# CPSC5610 Assignment 3

## CNN Image classifier for the SVHN dataset

### Overview

In this assignment, you will create a convolutional neural network that classifies real-world images digits. You will use concepts from what we learned this course in building, training, testing, validating and saving your Tensorflow classifier model.

This is an open-ended project.

### What to submit

- Please do this assignment in a folder.
- When you have completed the notebook, you will save this notebook including all the intermediate results/plots.
- Please also print out a pdf file from your finished notebook, and put it in the same folder.
- Before you submit, please move your data folder outside. It is too big to submit.
- Please include your saved models.
- Then zip your whole folder and submit the single zip file.

### Start

We'll start by running some imports, and loading the dataset. For this project you are free to make further imports throughout the notebook as you wish.

```
import os
import zipfile
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
import scipy.io
```

In this assignment, you will use the [SVHN dataset](). This is an image dataset of 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.

Please only use the pre-cropped datasets in Format 2.

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

## (20pts) Inspect and preprocess the dataset

- Extract the training and testing images and labels separately from the train and test dictionaries loaded for you.
- Select a random sample of images and corresponding labels from the dataset (at least 10), and display them in a figure.
- Convert the training and test images to grayscale by taking the average across all colour channels for each pixel. *Hint: retain the channel dimension, which will now have size 1.*
- Select a random sample of the grayscale images and corresponding labels from the dataset (at least 10), and display them in a figure.

# 1) Extract the training and testing images and labels separately from the train and test dictionaries loaded for you.

```
# Mount google drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
# Unzip SVHN data
zip_path = "/content/drive/My Drive/Seattle University/CPSC5610 - Artificial Intelligence/Data/svnh_data.zip"
extract_root = "/content"

with zipfile.ZipFile(zip_path, 'r') as zip_ref:
    zip_ref.extractall(extract_root)


# Load .mat files
data_directory = os.path.join(extract_root, "svnh_data")
train = scipy.io.loadmat(os.path.join(data_directory, "train_32x32.mat"))
test = scipy.io.loadmat(os.path.join(data_directory, "test_32x32.mat"))
extra = scipy.io.loadmat(os.path.join(data_directory, "extra_32x32.mat"))


# Subset extra dataset
#subset_size = 200000
#indices = np.random.choice(extra['X'].shape[-1], subset_size, replace=False)
#extra_X_subset = extra['X'][:, :, :, indices]
#extra_y_subset = extra['y'][indices]


# Transpose images from (32, 32, 3, N) to (N, 32, 32, 3)
train_images = train['X'].transpose(3, 0, 1, 2) # from (32, 32, 3, 73257) to (73257, 32, 32, 3)
test_images = test['X'].transpose(3, 0, 1, 2) # from (32, 32, 3, 26032) to (26032, 32, 32, 3)
extra_images = extra['X'].transpose(3, 0, 1, 2) # from (32, 32, 3, 531131) to (531131, 32, 32, 3)


# Flatten labels
train_labels = train['y'].flatten() # (73257,)
test_labels = test['y'].flatten() # (26032,)
extra_labels = extra['y'].flatten() # (531131,)
```

```
train_images.shape # samples, height, width, channels
```

```
(73257, 32, 32, 3)
```

```
train_labels.shape # samples
```

```
(73257,)
```

```
test_images.shape # samples, height, width, channels
```

```
(26032, 32, 32, 3)
```

```
test_labels.shape # samples
```

```
(26032,)
```

```
extra_images.shape # samples, height, width, channels
```

```
(531131, 32, 32, 3)
```

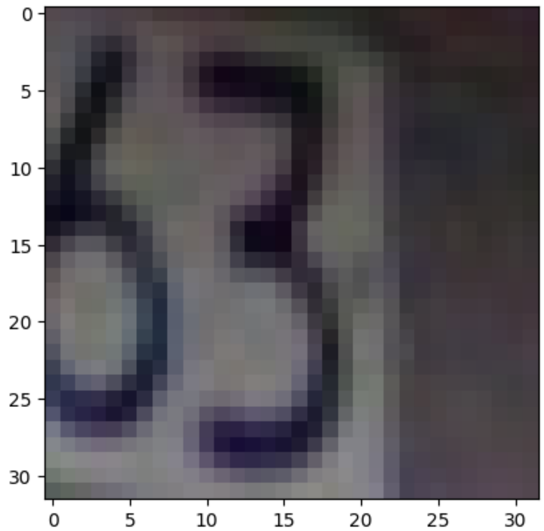
```
extra_labels.shape # samples
```

```
(531131,)
```

Examine a single image

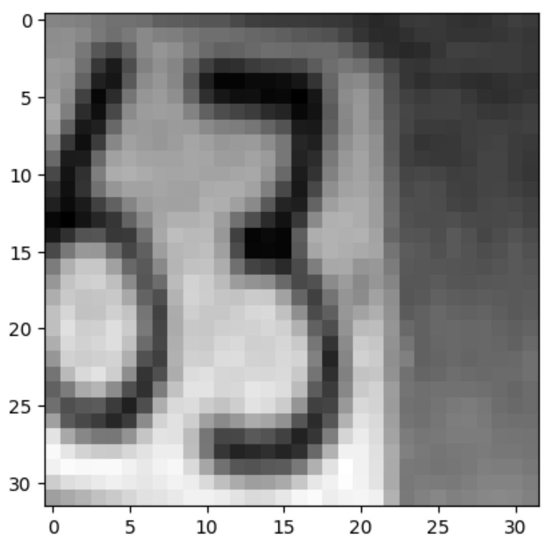
```
single_image = train_images[25]
single_label = train_labels[25]


plt.imshow(single_image)
print(f"Label: {single_label}")
```

```
Label: 3
```



```
single_image_gray = np.mean(single_image, axis=-1)
plt.imshow(single_image_gray, cmap="gray")
print(f"Label: {single_label}")
```

```
Label: 3
```



```
np.unique(train_labels)
```

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10], dtype=uint8)
```

```
np.unique(test_labels)
```

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10], dtype=uint8)
```

```
np.unique(extra_labels)
```

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10], dtype=uint8)
```

```
# Replaces '10' labels with '0' labels
train_labels[train_labels == 10] = 0
test_labels[test_labels == 10] = 0
extra_labels[extra_labels == 10] = 0
```

```
np.unique(train_labels)
```

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=uint8)
```

```
np.unique(test_labels)
```

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=uint8)
```

```
np.unique(extra_labels)
```

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=uint8)
```

```
# Normalize pixel values
train_images = train_images / 255.0
test_images = test_images / 255.0
extra_images = extra_images / 255.0
```

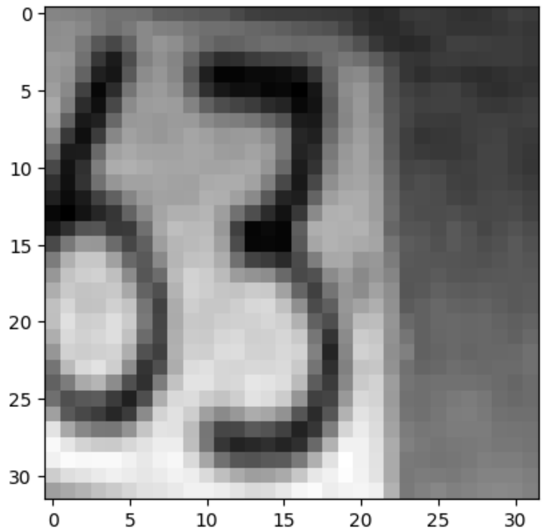
```
normalized_single_image = train_images[25]
```

```
normalized_single_image
```

```
array([[[0.32941176, 0.28627451, 0.30588235],
        [0.31764706, 0.28235294, 0.31372549],
        [0.30980392, 0.2745098 , 0.30980392],
        ...,
        [0.19215686, 0.13333333, 0.15686275],
        [0.19607843, 0.14509804, 0.17647059],
        [0.19215686, 0.12941176, 0.17254902]],

       [[0.3372549 , 0.30980392, 0.32156863],
        [0.33333333, 0.31372549, 0.3372549 ],
        [0.31764706, 0.29803922, 0.3254902 ],
        ...,
        [0.18431373, 0.13333333, 0.14509804],
        [0.18823529, 0.1372549 , 0.16078431],
        [0.18431373, 0.12156863, 0.15686275]],

       [[0.32941176, 0.32156863, 0.32941176],
        [0.3254902 , 0.32156863, 0.34117647],
        [0.27843137, 0.27058824, 0.29803922],
        ...,
        [0.19607843, 0.15294118, 0.15294118],
        [0.19607843, 0.15294118, 0.15686275],
        [0.18823529, 0.13333333, 0.15294118]],

       ...,

       [[0.50980392, 0.53333333, 0.50980392],
        [0.52941176, 0.54509804, 0.53333333],
        [0.52941176, 0.5254902 , 0.5372549 ],
        ...,
        [0.31372549, 0.26666667, 0.29803922],
        [0.31372549, 0.27058824, 0.29411765],
        [0.30196078, 0.26666667, 0.28235294]],

       [[0.43529412, 0.46666667, 0.43921569],
        [0.4745098 , 0.49803922, 0.47058824],
        [0.49019608, 0.49411765, 0.48627451],
        ...,
        [0.3254902 , 0.2745098 , 0.31764706],
        [0.3254902 , 0.2745098 , 0.30980392],
        [0.31372549, 0.27058824, 0.29803922]],

       [[0.34117647, 0.37254902, 0.36078431],
        [0.36862745, 0.39607843, 0.36862745],
        [0.4       , 0.4       , 0.39607843],
        ...,
        [0.3372549 , 0.28235294, 0.32941176],
        [0.33333333, 0.28235294, 0.32156863],
        [0.32156863, 0.2745098 , 0.30588235]]])
```

```
normalized_single_image_gray = np.mean(normalized_single_image, axis=-1)
plt.imshow(normalized_single_image_gray, cmap="gray")
```

```
<matplotlib.image.AxesImage at 0x7ac4e9fcadd0>
```



```
# One-hot encode the labels
cat_train_labels = tf.keras.utils.to_categorical(train_labels, num_classes=10)
cat_test_labels = tf.keras.utils.to_categorical(test_labels, num_classes=10)
cat_extra_labels = tf.keras.utils.to_categorical(extra_labels, num_classes=10)
```

```
train_labels[25]
```

```
np.uint8(3)
```

```
cat_train_labels[25]
```

```
array([0., 0., 0., 1., 0., 0., 0., 0., 0., 0.])
```

```
# Combine train and extra sets
train_images = np.concatenate((train_images, extra_images), axis=0)
cat_train_labels = np.concatenate((cat_train_labels, cat_extra_labels), axis=0)
```

```
train_images.shape
```

```
(604388, 32, 32, 3)
```

```
cat_train_labels.shape
```

```
(604388, 10)
```

## 2) Select a random sample of images and corresponding labels from the dataset (at least 10), and display them in a figure.

```
random_indices = np.random.choice(604388, size=20, replace=False)
```

```
random_indices
```

```
array([497288, 570002, 556502, 183622, 212624, 467273,  47412, 417272,
       490139, 141131, 316092, 196512,   4671, 508397, 260117,  16556,
        88078, 334103, 237877, 403208])
```

```
plt.figure(figsize=(15, 4))

for i, idx in enumerate(random_indices):
    image = train_images[idx, :, :, :] # shape: (32, 32, 3)
    label = cat_train_labels[idx]

    plt.subplot(1, 20, i + 1)
    plt.imshow(image)
```

```
    plt.title(f"{label}")
    plt.axis('off')

plt.tight_layout()
plt.show()
```

## 3) Convert the training and test images to grayscale by taking the average across all colour channels for each pixel. Hint: retain the channel dimension, which will now have size 1.

```
train_images_gray = np.mean(train_images, axis=-1, keepdims=True)  # shape: (123257, 32, 32, 1)
test_images_gray = np.mean(test_images, axis=-1, keepdims=True)    # shape: (26032, 32, 32, 1)
```

```
train_images_gray.shape
```

```
(604388, 32, 32, 1)
```

```
test_images_gray.shape
```

```
(26032, 32, 32, 1)
```

## 4) Select a random sample of the grayscale images and corresponding labels from the dataset (at least 10), and display them in a figure.

```
plt.figure(figsize=(15, 4))

for i, idx in enumerate(random_indices):
    image = train_images_gray[idx, :, :, :]
    label = cat_train_labels[idx]

    plt.subplot(1, 20, i + 1)
    plt.imshow(image, cmap="gray")
    plt.title(f"{label}")
    plt.axis('off')

plt.tight_layout()
plt.show()
```

```
from sklearn.model_selection import train_test_split
```

```
# Stratified split (15% validation)
train_imgs, val_imgs, train_lbls, val_lbls = train_test_split(
    train_images_gray,
    cat_train_labels,
    test_size=0.15,
    stratify=np.argmax(cat_train_labels, axis=1),
    random_state=42
)
```

```
train_imgs.shape
```

```
(513729, 32, 32, 1)
```

```
val_imgs.shape
```

```
(90659, 32, 32, 1)
```

```
train_lbls.shape
```

```
(513729, 10)
```

```
val_lbls.shape
```

```
(90659, 10)
```

## (40pts) CNN neural network classifier

- Build a CNN classifier model using the Sequential API. Your model should use the Conv2D, MaxPool2D, Flatten, Dense and Dropout layers. The final layer should again have a 10-way softmax output. Please use only what we learned in class.
- You should design and build the model yourself. Feel free to experiment with different CNN architectures. *Hint: to achieve a reasonable accuracy you won't need to use more than 2 or 3 convolutional layers and 2 fully connected layers.)*
- Compile and train the model (we recommend a maximum of 30 epochs), making use of both training and validation sets during the training run.
- Your model should track accuracy metric, and use early stopping during training.
- Plot the learning curves for loss vs epoch and accuracy vs epoch for both training and validation sets.
- Compute and display the loss and accuracy of the trained model on the test set.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPool2D, Flatten, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping


model = Sequential()

# Convolutional Block 1
model.add(Conv2D(filters=32, kernel_size=(3, 3), padding='same', activation='relu', input_shape=(32, 32, 1)))
model.add(MaxPool2D(pool_size=(2, 2)))

# Convolutional Block 2
model.add(Conv2D(filters=64, kernel_size=(3, 3), padding='same', activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2)))

# Convolutional Block 3
model.add(Conv2D(filters=128, kernel_size=(3, 3), padding='same', activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2)))

# Fully Connected Layers
model.add(Flatten())
model.add(Dense(units=256, activation='relu'))
model.add(Dropout(rate=0.5))
model.add(Dense(units=10, activation='softmax'))

# Compile
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
model.summary()
```

```
Model: "sequential"
```

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d (Conv2D) | (None, 32, 32, 32) | 320 |
| max_pooling2d (MaxPooling2D) | (None, 16, 16, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 16, 16, 64) | 18,496 |
| max_pooling2d_1 (MaxPooling2D) | (None, 8, 8, 64) | 0 |
| conv2d_2 (Conv2D) | (None, 8, 8, 128) | 73,856 |
| max_pooling2d_2 (MaxPooling2D) | (None, 4, 4, 128) | 0 |
| flatten (Flatten) | (None, 2048) | 0 |
| dense (Dense) | (None, 256) | 524,544 |
| dropout (Dropout) | (None, 256) | 0 |
| dense_1 (Dense) | (None, 10) | 2,570 |

```
Total params: 619,786 (2.36 MB)
Trainable params: 619,786 (2.36 MB)
Non-trainable params: 0 (0.00 B)
```

```
# Early stop
early_stop = EarlyStopping(monitor='val_loss', patience=3)

# Train
model.fit(train_imgs,train_lbls,epochs=30,validation_data=(val_imgs,val_lbls),callbacks=[early_stop])
```

```
Epoch 1/30
16055/16055 ━━━━━━━━━━━━━━━━━━━━ 59s 3ms/step - accuracy: 0.8205 - loss: 0.5608 - val_accuracy: 0.9549 - val_loss: 0.1622
Epoch 2/30
16055/16055 ━━━━━━━━━━━━━━━━━━━━ 51s 3ms/step - accuracy: 0.9484 - loss: 0.1826 - val_accuracy: 0.9640 - val_loss: 0.1366
Epoch 3/30
16055/16055 ━━━━━━━━━━━━━━━━━━━━ 50s 3ms/step - accuracy: 0.9575 - loss: 0.1535 - val_accuracy: 0.9629 - val_loss: 0.1375
Epoch 4/30
16055/16055 ━━━━━━━━━━━━━━━━━━━━ 51s 3ms/step - accuracy: 0.9612 - loss: 0.1412 - val_accuracy: 0.9672 - val_loss: 0.1276
Epoch 5/30
16055/16055 ━━━━━━━━━━━━━━━━━━━━ 53s 3ms/step - accuracy: 0.9640 - loss: 0.1326 - val_accuracy: 0.9688 - val_loss: 0.1213
Epoch 6/30
16055/16055 ━━━━━━━━━━━━━━━━━━━━ 52s 3ms/step - accuracy: 0.9655 - loss: 0.1278 - val_accuracy: 0.9693 - val_loss: 0.1194
Epoch 7/30
16055/16055 ━━━━━━━━━━━━━━━━━━━━ 51s 3ms/step - accuracy: 0.9667 - loss: 0.1240 - val_accuracy: 0.9693 - val_loss: 0.1225
Epoch 8/30
16055/16055 ━━━━━━━━━━━━━━━━━━━━ 51s 3ms/step - accuracy: 0.9675 - loss: 0.1200 - val_accuracy: 0.9711 - val_loss: 0.1174
Epoch 9/30
16055/16055 ━━━━━━━━━━━━━━━━━━━━ 50s 3ms/step - accuracy: 0.9686 - loss: 0.1153 - val_accuracy: 0.9680 - val_loss: 0.1324
Epoch 10/30
16055/16055 ━━━━━━━━━━━━━━━━━━━━ 51s 3ms/step - accuracy: 0.9690 - loss: 0.1162 - val_accuracy: 0.9688 - val_loss: 0.1252
Epoch 11/30
16055/16055 ━━━━━━━━━━━━━━━━━━━━ 51s 3ms/step - accuracy: 0.9701 - loss: 0.1137 - val_accuracy: 0.9713 - val_loss: 0.1188
<keras.src.callbacks.history.History at 0x7abdd0228710>
```

```
model.metrics_names # Check the metric names
```

```
['loss', 'compile_metrics']
```

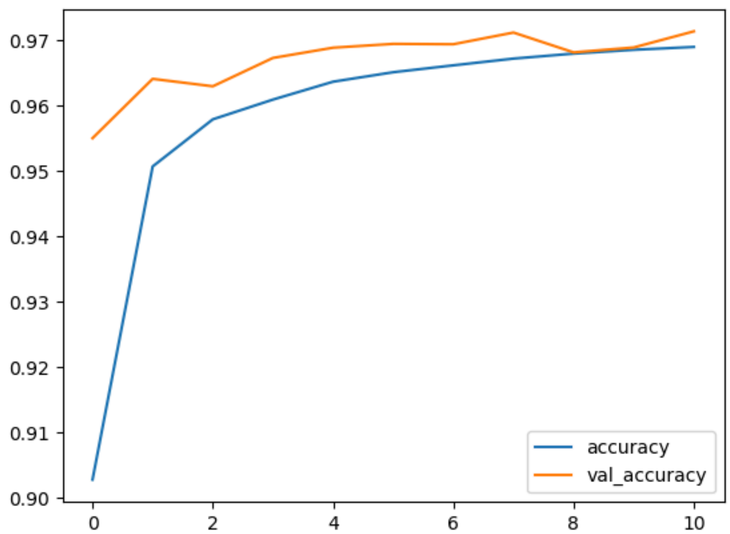
```
losses = pd.DataFrame(model.history.history)
```

```
losses
```

| | accuracy | loss | val_accuracy | val_loss |
|---|---|---|---|---|
| 0 | 0.902721 | 0.324831 | 0.954930 | 0.162200 |
| 1 | 0.950602 | 0.176437 | 0.963997 | 0.136565 |
| 2 | 0.957807 | 0.153704 | 0.962861 | 0.137525 |
| 3 | 0.960828 | 0.142849 | 0.967196 | 0.127583 |
| 4 | 0.963562 | 0.135306 | 0.968762 | 0.121255 |
| 5 | 0.965013 | 0.129435 | 0.969347 | 0.119449 |
| 6 | 0.966064 | 0.125630 | 0.969292 | 0.122537 |
| 7 | 0.967095 | 0.121628 | 0.971078 | 0.117439 |
| 8 | 0.967859 | 0.119363 | 0.968045 | 0.132404 |
| 9 | 0.968442 | 0.118479 | 0.968795 | 0.125223 |
| 10 | 0.968877 | 0.117038 | 0.971266 | 0.118845 |

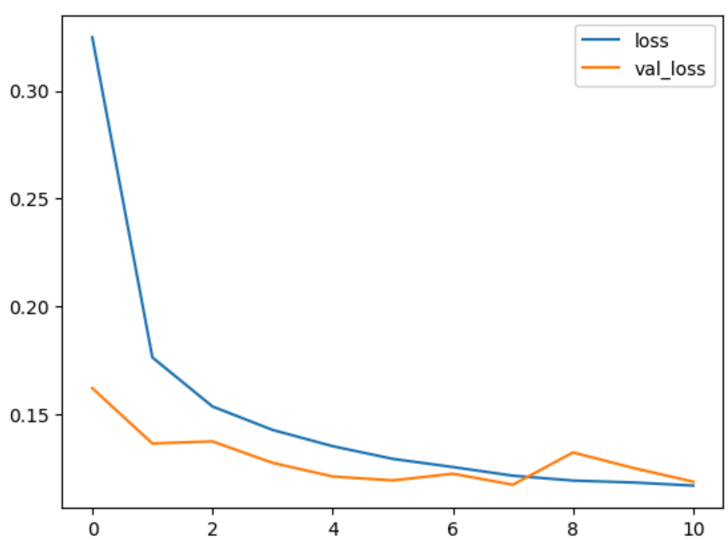
```
losses[['accuracy','val_accuracy']].plot()
```

<Axes: >




```
losses[['loss','val_loss']].plot()
```

<Axes: >




```
from sklearn.metrics import classification_report,confusion_matrix
```

```
predictions = model.predict(test_images_gray)
```

```
814/814 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```

```
predictions
```

```
array([[4.8619563e-11, 8.7852543e-09, 2.4123054e-07, ..., 1.6935695e-07,
        3.4333281e-09, 1.4450826e-08],
       [1.2798432e-09, 7.1566602e-09, 9.9999416e-01, ..., 2.2324438e-07,
        9.0855612e-10, 3.6524348e-09],
       [1.4622789e-08, 9.9998963e-01, 6.7177808e-07, ..., 9.8884368e-07,
        1.3059671e-08, 1.5191265e-08],
       ...,
       [6.8170480e-10, 1.3964177e-07, 4.4802335e-05, ..., 9.9995232e-01,
        3.3615491e-12, 3.8908124e-07],
       [1.2936059e-05, 7.7630782e-09, 1.3935372e-10, ..., 2.3640118e-10,
        1.5215099e-05, 1.1328984e-11],
       [1.9599569e-12, 1.4076382e-05, 4.7574801e-07, ..., 9.9998546e-01,
        5.5827988e-13, 1.5650263e-09]], dtype=float32)
```

```
pred_binary = predictions > 0.5
```

```
pred_binary
```

```
array([[False, False, False, ..., False, False, False],
       [False, False,  True, ..., False, False, False],
       [False,  True, False, ..., False, False, False],
       ...,
       [False, False, False, ...,  True, False, False],
       [False, False, False, ..., False, False, False],
       [False, False, False, ...,  True, False, False]])
```

```
pred_class = np.argmax(predictions, axis=1)
```

```
pred_class
```

```
array([5, 2, 1, ..., 7, 6, 7])
```

```
cat_test_labels[0]
```

```
array([0., 0., 0., 0., 0., 1., 0., 0., 0., 0.])
```

```
print(classification_report(test_labels,pred_class))
```

```
              precision    recall  f1-score   support

           0       0.92      0.96      0.94      1744
           1       0.95      0.97      0.96      5099
           2       0.97      0.95      0.96      4149
           3       0.92      0.94      0.93      2882
           4       0.97      0.95      0.96      2523
           5       0.95      0.94      0.94      2384
           6       0.93      0.94      0.94      1977
           7       0.96      0.94      0.95      2019
           8       0.94      0.91      0.93      1660
           9       0.93      0.93      0.93      1595

    accuracy                           0.95     26032
   macro avg       0.94      0.94      0.94     26032
weighted avg       0.95      0.95      0.95     26032
```

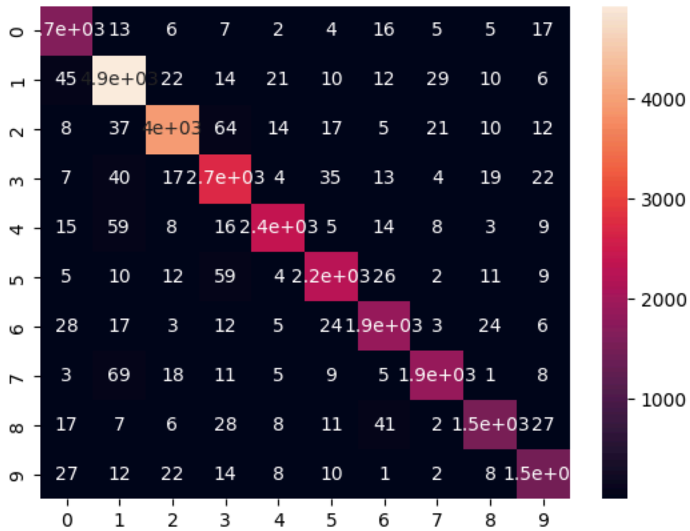
```
confusion_matrix(test_labels,pred_class)
```

```
array([[1669,   13,    6,    7,    2,    4,   16,    5,    5,   17],
       [  45, 4930,   22,   14,   21,   10,   12,   29,   10,    6],
       [   8,   37, 3961,   64,   14,   17,    5,   21,   10,   12],
       [   7,   40,   17, 2721,    4,   35,   13,    4,   19,   22],
       [  15,   59,    8,   16, 2386,    5,   14,    8,    3,    9],
       [   5,   10,   12,   59,    4, 2246,   26,    2,   11,    9],
       [  28,   17,    3,   12,    5,   24, 1855,    3,   24,    6],
       [   3,   69,   18,   11,    5,    9,    5, 1890,    1,    8],
       [  17,    7,    6,   28,    8,   11,   41,    2, 1513,   27],
       [  27,   12,   22,   14,    8,   10,    1,    2,    8, 1491]])
```

```
import seaborn as sns
```

```
sns.heatmap(confusion_matrix(test_labels,pred_class),annot=True)
```

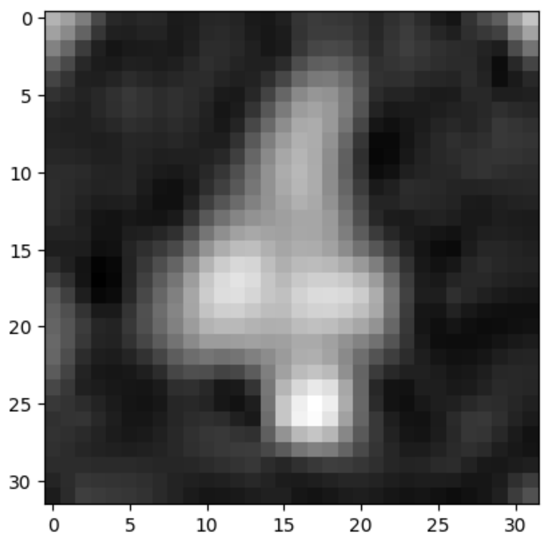
```
<Axes: >
```




```
my_number = test_images_gray[664]
```

```
plt.imshow(my_number.reshape(32, 32), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7abc97558090>
```




```
model.predict(my_number.reshape(1, 32, 32, 1))
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 401ms/step
array([[6.4053495e-07, 2.6309046e-05, 3.0764255e-05, 2.8490178e-06,
        9.9993253e-01, 6.6887559e-08, 1.5111578e-06, 4.9039277e-06,
        5.2862475e-08, 3.4097283e-07]], dtype=float32)
```

```
np.round(model.predict(my_number.reshape(1, 32, 32, 1)), 2)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
array([[0., 0., 0., 0., 1., 0., 0., 0., 0., 0.]], dtype=float32)
```

```
model.save('base_model_full_dataset.keras')
```

## (30pts) Improvement

- Try to use ImageDataGenerator to augment the data.
- Try to add BatchNomalization layers using Keras API. Please do a little research how this is done.

- Try to use a pre-trained CNN model for transfer learning. You make your choice and explain why.

Does any of the above help?

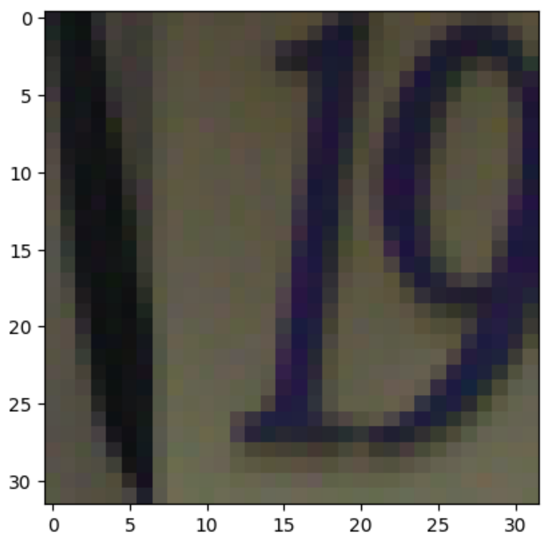
```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

```
#help(ImageDataGenerator)
```

```
train_gen = ImageDataGenerator(
    rotation_range=10,
    width_shift_range=0.1,
    height_shift_range=0.1,
    zoom_range=0.1,
    shear_range=8,
    fill_mode='nearest'
)

pass_gen = ImageDataGenerator()
```

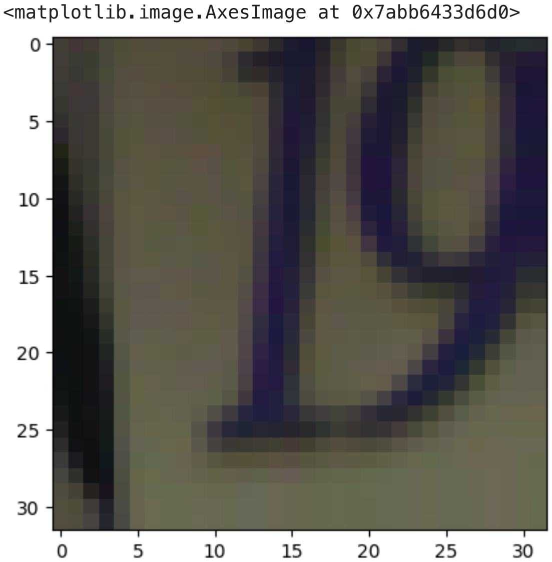
```
plt.imshow(train_images[0])
```

```
<matplotlib.image.AxesImage at 0x7abc9749e0d0>
```



```
plt.imshow(train_gen.random_transform(train_images[0]))
```

```
<matplotlib.image.AxesImage at 0x7abb6433d6d0>
```



```
BATCH = 64
```

```
train_gen = train_gen.flow(
    train_imgs, # numpy array (N,32,32,1)
    train_lbls, # numpy array (N,10)
    batch_size=BATCH,
    shuffle=True
)

val_gen = pass_gen.flow(
    val_imgs,
    val_lbls,
    batch_size=BATCH,
    shuffle=False
)

test_gen = pass_gen.flow(
    test_images_gray,
    cat_test_labels,
    batch_size=BATCH,
    shuffle=False
)


print("Samples :", train_gen.n)
print("Batch sz:", train_gen.batch_size)

batch_x, batch_y = train_gen[0]
print("Batch X shape:", batch_x.shape)
print("Batch Y shape:", batch_y.shape)
```

```
Samples : 513729
Batch sz: 64
Batch X shape: (64, 32, 32, 1)
Batch Y shape: (64, 10)
```

```
model2 = Sequential()

# Convolutional Block 1
model2.add(Conv2D(filters=32, kernel_size=(3, 3), padding='same', activation='relu', input_shape=(32, 32, 1)))
model2.add(MaxPool2D(pool_size=(2, 2)))

# Convolutional Block 2
model2.add(Conv2D(filters=64, kernel_size=(3, 3), padding='same', activation='relu'))
model2.add(MaxPool2D(pool_size=(2, 2)))

# Convolutional Block 3
model2.add(Conv2D(filters=128, kernel_size=(3, 3), padding='same', activation='relu'))
model2.add(MaxPool2D(pool_size=(2, 2)))

# Fully Connected Layers
model2.add(Flatten())
model2.add(Dense(units=256, activation='relu'))
model2.add(Dropout(rate=0.5))
model2.add(Dense(units=10, activation='softmax'))

# Compile
model2.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
# Train
model2.fit(
    train_gen,
    epochs=30,
    validation_data=val_gen,
    callbacks=[early_stop]
)
```

```
Epoch 1/30
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDat
  self._warn_if_super_not_called()
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 154s 19ms/step - accuracy: 0.7230 - loss: 0.8355 - val_accuracy: 0.9559 - val_loss: 0.1594
Epoch 2/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 150s 19ms/step - accuracy: 0.9193 - loss: 0.2731 - val_accuracy: 0.9666 - val_loss: 0.1258
Epoch 3/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 151s 19ms/step - accuracy: 0.9344 - loss: 0.2275 - val_accuracy: 0.9675 - val_loss: 0.1251
```

```
Epoch 4/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 152s 19ms/step - accuracy: 0.9415 - loss: 0.2026 - val_accuracy: 0.9671 - val_loss: 0.1223
Epoch 5/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 155s 19ms/step - accuracy: 0.9470 - loss: 0.1869 - val_accuracy: 0.9693 - val_loss: 0.1182
Epoch 6/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 153s 19ms/step - accuracy: 0.9492 - loss: 0.1784 - val_accuracy: 0.9717 - val_loss: 0.1104
Epoch 7/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 153s 19ms/step - accuracy: 0.9506 - loss: 0.1758 - val_accuracy: 0.9726 - val_loss: 0.1092
Epoch 8/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 159s 20ms/step - accuracy: 0.9532 - loss: 0.1668 - val_accuracy: 0.9726 - val_loss: 0.1065
Epoch 9/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 153s 19ms/step - accuracy: 0.9538 - loss: 0.1653 - val_accuracy: 0.9727 - val_loss: 0.1074
Epoch 10/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 152s 19ms/step - accuracy: 0.9552 - loss: 0.1598 - val_accuracy: 0.9737 - val_loss: 0.1043
Epoch 11/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 152s 19ms/step - accuracy: 0.9564 - loss: 0.1586 - val_accuracy: 0.9737 - val_loss: 0.1055
Epoch 12/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 153s 19ms/step - accuracy: 0.9572 - loss: 0.1563 - val_accuracy: 0.9748 - val_loss: 0.1034
Epoch 13/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 152s 19ms/step - accuracy: 0.9571 - loss: 0.1530 - val_accuracy: 0.9730 - val_loss: 0.1035
Epoch 14/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 153s 19ms/step - accuracy: 0.9590 - loss: 0.1492 - val_accuracy: 0.9751 - val_loss: 0.0984
Epoch 15/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 149s 19ms/step - accuracy: 0.9589 - loss: 0.1494 - val_accuracy: 0.9755 - val_loss: 0.0993
Epoch 16/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 148s 18ms/step - accuracy: 0.9590 - loss: 0.1482 - val_accuracy: 0.9736 - val_loss: 0.1005
Epoch 17/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 147s 18ms/step - accuracy: 0.9596 - loss: 0.1464 - val_accuracy: 0.9739 - val_loss: 0.1039
<keras.src.callbacks.history.History at 0x7abb64328710>
```

```
model2.metrics_names # Check the metric names
```

```
['loss', 'compile_metrics']
```

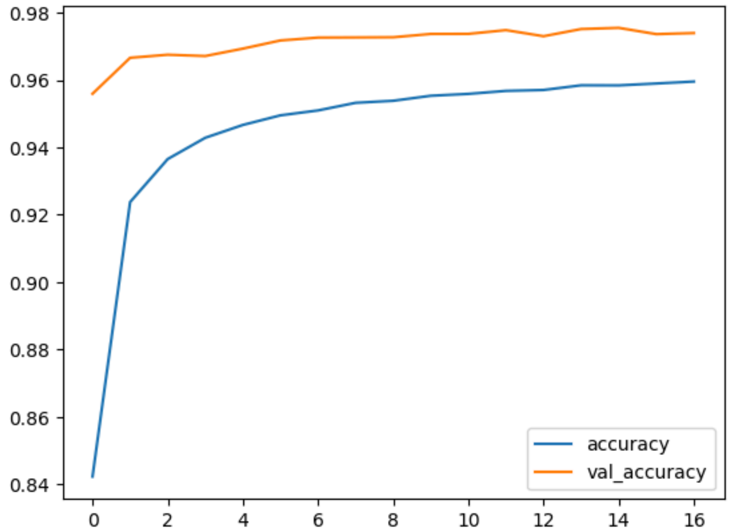
```
losses2 = pd.DataFrame(model2.history.history)
```

```
losses2
```

| | accuracy | loss | val_accuracy | val_loss |
|---|---|---|---|---|
| 0 | 0.842296 | 0.502098 | 0.955912 | 0.159390 |
| 1 | 0.923759 | 0.260971 | 0.966578 | 0.125800 |
| 2 | 0.936525 | 0.219445 | 0.967494 | 0.125083 |
| 3 | 0.942843 | 0.200806 | 0.967108 | 0.122278 |
| 4 | 0.946651 | 0.188646 | 0.969303 | 0.118165 |
| 5 | 0.949501 | 0.179973 | 0.971729 | 0.110425 |
| 6 | 0.950959 | 0.173497 | 0.972579 | 0.109186 |
| 7 | 0.953220 | 0.167676 | 0.972623 | 0.106470 |
| 8 | 0.953822 | 0.163964 | 0.972678 | 0.107391 |
| 9 | 0.955315 | 0.160435 | 0.973660 | 0.104333 |
| 10 | 0.955870 | 0.159602 | 0.973682 | 0.105471 |
| 11 | 0.956759 | 0.156551 | 0.974796 | 0.103416 |
| 12 | 0.957026 | 0.154638 | 0.972987 | 0.103511 |
| 13 | 0.958420 | 0.152850 | 0.975116 | 0.098370 |
| 14 | 0.958394 | 0.151383 | 0.975469 | 0.099337 |
| 15 | 0.958953 | 0.149758 | 0.973604 | 0.100506 |
| 16 | 0.959533 | 0.148404 | 0.973924 | 0.103896 |

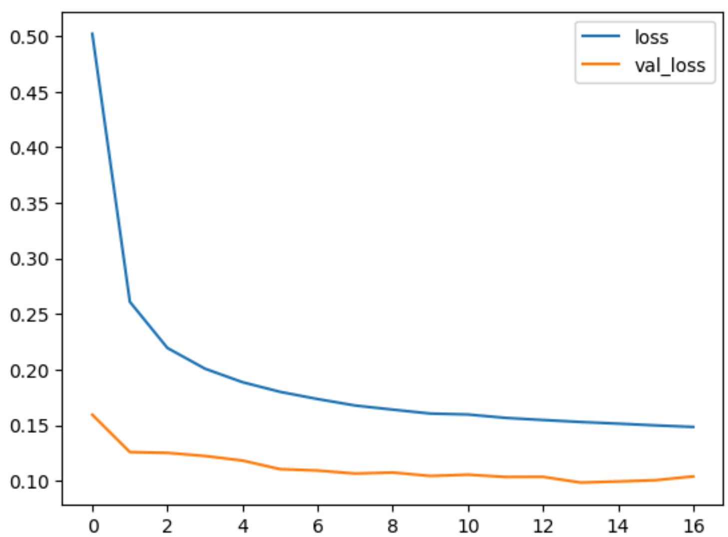
```
losses2[['accuracy','val_accuracy']].plot()
```

```
<Axes: >
```




```
losses2[['loss','val_loss']].plot()
```

```
<Axes: >
```




```
predictions2 = model2.predict(test_images_gray)
```

```
814/814 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```

```
predictions2
```

```
array([[5.2060019e-09, 4.3295935e-07, 1.9128575e-07, ..., 5.7688095e-07,
        2.2260602e-09, 2.5183297e-07],
       [9.9598385e-11, 4.6322217e-08, 9.9999964e-01, ..., 1.1171285e-07,
        1.4305229e-10, 2.2930874e-10],
       [2.7705939e-06, 9.9817336e-01, 1.3308752e-06, ..., 1.1998583e-05,
        2.5519222e-07, 4.2033093e-07],
       ...,
       [6.9868920e-09, 2.2034372e-05, 7.8806333e-06, ..., 9.9996006e-01,
        1.6232604e-10, 1.9304376e-07],
       [5.6024688e-05, 4.0376702e-07, 2.0019315e-09, ..., 5.9883138e-09,
        1.3196832e-06, 3.2170625e-08],
       [6.8687855e-10, 3.7536487e-05, 7.8305834e-07, ..., 9.9996173e-01,
        1.6771548e-12, 6.2388050e-09]], dtype=float32)
```

```
pred2_binary = predictions2 > 0.5
```

```
pred2_binary
```

```
array([[False, False, False, ..., False, False, False],
       [False, False,  True, ..., False, False, False],
```

```
       [False,  True, False, ..., False, False, False],
       ...,
       [False, False, False, ...,  True, False, False],
       [False, False, False, ..., False, False, False],
       [False, False, False, ...,  True, False, False]])
```

```
pred2_class = np.argmax(predictions2, axis=1)
```

```
pred2_class
```

```
array([5, 2, 1, ..., 7, 6, 7])
```

```
print(classification_report(test_labels,pred2_class))
```

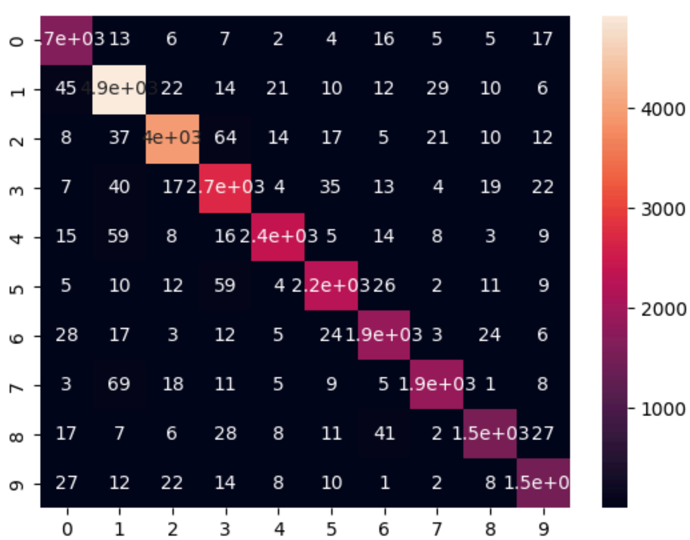
```
              precision    recall  f1-score   support

           0       0.93      0.96      0.95      1744
           1       0.97      0.96      0.97      5099
           2       0.97      0.98      0.97      4149
           3       0.94      0.95      0.94      2882
           4       0.96      0.97      0.97      2523
           5       0.96      0.95      0.95      2384
           6       0.95      0.95      0.95      1977
           7       0.96      0.95      0.96      2019
           8       0.95      0.92      0.94      1660
           9       0.95      0.92      0.94      1595

    accuracy                           0.96     26032
   macro avg       0.95      0.95      0.95     26032
weighted avg       0.96      0.96      0.96     26032
```

```
confusion_matrix(test_labels,pred2_class)
```

```
array([[1679,   10,    7,    8,    1,    7,   21,    4,    0,    7],
       [  22, 4915,   25,   27,   38,   11,   11,   37,    7,    6],
       [   5,   16, 4056,   16,   10,    8,    5,   24,    4,    5],
       [   5,   20,   24, 2729,    6,   33,   10,    6,   21,   28],
       [   6,   28,   16,    5, 2447,    3,    3,    4,    3,    8],
       [   5,   14,    6,   54,    5, 2268,   19,    1,    9,    3],
       [  21,   13,    4,    9,    5,   23, 1875,    3,   23,    1],
       [   2,   55,   20,   11,    6,    2,    0, 1919,    1,    3],
       [  15,    5,   13,   25,   11,    6,   36,    0, 1529,   20],
       [  38,   10,   23,   17,    9,    9,    3,    1,   11, 1474]])
```

```
sns.heatmap(confusion_matrix(test_labels,pred_class),annot=True)
```

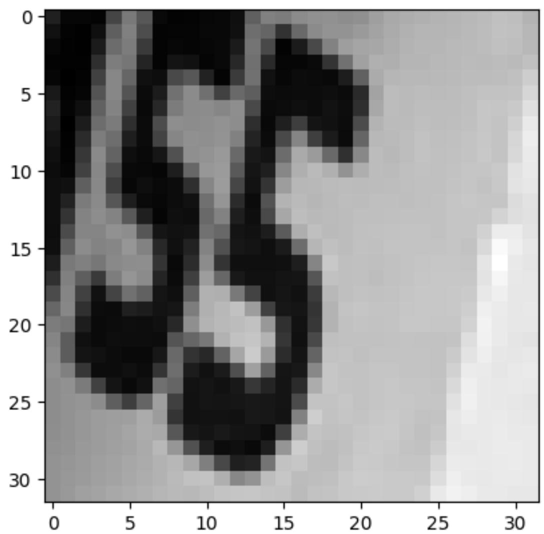
```
<Axes: >
```




```
my_number = test_images_gray[1000]
```

```
plt.imshow(my_number.reshape(32, 32), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7ac14dd7aa90>
```



```
model2.predict(my_number.reshape(1, 32, 32, 1))
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 247ms/step
array([[4.51854554e-10, 2.19837915e-07, 8.16593959e-10, 9.18656099e-07,
        1.22803447e-08, 9.99963164e-01, 3.54813783e-05, 7.46057272e-10,
        8.70424888e-09, 1.09917956e-07]], dtype=float32)
```

```
np.round(model2.predict(my_number.reshape(1, 32, 32, 1)), 2)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
array([[0., 0., 0., 0., 0., 1., 0., 0., 0., 0.]], dtype=float32)
```

```
model2.save('data_augmentation_model_full_dataset.keras')
```

Adding Batching Normalization

```
from tensorflow.keras.layers import BatchNormalization, Activation

model3 = Sequential()

# Convolutional Block 1
model3.add(Conv2D(filters=32, kernel_size=(3, 3), padding='same', use_bias=False, input_shape=(32, 32, 1)))
model3.add(BatchNormalization())
model3.add(Activation('relu'))
model3.add(MaxPool2D(pool_size=(2, 2)))

# Convolutional Block 2
model3.add(Conv2D(filters=64, kernel_size=(3, 3), padding='same', use_bias=False))
model3.add(BatchNormalization())
model3.add(Activation('relu'))
model3.add(MaxPool2D((2, 2)))

# Convolutional Block 3
model3.add(Conv2D(filters=128, kernel_size=(3, 3), padding='same', use_bias=False))
model3.add(BatchNormalization())
model3.add(Activation('relu'))
model3.add(MaxPool2D((2, 2)))

# Fully Connected Layers
model3.add(Flatten())
model3.add(Dense(units=256, activation='relu'))
model3.add(Dropout(rate=0.5))
model3.add(Dense(units=10, activation='softmax'))

# Compile
model3.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
# Train
model3.fit(
    train_gen,
    epochs=30,
    validation_data=val_gen,
    callbacks=[early_stop]
)
```

```
Epoch 1/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 162s 20ms/step - accuracy: 0.4983 - loss: 1.3425 - val_accuracy: 0.9453 - val_loss: 0.2114
Epoch 2/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 154s 19ms/step - accuracy: 0.8592 - loss: 0.4366 - val_accuracy: 0.9572 - val_loss: 0.1576
Epoch 3/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 162s 20ms/step - accuracy: 0.9382 - loss: 0.2218 - val_accuracy: 0.9713 - val_loss: 0.1136
Epoch 4/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 154s 19ms/step - accuracy: 0.9516 - loss: 0.1760 - val_accuracy: 0.9691 - val_loss: 0.1176
Epoch 5/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 153s 19ms/step - accuracy: 0.9569 - loss: 0.1581 - val_accuracy: 0.9733 - val_loss: 0.1059
Epoch 6/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 152s 19ms/step - accuracy: 0.9604 - loss: 0.1464 - val_accuracy: 0.9722 - val_loss: 0.1056
Epoch 7/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 153s 19ms/step - accuracy: 0.9618 - loss: 0.1398 - val_accuracy: 0.9744 - val_loss: 0.1000
Epoch 8/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 155s 19ms/step - accuracy: 0.9642 - loss: 0.1336 - val_accuracy: 0.9731 - val_loss: 0.1033
Epoch 9/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 153s 19ms/step - accuracy: 0.9654 - loss: 0.1288 - val_accuracy: 0.9638 - val_loss: 0.1329
Epoch 10/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 153s 19ms/step - accuracy: 0.9667 - loss: 0.1237 - val_accuracy: 0.9741 - val_loss: 0.0987
Epoch 11/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 151s 19ms/step - accuracy: 0.9670 - loss: 0.1239 - val_accuracy: 0.9754 - val_loss: 0.0949
Epoch 12/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 150s 19ms/step - accuracy: 0.9679 - loss: 0.1210 - val_accuracy: 0.9737 - val_loss: 0.1003
Epoch 13/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 148s 18ms/step - accuracy: 0.9685 - loss: 0.1192 - val_accuracy: 0.9749 - val_loss: 0.0965
Epoch 14/30
8028/8028 ━━━━━━━━━━━━━━━━━━━━ 149s 19ms/step - accuracy: 0.9690 - loss: 0.1164 - val_accuracy: 0.9714 - val_loss: 0.1066
<keras.src.callbacks.history.History at 0x7ac4ea04a990>
```

```
model3.metrics_names # Check the metric names
```

```
['loss', 'compile_metrics']
```

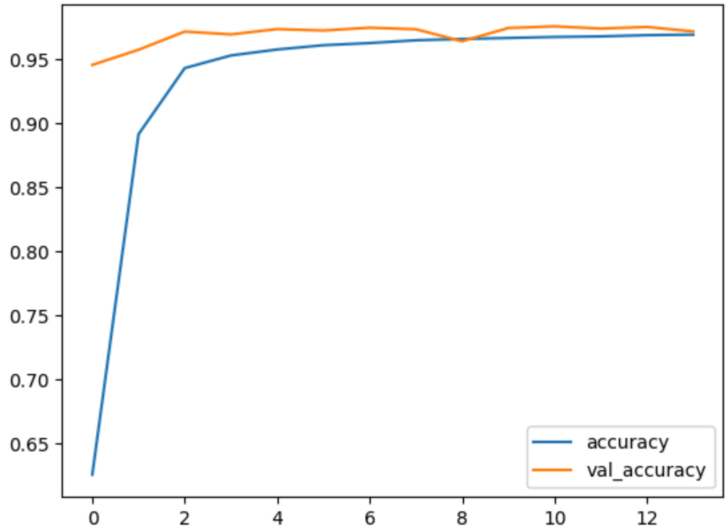
```
losses3 = pd.DataFrame(model3.history.history)
```

```
losses3
```

| | accuracy | loss | val_accuracy | val_loss |
|---|---|---|---|---|
| **0** | 0.625666 | 1.002552 | 0.945334 | 0.211423 |
| **1** | 0.891234 | 0.353513 | 0.957158 | 0.157647 |
| **2** | 0.942843 | 0.207207 | 0.971332 | 0.113594 |
| **3** | 0.952714 | 0.172306 | 0.969126 | 0.117628 |
| **4** | 0.957357 | 0.156275 | 0.973284 | 0.105890 |
| **5** | 0.960697 | 0.144803 | 0.972181 | 0.105557 |
| **6** | 0.962375 | 0.138645 | 0.974365 | 0.100029 |
| **7** | 0.964549 | 0.132129 | 0.973141 | 0.103281 |
| **8** | 0.965544 | 0.128588 | 0.963798 | 0.132867 |
| **9** | 0.966360 | 0.125442 | 0.974123 | 0.098695 |
| **10** | 0.967125 | 0.122985 | 0.975435 | 0.094902 |
| **11** | 0.967582 | 0.120684 | 0.973671 | 0.100347 |
| **12** | 0.968552 | 0.117752 | 0.974939 | 0.096470 |
| **13** | 0.968941 | 0.116763 | 0.971420 | 0.106648 |

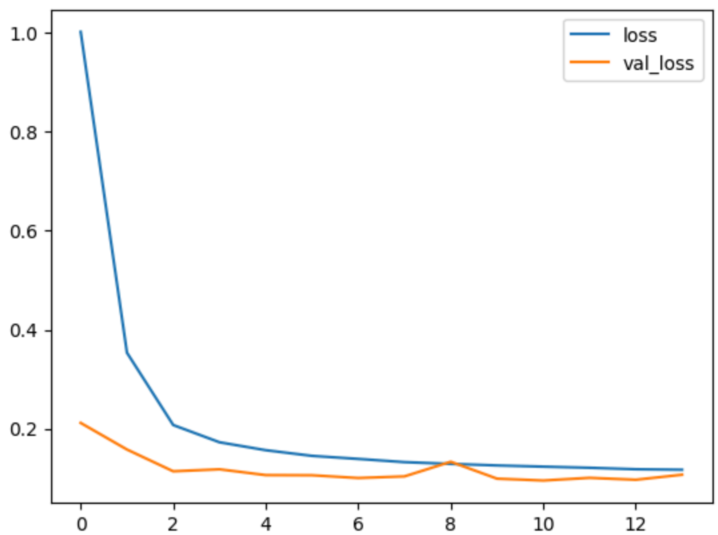
```
losses3[['accuracy','val_accuracy']].plot()
```

```
<Axes: >
```




```
losses3[['loss','val_loss']].plot()
```

```
<Axes: >
```




```
predictions3 = model3.predict(test_images_gray)
```

```
814/814 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```

```
predictions3
```

```
array([[2.8453124e-07, 2.8197126e-05, 8.7615354e-06, ..., 1.5913520e-05,
        5.3405046e-07, 4.4351059e-06],
       [8.0707914e-06, 6.1902298e-05, 9.9964201e-01, ..., 4.7926307e-05,
        2.4544610e-05, 3.5739791e-05],
       [6.1016585e-06, 9.9915576e-01, 2.3376668e-05, ..., 6.3453408e-05,
        1.7735758e-05, 1.9348902e-06],
       ...,
       [5.8625133e-08, 8.8640722e-05, 1.0469111e-04, ..., 9.9977797e-01,
        3.2194031e-08, 1.8442601e-05],
       [1.5912355e-03, 4.6303289e-04, 4.1217943e-05, ..., 5.1023730e-05,
        1.8465503e-04, 3.5647965e-05],
       [7.2829508e-08, 1.1128939e-03, 1.3698303e-05, ..., 9.9885786e-01,
        2.6150971e-08, 8.8013776e-06]], dtype=float32)
```

```
pred3_binary = predictions3 > 0.5
```

```
pred3_binary
```

```
array([[False, False, False, ..., False, False, False],
       [False, False,  True, ..., False, False, False],
```

```
            [False,  True, False, ..., False, False, False],
            ...,
            [False, False, False, ...,  True, False, False],
            [False, False, False, ..., False, False, False],
            [False, False, False, ...,  True, False, False]])
```

```
pred3_class = np.argmax(predictions3, axis=1)
```

```
pred3_class
```

```
array([5, 2, 1, ..., 7, 6, 7])
```

```
print(classification_report(test_labels,pred3_class))
```

```
              precision    recall  f1-score   support

           0       0.95      0.94      0.95      1744
           1       0.95      0.97      0.96      5099
           2       0.97      0.96      0.97      4149
           3       0.93      0.94      0.94      2882
           4       0.96      0.96      0.96      2523
           5       0.95      0.95      0.95      2384
           6       0.94      0.94      0.94      1977
           7       0.95      0.93      0.94      2019
           8       0.96      0.91      0.94      1660
           9       0.94      0.95      0.94      1595

    accuracy                           0.95     26032
   macro avg       0.95      0.95      0.95     26032
weighted avg       0.95      0.95      0.95     26032
```

```
confusion_matrix(test_labels,pred3_class)
```

```
array([[1645,   16,   11,   13,    3,    7,   30,    2,    0,   17],
       [  18, 4938,   17,   36,   41,   10,    6,   27,    3,    3],
       [   4,   39, 3999,   22,   17,    4,    3,   47,    5,    9],
       [   7,   27,   19, 2718,   10,   39,    8,    8,   17,   29],
       [   6,   44,   12,   11, 2429,    4,    5,    7,    2,    3],
       [   3,    8,    7,   59,    7, 2265,   19,    3,    5,    8],
       [  17,   12,    9,    9,    9,   25, 1866,    2,   24,    4],
       [   4,   99,   14,    4,    3,    3,    1, 1885,    1,    5],
       [  10,   12,   11,   24,    9,    9,   39,    4, 1518,   24],
       [  14,   10,   20,   13,    7,   10,    1,    1,    6, 1513]])
```

```
sns.heatmap(confusion_matrix(test_labels,pred3_class),annot=True)
```

```
<Axes: >
```

```
my_number = test_images_gray[3333]
```

```
plt.imshow(my_number.reshape(32, 32), cmap='gray')
```

<matplotlib.image.AxesImage at 0x7abac4748f50>