

# Integrating Metadata, Applying Augmentation, and Fine-Tuning

```
In [1]: import os
import copy
import pandas as pd
import torch
import torchvision
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader, WeightedRandomSampler
import torchvision.transforms as transforms
import torchvision.models as models
from PIL import Image
from sklearn.preprocessing import StandardScaler, LabelEncoder
import numpy as np
from sklearn.metrics import roc_auc_score
import torch.nn.functional as F
```

```
In [2]: device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Using device: {device.type}")
```

Using device: cuda

```
In [10]: CKPT_PATH = 'model.pth.tar'
N_CLASSES = 14
CLASS_NAMES = [ 'Atelectasis', 'Cardiomegaly', 'Effusion', 'Infiltration', 'Mass',
                 'Pneumothorax', 'Consolidation', 'Edema', 'Emphysema', 'Fibrosis',
DATA_DIR = 'images'
TEST_IMAGE_LIST = 'labels/test_list.txt'
BATCH_SIZE = 64
TRAIN_LIST = "labels/train_list.txt"
VALID_LIST = "labels/val_list.txt"
IMAGE_DIR = "images"
```

```
In [11]: # Load metadata
metadata = pd.read_csv("Data_Entry_2017.csv")

# Drop rows with missing age or gender (if any)
metadata = metadata.dropna(subset=["Patient Age", "Patient Gender"])

# Normalize age
scaler = StandardScaler()
metadata["age_scaled"] = scaler.fit_transform(metadata[["Patient Age"]])

# Encode gender as binary (Female=0, Male=1)
label_encoder = LabelEncoder()
metadata["gender_encoded"] = label_encoder.fit_transform(metadata["Patient Gender"])

# Create metadata dictionary
patient_info = {
    row["Image Index"]: (row["age_scaled"], row["gender_encoded"])
    for _, row in metadata.iterrows()
```

```

}
print(f"Metadata loaded for {len(patient_info)} images.")

```

Metadata loaded for 112120 images.

```

In [12]: class ChestXrayDataSet(Dataset):
    def __init__(self, data_dir, image_list_file, metadata, transform=None):
        image_names, labels = [], []
        with open(image_list_file, "r") as f:
            for line in f:
                items = line.split()
                image_name = items[0]
                label = [int(i) for i in items[1:]]
                image_name = os.path.join(data_dir, image_name)
                image_names.append(image_name)
                labels.append(label)

        self.image_names = image_names
        self.labels = labels
        self.metadata = metadata
        self.transform = transform

    def __getitem__(self, index):
        image_name = self.image_names[index]
        image = Image.open(image_name).convert('RGB')
        label = self.labels[index]

        base_name = os.path.basename(image_name)
        age, gender = self.metadata.get(base_name, (0.0, 0.0))

        if self.transform:
            image = self.transform(image)

        age_tensor = torch.tensor([age], dtype=torch.float32)
        gender_tensor = torch.tensor([gender], dtype=torch.float32)

        return image, torch.FloatTensor(label), age_tensor, gender_tensor

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

```

```

In [13]: class DenseNet121WithMetadata(nn.Module):
    def __init__(self, out_size):
        super(DenseNet121WithMetadata, self).__init__()
        # Load pretrained DenseNet
        self.densenet = models.densenet121(pretrained=True)

        # Get the feature size
        self.feature_size = self.densenet.classifier.in_features

        # Remove the original classifier
        self.densenet.classifier = nn.Identity()

        # Global pooling
        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))

```

```

# Create a new classifier that takes image features + metadata
self.classifier = nn.Sequential(
    nn.Dropout(0.2),
    nn.Linear(self.feature_size + 2, 1024), # +2 for age and gender
    nn.BatchNorm1d(1024),
    nn.ReLU(),
    nn.Dropout(0.2),
    nn.Linear(1024, 512),
    nn.BatchNorm1d(512),
    nn.ReLU(),
    nn.Dropout(0.2),
    nn.Linear(512, 256),
    nn.BatchNorm1d(256),
    nn.ReLU(),
    nn.Linear(256, out_size)
)

def forward(self, x, age, gender):
    # Extract features
    features = self.densenet.features(x)
    features = torch.relu(features)
    features = self.avgpool(features)
    features = torch.flatten(features, 1)

    # Combine metadata
    metadata = torch.cat([age, gender], dim=1)
    combined = torch.cat([features, metadata], dim=1)

    # Classify
    output = self.classifier(combined)
    return output

```

```

In [14]: def compute_AUCs(gt, pred):
    """Computes Area Under the Curve (AUC) from prediction scores.

    Args:
        gt: Pytorch tensor on GPU, shape = [n_samples, n_classes]
            true binary labels.
        pred: Pytorch tensor on GPU, shape = [n_samples, n_classes]
            can either be probability estimates of the positive class,
            confidence values, or binary decisions.

    Returns:
        List of AUROCs of all classes.
    """
    AUROCs = []
    gt_np = gt.cpu().numpy()
    pred_np = pred.cpu().numpy()
    for i in range(N_CLASSES):
        AUROCs.append(roc_auc_score(gt_np[:, i], pred_np[:, i]))
    return AUROCs

```

```

In [15]: # Data transformations
train_transforms = transforms.Compose([
    transforms.Resize(256),

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        transforms.RandomResizedCrop(224),
        transforms.RandomRotation(10),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ])

    valid_transforms = transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ])

```

In [18]:

```

train_dataset = ChestXrayDataSet(IMAGE_DIR, TRAIN_LIST, metadata=patient_info, tran
valid_dataset = ChestXrayDataSet(IMAGE_DIR, VALID_LIST, metadata=patient_info, tran

```

```

# Class counts in the same order as CLASS_NAMES
class_counts = [
    313, # Atelectasis
    141, # Cardiomegaly
    341, # Effusion
    580, # Infiltration
    111, # Mass
    151, # Nodule
    45, # Pneumonia
    141, # Pneumothorax
    136, # Consolidation
    62, # Edema
    86, # Emphysema
    117, # Fibrosis
    114, # Pleural_Thickening
    17 # Hernia
]

# Total samples and class weights
total_count = sum(class_counts)
class_weights = [total_count / count for count in class_counts]

# Keep weights on CPU for computing sample weights
class_weights_cpu = torch.tensor(class_weights, dtype=torch.float)

sample_weights = []
for data_tuple in train_dataset:
    label = data_tuple[1].float()
    weight = torch.sum(class_weights_cpu * label).item()
    sample_weights.append(weight)

sample_weights = torch.tensor(sample_weights, dtype=torch.float)

sampler = WeightedRandomSampler(weights=sample_weights, num_samples=len(sample_weig

trainloader = DataLoader(train_dataset, sampler=sampler, batch_size=64, pin_memory=
validloader = DataLoader(valid_dataset, batch_size=64, shuffle=False, pin_memory=Tr

```

```
In [19]: new_model = DenseNet121WithMetadata(N_CLASSES).to(device)

for param in new_model.densenet.parameters():
    param.requires_grad = False

# Unfreeze last dense block and transition
for param in new_model.densenet.features.denseblock4.parameters():
    param.requires_grad = True

for param in new_model.densenet.features.transition3.parameters():
    param.requires_grad = True

for param in new_model.classifier.parameters():
    param.requires_grad = True

trainable_params = [p for p in new_model.parameters() if p.requires_grad]
print(f"Number of trainable parameters: {sum(p.numel() for p in trainable_params):,}")

criterion = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(
    filter(lambda p: p.requires_grad, new_model.parameters()),
    lr=1e-4, weight_decay=5e-4
)
```

```
c:\Users\aroce\miniforge3\envs\572\Lib\site-packages\torchvision\models\_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be removed in the future, please use 'weights' instead.
```

```
warnings.warn(
c:\Users\aroce\miniforge3\envs\572\Lib\site-packages\torchvision\models\_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weights=DenseNet121_Weights.IMAGENET1K_V1`. You can also use `weights=DenseNet121_Weights.DEFAULT` to get the most up-to-date weights.
```

```
warnings.warn(msg)
```

```
Number of trainable parameters: 4,399,374
```

```
In [20]: def trainer(model, criterion, optimizer, trainloader, validloader, epochs=20, patience=10):
    train_loss, valid_loss, valid_accuracy = [], [], []
    best_auroc = 0.0
    best_model_weights = None
    counter = 0

    for epoch in range(epochs):
        model.train()
        epoch_train_loss = 0.0

        for images, labels, ages, genders in trainloader:
            images, labels = images.to(device), labels.to(device)
            ages, genders = ages.to(device), genders.to(device)

            optimizer.zero_grad()
            outputs = model(images, ages, genders)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
```

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        epoch_train_loss += loss.item() * images.size(0)

train_loss.append(epoch_train_loss / len(trainloader.dataset))

# Validation Phase
model.eval()
epoch_valid_loss = 0.0
all_labels = torch.FloatTensor().to(device)
all_outputs = torch.FloatTensor().to(device)

with torch.no_grad():
    for images, labels, ages, genders in validloader:
        images, labels = images.to(device), labels.to(device)
        ages, genders = ages.to(device), genders.to(device)

        outputs = model(images, ages, genders)
        loss = criterion(outputs, labels)
        epoch_valid_loss += loss.item() * images.size(0)

        all_labels = torch.cat((all_labels, labels), 0)
        all_outputs = torch.cat((all_outputs, outputs), 0)

# Calculate metrics
predictions = (all_outputs > 0.5).float()
correct = (predictions == all_labels).sum().item()
total = all_labels.numel()
accuracy = correct / total

aurocs = compute_AUCs(all_labels, all_outputs)
mean_auroc = np.mean(aurocs)

valid_loss.append(epoch_valid_loss / len(validloader.dataset))
valid_accuracy.append(accuracy)

if verbose:
    print(f"Epoch {epoch+1}/{epochs} - Train Loss: {train_loss[-1]:.4f}, Val
    print(f"Accuracy: {accuracy:.4f}, Mean AUROC: {mean_auroc:.4f}")

    if (epoch + 1) % 5 == 0 or epoch == epochs - 1:
        for i, auroc in enumerate(aurocs):
            print(f" {CLASS_NAMES[i]}: AUROC = {auroc:.4f}")

# Early stopping and model saving
if mean_auroc > best_auroc:
    best_auroc = mean_auroc
    best_model_weights = copy.deepcopy(model.state_dict())
    print(f" New best model with AUROC: {best_auroc:.4f}")
    counter = 0
else:
    counter += 1
    if counter >= patience:
        print(f" Early stopping triggered after {epoch+1} epochs")
        break

# Load the best model weights
if best_model_weights is not None:

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```
model.load_state_dict(best_model_weights)
print(f"Loaded best model with AUROC: {best_auroc:.4f}")

return {
    'train_loss': train_loss,
    'valid_loss': valid_loss,
    'valid_accuracy': valid_accuracy,
    'best_auroc': best_auroc
}
```

```
In [21]: new_model.to(device)
trainer(new_model, criterion, optimizer, trainloader, validloader, epochs=50, patie
```

Epoch 1/50 - Train Loss: 0.6150, Valid Loss: 0.5667  
Accuracy: 0.9497, Mean AUROC: 0.6157  
New best model with AUROC: 0.6157  
Epoch 2/50 - Train Loss: 0.4905, Valid Loss: 0.4570  
Accuracy: 0.9508, Mean AUROC: 0.6442  
New best model with AUROC: 0.6442  
Epoch 3/50 - Train Loss: 0.4239, Valid Loss: 0.3713  
Accuracy: 0.9498, Mean AUROC: 0.6760  
New best model with AUROC: 0.6760  
Epoch 4/50 - Train Loss: 0.3857, Valid Loss: 0.3343  
Accuracy: 0.9508, Mean AUROC: 0.6898  
New best model with AUROC: 0.6898  
Epoch 5/50 - Train Loss: 0.3634, Valid Loss: 0.2942  
Accuracy: 0.9499, Mean AUROC: 0.7046  
Atelectasis: AUROC = 0.6619  
Cardiomegaly: AUROC = 0.6726  
Effusion: AUROC = 0.7833  
Infiltration: AUROC = 0.5958  
Mass: AUROC = 0.6043  
Nodule: AUROC = 0.5362  
Pneumonia: AUROC = 0.7455  
Pneumothorax: AUROC = 0.8035  
Consolidation: AUROC = 0.7213  
Edema: AUROC = 0.8163  
Emphysema: AUROC = 0.6511  
Fibrosis: AUROC = 0.7172  
Pleural\_Thickening: AUROC = 0.6729  
Hernia: AUROC = 0.8821  
New best model with AUROC: 0.7046  
Epoch 6/50 - Train Loss: 0.3533, Valid Loss: 0.2782  
Accuracy: 0.9492, Mean AUROC: 0.7105  
New best model with AUROC: 0.7105  
Epoch 7/50 - Train Loss: 0.3408, Valid Loss: 0.2593  
Accuracy: 0.9489, Mean AUROC: 0.7114  
New best model with AUROC: 0.7114  
Epoch 8/50 - Train Loss: 0.3341, Valid Loss: 0.2519  
Accuracy: 0.9481, Mean AUROC: 0.7204  
New best model with AUROC: 0.7204  
Epoch 9/50 - Train Loss: 0.3192, Valid Loss: 0.2443  
Accuracy: 0.9465, Mean AUROC: 0.7174  
Epoch 10/50 - Train Loss: 0.3180, Valid Loss: 0.2333  
Accuracy: 0.9471, Mean AUROC: 0.7218  
Atelectasis: AUROC = 0.6849  
Cardiomegaly: AUROC = 0.7513  
Effusion: AUROC = 0.8118  
Infiltration: AUROC = 0.6088  
Mass: AUROC = 0.6355  
Nodule: AUROC = 0.5418  
Pneumonia: AUROC = 0.6996  
Pneumothorax: AUROC = 0.8191  
Consolidation: AUROC = 0.7208  
Edema: AUROC = 0.8056  
Emphysema: AUROC = 0.7062  
Fibrosis: AUROC = 0.7173  
Pleural\_Thickening: AUROC = 0.6455  
Hernia: AUROC = 0.9564



New best model with AUROC: 0.7218  
Epoch 11/50 - Train Loss: 0.3075, Valid Loss: 0.2285  
Accuracy: 0.9457, Mean AUROC: 0.7198  
Epoch 12/50 - Train Loss: 0.3004, Valid Loss: 0.2241  
Accuracy: 0.9474, Mean AUROC: 0.7236  
New best model with AUROC: 0.7236  
Epoch 13/50 - Train Loss: 0.2943, Valid Loss: 0.2213  
Accuracy: 0.9444, Mean AUROC: 0.7223  
Epoch 14/50 - Train Loss: 0.2920, Valid Loss: 0.2191  
Accuracy: 0.9477, Mean AUROC: 0.7256  
New best model with AUROC: 0.7256  
Epoch 15/50 - Train Loss: 0.2847, Valid Loss: 0.2201  
Accuracy: 0.9416, Mean AUROC: 0.7226  
Atelectasis: AUROC = 0.6794  
Cardiomegaly: AUROC = 0.7554  
Effusion: AUROC = 0.8127  
Infiltration: AUROC = 0.6143  
Mass: AUROC = 0.6082  
Nodule: AUROC = 0.5192  
Pneumonia: AUROC = 0.7357  
Pneumothorax: AUROC = 0.8308  
Consolidation: AUROC = 0.7113  
Edema: AUROC = 0.8265  
Emphysema: AUROC = 0.7140  
Fibrosis: AUROC = 0.6902  
Pleural\_Thickening: AUROC = 0.6559  
Hernia: AUROC = 0.9635  
Epoch 16/50 - Train Loss: 0.2762, Valid Loss: 0.2225  
Accuracy: 0.9428, Mean AUROC: 0.7286  
New best model with AUROC: 0.7286  
Epoch 17/50 - Train Loss: 0.2716, Valid Loss: 0.2296  
Accuracy: 0.9390, Mean AUROC: 0.7343  
New best model with AUROC: 0.7343  
Epoch 18/50 - Train Loss: 0.2660, Valid Loss: 0.2138  
Accuracy: 0.9414, Mean AUROC: 0.7333  
Epoch 19/50 - Train Loss: 0.2584, Valid Loss: 0.2289  
Accuracy: 0.9355, Mean AUROC: 0.7263  
Epoch 20/50 - Train Loss: 0.2567, Valid Loss: 0.2186  
Accuracy: 0.9388, Mean AUROC: 0.7278  
Atelectasis: AUROC = 0.7016  
Cardiomegaly: AUROC = 0.7802  
Effusion: AUROC = 0.8256  
Infiltration: AUROC = 0.6017  
Mass: AUROC = 0.6202  
Nodule: AUROC = 0.5364  
Pneumonia: AUROC = 0.7641  
Pneumothorax: AUROC = 0.8482  
Consolidation: AUROC = 0.7133  
Edema: AUROC = 0.8630  
Emphysema: AUROC = 0.6608  
Fibrosis: AUROC = 0.6840  
Pleural\_Thickening: AUROC = 0.6496  
Hernia: AUROC = 0.9404  
Epoch 21/50 - Train Loss: 0.2496, Valid Loss: 0.2115  
Accuracy: 0.9440, Mean AUROC: 0.7298  
Epoch 22/50 - Train Loss: 0.2419, Valid Loss: 0.2105

Accuracy: 0.9429, Mean AUROC: 0.7262  
Epoch 23/50 - Train Loss: 0.2376, Valid Loss: 0.2170  
Accuracy: 0.9384, Mean AUROC: 0.7243  
Epoch 24/50 - Train Loss: 0.2318, Valid Loss: 0.2111  
Accuracy: 0.9402, Mean AUROC: 0.7336  
Epoch 25/50 - Train Loss: 0.2234, Valid Loss: 0.2089  
Accuracy: 0.9417, Mean AUROC: 0.7215  
Atelectasis: AUROC = 0.6988  
Cardiomegaly: AUROC = 0.7512  
Effusion: AUROC = 0.8352  
Infiltration: AUROC = 0.6037  
Mass: AUROC = 0.6480  
Nodule: AUROC = 0.5403  
Pneumonia: AUROC = 0.5983  
Pneumothorax: AUROC = 0.8237  
Consolidation: AUROC = 0.7522  
Edema: AUROC = 0.8707  
Emphysema: AUROC = 0.7142  
Fibrosis: AUROC = 0.6718  
Pleural\_Thickening: AUROC = 0.6107  
Hernia: AUROC = 0.9821  
Early stopping triggered after 25 epochs  
Loaded best model with AUROC: 0.7343

```
Out[21]: {'train_loss': [0.6150076894563892,
    0.4905262444403622,
    0.42387798437904584,
    0.3856518385443697,
    0.3633594352131266,
    0.35329419158976155,
    0.34079630753420936,
    0.33410104391199413,
    0.31920621483010475,
    0.31799494007309015,
    0.30749466005956555,
    0.3003865083427762,
    0.2942822369618837,
    0.2919568213676514,
    0.28467885411000315,
    0.2761934056013576,
    0.27163809748266926,
    0.26600651799457076,
    0.25842904915091447,
    0.2566547337243406,
    0.2495752162475455,
    0.24194228084862796,
    0.23764604326230043,
    0.23177117166365171,
    0.2234396956398951],
  'valid_loss': [0.5666714046796163,
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    0.371339679479599,
    0.3343385257720947,
    0.2942291405200958,
    0.278245933453242,
    0.25931656138102216,
    0.25193688142299653,
    0.24427994549274445,
    0.23331503105163573,
    0.22846508328119913,
    0.22407191602389018,
    0.22131952675183614,
    0.21914870476722717,
    0.2200619997183482,
    0.22248999659220378,
    0.22964911778767905,
    0.21384362451235453,
    0.22886449948946636,
    0.21856773742039998,
    0.2115029188791911,
    0.21054298710823058,
    0.21701028501987457,
    0.21108198753992716,
    0.20893272856871287],
  'valid_accuracy': [0.9497142857142857,
    0.9507619047619048,
    0.9498095238095238,
    0.9507619047619048,
    0.9499047619047619,
    0.9492380952380952,
```

```
0.9488571428571428,  
0.9480952380952381,  
0.9464761904761905,  
0.9471428571428572,  
0.9457142857142857,  
0.9474285714285714,  
0.9443809523809524,  
0.9477142857142857,  
0.9416190476190476,  
0.9427619047619048,  
0.939047619047619,  
0.9414285714285714,  
0.9355238095238095,  
0.9387619047619048,  
0.944,  
0.9428571428571428,  
0.9383809523809524,  
0.9401904761904762,  
0.9417142857142857],  
'best_auroc': np.float64(0.734284917878435))}
```