In [1]:
```
import numpy as np
import nnfs
from nnfs.datasets import spiral_data
import matplotlib.pyplot as plt
```

In [2]:
```
import numpy as np
import cv2
import os

# Loads a MNIST dataset
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]:
```
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)
```

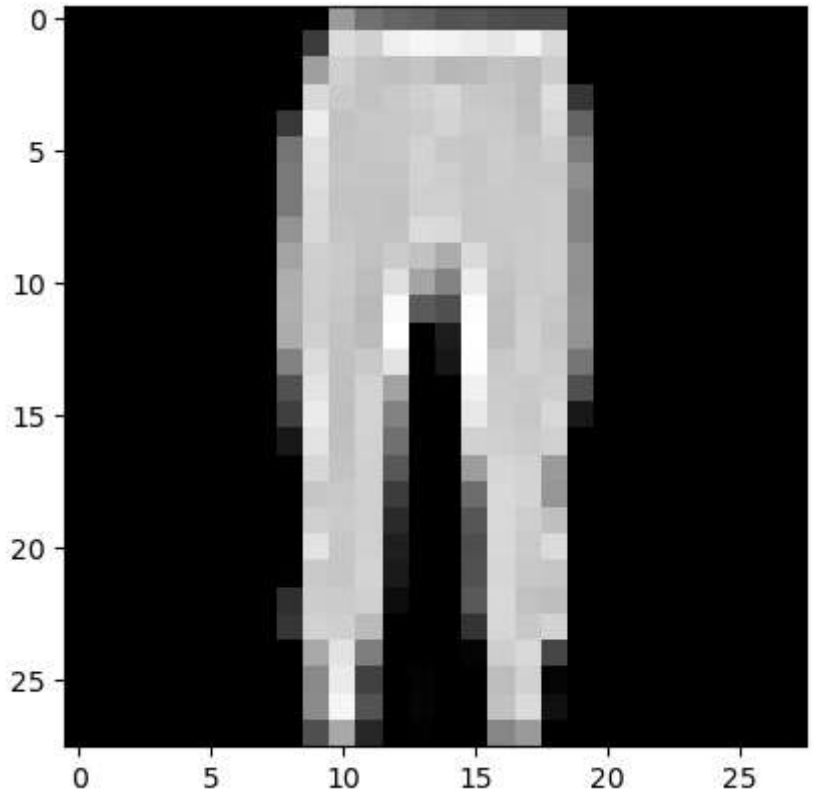
In [4]:
```
print(X.shape)
print(y.shape)
```

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

In [5]:
```
# Reshape to vectors
X = X.reshape(X.shape[0], -1)
X_test = X_test.reshape(X_test.shape[0], -1)
```

In [15]:
```
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 [7]:
```
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 [8]:

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

    def backward(self, dvalues):
        # Since we need to modify original variable,
        # let's make a copy of values first
        self.dinputs = dvalues.copy()
        # Zero gradient where input values were negative
        self.dinputs[self.inputs <= 0] = 0

class Activation_Softmax:
    def forward(self, inputs):
        # Remember input values
        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

    # Backward pass
```

```
    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 [9]:

```
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):
    def forward(self, y_pred, y_true):
        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):
        # Number of samples
        samples = len(dvalues)
        # Number of labels in every sample
        # We'll use the first sample to count them
        labels = len(dvalues[0])
        # If labels are sparse, turn them into one-hot vector
        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():
    # Creates activation and loss function objects
    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 [10]:

```
class Optimizer_SGD:
    """
    Vanilla option - SGD
    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

    # Call once before any parameter updates
```

```
    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:

            # If layer does not contain momentum arrays, create them
            # filled with zeros
            if not hasattr(layer, 'weight_momentums'):
                layer.weight_momentums = np.zeros_like(layer.weights)
                # If there is no momentum array for weights
                # The array doesn't exist for biases yet either.
                layer.bias_momentums = np.zeros_like(layer.biases)

            # Build weight updates with momentum - take previous
            # updates multiplied by retain factor and update with
            # current gradients
            weight_updates = self.momentum * layer.weight_momentums - self.current_lea
            layer.weight_momentums = weight_updates

            # Build bias updates
            bias_updates = self.momentum * layer.bias_momentums - self.current_learnir
            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 updates
        layer.weights += weight_updates
        layer.biases += bias_updates


    # Call once after any parameter updates
    def post_update_params(self):
        self.iterations += 1
```

In [11]:
```
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 = []
losses = []
learning_rate = []
```

In [12]:
```
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.append(accuracy)
        losses.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()
```

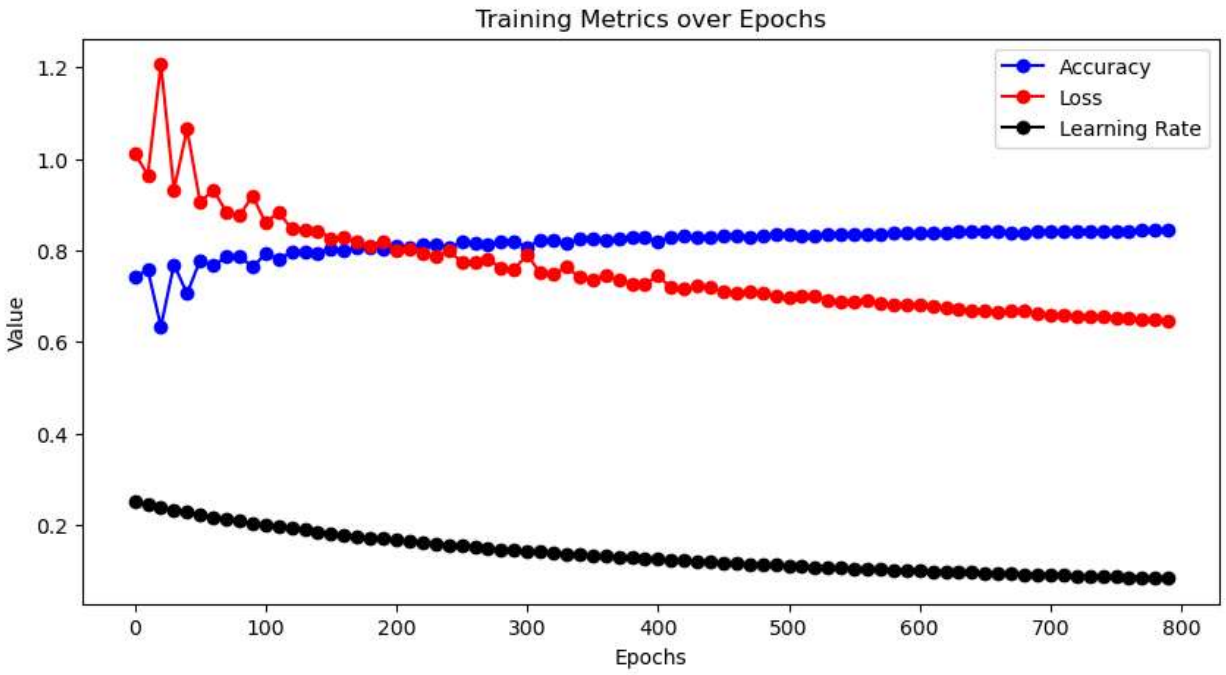
```
epoch: 0, acc: 0.112, loss: 2.308, lr: 1.0Rr: 0.00503451968865524
epoch: 10, acc: 0.100, loss: 10.680, lr: 0.9174311926605504Rr: 0.00838227200825124
epoch: 20, acc: 0.238, loss: 2.456, lr: 0.8403361344537815Rr: 0.4002204596130479
epoch: 30, acc: 0.335, loss: 2.184, lr: 0.7751937984496123Rr: 0.406407055266603
epoch: 40, acc: 0.313, loss: 2.323, lr: 0.7194244604316546Rr: 0.41817819724849087
epoch: 50, acc: 0.185, loss: 2.690, lr: 0.6711409395973155Rr: 0.42146232069142076
epoch: 60, acc: 0.169, loss: 2.628, lr: 0.628930817610063Rr: 0.4136935871644017
epoch: 70, acc: 0.298, loss: 2.170, lr: 0.591715976331361Rr: 0.4059028981217895
epoch: 80, acc: 0.341, loss: 2.039, lr: 0.5586592178770949Rr: 0.3975730039535512
epoch: 90, acc: 0.203, loss: 2.439, lr: 0.5291005291005291Rr: 0.3899865106487447
epoch: 100, acc: 0.174, loss: 2.643, lr: 0.5025125628140703Rr: 0.3868441508671544
epoch: 110, acc: 0.216, loss: 2.289, lr: 0.4784688995215311Rr: 0.3797515158791232
epoch: 120, acc: 0.213, loss: 2.312, lr: 0.4566210045662101Rr: 0.372698010463934
epoch: 130, acc: 0.369, loss: 1.812, lr: 0.4366812227074236Rr: 0.3661404638099571
epoch: 140, acc: 0.313, loss: 2.024, lr: 0.41841004184100417Rr: 0.36015653418287336
epoch: 150, acc: 0.273, loss: 2.745, lr: 0.4016064257028112Rr: 0.354834598073053
epoch: 160, acc: 0.268, loss: 2.216, lr: 0.3861003861003861Rr: 0.363729285424908
epoch: 170, acc: 0.285, loss: 2.277, lr: 0.3717472118959108Rr: 0.3602163278317301
epoch: 180, acc: 0.376, loss: 1.781, lr: 0.35842293906810035Rr: 0.3555415370514555
epoch: 190, acc: 0.424, loss: 1.571, lr: 0.3460207612456747Rr: 0.350705861404834
epoch: 200, acc: 0.487, loss: 1.648, lr: 0.33444816053511706Rr: 0.3457487538790493
epoch: 210, acc: 0.293, loss: 2.296, lr: 0.3236245954692557Rr: 0.3413210042822297
epoch: 220, acc: 0.321, loss: 1.915, lr: 0.31347962382445144Rr: 0.3377538457315041
epoch: 230, acc: 0.559, loss: 1.449, lr: 0.303951367781155Rr: 0.33392780742332573
epoch: 240, acc: 0.524, loss: 1.388, lr: 0.2949852507374631Rr: 0.33096544813019124
epoch: 250, acc: 0.586, loss: 1.239, lr: 0.28653295128939826Rr: 0.3271496283947017
epoch: 260, acc: 0.684, loss: 1.153, lr: 0.2785515320334262Rr: 0.3235672674391777
epoch: 270, acc: 0.507, loss: 1.536, lr: 0.2710027100271003Rr: 0.3202406986157577
epoch: 280, acc: 0.715, loss: 1.088, lr: 0.2638522427440633Rr: 0.3174255490015097
epoch: 290, acc: 0.666, loss: 1.139, lr: 0.2570694087403599Rr: 0.3141771709173613
epoch: 300, acc: 0.742, loss: 1.012, lr: 0.2506265664160401Rr: 0.3112368047446666
epoch: 310, acc: 0.758, loss: 0.965, lr: 0.24449877750611249Rr: 0.30831208082879535
epoch: 320, acc: 0.634, loss: 1.206, lr: 0.23866348448687355Rr: 0.30548624722338996
epoch: 330, acc: 0.769, loss: 0.932, lr: 0.2331002331002331Rr: 0.30288957612238476
epoch: 340, acc: 0.705, loss: 1.065, lr: 0.2277904328018223Rr: 0.3002569911403449
epoch: 350, acc: 0.779, loss: 0.905, lr: 0.22271714922048996Rr: 0.2978217357830459
epoch: 360, acc: 0.766, loss: 0.932, lr: 0.2178649237472767Rr: 0.2953227540733903
epoch: 370, acc: 0.786, loss: 0.884, lr: 0.21321961620469085Rr: 0.29296502410304565
epoch: 380, acc: 0.788, loss: 0.875, lr: 0.20876826722338204Rr: 0.29057677395294296
epoch: 390, acc: 0.763, loss: 0.919, lr: 0.20449897750511245Rr: 0.28834437103459526
epoch: 400, acc: 0.793, loss: 0.860, lr: 0.2004008016032064Rr: 0.28615070258906034
epoch: 410, acc: 0.781, loss: 0.883, lr: 0.1964636542396858Rr: 0.2839843248900268
epoch: 420, acc: 0.796, loss: 0.847, lr: 0.19267822736030826Rr: 0.28190963366499644
epoch: 430, acc: 0.795, loss: 0.846, lr: 0.1890359168241966Rr: 0.27983635092609416
epoch: 440, acc: 0.795, loss: 0.843, lr: 0.1855287569573284Rr: 0.2778848358064881
epoch: 450, acc: 0.803, loss: 0.827, lr: 0.18214936247723132Rr: 0.27591801748527817
epoch: 460, acc: 0.801, loss: 0.828, lr: 0.17889087656529518Rr: 0.273988602461581
epoch: 470, acc: 0.805, loss: 0.819, lr: 0.17574692442882248Rr: 0.27220016713795486
epoch: 480, acc: 0.808, loss: 0.811, lr: 0.17271157167530224Rr: 0.2703865720905306
epoch: 490, acc: 0.802, loss: 0.820, lr: 0.16977928692699493Rr: 0.26861669483552764
epoch: 500, acc: 0.810, loss: 0.800, lr: 0.1669449081803005Rr: 0.26690238550154544
epoch: 510, acc: 0.808, loss: 0.803, lr: 0.16420361247947454Rr: 0.2652118463588427
epoch: 520, acc: 0.811, loss: 0.793, lr: 0.16155088852988692Rr: 0.2635828164462515
epoch: 530, acc: 0.814, loss: 0.786, lr: 0.1589825119236884Rr: 0.2619655119386929
epoch: 540, acc: 0.806, loss: 0.799, lr: 0.1564945226917058Rr: 0.26040678962867503
epoch: 550, acc: 0.818, loss: 0.774, lr: 0.15408320493066255Rr: 0.25886856412269804
epoch: 560, acc: 0.816, loss: 0.774, lr: 0.15174506828528073Rr: 0.25735475951600567
epoch: 570, acc: 0.812, loss: 0.781, lr: 0.14947683109118085Rr: 0.2559052643244058
epoch: 580, acc: 0.820, loss: 0.761, lr: 0.14727540500736377Rr: 0.25445608755202737
epoch: 590, acc: 0.820, loss: 0.759, lr: 0.14513788098693758Rr: 0.25303260182852055
```

```
epoch: 600, acc: 0.806, loss: 0.790, lr: 0.14306151645207438Rr: 0.2516672522069906
epoch: 610, acc: 0.823, loss: 0.750, lr: 0.14104372355430184Rr: 0.2503171806493208
epoch: 620, acc: 0.823, loss: 0.748, lr: 0.13908205841446453Rr: 0.2489739183251788
epoch: 630, acc: 0.815, loss: 0.764, lr: 0.13717421124828533Rr: 0.24766286804043333
epoch: 640, acc: 0.825, loss: 0.741, lr: 0.13531799729364005Rr: 0.2464009886874537
epoch: 650, acc: 0.826, loss: 0.737, lr: 0.13351134846461948Rr: 0.2451360995633058
epoch: 660, acc: 0.821, loss: 0.746, lr: 0.13175230566534915Rr: 0.24389374011743867
epoch: 670, acc: 0.825, loss: 0.735, lr: 0.13003901170351104Rr: 0.24270128365512475
epoch: 680, acc: 0.829, loss: 0.727, lr: 0.12836970474967907Rr: 0.24150960021136902
epoch: 690, acc: 0.827, loss: 0.727, lr: 0.12674271229404308Rr: 0.2403316435284347
epoch: 700, acc: 0.819, loss: 0.744, lr: 0.1251564455569462Rr: 0.23918524891273077
epoch: 710, acc: 0.830, loss: 0.719, lr: 0.12360939431396786Rr: 0.2380717623508691
epoch: 720, acc: 0.831, loss: 0.716, lr: 0.12210012210012208Rr: 0.23695576625227158
epoch: 730, acc: 0.827, loss: 0.722, lr: 0.12062726176115804Rr: 0.23585843094784978
epoch: 740, acc: 0.828, loss: 0.720, lr: 0.11918951132300357Rr: 0.23479644469833075
epoch: 750, acc: 0.832, loss: 0.708, lr: 0.11778563015312131Rr: 0.23374401009231477
epoch: 760, acc: 0.832, loss: 0.707, lr: 0.11641443538998836Rr: 0.23270052992162304
epoch: 770, acc: 0.830, loss: 0.711, lr: 0.1150747986191024Rr: 0.23167483016860638
epoch: 780, acc: 0.831, loss: 0.707, lr: 0.11376564277588169Rr: 0.2306769069114837
epoch: 790, acc: 0.834, loss: 0.700, lr: 0.11248593925759279Rr: 0.22968870911631437
epoch: 800, acc: 0.834, loss: 0.698, lr: 0.11123470522803114Rr: 0.2287106643692249
epoch: 810, acc: 0.832, loss: 0.699, lr: 0.11001100110011001Rr: 0.22774802183629586
epoch: 820, acc: 0.832, loss: 0.699, lr: 0.1088139281828074Rr: 0.22680670862269828
epoch: 830, acc: 0.835, loss: 0.691, lr: 0.1076426264800861Rr: 0.22587869442193545
epoch: 840, acc: 0.836, loss: 0.689, lr: 0.10649627263045792Rr: 0.22495956771052214
epoch: 850, acc: 0.836, loss: 0.689, lr: 0.1053740779768177Rr: 0.22405349037474043
epoch: 860, acc: 0.835, loss: 0.690, lr: 0.10427528675703858Rr: 0.2231637868140928
epoch: 870, acc: 0.836, loss: 0.684, lr: 0.10319917440660475Rr: 0.22228897307046677
epoch: 880, acc: 0.837, loss: 0.681, lr: 0.10214504596527067Rr: 0.22142303956061293
epoch: 890, acc: 0.837, loss: 0.680, lr: 0.10111223458038422Rr: 0.22056818243880688
epoch: 900, acc: 0.837, loss: 0.680, lr: 0.10010010010010009Rr: 0.21972637330096356
epoch: 910, acc: 0.837, loss: 0.677, lr: 0.09910802775024777Rr: 0.21889786268828346
epoch: 920, acc: 0.839, loss: 0.674, lr: 0.09813542688910697Rr: 0.21808011934389276
epoch: 930, acc: 0.840, loss: 0.671, lr: 0.09718172983479105Rr: 0.2172717483608713
epoch: 940, acc: 0.841, loss: 0.669, lr: 0.09624639076034648Rr: 0.2164731677002239
epoch: 950, acc: 0.840, loss: 0.668, lr: 0.09532888465204957Rr: 0.21568463411760205
epoch: 960, acc: 0.840, loss: 0.666, lr: 0.09442870632672333Rr: 0.2149063782384027
epoch: 970, acc: 0.839, loss: 0.668, lr: 0.09354536950420955Rr: 0.21413904964009467
epoch: 980, acc: 0.838, loss: 0.669, lr: 0.09267840593141798Rr: 0.21338735583826487
epoch: 990, acc: 0.841, loss: 0.662, lr: 0.09182736455463728Rr: 0.21264512590920423
epoch: 1000, acc: 0.842, loss: 0.660, lr: 0.09099181073703366Rr: 0.21190822497789233
epoch: 1010, acc: 0.842, loss: 0.658, lr: 0.09017132551848513Rr: 0.21117964117771595
epoch: 1020, acc: 0.842, loss: 0.657, lr: 0.08936550491510277Rr: 0.21046016692546368
epoch: 1030, acc: 0.842, loss: 0.656, lr: 0.08857395925597873Rr: 0.20974990373548155
epoch: 1040, acc: 0.841, loss: 0.655, lr: 0.08779631255487269Rr: 0.20904912304126
epoch: 1050, acc: 0.842, loss: 0.653, lr: 0.08703220191470844Rr: 0.20835730436982514
epoch: 1060, acc: 0.843, loss: 0.651, lr: 0.08628127696289906Rr: 0.20767388518449204
epoch: 1070, acc: 0.843, loss: 0.650, lr: 0.0855431993156544Rr: 0.20699831315887868
epoch: 1080, acc: 0.844, loss: 0.648, lr: 0.08481764206955046Rr: 0.2063304252037452
epoch: 1090, acc: 0.844, loss: 0.646, lr: 0.08410428931875526Rr: 0.20567010121676432
```

In [17]:

```
epochs = range(0, 800, 10)
plt.figure(figsize=(10, 5))
plt.plot(epochs, accuracies[30:], label='Accuracy', marker='o', color="blue")
plt.plot(epochs, losses[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')
plt.xlabel('Epochs')
plt.ylabel('Value')
plt.legend()
```

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



In [14]:
```
# 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, acc: {accuracy:.3f}, loss: {loss:.3f}')
```

```
validation, acc: 0.825, loss: 0.645
```

In [ ]:
```

```