Capstone Project

Image classifier for the SVHN dataset

In this notebook, I create a neural network that classifies real-world images digits from the "Street View House Numbers" dataset.

Let's begin!

First, I'll import the libraries and modules that I will need throughout the notebook.

In [ ]:
```
import tensorflow as tf
from scipy.io import loadmat
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, Flatten, BatchNormalization, MaxPool2D, De
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import random
from sklearn.preprocessing import OneHotEncoder
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
```

To give some background, this dataset features over 600,000 digit images in all, and is a harder dataset than MNIST as the numbers appear in the context of natural scene images. SVHN is obtained from house numbers in Google Street View images.

- Y. Netzer, T. Wang, A. Coates, A. Bissacco, B. Wu and A. Y. Ng. "Reading Digits in Natural Images with Unsupervised Feature Learning". NIPS Workshop on Deep Learning and Unsupervised Feature Learning, 2011.

Your goal is to develop an end-to-end workflow for building, training, validating, evaluating and saving a neural network that classifies a real-world image into one of ten classes.

In [ ]:
```
# Load the dataset (Can be downloaded from the link above)

train = loadmat('data/train_32x32.mat')
test = loadmat('data/test_32x32.mat')
```

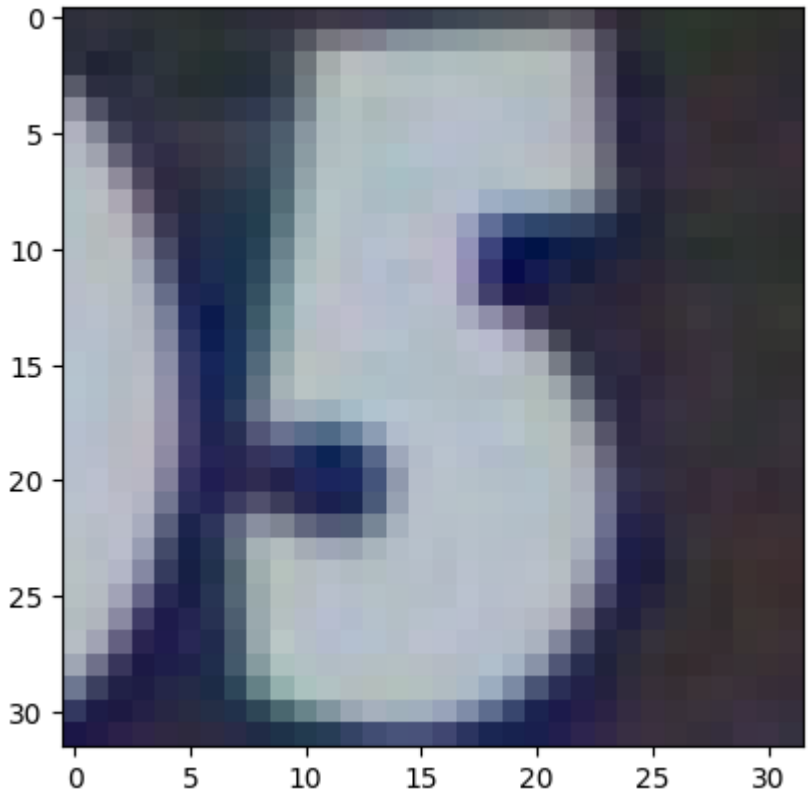
Both `train` and `test` are dictionaries with keys `X` and `y` for the input images and labels respectively.

1. Inspect and preprocess the dataset

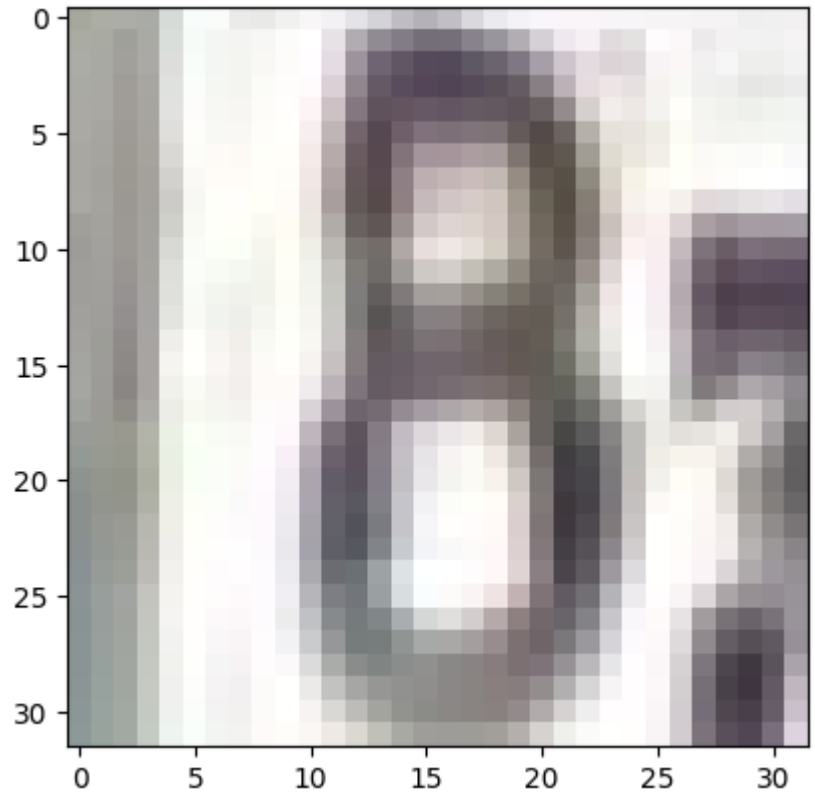
First, I extract the images from that dataset dictionaries, splitting them into separate variables. To demonstrate, I will sample 10 random images from the dataset along with their accompaying labels!

In [ ]:
```
X_train = train['X']
X_test = test['X']
y_train = train['y']
y_test = test['y']

X_train = np.moveaxis(X_train, -1, 0)
X_test = np.moveaxis(X_test, -1, 0)
```

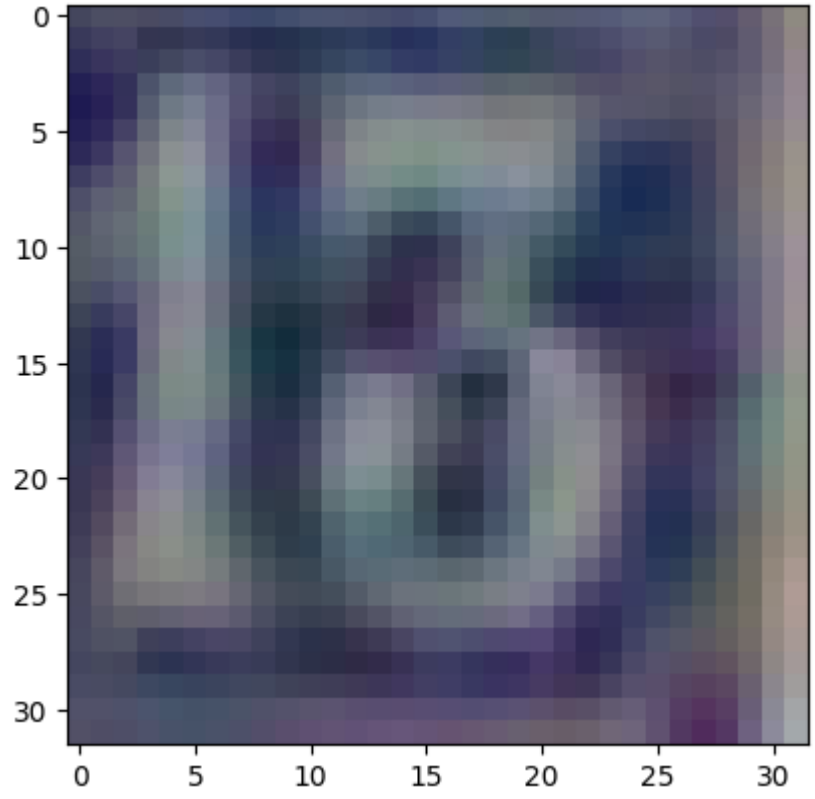
In [ ]:
```
sample_number_list = random.sample(range(0,73257),10)
for i in sample_number_list:
    plt.imshow(X_train[i,:,:,:])
    plt.show()
    print('Number', y_train[i])
```



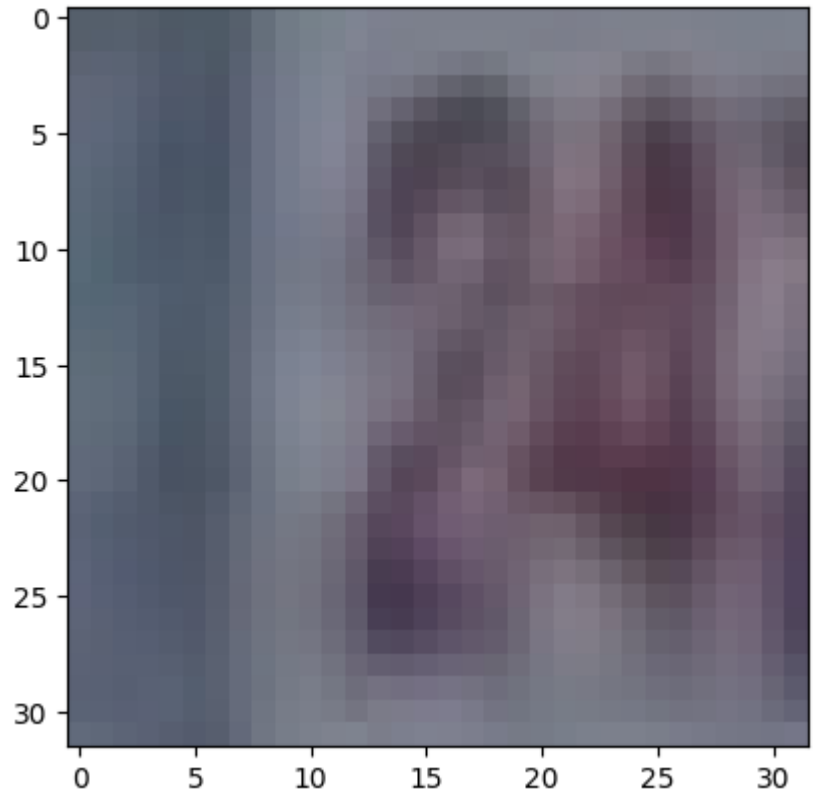

```
Number [5]
```



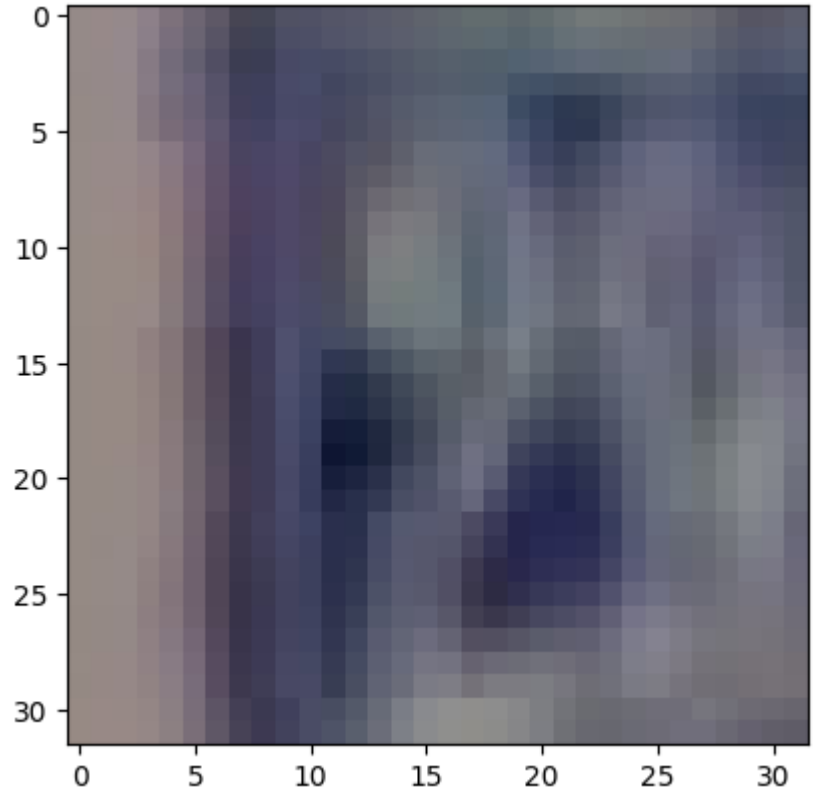

```
Number [8]
```



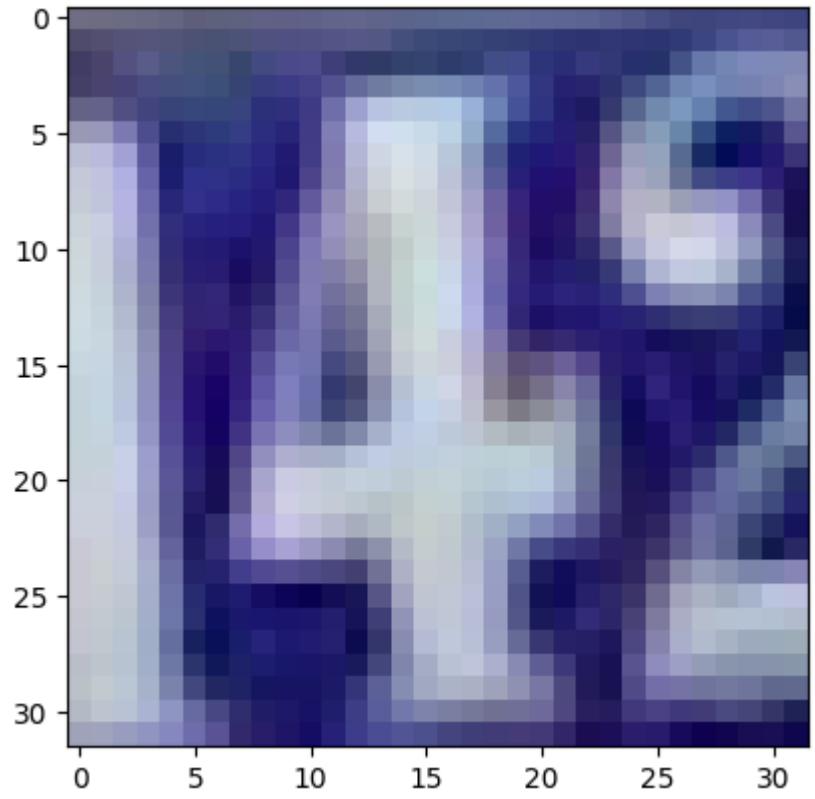

```
Number [3]
```



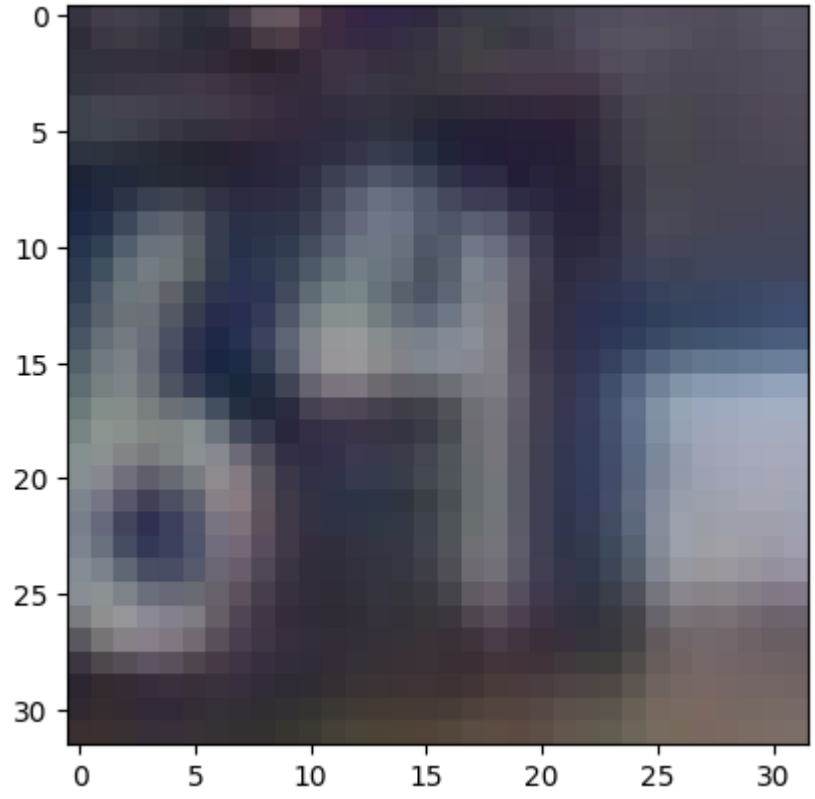
Number [2]



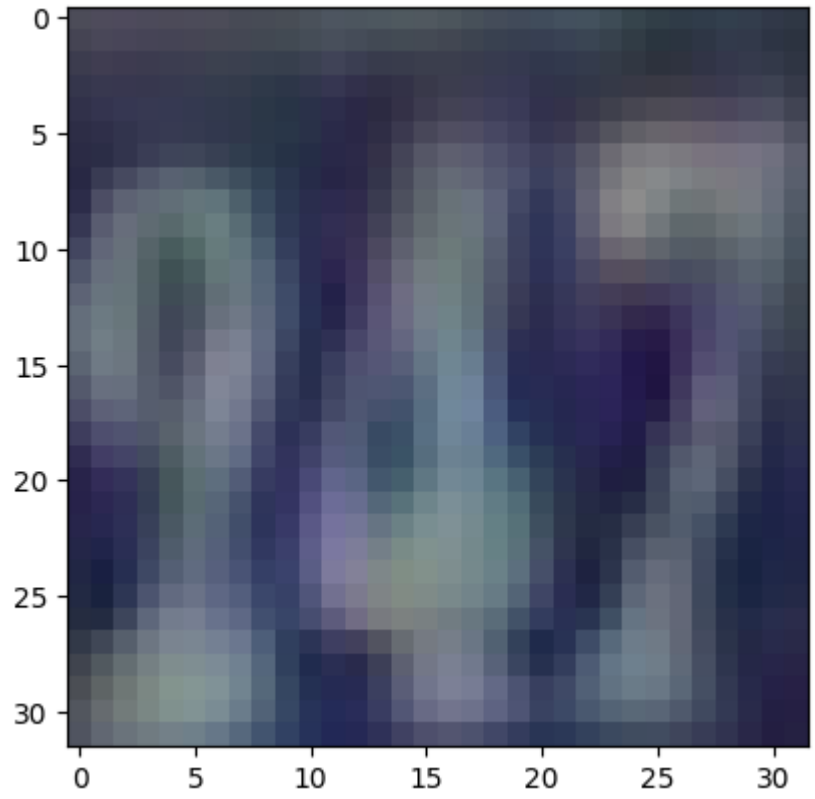
Number [2]



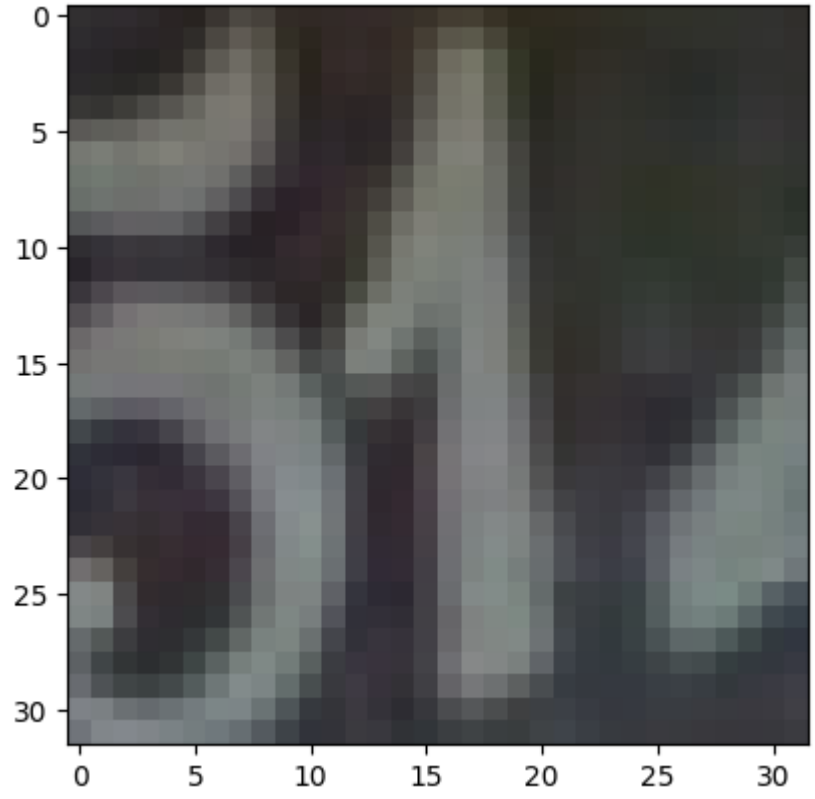

```
Number [4]
```



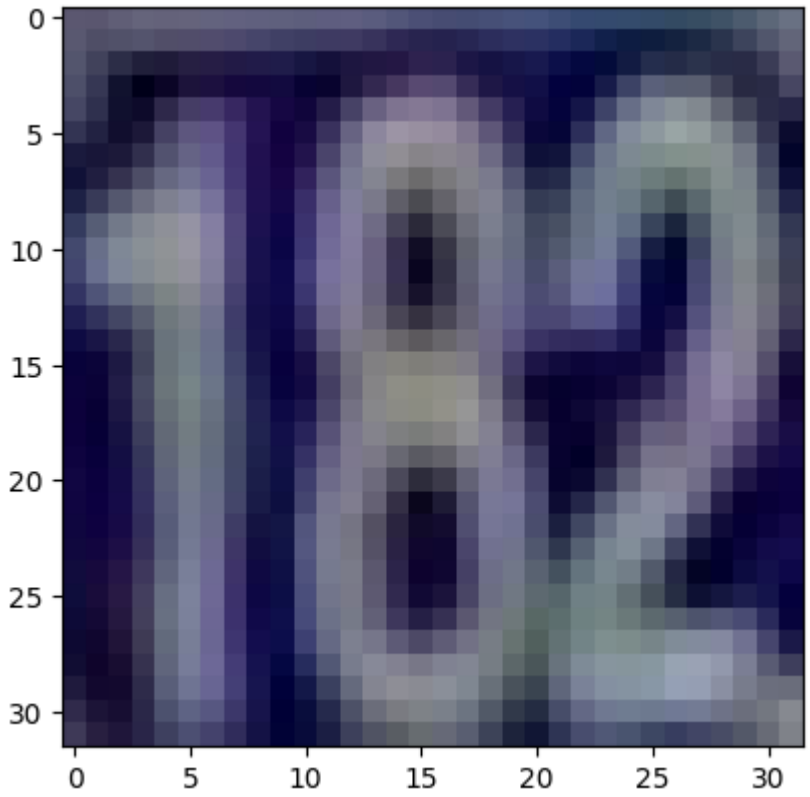

```
Number [4]
```




```
Number [4]
```




```
Number [1]
```

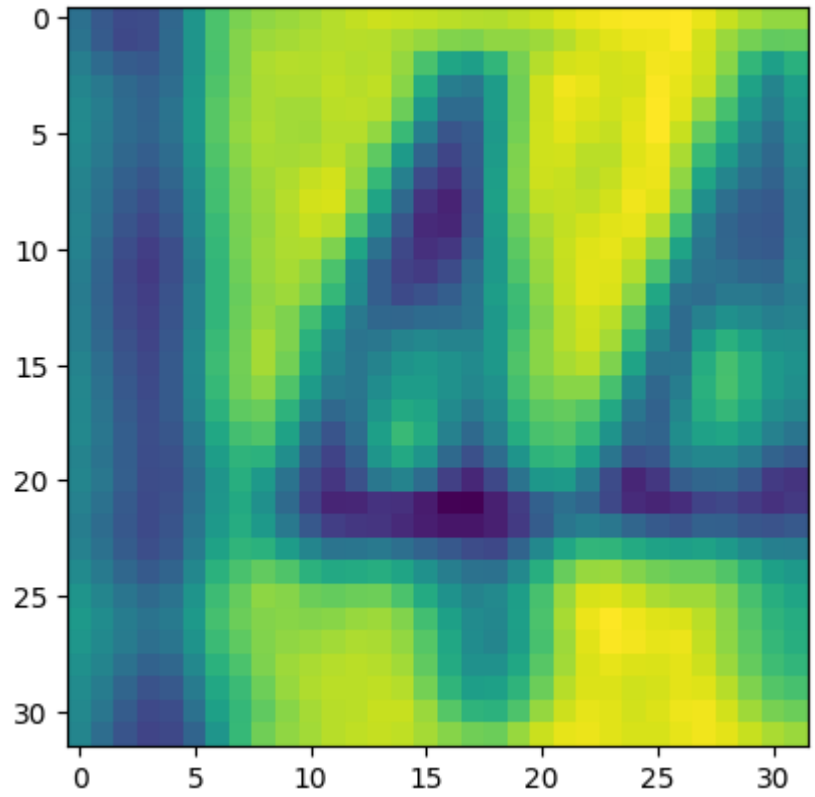



```
Number [8]
```

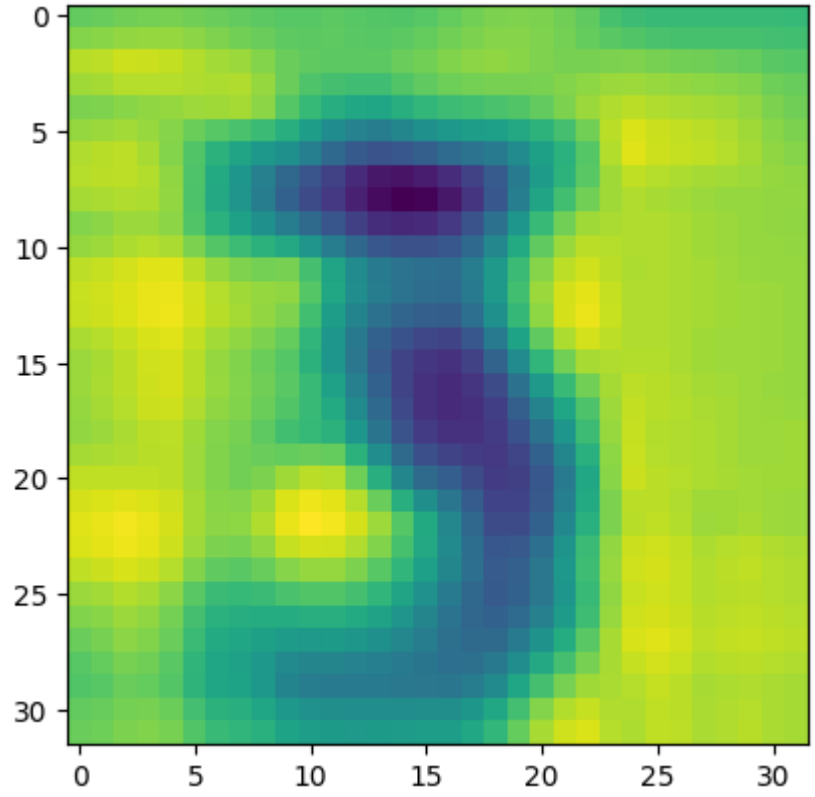
Here, I convert the images to greyscale using the `np.mean` function. This allows the image to be processed more easily, but is not necessarily required. Next, I normalize the array to values between 0 and 1 for easier processing as well.

In [ ]:
```
X_train_grey = np.mean(X_train, 3).reshape(73257, 32, 32,1)/255
X_test_grey = np.mean(X_test, 3).reshape(26032, 32, 32,1)/255
X_train_plt = np.mean(X_train, 3)
```

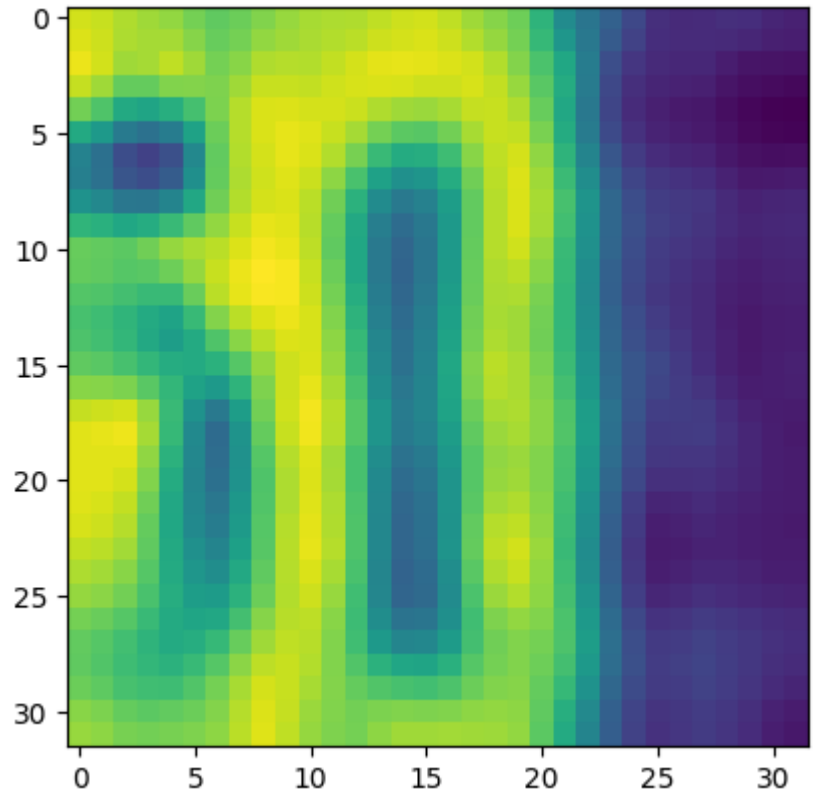
In [ ]:
```
sample_number_list = random.sample(range(0,73257),10)
for i in sample_number_list:
    plt.imshow(X_train_grey[i,:,:,0])
    plt.show()
    print('Number', y_train[i])
```



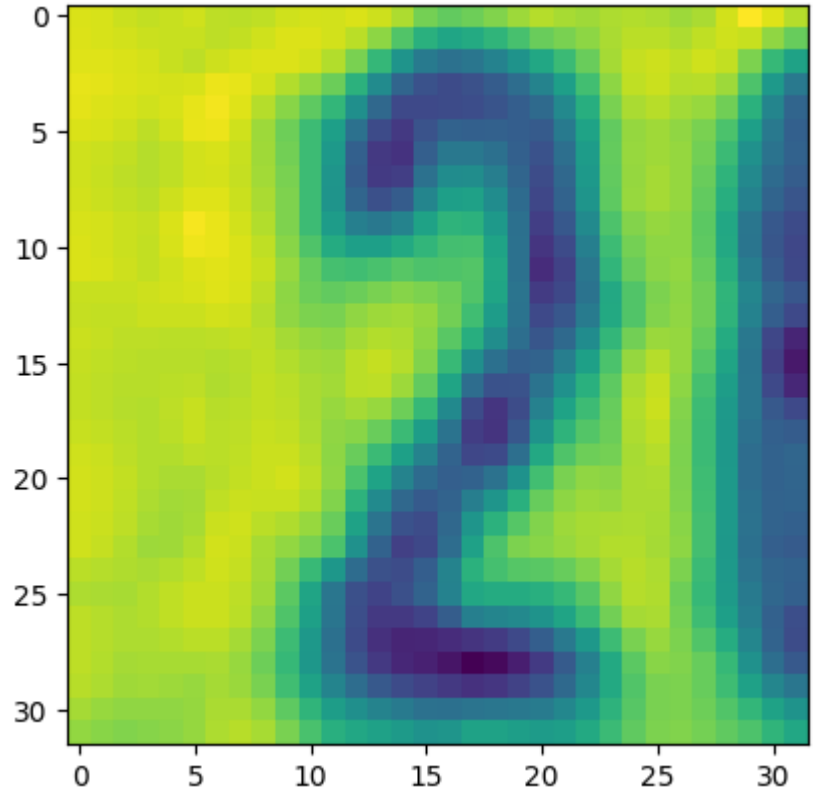
Number [4]



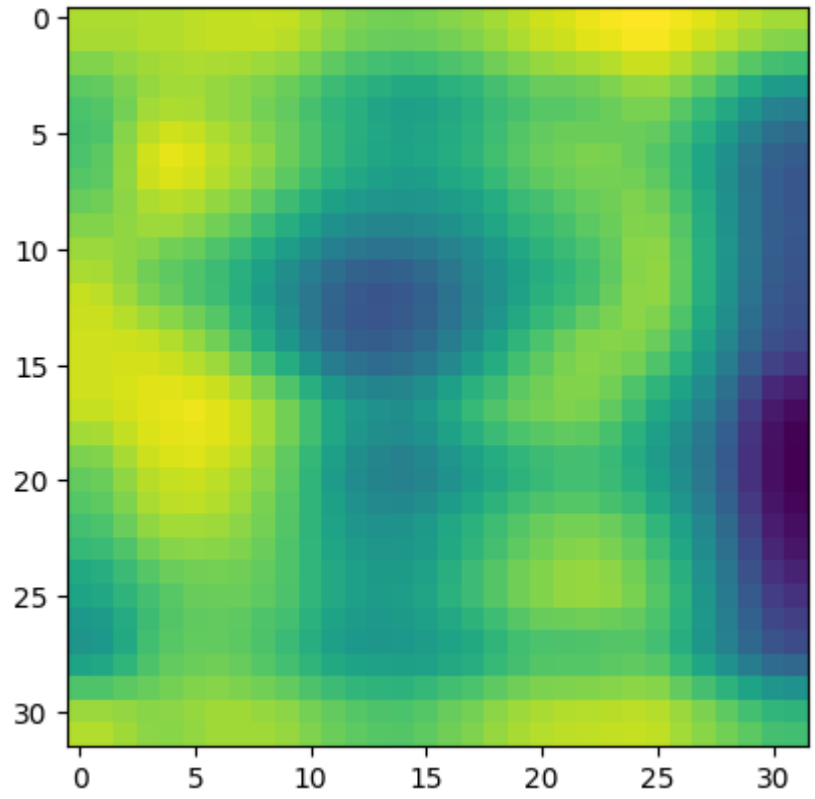
Number [3]



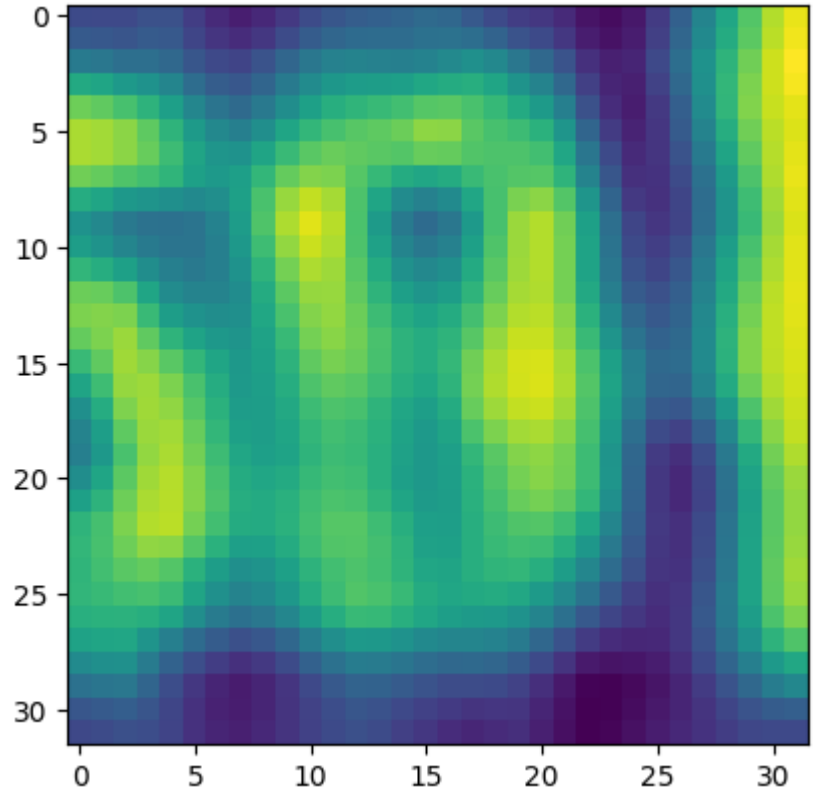
Number [1]



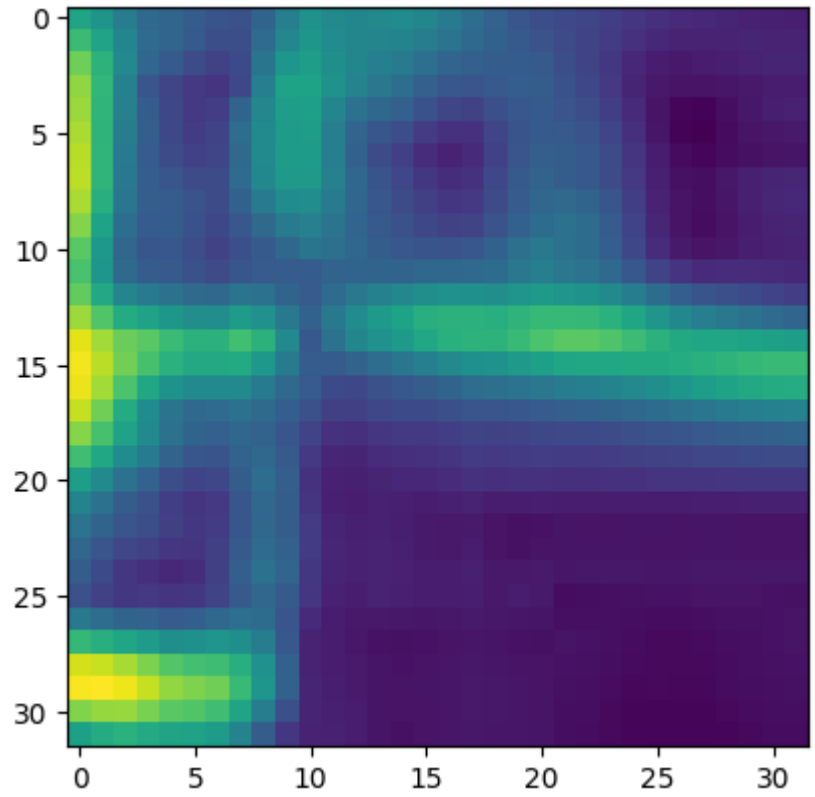
Number [2]



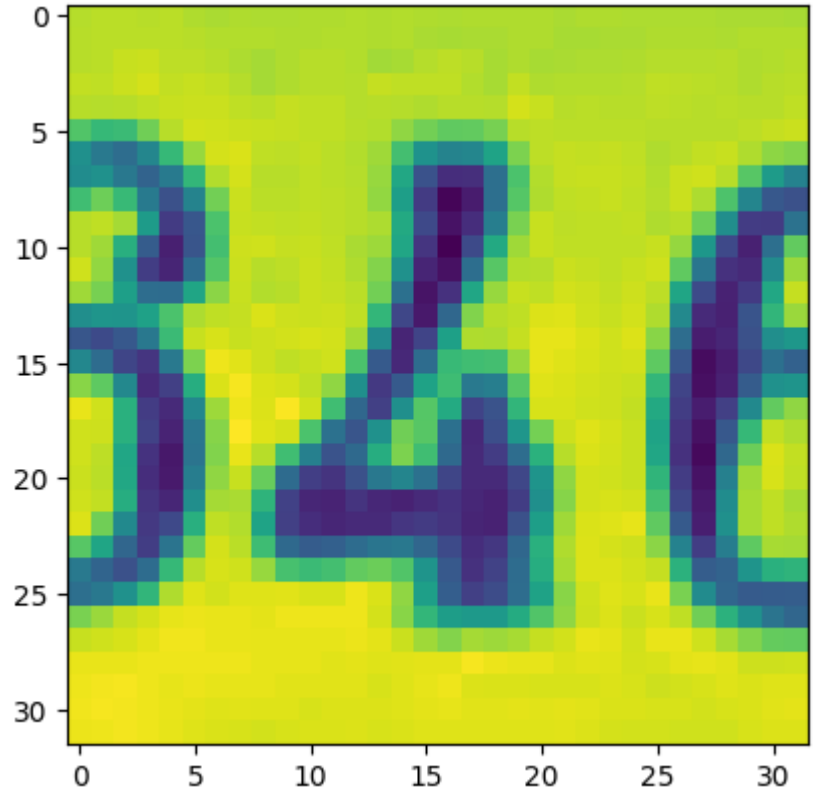
Number [6]



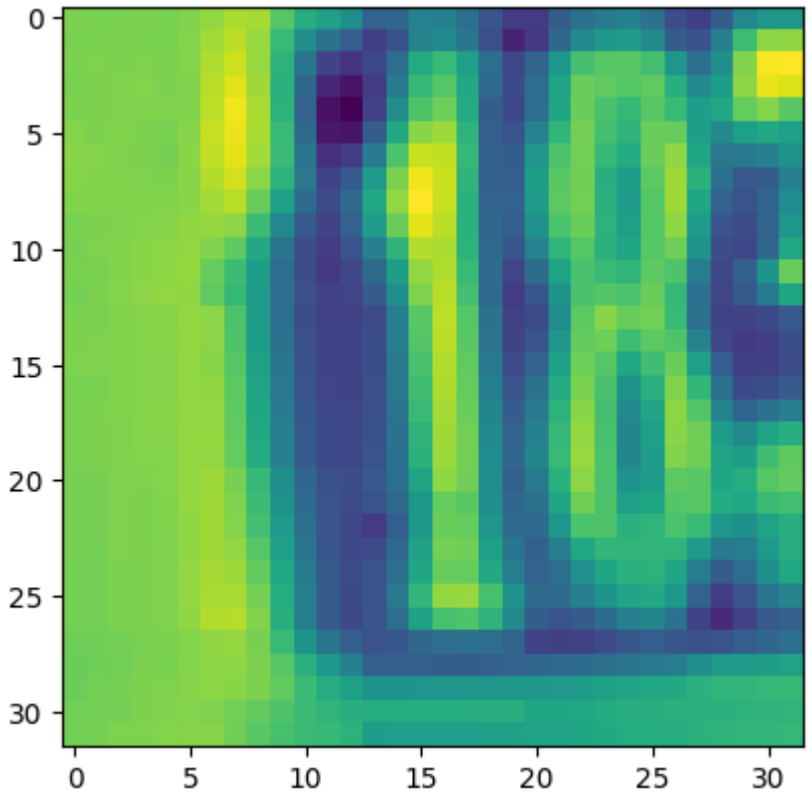
Number [10]



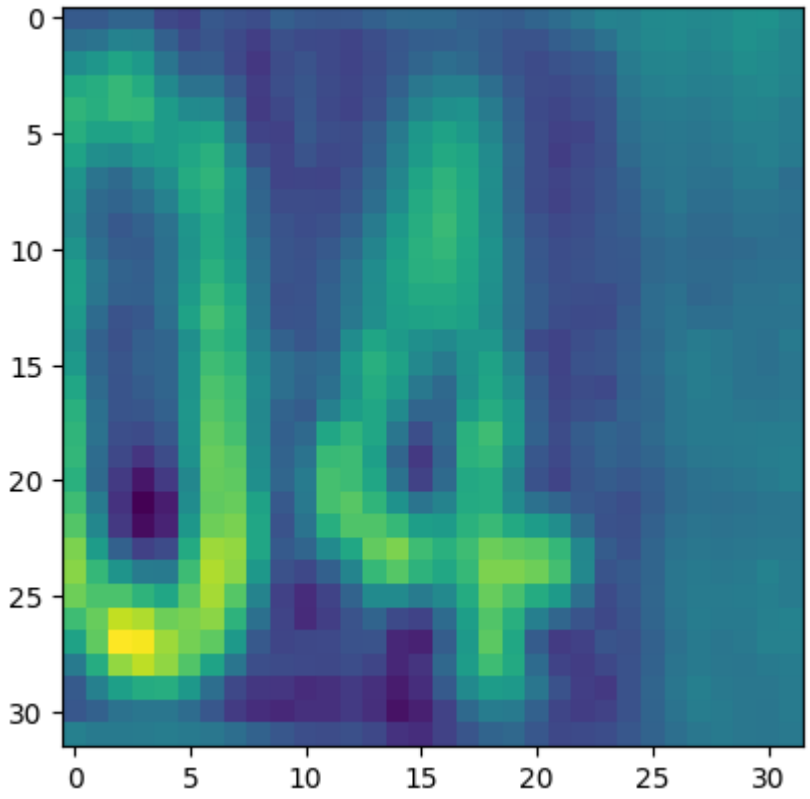
Number [4]



Number [4]




```
Number [1]
```




```
Number [4]
```

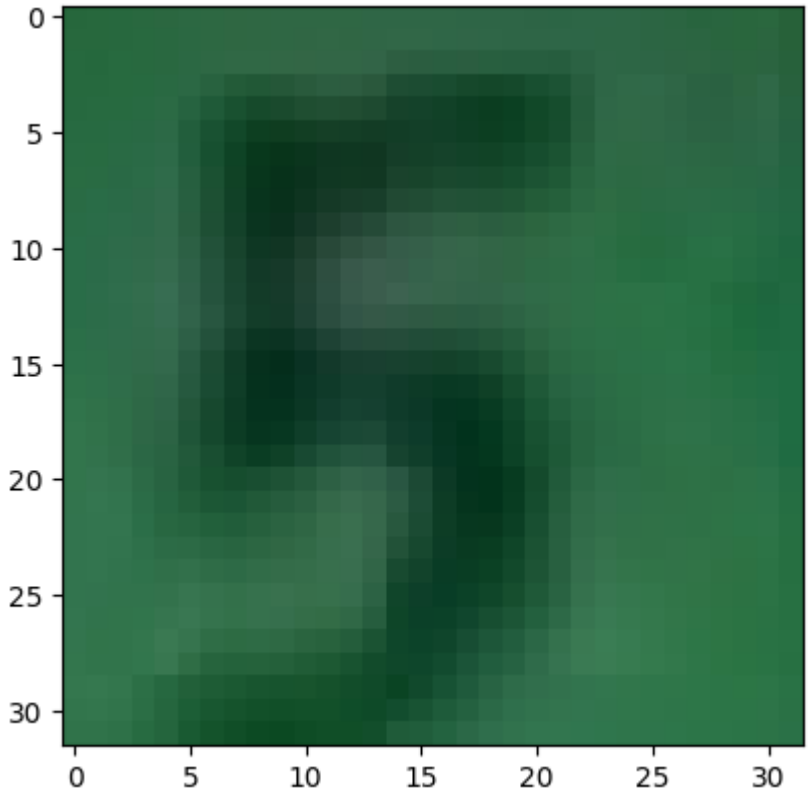
The OneHotEncoder function converts categorical features as noted in `y_train` and `y_test` to an array.

In [ ]:
```
encoder=OneHotEncoder().fit(y_train)
y_train_encoded = encoder.transform(y_train).toarray()
```

```
y_test_encoded = encoder.transform(y_test).toarray()
```

In [ ]:
```
plt.imshow(X_test[0])
```

Out[ ]:
```
<matplotlib.image.AxesImage at 0x2a11a581000>
```



In [ ]:
```
```

2. MLP neural network classifier

Now I can create my model! Throughout the next code blocks, I:

- Define basic callbacks: ModelCheckpoint and EarlyStopping
- Define my model - this basic one features 3 hidden dense layers and an output layer using the softmax activation function
- Compile my model using the Adam optimizer, calculating loss through categorical cross-entropy and using accuracy as the metric for optimization
- Train my model in 20 epochs, with a batch size of 128

In [ ]:
```
best_val_acc_path = 'best_val_acc/checkpoint'
best_val_acc = ModelCheckpoint(filepath = best_val_acc_path, save_weights_only=True, s
earlystopping = EarlyStopping(patience = 3, monitor='loss')

model_1 = Sequential([
    Flatten(input_shape=X_train[0].shape),
    Dense(512, activation = 'relu', ),
    Dense(128, activation = 'relu'),
    Dense(128, activation='relu'),
```

```
    Dense(10, activation ='softmax')
])

model_1.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 3072)              0

 dense (Dense)               (None, 512)               1573376

 dense_1 (Dense)             (None, 128)               65664

 dense_2 (Dense)             (None, 128)               16512

 dense_3 (Dense)             (None, 10)                1290

=================================================================
Total params: 1,656,842
Trainable params: 1,656,842
Non-trainable params: 0
_________________________________________________________________
```

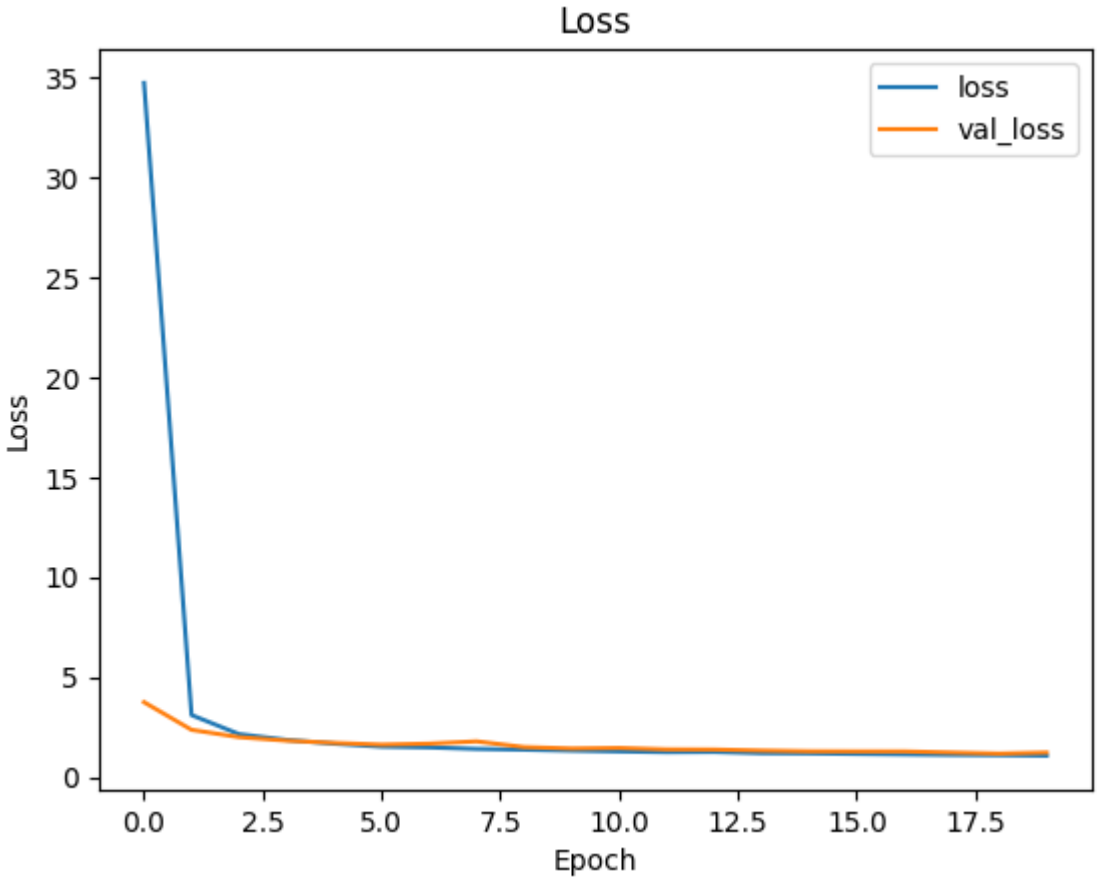
In [ ]:
```
model_1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'

history_1 = model_1.fit(X_train, y_train_encoded, epochs=20, validation_data = (X_test
```

```
Epoch 1/20
573/573 [==============================] - 8s 9ms/step - loss: 34.7351 - accuracy: 0.
1283 - val_loss: 3.7419 - val_accuracy: 0.0934
Epoch 2/20
573/573 [==============================] - 3s 6ms/step - loss: 3.0972 - accuracy: 0.1
584 - val_loss: 2.3574 - val_accuracy: 0.2086
Epoch 3/20
573/573 [==============================] - 3s 6ms/step - loss: 2.1423 - accuracy: 0.2
657 - val_loss: 1.9906 - val_accuracy: 0.3607
Epoch 4/20
573/573 [==============================] - 3s 6ms/step - loss: 1.8538 - accuracy: 0.3
845 - val_loss: 1.8163 - val_accuracy: 0.4165
Epoch 5/20
573/573 [==============================] - 3s 5ms/step - loss: 1.6627 - accuracy: 0.4
550 - val_loss: 1.7018 - val_accuracy: 0.4537
Epoch 6/20
573/573 [==============================] - 3s 5ms/step - loss: 1.5134 - accuracy: 0.5
083 - val_loss: 1.6143 - val_accuracy: 0.5047
Epoch 7/20
573/573 [==============================] - 2s 4ms/step - loss: 1.4765 - accuracy: 0.5
264 - val_loss: 1.6633 - val_accuracy: 0.4974
Epoch 8/20
573/573 [==============================] - 2s 4ms/step - loss: 1.4014 - accuracy: 0.5
528 - val_loss: 1.7790 - val_accuracy: 0.4520
Epoch 9/20
573/573 [==============================] - 3s 4ms/step - loss: 1.3640 - accuracy: 0.5
645 - val_loss: 1.4923 - val_accuracy: 0.5414
Epoch 10/20
573/573 [==============================] - 3s 5ms/step - loss: 1.3142 - accuracy: 0.5
832 - val_loss: 1.4225 - val_accuracy: 0.5652
Epoch 11/20
573/573 [==============================] - 3s 5ms/step - loss: 1.2746 - accuracy: 0.5
989 - val_loss: 1.4477 - val_accuracy: 0.5579
Epoch 12/20
573/573 [==============================] - 3s 4ms/step - loss: 1.2417 - accuracy: 0.6
099 - val_loss: 1.3773 - val_accuracy: 0.5940
Epoch 13/20
573/573 [==============================] - 2s 4ms/step - loss: 1.2517 - accuracy: 0.6
062 - val_loss: 1.3695 - val_accuracy: 0.5892
Epoch 14/20
573/573 [==============================] - 3s 5ms/step - loss: 1.1879 - accuracy: 0.6
305 - val_loss: 1.3185 - val_accuracy: 0.5986
Epoch 15/20
573/573 [==============================] - 3s 5ms/step - loss: 1.1757 - accuracy: 0.6
334 - val_loss: 1.2816 - val_accuracy: 0.6166
Epoch 16/20
573/573 [==============================] - 3s 5ms/step - loss: 1.1508 - accuracy: 0.6
400 - val_loss: 1.2756 - val_accuracy: 0.6124
Epoch 17/20
573/573 [==============================] - 3s 5ms/step - loss: 1.1294 - accuracy: 0.6
484 - val_loss: 1.2750 - val_accuracy: 0.6202
Epoch 18/20
573/573 [==============================] - 3s 5ms/step - loss: 1.1041 - accuracy: 0.6
572 - val_loss: 1.2203 - val_accuracy: 0.6265
Epoch 19/20
573/573 [==============================] - 4s 6ms/step - loss: 1.0886 - accuracy: 0.6
623 - val_loss: 1.1667 - val_accuracy: 0.6503
```

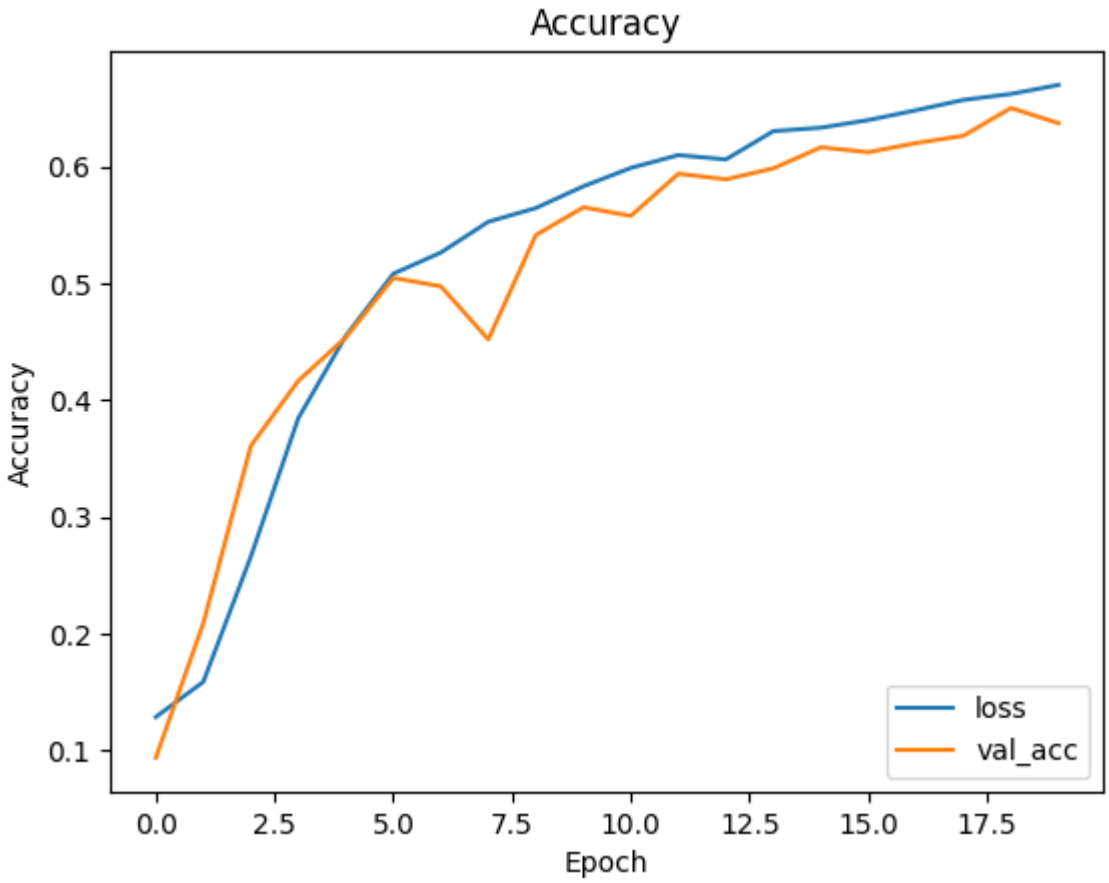
```
Epoch 20/20
573/573 [==============================] - 3s 6ms/step - loss: 1.0636 - accuracy: 0.6
701 - val_loss: 1.2180 - val_accuracy: 0.6373
```

Now that my model is trained, lets compare it to the validation set. It is important to check for overfitting, as the model will hypothetically be used in real-world scenarios.

In [ ]:
```
plt.plot(history_1.history['loss'])
plt.plot(history_1.history['val_loss'])
plt.legend(['loss','val_loss'], loc='upper right')
plt.title('Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show()
```



In [ ]:
```
plt.plot(history_1.history['accuracy'])
plt.plot(history_1.history['val_accuracy'])
plt.legend(['loss','val_acc'], loc='lower right')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.show()
```



Overall, not too bad, but we can do better!

3. CNN neural network classifier

I previously used a multi-layer perceptron to make predictions, but realistically, convolutional neural networks (CNNs) should be used in scenarios such as this one. We will do the same thing as before, but use CNNs instead. Note the usage of Conv2D, Maxpool2D, BatchNormalization, and Dropout in this model. The latter two are used as a method to prevent overfitting, while the former two are key parts of CNNs.

In [ ]:
```
best_val_acc_path_2='CNN/best'
best_val_acc=ModelCheckpoint(filepath = best_val_acc_path_2, save_best_only=True, moni
earlystopping = EarlyStopping(monitor='loss', patience=5, verbose=1)

model_2 = Sequential([
    Conv2D(filters= 16, kernel_size= 3, activation='relu', input_shape=X_train[0].shap
    MaxPool2D(pool_size= (3,3)),
    Conv2D(filters= 32, kernel_size = 3, padding='valid', activation='relu'),
    MaxPool2D(pool_size = (2,2), strides = 2),
    BatchNormalization(),
    Conv2D(filters= 32, kernel_size = 3, padding='valid', strides=2, activation='relu'
    Dropout(0.5),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.2),
    Dense(10, activation='softmax')
```

```
])

model_2.summary()
```

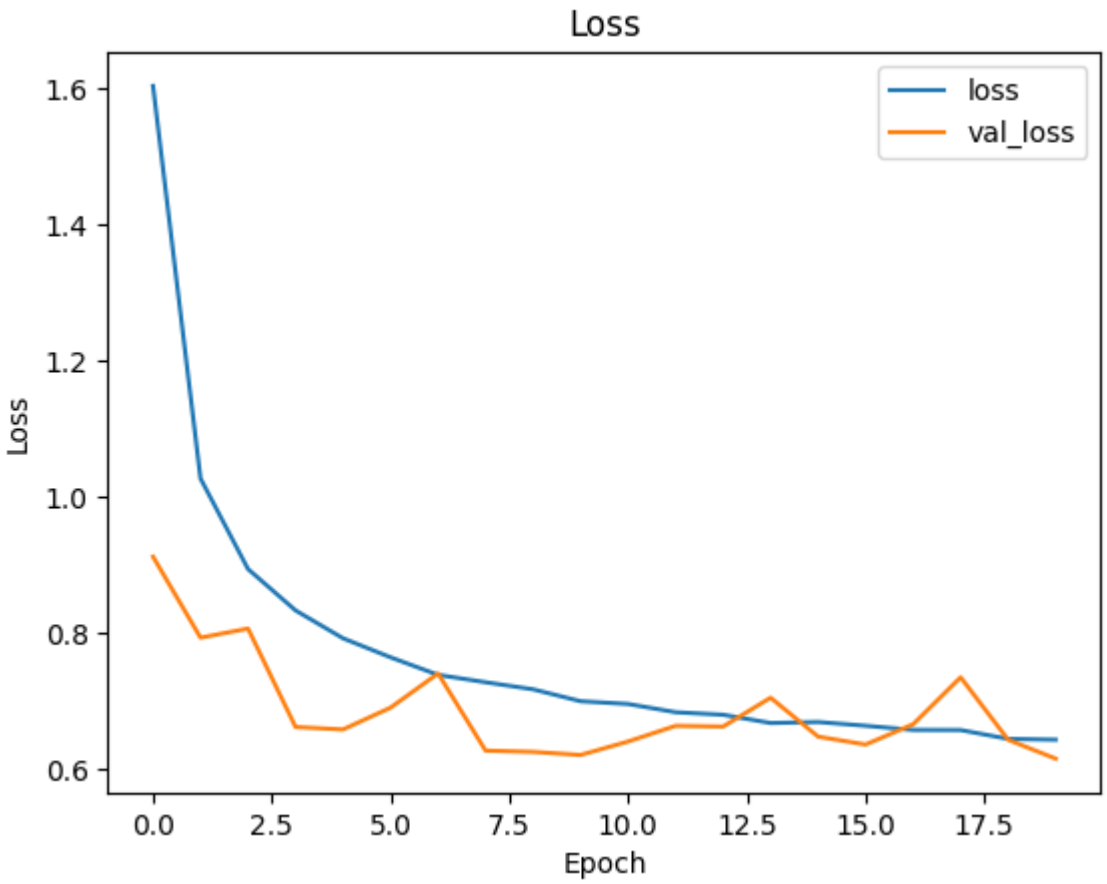
```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 30, 30, 16)        448

 max_pooling2d (MaxPooling2D  (None, 10, 10, 16)       0
 )

 conv2d_1 (Conv2D)           (None, 8, 8, 32)          4640

 max_pooling2d_1 (MaxPooling  (None, 4, 4, 32)         0
 2D)

 batch_normalization (BatchN  (None, 4, 4, 32)         128
 ormalization)

 conv2d_2 (Conv2D)           (None, 1, 1, 32)          9248

 dropout (Dropout)           (None, 1, 1, 32)          0

 flatten_1 (Flatten)         (None, 32)                0

 dense_4 (Dense)             (None, 128)               4224

 dropout_1 (Dropout)         (None, 128)               0

 dense_5 (Dense)             (None, 10)                1290

=================================================================
Total params: 19,978
Trainable params: 19,914
Non-trainable params: 64
_________________________________________________________________
```

In [ ]:
```
model_2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'

history_2 = model_2.fit(X_train, y_train_encoded, callbacks=[best_val_acc, earlystoppi
```

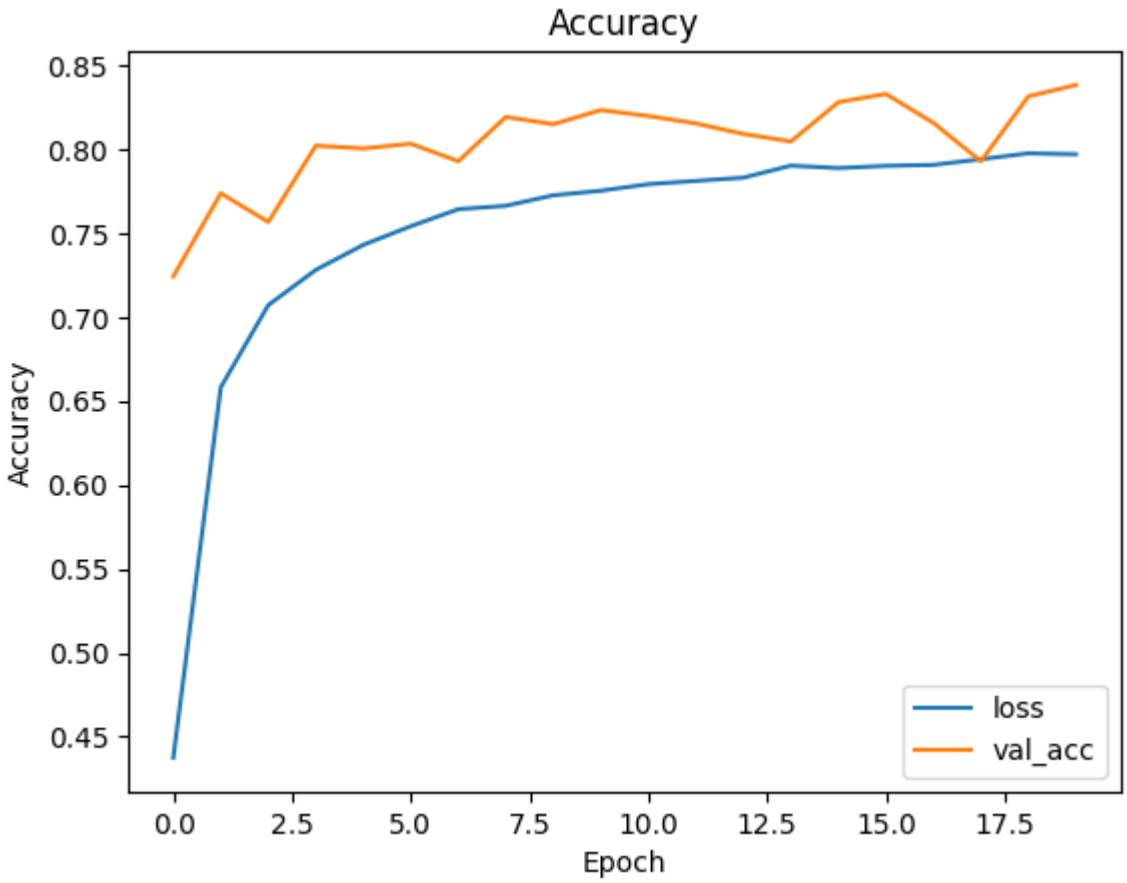
```
Epoch 1/20
573/573 [==============================] - 8s 8ms/step - loss: 1.6032 - accuracy: 0.4
375 - val_loss: 0.9126 - val_accuracy: 0.7243
Epoch 2/20
573/573 [==============================] - 4s 7ms/step - loss: 1.0272 - accuracy: 0.6
582 - val_loss: 0.7938 - val_accuracy: 0.7738
Epoch 3/20
573/573 [==============================] - 4s 7ms/step - loss: 0.8944 - accuracy: 0.7
072 - val_loss: 0.8072 - val_accuracy: 0.7567
Epoch 4/20
573/573 [==============================] - 4s 7ms/step - loss: 0.8338 - accuracy: 0.7
282 - val_loss: 0.6628 - val_accuracy: 0.8022
Epoch 5/20
573/573 [==============================] - 4s 7ms/step - loss: 0.7929 - accuracy: 0.7
431 - val_loss: 0.6592 - val_accuracy: 0.8005
Epoch 6/20
573/573 [==============================] - 4s 7ms/step - loss: 0.7650 - accuracy: 0.7
542 - val_loss: 0.6912 - val_accuracy: 0.8033
Epoch 7/20
573/573 [==============================] - 4s 8ms/step - loss: 0.7392 - accuracy: 0.7
643 - val_loss: 0.7413 - val_accuracy: 0.7929
Epoch 8/20
573/573 [==============================] - 4s 8ms/step - loss: 0.7284 - accuracy: 0.7
663 - val_loss: 0.6281 - val_accuracy: 0.8193
Epoch 9/20
573/573 [==============================] - 4s 7ms/step - loss: 0.7181 - accuracy: 0.7
726 - val_loss: 0.6263 - val_accuracy: 0.8150
Epoch 10/20
573/573 [==============================] - 4s 8ms/step - loss: 0.7006 - accuracy: 0.7
753 - val_loss: 0.6217 - val_accuracy: 0.8234
Epoch 11/20
573/573 [==============================] - 4s 7ms/step - loss: 0.6966 - accuracy: 0.7
792 - val_loss: 0.6415 - val_accuracy: 0.8198
Epoch 12/20
573/573 [==============================] - 4s 8ms/step - loss: 0.6844 - accuracy: 0.7
812 - val_loss: 0.6645 - val_accuracy: 0.8154
Epoch 13/20
573/573 [==============================] - 4s 7ms/step - loss: 0.6808 - accuracy: 0.7
831 - val_loss: 0.6634 - val_accuracy: 0.8092
Epoch 14/20
573/573 [==============================] - 4s 7ms/step - loss: 0.6686 - accuracy: 0.7
903 - val_loss: 0.7058 - val_accuracy: 0.8047
Epoch 15/20
573/573 [==============================] - 4s 7ms/step - loss: 0.6701 - accuracy: 0.7
888 - val_loss: 0.6487 - val_accuracy: 0.8281
Epoch 16/20
573/573 [==============================] - 4s 7ms/step - loss: 0.6646 - accuracy: 0.7
901 - val_loss: 0.6371 - val_accuracy: 0.8330
Epoch 17/20
573/573 [==============================] - 4s 7ms/step - loss: 0.6585 - accuracy: 0.7
907 - val_loss: 0.6668 - val_accuracy: 0.8158
Epoch 18/20
573/573 [==============================] - 4s 7ms/step - loss: 0.6583 - accuracy: 0.7
941 - val_loss: 0.7357 - val_accuracy: 0.7929
Epoch 19/20
573/573 [==============================] - 4s 6ms/step - loss: 0.6454 - accuracy: 0.7
976 - val_loss: 0.6441 - val_accuracy: 0.8316
```

```
Epoch 20/20
573/573 [==============================] - 4s 6ms/step - loss: 0.6442 - accuracy: 0.7
970 - val_loss: 0.6163 - val_accuracy: 0.8384
```

In [ ]:
```
plt.plot(history_2.history['loss'])
plt.plot(history_2.history['val_loss'])
plt.legend(['loss','val_loss'], loc='upper right')
plt.title('Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show()
```



In [ ]:
```
plt.plot(history_2.history['accuracy'])
plt.plot(history_2.history['val_accuracy'])
plt.legend(['loss','val_acc'], loc='lower right')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.show()
```



Note that the CNN achieved higher accuracy while having significantly less parameters than the MLP.

4. Get model predictions

Let's see what the network is doing! In this section, I load the best weights in both models and pit them against 5 randomly chosen image samples. I then plot the model's predictions to see how confident it is in its response.

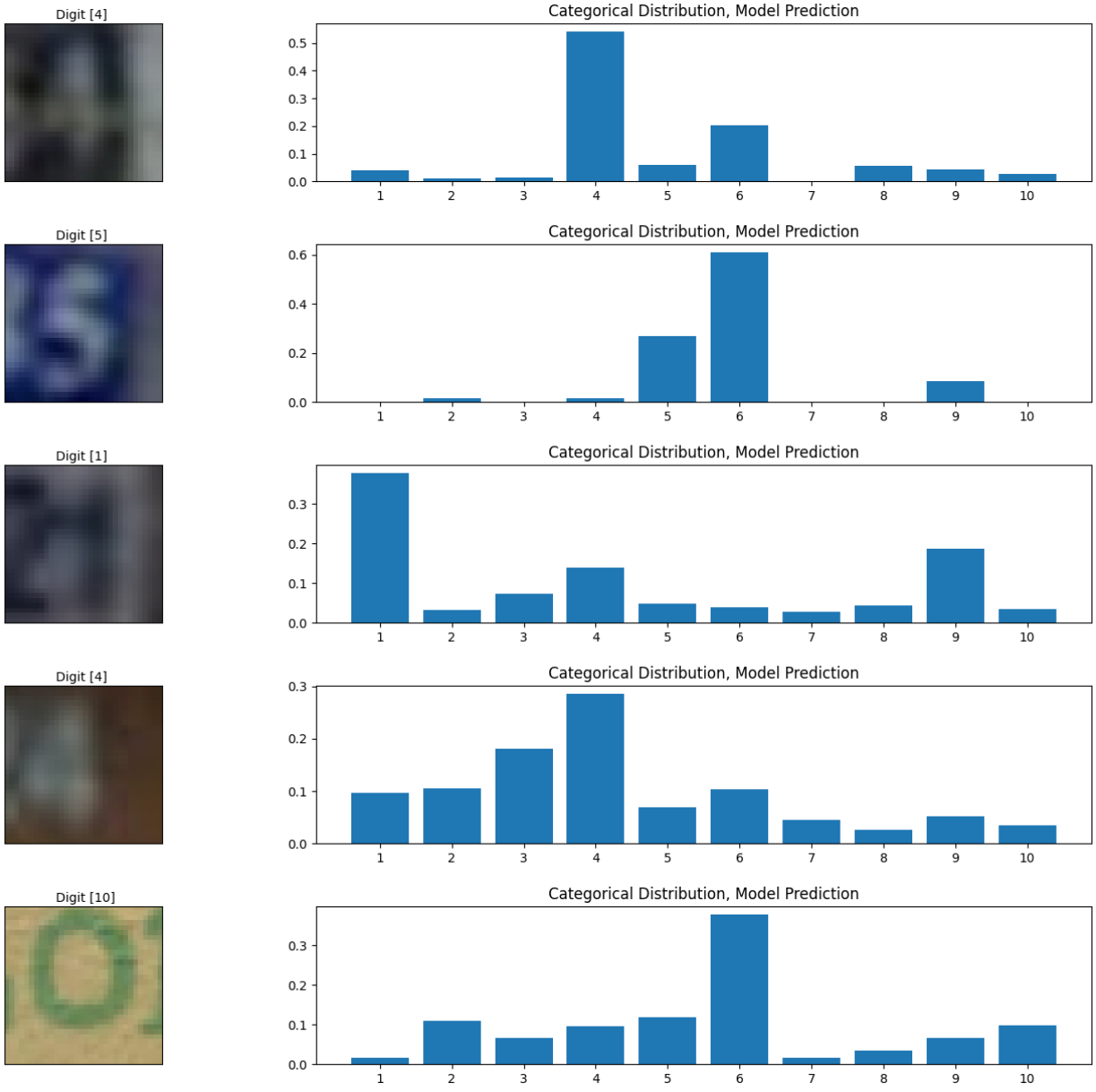
In [ ]:
```
model_1.load_weights(best_val_acc_path)
```

Out[ ]:
```
<tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x2a27e5a64d0>
```

In [ ]:
```
test_image = X_test.shape[0]

random1 = np.random.choice(test_image, 5)
random_test_image = X_test[random1, ...]
random_test_target = y_test[random1, ...]
prediction = model_1.predict(random_test_image)

graph, axes = plt.subplots(5, 2, figsize=(20, 15))
graph.subplots_adjust(hspace=0.4, wspace=-0.2)

for n, (predict, image, label) in enumerate(zip(prediction, random_test_image, random_
    axes[n,0].imshow(np.squeeze(image))
    axes[n,0].get_xaxis().set_visible(False)
```

```
    axes[n,0].get_yaxis().set_visible(False)
    axes[n,0].text(10., -1.5, f'Digit {label}')
    axes[n,1].bar(np.arange(1,11), predict)
    axes[n,1].set_xticks(np.arange(1,11))
    axes[n,1].set_title("Categorical Distribution, Model Prediction")
plt.show()
```

```
1/1 [==============================] - 0s 93ms/step
```



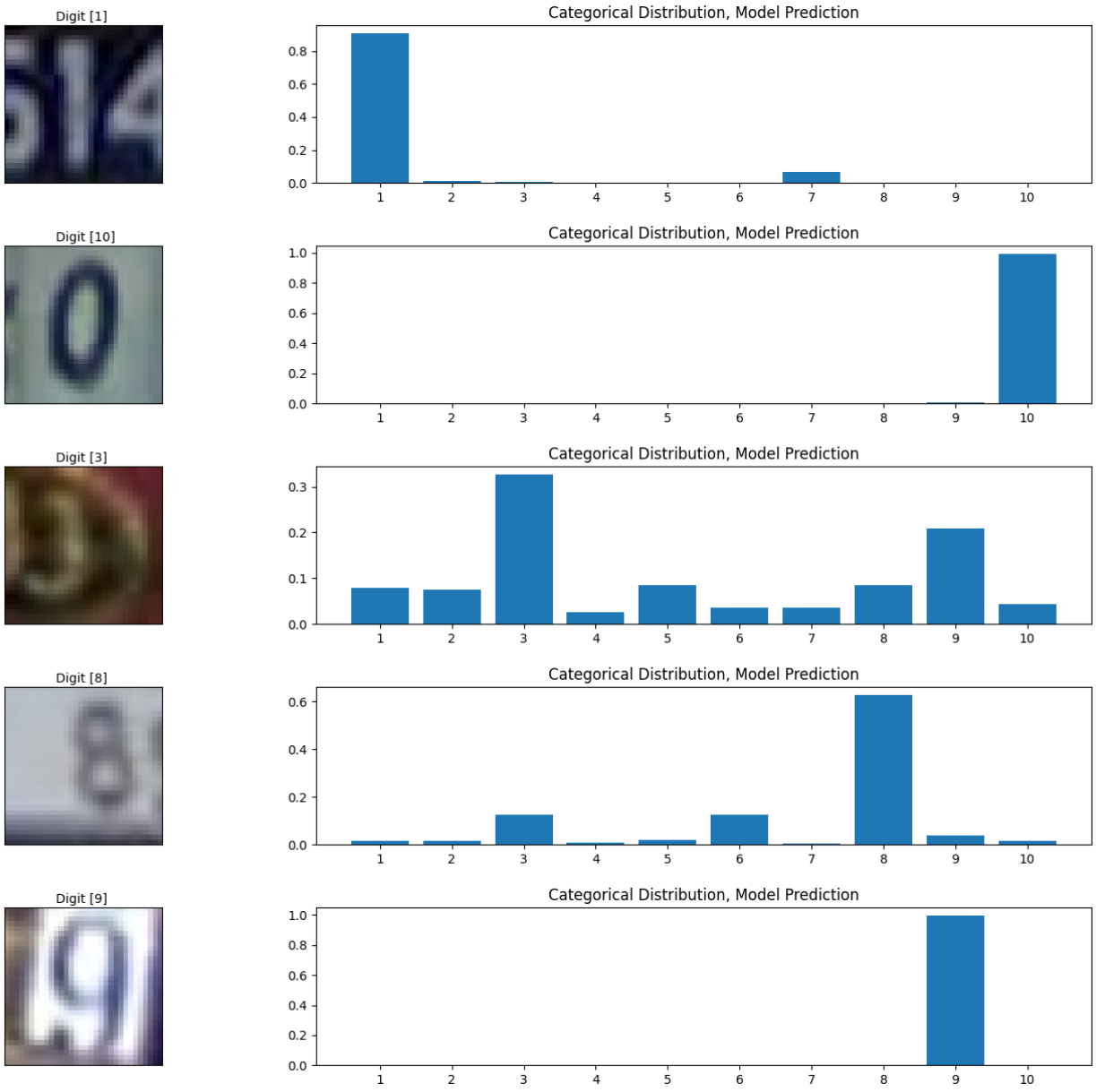
In [ ]:
```
model_2.load_weights(best_val_acc_path_2)
```

Out[ ]:
```
<tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x2a11a74c0d0>
```

In [ ]:
```
test_image = X_test.shape[0]

random1 = np.random.choice(test_image, 5)
random_test_image = X_test[random1, ...]
random_test_target = y_test[random1, ...]
prediction = model_2.predict(random_test_image)

graph, axes = plt.subplots(5, 2, figsize=(20, 15))
```

```
graph.subplots_adjust(hspace=0.4, wspace=-0.2)

for n, (predict, image, label) in enumerate(zip(prediction, random_test_image, random_
    axes[n,0].imshow(np.squeeze(image))
    axes[n,0].get_xaxis().set_visible(False)
    axes[n,0].get_yaxis().set_visible(False)
    axes[n,0].text(10., -1.5, f'Digit {label}')
    axes[n,1].bar(np.arange(1,11), predict)
    axes[n,1].set_xticks(np.arange(1,11))
    axes[n,1].set_title("Categorical Distribution, Model Prediction")
plt.show()
```

```
1/1 [==============================] - 0s 155ms/step
```



Note the higher confidence of the CNN as apposed to the MLP!

Through this notebook, I have compared MLPs and CNNs against each other under the SVHN dataset. It can be concluded that CNNs are much stronger than MLPs when it comes to computer vision, which is why they are the most popular method for static image analysis.