('ignore')
def seed_everything(seed):
    random.seed(seed)
    os.environ['PYTHONHASHSEED'] = str(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    torch.cuda.manual_seed(seed)
    torch.backends.cudnn.deterministic = True
    torch.backends.cudnn.benchmark = True

seed_everything(47)
```

In [4]:

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

In [5]:

```
class MelanomaDataset(Dataset):
    def __init__(self, df: pd.DataFrame, imfolder: str, train: bool = True, transforms = None, meta_fea
tures = None):
        """
        Class initialization
        Args:
            df (pd.DataFrame): DataFrame with data description
            imfolder (str): folder with images
            train (bool): flag of whether a training dataset is being initialized or testing one
            transforms: image transformation method to be applied
            meta_features (list): list of features with meta information, such as sex and age

        """
        self.df = df
        self.imfolder = imfolder
        self.transforms = transforms
        self.train = train
        self.meta_features = meta_features

    def __getitem__(self, index):
        im_path = os.path.join(self.imfolder, self.df.iloc[index]['image_name'] + '.jpg')
        x = cv2.imread(im_path)
        meta = np.array(self.df.iloc[index][self.meta_features].values, dtype=np.float32)

        if self.transforms:
            x = self.transforms(x)

        if self.train:
            y = self.df.iloc[index]['target']
            return (x, meta), y
        else:
            return (x, meta)

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


class Net(nn.Module):
    def __init__(self, arch, n_meta_features: int):
        super(Net, self).__init__()
        self.arch = arch
        if 'ResNet' in str(arch.__class__):
            self.arch.fc = nn.Linear(in_features=512, out_features=500, bias=True)
        if 'EfficientNet' in str(arch.__class__):
            self.arch._fc = nn.Linear(in_features=1280, out_features=500, bias=True)
        self.meta = nn.Sequential(nn.Linear(n_meta_features, 500),
                                  nn.BatchNorm1d(500),
                                  nn.ReLU(),
                                  nn.Dropout(p=0.2),
                                  nn.Linear(500, 250),  # FC layer output will have 250 features
                                  nn.BatchNorm1d(250),
                                  nn.ReLU(),
                                  nn.Dropout(p=0.2))
        self.ouput = nn.Linear(500 + 250, 1)

    def forward(self, inputs):
        """
        No sigmoid in forward because we are going to use BCEWithLogitsLoss
        Which applies sigmoid for us when calculating a loss
        """
        x, meta = inputs
        cnn_features = self.arch(x)
        meta_features = self.meta(meta)
        features = torch.cat((cnn_features, meta_features), dim=1)
        output = self.ouput(features)
        return output
```

In [6]:

```
class AdvancedHairAugmentation:
    """
    Impose an image of a hair to the target image

    Args:
        hairs (int): maximum number of hairs to impose
        hairs_folder (str): path to the folder with hairs images
    """

    def __init__(self, hairs: int = 5, hairs_folder: str = ""):
        self.hairs = hairs
        self.hairs_folder = hairs_folder

    def __call__(self, img):
        """
        Args:
            img (PIL Image): Image to draw hairs on.

        Returns:
            PIL Image: Image with drawn hairs.
        """
        n_hairs = random.randint(0, self.hairs)

        if not n_hairs:
            return img

        height, width, _ = img.shape  # target image width and height
        hair_images = [im for im in os.listdir(self.hairs_folder) if 'png' in im]

        for _ in range(n_hairs):
            hair = cv2.imread(os.path.join(self.hairs_folder, random.choice(hair_images)))
            hair = cv2.flip(hair, random.choice([-1, 0, 1]))
            hair = cv2.rotate(hair, random.choice([0, 1, 2]))

            h_height, h_width, _ = hair.shape  # hair image width and height
            roi_ho = random.randint(0, img.shape[0] - hair.shape[0])
            roi_wo = random.randint(0, img.shape[1] - hair.shape[1])
            roi = img[roi_ho:roi_ho + h_height, roi_wo:roi_wo + h_width]

            # Creating a mask and inverse mask
            img2gray = cv2.cvtColor(hair, cv2.COLOR_BGR2GRAY)
            ret, mask = cv2.threshold(img2gray, 10, 255, cv2.THRESH_BINARY)
            mask_inv = cv2.bitwise_not(mask)

            # Now black-out the area of hair in ROI
            img_bg = cv2.bitwise_and(roi, roi, mask=mask_inv)

            # Take only region of hair from hair image.
            hair_fg = cv2.bitwise_and(hair, hair, mask=mask)

            # Put hair in ROI and modify the target image
            dst = cv2.add(img_bg, hair_fg)

            img[roi_ho:roi_ho + h_height, roi_wo:roi_wo + h_width] = dst

        return img

    def __repr__(self):
        return f'{self.__class__.__name__}(hairs={self.hairs}, hairs_folder="{self.hairs_folder}")'
```

In [7]:

```
class DrawHair:
    """
    Draw a random number of pseudo hairs

    Args:
        hairs (int): maximum number of hairs to draw
        width (tuple): possible width of the hair in pixels
    """

    def __init__(self, hairs:int = 4, width:tuple = (1, 2)):
        self.hairs = hairs
        self.width = width

    def __call__(self, img):
        """
        Args:
            img (PIL Image): Image to draw hairs on.

        Returns:
            PIL Image: Image with drawn hairs.
        """
        if not self.hairs:
            return img

        width, height, _ = img.shape

        for _ in range(random.randint(0, self.hairs)):
            # The origin point of the line will always be at the top half of the image
            origin = (random.randint(0, width), random.randint(0, height // 2))
            # The end of the line
            end = (random.randint(0, width), random.randint(0, height))
            color = (0, 0, 0)  # color of the hair. Black.
            cv2.line(img, origin, end, color, random.randint(self.width[0], self.width[1]))

        return img

    def __repr__(self):
        return f'{self.__class__.__name__}(hairs={self.hairs}, width={self.width})'
```

In [8]:

```
class Microscope:
    """
    Cutting out the edges around the center circle of the image
    Imitating a picture, taken through the microscope

    Args:
        p (float): probability of applying an augmentation
    """

    def __init__(self, p: float = 0.5):
        self.p = p

    def __call__(self, img):
        """
        Args:
            img (PIL Image): Image to apply transformation to.

        Returns:
            PIL Image: Image with transformation.
        """
        if random.random() < self.p:
            circle = cv2.circle((np.ones(img.shape) * 255).astype(np.uint8), # image placeholder
                        (img.shape[0]//2, img.shape[1]//2), # center point of circle
                        random.randint(img.shape[0]//2 - 3, img.shape[0]//2 + 15), # radius
                        (0, 0, 0), # color
                        -1)

            mask = circle - 255
            img = np.multiply(img, mask)

        return img

    def __repr__(self):
        return f'{self.__class__.__name__}(p={self.p})'
```

In [9]:

```
train_transform = transforms.Compose([
    AdvancedHairAugmentation(hairs_folder='/kaggle/input/melanoma-hairs'),
    transforms.RandomResizedCrop(size=256, scale=(0.8, 1.0)),
    transforms.RandomHorizontalFlip(),
    transforms.RandomVerticalFlip(),
    Microscope(p=0.5),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],std=[0.229, 0.224, 0.225])
])
test_transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],std=[0.229, 0.224, 0.225])
])
```

In [10]:

```
arch = EfficientNet.from_pretrained('efficientnet-b1')
```

```
Downloading: "https://github.com/lukemelas/EfficientNet-PyTorch/releases/download/1.0/efficientnet-b1
-f1951068.pth" to /root/.cache/torch/checkpoints/efficientnet-b1-f1951068.pth
```

100% 30.1M/30.1M [00:03<00:00, 10.1MB/s]

```
Loaded pretrained weights for efficientnet-b1
```

In [11]:

```
train_df = pd.read_csv('/kaggle/input/jpeg-melanoma-256x256/train.csv')
test_df = pd.read_csv('/kaggle/input/jpeg-melanoma-256x256/test.csv')
```

In [12]:

```
# One-hot encoding of anatom_site_general_challenge feature
concat = pd.concat([train_df['anatom_site_general_challenge'], test_df['anatom_site_general_challenge'
]], ignore_index=True)
dummies = pd.get_dummies(concat, dummy_na=True, dtype=np.uint8, prefix='site')
train_df = pd.concat([train_df, dummies.iloc[:train_df.shape[0]]], axis=1)
test_df = pd.concat([test_df, dummies.iloc[train_df.shape[0]:].reset_index(drop=True)], axis=1)

# Sex features
train_df['sex'] = train_df['sex'].map({'male': 1, 'female': 0})
test_df['sex'] = test_df['sex'].map({'male': 1, 'female': 0})
train_df['sex'] = train_df['sex'].fillna(-1)
test_df['sex'] = test_df['sex'].fillna(-1)

# Age features
train_df['age_approx'] /= train_df['age_approx'].max()
test_df['age_approx'] /= test_df['age_approx'].max()
train_df['age_approx'] = train_df['age_approx'].fillna(0)
test_df['age_approx'] = test_df['age_approx'].fillna(0)

train_df['patient_id'] = train_df['patient_id'].fillna(0)
```

In [13]:

```
meta_features = ['sex', 'age_approx'] + [col for col in train_df.columns if 'site_' in col]
meta_features.remove('anatom_site_general_challenge')
```

In [14]:

```
test = MelanomaDataset(df=test_df,
                       imfolder='/kaggle/input/melanoma-external-malignant-256/test/test/',
                       train=False,
                       transforms=train_transform,  # For TTA
                       meta_features=meta_features)
```

In [15]:

```
skf = GroupKFold(n_splits=5)
```

In [16]:

```
epochs = 12  # Number of epochs to run
es_patience = 3  # Early Stopping patience - for how many epochs with no improvements to wait
TTA = 3 # Test Time Augmentation rounds

oof = np.zeros((len(train_df), 1))  # Out Of Fold predictions
preds = torch.zeros((len(test), 1), dtype=torch.float32, device=device)  # Predictions for test test

skf = KFold(n_splits=5, shuffle=True, random_state=47)
for fold, (train_idx, val_idx) in enumerate(skf.split(X=np.zeros(len(train_df)), y=train_df['target'],
groups=train_df['patient_id'].tolist()), 1):
    print('=' * 20, 'Fold', fold, '=' * 20)

    model_path = f'model_{fold}.pth'  # Path and filename to save model to
    best_val = 0  # Best validation score within this fold
    patience = es_patience  # Current patience counter
    arch = EfficientNet.from_pretrained('efficientnet-b1')
    model = Net(arch=arch, n_meta_features=len(meta_features))  # New model for each fold
    model = model.to(device)

    optim = torch.optim.Adam(model.parameters(), lr=0.001)
    scheduler = ReduceLROnPlateau(optimizer=optim, mode='max', patience=1, verbose=True, factor=0.2)
    criterion = nn.BCEWithLogitsLoss()

    train = MelanomaDataset(df=train_df.iloc[train_idx].reset_index(drop=True),
                            imfolder='/kaggle/input/melanoma-external-malignant-256/train/train/',
                            train=True,
                            transforms=train_transform,
                            meta_features=meta_features)
    val = MelanomaDataset(df=train_df.iloc[val_idx].reset_index(drop=True),
                            imfolder='/kaggle/input/melanoma-external-malignant-256/train/train/',
                            train=True,
                            transforms=test_transform,
                            meta_features=meta_features)

    train_loader = DataLoader(dataset=train, batch_size=64, shuffle=True, num_workers=2)
    val_loader = DataLoader(dataset=val, batch_size=16, shuffle=False, num_workers=2)
    test_loader = DataLoader(dataset=test, batch_size=16, shuffle=False, num_workers=2)

    for epoch in range(epochs):
        start_time = time.time()
        correct = 0
        epoch_loss = 0
        model.train()

        for x, y in train_loader:
            x[0] = torch.tensor(x[0], device=device, dtype=torch.float32)
            x[1] = torch.tensor(x[1], device=device, dtype=torch.float32)
            y = torch.tensor(y, device=device, dtype=torch.float32)
            optim.zero_grad()
            z = model(x)
            loss = criterion(z, y.unsqueeze(1))
            loss.backward()
            optim.step()
            pred = torch.round(torch.sigmoid(z))  # round off sigmoid to obtain predictions
            correct += (pred.cpu() == y.cpu().unsqueeze(1)).sum().item()  # tracking number of correctl
y predicted samples
            epoch_loss += loss.item()
        train_acc = correct / len(train_idx)

        model.eval()  # switch model to the evaluation mode
        val_preds = torch.zeros((len(val_idx), 1), dtype=torch.float32, device=device)
        with torch.no_grad():  # Do not calculate gradient since we are only predicting
            # Predicting on validation set
            for j, (x_val, y_val) in enumerate(val_loader):
                x_val[0] = torch.tensor(x_val[0], device=device, dtype=torch.float32)
                x_val[1] = torch.tensor(x_val[1], device=device, dtype=torch.float32)
                y_val = torch.tensor(y_val, device=device, dtype=torch.float32)
                z_val = model(x_val)
                val_pred = torch.sigmoid(z_val)
                val_preds[j*val_loader.batch_size:j*val_loader.batch_size + x_val[0].shape[0]] = val_pr
ed
            val_acc = accuracy_score(train_df.iloc[val_idx]['target'].values, torch.round(val_preds.cpu
()))
            val_roc = roc_auc_score(train_df.iloc[val_idx]['target'].values, val_preds.cpu())

            print('Epoch {:03}: | Loss: {:.3f} | Train acc: {:.3f} | Val acc: {:.3f} | Val roc_auc: {:.
3f} | Training time: {}'.format(
            epoch + 1,
            epoch_loss,
            train_acc,
            val_acc,
            val_roc,
            str(datetime.timedelta(seconds=time.time() - start_time))[:7]))

            scheduler.step(val_roc)

            if val_roc >= best_val:
                best_val = val_roc
                patience = es_patience  # Resetting patience since we have new best validation accuracy
                torch.save(model, model_path)  # Saving current best model
            else:
                patience -= 1
                if patience == 0:
                    print('Early stopping. Best Val roc_auc: {:.3f}'.format(best_val))
                    break

    model = torch.load(model_path)  # Loading best model of this fold
    model.eval()  # switch model to the evaluation mode
    val_preds = torch.zeros((len(val_idx), 1), dtype=torch.float32, device=device)
    with torch.no_grad():
        # Predicting on validation set once again to obtain data for OOF
        for j, (x_val, y_val) in enumerate(val_loader):
            x_val[0] = torch.tensor(x_val[0], device=device, dtype=torch.float32)
            x_val[1] = torch.tensor(x_val[1], device=device, dtype=torch.float32)
            y_val = torch.tensor(y_val, device=device, dtype=torch.float32)
            z_val = model(x_val)
            val_pred = torch.sigmoid(z_val)
            val_preds[j*val_loader.batch_size:j*val_loader.batch_size + x_val[0].shape[0]] = val_pred
        oof[val_idx] = val_preds.cpu().numpy()

        # Predicting on test set
        tta_preds = torch.zeros((len(test), 1), dtype=torch.float32, device=device)
        for _ in range(TTA):
            for i, x_test in enumerate(test_loader):
                x_test[0] = torch.tensor(x_test[0], device=device, dtype=torch.float32)
                x_test[1] = torch.tensor(x_test[1], device=device, dtype=torch.float32)
                z_test = model(x_test)
                z_test = torch.sigmoid(z_test)
                tta_preds[i*test_loader.batch_size:i*test_loader.batch_size + x_test[0].shape[0]] += z_
test
        preds += tta_preds / TTA

preds /= skf.n_splits
```

```
==================== Fold 1 ====================
Loaded pretrained weights for efficientnet-b1
Epoch 001: | Loss: 36.801 | Train acc: 0.981 | Val acc: 0.984 | Val roc_auc: 0.855 | Training time:
0:06:10
Epoch 002: | Loss: 32.468 | Train acc: 0.982 | Val acc: 0.984 | Val roc_auc: 0.861 | Training time:
0:05:43
Epoch 003: | Loss: 31.533 | Train acc: 0.982 | Val acc: 0.984 | Val roc_auc: 0.865 | Training time:
0:05:43
Epoch 004: | Loss: 30.699 | Train acc: 0.982 | Val acc: 0.984 | Val roc_auc: 0.805 | Training time:
0:05:44
Epoch 005: | Loss: 31.112 | Train acc: 0.982 | Val acc: 0.984 | Val roc_auc: 0.848 | Training time:
0:05:41
Epoch     5: reducing learning rate of group 0 to 2.0000e-04.
Epoch 006: | Loss: 28.712 | Train acc: 0.982 | Val acc: 0.983 | Val roc_auc: 0.881 | Training time:
0:05:40
Epoch 007: | Loss: 28.336 | Train acc: 0.982 | Val acc: 0.983 | Val roc_auc: 0.869 | Training time:
0:05:36
Epoch 008: | Loss: 27.044 | Train acc: 0.982 | Val acc: 0.983 | Val roc_auc: 0.889 | Training time:
0:05:41
Epoch 009: | Loss: 25.861 | Train acc: 0.982 | Val acc: 0.983 | Val roc_auc: 0.882 | Training time:
0:05:36
Epoch 010: | Loss: 25.634 | Train acc: 0.982 | Val acc: 0.983 | Val roc_auc: 0.882 | Training time:
0:05:33
Epoch    10: reducing learning rate of group 0 to 4.0000e-05.
Epoch 011: | Loss: 23.690 | Train acc: 0.982 | Val acc: 0.982 | Val roc_auc: 0.890 | Training time:
0:05:32
Epoch 012: | Loss: 22.932 | Train acc: 0.983 | Val acc: 0.980 | Val roc_auc: 0.890 | Training time:
0:05:33
==================== Fold 2 ====================
Loaded pretrained weights for efficientnet-b1
Epoch 001: | Loss: 36.410 | Train acc: 0.981 | Val acc: 0.984 | Val roc_auc: 0.826 | Training time:
0:05:33
Epoch 002: | Loss: 32.116 | Train acc: 0.982 | Val acc: 0.984 | Val roc_auc: 0.866 | Training time:
0:05:34
Epoch 003: | Loss: 31.813 | Train acc: 0.982 | Val acc: 0.984 | Val roc_auc: 0.790 | Training time:
0:05:39
Epoch 004: | Loss: 31.554 | Train acc: 0.982 | Val acc: 0.984 | Val roc_auc: 0.824 | Training time:
0:05:39
Epoch     4: reducing learning rate of group 0 to 2.0000e-04.
Epoch 005: | Loss: 29.596 | Train acc: 0.982 | Val acc: 0.984 | Val roc_auc: 0.883 | Training time:
0:05:41
Epoch 006: | Loss: 28.207 | Train acc: 0.982 | Val acc: 0.984 | Val roc_auc: 0.892 | Training time:
0:05:37
Epoch 007: | Loss: 28.667 | Train acc: 0.982 | Val acc: 0.984 | Val roc_auc: 0.888 | Training time:
0:05:38
Epoch 008: | Loss: 26.743 | Train acc: 0.982 | Val acc: 0.984 | Val roc_auc: 0.898 | Training time:
0:05:38
Epoch 009: | Loss: 25.984 | Train acc: 0.982 | Val acc: 0.983 | Val roc_auc: 0.898 | Training time:
0:05:41
Epoch 010: | Loss: 25.070 | Train acc: 0.982 | Val acc: 0.981 | Val roc_auc: 0.896 | Training time:
0:05:37
Epoch 011: | Loss: 24.005 | Train acc: 0.982 | Val acc: 0.982 | Val roc_auc: 0.905 | Training time:
0:05:38
Epoch 012: | Loss: 23.982 | Train acc: 0.982 | Val acc: 0.982 | Val roc_auc: 0.909 | Training time:
0:05:42
==================== Fold 3 ====================
Loaded pretrained weights for efficientnet-b1
Epoch 001: | Loss: 36.470 | Train acc: 0.981 | Val acc: 0.980 | Val roc_auc: 0.843 | Training time:
0:05:43
Epoch 002: | Loss: 32.402 | Train acc: 0.983 | Val acc: 0.980 | Val roc_auc: 0.836 | Training time:
0:05:40
Epoch 003: | Loss: 31.641 | Train acc: 0.983 | Val acc: 0.980 | Val roc_auc: 0.836 | Training time:
0:05:34
Epoch     3: reducing learning rate of group 0 to 2.0000e-04.
Epoch 004: | Loss: 28.960 | Train acc: 0.983 | Val acc: 0.980 | Val roc_auc: 0.897 | Training time:
0:05:32
Epoch 005: | Loss: 28.224 | Train acc: 0.983 | Val acc: 0.980 | Val roc_auc: 0.893 | Training time:
0:05:30
Epoch 006: | Loss: 27.237 | Train acc: 0.983 | Val acc: 0.980 | Val roc_auc: 0.886 | Training time:
0:05:29
Epoch     6: reducing learning rate of group 0 to 4.0000e-05.
Epoch 007: | Loss: 26.436 | Train acc: 0.983 | Val acc: 0.980 | Val roc_auc: 0.896 | Training time:
0:05:30
Early stopping. Best Val roc_auc: 0.897
==================== Fold 4 ====================
Loaded pretrained weights for efficientnet-b1
Epoch 001: | Loss: 36.347 | Train acc: 0.980 | Val acc: 0.983 | Val roc_auc: 0.834 | Training time:
0:05:31
Epoch 002: | Loss: 32.894 | Train acc: 0.982 | Val acc: 0.983 | Val roc_auc: 0.860 | Training time:
0:05:28
Epoch 003: | Loss: 31.367 | Train acc: 0.982 | Val acc: 0.983 | Val roc_auc: 0.775 | Training time:
0:05:30
Epoch 004: | Loss: 31.475 | Train acc: 0.982 | Val acc: 0.983 | Val roc_auc: 0.729 | Training time:
0:05:30
Epoch     4: reducing learning rate of group 0 to 2.0000e-04.
Epoch 005: | Loss: 29.529 | Train acc: 0.982 | Val acc: 0.983 | Val roc_auc: 0.853 | Training time:
0:05:30
Early stopping. Best Val roc_auc: 0.860
==================== Fold 5 ====================
Loaded pretrained weights for efficientnet-b1
Epoch 001: | Loss: 35.251 | Train acc: 0.981 | Val acc: 0.982 | Val roc_auc: 0.819 | Training time:
0:05:31
Epoch 002: | Loss: 31.948 | Train acc: 0.982 | Val acc: 0.982 | Val roc_auc: 0.806 | Training time:
0:05:28
Epoch 003: | Loss: 30.923 | Train acc: 0.982 | Val acc: 0.982 | Val roc_auc: 0.621 | Training time:
0:05:30
Epoch     3: reducing learning rate of group 0 to 2.0000e-04.
Epoch 004: | Loss: 28.534 | Train acc: 0.982 | Val acc: 0.982 | Val roc_auc: 0.859 | Training time:
0:05:30
Epoch 005: | Loss: 27.078 | Train acc: 0.982 | Val acc: 0.982 | Val roc_auc: 0.871 | Training time:
0:05:30
Epoch 006: | Loss: 26.096 | Train acc: 0.982 | Val acc: 0.982 | Val roc_auc: 0.846 | Training time:
0:05:30
Epoch 007: | Loss: 25.287 | Train acc: 0.982 | Val acc: 0.982 | Val roc_auc: 0.888 | Training time:
0:05:30
Epoch 008: | Loss: 24.804 | Train acc: 0.983 | Val acc: 0.982 | Val roc_auc: 0.878 | Training time:
0:05:28
Epoch 009: | Loss: 23.848 | Train acc: 0.982 | Val acc: 0.982 | Val roc_auc: 0.889 | Training time:
0:05:28
Epoch 010: | Loss: 23.485 | Train acc: 0.983 | Val acc: 0.981 | Val roc_auc: 0.868 | Training time:
0:05:27
Epoch 011: | Loss: 22.549 | Train acc: 0.983 | Val acc: 0.983 | Val roc_auc: 0.884 | Training time:
0:05:31
Epoch    11: reducing learning rate of group 0 to 4.0000e-05.
Epoch 012: | Loss: 19.676 | Train acc: 0.984 | Val acc: 0.982 | Val roc_auc: 0.891 | Training time:
0:05:27
```

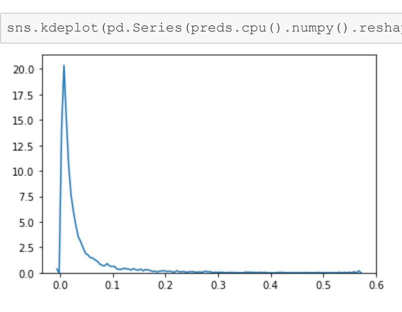
In [17]:

```
print('OOF: {:.3f}'.format(roc_auc_score(train_df['target'], oof)))
```

```
OOF: 0.885
```

In [18]:

```
sns.kdeplot(pd.Series(preds.cpu().numpy().reshape(-1,)));
```



In [19]:

```
# Saving OOF predictions so stacking would be easier
pd.Series(oof.reshape(-1,)).to_csv('oof.csv', index=False)
```

In [20]:

```
sub = pd.read_csv('/kaggle/input/siim-isic-melanoma-classification/sample_submission.csv')
sub['target'] = preds.cpu().numpy().reshape(-1,)
sub.to_csv('submission.csv', index=False)
```