In [1]:

```
"""
import things required
"""
import numpy as np
import matplotlib.pyplot as plt
import cv2
import os
```

In [2]:

```
"""
Helper functions to load data
"""
def load_mnist_dataset(dataset, path):
    """
    returns samples and lables specified by path and dataset params

    loop through each label and append image to X and label to y
    """
    labels = os.listdir(os.path.join(path, dataset))

    X = []
    y = []

    for label in labels:
        image_counter = 0
        for file in os.listdir(os.path.join(path, dataset, label)):
            image = cv2.imread(os.path.join(path, dataset, label, file), cv2.IMREAD_UN
            X.append(image)
            y.append(label)

    return np.array(X), np.array(y).astype('uint8')

def create_data_mnist(path):
    """
    returns train X, y and test X and y
    """
    X, y = load_mnist_dataset('train', path)
    X_test, y_test = load_mnist_dataset('test', path)

    return X, y, X_test, y_test
```

In [3]:

```
"""
get train and test data
scale data to be in range of -1 to 1 i.e. centered around 0
"""
X, y, X_test, y_test = create_data_mnist('fashion_mnist_images')

# Scale features
X = (X.astype(np.float32) - 127.5) / 127.5
X_test = (X_test.astype(np.float32) - 127.5) / 127.5

# print(X.min(), X.max())
# print(X.shape)
```

In [5]:

```
print(X.shape)
print(y.shape)
```

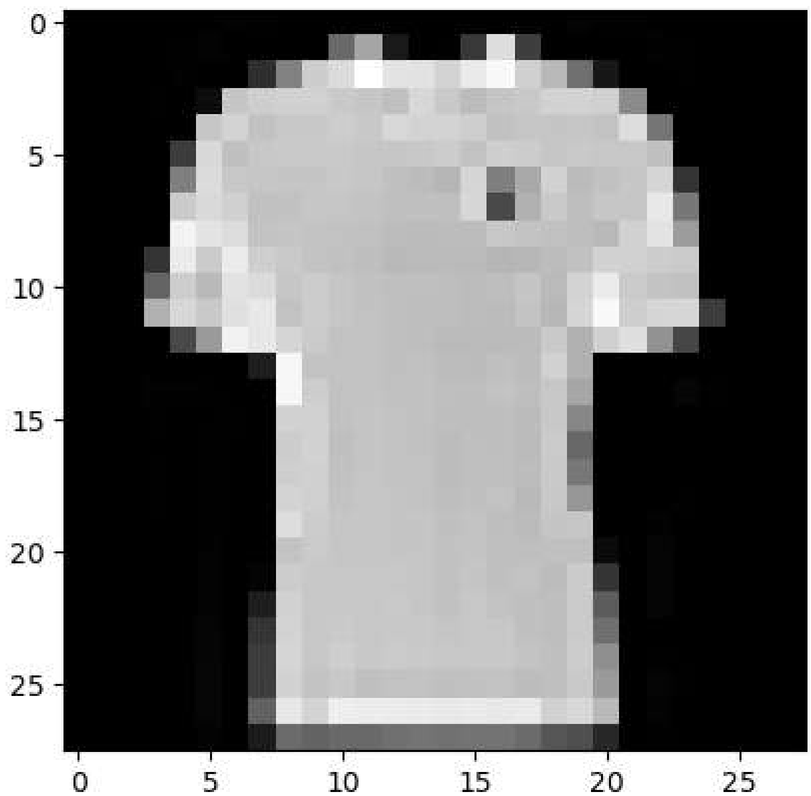
```
(60000, 28, 28)
(60000,)
```

In [6]:
```
"""
pixel size - 28 x 28 - 784 features
images are reshaped to be next to each other
"""
# Reshape to vectors
X = X.reshape(X.shape[0], -1)
X_test = X_test.reshape(X_test.shape[0], -1)
X.shape[1]
```

Out[6]:
```
784
```

In [7]:
```
"""
shuffle the keys to remove biase that might be caused towards one label
"""
keys = np.array(range(X.shape[0]))
print(keys[:10])
np.random.shuffle(keys)
X = X[keys]
y = y[keys]
plt.imshow((X[4].reshape(28, 28)), cmap='gray')
plt.show()
```

```
[0 1 2 3 4 5 6 7 8 9]
```



In [8]:
```
class Layer_Dense:
    def __init__(self, n_inputs, n_neurons,
                 weight_regularizer_l1=0, weight_regularizer_l2=0,
                 bias_regularizer_l1=0, bias_regularizer_l2=0):
        """
        n_inputs represents the no of features
        n_neurons represents the no of neurons we want in this particular layer
```

```
        weights are inputs x no of neurons - helps avoid transpose operation in dot pr
        weights range between -1 to +1 so tht they are close to each other and NN does

        biases is set to zero initially and if we encounter error where the entore out
        NN is zero we cqan intialize it to some value to avoid dead ANN

        rest four parameters referes to lambda that will be used for
        L1 and L2 regularization
        """
        self.weights = 0.01 * np.random.randn(n_inputs, n_neurons)
        self.biases = np.zeros((1, n_neurons))

        # Set regularization strength
        self.weight_regularizer_l1 = weight_regularizer_l1
        self.weight_regularizer_l2 = weight_regularizer_l2
        self.bias_regularizer_l1 = bias_regularizer_l1
        self.bias_regularizer_l2 = bias_regularizer_l2

    def forward(self, inputs):
        self.inputs = inputs
        self.output = np.dot(inputs, self.weights) + self.biases

    def backward(self, dvalues):
        # Gradients on parameters
        self.dweights = np.dot(self.inputs.T, dvalues)
        self.dbiases = np.sum(dvalues, axis=0, keepdims=True)

        # Gradients on regularization
        # L1 on weights
        if self.weight_regularizer_l1 > 0:
            dL1 = np.ones_like(self.weights)
            dL1[self.weights < 0] = -1
            self.dweights += self.weight_regularizer_l1 * dL1

        # L2 on weights
        if self.weight_regularizer_l2 > 0:
            self.dweights += 2 * self.weight_regularizer_l2 * \
            self.weights

        # L1 on biases
        if self.bias_regularizer_l1 > 0:
            dL1 = np.ones_like(self.biases)
            dL1[self.biases < 0] = -1
            self.dbiases += self.bias_regularizer_l1 * dL1

        # L2 on biases
        if self.bias_regularizer_l2 > 0:
            self.dbiases += 2 * self.bias_regularizer_l2 * \
            self.biases

        # Gradient on values
        self.dinputs = np.dot(dvalues, self.weights.T)
```

In [9]:
```
class Activation_ReLU:
    def forward(self, inputs):
        self.inputs = inputs
        self.output = np.maximum(0, inputs)
```

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```
    def backward(self, dvalues):
        self.dinputs = dvalues.copy()
        # input negative - gradient zero
        self.dinputs[self.inputs <= 0] = 0

class Activation_Softmax:
    def forward(self, inputs):
        self.inputs = inputs

        exp_values = np.exp(inputs - np.max(inputs, axis=1, keepdims=True))
        probabilities = exp_values / np.sum(exp_values, axis=1, keepdims=True)
        self.output = probabilities

    def backward(self, dvalues):
        # Create uninitialized array
        self.dinputs = np.empty_like(dvalues)

        # Enumerate outputs and gradients
        for index, (single_output, single_dvalues) in enumerate(zip(self.output, dvalu
            # Flatten output array
            single_output = single_output.reshape(-1, 1)
            # Calculate Jacobian matrix of the output and
            jacobian_matrix = np.diagflat(single_output) - np.dot(single_output, singl
            # Calculate sample-wise gradient
            # and add it to the array of sample gradients
            self.dinputs[index] = np.dot(jacobian_matrix, single_dvalues)
```

In [10]:

```
class Loss:
    def calculate(self, output, y):
        sample_losses = self.forward(output, y)
        mean_loss = np.mean(sample_losses)
        return mean_loss

    def regularization_loss(self, layer):

        regularization_loss = 0

        # L1 regularization - weights
        # calculate only when factor greater than 0
        if layer.weight_regularizer_l1 > 0:
            regularization_loss += layer.weight_regularizer_l1 * np.sum(np.abs(layer.w

        # L2 regularization - weights
        if layer.weight_regularizer_l2 > 0:
            regularization_loss += layer.weight_regularizer_l2 * np.sum(layer.weights

        # L1 regularization - biases
        # calculate only when factor greater than 0
        if layer.bias_regularizer_l1 > 0:
            regularization_loss += layer.bias_regularizer_l1 * np.sum(np.abs(layer.bia

        # L2 regularization - biases
        if layer.bias_regularizer_l2 > 0:
            regularization_loss += layer.bias_regularizer_l2 * np.sum(layer.biases * l

        return regularization_loss

class Loss_CategoricalCrossentropy(Loss):
```

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```
        samples = len(y_pred)

        # account for zero values -log(0) = inf and then remove biasis caused by its i
        y_pred_clipped = np.clip(y_pred, 1e-7, 1-1e-7)

        if len(y_true.shape) == 1:
            # y_true is in the form of [1, 0, 1, 1 ....]
            correct_confidences = y_pred_clipped[range(samples), y_true]

        elif len(y_true.shape) == 2:
            # y_true is in the form of matric [[0, 1, 0], [1, 0, 0], [0, 1, 0], [0, 1,
            correct_confidences = np.sum(y_pred_clipped * y_true, axis=1)

        negative_log_likelihood = - np.log(correct_confidences)

        return negative_log_likelihood

    def backward(self, dvalues, y_true):

        samples = len(dvalues)
        labels = len(dvalues[0])
        # convert to hot vector if not
        if len(y_true.shape) == 1:
            y_true = np.eye(labels)[y_true]
        # Calculate gradient
        self.dinputs = -y_true / dvalues
        # Normalize gradient
        self.dinputs = self.dinputs / samples

class Activation_Softmax_Loss_CategoricalCrossentropy():
    def __init__(self):
        self.activation = Activation_Softmax()
        self.loss = Loss_CategoricalCrossentropy()

    def forward(self, inputs, y_true):
        # Output layer's activation function
        self.activation.forward(inputs)
        # Set the output
        self.output = self.activation.output
        # Calculate and return loss value
        return self.loss.calculate(self.output, y_true)

    def backward(self, dvalues, y_true):
        # Number of samples
        samples = len(dvalues)
        # If labels are one-hot encoded,
        # turn them into discrete values
        if len(y_true.shape) == 2:
            y_true = np.argmax(y_true, axis=1)
        # Copy so we can safely modify
        self.dinputs = dvalues.copy()
        # Calculate gradient
        self.dinputs[range(samples), y_true] -= 1
        # Normalize gradient
        self.dinputs = self.dinputs / samples
```

In [ ]:

```
class Optimizer_SGD:
    """
```

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```
    Momentum option - if specified else default 0
    """
    def __init__(self, learning_rate=1.0, decay=0, momentum=0):
        self.learning_rate = learning_rate
        self.current_learning_rate = learning_rate
        self.decay = decay
        self.iterations = 0
        self.momentum = momentum

    def pre_update_params(self):
        if self.decay:
            self.current_learning_rate = self.learning_rate * (1. / (1. + self.decay *

    # Update parameters
    def update_params(self, layer):
        # If we use momentum
        if self.momentum:

            # create momentum array if not present along with biases
            if not hasattr(layer, 'weight_momentums'):
                layer.weight_momentums = np.zeros_like(layer.weights)
                layer.bias_momentums = np.zeros_like(layer.biases)

            weight_updates = self.momentum * layer.weight_momentums - self.current_lea
            layer.weight_momentums = weight_updates

            bias_updates = self.momentum * layer.bias_momentums - self.current_learnin
            layer.bias_momentums = bias_updates

        # Vanilla SGD updates (as before momentum update)
        else:
            weight_updates = -self.current_learning_rate * layer.dweights
            bias_updates = -self.current_learning_rate * layer.dbiases

        # Update weights and biases using either vanilla or momentum update
        layer.weights += weight_updates
        layer.biases += bias_updates

    def post_update_params(self):
        self.iterations += 1
```

In [12]:

```
"""
Features = 784
Samples = 60,000
class labels = 10 (0 - 9)

2 hidden layes - ReLU    - 128 neurons each
1 output layer - Softmax - 10 output neurons

Optimizer - SGD
learning rate decay - 0.01
l2 regularization - lambda - 5e-4 (0.0005)
"""

dense1 = Layer_Dense(X.shape[1], 128, weight_regularizer_l2=5e-4, bias_regularizer_l2=
activation1 = Activation_ReLU()
dense2 = Layer_Dense(128, 128)
activation2 = Activation_ReLU()
```

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```
loss_activation = Activation_Softmax_Loss_CategoricalCrossentropy()

optimizer = Optimizer_SGD(decay=0.01)

accuracies_sgd = []
losses_sgd = []
learning_rate = []
```

In [13]:
```
for epoch in range(1100):
    dense1.forward(X)
    activation1.forward(dense1.output)
    dense2.forward(activation1.output)
    activation2.forward(dense2.output)
    dense3.forward(activation2.output)
    data_loss = loss_activation.forward(dense3.output, y)

    regularization_loss = loss_activation.loss.regularization_loss(dense1) + loss_acti
        loss_activation.loss.regularization_loss(dense3)

    loss = data_loss + regularization_loss

    predictions = np.argmax(loss_activation.output, axis=1)
    if len(y.shape) == 2:
        y = np.argmax(y, axis=1)
    accuracy = np.mean(predictions==y)


    if not epoch % 10:
        accuracies_sgd.append(accuracy)
        losses_sgd.append(loss)
        learning_rate.append(optimizer.current_learning_rate)
        print(f'epoch: {epoch}, ' + f'acc: {accuracy:.3f}, ' + f'loss: {loss:.3f}, ' +
            + f'Rr: {regularization_loss}')

    loss_activation.backward(loss_activation.output, y)
    dense3.backward(loss_activation.dinputs)
    activation2.backward(dense3.dinputs)
    dense2.backward(activation2.dinputs)
    activation1.backward(dense2.dinputs)
    dense1.backward(activation1.dinputs)

    optimizer.pre_update_params()
    optimizer.update_params(dense1)
    optimizer.update_params(dense2)
    optimizer.update_params(dense3)
    optimizer.post_update_params()
```

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```
epoch: 0, acc: 0.096, loss: 2.308, lr: 1.0Rr: 0.005013977771864498
epoch: 10, acc: 0.215, loss: 1.837, lr: 0.9174311926605504Rr: 0.0052932212937370155
epoch: 20, acc: 0.136, loss: 2.335, lr: 0.8403361344537815Rr: 0.04673865016803641
epoch: 30, acc: 0.115, loss: 2.235, lr: 0.7751937984496123Rr: 0.0474798288857692
epoch: 40, acc: 0.264, loss: 1.982, lr: 0.7194244604316546Rr: 0.04845644284228443
epoch: 50, acc: 0.032, loss: 2.383, lr: 0.6711409395973155Rr: 0.054531087131002756
epoch: 60, acc: 0.191, loss: 2.169, lr: 0.628930817610063Rr: 0.058298930333085
epoch: 70, acc: 0.290, loss: 1.902, lr: 0.591715976331361Rr: 0.06091108234272053
epoch: 80, acc: 0.404, loss: 1.584, lr: 0.5586592178770949Rr: 0.06103500102755085
epoch: 90, acc: 0.284, loss: 1.997, lr: 0.5291005291005291Rr: 0.06156542051235255
epoch: 100, acc: 0.260, loss: 1.802, lr: 0.5025125628140703Rr: 0.06244491644395994
epoch: 110, acc: 0.296, loss: 1.776, lr: 0.47846889952153115Rr: 0.062347514228712556
epoch: 120, acc: 0.443, loss: 1.382, lr: 0.4566210045662101Rr: 0.06184696058734526
epoch: 130, acc: 0.377, loss: 1.670, lr: 0.4366812227074236Rr: 0.06137280013470734
epoch: 140, acc: 0.444, loss: 1.536, lr: 0.41841004184100417Rr: 0.061026834306485166
epoch: 150, acc: 0.274, loss: 2.170, lr: 0.4016064257028112Rr: 0.06323172384107752
epoch: 160, acc: 0.437, loss: 1.282, lr: 0.3861003861003861Rr: 0.06330501393918851
epoch: 170, acc: 0.422, loss: 1.249, lr: 0.3717472118959108Rr: 0.06292377386389489
epoch: 180, acc: 0.504, loss: 1.267, lr: 0.35842293906810035Rr: 0.0628429955397116
epoch: 190, acc: 0.504, loss: 1.204, lr: 0.3460207612456747Rr: 0.06270819805043129
epoch: 200, acc: 0.645, loss: 0.920, lr: 0.33444816053511706Rr: 0.06268877794827858
epoch: 210, acc: 0.613, loss: 0.986, lr: 0.3236245954692557Rr: 0.0627473869913912
epoch: 220, acc: 0.698, loss: 0.864, lr: 0.31347962382445144Rr: 0.06274600823106806
epoch: 230, acc: 0.570, loss: 1.094, lr: 0.303951367781155Rr: 0.06263656733423358
epoch: 240, acc: 0.724, loss: 0.830, lr: 0.2949852507374631Rr: 0.06330399699887226
epoch: 250, acc: 0.655, loss: 0.898, lr: 0.28653295128939826Rr: 0.06322070313499537
epoch: 260, acc: 0.692, loss: 0.792, lr: 0.2785515320334262Rr: 0.06318213180790545
epoch: 270, acc: 0.738, loss: 0.727, lr: 0.2710027100271003Rr: 0.06303626100208753
epoch: 280, acc: 0.737, loss: 0.719, lr: 0.2638522427440633Rr: 0.06286165327747592
epoch: 290, acc: 0.745, loss: 0.715, lr: 0.2570694087403599Rr: 0.06268488233834218
epoch: 300, acc: 0.730, loss: 0.771, lr: 0.2506265664160401Rr: 0.06256858738732937
epoch: 310, acc: 0.757, loss: 0.691, lr: 0.24449877750611249Rr: 0.06244367626578982
epoch: 320, acc: 0.777, loss: 0.655, lr: 0.23866348448687355Rr: 0.06230328555821758
epoch: 330, acc: 0.772, loss: 0.662, lr: 0.2331002331002331Rr: 0.06216682391738058
epoch: 340, acc: 0.782, loss: 0.643, lr: 0.2277904328018223Rr: 0.062016140057243097
epoch: 350, acc: 0.789, loss: 0.628, lr: 0.22271714922048996Rr: 0.061861290971575264
epoch: 360, acc: 0.784, loss: 0.635, lr: 0.2178649237472767Rr: 0.061721987516224784
epoch: 370, acc: 0.795, loss: 0.610, lr: 0.21321961620469085Rr: 0.06158392645501245
epoch: 380, acc: 0.798, loss: 0.604, lr: 0.20876826722338204Rr: 0.06143068306088759
epoch: 390, acc: 0.799, loss: 0.600, lr: 0.20449897750511245Rr: 0.061281684545059195
epoch: 400, acc: 0.802, loss: 0.593, lr: 0.2004008016032064Rr: 0.061136964685608586
epoch: 410, acc: 0.809, loss: 0.581, lr: 0.19646365422396858Rr: 0.06099000713993547
epoch: 420, acc: 0.807, loss: 0.580, lr: 0.19267822736030826Rr: 0.06084373711793871
epoch: 430, acc: 0.808, loss: 0.577, lr: 0.1890359168241966Rr: 0.060704230639868406
epoch: 440, acc: 0.813, loss: 0.566, lr: 0.1855287569573284Rr: 0.060561759363820064
epoch: 450, acc: 0.814, loss: 0.563, lr: 0.18214936247723132Rr: 0.06041537854882529
epoch: 460, acc: 0.816, loss: 0.560, lr: 0.17889087656529518Rr: 0.0602708228154078
epoch: 470, acc: 0.817, loss: 0.559, lr: 0.17574692442882248Rr: 0.06013205349882125
epoch: 480, acc: 0.820, loss: 0.553, lr: 0.17271157167530224Rr: 0.05999921052579664
epoch: 490, acc: 0.824, loss: 0.546, lr: 0.16977928692699493Rr: 0.05986440916753919
epoch: 500, acc: 0.806, loss: 0.573, lr: 0.1669449081803005Rr: 0.05973055005807647
epoch: 510, acc: 0.823, loss: 0.545, lr: 0.16420361247947454Rr: 0.059602475530373095
epoch: 520, acc: 0.826, loss: 0.538, lr: 0.16155088852988692Rr: 0.059469428513397544
epoch: 530, acc: 0.826, loss: 0.536, lr: 0.1589825119236884Rr: 0.0593332466644326
epoch: 540, acc: 0.826, loss: 0.536, lr: 0.1564945226917058Rr: 0.05919807306480461
epoch: 550, acc: 0.815, loss: 0.556, lr: 0.15408320493066255Rr: 0.05907423578497166
epoch: 560, acc: 0.826, loss: 0.533, lr: 0.15174506828528073Rr: 0.058977261611299805
epoch: 570, acc: 0.831, loss: 0.522, lr: 0.14947683109118085Rr: 0.058849791777276866
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js lr: 0.14727540500736377Rr: 0.058717920825117446
epoch: 590, acc: 0.829, loss: 0.527, lr: 0.14513788098693758Rr: 0.058588254714291216
```

```
epoch: 600, acc: 0.829, loss: 0.527, lr: 0.14306151645207438Rr: 0.058465667280048296
epoch: 610, acc: 0.832, loss: 0.521, lr: 0.14104372355430184Rr: 0.05834607563849975
epoch: 620, acc: 0.832, loss: 0.520, lr: 0.13908205841446453Rr: 0.05822787940905592
epoch: 630, acc: 0.832, loss: 0.520, lr: 0.13717421124828533Rr: 0.0581131494385723
epoch: 640, acc: 0.833, loss: 0.517, lr: 0.13531799729364005Rr: 0.0580000722328097
epoch: 650, acc: 0.835, loss: 0.512, lr: 0.13351134846461948Rr: 0.05788509508759707
epoch: 660, acc: 0.835, loss: 0.511, lr: 0.13175230566534915Rr: 0.057769045249777204
epoch: 670, acc: 0.835, loss: 0.512, lr: 0.13003901170351104Rr: 0.0576542116791727
epoch: 680, acc: 0.834, loss: 0.513, lr: 0.12836970474967907Rr: 0.0575428152855702
epoch: 690, acc: 0.834, loss: 0.512, lr: 0.12674271229404308Rr: 0.05743526960289972
epoch: 700, acc: 0.834, loss: 0.510, lr: 0.1251564455569462Rr: 0.0573304431793102
epoch: 710, acc: 0.835, loss: 0.506, lr: 0.12360939431396786Rr: 0.05722570104362908
epoch: 720, acc: 0.837, loss: 0.502, lr: 0.12210012210012208Rr: 0.057119473098698595
epoch: 730, acc: 0.838, loss: 0.500, lr: 0.12062726176115804Rr: 0.05701282029208169
epoch: 740, acc: 0.838, loss: 0.499, lr: 0.11918951132300357Rr: 0.056906645886608556
epoch: 750, acc: 0.839, loss: 0.497, lr: 0.11778563015312131Rr: 0.05680143324128258
epoch: 760, acc: 0.839, loss: 0.496, lr: 0.11641443538998836Rr: 0.056697394746520476
epoch: 770, acc: 0.840, loss: 0.496, lr: 0.1150747986191024Rr: 0.056594706953099226
epoch: 780, acc: 0.840, loss: 0.496, lr: 0.11376564277588169Rr: 0.05649359332149263
epoch: 790, acc: 0.840, loss: 0.497, lr: 0.11248593925759279Rr: 0.05639465694136939
epoch: 800, acc: 0.839, loss: 0.499, lr: 0.11123470522803114Rr: 0.056298882215286665
epoch: 810, acc: 0.839, loss: 0.499, lr: 0.11001100110011001Rr: 0.05620629109305979
epoch: 820, acc: 0.840, loss: 0.496, lr: 0.1088139281828074Rr: 0.056115367192420794
epoch: 830, acc: 0.841, loss: 0.493, lr: 0.1076426264800861Rr: 0.05602445699321481
epoch: 840, acc: 0.842, loss: 0.491, lr: 0.10649627263045792Rr: 0.05593307717217562
epoch: 850, acc: 0.842, loss: 0.489, lr: 0.1053740779768177Rr: 0.05584153908931848
epoch: 860, acc: 0.842, loss: 0.488, lr: 0.10427528675703858Rr: 0.05575044785597827
epoch: 870, acc: 0.843, loss: 0.487, lr: 0.10319917440660475Rr: 0.055660126060138856
epoch: 880, acc: 0.843, loss: 0.487, lr: 0.10214504596527067Rr: 0.05557079576235481
epoch: 890, acc: 0.843, loss: 0.487, lr: 0.10111223458038422Rr: 0.05548270680771946
epoch: 900, acc: 0.843, loss: 0.487, lr: 0.10010010010010009Rr: 0.05539601900605836
epoch: 910, acc: 0.843, loss: 0.486, lr: 0.09910802775024777Rr: 0.05531065275151828
epoch: 920, acc: 0.844, loss: 0.485, lr: 0.09813542688910697Rr: 0.05522636415299043
epoch: 930, acc: 0.844, loss: 0.485, lr: 0.09718172983479105Rr: 0.05514299624985183
epoch: 940, acc: 0.844, loss: 0.484, lr: 0.09624639076034648Rr: 0.05506043831713899
epoch: 950, acc: 0.844, loss: 0.483, lr: 0.09532888465204957Rr: 0.054978713251017934
epoch: 960, acc: 0.845, loss: 0.482, lr: 0.09442870632672333Rr: 0.054897777460828516
epoch: 970, acc: 0.845, loss: 0.481, lr: 0.09354536950420955Rr: 0.054817597759920185
epoch: 980, acc: 0.845, loss: 0.481, lr: 0.09267840593141798Rr: 0.054738194278115
epoch: 990, acc: 0.845, loss: 0.480, lr: 0.09182736455463728Rr: 0.054659533139755974
epoch: 1000, acc: 0.845, loss: 0.479, lr: 0.09099181073703366Rr: 0.05458161863224329
epoch: 1010, acc: 0.845, loss: 0.479, lr: 0.09017132551848513Rr: 0.054504494436765694
epoch: 1020, acc: 0.845, loss: 0.478, lr: 0.08936550491510277Rr: 0.054428168792544265
epoch: 1030, acc: 0.846, loss: 0.478, lr: 0.08857395925597873Rr: 0.054352662348855975
epoch: 1040, acc: 0.846, loss: 0.477, lr: 0.08779631255487269Rr: 0.054278006220644305
epoch: 1050, acc: 0.846, loss: 0.477, lr: 0.08703220191470844Rr: 0.05420418669212498
epoch: 1060, acc: 0.846, loss: 0.476, lr: 0.08628127696289906Rr: 0.05413109160948577
epoch: 1070, acc: 0.846, loss: 0.476, lr: 0.0855431993156544Rr: 0.05405867467525899
epoch: 1080, acc: 0.847, loss: 0.475, lr: 0.08481764206955046Rr: 0.05398690000759705
epoch: 1090, acc: 0.847, loss: 0.474, lr: 0.08410428931875526Rr: 0.05391577071235945
```

In [14]:
```python
epochs = range(0, 1100, 10)
plt.figure(figsize=(10, 5))
plt.plot(epochs, accuracies_sgd, label='Accuracy', marker='o', color="blue")
plt.plot(epochs, losses_sgd, label='Loss', marker='o', color='red')
plt.plot(epochs, learning_rate, label='Learning Rate', marker='o', color='black')
plt.title('Training Metrics over Epochs - SGD')
plt.xlabel('Epochs')
plt.legend()
```

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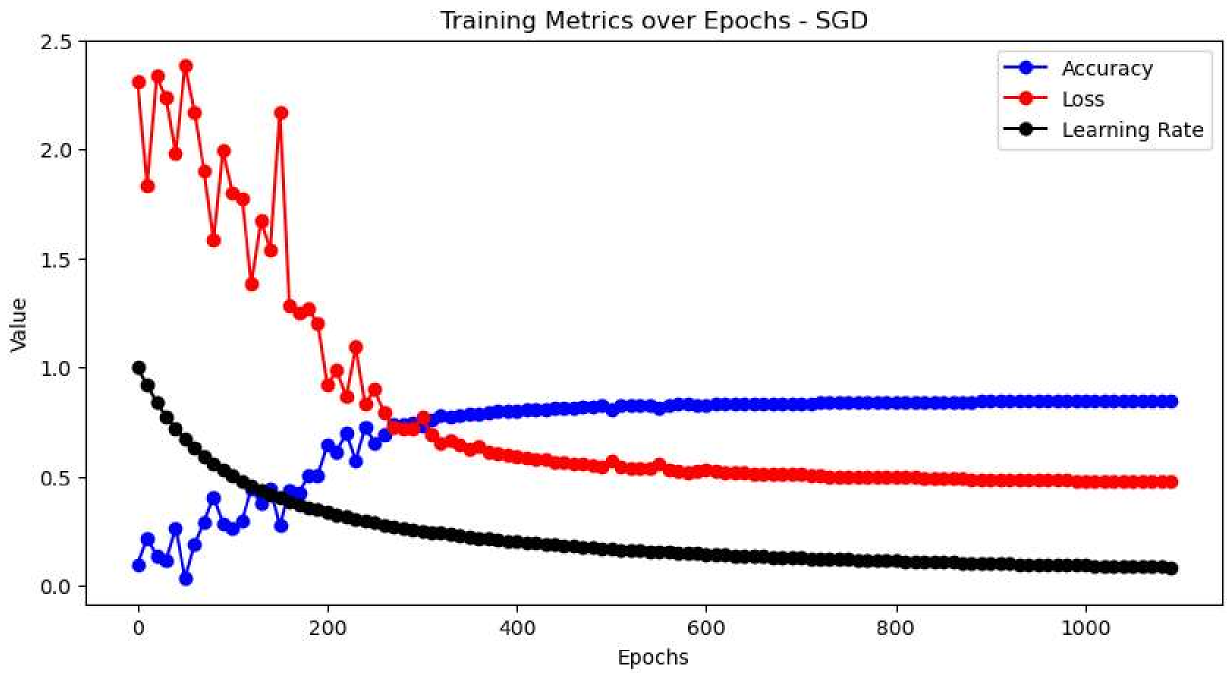
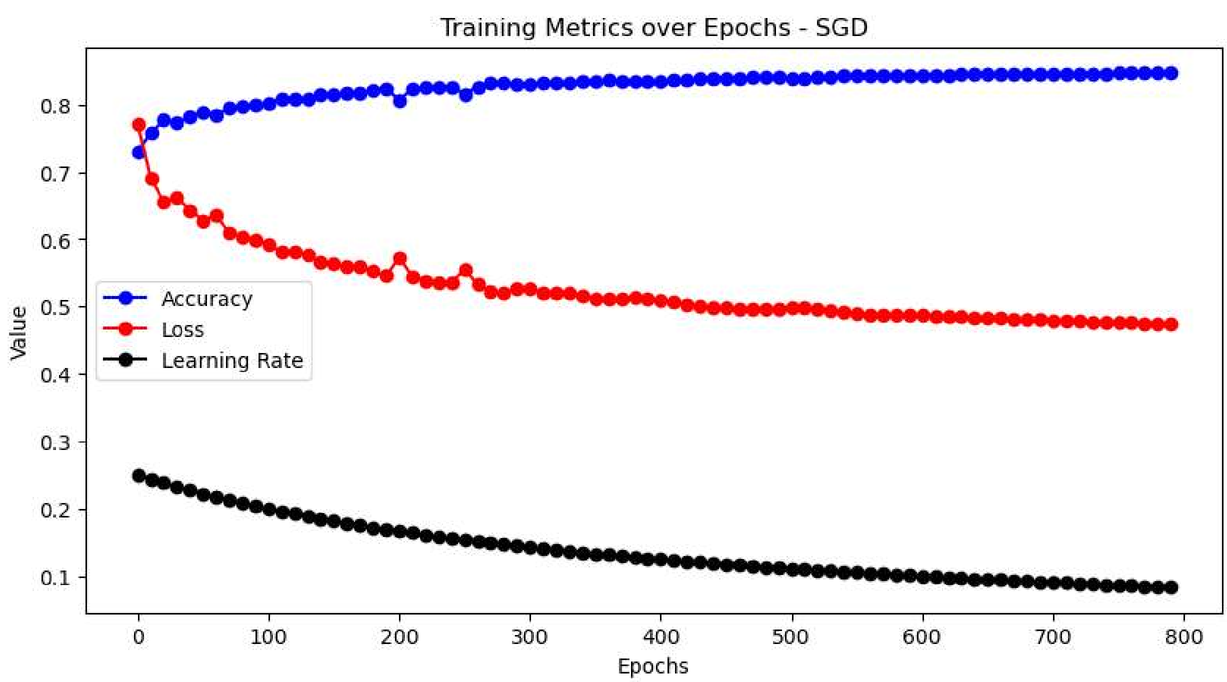
```
plt.savefig('training_metrics_plot.png')
plt.show()

epochs = range(0, 800, 10)
plt.figure(figsize=(10, 5))
plt.plot(epochs, accuracies_sgd[30:], label='Accuracy', marker='o', color="blue")
plt.plot(epochs, losses_sgd[30:], label='Loss', marker='o', color='red')
plt.plot(epochs, learning_rate[30:], label='Learning Rate', marker='o', color='black')
plt.title('Training Metrics over Epochs - SGD')
plt.xlabel('Epochs')
plt.ylabel('Value')
plt.legend()
plt.savefig('training_metrics_plot.png')
plt.show()
```





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```
dense1.forward(X_test)
activation1.forward(dense1.output)
dense2.forward(activation1.output)
activation2.forward(dense2.output)
dense3.forward(activation2.output)
data_loss = loss_activation.forward(dense3.output, y_test)

predictions = np.argmax(loss_activation.output, axis=1)
if len(y_test.shape) == 2:
    y_test = np.argmax(y, axis=1)
accuracy = np.mean(predictions==y_test)
print(f'validation - SGD, acc: {accuracy:.3f}, loss: {loss:.3f}')
```

```
validation - SGD, acc: 0.833, loss: 0.474
```

In [20]:

```
"""
Features = 784
Samples = 60,000
class labels = 10 (0 - 9)

2 hidden layes - ReLU    - 128 neurons each
1 output layer - Softmax - 10 output neurons

Optimizer - SGD with momentum (0.5)
learning rate decay - 0.01
l2 regularization - lambda - 5e-4 (0.0005)
"""

dense1 = Layer_Dense(X.shape[1], 128, weight_regularizer_l2=5e-4, bias_regularizer_l2=
activation1 = Activation_ReLU()
dense2 = Layer_Dense(128, 128)
activation2 = Activation_ReLU()
dense3 = Layer_Dense(128, 10)
loss_activation = Activation_Softmax_Loss_CategoricalCrossentropy()

optimizer = Optimizer_SGD(decay=0.01, momentum=0.5)

accuracies_mom = []
losses_mom = []
learning_rate = []
```

In [21]:

```
for epoch in range(1100):
    dense1.forward(X)
    activation1.forward(dense1.output)
    dense2.forward(activation1.output)
    activation2.forward(dense2.output)
    dense3.forward(activation2.output)
    data_loss = loss_activation.forward(dense3.output, y)

    regularization_loss = loss_activation.loss.regularization_loss(dense1) + loss_acti
        loss_activation.loss.regularization_loss(dense3)

    loss = data_loss + regularization_loss

    predictions = np.argmax(loss_activation.output, axis=1)
    if len(y.shape) == 2:
        y = np.argmax(y, axis=1)
    accuracy = np.mean(predictions==y)
```

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```
    if not epoch % 10:
        accuracies_mom.append(accuracy)
        losses_mom.append(loss)
        learning_rate.append(optimizer.current_learning_rate)
        print(f'epoch: {epoch}, ' + f'acc: {accuracy:.3f}, ' + f'loss: {loss:.3f}, ' +
             + f'Rr: {regularization_loss}')

    loss_activation.backward(loss_activation.output, y)
    dense3.backward(loss_activation.dinputs)
    activation2.backward(dense3.dinputs)
    dense2.backward(activation2.dinputs)
    activation1.backward(dense2.dinputs)
    dense1.backward(activation1.dinputs)

    optimizer.pre_update_params()
    optimizer.update_params(dense1)
    optimizer.update_params(dense2)
    optimizer.update_params(dense3)
    optimizer.post_update_params()
```

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```
epoch: 0, acc: 0.070, loss: 2.308, lr: 1.0Rr: 0.00503343727903207
epoch: 10, acc: 0.102, loss: 9.068, lr: 0.9174311926605504Rr: 0.007474826802391185
epoch: 20, acc: 0.158, loss: 2.516, lr: 0.8403361344537815Rr: 0.27192697559379725
epoch: 30, acc: 0.279, loss: 2.122, lr: 0.7751937984496123Rr: 0.26757800612310556
epoch: 40, acc: 0.272, loss: 2.356, lr: 0.7194244604316546Rr: 0.26561551479816753
epoch: 50, acc: 0.240, loss: 2.225, lr: 0.6711409395973155Rr: 0.2616486037013331
epoch: 60, acc: 0.230, loss: 4.213, lr: 0.628930817610063Rr: 0.2595395807597197
epoch: 70, acc: 0.423, loss: 2.184, lr: 0.591715976331361Rr: 0.40876334154444693
epoch: 80, acc: 0.402, loss: 1.914, lr: 0.5586592178770949Rr: 0.4016385205904229
epoch: 90, acc: 0.488, loss: 1.638, lr: 0.5291005291005291Rr: 0.39527351468614047
epoch: 100, acc: 0.502, loss: 1.463, lr: 0.5025125628140703Rr: 0.3878204130123266
epoch: 110, acc: 0.631, loss: 1.361, lr: 0.47846889952153115Rr: 0.3814228475238515
epoch: 120, acc: 0.647, loss: 1.227, lr: 0.4566210045662101Rr: 0.37504088735565233
epoch: 130, acc: 0.676, loss: 1.148, lr: 0.4366812227074236Rr: 0.36889374531970465
epoch: 140, acc: 0.710, loss: 1.124, lr: 0.41841004184100417Rr: 0.36337168187175656
epoch: 150, acc: 0.776, loss: 1.004, lr: 0.4016064257028112Rr: 0.35808043777823434
epoch: 160, acc: 0.761, loss: 1.036, lr: 0.3861003861003861Rr: 0.35305387279779993
epoch: 170, acc: 0.697, loss: 1.115, lr: 0.3717472118959108Rr: 0.3480981791843632
epoch: 180, acc: 0.742, loss: 0.979, lr: 0.35842293906810035Rr: 0.34340422955457034
epoch: 190, acc: 0.750, loss: 1.011, lr: 0.3460207612456747Rr: 0.3392647592514117
epoch: 200, acc: 0.784, loss: 0.916, lr: 0.33444816053511706Rr: 0.3351876274681324
epoch: 210, acc: 0.780, loss: 0.908, lr: 0.3236245954692557Rr: 0.3312183802860451
epoch: 220, acc: 0.799, loss: 0.863, lr: 0.31347962382445144Rr: 0.327274153870548
epoch: 230, acc: 0.810, loss: 0.843, lr: 0.303951367781155Rr: 0.32359019167753106
epoch: 240, acc: 0.806, loss: 0.848, lr: 0.2949852507374631Rr: 0.31997933097325565
epoch: 250, acc: 0.824, loss: 0.800, lr: 0.28653295128939826Rr: 0.3165544780166603
epoch: 260, acc: 0.772, loss: 0.921, lr: 0.2785515320334262Rr: 0.31318410556074927
epoch: 270, acc: 0.830, loss: 0.783, lr: 0.2710027100271003Rr: 0.310150728567035
epoch: 280, acc: 0.831, loss: 0.773, lr: 0.2638522427440633Rr: 0.30699763738602487
epoch: 290, acc: 0.832, loss: 0.770, lr: 0.2570694087403599Rr: 0.30399050153228235
epoch: 300, acc: 0.816, loss: 0.799, lr: 0.2506265664160401Rr: 0.30108325309492445
epoch: 310, acc: 0.840, loss: 0.745, lr: 0.24449877750611249Rr: 0.29833816033192995
epoch: 320, acc: 0.813, loss: 0.796, lr: 0.23866348448687355Rr: 0.29560779799951425
epoch: 330, acc: 0.842, loss: 0.731, lr: 0.2331002331002331Rr: 0.29302105604733414
epoch: 340, acc: 0.822, loss: 0.771, lr: 0.2277904328018223Rr: 0.2904695733488789
epoch: 350, acc: 0.846, loss: 0.717, lr: 0.22271714922048996Rr: 0.2880391724686652
epoch: 360, acc: 0.826, loss: 0.759, lr: 0.2178649237472767Rr: 0.28565436829422114
epoch: 370, acc: 0.848, loss: 0.706, lr: 0.21321961620469085Rr: 0.2833683516787223
epoch: 380, acc: 0.828, loss: 0.747, lr: 0.20876826722338204Rr: 0.28110098905397324
epoch: 390, acc: 0.850, loss: 0.696, lr: 0.20449897750511245Rr: 0.27894877703455734
epoch: 400, acc: 0.839, loss: 0.714, lr: 0.2004008016032064Rr: 0.2768103975354487
epoch: 410, acc: 0.853, loss: 0.685, lr: 0.19646365422396858Rr: 0.27476520377417696
epoch: 420, acc: 0.846, loss: 0.699, lr: 0.19267822736030826Rr: 0.27273632896736283
epoch: 430, acc: 0.854, loss: 0.677, lr: 0.1890359168241966Rr: 0.27080648261257756
epoch: 440, acc: 0.854, loss: 0.675, lr: 0.1855287569573284Rr: 0.2688844029505018
epoch: 450, acc: 0.854, loss: 0.673, lr: 0.18214936247723132Rr: 0.2670400261857702
epoch: 460, acc: 0.857, loss: 0.663, lr: 0.17889087656529518Rr: 0.2652248471908936
epoch: 470, acc: 0.844, loss: 0.691, lr: 0.17574692442882248Rr: 0.26344370501814346
epoch: 480, acc: 0.858, loss: 0.656, lr: 0.17271157167530224Rr: 0.2617415971846138
epoch: 490, acc: 0.858, loss: 0.654, lr: 0.16977928692699493Rr: 0.2600426286390037
epoch: 500, acc: 0.851, loss: 0.668, lr: 0.1669449081803005Rr: 0.25840563360391094
epoch: 510, acc: 0.860, loss: 0.645, lr: 0.16420361247947454Rr: 0.25680063631500005
epoch: 520, acc: 0.859, loss: 0.647, lr: 0.16155088852988692Rr: 0.255214599269414
epoch: 530, acc: 0.860, loss: 0.642, lr: 0.1589825119236884Rr: 0.2536944348514887
epoch: 540, acc: 0.862, loss: 0.635, lr: 0.1564945226917058Rr: 0.2521860111355852
epoch: 550, acc: 0.860, loss: 0.636, lr: 0.15408320493066255Rr: 0.2507017376340393
epoch: 560, acc: 0.860, loss: 0.635, lr: 0.15174506828528073Rr: 0.2492765087324014
epoch: 570, acc: 0.863, loss: 0.626, lr: 0.14947683109118085Rr: 0.2478632429819722
lr: 0.14727540500736377Rr: 0.24646963727647586
epoch: 590, acc: 0.853, loss: 0.649, lr: 0.14513788098693758Rr: 0.245116360690906
```

```
epoch: 600, acc: 0.865, loss: 0.618, lr: 0.14306151645207438Rr: 0.24380180424591147
epoch: 610, acc: 0.865, loss: 0.616, lr: 0.14104372355430184Rr: 0.24249199886800604
epoch: 620, acc: 0.862, loss: 0.620, lr: 0.13908205841446453Rr: 0.24120895968213402
epoch: 630, acc: 0.866, loss: 0.612, lr: 0.13717421124828533Rr: 0.23997083065036243
epoch: 640, acc: 0.867, loss: 0.608, lr: 0.13531799729364005Rr: 0.23873832464998349
epoch: 650, acc: 0.867, loss: 0.606, lr: 0.13351134846461948Rr: 0.23752516642494442
epoch: 660, acc: 0.867, loss: 0.605, lr: 0.13175230566534915Rr: 0.23633423717303495
epoch: 670, acc: 0.859, loss: 0.620, lr: 0.13003901170351104Rr: 0.2351814801993159
epoch: 680, acc: 0.868, loss: 0.599, lr: 0.12836970474967907Rr: 0.2340455106630411
epoch: 690, acc: 0.869, loss: 0.597, lr: 0.12674271229404308Rr: 0.23291826340858027
epoch: 700, acc: 0.869, loss: 0.595, lr: 0.1251564455569462Rr: 0.23180973508240504
epoch: 710, acc: 0.866, loss: 0.602, lr: 0.12360939431396786Rr: 0.23072340381855272
epoch: 720, acc: 0.869, loss: 0.592, lr: 0.12210012210012208Rr: 0.2296715342332999
epoch: 730, acc: 0.870, loss: 0.588, lr: 0.12062726176115804Rr: 0.22862277852564103
epoch: 740, acc: 0.870, loss: 0.587, lr: 0.11918951132300357Rr: 0.22758916323147182
epoch: 750, acc: 0.869, loss: 0.590, lr: 0.11778563015312131Rr: 0.2265751556642837
epoch: 760, acc: 0.870, loss: 0.586, lr: 0.11641443538998836Rr: 0.22558565524954838
epoch: 770, acc: 0.871, loss: 0.581, lr: 0.1150747986191024Rr: 0.22460566290643622
epoch: 780, acc: 0.871, loss: 0.579, lr: 0.11376564277588169Rr: 0.223638357836161
epoch: 790, acc: 0.872, loss: 0.578, lr: 0.11248593925759279Rr: 0.2226859364295567
epoch: 800, acc: 0.871, loss: 0.579, lr: 0.11123470522803114Rr: 0.22175009651495672
epoch: 810, acc: 0.871, loss: 0.578, lr: 0.11001100110011001Rr: 0.2208344680147308
epoch: 820, acc: 0.873, loss: 0.572, lr: 0.1088139281828074Rr: 0.21992957646301428
epoch: 830, acc: 0.873, loss: 0.570, lr: 0.1076426264800861Rr: 0.2190344781467941
epoch: 840, acc: 0.874, loss: 0.569, lr: 0.10649627263045792Rr: 0.21815191630845612
epoch: 850, acc: 0.874, loss: 0.568, lr: 0.1053740779768177Rr: 0.2172832579273551
epoch: 860, acc: 0.873, loss: 0.568, lr: 0.10427528675703858Rr: 0.21642896782519452
epoch: 870, acc: 0.874, loss: 0.566, lr: 0.10319917440660475Rr: 0.21558823470057467
epoch: 880, acc: 0.875, loss: 0.563, lr: 0.10214504596527067Rr: 0.21475829586756745
epoch: 890, acc: 0.875, loss: 0.561, lr: 0.10111223458038422Rr: 0.2139387607900529
epoch: 900, acc: 0.875, loss: 0.560, lr: 0.10010010010010009Rr: 0.21313044512539342
epoch: 910, acc: 0.875, loss: 0.559, lr: 0.09910802775024777Rr: 0.212333968036307
epoch: 920, acc: 0.875, loss: 0.558, lr: 0.09813542688910697Rr: 0.21154960267445724
epoch: 930, acc: 0.876, loss: 0.556, lr: 0.09718172983479105Rr: 0.21077618636725431
epoch: 940, acc: 0.877, loss: 0.554, lr: 0.09624639076034648Rr: 0.21001208928853926
epoch: 950, acc: 0.877, loss: 0.553, lr: 0.09532888465204957Rr: 0.20925735365297157
epoch: 960, acc: 0.877, loss: 0.552, lr: 0.09442870632672333Rr: 0.20851258711738974
epoch: 970, acc: 0.877, loss: 0.551, lr: 0.09354536950420955Rr: 0.20777785779444702
epoch: 980, acc: 0.877, loss: 0.549, lr: 0.09267840593141798Rr: 0.20705289202658866
epoch: 990, acc: 0.877, loss: 0.548, lr: 0.09182736455463728Rr: 0.2063370311657284
epoch: 1000, acc: 0.878, loss: 0.546, lr: 0.09099181073703366Rr: 0.20562971923802648
epoch: 1010, acc: 0.878, loss: 0.545, lr: 0.09017132551848513Rr: 0.20493095540384038
epoch: 1020, acc: 0.878, loss: 0.544, lr: 0.08936550491510277Rr: 0.2042408285638163
epoch: 1030, acc: 0.878, loss: 0.543, lr: 0.08857395925597873Rr: 0.20355937531311674
epoch: 1040, acc: 0.879, loss: 0.541, lr: 0.08779631255487269Rr: 0.2028862578301819
epoch: 1050, acc: 0.879, loss: 0.540, lr: 0.08703220191470844Rr: 0.20222128891233956
epoch: 1060, acc: 0.879, loss: 0.539, lr: 0.08628127696289906Rr: 0.2015643424047353
epoch: 1070, acc: 0.879, loss: 0.538, lr: 0.0855431993156544Rr: 0.20091534385054344
epoch: 1080, acc: 0.879, loss: 0.537, lr: 0.08481764206955046Rr: 0.20027405678769697
epoch: 1090, acc: 0.879, loss: 0.536, lr: 0.08410428931875526Rr: 0.1996403552875046
```

In [22]:

```python
epochs = range(0, 1100, 10)
plt.figure(figsize=(10, 5))
plt.plot(epochs, accuracies_mom, label='Accuracy', marker='o', color="blue")
plt.plot(epochs, losses_mom, label='Loss', marker='o', color='red')
plt.plot(epochs, learning_rate, label='Learning Rate', marker='o', color='black')
plt.title('Training Metrics over Epochs - SGD Momentum')
plt.xlabel('Epochs')
plt.legend()
```

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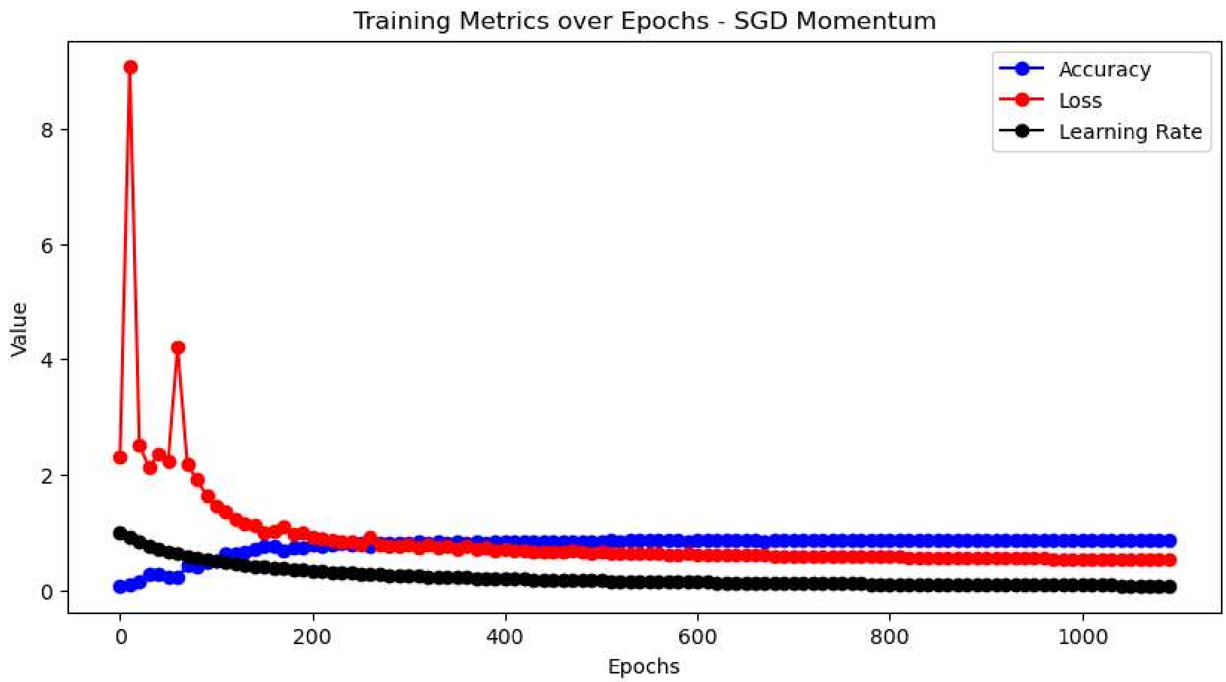
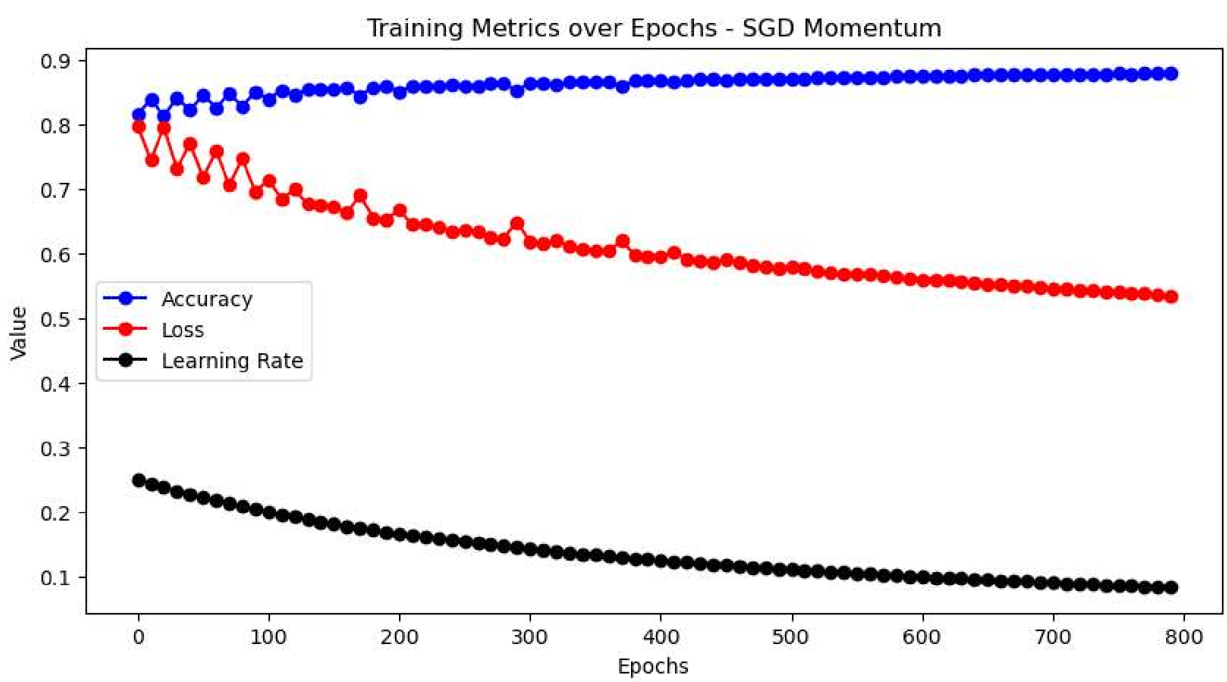
```
plt.savefig('training_metrics_plot.png')
plt.show()

epochs = range(0, 800, 10)
plt.figure(figsize=(10, 5))
plt.plot(epochs, accuracies_mom[30:], label='Accuracy', marker='o', color="blue")
plt.plot(epochs, losses_mom[30:], label='Loss', marker='o', color='red')
plt.plot(epochs, learning_rate[30:], label='Learning Rate', marker='o', color='black')
plt.title('Training Metrics over Epochs - SGD Momentum')
plt.xlabel('Epochs')
plt.ylabel('Value')
plt.legend()
plt.savefig('training_metrics_plot.png')
plt.show()
```





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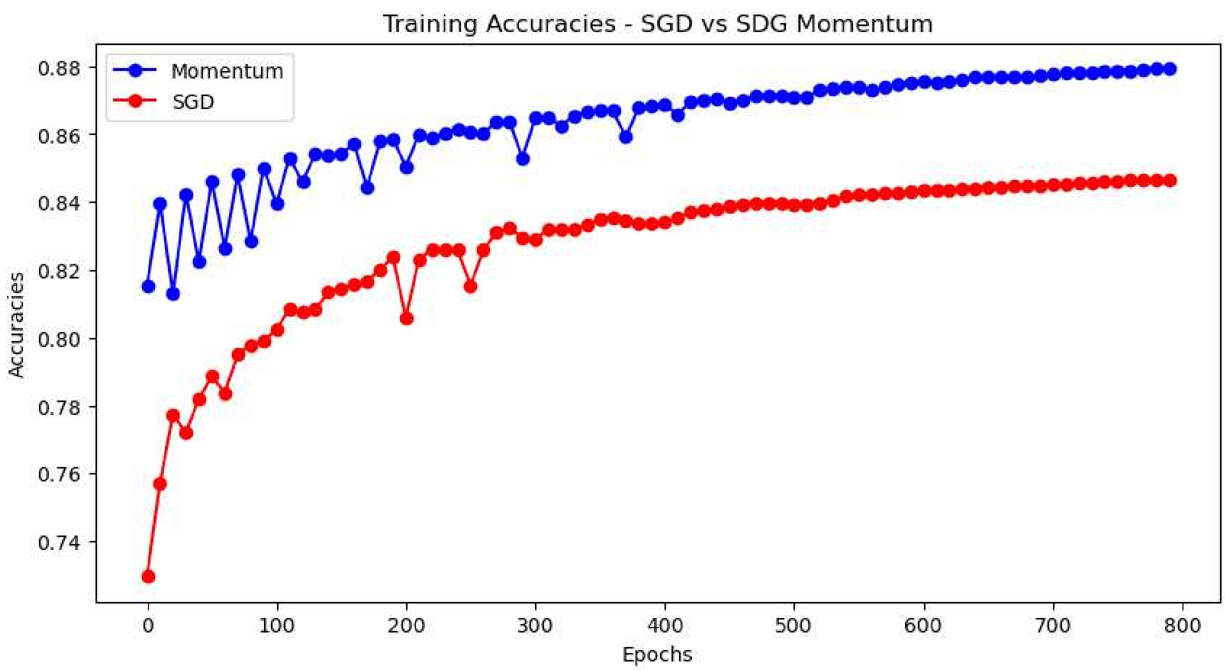
In [23]:
```
# Validate the model

dense1.forward(X_test)
activation1.forward(dense1.output)
dense2.forward(activation1.output)
activation2.forward(dense2.output)
dense3.forward(activation2.output)
data_loss = loss_activation.forward(dense3.output, y_test)

predictions = np.argmax(loss_activation.output, axis=1)
if len(y_test.shape) == 2:
    y_test = np.argmax(y, axis=1)
accuracy = np.mean(predictions==y_test)
print(f'validation - SGD Momentum, acc: {accuracy:.3f}, loss: {loss:.3f}')
```

```
validation - SGD Momentum, acc: 0.859, loss: 0.535
```

In [24]:
```
epochs = range(0, 800, 10)
plt.figure(figsize=(10, 5))
plt.plot(epochs, accuracies_mom[30:], label='Momentum', marker='o', color="blue")
plt.plot(epochs, accuracies_sgd[30:], label='SGD', marker='o', color='red')
plt.title('Training Accuracies - SGD vs SGD Momentum')
plt.xlabel('Epochs')
plt.ylabel('Accuracies')
plt.legend()
plt.savefig('training_metrics_plot.png')
plt.show()
```



In [25]:
```
epochs = range(0, 800, 10)
plt.figure(figsize=(10, 5))
plt.plot(epochs, losses_mom[30:], label='Momentum', marker='o', color="blue")
plt.plot(epochs, losses_sgd[30:], label='SGD', marker='o', color='red')
plt.title('Training Losses - SGD vs SGD Momentum')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
ng')
plt.show()
```

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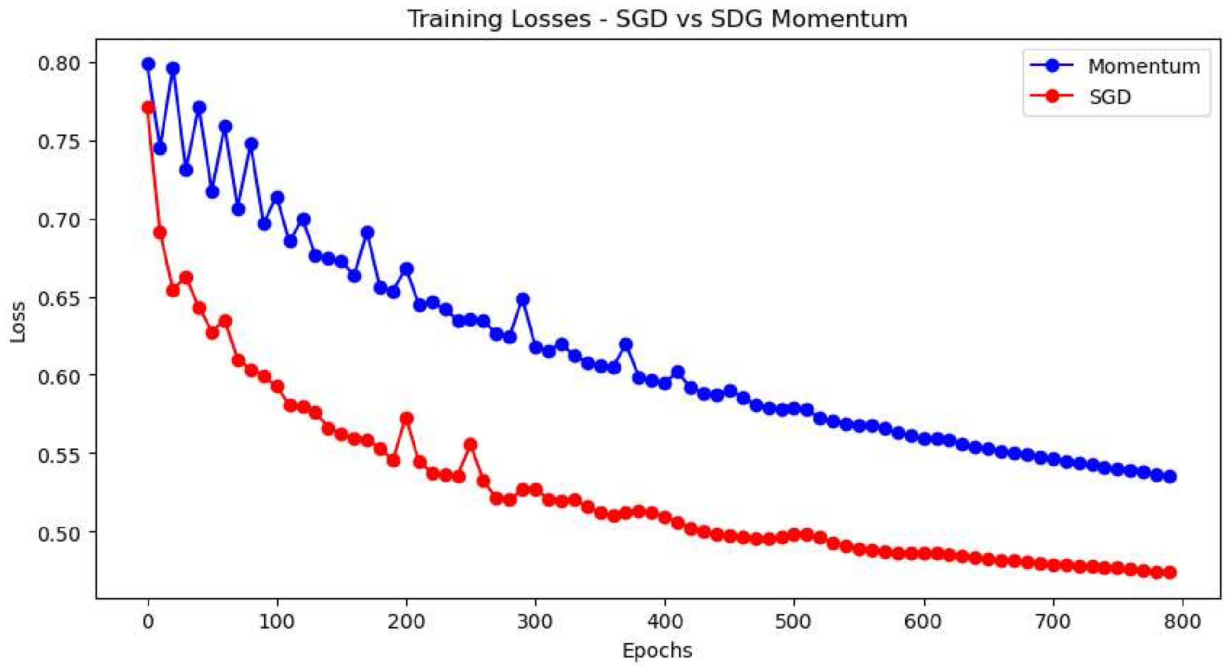

In [ ]:

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