Chest X-Ray Classification Project: Leveraging Deep Learning for Infiltration Detection

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.image as pli
import seaborn as sns
import os
import tensorflow as tf
from PIL import Image
import torch
from torch import nn
from tqdm import tqdm
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms, models
import pandas as pd
from sklearn.metrics import classification_report
from google.colab import drive
from torchvision import transforms
from torch.utils.data import ConcatDataset
from torchvision.models import mobilenet_v2, MobileNet_V2_Weights
import random
from sklearn.metrics import roc_curve, auc, confusion_matrix, ConfusionMatrixDisplay
```

In [3]:
```
print(os.cpu_count())
# for num_workers
```

```
4
```

In [4]:
```
base_path = "/kaggle/input/data"
labels_file = os.path.join(base_path, "Data_Entry_2017.csv")

labels_df = pd.read_csv(labels_file)

image_folders = [f"images_{str(i).zfill(3)}" for i in range(1, 13)]

data_tot = []
for _, row in labels_df.iterrows():
    image_name = row["Image Index"]
    labels = row["Finding Labels"].split('|')

    image_path = None
    for folder in image_folders:
        potential_path = os.path.join(base_path, folder, "images", image_name)
        if os.path.exists(potential_path):
            image_path = potential_path
            break

    if image_path:
        data_tot.append({'image_path': image_path, 'labels': labels})

print(f"Total number of images found: {len(data_tot)}")
print(data_tot[:5])
```

```
Total number of images found: 112120
[{'image_path': '/kaggle/input/data/images_001/images/00000001_000.png', 'labels': ['Cardiomegaly']}, {'image_path': '/kaggle/input/data/ima
ges_001/images/00000001_001.png', 'labels': ['Cardiomegaly', 'Emphysema']}, {'image_path': '/kaggle/input/data/images_001/images/00000001_00
2.png', 'labels': ['Cardiomegaly', 'Effusion']}, {'image_path': '/kaggle/input/data/images_001/images/00000002_000.png', 'labels': ['No Find
ing']}, {'image_path': '/kaggle/input/data/images_001/images/00000003_000.png', 'labels': ['Hernia']}]
```

In [6]:
```
labels_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 112120 entries, 0 to 112119
Data columns (total 12 columns):
 #   Column                       Non-Null Count   Dtype  
---  ------                       --------------   -----  
 0   Image Index                  112120 non-null  object 
 1   Finding Labels               112120 non-null  object 
 2   Follow-up #                  112120 non-null  int64  
 3   Patient ID                   112120 non-null  int64  
 4   Patient Age                  112120 non-null  int64  
 5   Patient Gender               112120 non-null  object 
 6   View Position                112120 non-null  object 
 7   OriginalImage[Width          112120 non-null  int64  
 8   Height]                      112120 non-null  int64  
 9   OriginalImagePixelSpacing[x  112120 non-null  float64
 10  y]                           112120 non-null  float64
 11  Unnamed: 11                  0 non-null       float64
dtypes: float64(3), int64(5), object(4)
memory usage: 10.3+ MB
```

In [7]:
```
labels_df.head()
```

```
/usr/local/lib/python3.10/dist-packages/pandas/io/formats/format.py:1458: RuntimeWarning: invalid value encountered in greater
  has_large_values = (abs_vals > 1e6).any()
/usr/local/lib/python3.10/dist-packages/pandas/io/formats/format.py:1459: RuntimeWarning: invalid value encountered in less
  has_small_values = ((abs_vals < 10 ** (-self.digits)) & (abs_vals > 0)).any()
/usr/local/lib/python3.10/dist-packages/pandas/io/formats/format.py:1459: RuntimeWarning: invalid value encountered in greater
  has_small_values = ((abs_vals < 10 ** (-self.digits)) & (abs_vals > 0)).any()
```

Out[7]:

	Image Index	Finding Labels	Follow-up #	Patient ID	Patient Age	Patient Gender	View Position	OriginalImage[Width	Height]	OriginalImagePixelSpacing[x
0	00000001_000.png	Cardiomegaly	0	1	58	M	PA	2682	2749	0.143
1	00000001_001.png	Cardiomegaly|Emphysema	1	1	58	M	PA	2894	2729	0.143
2	00000001_002.png	Cardiomegaly|Effusion	2	1	58	M	PA	2500	2048	0.168
3	00000002_000.png	No Finding	0	2	81	M	PA	2500	2048	0.171
4	00000003_000.png	Hernia	0	3	81	F	PA	2582	2991	0.143

In [8]:
```python
labels_df.shape
```

Out[8]:
```
(112120, 12)
```

In [9]:
```python
labels_df['Finding Labels'].value_counts()
```

Out[9]:
```
Finding Labels
No Finding                                                           60361
Infiltration                                                          9547
Atelectasis                                                           4215
Effusion                                                              3955
Nodule                                                                2705
                                                                     ...  
Consolidation|Edema|Effusion|Mass|Nodule                                 1
Edema|Infiltration|Mass|Pneumonia|Pneumothorax                           1
Consolidation|Effusion|Infiltration|Mass|Nodule|Pleural_Thickening|Pneumonia    1
Consolidation|Mass|Nodule|Pneumothorax                                   1
Cardiomegaly|Edema|Effusion|Fibrosis|Infiltration                        1
Name: count, Length: 836, dtype: int64
```

In [10]:
```python
num_class_1 = sum(["Infiltration" in r["labels"] for r in data_tot])
num_class_0 = sum(["Infiltration" not in r["labels"] for r in data_tot])

print(f"Class 1 (Infiltration): {num_class_1}")
print(f"Class 0 (Not Infiltration): {num_class_0}")
```

```
Class 1 (Infiltration): 19894
Class 0 (Not Infiltration): 92226
```

In [11]:
```python
class_1_data = [r for r in data_tot if "Infiltration" in r["labels"]]
class_0_data = [r for r in data_tot if "Infiltration" not in r["labels"]]

random.seed(42)
class_1_sampled = random.sample(class_1_data, 6000)
class_0_sampled = random.sample(class_0_data, 8000)

balanced_data = class_0_sampled + class_1_sampled

new_num_class_1 = sum(["Infiltration" in r["labels"] for r in balanced_data])
new_num_class_0 = sum(["Infiltration" not in r["labels"] for r in balanced_data])

print(f"New Class 1 (Infiltration): {new_num_class_1}")
print(f"New Class 0 (Not Infiltration): {new_num_class_0}")
```

```
New Class 1 (Infiltration): 6000
New Class 0 (Not Infiltration): 8000
```

In [12]:
```python
torch.manual_seed(42)
random.seed(42)
np.random.seed(42)
if torch.cuda.is_available():
    torch.cuda.manual_seed(42)
    torch.cuda.manual_seed_all(42)  # For multi-GPU
    torch.backends.cudnn.deterministic = True
    torch.backends.cudnn.benchmark = False
```

In [13]:
```python
tf.random.set_seed(42)
np.random.seed(42)
random.seed(42)
```

MobileNetV1 introduced **Depthwise Separable Convolutions**, splitting standard convolutions into two steps: a **depthwise convolution** (applying filters per channel) and a **pointwise convolution** (1x1 to combine channels). This drastically reduced computational cost and parameters compared to traditional CNNs, making the model efficient for mobile devices.

MobileNetV2 improved upon MobileNetV1 with **inverted residuals** and **linear bottlenecks**. Inverted residuals connect bottlenecks (with fewer channels) via shortcuts, reducing computation, while linear bottlenecks avoid non-linear activations in compressed layers to preserve critical information. These innovations increased efficiency and accuracy, further optimizing MobileNetV2 for resource-constrained environments.

Formulas for Precision, Recall, and F1-Score

1. **Precision**: Measures the proportion of correctly predicted positive instances among all predicted positives.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

---

2. **Recall (Sensitivity or True Positive Rate)**: Measures the proportion of correctly predicted positive instances among all actual positives.

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

---

3. **F1-Score**: The harmonic mean of precision and recall, used to balance both metrics when there is class imbalance.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Explanation of Variables:

- **True Positives (TP)**: Instances correctly classified as positive.
- **False Positives (FP)**: Instances incorrectly classified as positive.
- **False Negatives (FN)**: Instances incorrectly classified as negative.

TensorFlow Keras / MobileNetV2

In [14]:
```
def preprocess_item(image_path, label):
    image = tf.io.read_file(image_path)
    image = tf.image.decode_png(image, channels=3)
    image = tf.image.resize(image, [224, 224]) / 255.0
    return image, label

paths = [item['image_path'] for item in balanced_data]
labels = [1 if "Infiltration" in item["labels"] else 0 for item in balanced_data]

dataset = tf.data.Dataset.from_tensor_slices((paths, labels))
# Maps the preprocess_item function over the dataset with parallel processing to improve speed
# (num_parallel_calls=tf.data.AUTOTUNE)
dataset = dataset.map(lambda x, y: preprocess_item(x, y),
                      num_parallel_calls=tf.data.AUTOTUNE)
```

In [15]:
```
# Shuffle to improve your workout
dataset = dataset.shuffle(buffer_size=len(balanced_data))
dataset_nobatch = dataset
# Batch creation. Prefetch to load next batch in parallel
dataset = dataset.batch(64).prefetch(tf.data.AUTOTUNE)
```

In [16]:
```
for images, labels in dataset.take(1):
    print(f"Batch shape: {images.shape}, Labels shape: {labels.shape}")
```

```
Batch shape: (64, 224, 224, 3), Labels shape: (64,)
```

In [17]:
```
total_images = 0
for images, labels in dataset:
   total_images += images.shape[0]

print(f"Total_number_of: {total_images}")
```

```
Total_number_of: 14000
```

Model Description - Fine Tuning

A binary classification model is defined using MobileNetV2 as the base, pretrained on ImageNet. The base model is used as a feature extractor with its weights frozen (trainable=False).

Key components include:

- GlobalAveragePooling2D.
- A fully connected layer with 64 units and ReLU activation.
- An output layer with 1 unit and sigmoid activation for binary classification.
- Optimizer: Adam, configured with a learning rate of 0.001.
- Loss function: Binary crossentropy, suitable for binary classification tasks.
- Metric: Accuracy, to evaluate the model's performance.

In [18]:
```
base_model = tf.keras.applications.MobileNetV2(input_shape=(224, 224, 3),
                                               include_top=False, weights='imagenet')
# the pre-trained model uses weights derived from training on ImageNet
base_model.trainable = False

model_tf = tf.keras.Sequential([base_model,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')])

optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kern
els_1.0_224_no_top.h5
9406464/9406464 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

In [19]:
```
model_tf.compile(optimizer=optimizer,loss='binary_crossentropy',metrics=['accuracy'])
```

In [20]:
```
dataset = dataset.shuffle(buffer_size=len(balanced_data))
dataset_size = len(dataset)

test_size = int(dataset_size * 0.2)
train_size = dataset_size - test_size

test_set = dataset.take(test_size)  # Top 20% for the test
train_set = dataset.skip(test_size)  # Remaining 80% for training
```

In [21]:
```
print(f"Dataset (batch): {dataset_size}")
print(f"Test set (batch): {test_size}")
print(f"Training set (batch): {train_size}")
```

```
Dataset (batch): 219
Test set (batch): 43
Training set (batch): 176
```

In [22]:
```
history = model_tf.fit(train_set, epochs=4)
```

```
Epoch 1/4
176/176 ━━━━━━━━━━━━━━━━━━━━ 101s 85ms/step - accuracy: 0.6074 - loss: 0.6763
Epoch 2/4
176/176 ━━━━━━━━━━━━━━━━━━━━ 84s 56ms/step - accuracy: 0.6365 - loss: 0.6391
Epoch 3/4
176/176 ━━━━━━━━━━━━━━━━━━━━ 83s 56ms/step - accuracy: 0.6556 - loss: 0.6299
Epoch 4/4
176/176 ━━━━━━━━━━━━━━━━━━━━ 83s 56ms/step - accuracy: 0.6468 - loss: 0.6358
```

In [23]:
```
test_loss, test_accuracy = model_tf.evaluate(test_set)
print(f"Test Loss: {test_loss}, Test Accuracy: {test_accuracy}")
```

```
43/43 ━━━━━━━━━━━━━━━━━━━━ 78s 57ms/step - accuracy: 0.6748 - loss: 0.6134
Test Loss: 0.6101019978523254, Test Accuracy: 0.6809592843055725
```

In [24]:
```
y_true = []
y_pred = []
for images, labels in test_set:
    preds = model_tf.predict(images)
    y_true.extend(labels.numpy())
    y_pred.extend((preds > 0.5).astype(int).flatten())

print(classification_report(y_true, y_pred))
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 5s 14ms/step
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2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
              precision    recall  f1-score   support

           0       0.65      0.86      0.74      1539
           1       0.70      0.41      0.51      1213

    accuracy                           0.66      2752
   macro avg       0.67      0.63      0.63      2752
weighted avg       0.67      0.66      0.64      2752
```

Class 0 (Not Infiltration):

- **Precision**: 65% → Moderate ability to avoid false positives.
- **Recall**: 86% → Excellent ability to identify negatives correctly.

Class 1 (Infiltration):

- **Precision**: 70% → Good ability to avoid false positives.
- **Recall**: 41% → Low ability to capture positives (many false negatives).

Accuracy:

- 66% → Indicates acceptable general performance with room for improvement.

Pytorch / MobileNetV2

In [25]:
```
class ChestXRayDataset(Dataset):
    def __init__(self, data, transform=None):
        self.data = data
        self.transform = transform

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

    def __getitem__(self, idx):
        image_path = self.data[idx]['image_path']
        label = 1 if "Infiltration" in self.data[idx]['labels'] else 0
        image = Image.open(image_path).convert("RGB")

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

        return image, label
```

In [26]:
```
# Transformations
transform = transforms.Compose([
```

```
    transforms.Resize((224, 224)),
    transforms.ToTensor()])

dataset_pytorch = ChestXRayDataset(balanced_data, transform=transform)
train_size = int(0.8 * len(dataset_pytorch))
test_size = len(dataset_pytorch) - train_size

train_dataset, test_dataset = torch.utils.data.random_split(dataset_pytorch,
                                                            [train_size, test_size])
train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True, num_workers=2)
test_loader = DataLoader(test_dataset, batch_size=64, shuffle=False)
```

Model Description - Fine Tuning

A binary classification model is defined using MobileNetV2 as the base, pretrained on ImageNet. The base model is used as a feature extractor with its weights retained from the pretraining.

Key components include:

- A linear classifier, replacing the original output layer, with a single output logit for binary classification.
- Loss function: BCEWithLogitsLoss, which combines sigmoid activation and binary crossentropy for stable handling of logits.
- Optimizer: Adam, configured with a learning rate of 0.001.

In [27]:
```
# Pre-trained model
model = mobilenet_v2(weights=MobileNet_V2_Weights.DEFAULT)
model.classifier[1] = nn.Linear(model.last_channel, 1)  # Binary output
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = model.to(device)

# Loss and optimizer
criterion = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

```
Downloading: "https://download.pytorch.org/models/mobilenet_v2-7ebf99e0.pth" to /root/.cache/torch/hub/checkpoints/mobilenet_v2-7ebf99e0.pth
100%|██████████| 13.6M/13.6M [00:00<00:00, 112MB/s]
```

In [28]:
```
# Training
num_epochs = 4

for epoch in range(num_epochs):
    model.train()
    running_loss = 0.0
    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device).float()
        optimizer.zero_grad()
        outputs = model(images).squeeze()
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()

    print(f"Epoch {epoch+1}/{num_epochs}, Loss: {running_loss/len(train_loader):.4f}")
```

```
Epoch 1/4, Loss: 0.6444
Epoch 2/4, Loss: 0.6181
Epoch 3/4, Loss: 0.6057
Epoch 4/4, Loss: 0.5858
```

In [29]:
```
# Validation
model.eval()
y_true, y_pred = [], []
with torch.no_grad():
    for images, labels in test_loader:
        images, labels = images.to(device), labels.to(device)
        outputs = model(images).squeeze()
        preds = (torch.sigmoid(outputs) > 0.5).int()
        y_true.extend(labels.cpu().numpy())
        y_pred.extend(preds.cpu().numpy())

print("Test Classification Report:")
print(classification_report(y_true, y_pred))
```

```
Test Classification Report:
              precision    recall  f1-score   support

           0       0.67      0.77      0.72      1590
           1       0.63      0.51      0.56      1210

    accuracy                           0.66      2800
   macro avg       0.65      0.64      0.64      2800
weighted avg       0.65      0.66      0.65      2800
```

Class 0 (Not Infiltration):

- **Precision**: 67%
- **Recall**: 63%

Class 1 (Infiltration):

- **Precision**: 77%
- **Recall**: 51%

Accuracy:

- 66% → Indicates acceptable general performance with room for improvement.

Data Augmentation and Balancing for Class 1

This section implements data augmentation techniques to balance the dataset and improve the model's ability to detect positive cases (Class 1 - "Infiltration"). Augmentation is applied selectively to Class 1 images, and the augmented data is combined with the original dataset for training.

TensorFlow Keras / MobileNetV2 (with Data Augmentation)

In [30]:
```
class_1_sampled_to_augment = random.sample(class_1_sampled, 2000)
print(len(class_1_sampled_to_augment))
```

```
2000
```

In [31]:
```
def augment_image(image):
    # Augmentation operations
    image = tf.image.random_flip_left_right(image)  # Horizontal Flip
    image = tf.image.random_flip_up_down(image)    # Vertical Flip
    image = tf.image.rot90(image, k=np.random.randint(1, 4))  # Random rotation
    return image

# Preprocessing and augmentation function
def preprocess_and_augment(image_path, label):
    image = tf.io.read_file(image_path)
    image = tf.image.decode_png(image, channels=3)
    image = tf.image.resize(image, [224, 224]) / 255.0
    image = augment_image(image)
    return image, label

class_1_paths_to_augment = [item['image_path'] for item in class_1_sampled_to_augment]
class_1_labels_to_augment = [1] * len(class_1_paths_to_augment)
class_1_sampled_to_augment = tf.data.Dataset.from_tensor_slices((class_1_paths_to_augment,
                                                                 class_1_labels_to_augment))

class_1_sampled_augmented = class_1_sampled_to_augment.map(preprocess_and_augment,
                                                           num_parallel_calls=tf.data.AUTOTUNE)
```

In [32]:
```
augmented_count = sum(1 for _ in class_1_sampled_augmented)
print(f"Number of augmented samples: {augmented_count}")
```

```
Number of augmented samples: 2000
```

In [33]:
```
final_dataset = dataset_nobatch.concatenate(class_1_sampled_augmented)
print(len(final_dataset))
```

```
16000
```

In [34]:
```
# Apply shuffle and batching to the combined dataset
final_dataset = final_dataset.shuffle(buffer_size=len(final_dataset))
final_dataset = final_dataset.batch(64).prefetch(tf.data.AUTOTUNE)
```

In [35]:
```
dataset_size = len(final_dataset)
test_size = int(dataset_size * 0.2)
train_size = dataset_size - test_size

test_set = final_dataset.take(test_size)  # Top 20% for the test
train_set = final_dataset.skip(test_size)  # Remaining 80% for training
```

In [36]:
```
print(f"Dataset totale: {dataset_size}")
print(f"Test set: {test_size}")
print(f"Training set: {train_size}")
```

```
Dataset totale: 250
Test set: 50
Training set: 200
```

In [37]:
```
optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)
model_tf.compile(optimizer=optimizer, loss='binary_crossentropy', metrics=['accuracy'])
```

In [38]:
```
history = model_tf.fit(train_set, epochs=4, validation_data = test_set)
```

```
Epoch 1/4
200/200 ━━━━━━━━━━━━━━━━━━━━ 188s 500ms/step - accuracy: 0.6841 - loss: 0.5750 - val_accuracy: 0.7038 - val_loss: 0.5427
Epoch 2/4
200/200 ━━━━━━━━━━━━━━━━━━━━ 178s 485ms/step - accuracy: 0.6990 - loss: 0.5457 - val_accuracy: 0.7175 - val_loss: 0.5341
Epoch 3/4
200/200 ━━━━━━━━━━━━━━━━━━━━ 179s 487ms/step - accuracy: 0.7047 - loss: 0.5398 - val_accuracy: 0.7009 - val_loss: 0.5392
Epoch 4/4
200/200 ━━━━━━━━━━━━━━━━━━━━ 177s 481ms/step - accuracy: 0.7098 - loss: 0.5377 - val_accuracy: 0.7163 - val_loss: 0.5259
```

In [39]:
```
test_loss, test_accuracy = model_tf.evaluate(test_set)
print(f"Test Loss: {test_loss}, Test Accuracy: {test_accuracy}")
```

```
50/50 ━━━━━━━━━━━━━━━━━━━━ 83s 61ms/step - accuracy: 0.7145 - loss: 0.5348
Test Loss: 0.5229731798171997, Test Accuracy: 0.7221875190734863
```

In [40]:
```
y_true = []
y_pred = []

for images, labels in test_set:
    preds = model_tf.predict(images)
    y_true.extend(labels.numpy())
    y_pred.extend(preds.flatten())

y_true = np.array(y_true)
y_pred = np.array(y_pred)

thresholds = [0.4, 0.5]
for threshold in thresholds:
    y_pred_class = (y_pred > threshold).astype(int)
    print(f"Classification report for threshold = {threshold}")
    print(classification_report(y_true, y_pred_class))
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 2s 23ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
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2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
Classification report for threshold = 0.4
              precision    recall  f1-score   support

           0       0.71      0.71      0.71      1589
           1       0.72      0.71      0.71      1611

    accuracy                           0.71      3200
   macro avg       0.71      0.71      0.71      3200
weighted avg       0.71      0.71      0.71      3200

Classification report for threshold = 0.5
              precision    recall  f1-score   support

           0       0.67      0.87      0.75      1589
           1       0.81      0.57      0.67      1611

    accuracy                           0.72      3200
   macro avg       0.74      0.72      0.71      3200
weighted avg       0.74      0.72      0.71      3200
```

Class 0 (Not Infiltration)

- **Precision**: 67% → When the model predicts "Not Infiltration," it is correct 67% of the time. This means that 33% of these predictions are actually false negatives.

- **Recall**: 87% → The model successfully identifies 87% of all true negatives, demonstrating a strong ability to recognize cases without infiltration.

Class 1 (Infiltration)

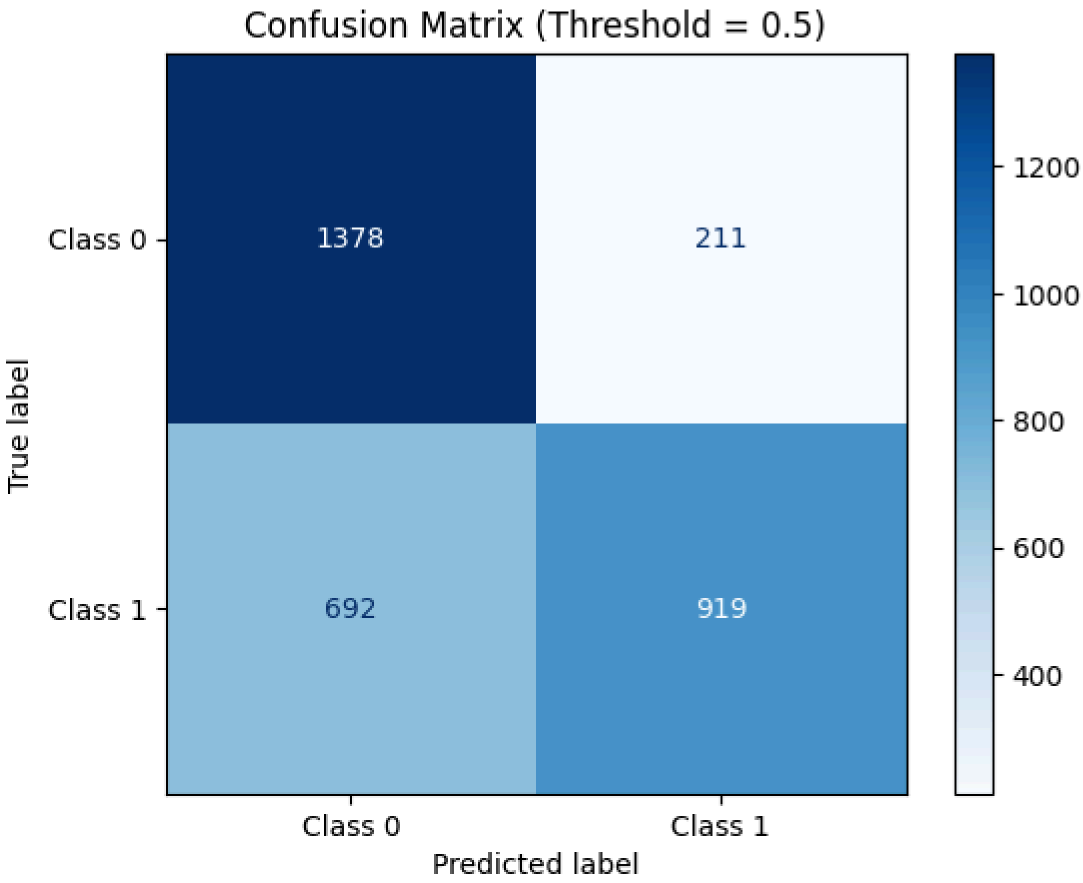
- **Precision**: 81% → When the model predicts "Infiltration," it is correct 81% of the time, indicating good performance in avoiding false positives.
- **Recall**: 57% → The model captures only 57% of actual infiltration cases, meaning 43% of true positives are missed, highlighting a need for improvement in detecting this class.

Accuracy

- 72% → The model achieves an overall accuracy of 72%, which is acceptable but leaves room for improvement, especially in correctly identifying infiltration cases.

In [41]:
```
threshold = 0.5
y_pred_class = (y_pred > threshold).astype(int)
cm = confusion_matrix(y_true, y_pred_class)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['Class 0', 'Class 1'])
disp.plot(cmap='Blues', values_format='d')
plt.title(f'Confusion Matrix (Threshold = {threshold})')
plt.show()
```



Model Description - Fine Tuning
A binary classification model is defined using MobileNetV2 as the base, pretrained on ImageNet. The base model is used as a feature extractor with its weights frozen (trainable=False).

Key components include:

- GlobalMaxPooling2D.
- A fully connected layer with 64 units and ReLU activation.
- An output layer with 1 unit and sigmoid activation for binary classification.
- Optimizer: Adam, configured with a learning rate of 0.001.
- Loss function: Binary crossentropy, suitable for binary classification tasks.
- Metric: Accuracy, to evaluate the model's performance.

In [42]:
```
model_tf_max = tf.keras.Sequential([base_model,
    tf.keras.layers.GlobalMaxPooling2D(),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')])
```

In [43]:
```
optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)
model_tf_max.compile(optimizer=optimizer, loss='binary_crossentropy', metrics=['accuracy'])
```

In [44]:
```
history = model_tf_max.fit(train_set, epochs=5,validation_data=test_set)

test_loss, test_accuracy = model_tf_max.evaluate(test_set)
print(f"Test Loss: {test_loss}, Test Accuracy: {test_accuracy}")
```

```
Epoch 1/5
200/200 ━━━━━━━━━━━━━━━━━━━━ 214s 634ms/step - accuracy: 0.6014 - loss: 1.1714 - val_accuracy: 0.6812 - val_loss: 0.5624
Epoch 2/5
200/200 ━━━━━━━━━━━━━━━━━━━━ 208s 563ms/step - accuracy: 0.6768 - loss: 0.5736 - val_accuracy: 0.6853 - val_loss: 0.5557
Epoch 3/5
200/200 ━━━━━━━━━━━━━━━━━━━━ 212s 588ms/step - accuracy: 0.6757 - loss: 0.5703 - val_accuracy: 0.6934 - val_loss: 0.5555
Epoch 4/5
200/200 ━━━━━━━━━━━━━━━━━━━━ 207s 573ms/step - accuracy: 0.6804 - loss: 0.5639 - val_accuracy: 0.6825 - val_loss: 0.5565
Epoch 5/5
200/200 ━━━━━━━━━━━━━━━━━━━━ 210s 558ms/step - accuracy: 0.6856 - loss: 0.5551 - val_accuracy: 0.7044 - val_loss: 0.5430
50/50 ━━━━━━━━━━━━━━━━━━━━ 101s 62ms/step - accuracy: 0.7048 - loss: 0.5465
Test Loss: 0.5513942837715149, Test Accuracy: 0.6943749785423279
```

In [45]:
```python
y_true = []
y_pred = []

for images, labels in test_set:
    preds = model_tf_max.predict(images)
    y_true.extend(labels.numpy())
    y_pred.extend(preds.flatten())

y_true = np.array(y_true)
y_pred = np.array(y_pred)

thresholds = [0.4, 0.5]
for threshold in thresholds:
    y_pred_class = (y_pred > threshold).astype(int)
    print(f"Classification report for threshold = {threshold}")
    print(classification_report(y_true, y_pred_class))
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 4s 16ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
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2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
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2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
Classification report for threshold = 0.4
              precision    recall  f1-score   support

           0       0.71      0.59      0.64      1592
           1       0.65      0.76      0.70      1608

    accuracy                           0.68      3200
   macro avg       0.68      0.67      0.67      3200
weighted avg       0.68      0.68      0.67      3200

Classification report for threshold = 0.5
              precision    recall  f1-score   support

           0       0.66      0.79      0.72      1592
           1       0.74      0.60      0.66      1608

    accuracy                           0.69      3200
   macro avg       0.70      0.69      0.69      3200
weighted avg       0.70      0.69      0.69      3200
```

Class 0 (Not Infiltration)

- **Precision**: 66%
- **Recall**: 79%

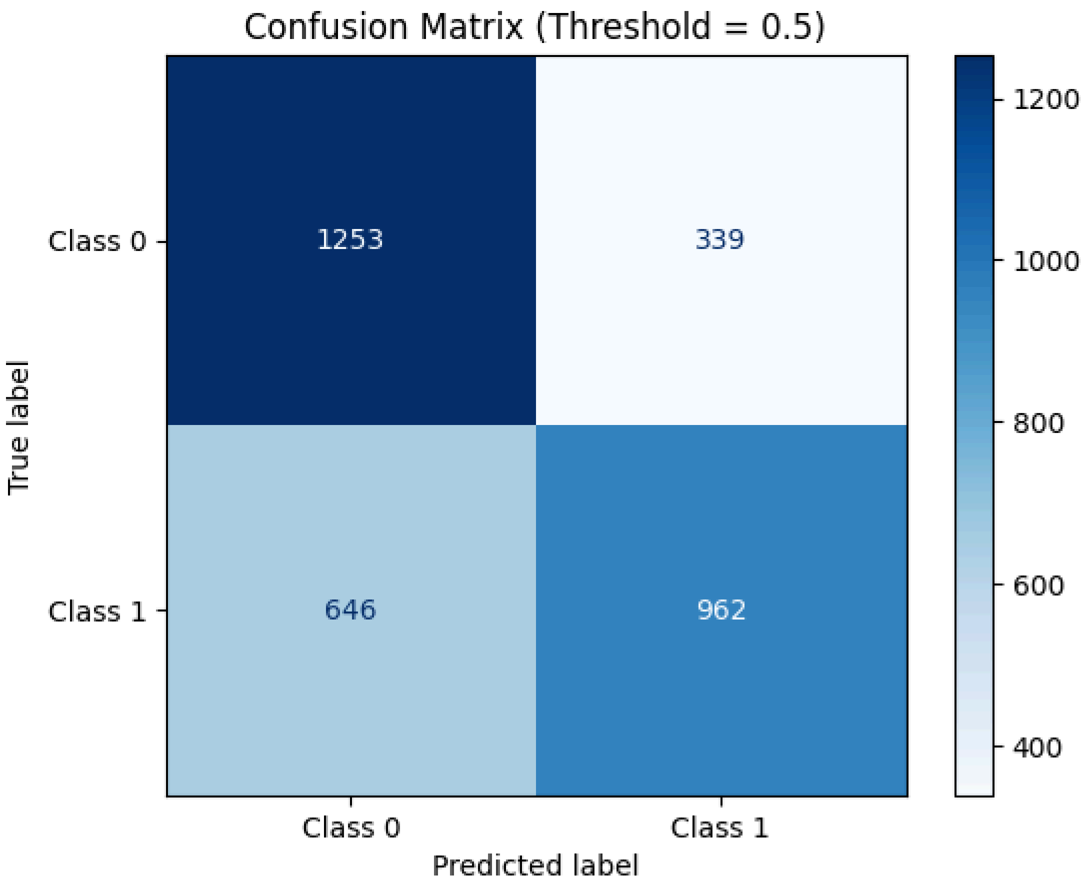
Class 1 (Infiltration)

- **Precision**: 74%
- **Recall**: 60% → The model captures 60% of actual infiltration cases, missing 40%.

Accuracy

- 69% → Moderate performance, with room for improvement in detecting infiltration cases.

In [46]:
```
threshold = 0.5
y_pred_class = (y_pred > threshold).astype(int)
cm = confusion_matrix(y_true, y_pred_class)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['Class 0', 'Class 1'])
disp.plot(cmap='Blues', values_format='d')
plt.title(f'Confusion Matrix (Threshold = {threshold})')
plt.show()
```



Pytorch / MobileNetV2 (with Data Augmentation)

In [47]:
```
# Transformations with Data Augmentation
augmentation_transforms = transforms.Compose([
    transforms.RandomHorizontalFlip(p=0.5),  # Horizontal Flip
    transforms.RandomVerticalFlip(p=0.5),    # Vertical Flip
    transforms.RandomRotation(degrees=90),   # Random rotation within 45°
    transforms.Resize((224, 224)),
    transforms.ToTensor()])

# Basic transformations (without augmentation)
base_transforms = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor()])

# Original dataset with basic transformations
base_dataset = ChestXRayDataset(balanced_data, transform=base_transforms)
```

In [48]:
```
# Dataset augmented for class 1 only
class_1_sampled_to_augment = random.sample(class_1_sampled, 2000)
class_1_data_augmented = ChestXRayDataset(class_1_sampled_to_augment,
                                          transform=augmentation_transforms)
print(len(class_1_data_augmented))

# Combine the original and augmented dataset
combined_dataset = ConcatDataset([base_dataset, class_1_data_augmented])
print(len(combined_dataset))
```

```
2000
16000
```

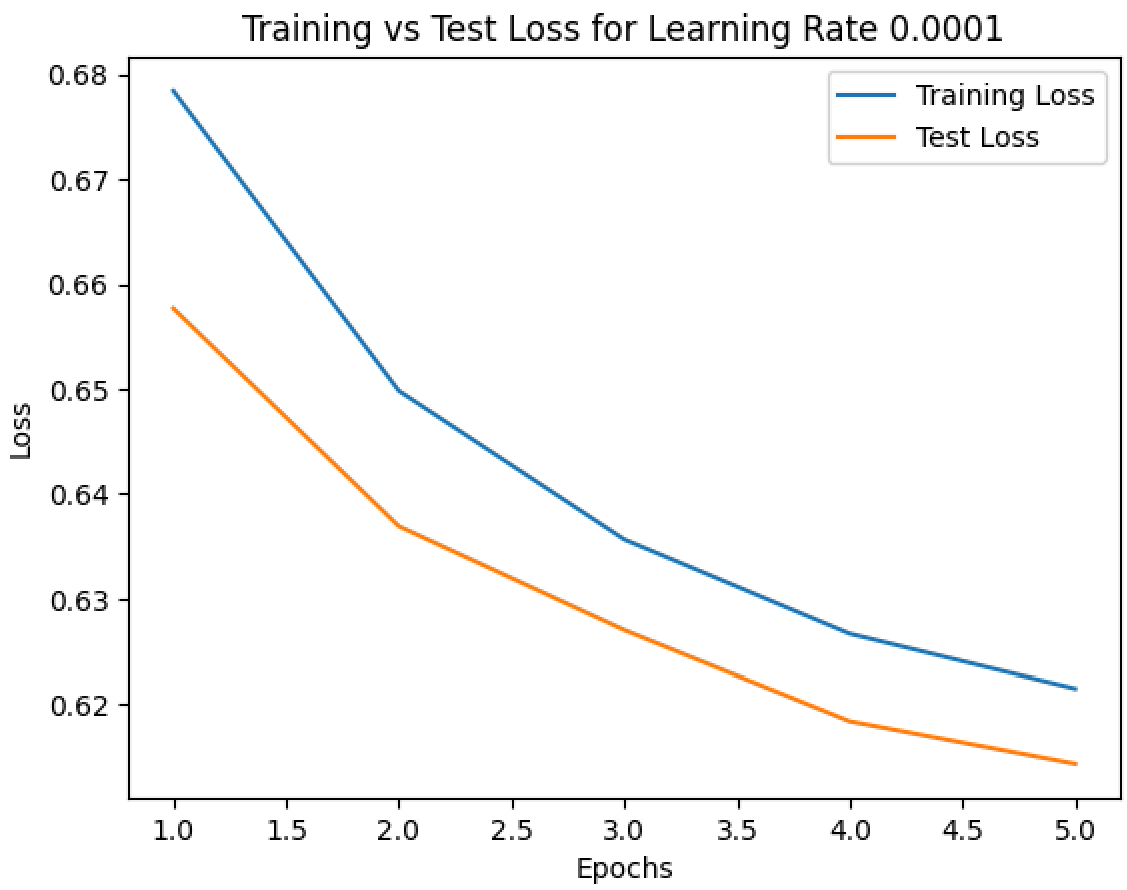
In [49]:
```
# DataLoader
train_size = int(0.8 * len(combined_dataset))
test_size = len(combined_dataset) - train_size

train_dataset, test_dataset = torch.utils.data.random_split(combined_dataset,
                                                            [train_size, test_size])
train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True, num_workers=2)
test_loader = DataLoader(test_dataset, batch_size=64, shuffle=False)
```

In [50]:
```
# Define a function to calculate test loss
def evaluate_model_loss(model, criterion, data_loader, device):
    model.eval()
    test_loss = 0.0
```

```python
    with torch.no_grad():
        for images, labels in data_loader:
            images, labels = images.to(device), labels.to(device).float()
            outputs = model(images).squeeze()
            loss = criterion(outputs, labels)
            test_loss += loss.item()
    return test_loss / len(data_loader)

# Update train_and_evaluate function
def train_and_evaluate(model, optimizer, learning_rate, num_epochs, train_loader,
                       test_loader, thresholds=[0.4, 0.5]):
    print(f"\n--- Training with Learning Rate: {learning_rate} ---")
    training_losses = []
    test_losses = []

    for epoch in range(num_epochs):
        # Training
        model.train()
        running_loss = 0.0
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device).float()
            optimizer.zero_grad()
            outputs = model(images).squeeze()
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()

        # Calculate average training loss
        training_loss = running_loss / len(train_loader)
        training_losses.append(training_loss)

        # Calculate test loss
        test_loss = evaluate_model_loss(model, criterion, test_loader, device)
        test_losses.append(test_loss)

        print(f"Epoch {epoch+1}/{num_epochs}, Training Loss: {training_loss:.4f},
        Test Loss: {test_loss:.4f}")

    # Evaluation
    model.eval()
    y_true, y_pred = [], []
    with torch.no_grad():
        for images, labels in test_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images).squeeze()
            probs = torch.sigmoid(outputs)
            y_true.extend(labels.cpu().numpy())
            y_pred.extend(probs.cpu().numpy())

    y_true = np.array(y_true)
    y_pred = np.array(y_pred)

    # Metrics for each threshold
    for threshold in thresholds:
        y_pred_class = (y_pred > threshold).astype(int)
        print(f"Classification report for threshold = {threshold}")
        print(classification_report(y_true, y_pred_class))

    # Return metrics and losses for analysis
    return y_true, y_pred, training_losses, test_losses

# Initialize models, optimizers, and train
results = {}
learning_rates = [0.001, 0.0001]

for lr in learning_rates:
    # Clone the base model
    model = mobilenet_v2(weights=MobileNet_V2_Weights.DEFAULT)
    model.classifier[1] = nn.Linear(model.last_channel, 1)
    model = model.to(device)

    # Define optimizer
    optimizer = optim.Adam(model.classifier.parameters(), lr=lr)

    # Train and evaluate
    y_true, y_pred, training_losses, test_losses = train_and_evaluate(model, optimizer,
                                                                      lr, num_epochs=5,
                                                                      train_loader=train_loader,
                                                                      test_loader=test_loader)
    # Store results for further analysis
    results[lr] = (y_true, y_pred, training_losses, test_losses)

    # Plot Training vs Test Loss for this learning rate
    plt.figure()
    plt.plot(range(1, len(training_losses) + 1), training_losses, label="Training Loss")
    plt.plot(range(1, len(test_losses) + 1), test_losses, label="Test Loss")
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.title(f"Training vs Test Loss for Learning Rate {lr}")
    plt.legend()
    plt.show()
```

```
--- Training with Learning Rate: 0.001 ---
Epoch 1/5, Training Loss: 0.6299, Test Loss: 0.6031
Epoch 2/5, Training Loss: 0.6031, Test Loss: 0.5979
Epoch 3/5, Training Loss: 0.5964, Test Loss: 0.6026
Epoch 4/5, Training Loss: 0.5941, Test Loss: 0.5954
Epoch 5/5, Training Loss: 0.5900, Test Loss: 0.6014
Classification report for threshold = 0.4
              precision    recall  f1-score   support

           0       0.72      0.30      0.42      1599
           1       0.56      0.88      0.68      1601

    accuracy                           0.59      3200
   macro avg       0.64      0.59      0.55      3200
weighted avg       0.64      0.59      0.55      3200

Classification report for threshold = 0.5
              precision    recall  f1-score   support

           0       0.69      0.56      0.62      1599
           1       0.63      0.75      0.68      1601

    accuracy                           0.65      3200
   macro avg       0.66      0.65      0.65      3200
weighted avg       0.66      0.65      0.65      3200
```


```
--- Training with Learning Rate: 0.0001 ---
Epoch 1/5, Training Loss: 0.6784, Test Loss: 0.6577
Epoch 2/5, Training Loss: 0.6498, Test Loss: 0.6369
Epoch 3/5, Training Loss: 0.6357, Test Loss: 0.6270
Epoch 4/5, Training Loss: 0.6267, Test Loss: 0.6184
Epoch 5/5, Training Loss: 0.6215, Test Loss: 0.6143
Classification report for threshold = 0.4
              precision    recall  f1-score   support

           0       0.69      0.39      0.50      1599
           1       0.58      0.83      0.68      1601

    accuracy                           0.61      3200
   macro avg       0.63      0.61      0.59      3200
weighted avg       0.63      0.61      0.59      3200

Classification report for threshold = 0.5
              precision    recall  f1-score   support

           0       0.66      0.70      0.68      1599
           1       0.68      0.64      0.66      1601

    accuracy                           0.67      3200
   macro avg       0.67      0.67      0.67      3200
weighted avg       0.67      0.67      0.67      3200
```



Classification report for threshold = 0.5, lr = 0.001

Class 0 (Not Infiltration)

- **Precision**: 69% → 69% of "Not Infiltration" predictions are correct.
- **Recall**: 56% → The model captures only 56% of actual negatives, missing many.

Class 1 (Infiltration)

- **Precision**: 63% → 63% of "Infiltration" predictions are correct.
- **Recall**: 75% → The model detects 75% of actual infiltration cases.

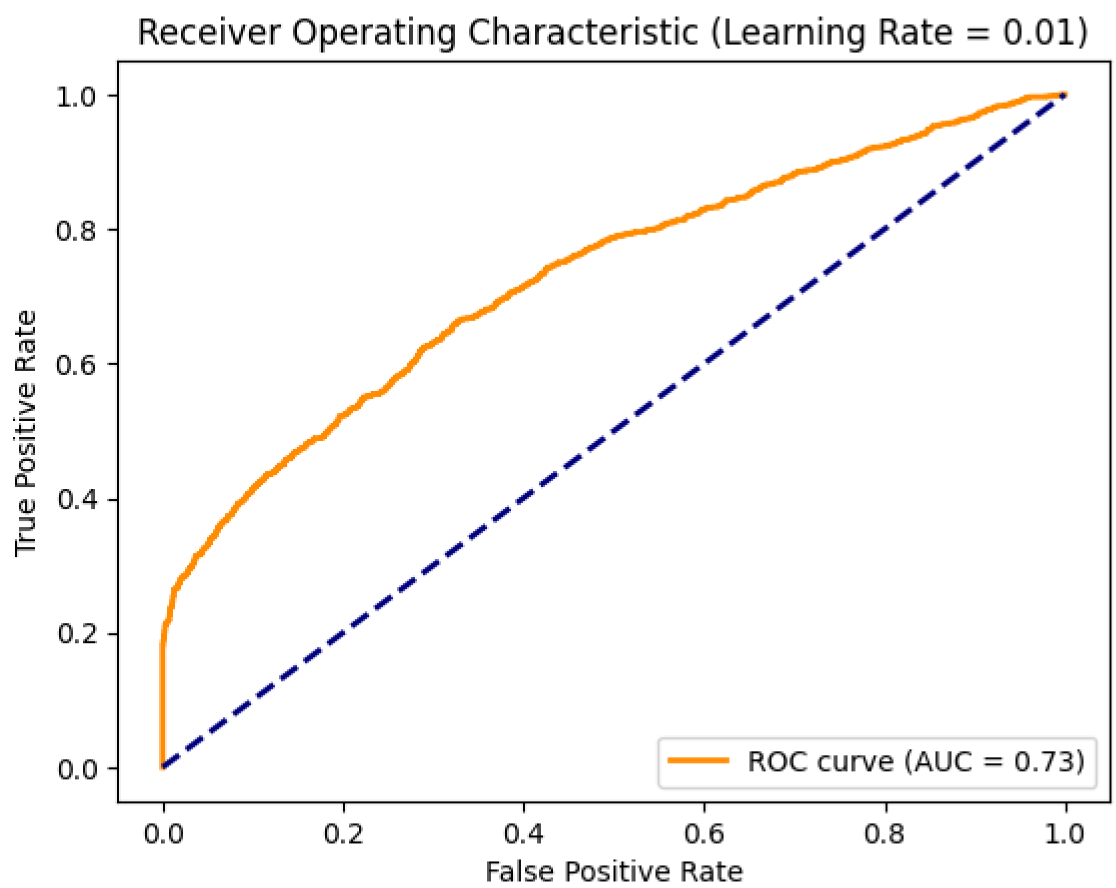
Accuracy

- **65%** → Balanced but moderate performance, with weaknesses in negative case detection.

In [51]:
```
y_true, y_pred = results[0.001][:2]
print(y_true, y_pred)
```

```
[1 1 1 ... 0 1 0] [0.29545334 0.58941996 0.4310601  ... 0.5337723  0.68424183 0.722143  ]
```

In [52]:
```
# ROC Curve
fpr, tpr, thresholds_roc = roc_curve(y_true, y_pred)
roc_auc = auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (Learning Rate = 0.001)')
plt.legend(loc='lower right')
plt.show()
```



In [53]:
```
for i, (thr, fp, tp) in enumerate(zip(thresholds_roc, fpr, tpr)):
    if i % 25 == 0:  # Print key thresholds
```

```python
        print(f"Threshold: {thr:.2f}, FPR: {fp:.2f}, TPR: {tp:.2f}")
```

```
Threshold: 1.99, FPR: 0.00, TPR: 0.00
Threshold: 0.83, FPR: 0.01, TPR: 0.24
Threshold: 0.79, FPR: 0.02, TPR: 0.28
Threshold: 0.77, FPR: 0.03, TPR: 0.30
Threshold: 0.76, FPR: 0.04, TPR: 0.32
Threshold: 0.74, FPR: 0.05, TPR: 0.34
Threshold: 0.73, FPR: 0.06, TPR: 0.36
Threshold: 0.72, FPR: 0.08, TPR: 0.38
Threshold: 0.70, FPR: 0.09, TPR: 0.40
Threshold: 0.69, FPR: 0.10, TPR: 0.41
Threshold: 0.68, FPR: 0.11, TPR: 0.43
Threshold: 0.67, FPR: 0.13, TPR: 0.44
Threshold: 0.67, FPR: 0.14, TPR: 0.46
Threshold: 0.66, FPR: 0.16, TPR: 0.47
Threshold: 0.65, FPR: 0.18, TPR: 0.49
Threshold: 0.64, FPR: 0.19, TPR: 0.50
Threshold: 0.63, FPR: 0.20, TPR: 0.53
Threshold: 0.62, FPR: 0.22, TPR: 0.54
Threshold: 0.61, FPR: 0.23, TPR: 0.55
Threshold: 0.60, FPR: 0.25, TPR: 0.57
Threshold: 0.59, FPR: 0.27, TPR: 0.59
Threshold: 0.59, FPR: 0.28, TPR: 0.60
Threshold: 0.58, FPR: 0.29, TPR: 0.62
Threshold: 0.57, FPR: 0.30, TPR: 0.63
Threshold: 0.56, FPR: 0.32, TPR: 0.65
Threshold: 0.55, FPR: 0.34, TPR: 0.67
Threshold: 0.54, FPR: 0.36, TPR: 0.68
Threshold: 0.54, FPR: 0.38, TPR: 0.70
Threshold: 0.53, FPR: 0.39, TPR: 0.71
Threshold: 0.52, FPR: 0.41, TPR: 0.72
Threshold: 0.51, FPR: 0.42, TPR: 0.73
Threshold: 0.50, FPR: 0.44, TPR: 0.75
Threshold: 0.49, FPR: 0.46, TPR: 0.76
Threshold: 0.48, FPR: 0.48, TPR: 0.77
Threshold: 0.48, FPR: 0.49, TPR: 0.79
Threshold: 0.47, FPR: 0.52, TPR: 0.79
Threshold: 0.46, FPR: 0.55, TPR: 0.81
Threshold: 0.45, FPR: 0.59, TPR: 0.82
Threshold: 0.44, FPR: 0.60, TPR: 0.83
Threshold: 0.43, FPR: 0.63, TPR: 0.84
Threshold: 0.42, FPR: 0.65, TPR: 0.86
Threshold: 0.41, FPR: 0.67, TPR: 0.87
Threshold: 0.40, FPR: 0.70, TPR: 0.88
Threshold: 0.39, FPR: 0.73, TPR: 0.89
Threshold: 0.38, FPR: 0.75, TPR: 0.90
Threshold: 0.37, FPR: 0.78, TPR: 0.91
Threshold: 0.35, FPR: 0.81, TPR: 0.93
Threshold: 0.34, FPR: 0.83, TPR: 0.94
Threshold: 0.33, FPR: 0.85, TPR: 0.95
Threshold: 0.31, FPR: 0.88, TPR: 0.96
Threshold: 0.29, FPR: 0.91, TPR: 0.97
Threshold: 0.26, FPR: 0.94, TPR: 0.98
Threshold: 0.25, FPR: 0.96, TPR: 0.99
```

In [54]:
```python
# Confusion Matrix for threshold = 0.5
threshold = 0.5
y_pred_class = (y_pred > threshold).astype(int)
cm = confusion_matrix(y_true, y_pred_class)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['Class 0', 'Class 1'])
disp.plot(cmap='Blues', values_format='d')
plt.title('Confusion Matrix (Learning Rate = 0.001, Threshold = 0.5)')
plt.show()
```