Week 4: Multi-class Classification

Welcome to this assignment! In this exercise, you will get a chance to work on a multi-class classification problem. You will be using the Sign Language MNIST dataset, which contains 28x28 images of hands depicting the 26 letters of the English alphabet.

You will need to pre-process the data so that it can be fed into your convolutional neural network to correctly classify each image as the letter it represents.

Let's get started!

NOTE: *To prevent errors from the autograder, please avoid editing or deleting non-graded cells in this notebook . Please only put your solutions in between the `### START CODE HERE` and `### END CODE HERE` code comments, and refrain from adding any new cells.*

```
# grader-required-cell

import csv
import string
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import ImageDataGenerator, array_to_img
```

Download the training and test sets (the test set will actually be used as a validation set):

```
!pip install gdown==5.1.0
```

```
Requirement already satisfied: gdown==5.1.0 in /usr/local/lib/python3.10/dist
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.10/di
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: requests[socks] in /usr/local/lib/python3.10/d
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.10/dis
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/pyt
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.1
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.1
Requirement already satisfied: PySocks!=1.5.7,>=1.5.6 in /usr/local/lib/pytho
```

```
# sign_mnist_train.csv
!gdown --id 1z0DkA9BytlLxO1C0BAWzknLyQmZAp0HR
# sign_mnist_test.csv
!gdown --id 1z1BIj4qmri59GWBG4ivMNFtpZ4AXIbzg
```

```
/usr/local/lib/python3.10/dist-packages/gdown/__main__.py:132: FutureWarning:
  warnings.warn(
```

```
Downloading...
From: https://drive.google.com/uc?id=1z0DkA9BytlLxO1C0BAWzknLyQmZAp0HR
To: /content/sign_mnist_train.csv
100% 83.3M/83.3M [00:02<00:00, 39.6MB/s]
/usr/local/lib/python3.10/dist-packages/gdown/__main__.py:132: FutureWarning:
  warnings.warn(
Downloading...
From: https://drive.google.com/uc?id=1z1BIj4qmri59GWBG4ivMNFtpZ4AXIbzg
To: /content/sign_mnist_test.csv
100% 21.8M/21.8M [00:00<00:00, 44.5MB/s]
```

Define some globals with the path to both files you just downloaded:

```
# grader-required-cell

TRAINING_FILE = './sign_mnist_train.csv'
VALIDATION_FILE = './sign_mnist_test.csv'
```

Unlike previous assignments, you will not have the actual images provided, instead you will have the data serialized as `csv` files.

Take a look at how the data looks like within the `csv` file:

```
# grader-required-cell

with open(TRAINING_FILE) as training_file:
  line = training_file.readline()
  print(f"First line (header) looks like this:\n{line}")
  line = training_file.readline()
  print(f"Each subsequent line (data points) look like this:\n{line}")
```

```
First line (header) looks like this:
label,pixel1,pixel2,pixel3,pixel4,pixel5,pixel6,pixel7,pixel8,pixel9,pixel10,|

Each subsequent line (data points) look like this:
3,107,118,127,134,139,143,146,150,153,156,158,160,163,165,159,166,168,170,170
```

As you can see, each file includes a header (the first line) and each subsequent data point is represented as a line that contains 785 values.

The first value is the label (the numeric representation of each letter) and the other 784 values are the value of each pixel of the image. Remember that the original images have a resolution of 28x28, which sums up to 784 pixels.

Parsing the dataset

Now complete the `parse_data_from_input` below.

This function should be able to read a file passed as input and return 2 numpy arrays, one containing the labels and one containing the 28x28 representation of each image within the file. These numpy arrays should have type `float64`.

A couple of things to keep in mind:

- The first line contains the column headers, so you should ignore it.
- Each successive line contains 785 comma-separated values between 0 and 255
    - The first value is the label
    - The rest are the pixel values for that picture

Hint:

You have two options to solve this function.

- 1. One is to use `csv.reader` and create a for loop that reads from it, if you take this approach take this into consideration:
    - `csv.reader` returns an iterable that returns a row of the csv file in each iteration. Following this convention, row[0] has the label and row[1:] has the 784 pixel values.
    - To reshape the arrays (going from 784 to 28x28), you can use functions such as `np.array_split` or `np.reshape`.
    - For type conversion of the numpy arrays, use the method `np.ndarray.astype`.
- 2. The other one is to use `np.loadtxt`. You can find the documentation here.

Regardless of the method you chose, your function should finish its execution in under 1 minute. If you see that your function is taking a long time to run, try changing your implementation.

```
# grader-required-cell

# GRADED FUNCTION: parse_data_from_input
def parse_data_from_input(filename):
  """
  Parses the images and labels from a CSV file

  Args:
    filename (string): path to the CSV file

  Returns:
    images, labels: tuple of numpy arrays containing the images and labels
  """
  with open(filename) as file:
    ### START CODE HERE

    # Use csv.reader, passing in the appropriate delimiter
    # Remember that csv.reader can be iterated and returns one line in each itera
    csv_reader = csv.reader(file, delimiter=',') # Changed delimiter to ',' assum

    labels = []
    images = []

    for i, row in enumerate(csv_reader):
       if i > 0:
        labels.append(row[0])
        images.append(row[1:])

    images = np.array(images, dtype=np.float64)
    labels = np.array(labels, dtype=np.float64)

    images = images.reshape(images.shape[0], 28, 28 )


    ### END CODE HERE

    return images, labels


# grader-required-cell

# Test your function
training_images, training_labels = parse_data_from_input(TRAINING_FILE)
validation_images, validation_labels = parse_data_from_input(VALIDATION_FILE)

print(f"Training images has shape: {training_images.shape} and dtype: {training_i
print(f"Training labels has shape: {training_labels.shape} and dtype: {training_l
print(f"Validation images has shape: {validation_images.shape} and dtype: {valida
print(f"Validation labels has shape: {validation_labels.shape} and dtype: {valida
```

```
Training images has shape: (27455, 28, 28) and dtype: float64
Training labels has shape: (27455,) and dtype: float64
Validation images has shape: (7172, 28, 28) and dtype: float64
Validation labels has shape: (7172,) and dtype: float64
```

Expected Output:

```
Training images has shape: (27455, 28, 28) and dtype: float64
Training labels has shape: (27455,) and dtype: float64
Validation images has shape: (7172, 28, 28) and dtype: float64
Validation labels has shape: (7172,) and dtype: float64
```

Visualizing the numpy arrays

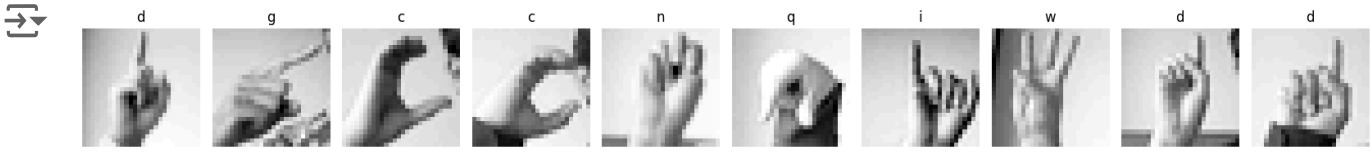
Now that you have converted the initial csv data into a format that is compatible with computer vision tasks, take a moment to actually see how the images of the dataset look like:

```
# Plot a sample of 10 images from the training set
def plot_categories(training_images, training_labels):
  fig, axes = plt.subplots(1, 10, figsize=(16, 15))
  axes = axes.flatten()
  letters = list(string.ascii_lowercase)

  for k in range(10):
    img = training_images[k]
    img = np.expand_dims(img, axis=-1)
    img = array_to_img(img)
    ax = axes[k]
    ax.imshow(img, cmap="Greys_r")
    ax.set_title(f"{letters[int(training_labels[k])]}")
    ax.set_axis_off()

  plt.tight_layout()
  plt.show()

plot_categories(training_images, training_labels)
```



Creating the generators for the CNN

Now that you have successfully organized the data in a way that can be easily fed to Keras' `ImageDataGenerator`, it is time for you to code the generators that will yield batches of images,

both for training and validation. For this complete the `train_val_generators` function below.

Some important notes:

- The images in this dataset come in the same resolution so you don't need to set a custom `target_size` in this case. In fact, you can't even do so because this time you will not be using the `flow_from_directory` method (as in previous assignments). Instead you will use the `flow` method.
- You need to add the "color" dimension to the numpy arrays that encode the images. These are black and white images, so this new dimension should have a size of 1 (instead of 3, which is used when dealing with colored images). Take a look at the function `np.expand_dims` for this.

```
# grader-required-cell

# GRADED FUNCTION: train_val_generators
def train_val_generators(training_images, training_labels, validation_images, val
  """
  Creates the training and validation data generators

  Args:
    training_images (array): parsed images from the train CSV file
    training_labels (array): parsed labels from the train CSV file
    validation_images (array): parsed images from the test CSV file
    validation_labels (array): parsed labels from the test CSV file

  Returns:
    train_generator, validation_generator - tuple containing the generators
  """
  ### START CODE HERE

  # In this section you will have to add another dimension to the data
  # So, for example, if your array is (10000, 28, 28)
  # You will need to make it (10000, 28, 28, 1)
  # Hint: np.expand_dims
  training_images = training_images.reshape(training_images.shape[0], training_im
  validation_images = validation_images.reshape(validation_images.shape[0], valid

  # Instantiate the ImageDataGenerator class
  # Don't forget to normalize pixel values
  # and set arguments to augment the images (if desired)
  train_datagen = ImageDataGenerator(
        rescale=1.0 / 255
        # rotation_range=40,
        # width_shift_range=0.2,
        # height_shift_range=0.2,
        # shear_range=0.2,
        # zoom_range=0.2,
        # horizontal_flip=True,
        # fill_mode='nearest'
    )


  # Pass in the appropriate arguments to the flow method
  train_generator = train_datagen.flow(x=training_images,
                                       y=training_labels,
                                       batch_size=32)


  # Instantiate the ImageDataGenerator class (don't forget to set the rescale arg
  # Remember that validation data should not be augmented
  validation_datagen = ImageDataGenerator(rescale=1.0 / 255)

  # Pass in the appropriate arguments to the flow method
  validation_generator = validation_datagen.flow(x=validation_images,
                                                 y=validation_labels,
                                                 batch_size=32)
```

```
    ### END CODE HERE

    return train_generator, validation_generator


# grader-required-cell

# Test your generators
train_generator, validation_generator = train_val_generators(training_images, tra

print(f"Images of training generator have shape: {train_generator.x.shape}")
print(f"Labels of training generator have shape: {train_generator.y.shape}")
print(f"Images of validation generator have shape: {validation_generator.x.shape}
print(f"Labels of validation generator have shape: {validation_generator.y.shape}
```

```
Images of training generator have shape: (27455, 28, 28, 1)
Labels of training generator have shape: (27455,)
Images of validation generator have shape: (7172, 28, 28, 1)
Labels of validation generator have shape: (7172,)
```

Expected Output:

```
Images of training generator have shape: (27455, 28, 28, 1)
Labels of training generator have shape: (27455,)
Images of validation generator have shape: (7172, 28, 28, 1)
Labels of validation generator have shape: (7172,)
```

Coding the CNN

One last step before training is to define the architecture of the model.

Complete the `create_model` function below. This function should return a Keras' model that uses the `Sequential` or the `Functional` API.

The last layer of your model should have a number of units equal to the number of letters in the English alphabet. It should also use an activation function that will output the probabilities per letter.

Note: The documentation of the dataset mentions that there are actually no cases for the last letter, Z, and this will allow you to reduce the recommended number of output units above by one. If you're not yet convinced, you can safely ignore this fact for now and study it later. You will pass the assignment even without this slight optimization.

Aside from defining the architecture of the model, you should also compile it so make sure to use a `loss` function that is suitable for multi-class classification.

Note that you should use no more than 2 Conv2D and 2 MaxPooling2D layers to achieve the desired performance.

```
from tensorflow.keras.optimizers import RMSprop
def create_model():

    ### START CODE HERE

    DESIRED_ACCURACY = 0.999

    class myCallback(tf.keras.callbacks.Callback):
        def on_epoch_end(self, epoch, logs = {}):
            if(logs.get('acc') > DESIRED_ACCURACY):
                print("\nLoss is low so cancelling training!")
                self.model.stop_training = True

    # index, value = np.unique(training_labels, return_counts=True)
    # nb_features = len(i)

    # Define the model
    # Use no more than 2 Conv2D and 2 MaxPooling2D
    model = tf.keras.models.Sequential([
        tf.keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=(28, 28,
        tf.keras.layers.MaxPooling2D(2,2),
        tf.keras.layers.Conv2D(32, (3,3), activation='relu'),
        tf.keras.layers.MaxPooling2D(2,2),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(512, activation='relu'),
        tf.keras.layers.Dense(256, activation='relu'),
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.Dense(26, activation='softmax')
    ])

    # Compile Model.
    model.compile(
        optimizer='adam',#RMSprop(learning_rate = 0.0003),
        loss='sparse_categorical_crossentropy',
        metrics=['accuracy']
    )



    # Set the training parameters
    # model.compile(loss = 'categorical_crossentropy', optimizer='rmsprop', metri
    ### END CODE HERE
    return model



# Save your model
model = create_model()

# Train your model
history = model.fit(train_generator,
                    epochs=15,
                    validation_data=validation_generator)
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_c
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Epoch 1/15
/usr/local/lib/python3.10/dist-packages/keras/src/trainers/data_adapters/py_da
  self._warn_if_super_not_called()
858/858 ━━━━━━━━━━━━━━━━━━━━ 13s 9ms/step - accuracy: 0.4749 - loss: 1.7016 -
Epoch 2/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - accuracy: 0.9816 - loss: 0.0621 - v
Epoch 3/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - accuracy: 0.9878 - loss: 0.0358 - v
Epoch 4/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.9983 - loss: 0.0057 - v
Epoch 5/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.9982 - loss: 0.0062 - v
Epoch 6/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 5s 4ms/step - accuracy: 1.0000 - loss: 8.6058e-05
Epoch 7/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 6s 5ms/step - accuracy: 1.0000 - loss: 3.8424e-05
Epoch 8/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 1.0000 - loss: 2.0858e-05
Epoch 9/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 1.0000 - loss: 1.4587e-05
Epoch 10/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 1.0000 - loss: 8.6526e-06
Epoch 11/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 1.0000 - loss: 5.6729e-06
Epoch 12/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 6s 5ms/step - accuracy: 1.0000 - loss: 3.6082e-06
Epoch 13/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 6s 6ms/step - accuracy: 1.0000 - loss: 2.2664e-06
Epoch 14/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy: 1.0000 - loss: 1.5249e-06
Epoch 15/15
858/858 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 1.0000 - loss: 1.0222e-06
```

Now take a look at your training history:

```
    # Plot the chart for accuracy and loss on both training and validation
    acc = history.history['accuracy']
    val_acc = history.history['val_accuracy']
    loss = history.history['loss']
    val_loss = history.history['val_loss']

    epochs = range(len(acc))

    plt.plot(epochs, acc, 'r', label='Training accuracy')
    plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
    plt.title('Training and validation accuracy')
    plt.legend()
    plt.figure()

    plt.plot(epochs, loss, 'r', label='Training Loss')
    plt.plot(epochs, val_loss, 'b', label='Validation Loss')
    plt.title('Training and validation loss')
    plt.legend()

    plt.show()
```

You will not be graded based on the accuracy of your model but try making it as high as possible for both training and validation, as an optional exercise, **after submitting your notebook for grading**.

A reasonable benchmark is to achieve over 99% accuracy for training and over 95% accuracy for validation within 15 epochs. Try tweaking your model's architecture or the augmentation techniques to see if you can achieve these levels of accuracy.

Download your notebook for grading

You will need to submit your solution notebook for grading. The following code cells will check if this notebook's grader metadata (i.e. hidden data in the notebook needed for grading) is not modified by your workspace. This will ensure that the autograder can evaluate your code properly. Depending on its output, you will either:

- *if the metadata is intact*: Download the current notebook. Click on the File tab on the upper left corner of the screen then click on `Download -> Download .ipynb.` You can name it anything you want as long as it is a valid `.ipynb` (jupyter notebook) file.

- *if the metadata is missing*: A new notebook with your solutions will be created on this Colab workspace. It should be downloaded automatically and you can submit that to the grader.