```
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.nn.init as init
import os
from datetime import datetime

from torch.utils.data import Dataset, DataLoader
```

## Question 2

CNN training: Train a Convolutional Neural Network on the simulated data for each of the nine simulation settings. The goal is to use the CNN to predict the cancer status yi based on the simulated images Xi. Additionally, generate a test set of 1000 subjects using the same data generation process and evaluate the CNN's performance in terms of classification accuracy. You are free to build a CNN with arbitrary hyperparameter setting. Conduct at least 10 independent experiments for each setting by generating new datasets each time, and report the hyperparameters for the CNN, the mean and standard deviation of the classification accuracy achieved by your CNN model.

## MODEL 2

```
In [3]: model2 = torch.nn.Sequential()
    model2.add_module('conv1', torch.nn.Conv2d(in_channels=1, out_channels=2, kernel_size
    model2.add_module('relu1', torch.nn.ReLU())
    model2.add_module('pool1', torch.nn.MaxPool2d(kernel_size = 2))

model2.add_module('conv2', torch.nn.Conv2d(in_channels=2, out_channels=4, kernel_size
    model2.add_module('relu2', torch.nn.ReLU())
    model2.add_module('pool2', torch.nn.MaxPool2d(kernel_size = 2))

model2.add_module('conv3', torch.nn.Conv2d(in_channels=4, out_channels=8, kernel_size
    model2.add_module('relu3', torch.nn.ReLU())
    model2.add_module('pool3', torch.nn.MaxPool2d(kernel_size = 2))

model2.add_module('fc1', torch.nn.Flatten())

model2.add_module('fc2', torch.nn.Linear(128, 10))
    model2.add_module('relu7', torch.nn.ReLU())
    model2.add_module('fc2', torch.nn.Linear(10, 1))

model2.add_module('sigmoid', torch.nn.Sigmoid())
```

```
In [4]: def simulateData(n, mu_c, mu_n):
    y = np.random.choice([0, 1], size = n, p = [0.5, 0.5])
    m_i = np.random.poisson(lam = mu_c, size = n) * y + np.random.poisson(lam = mu_n,
```

```
simulated_data = np.zeros([n, 32, 32])
    for i in range(n):
        random_indices = np.random.choice(32 * 32, m_i[i], replace = False)
        row_indices, col_indices = np.unravel_index(random_indices, (32, 32))
        Bi = np.zeros([32, 32])
        Bi[row_indices, col_indices] = 1
        epsilon_i = np.random.normal(loc = 0, scale = np.sqrt(0.04), size = (32, 32))
        simulated_data[i] = Bi + epsilon_i
    return y, simulated_data
class dataSetPytorch(Dataset):
   def __init__(self, x, y):
        self.x = torch.from_numpy(x.reshape([-1, 1, 32, 32])).float()
        self.y = torch.from numpy(y)
   def __len__(self):
       return len(self.x)
   def __getitem__(self, idx):
        return self.x[idx], self.y[idx]
# Use that to make train and validation data here.
def makeDataLoader(numExperiments = 10):
    n = [200, 500, 1000, 200, 500, 1000, 200, 500, 1000]
    mu_n = [5, 5, 5, 5, 5, 5, 5, 5, 5]
    mu_c = [10, 10, 10, 20, 20, 20, 30, 30, 30]
    dataLoader experiment data = []
    for experiment in range(numExperiments):
        dataLoader settings = []
        for setting in range(9):
            y, simulated_data = simulateData(n = n[setting],
                                             mu_c = mu_c[setting],
                                             mu_n = mu_n[setting])
            datasetSetting = dataSetPytorch(simulated_data, y)
            dataLoader = DataLoader(datasetSetting, batch_size=25, shuffle = True)
            dataLoader_settings.append(dataLoader)
        dataLoader experiment data.append(dataLoader settings)
    return dataLoader_experiment_data
def makeTestLoader(numExperiments = 10):
   n test = 1000
   mu_n = [5, 5, 5, 5, 5, 5, 5, 5, 5]
    mu_c = [10, 10, 10, 20, 20, 20, 30, 30, 30]
    dataLoader_experiment_data = []
   for experiment in range(numExperiments):
        dataLoader_settings = []
        for setting in range(9):
            y, simulated_data = simulateData(n = n_test,
                                             mu_c = mu_c[setting],
                                             mu_n = mu_n[setting])
            datasetSetting = dataSetPytorch(simulated_data, y)
            dataLoader = DataLoader(datasetSetting, batch_size=25, shuffle = True)
            dataLoader_settings.append(dataLoader)
```

```
dataLoader_experiment_data.append(dataLoader_settings)

return dataLoader_experiment_data
```

```
In [5]: dataLoader_all_experiments_train = makeDataLoader(numExperiments = 10)
    dataLoader_all_experiments_val = makeDataLoader(numExperiments = 10)
```

## Training the models

```
In [7]: def train(name, model, train_dl, valid_dl, num_epochs = 200):
            # reinitialize weights!
             reset_weights(model)
            loss fn = torch.nn.BCELoss()
            optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
            loss_hist_train = [0] * num_epochs
            accuracy_hist_train = [0] * num_epochs
            loss_hist_valid = [0] * num_epochs
            accuracy_hist_valid = [0] * num_epochs
            best_loss = torch.inf
            for epoch in range(num_epochs):
                model.train()
                for x_batch, y_batch in train_dl:
                     pred = model(x_batch)[:, 0]
                     loss = loss_fn(pred, y_batch.float())
                      print("pred", pred, "observed", y_batch)
                     loss.backward()
                    optimizer.step()
                    optimizer.zero_grad()
                    loss_hist_train[epoch] += loss.item() * y_batch.size(0)
                     is_correct = ((pred >= 0.5).float() == y_batch).float()
                       print(is_correct)
                     accuracy_hist_train[epoch] += is_correct.sum()
                loss_hist_train[epoch] /= len(train_dl.dataset)
                accuracy_hist_train[epoch] /= len(train_dl.dataset)
                model.eval()
                with torch.no_grad():
                     for x_batch, y_batch in valid_dl:
                         pred = model(x_batch)[:, 0]
                         loss = loss_fn(pred, y_batch.float())
                         loss_hist_valid[epoch] += loss.item() * y_batch.size(0)
```

```
is_correct = ((pred >= 0.5).float() == y_batch).float()
                accuracy_hist_valid[epoch] += is_correct.sum()
        loss_hist_valid[epoch] /= len(valid_dl.dataset)
        accuracy_hist_valid[epoch] /= len(valid_dl.dataset)
        if (best_loss > loss_hist_valid[epoch]):
            path = name + "_" + datetime.now().strftime("%d_%m_%Y") + "_epoch_" + str(
            saveModel(model, path)
            best_loss = loss_hist_valid[epoch]
    return loss_hist_train, loss_hist_valid, accuracy_hist_train, accuracy_hist_valid
def plotModelPerformance(modelNum, dataSettingNum, loss_hist_train, loss_hist_valid,
                         accuracy hist train, accuracy hist valid):
    epochsX = np.arange(len(loss_hist_train)) + 1
    plt.figure(figsize=(10, 2))
   plt.subplot(1, 2, 1)
    plt.plot(epochsX, loss_hist_train, label = "train")
   plt.plot(epochsX, loss_hist_valid, label = "validation")
   plt.ylabel('Loss')
   plt.xlabel('Epoch')
   plt.legend()
   plt.subplot(1, 2, 2)
    epochsX = np.arange(len(accuracy hist train)) + 1
   plt.plot(epochsX, accuracy_hist_train, label = "train")
    plt.plot(epochsX, accuracy_hist_valid, label = "validation")
    plt.ylabel('Accuracy')
   plt.xlabel('Epoch')
   plt.legend()
   plt.suptitle("Model" + str(modelNum) + " - Data Setting " + str(dataSettingNum))
   plt.show()
    return
```

Note: In the print statment its supposed to be print("Experiment:", experiment, "Setting:", setting + 1) but forgot to change it when i ran the long experiment ..

```
In [9]:
    numExperiments = 10
    numSettings = 9
    for experiment in range(numExperiments):
        dataLoader_individual_experiment_train = dataLoader_all_experiments_train[experiment]

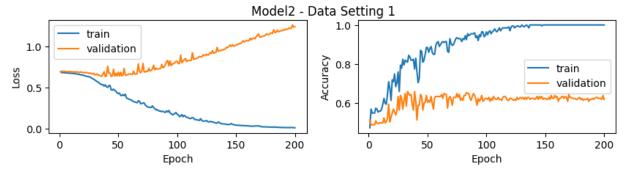
    for setting in range(numSettings):
        print("Experiment:", experiment, "Setting:", setting)
        folderPath = 'setting' + str(setting + 1)
        if not os.path.exists(folderPath):
            # Create the folder
            os.makedirs(folderPath)

        n = len(dataLoader_individual_experiment_train[setting].dataset)
        print("N:", n)

        modelName = "./" + folderPath + "/modelSetting" + str(setting + 1) + "_Experim
```

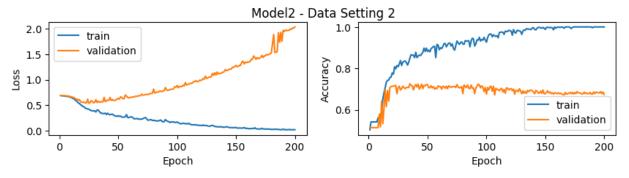
Experiment: 0 Setting: 0

N: 200



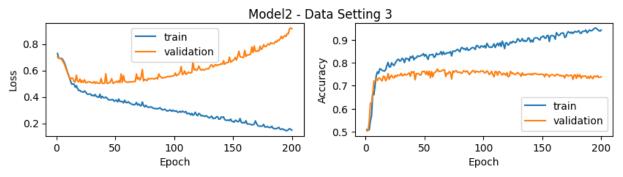
Experiment: 0 Setting: 1

N: 500

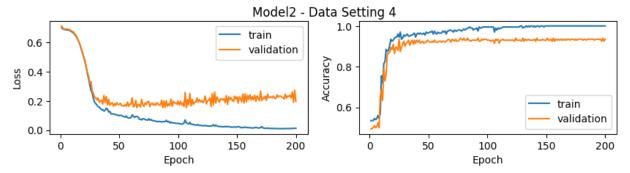


Experiment: 0 Setting: 2

N: 1000

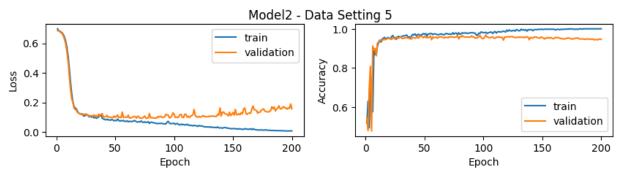


Experiment: 0 Setting: 3



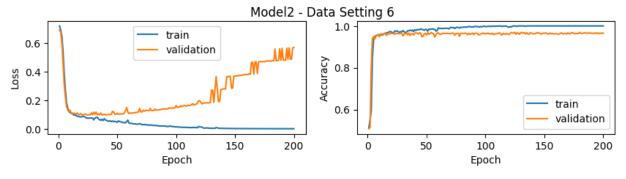
Experiment: 0 Setting: 4

N: 500



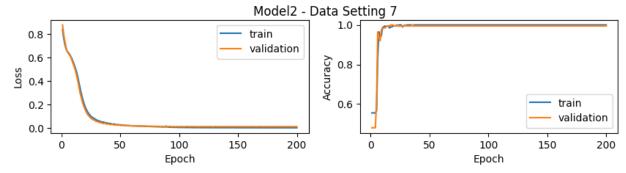
Experiment: 0 Setting: 5

N: 1000



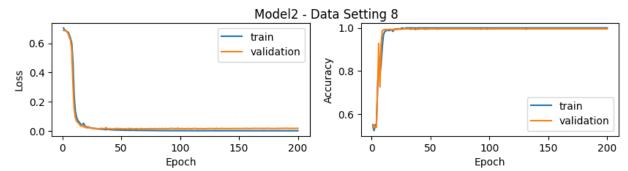
Experiment: 0 Setting: 6

N: 200

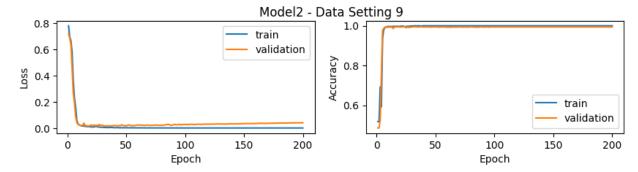


Experiment: 0 Setting: 7

N: 500

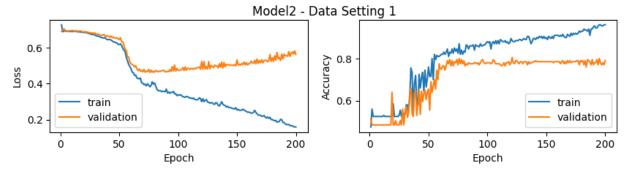


Experiment: 0 Setting: 8



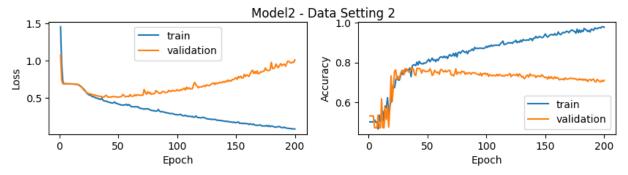
Experiment: 1 Setting: 0

N: 200



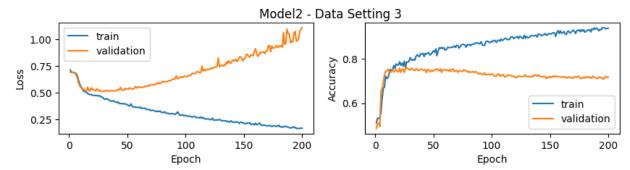
Experiment: 1 Setting: 1

N: 500

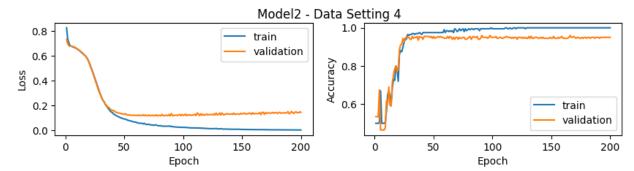


Experiment: 1 Setting: 2

N: 1000

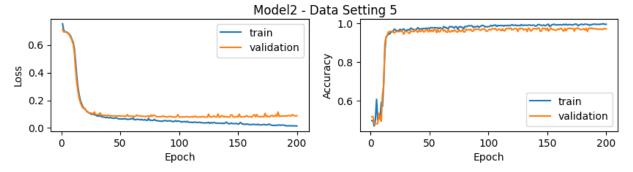


Experiment: 1 Setting: 3



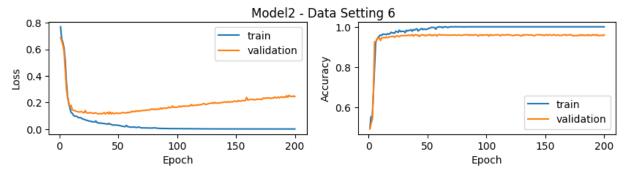
Experiment: 1 Setting: 4

N: 500



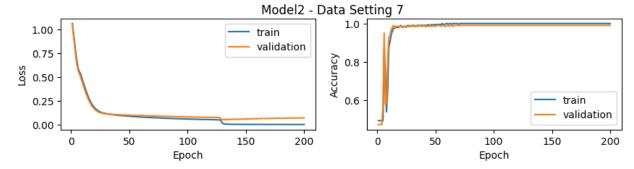
Experiment: 1 Setting: 5

N: 1000

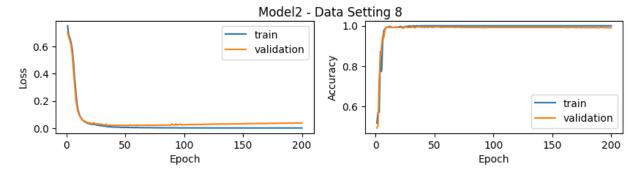


Experiment: 1 Setting: 6

N: 200

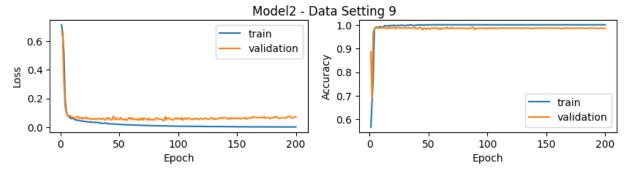


Experiment: 1 Setting: 7



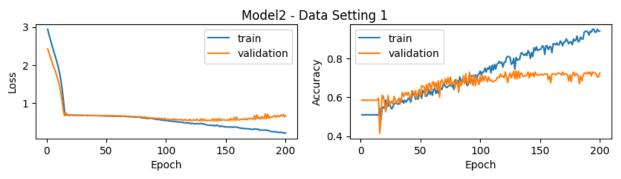
Experiment: 1 Setting: 8

N: 1000



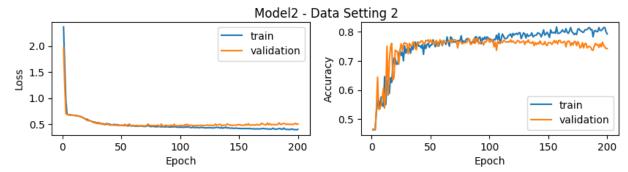
Experiment: 2 Setting: 0

N: 200

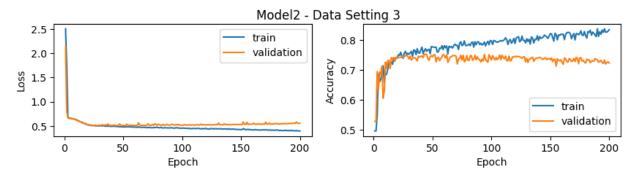


Experiment: 2 Setting: 1

N: 500

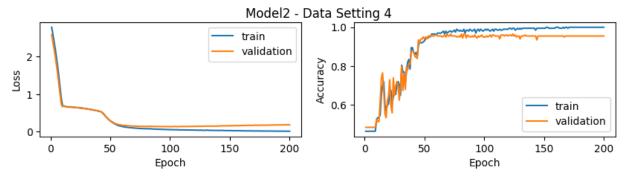


Experiment: 2 Setting: 2



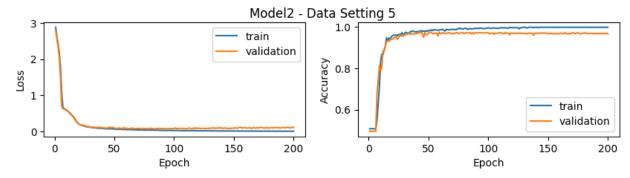
Experiment: 2 Setting: 3

N: 200



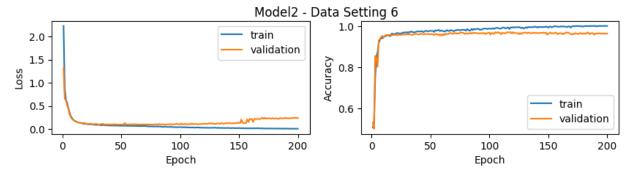
Experiment: 2 Setting: 4

N: 500

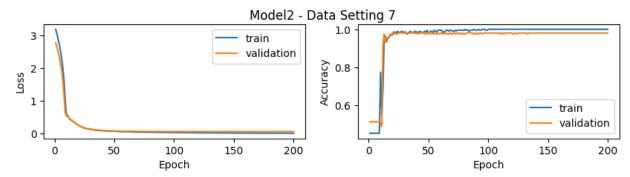


Experiment: 2 Setting: 5

N: 1000

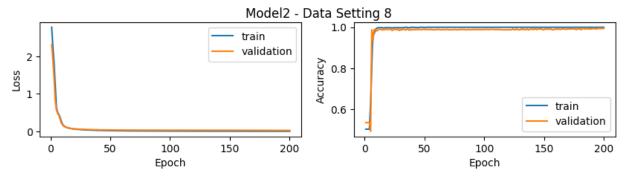


Experiment: 2 Setting: 6



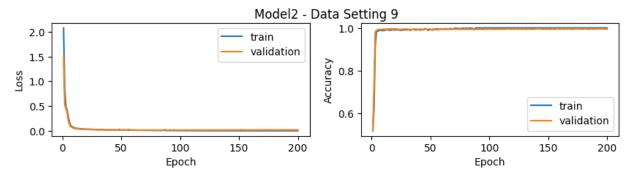
Experiment: 2 Setting: 7

N: 500



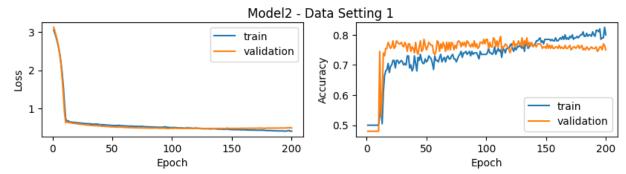
Experiment: 2 Setting: 8

N: 1000

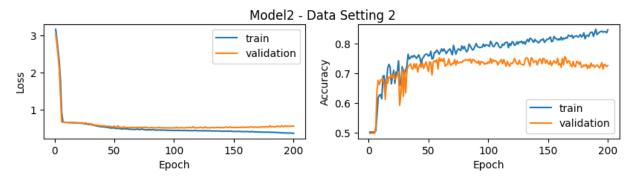


Experiment: 3 Setting: 0

N: 200

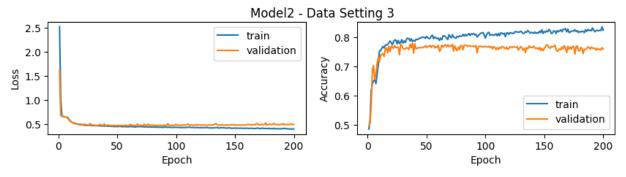


Experiment: 3 Setting: 1



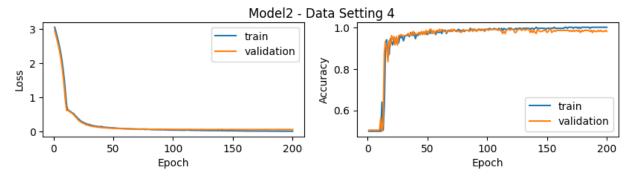
Experiment: 3 Setting: 2

N: 1000



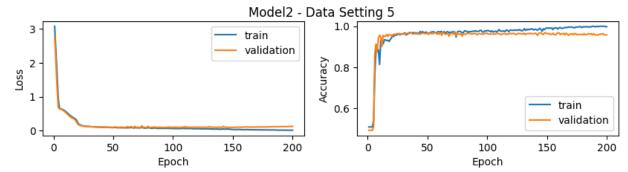
Experiment: 3 Setting: 3

N: 200

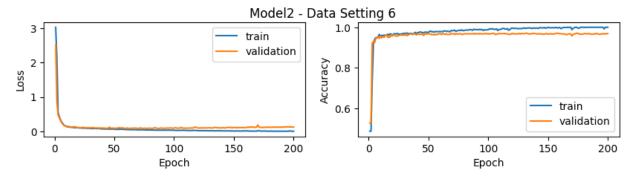


Experiment: 3 Setting: 4

N: 500

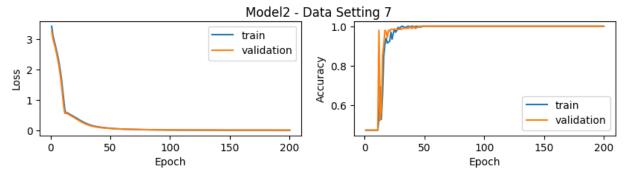


Experiment: 3 Setting: 5



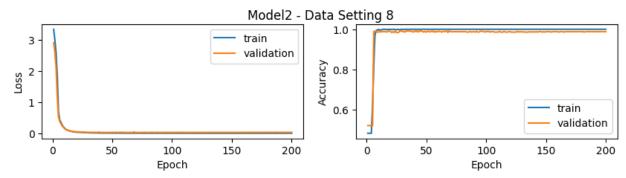
Experiment: 3 Setting: 6

N: 200



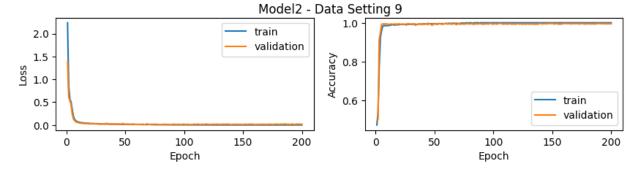
Experiment: 3 Setting: 7

N: 500

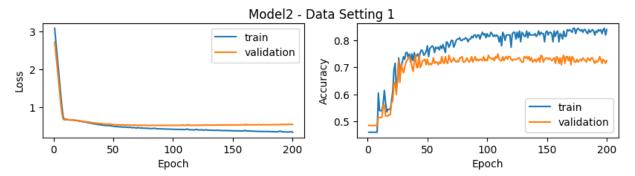


Experiment: 3 Setting: 8

N: 1000

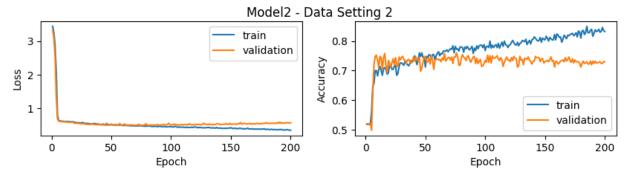


Experiment: 4 Setting: 0



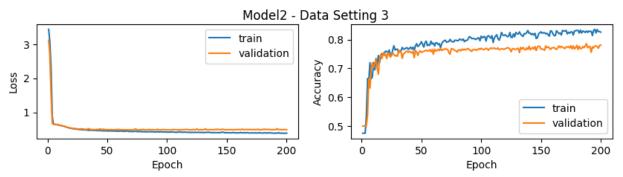
Experiment: 4 Setting: 1

N: 500



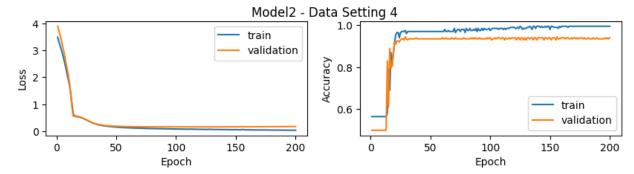
Experiment: 4 Setting: 2

N: 1000

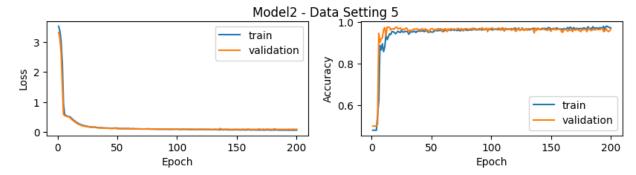


Experiment: 4 Setting: 3

N: 200

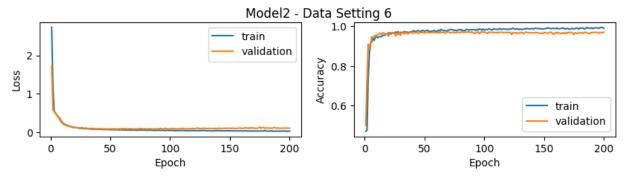


Experiment: 4 Setting: 4



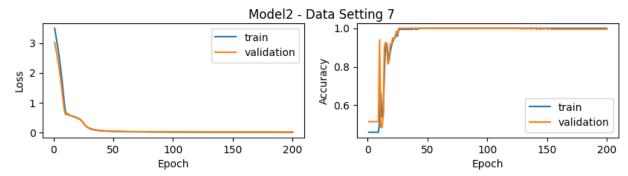
Experiment: 4 Setting: 5

N: 1000



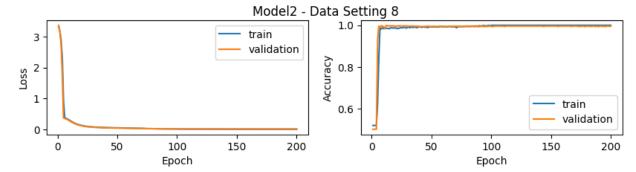
Experiment: 4 Setting: 6

N: 200

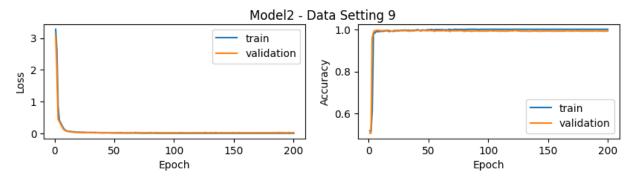


Experiment: 4 Setting: 7

N: 500

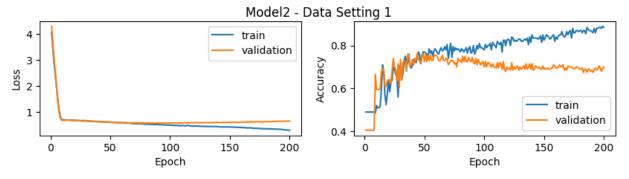


Experiment: 4 Setting: 8



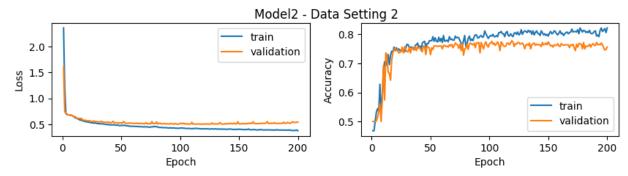
Experiment: 5 Setting: 0

N: 200



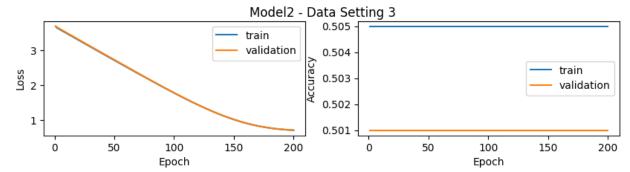
Experiment: 5 Setting: 1

N: 500

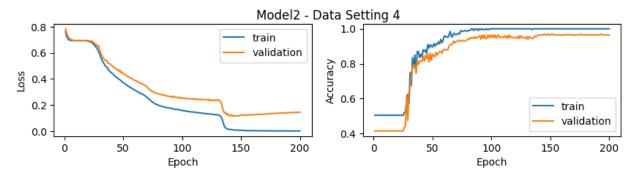


Experiment: 5 Setting: 2

N: 1000

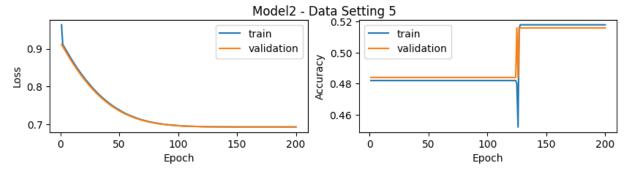


Experiment: 5 Setting: 3



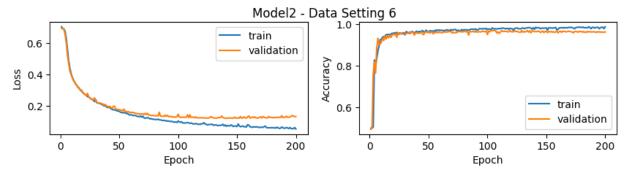
Experiment: 5 Setting: 4

N: 500



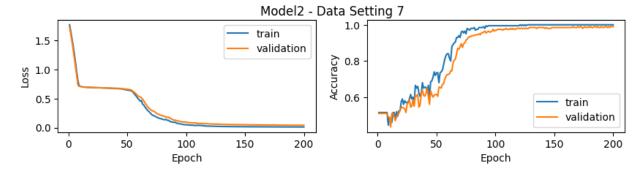
Experiment: 5 Setting: 5

N: 1000

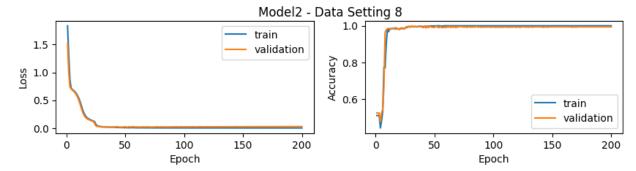


Experiment: 5 Setting: 6

N: 200

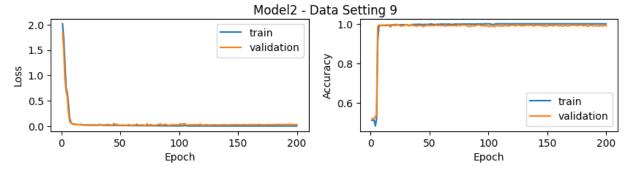


Experiment: 5 Setting: 7



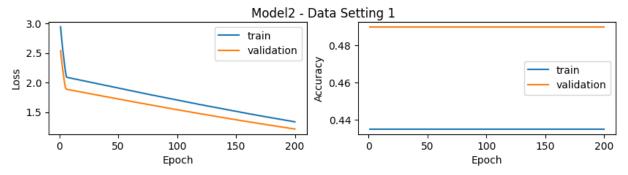
Experiment: 5 Setting: 8

N: 1000



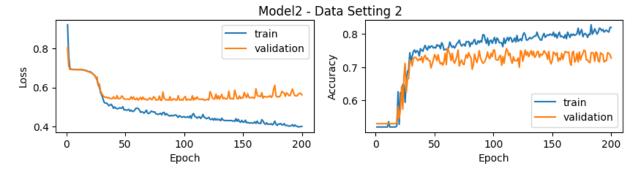
Experiment: 6 Setting: 0

N: 200

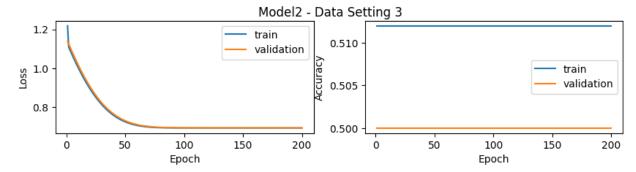


Experiment: 6 Setting: 1

N: 500

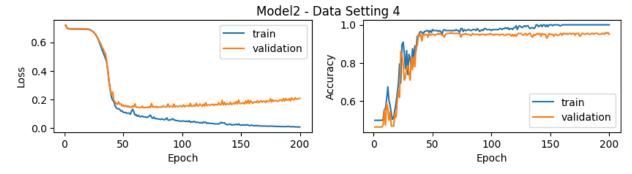


Experiment: 6 Setting: 2



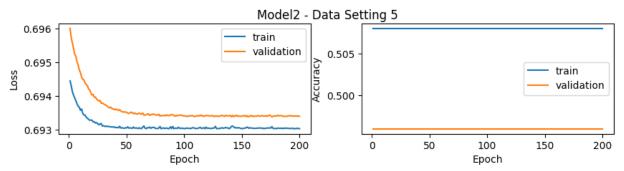
Experiment: 6 Setting: 3

N: 200



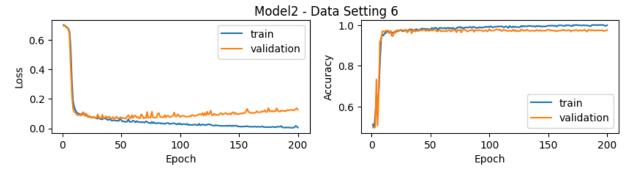
Experiment: 6 Setting: 4

N: 500

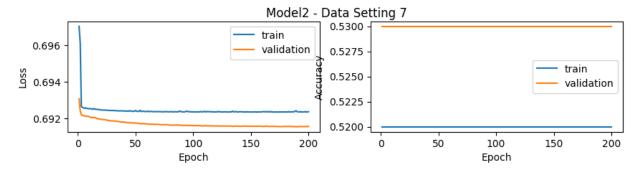


Experiment: 6 Setting: 5

N: 1000

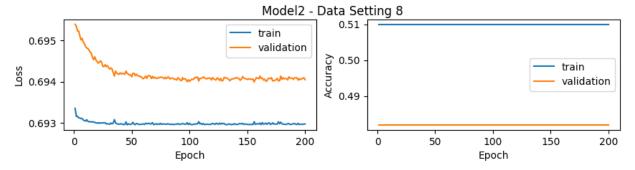


Experiment: 6 Setting: 6



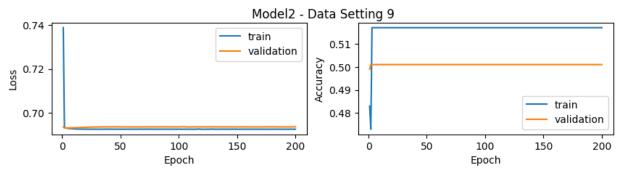
Experiment: 6 Setting: 7

N: 500



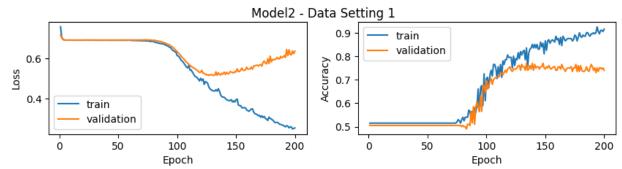
Experiment: 6 Setting: 8

N: 1000

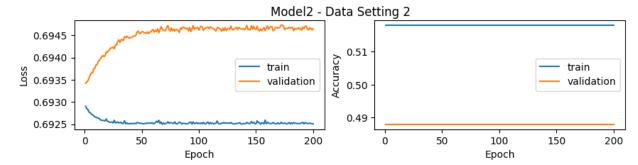


Experiment: 7 Setting: 0

N: 200

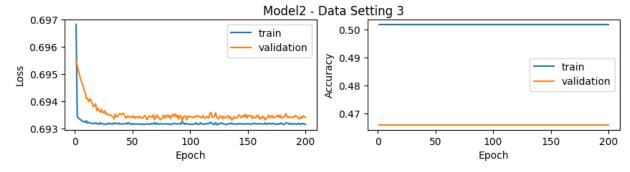


Experiment: 7 Setting: 1



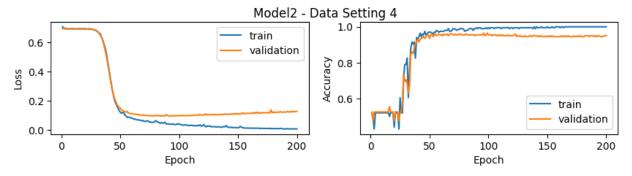
Experiment: 7 Setting: 2

N: 1000



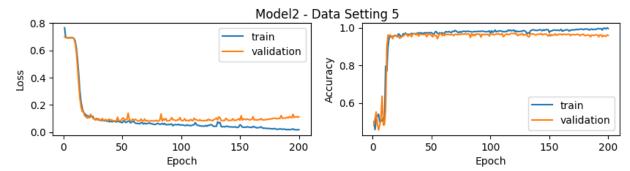
Experiment: 7 Setting: 3

N: 200

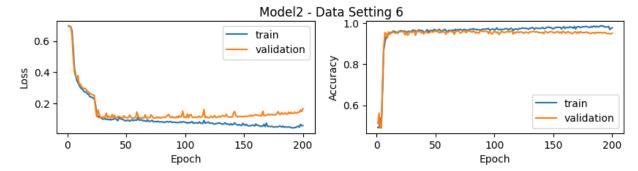


Experiment: 7 Setting: 4

N: 500

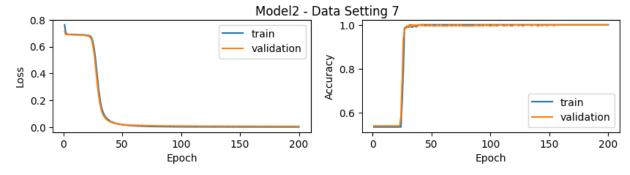


Experiment: 7 Setting: 5



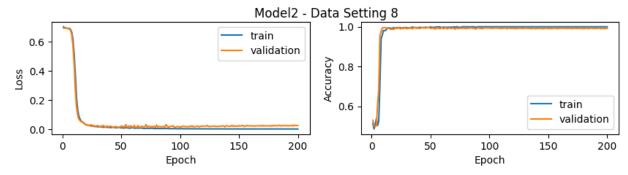
Experiment: 7 Setting: 6

N: 200



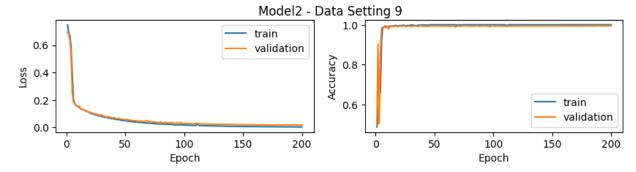
Experiment: 7 Setting: 7

N: 500

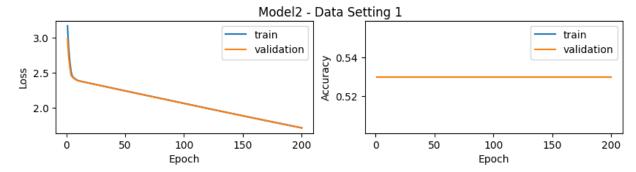


Experiment: 7 Setting: 8

N: 1000

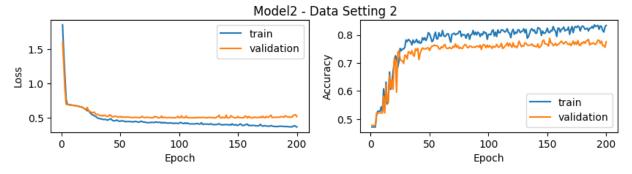


Experiment: 8 Setting: 0



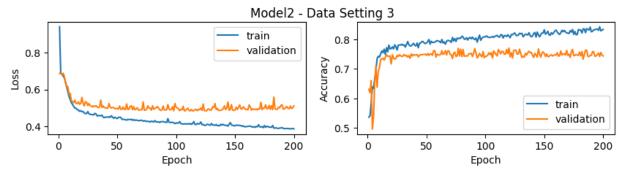
Experiment: 8 Setting: 1

N: 500



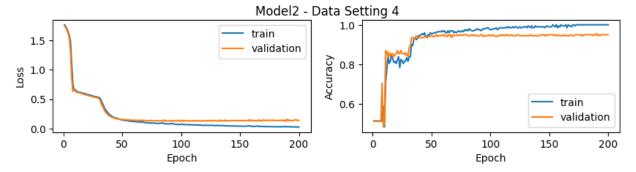
Experiment: 8 Setting: 2

N: 1000

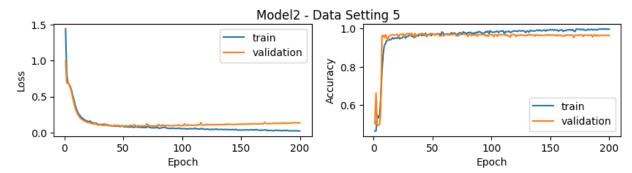


Experiment: 8 Setting: 3

N: 200

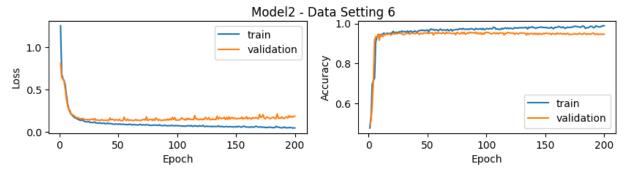


Experiment: 8 Setting: 4



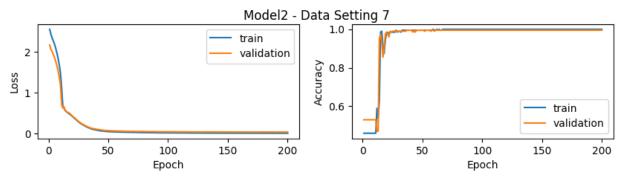
Experiment: 8 Setting: 5

N: 1000



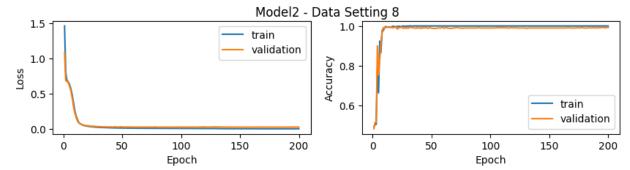
Experiment: 8 Setting: 6

N: 200

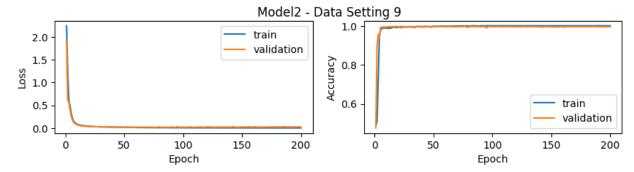


Experiment: 8 Setting: 7

N: 500

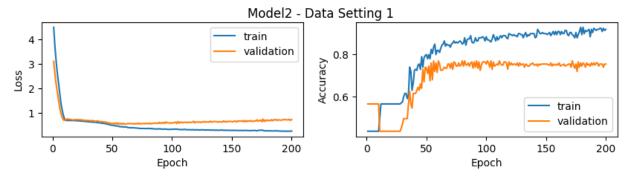


Experiment: 8 Setting: 8



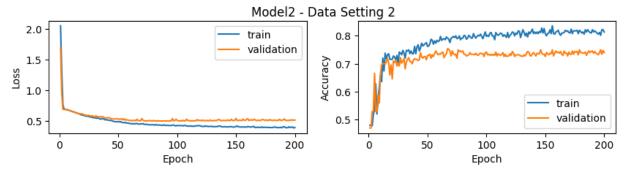
Experiment: 9 Setting: 0

N: 200



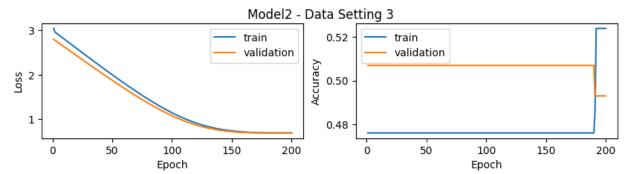
Experiment: 9 Setting: 1

N: 500

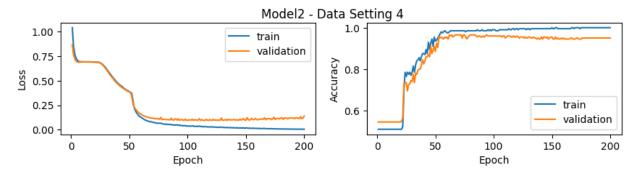


Experiment: 9 Setting: 2

N: 1000

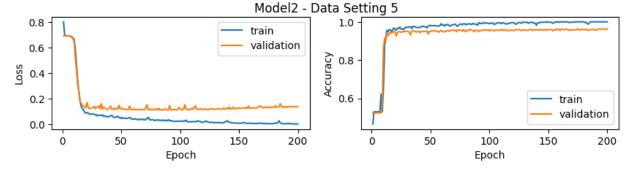


Experiment: 9 Setting: 3



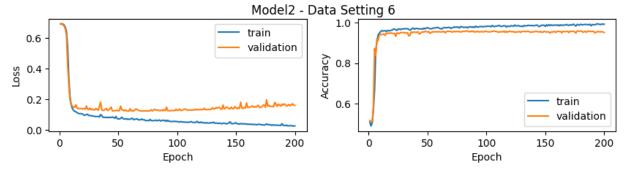
Experiment: 9 Setting: 4

N: 500



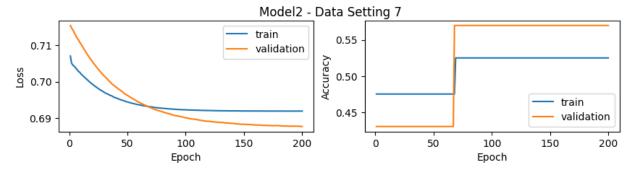
Experiment: 9 Setting: 5

N: 1000

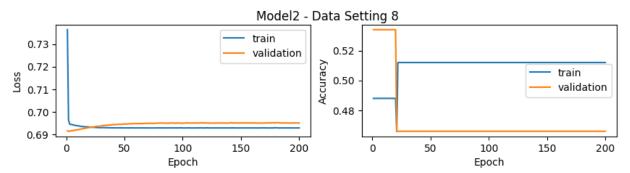


Experiment: 9 Setting: 6

N: 200

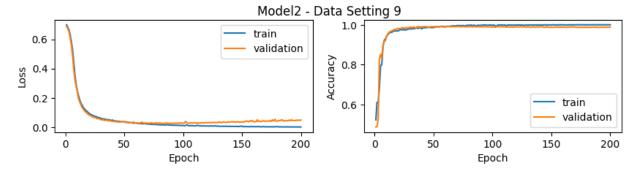


Experiment: 9 Setting: 7



Experiment: 9 Setting: 8

N: 1000



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