In [52]:
```
import numpy as np
import nnfs
from nnfs.datasets import spiral_data
import matplotlib.pyplot as plt
```

In [53]:
```
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 [54]:
```
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 [55]:
```
print(X.shape)
print(y.shape)
```

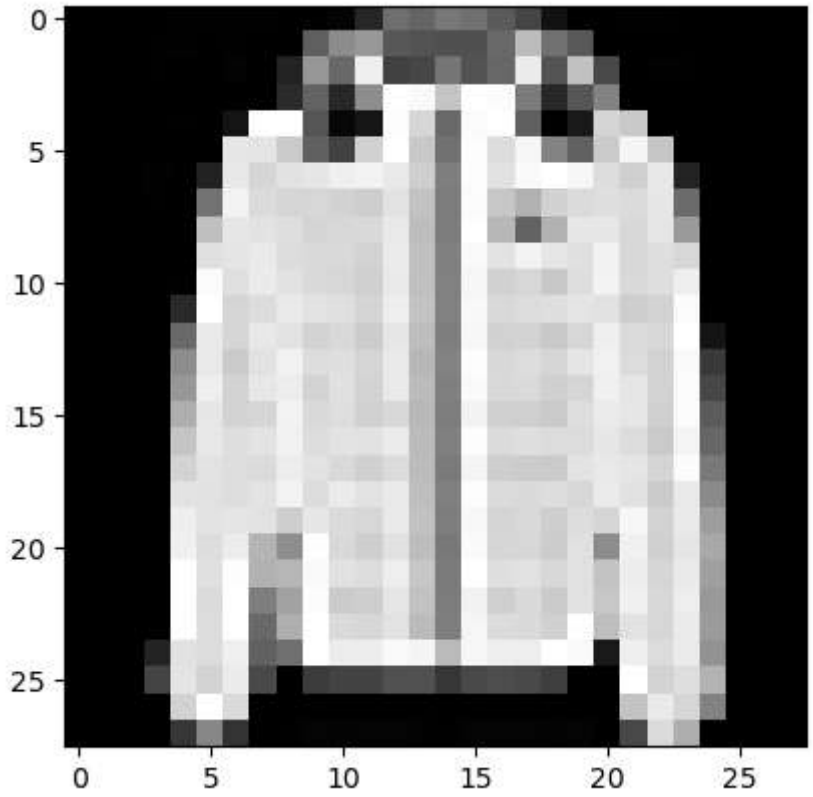
```
(60000, 28, 28)
(60000,)
```

In [56]:
```
# Reshape to vectors
X = X.reshape(X.shape[0], -1)
X_test = X_test.reshape(X_test.shape[0], -1)
```

In [104…

```
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 [100…

```
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 [101…

```
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 [60]:

```
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 [61]:

```
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 [73]:
```
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 [91]:
```
for epoch in range(500):
    dense1.forward(X)
    activation1.forward(dense1.output)
    dense2.forward(activation1.output)
```

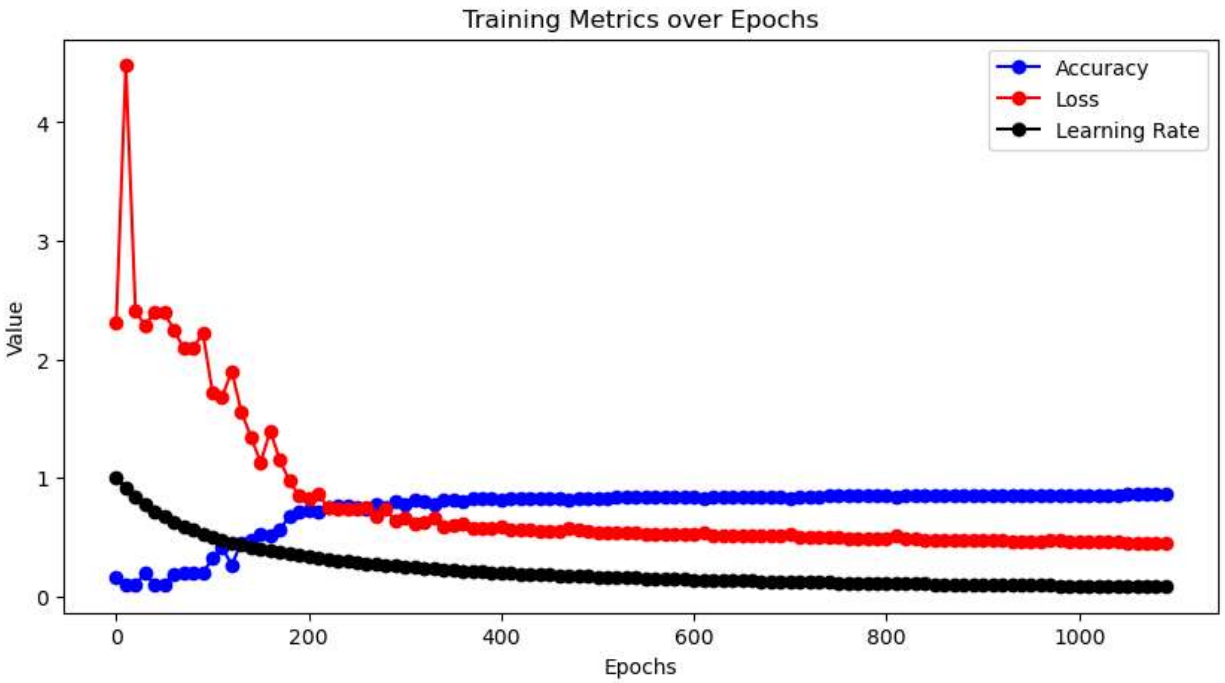
```
    activation2.forward(dense2.output)
    dense3.forward(activation2.output)
    data_loss = loss_activation.forward(dense3.output, y)

    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: 0.839, loss: 0.523, lr: 0.14306151645207438Rr: 0.0728328941363401
epoch: 10, acc: 0.832, loss: 0.539, lr: 0.14104372355430184Rr: 0.07249486494390431
epoch: 20, acc: 0.840, loss: 0.519, lr: 0.13908205841446453Rr: 0.07220264282913928
epoch: 30, acc: 0.841, loss: 0.517, lr: 0.13717421124828533Rr: 0.07187326258439371
epoch: 40, acc: 0.842, loss: 0.515, lr: 0.13531799729364005Rr: 0.0715458592218554
epoch: 50, acc: 0.842, loss: 0.513, lr: 0.13351134846461948Rr: 0.07122387632568698
epoch: 60, acc: 0.843, loss: 0.512, lr: 0.13175230566534915Rr: 0.07090775334519181
epoch: 70, acc: 0.843, loss: 0.510, lr: 0.13003901170351104Rr: 0.07059741898960634
epoch: 80, acc: 0.844, loss: 0.508, lr: 0.12836970474967907Rr: 0.07029324495361015
epoch: 90, acc: 0.843, loss: 0.508, lr: 0.12674271229404308Rr: 0.06999605535443824
epoch: 100, acc: 0.832, loss: 0.531, lr: 0.1251564455569462Rr: 0.06972342506256138
epoch: 110, acc: 0.845, loss: 0.504, lr: 0.12360939431396786Rr: 0.0694688196460336
epoch: 120, acc: 0.846, loss: 0.502, lr: 0.12210012210012208Rr: 0.06918904041393766
epoch: 130, acc: 0.846, loss: 0.500, lr: 0.12062726176115804Rr: 0.06891211244341199
epoch: 140, acc: 0.847, loss: 0.498, lr: 0.11919851132300357Rr: 0.06863923809994117
epoch: 150, acc: 0.848, loss: 0.496, lr: 0.11778563015312131Rr: 0.06837057418432571
epoch: 160, acc: 0.848, loss: 0.495, lr: 0.11641443538998836Rr: 0.06810630467110856
epoch: 170, acc: 0.849, loss: 0.493, lr: 0.1150747986191024Rr: 0.06784662732417243
epoch: 180, acc: 0.849, loss: 0.491, lr: 0.11376564277588169Rr: 0.0675913599441077
epoch: 190, acc: 0.850, loss: 0.490, lr: 0.11248593925759279Rr: 0.06734068184599792
epoch: 200, acc: 0.849, loss: 0.492, lr: 0.11123470522803114Rr: 0.06709623900376309
epoch: 210, acc: 0.839, loss: 0.514, lr: 0.11001100110011001Rr: 0.06687653755630929
epoch: 220, acc: 0.851, loss: 0.485, lr: 0.1088139281828074Rr: 0.06666106815561916
epoch: 230, acc: 0.851, loss: 0.484, lr: 0.1076426264800861Rr: 0.06642801796171957
epoch: 240, acc: 0.852, loss: 0.482, lr: 0.10649627263045792Rr: 0.06619845840528867
epoch: 250, acc: 0.853, loss: 0.480, lr: 0.1053740779768177Rr: 0.0659723244968744
epoch: 260, acc: 0.853, loss: 0.479, lr: 0.10427528675703858Rr: 0.06574952083087482
epoch: 270, acc: 0.854, loss: 0.477, lr: 0.10319917440660475Rr: 0.06552977676733339
epoch: 280, acc: 0.854, loss: 0.476, lr: 0.10214504596527067Rr: 0.06531338502787754
epoch: 290, acc: 0.854, loss: 0.476, lr: 0.10111223458038422Rr: 0.06510087256352358
epoch: 300, acc: 0.853, loss: 0.478, lr: 0.10010010010010009Rr: 0.06489425033260518
epoch: 310, acc: 0.851, loss: 0.481, lr: 0.09910802775024777Rr: 0.0646995218724174
epoch: 320, acc: 0.855, loss: 0.472, lr: 0.09813542688910697Rr: 0.06450387769457161
epoch: 330, acc: 0.857, loss: 0.469, lr: 0.09718172983479105Rr: 0.06430287487283957
epoch: 340, acc: 0.857, loss: 0.468, lr: 0.09624639076034648Rr: 0.06410375340141714
epoch: 350, acc: 0.857, loss: 0.467, lr: 0.09532888465204957Rr: 0.06390718814754749
epoch: 360, acc: 0.857, loss: 0.466, lr: 0.09442870632672333Rr: 0.06371353793745388
epoch: 370, acc: 0.856, loss: 0.470, lr: 0.09354536950420955Rr: 0.06352511081027587
epoch: 380, acc: 0.855, loss: 0.472, lr: 0.09267840593141798Rr: 0.06334816062847623
epoch: 390, acc: 0.858, loss: 0.463, lr: 0.09182736455463728Rr: 0.06316669502805544
epoch: 400, acc: 0.859, loss: 0.461, lr: 0.09099181073703366Rr: 0.06298134987317147
epoch: 410, acc: 0.859, loss: 0.460, lr: 0.09017132551848513Rr: 0.06279830383425015
epoch: 420, acc: 0.859, loss: 0.460, lr: 0.08936550491510277Rr: 0.06261805855716635
epoch: 430, acc: 0.858, loss: 0.463, lr: 0.0885739592559787 3Rr: 0.0624426786301628
epoch: 440, acc: 0.859, loss: 0.461, lr: 0.08779631255487269Rr: 0.06227186759097666
epoch: 450, acc: 0.860, loss: 0.457, lr: 0.08703220191470844Rr: 0.062099684438484425
epoch: 460, acc: 0.860, loss: 0.456, lr: 0.08628127696289906Rr: 0.06192744116744557
epoch: 470, acc: 0.860, loss: 0.456, lr: 0.0855431993156544Rr: 0.06175787132019155
epoch: 480, acc: 0.860, loss: 0.456, lr: 0.08481764206955046Rr: 0.06159192508070434
epoch: 490, acc: 0.861, loss: 0.454, lr: 0.08410428931875526Rr: 0.061427073152394214
```

In [97]:

```
epochs = range(0, 1100, 10)
plt.figure(figsize=(10, 5))
plt.plot(epochs, accuracies, label='Accuracy', marker='o', color="blue")
plt.plot(epochs, losses, label='Loss', marker='o', color='red')
plt.plot(epochs, learning_rate, 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 [98]:
```
# 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: 0.843, loss: 0.453
```

In [ ]:
```

```