Coursework

January 6, 2024

1 IN3063 - Coursework

1.1 Libraries

[56]:
```
import math
import numpy as np
from numpy.random import default_rng
import matplotlib.pyplot as plt
```

1.2 Sigmoid & ReLU

- Reference:
  - https://towardsdatascience.com/lets-code-a-neural-network-in-plain-numpy-ae7e74410795
  - https://www.sharpsightlabs.com/blog/numpy-relu/
  - Lab 6

[287]:
```
# Forward pass for Sigmoid
def forward_sigmoid(x):
    return 1 / (1 + np.exp(-x))

# Backward pass for Sigmoid
def backward_sigmoid(x):
    return forward_sigmoid(x) * (1 - forward_sigmoid(x))
```

[288]:
```
# Forward pass for ReLU
def forward_relu(x):
    return np.maximum(0, x)

# Backward pass for ReLU
def backward_relu(x):
    return np.where(x > 0, 1, 0)
```

1.3 Softmax

- Using the Numpy version
- Reference:
  - https://towardsdatascience.com/softmax-function-simplified-714068bf8156
  - https://en.wikipedia.org/wiki/Softmax_function

– https://www.sharpsightlabs.com/blog/numpy-softmax/

[289]:
```
# Forward pass for Softmax
def forward_softmax(x):
    exponential = np.exp(x - np.max(x))
    return exponential / exponential.sum() # calculates softmax probability

# Backward pass for Softmax
def backward_softmax(x):
    return np.reshape(forward_softmax(x) * (1 - forward_softmax(x)), (1, -1)) #␣
 ↪computes gradient of softmax

# Testing:
x = np.array([100.0, 2000.0, 300.0]) # large numbers
print("Forward pass result:", forward_softmax(x))
print("Backward pass result:", backward_softmax(x))
print ("\n")

x = np.array([1.0, 2.0, 3.0]) # small numbers
print("Forward pass result:", forward_softmax(x))
print("Backward pass result:", backward_softmax(x))
```

```
Forward pass result: [0. 1. 0.]
Backward pass result: [[0. 0. 0.]]


Forward pass result: [0.09003057 0.24472847 0.66524096]
Backward pass result: [[0.08192507 0.18483645 0.22269543]]
```

1.4 Dropout

- References
  - Lecture 7
  - https://stackoverflow.com/questions/70836518/typeerror-bad-operand-type-for-unary-list-python
  - https://stackoverflow.com/questions/25854380/enforce-arguments-to-a-specific-list-of-values

[290]:
```
'''
Valid value structure constants.
They're defined here so they aren't recreated every time the function is ran.
'''
ACTIVATION_FUNCTIONS = {
    "sigmoid": [forward_sigmoid, backward_sigmoid],
    "relu": [forward_relu, backward_relu],
    "softmax": [forward_softmax, backward_softmax]
}
```

```python
VALID_DIRECTIONS = ["forward", "backward"]

'''
Dropout function
    x = input vector
    probability is a float between 0.0 and 1.0
    activation_function is a string that corresponds to one of the key values␣
 ↪above
        determines which activation function to use
    direction is a string that corresponds to one of the array values above
        determines whether to use a forward or backward pass activation function
    inverted is a boolean
        determines whether or not use inverted dropout
    train is a boolean
        determines whether to train or test
'''
def dropout(x, probability, activation_function, direction, inverted, train):
    if activation_function not in ACTIVATION_FUNCTIONS.keys():
        raise ValueError(f"Activation function must be one of␣
 ↪{ACTIVATION_FUNCTIONS.keys()}")

    if direction not in VALID_DIRECTIONS:
        raise ValueError(f"Direction must be one of {VALID_DIRECTIONS}")

    value_index = 0 if direction == "forward" else 1

    H1 = ACTIVATION_FUNCTIONS[activation_function][value_index](x)
    mask = (np.random.rand(*H1.shape) < probability)

    if inverted:
        return H1 * (mask / probability) if train else H1
    else:
        return H1 * mask if train else H1 * probability

# Testing the function
#     Starting by defining x
x = np.array([2.0, 4.0, 7.0, 8.0])

#     Training
H1_dropped = dropout(x, 0.5, "sigmoid", "forward", False, True)
print(H1_dropped)

#     Testing
H1_dropped = dropout(x, 0.5, "sigmoid", "forward", False, False)
print(H1_dropped)

#     Training, inverted
```

```
H1_dropped = dropout(x, 0.5, "sigmoid", "forward", True, True)
print(H1_dropped)

#     Testing, inverted
H1_dropped = dropout(x, 0.5, "sigmoid", "forward", True, True)
print(H1_dropped)
```

```
[0.88079708 0.98201379 0.         0.99966465]
[0.44039854 0.4910069  0.49954447 0.49983232]
[0.         0.         1.9981779 1.9993293]
[0.         0.         1.9981779 0.        ]
```

1.5 Optimizers

References: - Lecture 8 - Lecture 9 - https://www.kdnuggets.com/2020/12/optimization-algorithms-neural-networks.html - http://deeplearning.stanford.edu/tutorial/supervised/OptimizationStochasticG - https://keras.io/api/optimizers/sgd/ - https://towardsdatascience.com/neural-network-optimizers-from-scratch-in-python-af76ee087aab

[291]:
```
class SGDOptimizer:
    def __init__(self, learning_rate):
        self.learning_rate = learning_rate
        # initialises the learning rate with parameter inputed by the user

    def update(self, parameter, gradient):
        return parameter - self.learning_rate * gradient
        # updates the parameter according to the learning rate (from init␣
 ↪function) and gradient

class SGDMomentumOptimizer:
    def __init__(self, learning_rate, momentum):
        self.learning_rate = learning_rate
        self.momentum = momentum
        self.velocities = {}
        # initialises the parameters

    def update(self, parameter, gradient):
        param_id = (parameter.shape, parameter.dtype)
        # gives each parameter a unique identifier

        # Initialise the velocity for this parameter if it hasn't been␣
 ↪initialized yet
        if param_id not in self.velocities:
            # check if the velocity for the parameter has been initialised, if␣
 ↪not it gets initialised with 0's
            self.velocities[param_id] = np.zeros_like(parameter)

        # this is where the velocities get updated using the formula below
```

```python
        # the momentum determines how much of the velocity is retained
        # the current gradient also has an effect on the updated velocities
        self.velocities[param_id] = self.momentum * self.velocities[param_id] +␣
↪self.learning_rate * gradient
        return parameter - self.velocities[param_id]
```

1.6 Neural Network

References: - Lecture 6 - Lecture 7 - https://towardsdatascience.com/step-by-step-guide-to-building-your-own-neural-network-from-scratch-df64b1c5ab6e - https://towardsdatascience.com/understanding-backpropagation-algorithm-7bb3aa2f95fd

Loading the Dataset

To load the MNIST dataset, we created a function that parses the files in the way described in the resource http://yann.lecun.com/exdb/mnist/. The key thing to note is that the bytes are unsigned and in big endian, hence the use of the format `>HBB` in the `struct.unpack` call, as per the documentation (https://docs.python.org/3/library/struct.html#byte-order-size-and-alignment).

[292]:
```python
# Reading the MNIST dataset as per http://yann.lecun.com/exdb/mnist/
import os
import struct

def read_idx(filename):
    with open(filename, 'rb') as file:
        # Read two bytes (big endian and unsigned)
        zero, data_type, dims = struct.unpack('>HBB', file.read(4))
        # Four byte integer big endian
        shape = tuple(struct.unpack('>I', file.read(4))[0] for d in range(dims))
        return np.frombuffer(file.read(), dtype=np.uint8).reshape(shape)

def load_mnist(path):
    # Paths to the files
    train_images_path = os.path.join(path, 'train-images-idx3-ubyte')
    train_labels_path = os.path.join(path, 'train-labels-idx1-ubyte')
    test_images_path = os.path.join(path, 't10k-images-idx3-ubyte')
    test_labels_path = os.path.join(path, 't10k-labels-idx1-ubyte')

    # Loading the datasets
    train_images = read_idx(train_images_path)
    train_labels = read_idx(train_labels_path)
    test_images = read_idx(test_images_path)
    test_labels = read_idx(test_labels_path)

    return train_images, train_labels, test_images, test_labels
```

[293]:
```python
# labels are just an array of 6000 elements; we need them as arrays of 10␣
↪elements
```

```
# 10 elements because MNIST can be digits 0-9; we need all elements to be 0␣
↪except
# the correct element, which will be 1.
def one_hot_encode(labels):
    one_hot_labels = np.zeros((len(labels), 10))
    one_hot_labels[np.arange(len(labels)), labels] = 1
    return one_hot_labels
```

[294]:
```
class NeuralNet:
    def __init__(
        self,
        activation_function,
        neurons: list,
        learning_rate,
        optimizer,
        dropout_prob=None,
    ):
        """
        Initialises a new instance of the NeuralNet class.

        Parameters:
        activation_function (func): The activation function to be used in the␣
↪network layers.
                                    The function is used in all layers.
        neurons (list of int): The number of neurons in each layer. This should␣
↪be a list where each element represents
                                the number of neurons in the respective layer␣
↪of the network (input not included, output included and should be 10 for␣
↪MNIST)
        learning_rate (float): Number between 0-1 specifying the learning rate␣
↪of the NN.
        optimizer (func): Which optimizer to use (momentum / no momentum).
        dropout_prob (float): Optional- if specified, use dropout with this␣
↪probability between 0-1.
                                Otherwise, no dropout.
        """

        ACTIVATION_FUNCTIONS = {
            "sigmoid": [forward_sigmoid, backward_sigmoid],
            "relu": [forward_relu, backward_relu],
        }

        self.activation_function = ACTIVATION_FUNCTIONS[activation_function]
        self.neurons = neurons
        self.layers = len(self.neurons)
        self.learning_rate = learning_rate
        self.optimizer = optimizer
```

```
        self.dropout_prob = dropout_prob
        # Will be initialised once features are known
        self.weights = []
        self.biases = []

    def init_weights_and_biases(self, input_features):
        # Initialise weights and biases based on the layers, neurons, and input␣
↪features
        # Fully connected through weights
        for i in range(self.layers):
            if i == 0:
                # input layer matrix needs to have as many columns as neurons
                layer_weights = np.random.randn(self.neurons[i],␣
↪input_features) * 0.01
            else:
                # weights matrix with a column for each node in the previous␣
↪layer and a row for each node in the current layer
                layer_weights = (
                    np.random.randn(self.neurons[i], self.neurons[i - 1]) * 0.01
                )
            layer_bias = np.zeros((self.neurons[i], 1))
            self.weights.append(layer_weights)
            self.biases.append(layer_bias)

    def forward_pass(self, X, is_training=True):
        activations = [X]
        for i in range(self.layers):
            Z = np.dot(self.weights[i], activations[-1]) + self.biases[i]
            A = self.apply_activation(Z)
            # Only apply dropout if a probability is specified and when training
            if self.dropout_prob and is_training:
                A = self.dropout(A, inverted=False)
            activations.append(A)
        return activations

    def dropout(self, A, inverted=True):
        if self.dropout_prob == 0:
            return A

        mask = np.random.rand(*A.shape) < (1 - self.dropout_prob)

        if inverted:
            A *= mask / (1 - self.dropout_prob)
        else:
            A *= mask
        return A
```

```
    def apply_activation(self, Z):
        return self.activation_function[0](Z)

    def backward_pass(self, Y, activations):
        m = Y.shape[1]
        n = len(self.weights)
        gradients = {}

        # Output layer
        dA = activations[-1] - Y  # Derivative of loss wrt (with respect to)␣
↪output

        for i in reversed(range(n)):
            dZ = dA * self.activation_function[1](
                activations[i + 1]
            )  # gradient of loss wrt pre-activation values
            dW = np.dot(dZ, activations[i].T) / m  # gradient of loss wrt␣
↪weights
            db = np.sum(dZ, axis=1, keepdims=True) / m  # gradient of loss wrt␣
↪biases
            if i > 0:
                dA = np.dot(self.weights[i].T, dZ)

            gradients["dW" + str(i + 1)] = dW
            gradients["db" + str(i + 1)] = db

        return gradients

    def update_weights_and_biases(self, gradients, learning_rate):
        for i in range(self.layers):
            self.weights[i] = self.optimizer.update(
                self.weights[i], gradients["dW" + str(i + 1)]
            )
            self.biases[i] = self.optimizer.update(
                self.biases[i], gradients["db" + str(i + 1)]
            )

    def calculate_loss(self, Y_pred, Y_true):
        # Mean Squared Error
        return np.mean((Y_pred - Y_true) ** 2)

    def train_network(self, epochs, batch_size, X_train, Y_train):

        input_features = X_train.shape[1]

        # Initialise weights & biases
        self.init_weights_and_biases(input_features)
```

```python
        loss_across_epochs = []

        for epoch in range(epochs):
            total_loss = 0
            # Iterate batches
            for i in range(0, X_train.shape[0], batch_size):
                X_batch = X_train[i : i + batch_size].T
                Y_batch = Y_train[i : i + batch_size].T

                # Forward pass over the batch
                activations = self.forward_pass(X_batch, is_training=True)

                # Backward pass over the batch (get gradients)
                gradients = self.backward_pass(Y_batch, activations)

                # Update weights & biases
                self.update_weights_and_biases(gradients, self.learning_rate)

                Y_pred = activations[-1]
                total_loss += self.calculate_loss(Y_pred, Y_batch)

            average_loss = total_loss / (X_train.shape[0] / batch_size)
            loss_across_epochs.append(average_loss)

            print(f"Epoch {epoch+1}/{epochs}, Loss: {average_loss}")

        return loss_across_epochs

    def evaluate_model(self, X_test, Y_test):
        # Forward pass
        activations = self.forward_pass(
            X_test.T, is_training=False
        )  # Transpose X_test for correct shape
        Y_pred = activations[-1]

        # Convert predictions to labels
        predictions = np.argmax(Y_pred, axis=0)
        labels = np.argmax(Y_test.T, axis=0)  # Transpose Y_test for correct shape

        # Calculate accuracy
        accuracy = np.mean(predictions == labels)

        # Calculate loss
        loss = self.calculate_loss(
            Y_pred, Y_test.T
        )  # Transpose Y_test for correct shape
```

```
        return accuracy, loss
```

2 Training and evaluating the NeuralNet

Works for sigmoid, relu, SDGOptimizer, SDGMomentumOptimizer, as well as any other optimizer, given it has an update() method that takes two parameters (parameter, gradient).

[297]:
```
train_images, train_labels, test_images, test_labels = load_mnist('./dataset')

# Reshape and normalize
train_images = train_images.reshape(train_images.shape[0], -1) / 255.0
test_images = test_images.reshape(test_images.shape[0], -1) / 255.0
train_labels = one_hot_encode(train_labels)
test_labels = one_hot_encode(test_labels)

learning_rate = 0.5
# Pick either of these optimizers for the Neural Net
optimizer = SGDOptimizer(learning_rate=learning_rate)
#optimizer = SGDMomentumOptimizer(learning_rate=learning_rate, momentum=0.4)

# Create an instance of NeuralNet
# Layer architecture is 784 (implied) -> 128 -> 10 (output layer, not implied)
nn = NeuralNet(activation_function='relu', neurons=[128, 10],
 ↪learning_rate=learning_rate, optimizer=optimizer, dropout_prob=0.2)

# Train the network
loss_across = nn.train_network(epochs=50, batch_size=30, X_train=train_images,
 ↪Y_train=train_labels)
```

```
Epoch 1/50, Loss: 0.03390254307303478
Epoch 2/50, Loss: 0.02816005193153596
Epoch 3/50, Loss: 0.02697968813614113
Epoch 4/50, Loss: 0.026226631195133507
Epoch 5/50, Loss: 0.02641710324894142
Epoch 6/50, Loss: 0.02595404500147813
Epoch 7/50, Loss: 0.02568415643921529
Epoch 8/50, Loss: 0.025466489174115987
Epoch 9/50, Loss: 0.025148231069256295
Epoch 10/50, Loss: 0.024811739634619443
Epoch 11/50, Loss: 0.02475100151742513
Epoch 12/50, Loss: 0.02494105474019656
Epoch 13/50, Loss: 0.024579079890569417
Epoch 14/50, Loss: 0.02449036083387497
Epoch 15/50, Loss: 0.024444105004426314
Epoch 16/50, Loss: 0.023916003329264256
Epoch 17/50, Loss: 0.024272995206977364
```

```
Epoch 18/50, Loss: 0.024322999828856568
Epoch 19/50, Loss: 0.024271488548834912
Epoch 20/50, Loss: 0.024200687770781968
Epoch 21/50, Loss: 0.023994657748351623
Epoch 22/50, Loss: 0.02394248128582499
Epoch 23/50, Loss: 0.02416034243018991
Epoch 24/50, Loss: 0.02370827116424546
Epoch 25/50, Loss: 0.023912230621997925
Epoch 26/50, Loss: 0.02376404871616121
Epoch 27/50, Loss: 0.023796150592973676
Epoch 28/50, Loss: 0.023639838992915548
Epoch 29/50, Loss: 0.023562931217935696
Epoch 30/50, Loss: 0.02348189475711687
Epoch 31/50, Loss: 0.023568316753041406
Epoch 32/50, Loss: 0.02385269365629492
Epoch 33/50, Loss: 0.02359294380710883
Epoch 34/50, Loss: 0.023605195649849565
Epoch 35/50, Loss: 0.023570605473642044
Epoch 36/50, Loss: 0.023277337895897268
Epoch 37/50, Loss: 0.023315471853325154
Epoch 38/50, Loss: 0.023369171637125957
Epoch 39/50, Loss: 0.023470617049395383
Epoch 40/50, Loss: 0.02312871862037317
Epoch 41/50, Loss: 0.023590135163844117
Epoch 42/50, Loss: 0.023359871342501053
Epoch 43/50, Loss: 0.02329029250538721
Epoch 44/50, Loss: 0.02324440583147667
Epoch 45/50, Loss: 0.023202939162094365
Epoch 46/50, Loss: 0.02254866064896376
Epoch 47/50, Loss: 0.023019302634705037
Epoch 48/50, Loss: 0.022884140407613374
Epoch 49/50, Loss: 0.023310394202926788
Epoch 50/50, Loss: 0.02274453466260006
```

[298]:

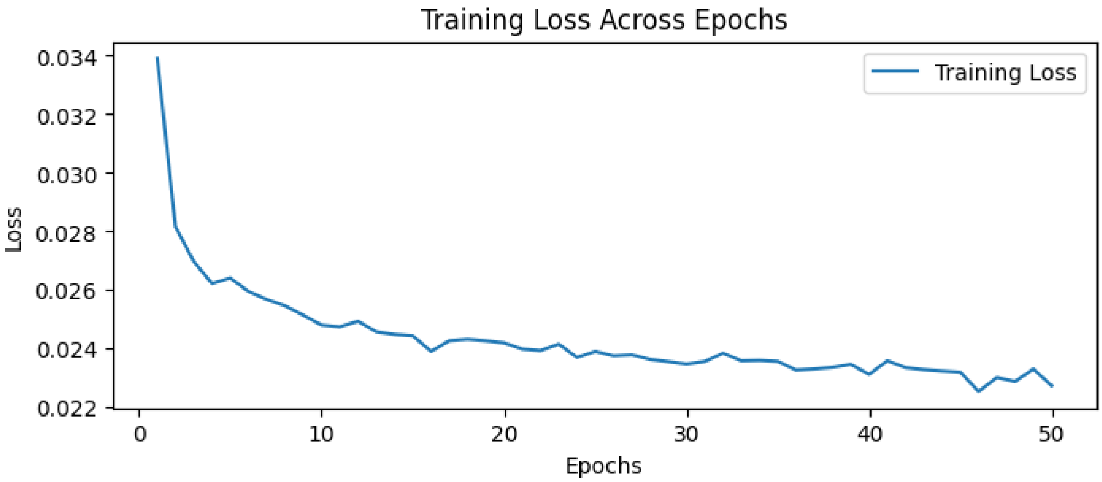
```
accuracy, loss = nn.evaluate_model(test_images, test_labels)
print(f"Test Accuracy: {accuracy*100:.2f}%")
print(f"Test Loss: {loss}")
```

```
Test Accuracy: 96.95%
Test Loss: 0.007535240007468593
```

[301]:

```
epochs = range(1, len(loss_across)+1)

plt.figure(figsize=(8,3))
plt.plot(epochs, loss_across, label='Training Loss')
plt.title('Training Loss Across Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
```

```
plt.legend()
plt.show()
```



3 Plotting Results

References: - https://matplotlib.org/stable/api/index.html - Lab 02

[326]:
```
# Checkpoint function
import json

def save_results(results, filename="results.json"):
    with open(filename, 'w') as f:
        json.dump(results, f)

def load_results(filename="results.json"):
    with open(filename, 'r') as f:
        return json.load(f)
```

[ ]:
```
train_images, train_labels, test_images, test_labels = load_mnist('./dataset')

# Reshape and normalize
train_images = train_images.reshape(train_images.shape[0], -1) / 255.0
test_images = test_images.reshape(test_images.shape[0], -1) / 255.0
train_labels = one_hot_encode(train_labels)
test_labels = one_hot_encode(test_labels)
```

Here we will iterate through all combinations of the below parameters to then plot the various results and see what worked best and other interesting results. This took around 48 hours to compute with 32GB of RAM so I do not suggest running it.

[332]:

```python
# All parameters configurations that we will try out to plot afterwards
layers = [[128, 10], [256, 10], [256, 128, 10]]
activation_funcs = ["sigmoid", "relu"]
optimizers = [SGDOptimizer, SGDMomentumOptimizer]
momentums = [.4, .6, .8]
learning_rates = [.2, .5, .7]
batch_sizes = [15, 30, 45, 80]
dropout_probs = [0, .1, .2, .4]
epochs = 50
```

[ ]:

```python
results = []

for layer in layers:
    for activation_f in activation_funcs:
        for learning_rate in learning_rates:
            for batch_size in batch_sizes:
                for dropout_prob in dropout_probs:
                    for optimizer_f in optimizers:
                        if optimizer_f == SGDOptimizer:
                            print(f"[+] {activation_f} - LR: {learning_rate} -␣
↪BS: {batch_size} - DP: {dropout_prob} - OP: SGD")
                            optimizer =␣
↪SGDOptimizer(learning_rate=learning_rate)
                            nn = NeuralNet(activation_function=activation_f,
                                           neurons=layer,
                                           learning_rate=learning_rate,
                                           optimizer=optimizer,
                                           dropout_prob=dropout_prob)
                            loss_across = nn.train_network(epochs=epochs,
                                                           ␣
↪batch_size=batch_size,
                                                           X_train=train_images,
                                                           Y_train=train_labels)
                            accuracy, loss = nn.evaluate_model(test_images,␣
↪test_labels)

                            results.append({
                                "activation": activation_f,
                                "optimizer": "SGDOptimizer",
                                "learning_rate": learning_rate,
                                "batch_size": batch_size,
                                "layer": layer,
                                "dropout_prob": dropout_prob,
                                "accuracy": accuracy,
                                "loss": loss,
                                "loss_across": loss_across,
                            })
```

```
                        save_results(results)
                else:
                    for momentum in momentums:
                        print(f"[+] {activation_f} - LR:␣
↪{learning_rate} - BS: {batch_size} - DP: {dropout_prob} - MO: {momentum}")
                        optimizer =␣
↪SGDMomentumOptimizer(learning_rate=learning_rate, momentum=momentum)
                        nn = NeuralNet(activation_function=activation_f,
                                       neurons=layer,
                                       learning_rate=learning_rate,
                                       optimizer=optimizer,
                                       dropout_prob=dropout_prob)

                        loss_across = nn.train_network(epochs=epochs,
                                                                  ␣
↪batch_size=batch_size,
                                                                 ␣
↪X_train=train_images,
                                                                 ␣
↪Y_train=train_labels)

                        accuracy, loss = nn.evaluate_model(test_images,␣
↪test_labels)

                        results.append({
                            "activation": activation_f,
                            "optimizer": "SGDMomentumOptimizer",
                            "momentum": momentum,
                            "learning_rate": learning_rate,
                            "batch_size": batch_size,
                            "layer": layer,
                            "dropout_prob": dropout_prob,
                            "accuracy": accuracy,
                            "loss": loss,
                            "loss_across": loss_across,
                        })
                        save_results(results)
```

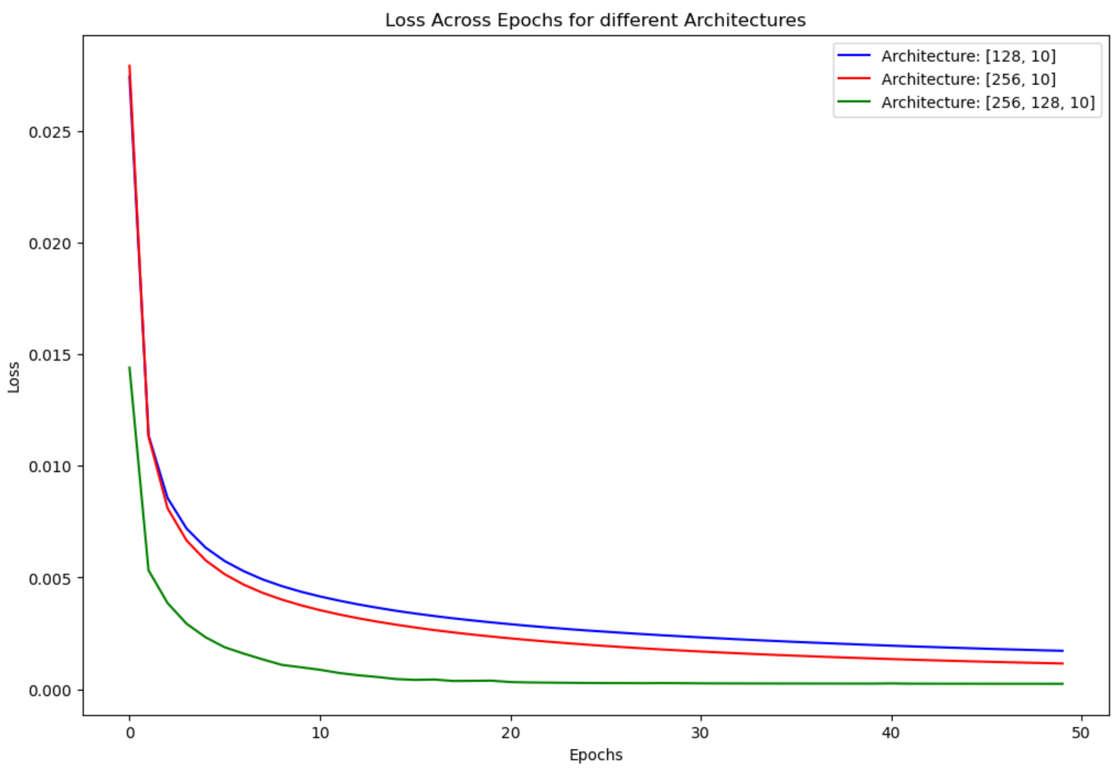
[ ]:
```
len(results)
```

[ ]: 1152

4 Plotting Loss across epochs for each architecture

Using our brute-force results, we can now draw various plots of the effect of different parameters on different architectures.

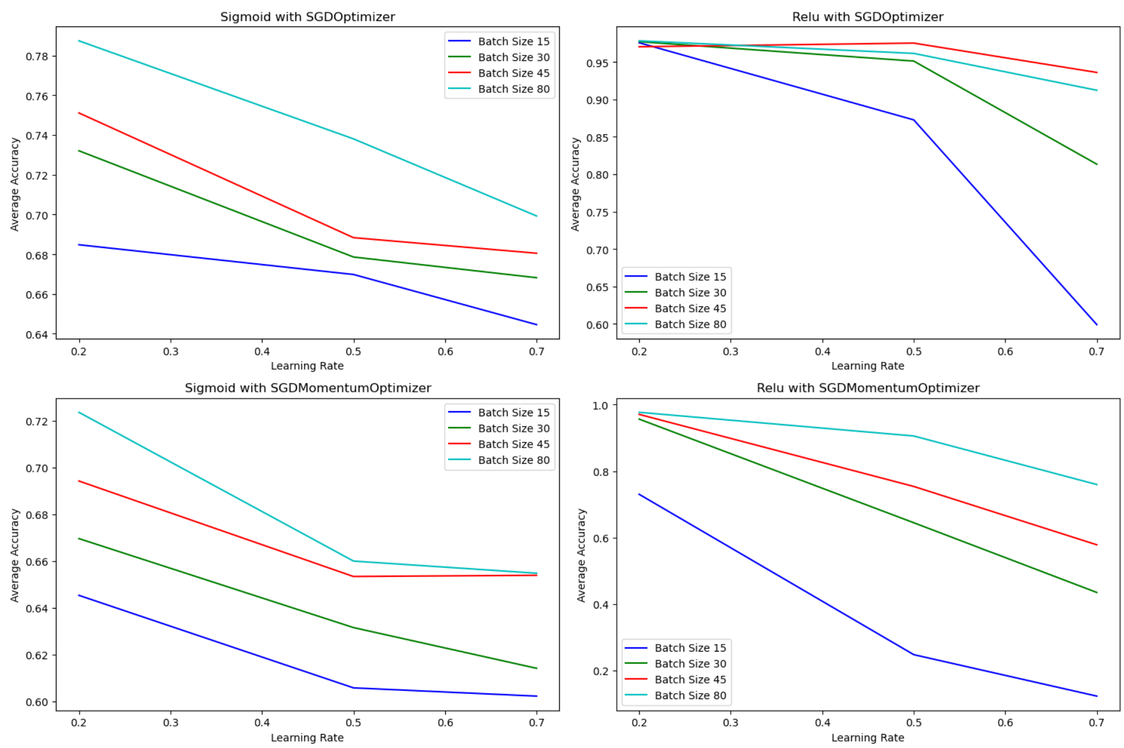
[ ]:
```
plt.figure(figsize=(12, 8))
colours = ['blue', 'red', 'green']

for i, layer in enumerate(layers):
    # Find the entry with the highest accuracy for this architecture
    best_entry = max((item for item in results if item['layer'] == layer),␣
 ↪key=lambda x: x['accuracy'])

    plt.plot(best_entry['loss_across'], label=f'Architecture: {layer}',␣
 ↪color=colours[i])

    plt.title(f'Loss Across Epochs for different Architectures')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



5 Plotting impact of learning rate for activation/optimizer combinations

[ ]:
```
colors = ['b', 'g', 'r', 'c', 'm', 'y']
architecture = [256, 128, 10]

fig, axes = plt.subplots(2, 2, figsize=(15, 10))

# Titles for each subplot
titles = [
    "Sigmoid with SGDOptimizer",
    "Relu with SGDOptimizer",
    "Sigmoid with SGDMomentumOptimizer",
    "Relu with SGDMomentumOptimizer"
]

# Arrange the data and plots
for i, (activation, optimizer) in enumerate([
    ("sigmoid", "SGDOptimizer"),
    ("relu", "SGDOptimizer"),
    ("sigmoid", "SGDMomentumOptimizer"),
    ("relu", "SGDMomentumOptimizer")
]):
    ax = axes[i//2, i%2]  # Determine the correct subplot

    # Filter data for the specific activation function and optimizer
    filtered_data = [entry for entry in results if entry['activation'] ==␣
 ↪activation and entry['optimizer'] == optimizer]

    # Plot each batch size with different color
    for batch_size, color in zip(batch_sizes, colors):
        # Calculate average accuracy for each learning rate
        accuracies = []
        for lr in learning_rates:
            # Filter data for specific learning rate and batch size
            lr_data = [entry['accuracy'] for entry in filtered_data if␣
 ↪entry['learning_rate'] == lr and entry['batch_size'] == batch_size]
            avg_accuracy = sum(lr_data) / len(lr_data) if lr_data else None  #␣
 ↪Calculate average if data is available
            accuracies.append(avg_accuracy)

        # Plotting the line for each batch size
        ax.plot(learning_rates, accuracies, color=color, label=f'Batch Size␣
 ↪{batch_size}')

    ax.set_title(titles[i])
    ax.set_xlabel('Learning Rate')
```

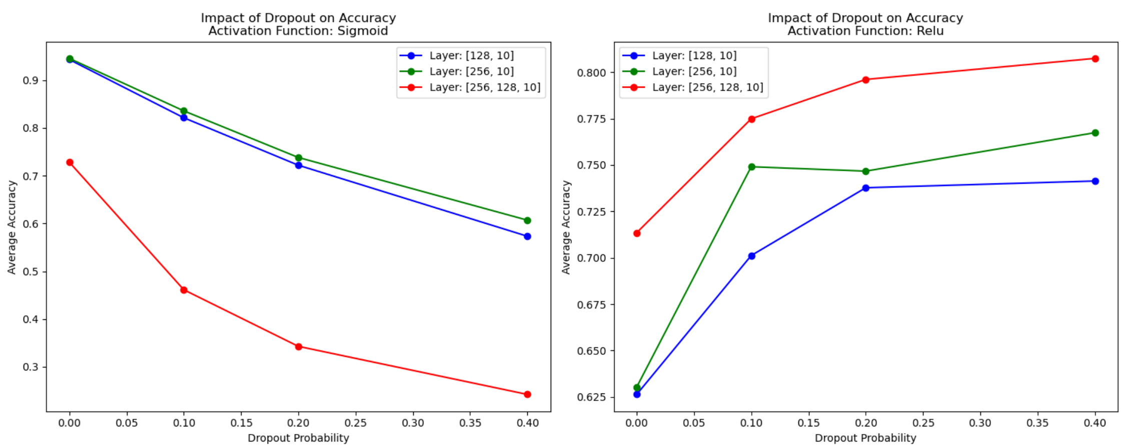
```
    ax.set_ylabel('Average Accuracy')
    ax.legend()

plt.tight_layout()
plt.show()
```



6 Plotting dropout impact for different architectures, separated by activation function

[ ]:
```
colors = ['b', 'g', 'r']

# Create subplots
fig, axes = plt.subplots(1, 2, figsize=(15, 6))  # 1 row, 2 columns for sigmoid␣
 ↪and relu

# Iterate through each activation function and plot
for idx, activation_f in enumerate(activation_funcs):
    ax = axes[idx]

    # For each layer architecture
    for layer, color in zip(layers, colors):
        accuracies = []
```

```
        # Collect accuracies for each dropout probability
        for dropout in dropout_probs:
            # Filter results for the specific combination
            layer_data = [entry for entry in results if entry['layer'] == layer and entry['activation'] == activation_f and entry['dropout_prob'] == dropout]
            avg_accuracy = sum([d['accuracy'] for d in layer_data]) / len(layer_data) if layer_data else None
            accuracies.append(avg_accuracy)

        # Plotting for each architecture
        ax.plot(dropout_probs, accuracies, color=color, marker='o', label=f'Layer: {layer}')

    ax.set_title(f'Impact of Dropout on Accuracy\nActivation Function: {activation_f.capitalize()}')
    ax.set_xlabel('Dropout Probability')
    ax.set_ylabel('Average Accuracy')
    ax.legend()

plt.tight_layout()
plt.show()
```



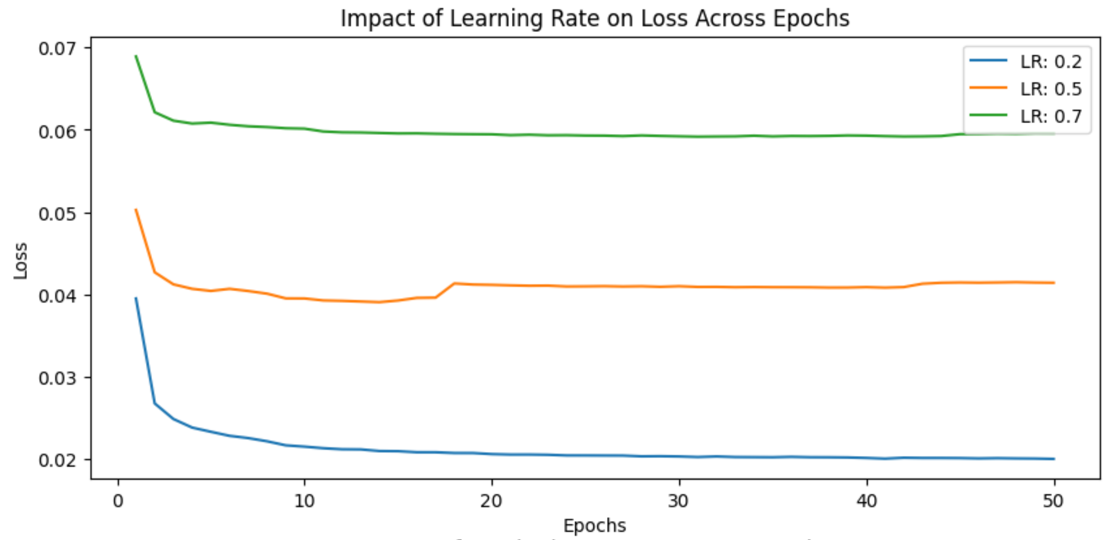
[338]:
```
# Function to calculate average loss across multiple runs
def average_loss_across_runs(specific_results):
    # Get all loss arrays
    all_losses = np.array([res['loss_across'] for res in specific_results])
    # Calculate the mean across all runs
    avg_loss = np.mean(all_losses, axis=0)
    return avg_loss
```

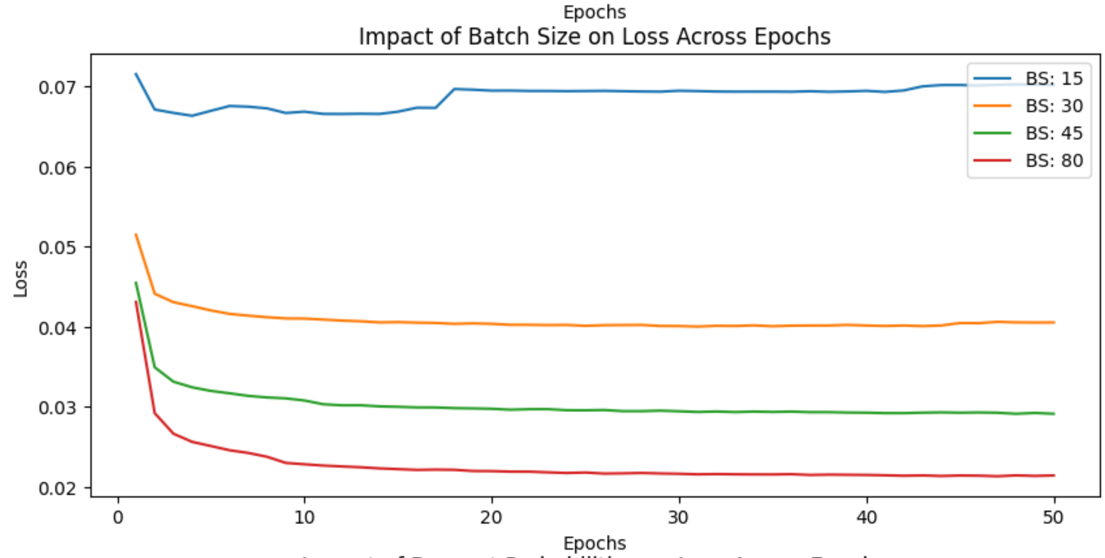
[341]:

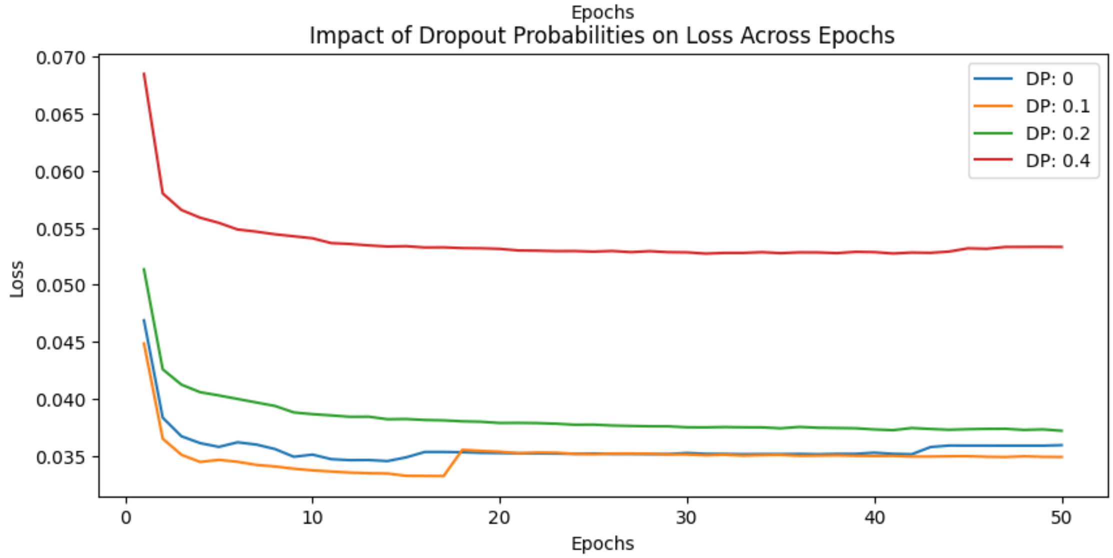
```
# Create subplots
fig, axes = plt.subplots(3, 1, figsize=(10, 15))

# Plot for varying learning rates
for lr in learning_rates:
    specific_results = [r for r in results if r['activation'] ==␣
↪best_result['activation']
                        and r['optimizer'] == best_result['optimizer']
                        and r['momentum'] == best_result['momentum']
                        and r['layer'] == best_result['layer']
                        and r['learning_rate'] == lr]
    if specific_results:
        avg_loss_across = average_loss_across_runs(specific_results)
        axes[0].plot(range(1, len(avg_loss_across)+1), avg_loss_across,␣
↪label=f'LR: {lr}')

axes[0].set_title('Impact of Learning Rate on Loss Across Epochs')
axes[0].set_xlabel('Epochs')
axes[0].set_ylabel('Loss')
axes[0].legend()

# Plot for varying batch sizes
for bs in batch_sizes:
    specific_results = [r for r in results if r['activation'] ==␣
↪best_result['activation']
                        and r['optimizer'] == best_result['optimizer']
                        and r['momentum'] == best_result['momentum']
                        and r['layer'] == best_result['layer']
                        and r['batch_size'] == bs]
    if specific_results:
        avg_loss_across = average_loss_across_runs(specific_results)
        axes[1].plot(range(1, len(avg_loss_across)+1), avg_loss_across,␣
↪label=f'BS: {bs}')

axes[1].set_title('Impact of Batch Size on Loss Across Epochs')
axes[1].set_xlabel('Epochs')
axes[1].set_ylabel('Loss')
axes[1].legend()

# Plot for varying dropout probabilities
for dp in dropout_probs:
    specific_results = [r for r in results if r['activation'] ==␣
↪best_result['activation']
                        and r['optimizer'] == best_result['optimizer']
                        and r['momentum'] == best_result['momentum']
                        and r['layer'] == best_result['layer']
                        and r['dropout_prob'] == dp]
```

```
    if specific_results:
        avg_loss_across = average_loss_across_runs(specific_results)
        axes[2].plot(range(1, len(avg_loss_across)+1), avg_loss_across,␣
↪label=f'DP: {dp}')

axes[2].set_title('Impact of Dropout Probabilities on Loss Across Epochs')
axes[2].set_xlabel('Epochs')
axes[2].set_ylabel('Loss')
axes[2].legend()
```

[341]: <matplotlib.legend.Legend at 0x7efd04d847c0>


Impact of Learning Rate on Loss Across Epochs
LR: 0.2
LR: 0.5
LR: 0.7
Loss
0.07
0.06
0.05
0.04
0.03
0.02
0
10
20
30
40
50
Epochs


Impact of Batch Size on Loss Across Epochs
BS: 15
BS: 30
BS: 45
BS: 80
Loss
0.07
0.06
0.05
0.04
0.03
0.02
0
10
20
30
40
50
Epochs


Impact of Dropout Probabilities on Loss Across Epochs
DP: 0
DP: 0.1
DP: 0.2
DP: 0.4
Loss
0.070
0.065
0.060
0.055
0.050
0.045
0.040
0.035
0
10
20
30
40
50
Epochs

7 Taking a look at our 'best' result and its configuration

[327]:
```
results = load_results()
```

[342]:
```
accuracies = [i['accuracy'] for i in results]
```

[343]:
```
# Our best result across the board
best_result = [re for re in results if re['accuracy'] == max(accuracies)][0]
```

[345]:
```
best_result
```

[345]:
```
{'activation': 'relu',
 'optimizer': 'SGDMomentumOptimizer',
 'momentum': 0.6,
 'learning_rate': 0.5,
 'batch_size': 45,
 'layer': [256, 128, 10],
 'dropout_prob': 0,
 'accuracy': 0.9858,
 'loss': 0.002780826218288223,
 'loss_across': [0.014405494777687102,
  0.0053263236577529936,
  0.0038552118788943894,
  0.0029301502456128303,
  0.0023201844806740495,
  0.0018755845695625282,
  0.0015907767144778759,
  0.0013323551699570286,
  0.0010867660570402342,
  0.0009796903900065725,
  0.0008662094041064235,
  0.0007255670113295868,
  0.0006226301547266212,
  0.0005457292834077984,
  0.00045067427836683693,
  0.00041404332060183496,
  0.00043004016654067624,
  0.00036474923926815915,
  0.00037126894530133776,
  0.00037873391021233673,
  0.0003181119111929249,
  0.0002998006439637034,
  0.000290996920738343,
  0.0002827005227520857,
  0.0002753303354642801,
  0.00027152851558835987,
  0.00027095678303912376,
```

```
0.00026637286913308616,
0.0002715131557211232,
0.0002662285788145819,
0.00025930246949064904,
0.00025669964699851026,
0.00025496706815974525,
0.0002536532698594354,
0.00025234911177045446,
0.000251307298705052,
0.00025028836237444684,
0.0002493725164415496,
0.00024847303253728746,
0.00024763706524916283,
0.00025611505435291774,
0.00024560296054064115,
0.00024416084652588535,
0.00024317001394341635,
0.00024232594743593255,
0.00024155462249821763,
0.00024084120137143832,
0.00024018123872828381,
0.0002395854704108304,
0.0002390053760604681]}
```

8 Demonstration of our 'strongest' configuration with seed

[344]:
```
np.random.seed(31415)
```

[346]:
```
train_images, train_labels, test_images, test_labels = load_mnist('./dataset')

# Reshape and normalize
train_images = train_images.reshape(train_images.shape[0], -1) / 255.0
test_images = test_images.reshape(test_images.shape[0], -1) / 255.0
train_labels = one_hot_encode(train_labels)
test_labels = one_hot_encode(test_labels)

learning_rate = 0.5
optimizer = SGDMomentumOptimizer(learning_rate=learning_rate, momentum=0.6)

# Create an instance of NeuralNet
nn = NeuralNet(activation_function='relu', neurons=[256, 128, 10],␣
↪learning_rate=learning_rate, optimizer=optimizer, dropout_prob=0)

# Train the network
loss_across = nn.train_network(epochs=50, batch_size=45, X_train=train_images,␣
↪Y_train=train_labels)
```

```python
accuracy, loss = nn.evaluate_model(test_images, test_labels)
print(f"Test Accuracy: {accuracy*100:.2f}%")
print(f"Test Loss: {loss}")
```

```
Epoch 1/50, Loss: 0.015010194577403303
Epoch 2/50, Loss: 0.00538919363172571
Epoch 3/50, Loss: 0.0038060114899221716
Epoch 4/50, Loss: 0.002981839985524173
Epoch 5/50, Loss: 0.0023220988595752954
Epoch 6/50, Loss: 0.0019225727967120286
Epoch 7/50, Loss: 0.0015735827778019938
Epoch 8/50, Loss: 0.001325988876294501
Epoch 9/50, Loss: 0.0011224122021368152
Epoch 10/50, Loss: 0.0009541293843486546
Epoch 11/50, Loss: 0.0008647151696519236
Epoch 12/50, Loss: 0.0007140833629687893
Epoch 13/50, Loss: 0.0006404686179473753
Epoch 14/50, Loss: 0.0005340527116229235
Epoch 15/50, Loss: 0.00047090112008215214
Epoch 16/50, Loss: 0.00042594176464794885
Epoch 17/50, Loss: 0.0003771006401045921
Epoch 18/50, Loss: 0.00036983290167944867
Epoch 19/50, Loss: 0.000336334974034136
Epoch 20/50, Loss: 0.00031255390775191387
Epoch 21/50, Loss: 0.000294915434286711
Epoch 22/50, Loss: 0.0002882188300587984
Epoch 23/50, Loss: 0.00028005595054541525
Epoch 24/50, Loss: 0.0002750256944385325
Epoch 25/50, Loss: 0.00027146164705460285
Epoch 26/50, Loss: 0.0002679800447929566
Epoch 27/50, Loss: 0.00026248160083883735
Epoch 28/50, Loss: 0.00025703716492553
Epoch 29/50, Loss: 0.00025637957835955534
Epoch 30/50, Loss: 0.0002521520307009694
Epoch 31/50, Loss: 0.00025721451657541815
Epoch 32/50, Loss: 0.00024741281118729027
Epoch 33/50, Loss: 0.00024535670137500984
Epoch 34/50, Loss: 0.00024724226575868855
Epoch 35/50, Loss: 0.00024241507308163306
Epoch 36/50, Loss: 0.00024069088208388676
Epoch 37/50, Loss: 0.0002396405449662239
Epoch 38/50, Loss: 0.00023853445259492827
Epoch 39/50, Loss: 0.00023726875630970725
Epoch 40/50, Loss: 0.00023644907257395817
Epoch 41/50, Loss: 0.00023526499975830352
Epoch 42/50, Loss: 0.00023443775653891565
Epoch 43/50, Loss: 0.0002336312852924422
```

```
Epoch 44/50, Loss: 0.00023299939231031106
Epoch 45/50, Loss: 0.00023239960550326482
Epoch 46/50, Loss: 0.00023176608506140538
Epoch 47/50, Loss: 0.00023115430586035523
Epoch 48/50, Loss: 0.0002305575206530916
Epoch 49/50, Loss: 0.00022996645485041673
Epoch 50/50, Loss: 0.00022944211944083144
Test Accuracy: 98.48%
Test Loss: 0.0031567484649270682
```

9 Task 2

[4]:
```
# Import required libraries
import torch
from torchvision import transforms
from torchvision.datasets import ImageFolder
import torchvision.models as models
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data.dataloader import DataLoader
from torch.utils.data import random_split
from torchvision.utils import make_grid
import matplotlib.pyplot as plt
import glob,os
import matplotlib.image as mpimg
from datetime import datetime
```

[2]:
```
# Seed for reproducibility
torch.manual_seed(3063)
```

[2]:
```
<torch._C.Generator at 0x7f932e9b9910>
```

[3]:
```
#Check if GPU is available
if torch.cuda.is_available():
    device = torch.device('cuda')
else:
    device = torch.device('cpu')
print("Device:",device)
```

```
Device: cpu
```

[4]:
```
dataset_root = './dataset/chest_xray/'
```

9.0.1 Loading Data

Note: We apply transforms.Grayscale since these are x-rays and we do not need the RGB.

[5]:
```
labels = ['NORMAL', 'PNEUMONIA']
image_dims = (120, 120)

train_dir = os.path.join(dataset_root, 'train')
test_dir = os.path.join(dataset_root, 'test')
val_dir = os.path.join(dataset_root, 'val')

train_data = ImageFolder(train_dir, transform=transforms.Compose([
    transforms.Resize(image_dims),
    transforms.Grayscale(num_output_channels=1),
    transforms.ToTensor()
]))
test_data = ImageFolder(test_dir, transform=transforms.Compose([
    transforms.Resize(image_dims),
    transforms.Grayscale(num_output_channels=1),
    transforms.ToTensor()
]))
val_data = ImageFolder(val_dir, transform=transforms.Compose([
    transforms.Resize(image_dims),
    transforms.Grayscale(num_output_channels=1),
    transforms.ToTensor()
]))
```

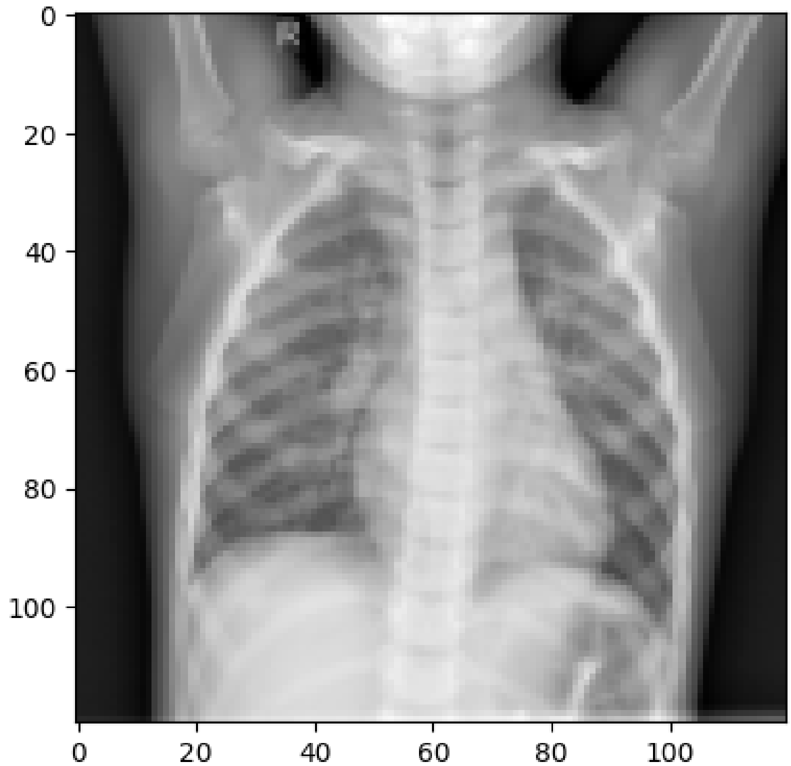
[6]:
```
img, label = train_data[0]
print(img.shape,label)
print("Classes: ", train_data.classes)
```

```
torch.Size([1, 120, 120]) 0
Classes:  ['NORMAL', 'PNEUMONIA']
```

9.1 Example image

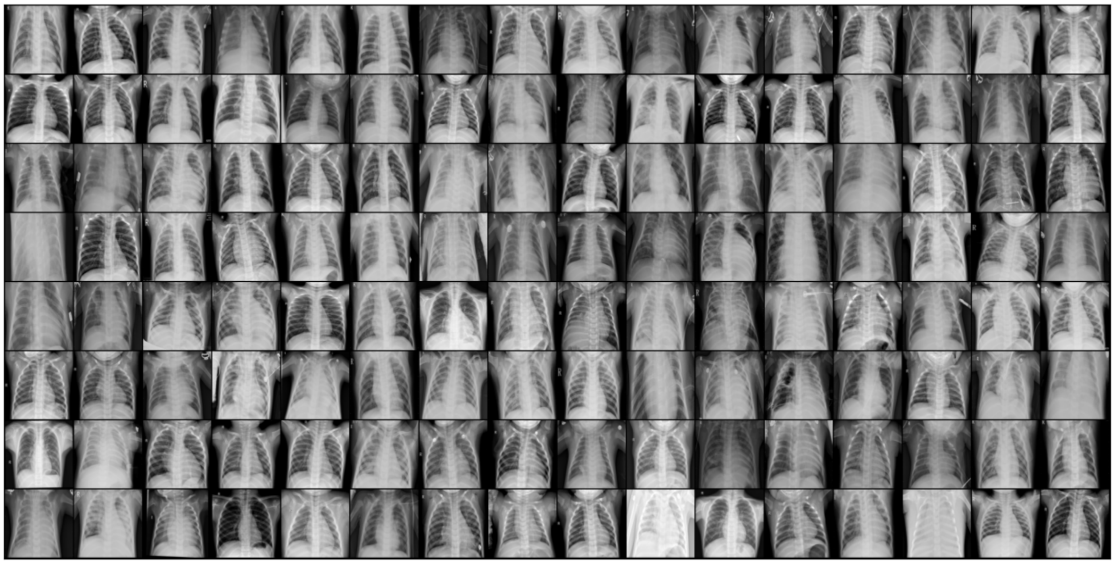
[9]:
```
# Squeeze reduces tensore to heigh,width, cmap=gray since grayscaled.
plt.imshow(img.squeeze(), cmap='gray')
```

[9]:
```
<matplotlib.image.AxesImage at 0x7fdfb2846d30>
```



[8]:
```
# Load training data
# Double the batch size for val and test, as we don't have backpropagation␣
↪(more efficient)
batch_size = 128
train_dl = DataLoader(train_data, batch_size, shuffle=True, num_workers=4,␣
↪pin_memory=True)
val_dl = DataLoader(val_data, batch_size*2, num_workers=4, pin_memory=True)
test_dl = DataLoader(test_data, batch_size*2, num_workers=4, pin_memory=True)
```

[11]:
```
# Reference: Taken verbatim from Lab 9.4
def show_batch(dl):
    """Plot images grid of single batch"""
    for images, labels in dl:
        fig,ax = plt.subplots(figsize = (16,12))
        ax.set_xticks([])
        ax.set_yticks([])
        ax.imshow(make_grid(images,nrow=16).permute(1,2,0))
        break

show_batch(train_dl)
```



9.2 Base Model Definition

- Ref: https://pytorch.org/tutorials/beginner/introyt/modelsyt_tutorial.html#convolutional-layers

[9]:
```
class XrayClassification(nn.Module):
    def __init__(self):
        super(XrayClassification, self).__init__()
        self.network = nn.Sequential(
            # Initial feature extraction
            nn.Conv2d(1, 32, kernel_size=3, padding='same'),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.MaxPool2d(2, stride=2, padding=1),

            # Increasing depth to capture more complex features
            nn.Conv2d(32, 64, kernel_size=3, padding='same'),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.MaxPool2d(2, stride=2, padding=1),

            # Doubling depth to capture more abstract and complex features
            nn.Conv2d(64, 128, kernel_size=3, padding='same'),
            nn.BatchNorm2d(128),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.MaxPool2d(2, stride=2, padding=1),
```

```
            # Doubling depth again
            nn.Conv2d(128, 256, kernel_size=3, padding='same'),
            nn.BatchNorm2d(256),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.MaxPool2d(2, stride=2, padding=1),

            nn.Conv2d(256, 256, kernel_size=3, padding='same'),
            nn.BatchNorm2d(256),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.MaxPool2d(2, stride=2, padding=1),

            nn.Flatten(),

            nn.Linear(6400, 128),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Linear(128, 1),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.network(x)
```

[10]:
```
xc = XrayClassification()
print(xc)
```

```
XrayClassification(
  (network): Sequential(
    (0): Conv2d(1, 32, kernel_size=(3, 3), stride=(1, 1), padding=same)
    (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=2, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (4): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=same)
    (5): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (6): ReLU()
    (7): Dropout(p=0.2, inplace=False)
    (8): MaxPool2d(kernel_size=2, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (9): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=same)
    (10): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (11): ReLU()
```

```
    (12): Dropout(p=0.2, inplace=False)
    (13): MaxPool2d(kernel_size=2, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (14): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=same)
    (15): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (16): ReLU()
    (17): Dropout(p=0.2, inplace=False)
    (18): MaxPool2d(kernel_size=2, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (19): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=same)
    (20): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (21): ReLU()
    (22): Dropout(p=0.2, inplace=False)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (24): Flatten(start_dim=1, end_dim=-1)
    (25): Linear(in_features=6400, out_features=128, bias=True)
    (26): ReLU()
    (27): Dropout(p=0.2, inplace=False)
    (28): Linear(in_features=128, out_features=1, bias=True)
    (29): Sigmoid()
  )
)
```

[21]:
```
# We use the accuracy, evaluate, and fit method from IN3063 Lab 9.4, with only␣
↪slight modifications
# Also used PyTorch docs for reference here: https://pytorch.org/tutorials/
↪beginner/basics/optimization_tutorial.html#full-implementation

def accuracy(outputs, labels):
    preds = outputs.round()  # Convert probabilities to 0 or 1
    return torch.tensor(torch.sum(preds == labels).item() / len(preds))

# no_grad ensures no gradients are computed
@torch.no_grad()
def evaluate(model, val_loader, device):
    model.eval()
    outputs = []
    for images, labels in val_loader:
        images, labels = images.to(device), labels.to(device)
        # Get prediction and loss & accuracy
        out = model(images)
        loss = F.binary_cross_entropy(out.squeeze(), labels.type_as(out))
        acc = accuracy(out.squeeze(), labels)  # Squeeze to remove channel␣
↪dimension
```

```
        outputs.append({'val_loss': loss.item(), 'val_acc': acc})

    batch_losses = [x['val_loss'] for x in outputs]
    epoch_loss = torch.mean(torch.tensor(batch_losses))  # Combine losses
    batch_accs = [x['val_acc'] for x in outputs]
    epoch_acc = torch.mean(torch.tensor(batch_accs))  # Combine accuracies
    return {'val_loss': epoch_loss.item(), 'val_acc': epoch_acc.item()}

def fit(epochs, lr, model, train_loader, val_loader, opt_func=torch.optim.SGD,␣
 ↪device=None):
    history = []
    optimizer = opt_func(model.parameters(), lr)
    for epoch in range(epochs):
        start = datetime.now()
        model.train()
        train_losses = []
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device)
            # Compute Prediction and get Loss
            out = model(images)
            loss = F.binary_cross_entropy(out.squeeze(), labels.type_as(out))
            train_losses.append(loss.item())

            # Backpropagation
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()

        result = evaluate(model, val_loader, device)
        result['train_loss'] = torch.mean(torch.tensor(train_losses)).item()
        print(f"Epoch [{epoch}], train_loss: {result['train_loss']:.4f},␣
 ↪val_loss: {result['val_loss']:.4f}, val_acc: {result['val_acc']:.4f}")
        print(f"Time taken for epoch {epoch}: {datetime.now()-start}")
        history.append(result)
    return history
```

[316]:

```
xc.to(device)

num_epochs = 10
opt_func = torch.optim.Adam
lr = 0.001
# fitting the model on training data and record the result after each epoch
history = fit(num_epochs, lr, xc, train_dl, val_dl, opt_func)
```

```
Epoch [0], train_loss: 0.3368, val_loss: 3.6626, val_acc: 0.5000
Time taken for epoch 0: 0:01:21.904359
Epoch [1], train_loss: 0.1294, val_loss: 1.6831, val_acc: 0.5000
Time taken for epoch 1: 0:01:22.360298
```

```
Epoch [2], train_loss: 0.0864, val_loss: 1.9061, val_acc: 0.5000
Time taken for epoch 2: 0:01:23.927975
Epoch [3], train_loss: 0.0755, val_loss: 2.6360, val_acc: 0.5000
Time taken for epoch 3: 0:01:23.821765
Epoch [4], train_loss: 0.0595, val_loss: 2.4093, val_acc: 0.5000
Time taken for epoch 4: 0:01:22.704077
Epoch [5], train_loss: 0.0437, val_loss: 2.9708, val_acc: 0.5000
Time taken for epoch 5: 0:01:20.656098
Epoch [6], train_loss: 0.0415, val_loss: 2.1242, val_acc: 0.5000
Time taken for epoch 6: 0:01:25.157408
Epoch [7], train_loss: 0.0415, val_loss: 0.5924, val_acc: 0.8125
Time taken for epoch 7: 0:01:19.208091
Epoch [8], train_loss: 0.0344, val_loss: 2.5513, val_acc: 0.5000
Time taken for epoch 8: 0:01:24.977556
Epoch [9], train_loss: 0.0254, val_loss: 3.1876, val_acc: 0.5000
Time taken for epoch 9: 0:01:25.872538
```

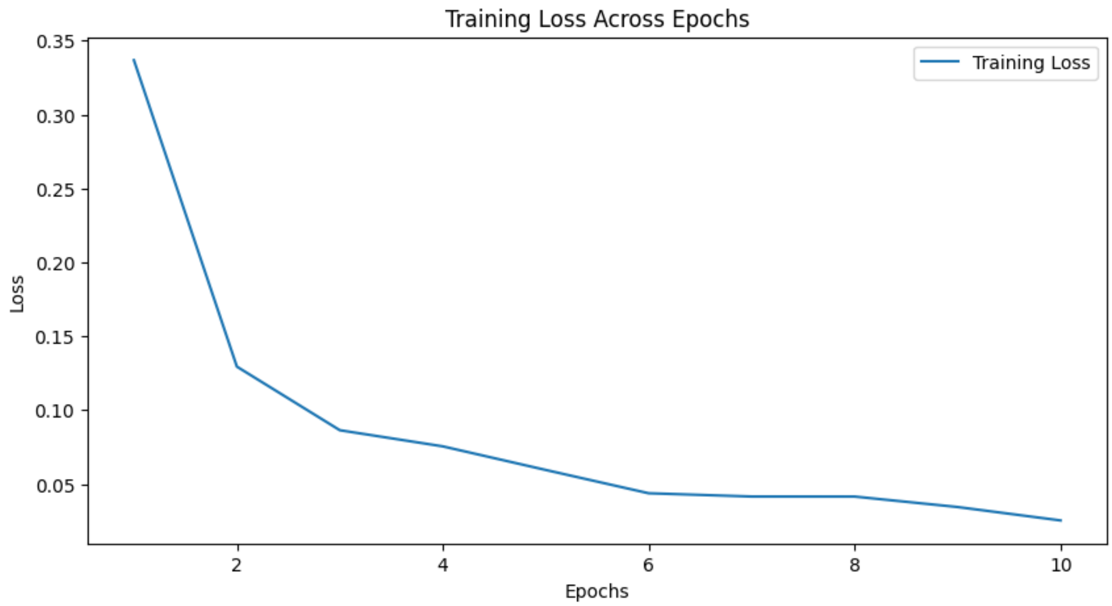
[317]:

```
# Evaluate on test data
test_results = evaluate(xc, test_dl, None)
print(f'Test Loss: {test_results["val_loss"]}, Test Accuracy:␣
↪{test_results["val_acc"]}')
```

```
Test Loss: 3.047215461730957, Test Accuracy: 0.6966145634651184
```

[318]:

```
train_losses = [x['train_loss'] for x in history]
epochs = range(1, len(history)+1)

plt.figure(figsize=(10,5))
plt.plot(epochs, train_losses, label='Training Loss')
plt.title('Training Loss Across Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



9.3 2.c Improvements

We replaced the last convolutional layer (256,256) with a convolutional layer in the middle of the network, which also preserves the input size (64,64). It is not followed by a dropout. For further reference see section 2.c of the report.

[13]:
```
xc = XrayClassification()

xc.network = nn.Sequential(
            # Initial feature extraction
            nn.Conv2d(1, 32, kernel_size=3, padding='same'),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.MaxPool2d(2, stride=2, padding=1),

            # Increasing depth to capture more complex features
            nn.Conv2d(32, 64, kernel_size=3, padding='same'),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.Dropout(0.1),
            nn.MaxPool2d(2, stride=2, padding=1),

            # Maintaining depth to refine/combine features before moving on
            nn.Conv2d(64, 64, kernel_size=3, padding='same'),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            # No dropout at this layer
```

```python
            nn.MaxPool2d(2, stride=2, padding=1),

            # Doubling depth to capture more abstract and complex features
            nn.Conv2d(64, 128, kernel_size=3, padding='same'),
            nn.BatchNorm2d(128),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.MaxPool2d(2, stride=2, padding=1),

            # Doubling depth again
            nn.Conv2d(128, 256, kernel_size=3, padding='same'),
            nn.BatchNorm2d(256),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.MaxPool2d(2, stride=2, padding=1),

            nn.Flatten(),

            nn.Linear(6400, 128),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Linear(128, 1),
            nn.Sigmoid()
        )

print(xc)
```

```
XrayClassification(
  (network): Sequential(
    (0): Conv2d(1, 32, kernel_size=(3, 3), stride=(1, 1), padding=same)
    (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=2, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (4): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=same)
    (5): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (6): ReLU()
    (7): Dropout(p=0.1, inplace=False)
    (8): MaxPool2d(kernel_size=2, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (9): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=same)
    (10): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (11): ReLU()
    (12): MaxPool2d(kernel_size=2, stride=2, padding=1, dilation=1,
ceil_mode=False)
```

```
    (13): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=same)
    (14): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (15): ReLU()
    (16): Dropout(p=0.2, inplace=False)
    (17): MaxPool2d(kernel_size=2, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (18): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=same)
    (19): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (20): ReLU()
    (21): Dropout(p=0.2, inplace=False)
    (22): MaxPool2d(kernel_size=2, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (23): Flatten(start_dim=1, end_dim=-1)
    (24): Linear(in_features=6400, out_features=128, bias=True)
    (25): ReLU()
    (26): Dropout(p=0.2, inplace=False)
    (27): Linear(in_features=128, out_features=1, bias=True)
    (28): Sigmoid()
  )
)
```

[320]:

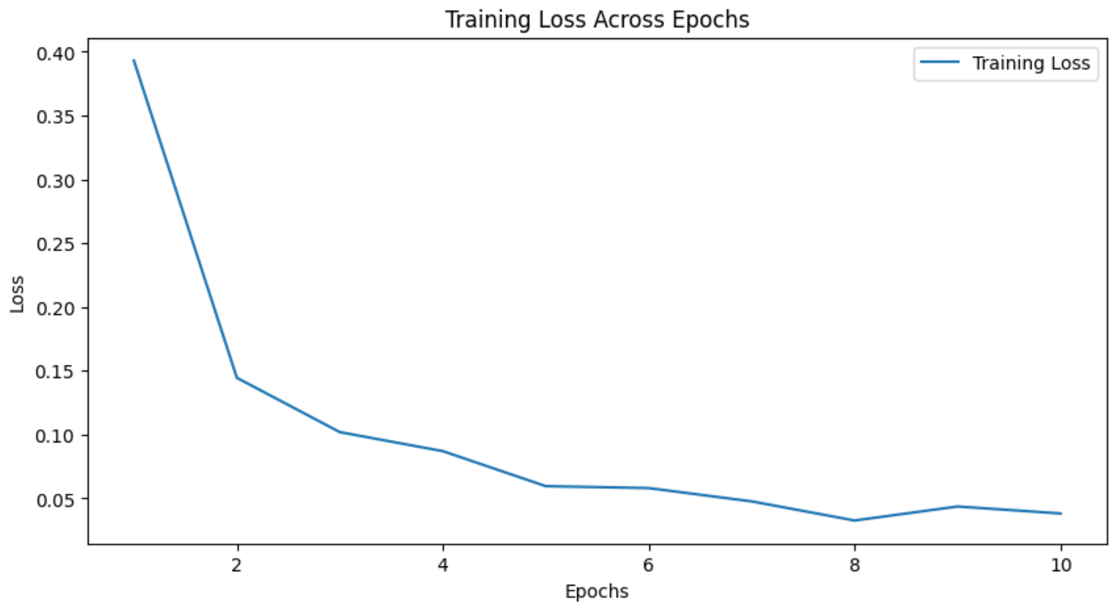
```
# Load training data
batch_size = 128
train_dl = DataLoader(train_data, batch_size, shuffle=True, num_workers=4,␣
 ↪pin_memory=True)
val_dl = DataLoader(val_data, batch_size*2, num_workers=4, pin_memory=True)
test_dl = DataLoader(test_data, batch_size*2, num_workers=4, pin_memory=True)

xc.to(device)

# Same parameters
num_epochs = 10
opt_func = torch.optim.Adam
lr = 0.001
# fitting the model on training data and record the result after each epoch
history = fit(num_epochs, lr, xc, train_dl, val_dl, opt_func)

# Evaluate on test data
test_results = evaluate(xc, test_dl, None)
print(f'Test Loss: {test_results["val_loss"]}, Test Accuracy:␣
 ↪{test_results["val_acc"]}')
```

```
Epoch [0], train_loss: 0.3930, val_loss: 3.2910, val_acc: 0.5000
Time taken for epoch 0: 0:01:05.497665
Epoch [1], train_loss: 0.1445, val_loss: 1.3921, val_acc: 0.5000
Time taken for epoch 1: 0:01:05.179929
```

```
Epoch [2], train_loss: 0.1020, val_loss: 1.4386, val_acc: 0.6250
Time taken for epoch 2: 0:01:04.708917
Epoch [3], train_loss: 0.0871, val_loss: 1.7208, val_acc: 0.5000
Time taken for epoch 3: 0:01:02.135513
Epoch [4], train_loss: 0.0596, val_loss: 0.5258, val_acc: 0.7500
Time taken for epoch 4: 0:01:01.681421
Epoch [5], train_loss: 0.0581, val_loss: 1.1457, val_acc: 0.5625
Time taken for epoch 5: 0:01:04.882095
Epoch [6], train_loss: 0.0477, val_loss: 0.3052, val_acc: 0.8750
Time taken for epoch 6: 0:01:02.446170
Epoch [7], train_loss: 0.0327, val_loss: 0.1528, val_acc: 1.0000
Time taken for epoch 7: 0:01:00.057767
Epoch [8], train_loss: 0.0437, val_loss: 0.1629, val_acc: 0.9375
Time taken for epoch 8: 0:01:00.343649
Epoch [9], train_loss: 0.0382, val_loss: 1.2053, val_acc: 0.5625
Time taken for epoch 9: 0:01:01.079018
Test Loss: 1.7412151098251343, Test Accuracy: 0.7330729365348816
```

[321]:

```
train_losses = [x['train_loss'] for x in history]
epochs = range(1, len(history)+1)

plt.figure(figsize=(10,5))
plt.plot(epochs, train_losses, label='Training Loss')
plt.title('Training Loss Across Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



9.4 2.d Model optimisation

- We will use RayTune to automate the optimisation process
- To do so, we change the class to make some value configurable (the dropout rates)
- Used the PyTorch docs as guidance: https://pytorch.org/tutorials/beginner/hyperparameter_tuning_tutoria

[5]:
```
from ray import tune
from ray.air import session
from ray.train import Checkpoint
import tempfile
import os
```

[6]:
```
# Wrap data loaders in a function to share between different trials
def load_data(data_dir="/home/outlaw/Desktop/Uni/IN3063/coursework/up_to_date/
↪IN3063-Coursework/dataset/chest_xray/"):
    labels = ['NORMAL', 'PNEUMONIA']
    image_dims = (120, 120)
    train_dir = os.path.join(data_dir, 'train')
    test_dir = os.path.join(data_dir, 'test')
    val_dir = os.path.join(data_dir, 'val')

    train_data = ImageFolder(train_dir, transform=transforms.Compose([
        transforms.Resize(image_dims),
        transforms.Grayscale(num_output_channels=1),
        transforms.ToTensor()
    ]))
    test_data = ImageFolder(test_dir, transform=transforms.Compose([
        transforms.Resize(image_dims),
        transforms.Grayscale(num_output_channels=1),
        transforms.ToTensor()
    ]))
    val_data = ImageFolder(val_dir, transform=transforms.Compose([
        transforms.Resize(image_dims),
        transforms.Grayscale(num_output_channels=1),
        transforms.ToTensor()
    ]))

    return train_data, test_data, val_data
```

[7]:
```
class XrayClassification(nn.Module):
    def __init__(self, d1=0.1, d2=0.2, d3=0.2, d4=0.2):
        super(XrayClassification, self).__init__()
        self.network = nn.Sequential(
            nn.Conv2d(1, 32, kernel_size=3, padding='same'),
            nn.BatchNorm2d(32),
            nn.ReLU(),
```

```
            nn.MaxPool2d(2, stride=2, padding=1),

            nn.Conv2d(32, 64, kernel_size=3, padding='same'),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            # Replaced hardcoded value with parameter
            nn.Dropout(d1),
            nn.MaxPool2d(2, stride=2, padding=1),

            nn.Conv2d(64, 64, kernel_size=3, padding='same'),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.MaxPool2d(2, stride=2, padding=1),

            nn.Conv2d(64, 128, kernel_size=3, padding='same'),
            nn.BatchNorm2d(128),
            nn.ReLU(),
            # Replaced hardcoded value with parameter
            nn.Dropout(d2),
            nn.MaxPool2d(2, stride=2, padding=1),

            nn.Conv2d(128, 256, kernel_size=3, padding='same'),
            nn.BatchNorm2d(256),
            nn.ReLU(),
            # Replaced hardcoded value with parameter
            nn.Dropout(d3),
            nn.MaxPool2d(2, stride=2, padding=1),

            nn.Flatten(),

            nn.Linear(6400, 128),
            nn.ReLU(),
            # Replaced hardcoded value with parameter
            nn.Dropout(d4),
            nn.Linear(128, 1),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.network(x)
```

[8]:

```
def train_network(config, data_dir=None):
    dropouts = config["dropout_rates"]
    # Create model with parameters
    xc = XrayClassification(dropouts[0], dropouts[1], dropouts[2], dropouts[3])

    # Set device type
```

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

    xc.to(device)
    optimizer = torch.optim.Adam(xc.parameters(), 0.001)

    checkpoint = session.get_checkpoint()

    if checkpoint:
        checkpoint_state = checkpoint.to_dict()
        start_epoch = checkpoint_state["epoch"]
        xc.load_state_dict(checkpoint_state["net_state_dict"])
        optimizer.load_state_dict(checkpoint_state["optimizer_state_dict"])
    else:
        start_epoch = 0

    # Load data directories
    train_data, test_data, val_data = load_data()

    # Create data loaders with set batch size
    batch_size = 128
    train_dl = DataLoader(train_data, batch_size, shuffle=True, num_workers=4, pin_memory=True)
    val_dl = DataLoader(val_data, batch_size*2, shuffle=True, num_workers=4, pin_memory=True)
    test_dl = DataLoader(test_data, batch_size*2, num_workers=4, pin_memory=True)

    # Run for ten epochs
    for epoch in range(start_epoch, 10):
        running_loss = 0.0
        epoch_steps = 0

        xc.train()

        train_losses = []
        i = 0
        for images, labels in train_dl:
            images, labels = images.to(device), labels.to(device)
            # Compute Prediction and get Loss
            out = xc(images)
            loss = F.binary_cross_entropy(out.squeeze(), labels.type_as(out))
            train_losses.append(loss.item())

            # Backpropagation
```

```
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()

            # Print statistics
            running_loss += loss.item()
            epoch_steps += 1
            if i % 2000 == 1999:
                print(
                "[%d, %5d] loss: %.3f"
                % (epoch + 1, i+1, running_loss / epoch_steps)
                )
                running_loss = 0.0
            i += 1

        # Validation loss
        val_loss = 0.0
        val_steps = 0
        total = 0
        correct = 0

        xc.eval()
        for images, labels in val_dl:
            with torch.no_grad():
                images, labels = images.to(device), labels.to(device)
                # Get prediction and loss & accuracy
                out = xc(images)
                predicted = torch.round(out.squeeze())
                total += labels.size(0)
                correct += (predicted == labels).sum().item()

                loss = F.binary_cross_entropy(out.squeeze(), labels.type_as(out))
                val_loss += loss.cpu().numpy()
                val_steps += 1

        checkpoint_data = {
            "epoch": epoch,
            "net_state_dict": xc.state_dict(),
            "optimizer_state_dict": optimizer.state_dict(),
        }

        with tempfile.TemporaryDirectory() as tempdir:
            torch.save(checkpoint_data, os.path.join(tempdir, "checkpoint.pt"))

            session.report(
                {
```

```
                    "train_loss": running_loss / epoch_steps,
                    "val_loss": val_loss / val_steps,
                    "val_accuracy": correct / total
                }, checkpoint=Checkpoint.from_directory(tempdir)
            )

    print("Finished Training")
```

[9]:
```
dropout_combinations = [
    [0.2, 0.2, 0.2, 0.2],  # Base values
    [0.1, 0.2, 0.2, 0.3],  # Ascending dropout rate (as hidden layers get␣
 ↪larger)
    [0.2, 0.3, 0.3, 0.4],  # Higher ascending values
    [tune.uniform(0.0, 0.5) for i in range(4)],   # random values between 0-0.5
    [tune.uniform(0.0, 0.5) for i in range(4)],   # random values between 0-0.5
]

config = {
    "dropout_rates": tune.grid_search(dropout_combinations),
}
```

[10]:
```
result = tune.run(train_network, config=config)
```

```
2024-01-06 13:42:40,303 INFO worker.py:1724 -- Started a local Ray instance.
2024-01-06 13:42:40,811 INFO tune.py:220 -- Initializing Ray automatically. For
cluster usage or custom Ray initialization, call `ray.init(…)` before
`tune.run(…)`.
2024-01-06 13:42:40,813 INFO tune.py:583 -- [output] This uses the legacy output
and progress reporter, as Jupyter notebooks are not supported by the new engine,
yet. For more information, please see https://github.com/ray-
project/ray/issues/36949
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.HTML object>
```

```
(train_network pid=200744) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00001_1_dropout_rates=0_1_0_2_0_2_0_3_2024-01-0
6_13-42-40/checkpoint_000000)
(train_network pid=200751) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00004_4_dropout_rates=0_08449031577459876_0_085
2932095732149_0_23113829167004468_0_13364241349375944,0=0.0845,_2024-01-06_13-42
-40/checkpoint_000000) [repeated 3x across cluster] (Ray deduplicates logs
by default. Set RAY_DEDUP_LOGS=0 to disable log deduplication, or see
https://docs.ray.io/en/master/ray-observability/ray-logging.html#log-
deduplication for more options.)
```

```
(train_network pid=200745) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00002_2_dropout_rates=0_2_0_3_0_3_0_4_2024-01-0
6_13-42-40/checkpoint_000001) [repeated 2x across cluster]
(train_network pid=200744) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00001_1_dropout_rates=0_1_0_2_0_2_0_3_2024-01-0
6_13-42-40/checkpoint_000001) [repeated 2x across cluster]
(train_network pid=200751) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00004_4_dropout_rates=0_08449031577459876_0_085
2932095732149_0_23113829167004468_0_13364241349375944,0=0.0845,_2024-01-06_13-42
-40/checkpoint_000001)
(train_network pid=200749) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00003_3_dropout_rates=0_28850982656069835_0_233
12158482958_0_49212581227265284_0_44739882323173846,0=0.2885,1=_2024-01-06_13-42
-40/checkpoint_000001)
(train_network pid=200745) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00002_2_dropout_rates=0_2_0_3_0_3_0_4_2024-01-0
6_13-42-40/checkpoint_000002)
(train_network pid=200744) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00001_1_dropout_rates=0_1_0_2_0_2_0_3_2024-01-0
6_13-42-40/checkpoint_000002)
(train_network pid=200743) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00000_0_dropout_rates=0_2_0_2_0_2_0_2_2024-01-0
6_13-42-40/checkpoint_000002)
(train_network pid=200751) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00004_4_dropout_rates=0_08449031577459876_0_085
2932095732149_0_23113829167004468_0_13364241349375944,0=0.0845,_2024-01-06_13-42
-40/checkpoint_000002)
(train_network pid=200745) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00002_2_dropout_rates=0_2_0_3_0_3_0_4_2024-01-0
6_13-42-40/checkpoint_000003) [repeated 2x across cluster]
(train_network pid=200744) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00001_1_dropout_rates=0_1_0_2_0_2_0_3_2024-01-0
6_13-42-40/checkpoint_000003)
(train_network pid=200749) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00003_3_dropout_rates=0_28850982656069835_0_233
12158482958_0_49212581227265284_0_44739882323173846,0=0.2885,1=_2024-01-06_13-42
-40/checkpoint_000003)
```

```
(train_network pid=200751) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00004_4_dropout_rates=0_08449031577459876_0_085
2932095732149_0_23113829167004468_0_13364241349375944,0=0.0845,_2024-01-06_13-42
-40/checkpoint_000003) [repeated 2x across cluster]
(train_network pid=200745) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00002_2_dropout_rates=0_2_0_3_0_3_0_4_2024-01-0
6_13-42-40/checkpoint_000004)
(train_network pid=200749) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00003_3_dropout_rates=0_28850982656069835_0_233
12158482958_0_49212581227265284_0_44739882323173846,0=0.2885,1=_2024-01-06_13-42
-40/checkpoint_000004)
(train_network pid=200743) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00000_0_dropout_rates=0_2_0_2_0_2_0_2_2024-01-0
6_13-42-40/checkpoint_000004) [repeated 2x across cluster]
(train_network pid=200751) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00004_4_dropout_rates=0_08449031577459876_0_085
2932095732149_0_23113829167004468_0_13364241349375944,0=0.0845,_2024-01-06_13-42
-40/checkpoint_000004)
(train_network pid=200744) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00001_1_dropout_rates=0_1_0_2_0_2_0_3_2024-01-0
6_13-42-40/checkpoint_000005)
(train_network pid=200749) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00003_3_dropout_rates=0_28850982656069835_0_233
12158482958_0_49212581227265284_0_44739882323173846,0=0.2885,1=_2024-01-06_13-42
-40/checkpoint_000005) [repeated 2x across cluster]
(train_network pid=200743) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00000_0_dropout_rates=0_2_0_2_0_2_0_2_2024-01-0
6_13-42-40/checkpoint_000005) [repeated 2x across cluster]
(train_network pid=200744) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00001_1_dropout_rates=0_1_0_2_0_2_0_3_2024-01-0
6_13-42-40/checkpoint_000006)
(train_network pid=200745) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00002_2_dropout_rates=0_2_0_3_0_3_0_4_2024-01-0
6_13-42-40/checkpoint_000006)
(train_network pid=200749) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00003_3_dropout_rates=0_28850982656069835_0_233
12158482958_0_49212581227265284_0_44739882323173846,0=0.2885,1=_2024-01-06_13-42
```

```
-40/checkpoint_000006)
(train_network pid=200743) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00000_0_dropout_rates=0_2_0_2_0_2_0_2_2024-01-0
6_13-42-40/checkpoint_000006)
(train_network pid=200751) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00004_4_dropout_rates=0_08449031577459876_0_085
2932095732149_0_23113829167004468_0_13364241349375944,0=0.0845,_2024-01-06_13-42
-40/checkpoint_000006)
(train_network pid=200744) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00001_1_dropout_rates=0_1_0_2_0_2_0_3_2024-01-0
6_13-42-40/checkpoint_000007)
(train_network pid=200745) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00002_2_dropout_rates=0_2_0_3_0_3_0_4_2024-01-0
6_13-42-40/checkpoint_000007)
(train_network pid=200749) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00003_3_dropout_rates=0_28850982656069835_0_233
12158482958_0_49212581227265284_0_44739882323173846,0=0.2885,1=_2024-01-06_13-42
-40/checkpoint_000007)
(train_network pid=200751) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00004_4_dropout_rates=0_08449031577459876_0_085
2932095732149_0_23113829167004468_0_13364241349375944,0=0.0845,_2024-01-06_13-42
-40/checkpoint_000007) [repeated 2x across cluster]
(train_network pid=200744) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00001_1_dropout_rates=0_1_0_2_0_2_0_3_2024-01-0
6_13-42-40/checkpoint_000008)
(train_network pid=200745) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00002_2_dropout_rates=0_2_0_3_0_3_0_4_2024-01-0
6_13-42-40/checkpoint_000008)
(train_network pid=200743) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00000_0_dropout_rates=0_2_0_2_0_2_0_2_2024-01-0
6_13-42-40/checkpoint_000008) [repeated 2x across cluster]
(train_network pid=200751) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00004_4_dropout_rates=0_08449031577459876_0_085
2932095732149_0_23113829167004468_0_13364241349375944,0=0.0845,_2024-01-06_13-42
-40/checkpoint_000008)

(train_network pid=200744) Finished Training

(train_network pid=200744) Checkpoint successfully created at:
```

```
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00001_1_dropout_rates=0_1_0_2_0_2_0_3_2024-01-0
6_13-42-40/checkpoint_000009)
(train_network pid=200745) Finished Training
(train_network pid=200745) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00002_2_dropout_rates=0_2_0_3_0_3_0_4_2024-01-0
6_13-42-40/checkpoint_000009)
(train_network pid=200749) Finished Training
(train_network pid=200749) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00003_3_dropout_rates=0_28850982656069835_0_233
12158482958_0_49212581227265284_0_44739882323173846,0=0.2885,1=_2024-01-06_13-42
-40/checkpoint_000009)
(train_network pid=200743) Finished Training
(train_network pid=200743) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00000_0_dropout_rates=0_2_0_2_0_2_0_2_2024-01-0
6_13-42-40/checkpoint_000009)
(train_network pid=200751) Finished Training
(train_network pid=200751) Checkpoint successfully created at:
Checkpoint(filesystem=local, path=/home/outlaw/ray_results/train_network_2024-01
-06_13-42-40/train_network_7634e_00004_4_dropout_rates=0_08449031577459876_0_085
2932095732149_0_23113829167004468_0_13364241349375944,0=0.0845,_2024-01-06_13-42
-40/checkpoint_000009)
2024-01-06 14:20:21,383 INFO tune.py:1042 -- Total run time: 2260.57 seconds
(2260.54 seconds for the tuning loop).
```

[12]:
```
best_trial = result.get_best_trial("val_loss", "min", "last")
```

[14]:
```
print(f"Best trial config: {best_trial.config}")
print(f"Best trial final validation loss: {best_trial.last_result['val_loss']}")
print(f"Best trial final validation accuracy: {best_trial.
  ↪last_result['val_accuracy']}")
```

```
Best trial config: {'dropout_rates': [0.1, 0.2, 0.2, 0.3]}
Best trial final validation loss: 0.13262000679969788
Best trial final validation accuracy: 1.0
```

[23]:
```
# Load testing data
_, test_data, _ = load_data()

batch_size = 128
test_dl = DataLoader(test_data, batch_size*2, num_workers=4, pin_memory=True)
```

```python
# Load the config of our best result
dropout_rates = best_trial.config['dropout_rates']
best_model = XrayClassification(dropout_rates[0], dropout_rates[1], dropout_rates[2], dropout_rates[3])

if torch.cuda.is_available():
    device = torch.device('cuda')
else:
    device = torch.device('cpu')

best_model.to(device)
best_checkpoint = best_trial.checkpoint

# Load the state from the checkpoint
with best_checkpoint.as_directory() as checkpoint_dir:
    checkpoint_dict = torch.load(os.path.join(checkpoint_dir, "checkpoint.pt"))
    best_model.load_state_dict(checkpoint_dict["net_state_dict"])

# Evaluate on test data (we use the evaluate method defined at the start of Task 2)
test_results = evaluate(best_model, test_dl, None)
print(f'Test Loss: {test_results["val_loss"]}, Test Accuracy: {test_results["val_acc"]}')
```

```
Test Loss: 0.7588803172111511, Test Accuracy: 0.8108258843421936
```