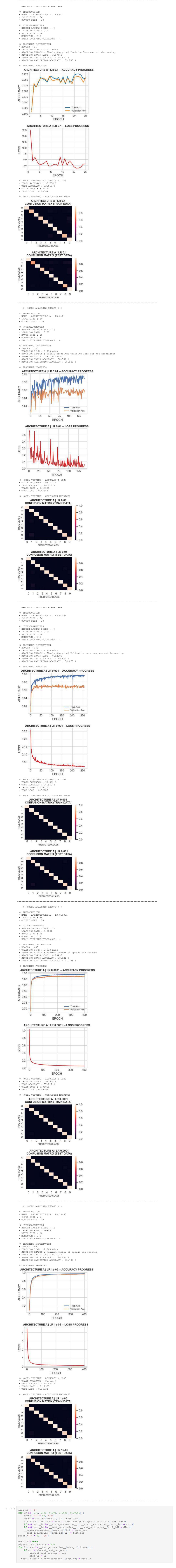
import torch import torch.nn as nn import json import pickle import numpy as np from random import shuffle, random from time import time import seaborn as sns import matplotlib.pyplot as plt from collections import Counter from math import log2 # Extract data from the specified location def Extract Data (loc) : file = open(loc, 'r') data = file.read() $data = data.split('\n')[:-1]$ data = [x.split(',') for x in data] data = [(x[:-1], eval(x[-1])) for x in data] data = [([eval(x) for x in X], _) for X, _ in data] return data # Given the probability distribution of a discrete attribute for its different values # in the form of a vector, find the entropy of that attribute. def Entropy (dist) : vals = np.array(list(dist.values())) vals = vals / vals.sum() s = sum(vals * np.log2(vals))**if** (s == 0.0) : **return** 0 return -1 * s # Given the data matrix, study the various properties of the attributes. def Study_Attributes (data_matrix) : std_dev_atts = np.std(data_matrix, axis = 0) # Study standard deviation in the values of the attributes fig = plt.figure() ax = fig.add subplot() sns.set(font scale = 1.2)sns.heatmap(std dev atts.reshape((8, 8))) plt.title('STD. DEVIATION IN THE ATTRIBUTE VALUES\n', fontsize=13, fontweight='bold') ax.axes.get_xaxis().set_visible(False) ax.axes.get yaxis().set visible(False) plt.plot() plt.savefig('PREPROCESSING std dev attributes.png') # Study diversity in the values of the attributes distinct_att_vals = np.zeros(64, dtype = np.int32) attribute entropies = [] for att in range(64) : dist = Counter(data matrix[:, att]) distinct_att_vals[att] = len(dist.keys()) attribute_entropies.append(Entropy(dist)) attribute_entropies = np.array(attribute_entropies) fig = plt.figure() ax = fig.add subplot() sns.set(font scale = 1.2)sns.heatmap(distinct att vals.reshape((8, 8))) plt.title('DIVERSITY IN THE ATTRIBUTE VALUES\n', fontsize=13, fontweight='bold') ax.axes.get_xaxis().set_visible(False) ax.axes.get_yaxis().set_visible(False) plt.plot() plt.savefig('PREPROCESSING diversity attributes.png') # Study entropy in the values of the attributes fig = plt.figure() ax = fig.add subplot() sns.set(font scale = 1.2)sns.heatmap(attribute_entropies.reshape((8, 8))) plt.title('ENTROPY OF THE ATTRIBUTES\n', fontsize=13, fontweight='bold') ax.axes.get xaxis().set visible(False) ax.axes.get yaxis().set visible(False) plt.plot() plt.savefig('PREPROCESSING entropy attributes.png') return std dev atts, distinct att vals, attribute entropies # Filter those attributes that have entropy below some threshold. Please refer # to the report for more theoretical details. def Filter_Attributes (data , entropy_thresh = 0.1) : X = np.array([X for X, _ in data]) _, _, attribute_entropies = Study_Attributes(X) $data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute_entropies[t] >= entropy thresh], y) for X, y in data_filtered = [([X[t] for t in range(64) if attribute$ return data filtered # Load data from the given locations. One location is for # the training data and the other is for test data. def Load_Data (loc1 , loc2) : data = Extract_Data(loc1) + Extract Data(loc2) # merge the sub-datasets data = Filter Attributes(data) # filter attributes return data # Split the entire dataset into train & test in the given ratio. def Split (data , train_split_ratio = 0.8) : shuffle (data) size = round(train split ratio * len(data)) train_set = data[:size] test set = data[size:] return train_set, test_set # Train & test both should have a balanced frequency of data samples # from each of the class otherwise unreliable results can be obtained. class_samples = [[xy for xy in data if xy[1] == c] for c in range(10)] [shuffle(_) **for** _ **in** class_samples] train set = [] test set = [] for c in range(10) : b = random() * 0.4 - 0.2 # small deviations = round((train_split_ratio + b) * len(class_samples[c])) train_set.extend(class_samples[c][:s]) test_set.extend(class_samples[c][s:]) shuffle(train set) shuffle(test set) return train set, test set In [4]: # Package the train data into mini-batches of the given size and # return the list of batches. def Make Batches (train_data , batch_size = 32) : shuffle(train data) batches = list() for start in range(0, len(train data), batch size) : end = start + batch size batch, labels = list(zip(*train_data[start:end])) labels = torch.Tensor(labels).long() batch = torch.Tensor(batch).float() batches.append((batch, labels)) return batches # Multi-Layer Perceptron Classifier class Handwritten Digits Classifier (nn.Module) : def __init__ (self , name , input_size , hidden_layer_sizes , output size , lr = 0.01 , momentum = 0.8 , early stopping tol = 4) : super(Handwritten_Digits_Classifier, self).__init__() self. name = name self. input size = input size self. hidden layer sizes = hidden layer sizes self.__output_size = output_size self. hidden layers = [] hidden input size = input size for size in hidden layer sizes : layer = nn.Linear(hidden input size, size, bias = True) self. hidden layers.append(layer) hidden_input_size = size self. output layer = nn.Linear(hidden input size, output size, bias = True) self. loss = nn.CrossEntropyLoss() self. optimizer = torch.optim.SGD(self.parameters(), lr = lr, momentum = momentum) self. training history = { 'train loss progress' : [], 'train acc progress' : [], 'valid_acc_progress' : [] # Additional information self. stopping reason = 'Kernel interrupted' self.__learning_rate = lr self. momentum = momentum self. early stopping_tol = early_stopping_tol self. training time = None self. batch size = None def forward (self , batch input) : batch output = batch input for layer in self. hidden layers : batch output = layer(batch output) batch_output = self.__output_layer(batch_output) return batch output def backward (self , pred_label_dist , true_labels) : loss = self. loss(pred label dist, true labels) self.__optimizer.zero_grad() loss.backward() self. optimizer.step() return loss.item() def accuracy (self , data) : self.eval() total correct = 0 tensor samples = Make Batches(data, 1) for , (sample, label) in enumerate(tensor samples) : label dist = self(sample) pred = torch.argmax(label dist, dim = 1) corr count = (pred == label).sum() total correct += corr count self.train() return total correct.item() / len(data) def loss (self , data) : self.eval() total loss = 0 tensor samples = Make Batches(data, 1) for _, (sample, label) in enumerate(tensor_samples) : label dist = self(sample) total loss += self. loss(label dist, label).item() self.train() return total_loss / len(data) def predict (self , x) : x = np.array(x, dtype = np.float32).reshape((1, -1))x = torch.from numpy(x)label dist = self(x)pred = torch.argmax(label dist, dim = 1) return pred.item() def confusion matrix (self , data) : cf = np.zeros((10, 10), dtype = np.int32)for x, y in data : cf[y][self._predict(x)] += 1 return cf def _plot_confusion_matrix (self , data , loc , title = 'CONFUSION MATRIX (TRAIN DATA)') : cf = self. confusion matrix(data) fig = plt.figure(figsize=(4, 3)) ax = fig.add subplot() sns.set(font scale = 1.0) sns.heatmap(cf / np.sum(cf, axis = 1).reshape(10, 1)) plt.title(self. name + '\n' + title, fontsize=11, fontweight='bold') plt.xlabel('PREDICTED CLASS', fontsize=9) plt.ylabel('TRUE CLASS', fontsize=9) plt.tight layout() plt.show() return def plot training history (self , loc) : fontsize = 12plt.style.use('seaborn-whitegrid') epochs = len(self. training history['train loss progress']) X = list(range(1, 1 + epochs))plt.figure(figsize=(4.2, 3.2)) plt.plot(X, self.__training_history['train_acc_progress'], linewidth = 2.2) plt.plot(X, self. training history['valid acc progress'], linewidth = 1.9) plt.xlabel('EPOCH', fontsize=fontsize) plt.ylabel('ACCURACY', fontsize=fontsize) plt.legend(['Train Acc.', 'Validation Acc.'], fontsize = 9) plt.title(self. name + ' -- ACCURACY PROGRESS', fontsize=11, fontweight='bold') plt.tight layout() plt.show() plt.figure(figsize=(4.2, 3.2)) plt.plot(X, self.__training_history['train_loss_progress'], linewidth = 2, color = '#d62728') plt.xlabel('EPOCH', fontsize=fontsize) plt.ylabel('LOSS', fontsize=fontsize) plt.title(self.__name + ' -- LOSS PROGRESS', fontsize=11, fontweight='bold') plt.tight layout() plt.show() return # Prints a detailed report about training, accuracies, losses etc including the # plots and confusion matrices. def model analysis report (self , train data , test data) : print(' +++ MODEL ANALYSIS REPORT +++') print('\n >> INTRODUCTION') print(' • NAME :', self. name) print(' • INPUT SIZE :', self.__input_size) print(' • OUTPUT SIZE :', self.__output_size) print('\n >> HYPERPARAMETERS') print(' • HIDDEN LAYERS SIZES :', self. hidden layer sizes) print(' • LEARNING RATE :', self. learning rate) print(' • BATCH SIZE :', self.__batch_size) print(' • MOMENTUM :', self. momentum) print(' • EARLY STOPPING TOLERANCE :', self.__early_stopping_tol) print('\n >> TRAINING INFORMATION') print(' • EPOCHS :', len(self. training history['train loss progress'])) print(' • TRAINING TIME : {:.3f} mins'.format(self. training time / 60)) print(' • STOPPING REASON :', self. stopping reason) print(' • STOPPING TRAIN LOSS : {:.5f}'.format(self.__training_history['train_loss_progress'][-1])) print(' • STOPPING TRAIN ACCURACY : {:.3f} %'. format(100 * self.__training_history['train_acc_progress'][-1])) print(' • STOPPING VALIDATION ACCURACY : {:.3f} %'. format(100 * self.__training_history['valid_acc_progress'][-1])) print('\n >> TRAINING PROGRESS') self._plot_training_history(self.__name + str(self.__learning_rate)[2:] + 'prog.png') print('\n >> MODEL TESTING - ACCURACY & LOSS') train acc = 100 * self. accuracy(train data) test acc = 100 * self. accuracy(test_data) print(' • TRAIN ACCURACY : {:.3f} %'.format(train_acc)) print(' • TEST ACCURACY : {:.3f} %'.format(test acc)) print(' • TRAIN LOSS : {:.5f}'.format(self. loss(train data))) print(' • TEST LOSS : {:.5f}'.format(self._loss(test_data))) print('\n >> MODEL TESTING - CONFUSION MATRICES') self._plot_confusion_matrix(train_data, self.__name + str(self.__learning_rate)[2:] + 'train_cf.png', title = 'CONFUSION MATRIX (TRAIN DATA)') self._plot_confusion_matrix(test_data, self.__name + str(self.__learning_rate)[2:] + 'test_cf.png', title = 'CONFUSION MATRIX (TEST DATA)') return train_acc, test_acc # Strict training is used when we have to train a model for a specific number of epochs, no matter if # the model starts to over-fit or the train loss starts increasing. So the model must be trained exactly # for a certain number of epochs, without early-stopping, therefore there is no need for validation set. # Though, the accuracy of the model on the test set is registered while training, after every epoch. This # type of training is used only while tuning the hyperparameter "Number of Training Epochs" in the 4th part def _strict_train (self , total_epochs , train_data , test_data , batch size = 16 , verbose = False , verboseGap = 1) : self.train() train acc prog = [] test_acc_prog = [] for epoch in range(1, 1 + total epochs) : total loss = 0.0total correct = 0 batches = Make_Batches(train_data, batch_size) for , (batch, labels) in enumerate(batches) : label dists = self(batch) loss = self.backward(label dists, labels) total loss += loss pred = torch.argmax(label dists, dim = 1) corr_count = (pred == labels).sum() total_correct += corr_count train acc = self. accuracy(train data) avg loss = round(self. loss(train data), 5) test_acc = round(self._accuracy(test_data), 5) train_acc_prog.append(train_acc) test_acc_prog.append(test_acc) if verbose and (epoch - 1) % verboseGap == 0 : print(' EPOCH : {:3d} | TRAIN LOSS : {:.5f} | TRAIN ACC. : {:.5f} | TEST ACC. : {:.5f} '. format(epoch, avg loss, train acc, test acc)) self.eval() return train_acc_prog, test_acc_prog # Training on the train data. The training can terminate due to -# EARLY STOPPING (very common) - when validation accuracy starts decreasing or train loss starts increasing # MAX EPOCHS REACHED (rare) - when the model is trained for the maximum allowed number of epochs. # TERMINAL ACCURACY REACHED (very rare) - when model's accuracy on train set exceeds a very high threshold. def _train (self , train_data , validation_ratio = 0.2 , batch_size = 16 , total_epochs = 200 , terminal_train_acc = 99.0 , verbose = False) : self.__batch_size = batch_size self.train() L = len(train_data) train size = int(0.8 \star L) train set = train data[:train size] valid_set = train_data[train_size:] train_loss_change = [1] * self.__early_stopping_tol valid acc change = [1] * self.__early_stopping_tol last train loss = float('inf') last valid acc = 0.0 start_time = time() for epoch in range(1, 1 + total_epochs) : total loss = 0.0total correct = 0 batches = Make_Batches(train_set, batch_size) for _, (batch, labels) in enumerate(batches) : label dists = self(batch) loss = self.backward(label_dists, labels) total loss += loss pred = torch.argmax(label_dists, dim = 1) corr count = (pred == labels).sum() total_correct += corr_count train acc = self. accuracy(train set) avg loss = round(self. loss(train set), 5) valid_acc = round(self._accuracy(valid_set), 5) self. training history['train loss progress'].append(avg loss) self. training history['train acc progress'].append(train acc) self.__training_history['valid_acc_progress'].append(valid_acc) if verbose : print(' EPOCH : {:3d} | TRAIN LOSS : {:.5f} | TRAIN ACC. : {:.5f} | VALIDATION ACC. : {:.5f} ' format(epoch, avg_loss, train_acc, valid_acc)) if train acc >= terminal train acc : self. training time = time() - start time if verbose : print('\n [STOPPING : Terminal training accuracy reached]') self.__stopping_reason = 'Terminal training accuracy was reached' self.eval() return if valid_acc >= last_valid_acc : valid_acc_change = valid_acc_change[1:] + [1] last_valid_acc = valid_acc else : valid_acc_change = valid_acc_change[1:] + [0] if sum(valid acc change) == 0 : self.__training_time = time() - start_time if verbose : print('\n [EARLY STOPPING : Validation Accuracy not increasing]') self.__stopping_reason = '[Early Stopping] Validation accuracy was not increasing' self.eval() return last_valid_acc = valid_acc if avg_loss <= last_train_loss :</pre> train_loss_change = train_loss_change[1:] + [1] last_train_loss = avg_loss train_loss_change = train_loss_change[1:] + [0] if sum(train_loss_change) == 0 : self.__training_time = time() - start_time if verbose : print('\n [EARLY STOPPING : Training Loss not decreasing]') self.__stopping_reason = '[Early Stopping] Training loss was not decreasing' self.eval() return last_train_loss = avg_loss self.__training_time = time() - start_time if verbose : print('\n [STOPPING : Max no. of training epochs reached]') self. stopping reason = 'Maximum number of epochs was reached' self.eval() return def Data_Matrix (data) : $X = [x for x, _in data]$ X = np.array(X)X = X.transpose() return X def Covariance Matrix (data) : N = len(data)X = Data_Matrix(data) mean = X.mean(axis = 1)mean = np.tile(mean, (N,1)).transpose() X_minus_mean = X - mean cov = np.matmul(X_minus_mean, X_minus_mean.transpose()) return cov / N # Return the first and second principal component directions for the # given data matrix. def PCA_Component_Weights (data , verbose = False) : cov = Covariance_Matrix(data) d = cov.shape[0]if verbose : eig = list(np.linalg.eig(cov)[0]) eig.sort(reverse = True) for i in range(len(eig)) : print(' EIGEN VAL {:2d} : {:.5f}'.format(i+1, eig[i])) eig = np.linalg.eig(cov) W = [(i, eig[1][:,i]) for i in range(d)] # all the components W.sort(key = lambda k: eig[0][k[0]], reverse = True) # sort the components by their corresponding eigen-value $W = [t for_, t in W]$ return np.array(W[:2]) # return the 1st & 2nd principal component directions # Given the matrix W, this function returns the reduced dimensionality # data points for the given data (reduced to 2 dimensions). def Two Dim Points (data , W) : x_higher = Data_Matrix(data) $x_2d = np.matmul(W, x_higher).transpose()$ l = len(data)transformed = [[list(x 2d[i]), data[i][1]] for i in range(l)] return transformed # Plots data samples (reduced to 2 dimensions) on a Cartesian plane, belonging to the given classes def Plot_2D_Transformed_Data (data_full , classes = list(range(10)) , s = 3 , alpha = 1) : data = [[x, y] for x, y in data_full if y in classes] points = [p for p, _ in data] x, y = list(zip(*points))colors = ['#1aa3ff', '#ff8c00', 'tab:green', '#ff1a1a', '#d24dff', '#bf8040', '#ff4da6', '#DCDCDC', '#ffff1a', '#8cffff'] col = [colors[t[1]] for t in data] plt.style.use("dark_background") plt.figure(figsize=(4, 3)) plt.scatter(x, y, color = col, s = s, alpha = alpha)plt.grid(False) filename = 'PART5 classes' for c in classes : filename += ' ' + str(c) filename += '.png' title = 'CLASSES - ' + str(classes) plt.title(title, fontsize=11, fontweight='bold') plt.tight layout() plt.savefig(filename) plt.show() plt.style.use("default") def Plot_All_Classes_In_2D (data_full) : colors = ['#1aa3ff', '#ff8c00', 'tab:green', '#ff1a1a', '#d24dff', '#bf8040', '#ff4da6', '#DCDCDC', '#ffff1a', '#8cffff'] for c in range(10) : data = [[x, y] for x, y in data_full if y == c] points = [p for p, _ in data] x, y = list(zip(*points))col = [colors[t[1]] for t in data] plt.style.use("dark_background") plt.grid(False) plt.subplot(4, 3, c+1)plt.scatter(x, y, color = col, s = 3) plt.tight_layout() plt.savefig('PART5_all_classes.png') plt.show() plt.style.use("default") # A helper function that trains and returns an MLP classifier with the given hyperparameters. def Trainer (arch , lr , train_data , batch_size = 16 , momentum = 0.8 , early_stopping_tol = 4) : layers = { 'A' : [], 'B' : [2], : [6], 'D' : [2, 3], 'E' : [3, 2] input dim = len(train data[0][0]) model_name = 'ARCHITECTURE ' + arch + ' | LR ' + str(lr) model = Handwritten Digits Classifier (model name, input dim, layers[arch], 10, lr = lr, momentum = momentum, early stopping tol = early stopping tol) model._train(train_data, total_epochs = 400, batch_size = batch_size) return model data = Load_Data('optdigits.tra', 'optdigits.tes') train data, test data = Split(data, 0.75) STD. DEVIATION IN THE ATTRIBUTE VALUES - 6 **DIVERSITY IN THE ATTRIBUTE VALUES** - 16 - 14 **ENTROPY OF THE ATTRIBUTES** - 3.5 - 3.0 - 1.5 - 1.0 **PART 02** The following MLP architectures are trained, on the preprocessed dataset, 5 times with the learning rates as 10-1, 10-2, 10-3, 10-4 and 10-5. The length of the list denotes the number of hidden layers and the list itself consists of the number of nodes in each hidden layer (in the respective order from the input layer to the output layer). (A) Hidden Layers - [] (B) Hidden Layers - [2] (C) Hidden Layers - [6] (D) Hidden Layers - [2, 3] (E) Hidden Layers - [3, 2] Train 5 MLP models for each of the above architectures, with each one of the above 5 learning rates (25 models in total). Report the various details related to training like training time and number of epochs. Finally evaluate each of the models post-training on the training set and test set and report their respective accuracies and losses. best lr for mlp architectures = dict() __train_accuracies__ = dict() __test_accuracies__ = dict() In [14]: arch id = 'A' for lr in [0.1, 0.01, 0.001, 0.0001, 0.00001] : print('--' * 50, '\n') model = Trainer(arch id, lr, train data) train acc, test acc = model. model analysis report(train data, test data) if not arch_id in __train_accuracies__ : __train_accuracies__[arch_id] = dict()
if not arch_id in __test_accuracies__ : __test_accuracies__[arch_id] = dict() __train_accuracies__[arch_id][lr] = train_acc test accuracies__[arch_id][lr] = test_acc print('--' * 50, '\n') best lr = None highest test acc obs = 0.0for lr, acc in __test_accuracies__[arch_id].items() : if acc > highest_test_acc_obs : highest test acc obs = acc best lr = lr _best_lr_for_mlp_architectures__[arch_id] = best_lr



for lr, acc in __test_accuracies__[arch_id].items() :

__best_lr_for_mlp_architectures__[arch_id] = best_lr

if acc > highest_test_acc_obs :
 highest_test_acc_obs = acc

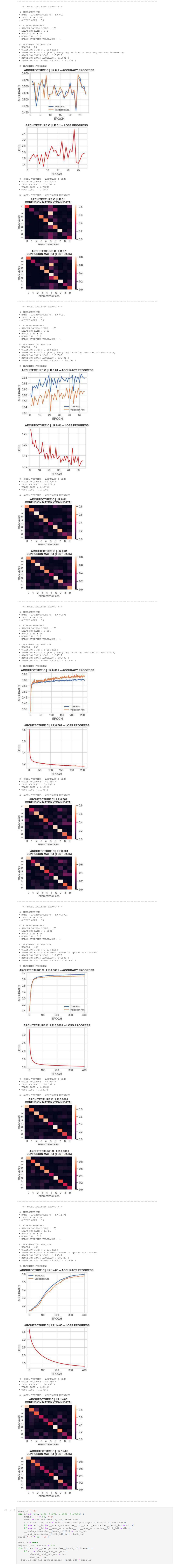
best_lr = lr

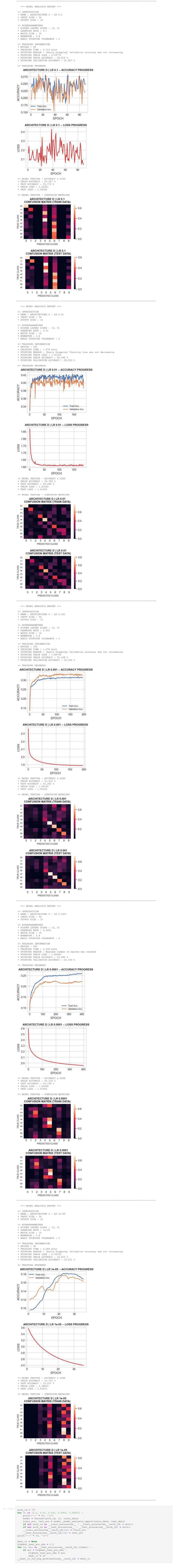
+++ MODEL ANALYSIS REPORT +++

• NAME : ARCHITECTURE B | LR 0.1

>> INTRODUCTION

• INPUT SIZE : 54

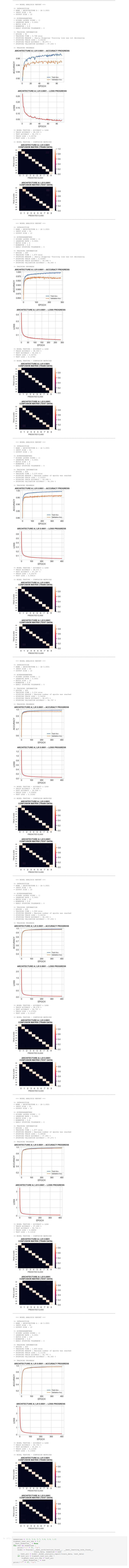


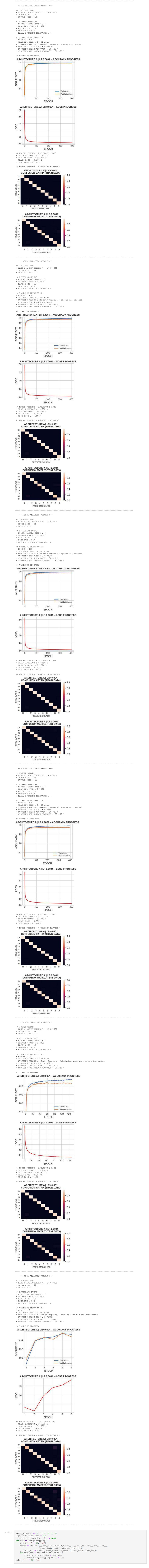


• NAME : ARCHITECTURE E LR 0.1 • INPUT SIZE : 54 • OUTPUT SIZE : 10 >> HYPERPARAMETERS • HIDDEN LAYERS SIZES : [3, 2] • LEARNING RATE : 0.1 • BATCH SIZE : 16 • MOMENTUM : 0.8 • EARLY STOPPING TOLERANCE : 4 >> TRAINING INFORMATION • EPOCHS : 205 • TRAINING TIME : 1.631 mins • STOPPING REASON : [Early Stopping] Validation accuracy was not increasing • STOPPING TRAIN LOSS : 2.00423 • STOPPING TRAIN ACCURACY : 21.619 % • STOPPING VALIDATION ACCURACY : 22.301 %	
ARCHITECTURE E LR 0.1 ACCURACY PROGRESS 0.28 Train Acc. Validation Acc. 0.26 0.24 0.22 0.20	
0 50 100 150 200 EPOCH ARCHITECTURE E LR 0.1 LOSS PROGRESS 2.10 2.08 2.06 2.04 2.02 2.00	
1.98 0 50 100 150 200 EPOCH >> MODEL TESTING - ACCURACY & LOSS • TRAIN ACCURACY : 21.756 % • TEST ACCURACY : 21.708 % • TRAIN LOSS : 2.00306 • TEST LOSS : 1.99366 >> MODEL TESTING - CONFUSION MATRICES ARCHITECTURE E LR 0.1 CONFUSION MATRIX (TRAIN DATA)	
- 0.6 - 0.4 - 0.2 - 0.0 - 0.0 - 0.1 - 0.2 - 0.0 - 0.0 - 0.8	
- 0.6 - 0.4 - 0.2 - 0.0 - 0.1 - 0.2 - 0.0 - 0.1 - 0.2 - 0.0 - 0.1 - 0.2 - 0.1 - 0.2 - 0.2 - 0.0 - 0.1 - 0.2 - 0.1 - 0.2 - 0.2 - 0.0 - 0.1 - 0.2 - 0.2 - 0.0 - 0.1 - 0.2 - 0.2 - 0.0	
>> INTRODUCTION • NAME : ARCHITECTURE E LR 0.01 • INPUT SIZE : 54 • OUTPUT SIZE : 10 >> HYPERPARAMETERS • HIDDEN LAYERS SIZES : [3, 2] • LEARNING RATE : 0.01 • BATCH SIZE : 16 • MOMENTUM : 0.8 • EARLY STOPPING TOLERANCE : 4 >> TRAINING INFORMATION • EPOCHS : 120 • TRAINING TIME : 0.958 mins • STOPPING REASON : [Early Stopping] Training loss was not decreasing • STOPPING TRAIN LOSS : 1.84127	
• STOPPING TRAIN ACCURACY: 29.241 % • STOPPING VALIDATION ACCURACY: 29.300 % >> TRAINING PROGRESS ARCHITECTURE E LR 0.01 ACCURACY PROGRESS 0.32 0.32 0.32 0.28	
0.26	
1.875 1.850 0 25 50 75 100 125 EPOCH >> MODEL TESTING - ACCURACY & LOSS • TRAIN ACCURACY : 29.253 % • TEST ACCURACY : 29.680 % • TRAIN LOSS : 1.84567 • TEST LOSS : 1.83232 >> MODEL TESTING - CONFUSION MATRICES ARCHITECTURE E LR 0.01 CONFUSION MATRIX (TRAIN DATA)	
ARCHITECTURE E LR 0.01 CONFUSION MATRIX (TEST DATA)	
TANE CLASS - 0.5 - 0.4 - 0.3 - 0.2 - 0.1 0.0 0 1 2 3 4 5 6 7 8 9 PREDICTED CLASS	
+++ MODEL ANALYSIS REPORT +++ >> INTRODUCTION • NAME : ARCHITECTURE E LR 0.001 • INPUT SIZE : 54 • OUTPUT SIZE : 10 >> HYPERPARAMETERS • HIDDEN LAYERS SIZES : [3, 2] • LEARNING RATE : 0.001 • BATCH SIZE : 16 • MOMENTUM : 0.8 • EARLY STOPPING TOLERANCE : 4 >> TRAINING INFORMATION • EPOCHS : 270 • TRAINING TIME : 2.146 mins	
• STOPPING REASON: [Early Stopping] Validation accuracy was not increasing • STOPPING TRAIN LOSS: 1.90870 • STOPPING TRAIN ACCURACY: 30.071 % • STOPPING VALIDATION ACCURACY: 30.130 % >> TRAINING PROGRESS ARCHITECTURE E LR 0.001 ACCURACY PROGRESS 0.30 0.25	
0.10 Train Acc. Validation Acc. 0 50 100 150 200 250 EPOCH ARCHITECTURE E LR 0.001 LOSS PROGRESS 2.5 2.4 2.3	
22 2.1 2.0 1.9 0 50 100 150 200 250 EPOCH >> MODEL TESTING - ACCURACY & LOSS • TRAIN ACCURACY : 30.083 % • TEST ACCURACY : 30.463 % • TRAIN LOSS : 1.90318 • TEST LOSS : 1.89050 >> MODEL TESTING - CONFUSION MATRICES	
ARCHITECTURE E LR 0.001 CONFUSION MATRIX (TRAIN DATA) - 0.6 - 0.4 - 0.2 0 1 2 3 4 5 6 7 8 9 PREDICTED CLASS	
ARCHITECTURE E LR 0.001 CONFUSION MATRIX (TEST DATA) - 0.6 - 0.4 - 0.2 - 0.0 - 0.1 - 0.2 - 0.0	
+++ MODEL ANALYSIS REPORT +++ >> INTRODUCTION • NAME : ARCHITECTURE E LR 0.0001 • INPUT SIZE : 54 • OUTPUT SIZE : 10 >> HYPERPARAMETERS • HIDDEN LAYERS SIZES : [3, 2] • LEARNING RATE : 0.0001 • BATCH SIZE : 16 • MOMENTUM : 0.8 • EARLY STOPPING TOLERANCE : 4	
>> TRAINING INFORMATION • EPOCHS: 400 • TRAINING TIME: 3.181 mins • STOPPING REASON: Maximum number of epochs was reached • STOPPING TRAIN LOSS: 1.86678 • STOPPING TRAIN ACCURACY: 34.104 % • STOPPING VALIDATION ACCURACY: 30.961 % >> TRAINING PROGRESS ARCHITECTURE E LR 0.0001 - ACCURACY PROGRESS 0.35 Train Acc. Validation Acc.	
0.25 0.20 0.15 0.10 0 100 200 300 400 EPOCH ARCHITECTURE E LR 0.0001 LOSS PROGRESS 2.6	
2.4 2.0 2.0 2.0 EPOCH >> MODEL TESTING - ACCURACY & LOSS • TRAIN ACCURACY: 33.476 % • TEST ACCURACY: 32.598 % • TRAIN LOSS: 1.87046 ETRAIN LOSS: 1.87046	
TEST LOSS: 1.87454 >> MODEL TESTING - CONFUSION MATRICES ARCHITECTURE E LR 0.0001 CONFUSION MATRIX (TRAIN DATA) - 0.8 - 0.6 - 0.4 - 0.2	
0 1 2 3 4 5 6 7 8 9 PREDICTED CLASS ARCHITECTURE E LR 0.0001 CONFUSION MATRIX (TEST DATA) - 0.8 - 0.6 - 0.4 - 0.2	
0 1 2 3 4 5 6 7 8 9 PREDICTED CLASS +++ MODEL ANALYSIS REPORT +++ >> INTRODUCTION • NAME : ARCHITECTURE E LR 1e-05 • INPUT SIZE : 54 • OUTPUT SIZE : 10 >> HYPERPARAMETERS • HIDDEN LAYERS SIZES : [3, 2] • LEARNING RATE : 1e-05 • BATCH SIZE : 16 • MOMENTUM : 0.8	
• EARLY STOPPING TOLERANCE : 4 >> TRAINING INFORMATION • EPOCHS : 400 • TRAINING TIME : 3.213 mins • STOPPING REASON : Maximum number of epochs was reached • STOPPING TRAIN LOSS : 2.02611 • STOPPING TRAIN ACCURACY : 24.081 % • STOPPING VALIDATION ACCURACY : 23.606 % >> TRAINING PROGRESS ARCHITECTURE E LR 1e-05 ACCURACY PROGRESS Train Acc. Validation Acc.	
0.175 0.150 0.125 0.100 0 100 200 300 400 EPOCH ARCHITECTURE E LR 1e-05 LOSS PROGRESS 2.8	
2.6 2.2 2.0 0 100 200 300 400 EPOCH >> MODEL TESTING - ACCURACY & LOSS • TRAIN ACCURACY: 23.986 %	
• TEST ACCURACY: 22.989 % • TRAIN LOSS: 2.03159 • TEST LOSS: 2.06213 >> MODEL TESTING - CONFUSION MATRICES ARCHITECTURE E LR 1e-05 CONFUSION MATRIX (TRAIN DATA) 0 88 - 0.6 - 0.4 - 0.2	
ARCHITECTURE E LR 1e-05 CONFUSION MATRIX (TEST DATA) - 0.8 - 0.6 - 0.4	
In [19]: for arch in ['A', 'B', 'C', 'D', 'E']: print(' Best learning rate for Architecture', arch, ':', _best_lr_for_mlp_architectures_[arch] Best learning rate for Architecture A: 0.0001 Best learning rate for Architecture B: 0.0001 Best learning rate for Architecture C: 0.0001 Best learning rate for Architecture D: 0.001)
Best learning rate for Architecture E : 0.0001 In [20]: for arch in ['A', 'B', 'C', 'D', 'E'] : print('\n +++ ACCURACIES ON TRAIN SET FOR ARCHITECTURE', arch, '+++') for lr in range(1, 6) : print(' > LR = le-' + str(lr), ':', round(_train_accuracies[arch][10**-lr], 4), '%') +++ ACCURACIES ON TRAIN SET FOR ARCHITECTURE A +++	
> LR = 1e-2 : 25.3855 % > LR = 1e-3 : 31.0558 % > LR = 1e-4 : 33.6655 % > LR = 1e-5 : 12.5267 % +++ ACCURACIES ON TRAIN SET FOR ARCHITECTURE C +++ > LR = 1e-1 : 51.6963 % > LR = 1e-2 : 62.7995 % > LR = 1e-2 : 60.2847 % > LR = 1e-4 : 67.0463 % > LR = 1e-5 : 59.3594 % +++ ACCURACIES ON TRAIN SET FOR ARCHITECTURE D +++ > LR = 1e-1 : 24.0569 % > LR = 1e-2 : 39.7865 % > LR = 1e-3 : 31.4116 % > LR = 1e-4 : 25.1246 % > LR = 1e-5 : 16.7023 %	
<pre>+++ ACCURACIES ON TRAIN SET FOR ARCHITECTURE E +++</pre>	
> LR = 1e-4 : 97.0107 % > LR = 1e-5 : 95.5872 % +++ ACCURACIES ON TEST SET FOR ARCHITECTURE B +++ > LR = 1e-1 : 24.911 % > LR = 1e-2 : 24.911 % > LR = 1e-3 : 30.3915 % > LR = 1e-4 : 35.4448 % > LR = 1e-5 : 13.3096 % +++ ACCURACIES ON TEST SET FOR ARCHITECTURE C +++ > LR = 1e-1 : 53.3808 % > LR = 1e-2 : 60.0712 % > LR = 1e-3 : 59.2883 % > LR = 1e-4 : 66.1922 % > LR = 1e-5 : 60.4982 % +++ ACCURACIES ON TEST SET FOR ARCHITECTURE D +++	
> LR = 1e-1 : 23.7722 % > LR = 1e-2 : 40.4982 % > LR = 1e-3 : 32.242 % > LR = 1e-4 : 24.1281 % > LR = 1e-5 : 15.2313 % +++ ACCURACIES ON TEST SET FOR ARCHITECTURE E +++ > LR = 1e-1 : 21.7082 % > LR = 1e-2 : 29.6797 % > LR = 1e-3 : 30.4626 % > LR = 1e-4 : 32.5979 % > LR = 1e-5 : 22.9893 % PART 03 For the results obtained in the second part, graphs of accuracy of each model architecture v/s learning rate and accuracy for learning rate v/s architecture are plotted.	or each
Plot the accuracy of the trained model on the test set v/s the model architecture (number of hidden layers and their sizes), the learning rate on the same graph. Plot the accuracy of the trained model on the test set v/s the learning rate, for each model architecture on the same graph. Infer from the results the dependence of the quality of the MLP models on the model architecture and try to explain it. In [22]: layers = {	
<pre>In [23]: fontsize = 10 plt.style.use('seaborn-whitegrid') fig = plt.figure(figsize=(5, 4)) ax = fig.add_subplot() for arch in ['A', 'B', 'C', 'D', 'E']: X = list(test_accuracies[arch].keys()) Y = list(test_accuracies[arch].values()) ax.plot(X, Y, linewidth = 2) ax.set_xscale('log') plt.xlabel('LEARNING RATE', fontsize=fontsize, fontweight='bold') plt.ylabel('ACCURACY', fontsize=fontsize, fontweight='bold') plt.legend(['Model ' + arch + ': ' + str(layers[arch]) for arch in ['A', 'B', 'C', 'D', 'E']],</pre>	
ACCURACY V/S LEARNING RATE 100 Model A: [] Model B: [2] Model C: [6] Model D: [2, 3] Model E: [3, 2]	
In [24]: fontsize = 10 plt.style.use('seaborn-whitegrid') fig = plt.figure(figsize=(5, 4)) ax = fig.add_subplot() for lr in [0.1, 0.01, 0.001, 0.0001]:	
<pre>X = ['A', 'B', 'C', 'D', 'E'] Y = [_test_accuracies[arch][lr] for arch in X] ax.plot(list(range(1,6)), Y, linewidth = 1.85) plt.xlabel('MODEL ARCHITECTURE', fontsize=fontsize, fontweight='bold') plt.ylabel('ACCURACY', fontsize=fontsize, fontweight='bold') plt.legend(['LR le-' + str(lr) for lr in [1, 2, 3, 4, 5]], fontsize = 9, prop={'weight':'bold'}) plt.title('ACCURACY V/S MODEL ARCHITECTURE', fontsize = 11, fontweight = 'bold') xticks = [arch + '-' + str(layers[arch]) for arch in ['A', 'B', 'C', 'D', 'E']] plt.xticks(list(range(1,6)), xticks, rotation = 'vertical') plt.tight_layout() plt.savefig('PART3_acc_vs_model.png') plt.show() ACCURACY V/S MODEL ARCHITECTURE 100</pre>	
100 80 LR 1e-1 LR 1e-2 LR 1e-3 LR 1e-4 LR 1e-5	
MODEL ARCHITECTURE PART 04 The best architecture and its optimal learning rate as found from the results of the second part are reported. For an MLP classification models with the best architecture found in the second part and its optimal learning rate by varying following hyperparameters with the corresponding values and keeping the other hyperparameters constant at their default of BATCH SIZE - [2, 4, 8, 16, 32, 64, 128]	the first
MOMENTUM - [0.5 , 0.6 , 0.7 , 0.8 , 0.9 , 1.0] EARLY STOPPING TOL - [1 , 2 , 3 , 4 , 5 , 6] TRAINING EPOCHS - [1 to 800] Evaluate each of the above models (20 in total) on the train and test set and deduce the most suitable hyperparameters for architecture of the MLP classifier and its corresponding best learning rate. Justify the trends in the performances of the movarying hyperparameters. In [25]: best_architecture_found = Nonebest_learning_rate_found = None layers = { 'A' : [1, 'B' : [2], 'C' : [6],	
<pre>In [26]: batch_sizes = [2, 4, 8, 16, 32, 64, 128] highest_test_acc_obs = 0.0 best_batch_size = None for bs in batch_sizes: print('' * 50, '\n') model = Trainer(best_architecture_found,best_learning_rate_found,</pre>	

+++ MODEL ANALYSIS REPORT +++

>> INTRODUCTION





• STOPPING TRAIN LOSS: 0.19030 • STOPPING TRAIN ACCURACY: 94.632 • STOPPING VALIDATION ACCURACY: 9 >> TRAINING PROGRESS ARCHITECTURE A LR 0.0001 ACCURACY: 9 0.95 0.90 0.85 0.80 0.75	92.645 %
0.70 0.65 2.5 5.0 7.5 1 EPOCH ARCHITECTURE A LR 0.0001	Train Acc. Validation Acc. 10.0 12.5 LOSS PROGRESS
0.8 0.6 0.4 0.2 2.5 5.0 7.5 1 EPOCH >> MODEL TESTING - ACCURACY & LOSS	10.0 12.5
 TRAIN ACCURACY: 94.235 % TEST ACCURACY: 93.523 % TRAIN LOSS: 0.19930 TEST LOSS: 0.21725 >> MODEL TESTING - CONFUSION MATRI ARCHITECTURE A LR 0.000 CONFUSION MATRIX (TRAIN DATE)	ICES 01 ATA) - 0.8
0 1 2 3 4 5 6 7 8 PREDICTED CLASS ARCHITECTURE A LR 0.000 CONFUSION MATRIX (TEST DA	001
TRUE CLASS 0 1 2 3 4 5 6 7 8 PREDICTED CLASS	- 0.8 - 0.6 - 0.4 - 0.2 - 0.0
+++ MODEL ANALYSIS REPORT +++ >> INTRODUCTION • NAME : ARCHITECTURE A LR 0.000 • INPUT SIZE : 54 • OUTPUT SIZE : 10 >> HYPERPARAMETERS • HIDDEN LAYERS SIZES : [] • LEARNING RATE : 0.0001 • BATCH SIZE : 16)1
 MOMENTUM: 0.8 EARLY STOPPING TOLERANCE: 2 >> TRAINING INFORMATION EPOCHS: 21 TRAINING TIME: 0.108 mins 	94.781 %
0.9 ACCURACY 0.8 0.7 0.6	Train Acc. Validation Acc.
0 5 10 1 EPOCH ARCHITECTURE A LR 0.0001 1.2 1.0 0.8 SSO 0.6	LOSS PROGRESS
0.4 0.2 0 5 10 EPOCH >> MODEL TESTING - ACCURACY & LOSS • TRAIN ACCURACY : 95.397 % • TEST ACCURACY : 95.018 % • TRAIN LOSS : 0.15647 • TEST LOSS : 0.16910	15 20
TRUE CLASS ARCHITECTURE A LR 0.000 CONFUSION MATRIX (TRAIN DA	01
0 1 2 3 4 5 6 7 8 PREDICTED CLASS ARCHITECTURE A LR 0.000 CONFUSION MATRIX (TEST DA	001
O 1 2 3 4 5 6 7 8 PREDICTED CLASS +++ MODEL ANALYSIS REPORT +++ >> INTRODUCTION • NAME : ARCHITECTURE A LR 0.000	
• INPUT SIZE : 54 • OUTPUT SIZE : 10 >> HYPERPARAMETERS • HIDDEN LAYERS SIZES : [] • LEARNING RATE : 0.0001 • BATCH SIZE : 16 • MOMENTUM : 0.8 • EARLY STOPPING TOLERANCE : 3 >> TRAINING INFORMATION • EPOCHS : 89 • TRAINING TIME : 0.449 mins • STOPPING REASON : [Early Stoppin • STOPPING TRAIN LOSS : 0.08219	ng] Validation accuracy was not increasing
• STOPPING TRAIN LOSS: 0.08219 • STOPPING TRAIN ACCURACY: 97.835 • STOPPING VALIDATION ACCURACY: 9 >> TRAINING PROGRESS ARCHITECTURE A LR 0.0001 AC	5 % 95.848 %
0.6	Train Acc. Validation Acc. 80 LOSS PROGRESS
0.8 SS 0.6 0.4 0.2 0 20 40 6 EPOCH	60 80
>> MODEL TESTING - ACCURACY & LOSS • TRAIN ACCURACY : 97.438 % • TEST ACCURACY : 96.299 % • TRAIN LOSS : 0.09294 • TEST LOSS : 0.12856 >> MODEL TESTING - CONFUSION MATRI ARCHITECTURE A LR 0.000 CONFUSION MATRIX (TRAIN DA	ICES 01 ATA) - 0.8
E	001
	- 0.8 - 0.6 - 0.4 - 0.2 - 0.0
+++ MODEL ANALYSIS REPORT +++ >> INTRODUCTION • NAME : ARCHITECTURE A LR 0.000 • INPUT SIZE : 54 • OUTPUT SIZE : 10 >> HYPERPARAMETERS • HIDDEN LAYERS SIZES : [] • LEARNING RATE : 0.0001 • BATCH SIZE : 16 • MOMENTUM : 0.8 • EARLY STOPPING TOLERANCE : 4)1
	2 % 97.034 %
0.9 O.8 O.7 O 100 200 EPOCH	Train Acc. Validation Acc. 300 400
ARCHITECTURE A LR 0.0001 1.0 0.8 SS 0.6 0.4 0.2	LOSS PROGRESS
0.2 0.0 100 EPOCH >> MODEL TESTING - ACCURACY & LOSS • TRAIN ACCURACY : 98.600 % • TEST ACCURACY : 96.584 % • TRAIN LOSS : 0.05321 • TEST LOSS : 0.11774 >> MODEL TESTING - CONFUSION MATRI ARCHITECTURE A LR 0.000 CONFUSION MATRIX (TRAIN DA	ICES
TRUE CLASS TRUE CLASS O 1 2 3 4 5 6 7 8 O 1 2 3 4 5 6 7 8	- 0.8 - 0.6 - 0.4 - 0.2
TRUE CLASS 7 6 5 4 3 2 1 0 ARCHITECTURE A LR 0.000 CONFUSION MATRIX (TEST DATE OF TEXT OF	001
O 1 2 3 4 5 6 7 8 PREDICTED CLASS +++ MODEL ANALYSIS REPORT +++ >> INTRODUCTION • NAME : ARCHITECTURE A LR 0.000 • INPUT SIZE : 54 • OUTPUT SIZE : 10	3 9
>> HYPERPARAMETERS • HIDDEN LAYERS SIZES : [] • LEARNING RATE : 0.0001 • BATCH SIZE : 16 • MOMENTUM : 0.8 • EARLY STOPPING TOLERANCE : 5 >> TRAINING INFORMATION • EPOCHS : 400 • TRAINING TIME : 2.022 mins • STOPPING REASON : Maximum number • STOPPING TRAIN LOSS : 0.04368 • STOPPING TRAIN ACCURACY : 98.992 • STOPPING VALIDATION ACCURACY : 9 >> TRAINING PROGRESS	2 %
ARCHITECTURE A LR 0.0001 AC 1.0 0.9 0.8 0.7	— Train Acc.
0.6 0 100 200 EPOCH ARCHITECTURE A LR 0.0001 1.2 1.0 0.8 SO 0.6	Validation Acc. 300 400
90.6 0.4 0.2 0.0 0 100 200 EPOCH >> MODEL TESTING - ACCURACY & LOSS • TRAIN ACCURACY : 98.600 % • TEST ACCURACY : 96.868 % • TRAIN LOSS : 0.05345 • TEST LOSS : 0.11275	300 400
	01 ATA) - 0.8 - 0.6 - 0.4
O 1 2 3 4 5 6 7 8 PREDICTED CLASS ARCHITECTURE A LR 0.000 CONFUSION MATRIX (TEST DA	001
0 1 2 3 4 5 6 7 8 PREDICTED CLASS +++ MODEL ANALYSIS REPORT +++ >> INTRODUCTION	- 0.4 - 0.2 0.0 3 9
 NAME: ARCHITECTURE A LR 0.000 INPUT SIZE: 54 OUTPUT SIZE: 10 >> HYPERPARAMETERS HIDDEN LAYERS SIZES: [] LEARNING RATE: 0.0001 BATCH SIZE: 16 MOMENTUM: 0.8 EARLY STOPPING TOLERANCE: 6 >> TRAINING INFORMATION EPOCHS: 400 TRAINING TIME: 2.049 mins STOPPING REASON: Maximum number 	
	4 % 97.509 %
0.6 0 100 200 EPOCH ARCHITECTURE A LR 0.0001	Train Acc. Validation Acc. 300 400 LOSS PROGRESS
1.0 0.8 SS 0.6 0.4 0.2 0.0 0 100 200 EPOCH	300 400
>> MODEL TESTING - ACCURACY & LOSS • TRAIN ACCURACY : 98.505 % • TEST ACCURACY : 96.940 % • TRAIN LOSS : 0.05062 • TEST LOSS : 0.11652 >> MODEL TESTING - CONFUSION MATRI ARCHITECTURE A LR 0.000 CONFUSION MATRIX (TRAIN DA	ICES 01 ATA) - 0.8
1 2 3 4 5 6 7 8 PREDICTED CLASS ARCHITECTURE A LR 0.000 CONFUSION MATRIX (TEST DATE OF TEST DATE.	001
The state of the s	- 1.0 - 0.8 - 0.6 - 0.4 - 0.2 - 0.0
<pre>input_dim = len(train_data[0][0]) model = Handwritten_Digits_Classif. train_acc_prog, test_acc_prog = mod EPOCH : 1 TRAIN LOSS : 0.39258 EPOCH : 11 TRAIN LOSS : 0.19186 EPOCH : 21 TRAIN LOSS : 0.96618 EPOCH : 31 TRAIN LOSS : 0.10851 EPOCH : 41 TRAIN LOSS : 0.12537</pre>	Fier('PART4_Best_Epoch_Num', input_dim, layers[best_architecture_foundedstrict_train(800, train_data, test_data, verbose = True, verboseGap = 10) B TRAIN ACC. : 0.93594 TEST ACC. : 0.93594 G TRAIN ACC. : 0.97177 TEST ACC. : 0.94947 B TRAIN ACC. : 0.91815 TEST ACC. : 0.91673 I TRAIN ACC. : 0.98197 TEST ACC. : 0.95658 T TRAIN ACC. : 0.97699 TEST ACC. : 0.95658 I TRAIN ACC. : 0.98624 TEST ACC. : 0.97011
EPOCH: 41 TRAIN LOSS: 0.12537 EPOCH: 51 TRAIN LOSS: 0.07681 EPOCH: 61 TRAIN LOSS: 0.26172 EPOCH: 71 TRAIN LOSS: 0.05631 EPOCH: 81 TRAIN LOSS: 0.19401 EPOCH: 91 TRAIN LOSS: 0.19401 EPOCH: 91 TRAIN LOSS: 0.06497 EPOCH: 101 TRAIN LOSS: 0.15691 EPOCH: 111 TRAIN LOSS: 0.07640 EPOCH: 121 TRAIN LOSS: 0.07640 EPOCH: 131 TRAIN LOSS: 0.04533 EPOCH: 131 TRAIN LOSS: 0.05191 EPOCH: 141 TRAIN LOSS: 0.03842 EPOCH: 151 TRAIN LOSS: 0.15813 EPOCH: 161 TRAIN LOSS: 0.04617 EPOCH: 171 TRAIN LOSS: 0.10016 EPOCH: 181 TRAIN LOSS: 0.04707	7 TRAIN ACC. : 0.97699 TEST ACC. : 0.95658 1 TRAIN ACC. : 0.98624 TEST ACC. : 0.97011 2 TRAIN ACC. : 0.96584 TEST ACC. : 0.95018 1 TRAIN ACC. : 0.98861 TEST ACC. : 0.96584 1 TRAIN ACC. : 0.96797 TEST ACC. : 0.95089 7 TRAIN ACC. : 0.98790 TEST ACC. : 0.95801 1 TRAIN ACC. : 0.97556 TEST ACC. : 0.96584 0 TRAIN ACC. : 0.98648 TEST ACC. : 0.96584 0 TRAIN ACC. : 0.988648 TEST ACC. : 0.96584 0 TRAIN ACC. : 0.99241 TEST ACC. : 0.97580 1 TRAIN ACC. : 0.99241 TEST ACC. : 0.97580 1 TRAIN ACC. : 0.98980 TEST ACC. : 0.96655 2 TRAIN ACC. : 0.99170 TEST ACC. : 0.94662 7 TRAIN ACC. : 0.98956 TEST ACC. : 0.96655 6 TRAIN ACC. : 0.98458 TEST ACC. : 0.96797 7 TRAIN ACC. : 0.99146 TEST ACC. : 0.96797 8 TRAIN ACC. : 0.99146 TEST ACC. : 0.97011
EPOCH : 201 TRAIN LOSS : 0.02707 EPOCH : 211 TRAIN LOSS : 0.15018 EPOCH : 221 TRAIN LOSS : 0.02852 EPOCH : 231 TRAIN LOSS : 0.03001 EPOCH : 241 TRAIN LOSS : 0.04279 EPOCH : 251 TRAIN LOSS : 0.08030 EPOCH : 251 TRAIN LOSS : 0.08030 EPOCH : 261 TRAIN LOSS : 0.04231 EPOCH : 271 TRAIN LOSS : 0.03861 EPOCH : 281 TRAIN LOSS : 0.03948 EPOCH : 291 TRAIN LOSS : 0.02091 EPOCH : 301 TRAIN LOSS : 0.01852 EPOCH : 311 TRAIN LOSS : 0.01176 EPOCH : 321 TRAIN LOSS : 0.06196 EPOCH : 331 TRAIN LOSS : 0.02698 EPOCH : 341 TRAIN LOSS : 0.01327 EPOCH : 351 TRAIN LOSS : 0.01327 EPOCH : 351 TRAIN LOSS : 0.01327	7 TRAIN ACC. : 0.99312 TEST ACC. : 0.96512 8 TRAIN ACC. : 0.97912 TEST ACC. : 0.94804 2 TRAIN ACC. : 0.99359 TEST ACC. : 0.96014 1 TRAIN ACC. : 0.99217 TEST ACC. : 0.96370 9 TRAIN ACC. : 0.99146 TEST ACC. : 0.96584 0 TRAIN ACC. : 0.98624 TEST ACC. : 0.96584 1 TRAIN ACC. : 0.99170 TEST ACC. : 0.97011 1 TRAIN ACC. : 0.98932 TEST ACC. : 0.96085 8 TRAIN ACC. : 0.99241 TEST ACC. : 0.96441 1 TRAIN ACC. : 0.99478 TEST ACC. : 0.96370 2 TRAIN ACC. : 0.99668 TEST ACC. : 0.96584 6 TRAIN ACC. : 0.99668 TEST ACC. : 0.96797 6 TRAIN ACC. : 0.998336 TEST ACC. : 0.95730 8 TRAIN ACC. : 0.99836 TEST ACC. : 0.95730 6 TRAIN ACC. : 0.99336 TEST ACC. : 0.96085 7 TRAIN ACC. : 0.998031 TEST ACC. : 0.96299 6 TRAIN ACC. : 0.98031 TEST ACC. : 0.96299
EPOCH: 361 TRAIN LOSS: 0.01967 EPOCH: 371 TRAIN LOSS: 0.02316 EPOCH: 381 TRAIN LOSS: 0.04677 EPOCH: 391 TRAIN LOSS: 0.09123 EPOCH: 401 TRAIN LOSS: 0.04411	7 TRAIN ACC. : 0.99620 TEST ACC. : 0.96655 6 TRAIN ACC. : 0.99359 TEST ACC. : 0.95730 7 TRAIN ACC. : 0.98932 TEST ACC. : 0.96014 3 TRAIN ACC. : 0.98600 TEST ACC. : 0.96014 1 TRAIN ACC. : 0.99051 TEST ACC. : 0.96370 8 TRAIN ACC. : 0.99383 TEST ACC. : 0.96655 3 TRAIN ACC. : 0.99478 TEST ACC. : 0.96441 0 TRAIN ACC. : 0.99526 TEST ACC. : 0.96299 6 TRAIN ACC. : 0.99692 TEST ACC. : 0.96299 6 TRAIN ACC. : 0.99644 TEST ACC. : 0.96797 2 TRAIN ACC. : 0.99549 TEST ACC. : 0.96868 5 TRAIN ACC. : 0.99520 TEST ACC. : 0.96441 2 TRAIN ACC. : 0.99098 TEST ACC. : 0.96370 5 TRAIN ACC. : 0.99241 TEST ACC. : 0.96370 5 TRAIN ACC. : 0.99786 TEST ACC. : 0.96370
EPOCH: 511 TRAIN LOSS: 0.08020 EPOCH: 521 TRAIN LOSS: 0.02894 EPOCH: 531 TRAIN LOSS: 0.01900 EPOCH: 541 TRAIN LOSS: 0.05515 EPOCH: 551 TRAIN LOSS: 0.05515 EPOCH: 551 TRAIN LOSS: 0.01001 EPOCH: 561 TRAIN LOSS: 0.00811 EPOCH: 571 TRAIN LOSS: 0.02071 EPOCH: 581 TRAIN LOSS: 0.03964 EPOCH: 591 TRAIN LOSS: 0.03964 EPOCH: 601 TRAIN LOSS: 0.0338 EPOCH: 601 TRAIN LOSS: 0.03038 EPOCH: 621 TRAIN LOSS: 0.08628 EPOCH: 631 TRAIN LOSS: 0.02108 EPOCH: 641 TRAIN LOSS: 0.02229 EPOCH: 641 TRAIN LOSS: 0.02486 EPOCH: 651 TRAIN LOSS: 0.00269	O TRAIN ACC. : 0.98577 TEST ACC. : 0.95445 4 TRAIN ACC. : 0.99288 TEST ACC. : 0.96655 O TRAIN ACC. : 0.99383 TEST ACC. : 0.96370 5 TRAIN ACC. : 0.98861 TEST ACC. : 0.95872 1 TRAIN ACC. : 0.99692 TEST ACC. : 0.96584 1 TRAIN ACC. : 0.99786 TEST ACC. : 0.96512 1 TRAIN ACC. : 0.99407 TEST ACC. : 0.95872 4 TRAIN ACC. : 0.99098 TEST ACC. : 0.96299 5 TRAIN ACC. : 0.98624 TEST ACC. : 0.95801 8 TRAIN ACC. : 0.99241 TEST ACC. : 0.95801 8 TRAIN ACC. : 0.99505 TEST ACC. : 0.96797 9 TRAIN ACC. : 0.99359 TEST ACC. : 0.96441 6 TRAIN ACC. : 0.99359 TEST ACC. : 0.96085 O TRAIN ACC. : 0.99359 TEST ACC. : 0.96085 O TRAIN ACC. : 0.99905 TEST ACC. : 0.96229
EPOCH: 661 TRAIN LOSS: 0.00269 EPOCH: 671 TRAIN LOSS: 0.04802 EPOCH: 681 TRAIN LOSS: 0.04718 EPOCH: 691 TRAIN LOSS: 0.01205 EPOCH: 701 TRAIN LOSS: 0.00711 EPOCH: 711 TRAIN LOSS: 0.03215 EPOCH: 721 TRAIN LOSS: 0.03215 EPOCH: 731 TRAIN LOSS: 0.00867 EPOCH: 731 TRAIN LOSS: 0.00689 EPOCH: 741 TRAIN LOSS: 0.01693 EPOCH: 751 TRAIN LOSS: 0.03074 EPOCH: 761 TRAIN LOSS: 0.00325 EPOCH: 771 TRAIN LOSS: 0.00292 EPOCH: 781 TRAIN LOSS: 0.002699 EPOCH: 791 TRAIN LOSS: 0.01267	9 TRAIN ACC. : 0.99905 TEST ACC. : 0.96228 2 TRAIN ACC. : 0.98956 TEST ACC. : 0.95872 8 TRAIN ACC. : 0.99004 TEST ACC. : 0.96441 5 TRAIN ACC. : 0.99715 TEST ACC. : 0.96157 1 TRAIN ACC. : 0.99810 TEST ACC. : 0.96299 5 TRAIN ACC. : 0.99407 TEST ACC. : 0.96014 7 TRAIN ACC. : 0.99715 TEST ACC. : 0.96085 9 TRAIN ACC. : 0.99810 TEST ACC. : 0.96085 3 TRAIN ACC. : 0.99820 TEST ACC. : 0.96299 4 TRAIN ACC. : 0.99217 TEST ACC. : 0.96299 5 TRAIN ACC. : 0.99858 TEST ACC. : 0.96299 2 TRAIN ACC. : 0.99834 TEST ACC. : 0.96298 9 TRAIN ACC. : 0.99841 TEST ACC. : 0.96288 9 TRAIN ACC. : 0.999526 TEST ACC. : 0.95943 7 TRAIN ACC. : 0.99526 TEST ACC. : 0.95801
<pre>best_no_of_epochs = np.argmax(fontsize = 12 plt.style.use('seaborn-whitegrid') epochs = len(test_acc_prog) X = list(range(1, 1 + epochs)) plt.figure(figsize=(4.4, 3.4)) plt.plot(X, train_acc_prog, linewid plt.plot(X, test_acc_prog, linewid plt.xlabel('EPOCH', fontsize = 12) plt.ylabel('ACCURACY', fontsize = 2) plt.legend(['Train Acc.', 'Test Acc plt.title('ACCURACY V/S NO. OF EPOc plt.tight_layout()</pre>	<pre>(test_acc_prog) + 1 idth = 1) dth = 1)</pre>
ACCURACY V/S NO. CONTROL OF THE PROPERTY OF TH	OF EPOCHS
0.92 0.90 200 EPOCH print(' The best architecture is Alwith hidden layers', layers print(' The best hyperparameters for print(' • LEARNING RATE:', _best	s[best_architecture_found]) Found for this architecture are as follows :-') st_learning_rate_found)
<pre>print('</pre>	st_learning_rate_found) patch_size) mentum) CE :',best_early_stopping_tol) st_no_of_epochs)
The dimension of the feature vectors is red a Cartesian plane with all data points of the Build the covariance matrix on the 54 attrib matrix (or weights) to reduce the dimension training and testing) and transform them in	
- Plot for data points from all the classes. W = PCA_Component_Weights(train_datain_data_2D = Two_Dim_Points(traitest_data_2D = Two_Dim_Points(test_full_data_2D = train_data_2D + test_data_2D = train_data_2D + test_data_2D = train_data_2D + test_data_2D + test	ata, verbose = True) ain_data, W) c_data, W)
EIGEN VAL 7 : 34.02768 EIGEN VAL 8 : 43.64645 EIGEN VAL 9 : 42.28729 EIGEN VAL 10 : 37.90186 EIGEN VAL 11 : 28.60360 EIGEN VAL 12 : 26.94584 EIGEN VAL 13 : 22.56745 EIGEN VAL 14 : 19.97957 EIGEN VAL 15 : 17.43580 EIGEN VAL 16 : 16.94269 EIGEN VAL 17 : 15.23251 EIGEN VAL 18 : 14.91053 EIGEN VAL 19 : 11.99506 EIGEN VAL 20 : 11.66876 EIGEN VAL 21 : 10.90312 EIGEN VAL 22 : 9.87161 EIGEN VAL 23 : 9.13338	
EIGEN VAL 23 : 9.13338 EIGEN VAL 24 : 8.85467 EIGEN VAL 25 : 8.18030 EIGEN VAL 26 : 7.46023 EIGEN VAL 27 : 6.84554 EIGEN VAL 28 : 6.22525 EIGEN VAL 29 : 5.64345 EIGEN VAL 30 : 5.16417 EIGEN VAL 31 : 4.80173 EIGEN VAL 32 : 4.36406 EIGEN VAL 33 : 4.21928 EIGEN VAL 34 : 4.00337 EIGEN VAL 35 : 3.91649 EIGEN VAL 36 : 3.73727 EIGEN VAL 37 : 3.20314	
EIGEN VAL 31: 4.80173 EIGEN VAL 32: 4.36406 EIGEN VAL 33: 4.21928 EIGEN VAL 34: 4.00337 EIGEN VAL 35: 3.91649 EIGEN VAL 36: 3.73727	

EIGEN VAL 52 : 0.10978 EIGEN VAL 53 : 0.07118 EIGEN VAL 54 : 0.04020

for c in range(10) :

Plot_2D_Transformed_Data(full_data_2D, [c])

In [34]:

+++ MODEL ANALYSIS REPORT +++

• NAME : ARCHITECTURE A | LR 0.0001

>> INTRODUCTION

• INPUT SIZE : 54 • OUTPUT SIZE : 10

>> HYPERPARAMETERS

• BATCH SIZE : 16 • MOMENTUM : 0.8

• EPOCHS : 14

• HIDDEN LAYERS SIZES : []
• LEARNING RATE : 0.0001

>> TRAINING INFORMATION

• EARLY STOPPING TOLERANCE : 1

• TRAINING TIME : 0.070 mins

