GitHub: https://github.com/AnishKoppula1/NeuralAssignment9.git

1. Add one more hidden layer to autoencoder

In [6]:
```python
input_img = Input(shape=(784,))
#Adding hidden layer to encoding
hiddenLayer_en=Dense(512,activation='relu')(input_img)
# "encoded" is the encoded representation of the input
encoded = Dense(encoding_dim, activation='relu')(hiddenLayer_en) #Undercomplete Encoding
#Adding hidden layer to decoding
hiddenLayer_de=Dense(512,activation='relu')(encoded)
# "decoded" is the lossy reconstruction of the input
decoded = Dense(784, activation='sigmoid')(hiddenLayer_de)


# this model maps an input to its reconstruction
autoencoder = Model(input_img, decoded)
# this model maps an input to its encoded representation
autoencoder.compile(optimizer='adam', loss='binary_crossentropy',metrics=['accuracy'])


from keras.datasets import mnist, fashion_mnist
import numpy as np

(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()

#Converting into float & Scaling Data
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.

#Setting Up data from 28*28 to 784 for the width & height of image
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))

#Fitting/training the model
autoencoder.fit(x_train, x_train,
                epochs=5,
                batch_size=128,
                shuffle=True,
                validation_data=(x_test, x_test))
```

```
Epoch 1/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 8s 13ms/step - accuracy: 0.0095 - loss: 0.3772 - val_accuracy: 0.0191 - val_loss: 0.2930
Epoch 2/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 11ms/step - accuracy: 0.0204 - loss: 0.2887 - val_accuracy: 0.0254 - val_loss: 0.2840
Epoch 3/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 11ms/step - accuracy: 0.0243 - loss: 0.2809 - val_accuracy: 0.0268 - val_loss: 0.2801
Epoch 4/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 6s 13ms/step - accuracy: 0.0280 - loss: 0.2772 - val_accuracy: 0.0298 - val_loss: 0.2780
Epoch 5/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 6s 13ms/step - accuracy: 0.0333 - loss: 0.2753 - val_accuracy: 0.0343 - val_loss: 0.2763
```

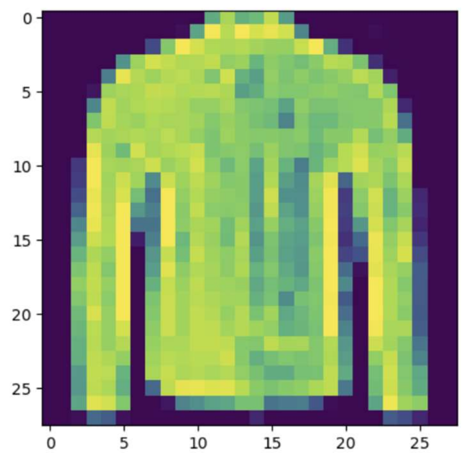
Out[6]:
```
<keras.src.callbacks.history.History at 0x2bf8350b890>
```

2. Do the prediction on the test data and then visualize one of the reconstructed version of that test data. Also, visualize the same test data before reconstruction using Matplotlib

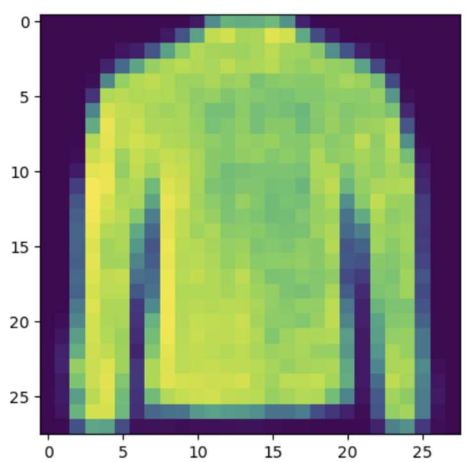
In [7]:
```
#predicting on the test data
prediction = autoencoder.predict(x_test)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
```

In [8]:
```
#Input Image
from matplotlib import pyplot as plt
plt.imshow(x_test[50].reshape(28,28))
plt.show()
```



In [9]:
```
#reconstructed Image
from matplotlib import pyplot as plt
plt.imshow(prediction[50].reshape(28,28))
plt.show()
```



3. Repeat the question 2 on the denoisening autoencoder

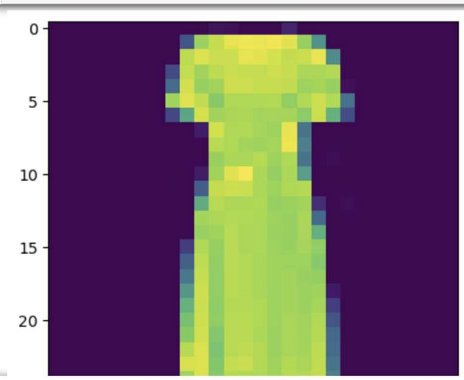
In [10]:
```
from keras.layers import Input, Dense
from keras.models import Model


# this is the size of our encoded representations
encoding_dim = 32  # 32 floats -> compression of factor 24.5, assuming the input is 784 floats


# this is our input placeholder
input_img = Input(shape=(784,))
# "encoded" is the encoded representation of the input
encoded = Dense(encoding_dim, activation='relu')(input_img) #Undercomplete Encoding
# "decoded" is the lossy reconstruction of the input
decoded = Dense(784, activation='sigmoid')(encoded)
     # this model maps an input to its reconstruction
autoencoder = Model(input_img, decoded)
# this model maps an input to its encoded representation
autoencoder.compile(optimizer='adam', loss='binary_crossentropy',metrics=['accuracy'])


from keras.datasets import mnist, fashion_mnist
import numpy as np

(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()
x_train = x_train[:6000]
x_test = x_test[:1000]

#Converting into float & Scaling Data
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.


#Setting Up data from 28*28 to 784 for the width & height of image
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))
```

In [11]:
```
noise_factor = 0.5
x_train_noisy = x_train + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=x_train.shape)
x_test_noisy = x_test + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=x_test.shape)
```

In [12]:
```
history = autoencoder.fit(x_train_noisy, x_train,
                epochs=10,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test_noisy, x_test_noisy))
```

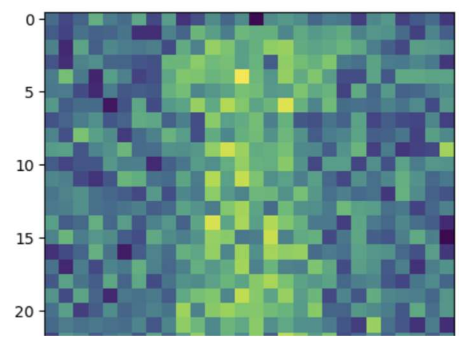
In [13]:

```
from matplotlib import pyplot as plt
plt.imshow(x_train[50].reshape(28,28))
plt.show()
```



In [14]:

```
from matplotlib import pyplot as plt
plt.imshow(x_train_noisy[50].reshape(28,28))
plt.show()
```



4. plot loss and accuracy using the history object

In [18]:
```
autoencoder.metrics_names
```

Out[18]: ['loss', 'compile_metrics']

In [19]:
```
import matplotlib.pyplot as plt
plt.plot(history.history['accuracy'])
plt.plot(history.history['loss'])
plt.title('model accuracy vs loss')
plt.xlabel('epoch')
plt.legend(['accuray','loss'], loc='upper left')
plt.show()
```