1.2 Symbol Recognition with a CNN - Training the Model

August 5, 2019

1 1.2 Symbol Recognition with a CNN - Training the Model

In this notebook, we train a convolutional neural network that is capable of detecting mathematical symbols. Note that main goal of this exploration is to get a sense for what type of model might be a reasonable encoder for our seq2seq model. After all, the encoder must be able to effectively represent the various mathematical symbols present in formulas. In some ways, the formula problem is easier – since the input formulas are not handwritten – and in some ways it is a harder problem – since formulas can be quite long and complex. In any case, this exploration will serve as a reasonable starting point.

```
In [9]: import tensorflow as tf
        import numpy as np
        import pandas as pd
        import scipy
        import matplotlib.pyplot as plt

        import random
```

```
In [10]: print(tf.__version__)
         print(tf.test.is_gpu_available())
         print(tf.test.is_built_with_cuda())
         print(tf.test.gpu_device_name())
```

```
2.0.0-beta1
False
False
```

```
In [11]: import os

         ### Make sure our data is in order
         data_base_dir = "../data"
         figs_base_dir = "../figs"
         model_base_dir = "../models"

         original_data_path = data_base_dir + "/original/symbol/"
```

```
processed_data_path = data_base_dir + "/processed/symbol/"
pickle_data_path = data_base_dir + "/pickle/symbol/"
model_data_path = model_base_dir + "/symbol"

assert os.path.exists(original_data_path), "Original data path does not exist."
assert os.path.isdir(processed_data_path), "Original data path exists, but is not a di

if not os.path.exists(processed_data_path):
    print("Creating processed data path...")
    os.mkdir(processed_data_path)
```

1.1 Load data

Below, we unpickle the data.

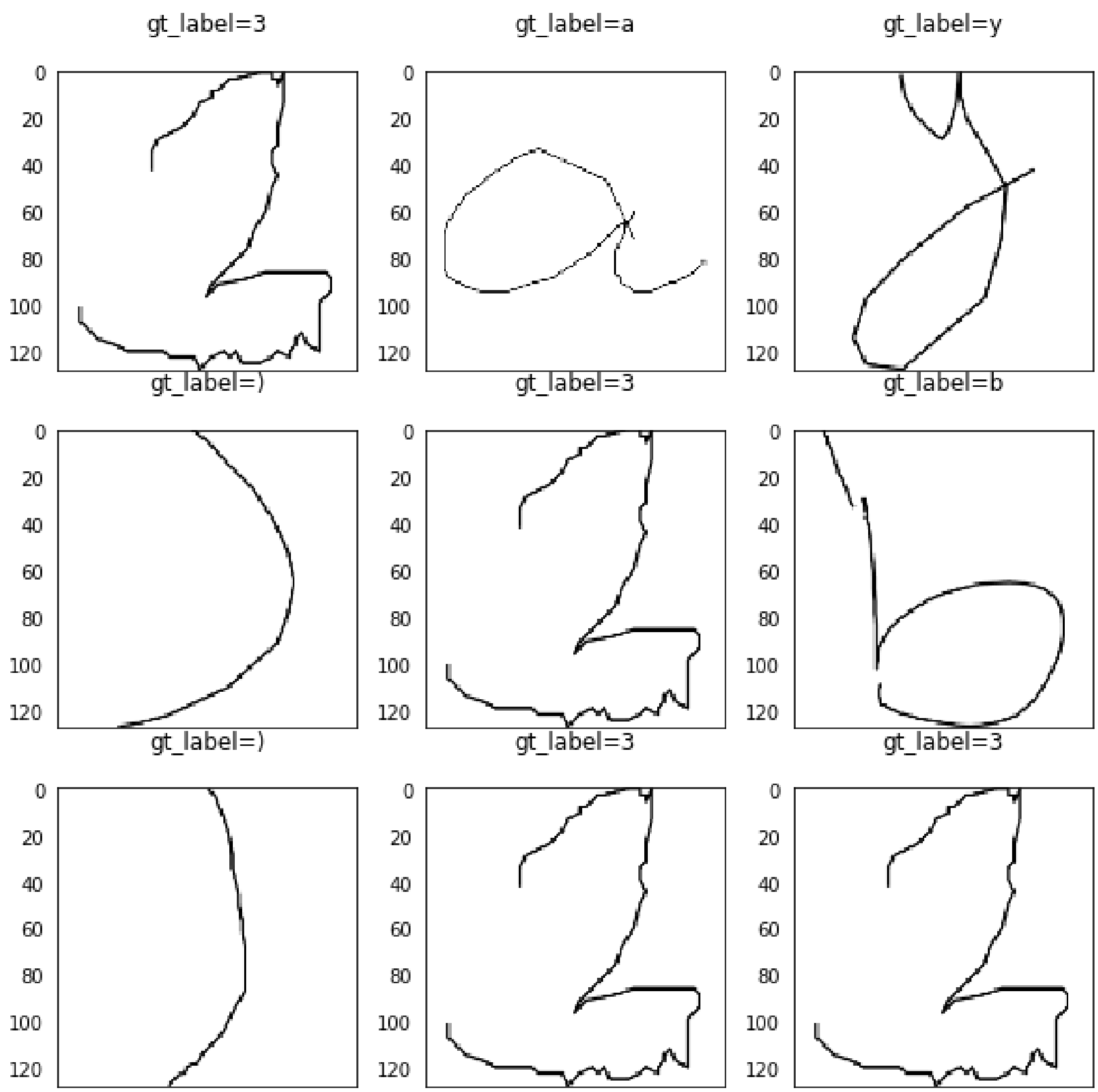
```
In [12]: import pickle

         with open(f"{pickle_data_path}labels.pickle", 'rb') as handle:
             unique_labels = pickle.load(handle)
             unique_labels.sort()

         with open(f"{pickle_data_path}train_labels.pickle", 'rb') as handle:
             train_labels = pickle.load(handle)

         with open(f"{pickle_data_path}train_images.pickle", 'rb') as handle:
             train_images = pickle.load(handle)

         with open(f"{pickle_data_path}test_labels.pickle", 'rb') as handle:
             test_labels = pickle.load(handle)

         with open(f"{pickle_data_path}test_images.pickle", 'rb') as handle:
             test_images = pickle.load(handle)

         print("Data loading complete.")
         print(f"Got {len(train_images)} training images and {len(train_labels)} labels.")
         print(f"Got {len(test_images)} test images and {len(test_labels)} labels.")
         print(f"Found {len(unique_labels)} total unique labels.")
```

```
Data loading complete.
Got 51 training images and 51 labels.
Got 31 test images and 31 labels.
Found 101 total unique labels.
```

Next, plot some sample images from the training dataset:

```
In [13]: import random

         def plot_indices(indices, images, labels, label_category_names, size=(128,128), metada
```

```python
    fig, ax = plt.subplots(nrows=3, ncols=3, figsize=(10,10))
    index = 0
    for row in ax:
        for col in row:
            # Get image & label
            idx = indices[index]
            image = tf.reshape(images[idx], size)
            label = labels[idx]

            if metadata is not None:
                meta = f"meta={metadata[index]}"
            else:
                meta = ''


            col.tick_params(
                axis='both',
                which='both',
                left=False,
                right=False,
                bottom=False,
                top=False,
                labelbottom=False,
            )
            col.imshow(image, cmap='gray', vmin=0, vmax=1.0)
            col.set_title(f"gt_label={label}\n{meta}")

            index += 1

    if save and name is not None:
        print("Saving figure...")
        plt.savefig(name)

# Plot some random images
random_indices = [random.randint(0, len(train_images)) for i in range(0,9)]
plot_indices(random_indices, train_images, train_labels, unique_labels)
```




```
In [14]: # Convert from label to category
         train_cat = [unique_labels.index(label) for label in train_labels]
         test_cat = [unique_labels.index(label) for label in test_labels]
```

1.1.1 Simple Binary classification model

As a basic sanity check, lets train a simple binary classication model that predicts if an image contains a '-' symbol. We will use a model with 2 dense layers trained with the Adam optimizer and a binary cross-entropy loss function (as appropriate for binary classifcation). The performance of this model should provide an upper bound on the performance we can expect for a k-class classification model.

```
In [15]: from tensorflow.keras import models, layers
```

```python
####################################
#### Binary classification model ####
####################################

learning_rate = 0.0001
size = (128,128)
# if model is not None:
#     del model

model = models.Sequential([
    layers.Flatten(input_shape=(size[0], size[1])),
    layers.Dense(128, activation='relu'),
    layers.Dense(1, activation='sigmoid')
])


model.summary()

model.compile(optimizer=tf.optimizers.Adam(learning_rate),
              loss='binary_crossentropy',
              metrics=['accuracy'])

binary_train_labels = [1 if unique_labels[label] == '-' else 0 for label in train_cat]
binary_test_labels = [1 if unique_labels[label] == '-' else 0 for label in test_cat]
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (None, 16384)             0
_________________________________________________________________
dense (Dense)                (None, 128)               2097280
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129
=================================================================
Total params: 2,097,409
Trainable params: 2,097,409
Non-trainable params: 0
_________________________________________________________________
```

```python
In [16]: history = model.fit(
             train_images,
             binary_train_labels,
             validation_data=(test_images, binary_test_labels),
             batch_size=32,
             epochs=50)
```

```
WARNING: Logging before flag parsing goes to stderr.
```

```
W0804 15:17:22.177819 4499281344 deprecation.py:323] From /Users/erikbeerepoot/.virtualenvs/ml-
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where


Train on 51 samples, validate on 31 samples
Epoch 1/50
51/51 [==============================] - 0s 7ms/sample - loss: 0.5354 - accuracy: 0.4706 - val_
Epoch 2/50
51/51 [==============================] - 0s 348us/sample - loss: 1.1593 - accuracy: 0.9216 - va
Epoch 3/50
51/51 [==============================] - 0s 371us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 4/50
51/51 [==============================] - 0s 372us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 5/50
51/51 [==============================] - 0s 431us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 6/50
51/51 [==============================] - 0s 399us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 7/50
51/51 [==============================] - 0s 393us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 8/50
51/51 [==============================] - 0s 422us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 9/50
51/51 [==============================] - 0s 454us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 10/50
51/51 [==============================] - 0s 383us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 11/50
51/51 [==============================] - 0s 447us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 12/50
51/51 [==============================] - 0s 414us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 13/50
51/51 [==============================] - 0s 387us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 14/50
51/51 [==============================] - 0s 410us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 15/50
51/51 [==============================] - 0s 473us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 16/50
51/51 [==============================] - 0s 429us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 17/50
51/51 [==============================] - 0s 390us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 18/50
51/51 [==============================] - 0s 409us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 19/50
51/51 [==============================] - 0s 414us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 20/50
51/51 [==============================] - 0s 374us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 21/50
51/51 [==============================] - 0s 416us/sample - loss: 1.2098 - accuracy: 0.9216 - va
```

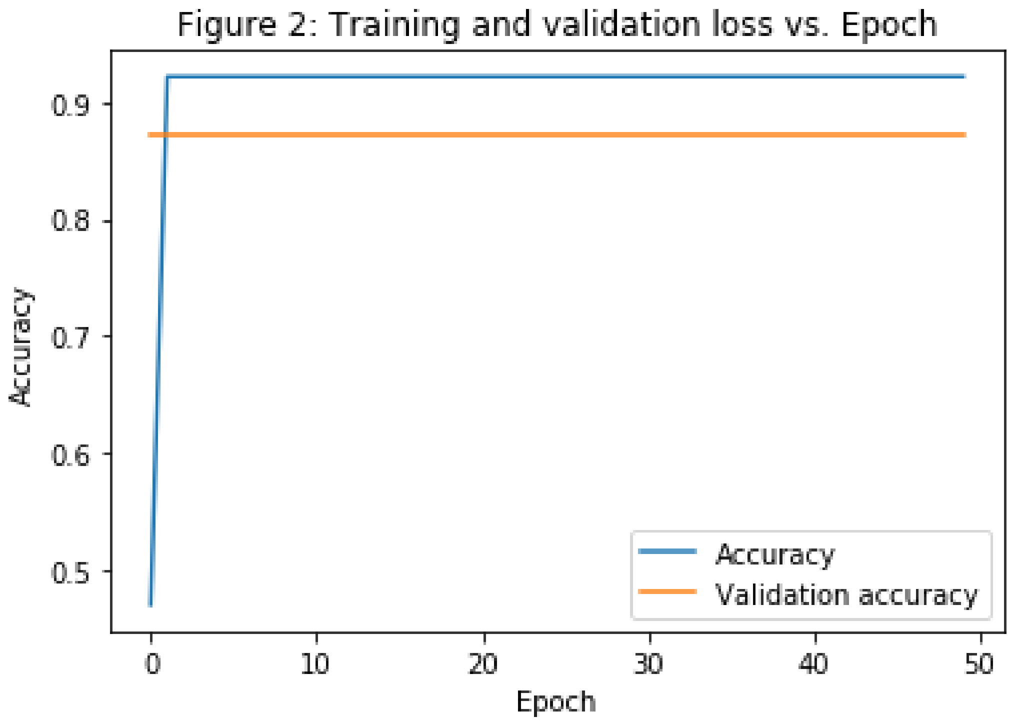
```
Epoch 22/50
51/51 [==============================] - 0s 419us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 23/50
51/51 [==============================] - 0s 384us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 24/50
51/51 [==============================] - 0s 411us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 25/50
51/51 [==============================] - 0s 397us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 26/50
51/51 [==============================] - 0s 389us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 27/50
51/51 [==============================] - 0s 405us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 28/50
51/51 [==============================] - 0s 415us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 29/50
51/51 [==============================] - 0s 370us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 30/50
51/51 [==============================] - 0s 406us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 31/50
51/51 [==============================] - 0s 395us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 32/50
51/51 [==============================] - 0s 381us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 33/50
51/51 [==============================] - 0s 433us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 34/50
51/51 [==============================] - 0s 435us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 35/50
51/51 [==============================] - 0s 390us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 36/50
51/51 [==============================] - 0s 427us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 37/50
51/51 [==============================] - 0s 426us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 38/50
51/51 [==============================] - 0s 369us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 39/50
51/51 [==============================] - 0s 431us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 40/50
51/51 [==============================] - 0s 358us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 41/50
51/51 [==============================] - 0s 436us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 42/50
51/51 [==============================] - 0s 359us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 43/50
51/51 [==============================] - 0s 402us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 44/50
51/51 [==============================] - 0s 429us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 45/50
51/51 [==============================] - 0s 373us/sample - loss: 1.2098 - accuracy: 0.9216 - va
```

```
Epoch 46/50
51/51 [==============================] - 0s 392us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 47/50
51/51 [==============================] - 0s 425us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 48/50
51/51 [==============================] - 0s 366us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 49/50
51/51 [==============================] - 0s 417us/sample - loss: 1.2098 - accuracy: 0.9216 - va
Epoch 50/50
51/51 [==============================] - 0s 376us/sample - loss: 1.2098 - accuracy: 0.9216 - va
```

In [17]:
```
import pandas as pd
def plot_history(history, filename=None):
    hist = pd.DataFrame(history.history)
    hist['epoch'] = history.epoch

    plt.figure()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.plot(hist['epoch'], hist['accuracy'], label='Accuracy')
    plt.plot(hist['epoch'], hist['val_accuracy'], label='Validation accuracy')

    plt.title("Figure 2: Training and validation loss vs. Epoch")
    plt.legend()

    if filename is not None:
        plt.savefig(filename)

    plt.show()
```

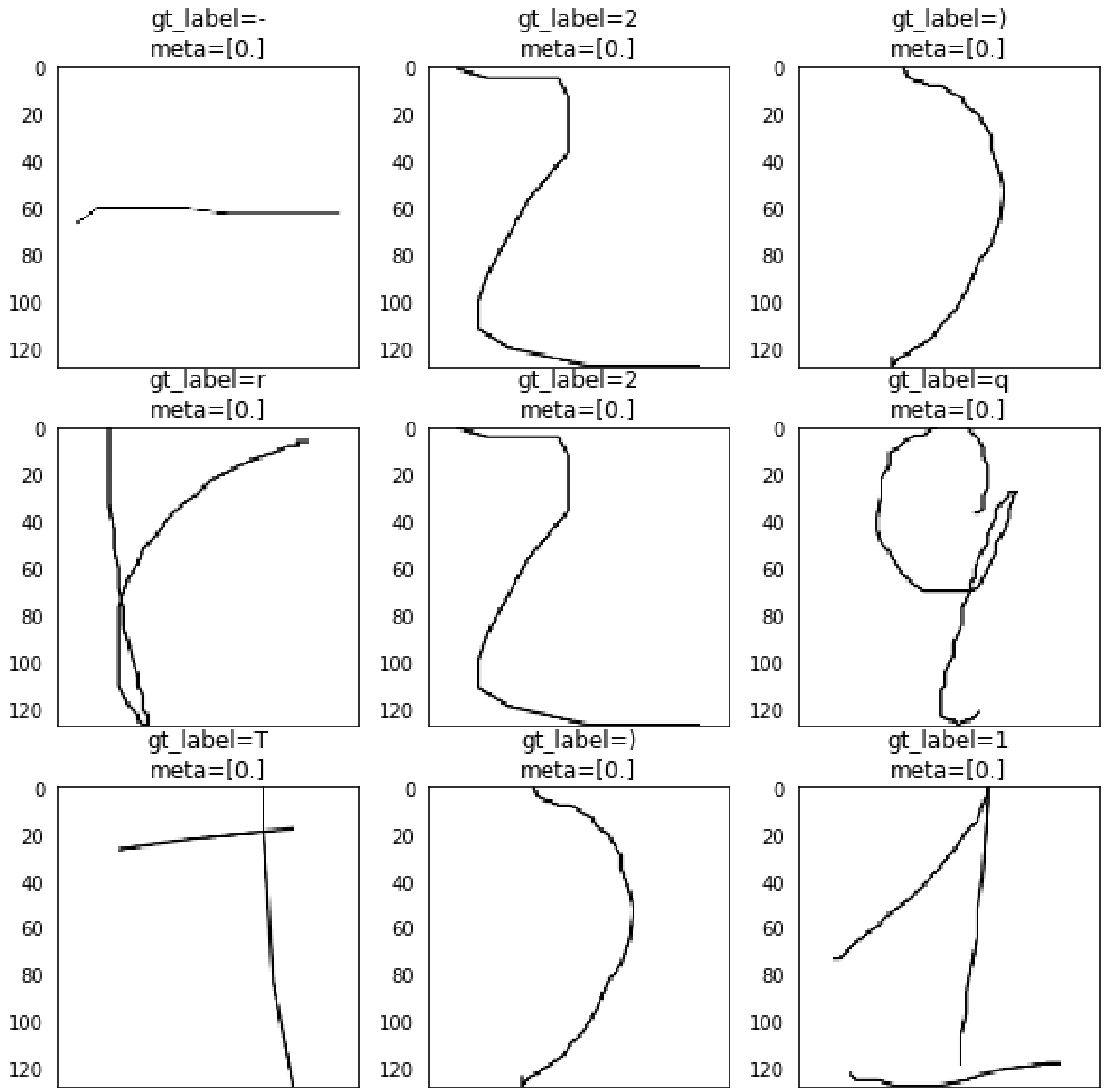
From the training plot below, at 50 epochs, we can see the training curve has not quite levelled out. Hence, we can improve our results by increasing the training time.

In [18]:
```
plot_history(history, f"{figs_base_dir}/symbol-simple-accuracy.pdf")
```



Now, let's plot some sample predictions along with the ground truth labels and associated confidence to empirically gauge the quality of the predictions made. On each of the subplots, the ground truth label is denoted by `gt_label` and `meta` indicates the confidence that this particular symbol is a `-`. Trained on enough data, the network can make reasonable predictions.

```
In [26]: # Select some random images from the training set
         random_indices = [random.randint(0, len(test_images)) for i in range(0,9)]

         # Predict the labels
         random_images = np.array([test_images[idx] for idx in random_indices])
         predictions = model.predict(random_images)

         # Plot
         plot_indices(random_indices, test_images, test_labels, unique_labels, metadata=predict
```



We can observe that the model is able to predict the correct label with confidence, but is prone to false positives.

Now, let's try a more complicated model.

1.2 Binary classification with Convolutional Neural nets

```
In [27]: # Add CNNs for features
         conv_model = models.Sequential()
         conv_model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(size[0], siz
         conv_model.add(layers.MaxPooling2D((2, 2)))
         conv_model.add(layers.Conv2D(64, (3, 3), activation='relu'))
         conv_model.add(layers.MaxPooling2D((2, 2)))
         conv_model.add(layers.Conv2D(64, (3, 3), activation='relu'))
```

```
    # Add dense layers for classification
    conv_model.add(layers.Flatten(input_shape=(size[0], size[1], 1)))
    conv_model.add(layers.Dense(25, activation='relu'))
    conv_model.add(layers.Dense(1, activation='sigmoid'))

    conv_model.compile(optimizer=tf.optimizers.Adam(learning_rate),
                  loss='binary_crossentropy',
                  metrics=['accuracy'])

    conv_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 126, 126, 32)      320
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 63, 63, 32)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 61, 61, 64)        18496
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 30, 30, 64)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 28, 28, 64)        36928
_________________________________________________________________
flatten_2 (Flatten)          (None, 50176)             0
_________________________________________________________________
dense_4 (Dense)              (None, 25)                1254425
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 26
=================================================================
Total params: 1,310,195
Trainable params: 1,310,195
Non-trainable params: 0
_________________________________________________________________
```

```
In [28]: img_train = np.expand_dims(train_images,axis=3)
         img_test = np.expand_dims(test_images,axis=3)

         conv_history = conv_model.fit(
             img_train,
             binary_train_labels,
             validation_data=(img_test, binary_test_labels),
             batch_size=32,
             epochs=50)
```

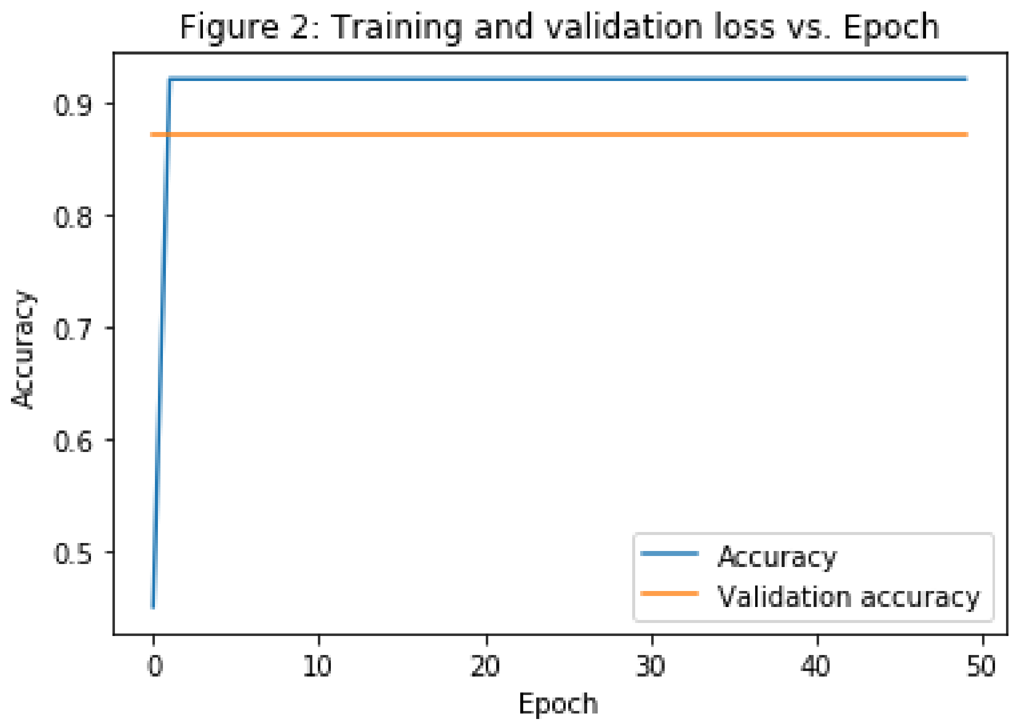
```
Train on 51 samples, validate on 31 samples
Epoch 1/50
```

```
51/51 [==============================] - 1s 15ms/sample - loss: 0.7524 - accuracy: 0.4510 - val
Epoch 2/50
51/51 [==============================] - 0s 8ms/sample - loss: 0.4949 - accuracy: 0.9216 - val_
Epoch 3/50
51/51 [==============================] - 0s 7ms/sample - loss: 0.3851 - accuracy: 0.9216 - val_
Epoch 4/50
51/51 [==============================] - 0s 8ms/sample - loss: 0.3176 - accuracy: 0.9216 - val_
Epoch 5/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2775 - accuracy: 0.9216 - val_
Epoch 6/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2720 - accuracy: 0.9216 - val_
Epoch 7/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2822 - accuracy: 0.9216 - val_
Epoch 8/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2950 - accuracy: 0.9216 - val_
Epoch 9/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.3038 - accuracy: 0.9216 - val_
Epoch 10/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.3038 - accuracy: 0.9216 - val_
Epoch 11/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2983 - accuracy: 0.9216 - val_
Epoch 12/50
51/51 [==============================] - 0s 10ms/sample - loss: 0.2888 - accuracy: 0.9216 - va
Epoch 13/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2810 - accuracy: 0.9216 - val_
Epoch 14/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2732 - accuracy: 0.9216 - val_
Epoch 15/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2737 - accuracy: 0.9216 - val_
Epoch 16/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2751 - accuracy: 0.9216 - val_
Epoch 17/50
51/51 [==============================] - 0s 8ms/sample - loss: 0.2729 - accuracy: 0.9216 - val_
Epoch 18/50
51/51 [==============================] - 0s 8ms/sample - loss: 0.2741 - accuracy: 0.9216 - val_
Epoch 19/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2741 - accuracy: 0.9216 - val_
Epoch 20/50
51/51 [==============================] - 0s 8ms/sample - loss: 0.2730 - accuracy: 0.9216 - val_
Epoch 21/50
51/51 [==============================] - 0s 8ms/sample - loss: 0.2712 - accuracy: 0.9216 - val_
Epoch 22/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2701 - accuracy: 0.9216 - val_
Epoch 23/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2688 - accuracy: 0.9216 - val_
Epoch 24/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2686 - accuracy: 0.9216 - val_
Epoch 25/50
```

```
51/51 [==============================] - 0s 9ms/sample - loss: 0.2685 - accuracy: 0.9216 - val_
Epoch 26/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2702 - accuracy: 0.9216 - val_
Epoch 27/50
51/51 [==============================] - 0s 8ms/sample - loss: 0.2674 - accuracy: 0.9216 - val_
Epoch 28/50
51/51 [==============================] - 0s 8ms/sample - loss: 0.2690 - accuracy: 0.9216 - val_
Epoch 29/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2655 - accuracy: 0.9216 - val_
Epoch 30/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2657 - accuracy: 0.9216 - val_
Epoch 31/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2643 - accuracy: 0.9216 - val_
Epoch 32/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2635 - accuracy: 0.9216 - val_
Epoch 33/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2619 - accuracy: 0.9216 - val_
Epoch 34/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2637 - accuracy: 0.9216 - val_
Epoch 35/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2608 - accuracy: 0.9216 - val_
Epoch 36/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2597 - accuracy: 0.9216 - val_
Epoch 37/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2573 - accuracy: 0.9216 - val_
Epoch 38/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2578 - accuracy: 0.9216 - val_
Epoch 39/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2561 - accuracy: 0.9216 - val_
Epoch 40/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2526 - accuracy: 0.9216 - val_
Epoch 41/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2508 - accuracy: 0.9216 - val_
Epoch 42/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2515 - accuracy: 0.9216 - val_
Epoch 43/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2472 - accuracy: 0.9216 - val_
Epoch 44/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2448 - accuracy: 0.9216 - val_
Epoch 45/50
51/51 [==============================] - 0s 8ms/sample - loss: 0.2437 - accuracy: 0.9216 - val_
Epoch 46/50
51/51 [==============================] - 0s 8ms/sample - loss: 0.2390 - accuracy: 0.9216 - val_
Epoch 47/50
51/51 [==============================] - 0s 8ms/sample - loss: 0.2351 - accuracy: 0.9216 - val_
Epoch 48/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2353 - accuracy: 0.9216 - val_
Epoch 49/50
```

```
51/51 [==============================] - 0s 8ms/sample - loss: 0.2275 - accuracy: 0.9216 - val_
Epoch 50/50
51/51 [==============================] - 0s 9ms/sample - loss: 0.2257 - accuracy: 0.9216 - val_
```

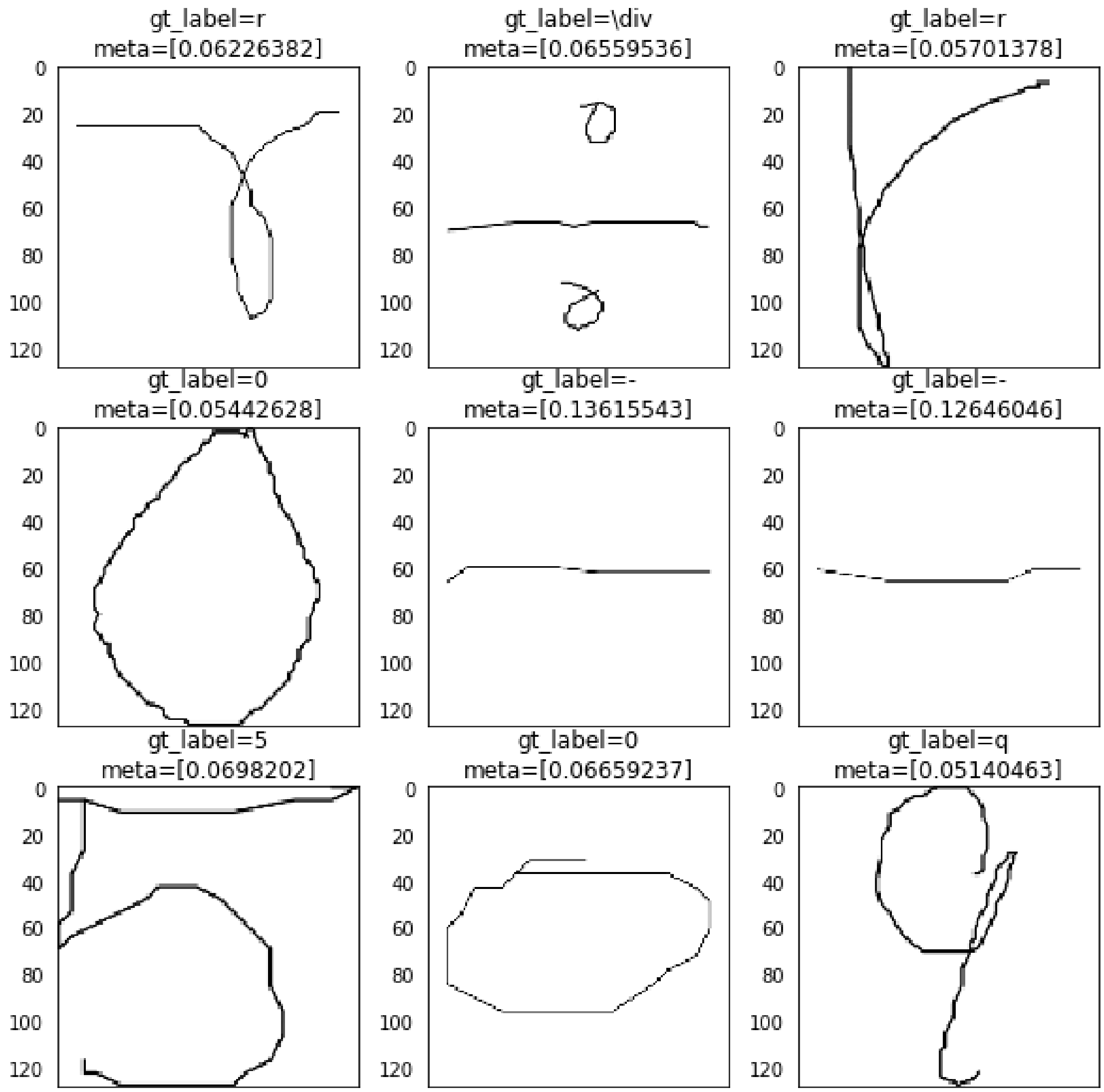
```
In [30]: plot_history(conv_history, f"{figs_base_dir}/symbol-conv-accuracy.pdf")
```



Again, we plot some examples with the ground truth label, and the confidence that this is a - symbol. This model performs better.

```
In [33]: # Select some random images from the training set
         random_indices = [random.randint(0, len(test_images) - 1) for i in range(0,9)]

         # Predict the labels
         random_images = np.array([test_images[idx] for idx in random_indices])
         random_images = np.expand_dims(random_images,axis=4)
         predictions = conv_model.predict(random_images)

         # Plot
         plot_indices(random_indices, test_images, test_labels, unique_labels, metadata=predict
```

```
/Users/erikbeerepoot/.virtualenvs/ml-tf1/lib/python3.7/site-packages/ipykernel_launcher.py:6: 
```



1.3 Multi-class classification with Convolutional Neural nets

Using convolutional layers led to a increase in the accuracy of the model (of almost 4%). Emperically, the confidence level of the predictions in a given prediction has also increased – the model is more sure about both positive and negative predicitions. Next, we will try to applying this same model but predict additional classes.

Here, we'll use sparse categorical cross entropy – this loss is appropriate when losses are computed over k classes, and labels are provided as integers.

First, compute those labels:

```
In [34]: train_labels_cat = [unique_labels.index(label) for label in train_labels]
         test_labels_cat = [unique_labels.index(label) for label in test_labels]
```

Next, create our deep convolutional model. Note the use of the softmax activation in the last layer with the number of units equal to the number of classes.

```
In [35]: from tensorflow.keras import metrics

         # Add CNNs for features
         k_conv_model = models.Sequential()
         k_conv_model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(size[0], si
         k_conv_model.add(layers.MaxPooling2D((2, 2)))
         k_conv_model.add(layers.Conv2D(64, (3, 3), activation='relu'))
         k_conv_model.add(layers.MaxPooling2D((2, 2)))
         k_conv_model.add(layers.Conv2D(64, (3, 3), activation='relu'))

         # Add dense layers for classification
         k_conv_model.add(layers.Flatten(input_shape=(size[0], size[1], 1)))
         k_conv_model.add(layers.Dense(25, activation='relu'))
         k_conv_model.add(layers.Dense(len(unique_labels), activation='softmax'))

         k_conv_model.compile(optimizer=tf.optimizers.Adam(learning_rate),
                        loss=tf.losses.SparseCategoricalCrossentropy(),
                        metrics=[metrics.sparse_categorical_accuracy])

         k_conv_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_6 (Conv2D)            (None, 126, 126, 32)      320
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 63, 63, 32)        0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 61, 61, 64)        18496
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 30, 30, 64)        0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 28, 28, 64)        36928
_________________________________________________________________
flatten_3 (Flatten)          (None, 50176)             0
_________________________________________________________________
dense_6 (Dense)              (None, 25)                1254425
_________________________________________________________________
dense_7 (Dense)              (None, 101)               2626
=================================================================
Total params: 1,312,795
Trainable params: 1,312,795
Non-trainable params: 0
_________________________________________________________________
```

Finally, let's train our model:

```
In [36]: k_conv_model_history = k_conv_model.fit(
             img_train,
             train_labels_cat,
             validation_data=(img_test, test_labels_cat),
             batch_size=32,
             epochs=50)
```

```
Train on 51 samples, validate on 31 samples
Epoch 1/50
51/51 [==============================] - 1s 17ms/sample - loss: 4.6330 - sparse_categorical_acc
Epoch 2/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.5873 - sparse_categorical_accu
Epoch 3/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.5629 - sparse_categorical_accu
Epoch 4/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.5504 - sparse_categorical_accu
Epoch 5/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.5444 - sparse_categorical_accu
Epoch 6/50
51/51 [==============================] - 0s 7ms/sample - loss: 4.5411 - sparse_categorical_accu
Epoch 7/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.5376 - sparse_categorical_accu
Epoch 8/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.5306 - sparse_categorical_accu
Epoch 9/50
51/51 [==============================] - 0s 10ms/sample - loss: 4.5272 - sparse_categorical_acc
Epoch 10/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.5222 - sparse_categorical_accu
Epoch 11/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.5183 - sparse_categorical_accu
Epoch 12/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.5138 - sparse_categorical_accu
Epoch 13/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.5095 - sparse_categorical_accu
Epoch 14/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.5096 - sparse_categorical_accu
Epoch 15/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.5030 - sparse_categorical_accu
Epoch 16/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.4993 - sparse_categorical_accu
Epoch 17/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.4949 - sparse_categorical_accu
Epoch 18/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.4901 - sparse_categorical_accu
Epoch 19/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.4898 - sparse_categorical_accu
```

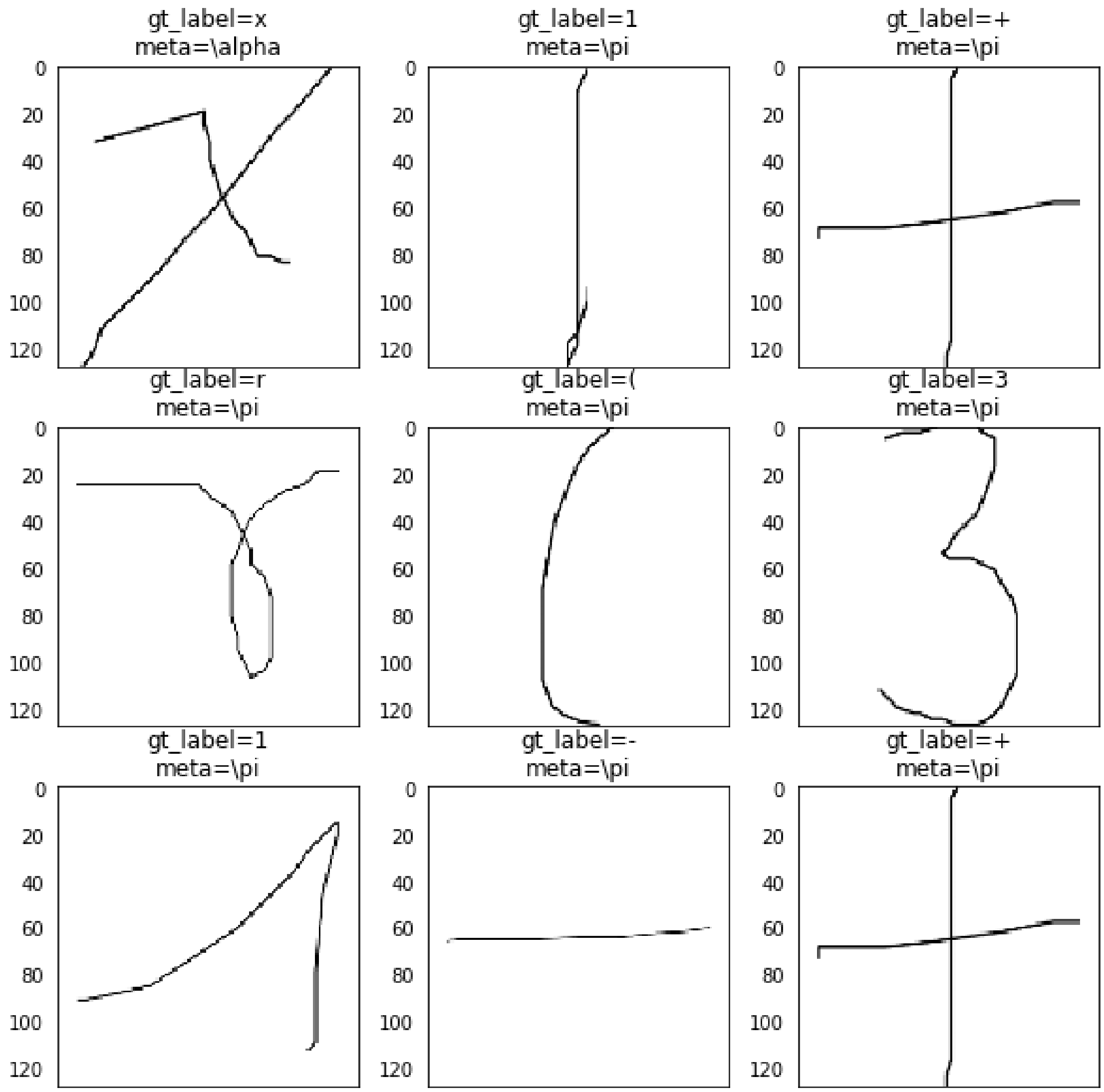
```
Epoch 20/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.4826 - sparse_categorical_accu
Epoch 21/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.4782 - sparse_categorical_accu
Epoch 22/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.4705 - sparse_categorical_accu
Epoch 23/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.4672 - sparse_categorical_accu
Epoch 24/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.4599 - sparse_categorical_accu
Epoch 25/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.4539 - sparse_categorical_accu
Epoch 26/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.4484 - sparse_categorical_accu
Epoch 27/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.4421 - sparse_categorical_accu
Epoch 28/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.4344 - sparse_categorical_accu
Epoch 29/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.4291 - sparse_categorical_accu
Epoch 30/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.4234 - sparse_categorical_accu
Epoch 31/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.4159 - sparse_categorical_accu
Epoch 32/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.4072 - sparse_categorical_accu
Epoch 33/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.3998 - sparse_categorical_accu
Epoch 34/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.3888 - sparse_categorical_accu
Epoch 35/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.3789 - sparse_categorical_accu
Epoch 36/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.3708 - sparse_categorical_accu
Epoch 37/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.3581 - sparse_categorical_accu
Epoch 38/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.3447 - sparse_categorical_accu
Epoch 39/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.3281 - sparse_categorical_accu
Epoch 40/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.3160 - sparse_categorical_accu
Epoch 41/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.3024 - sparse_categorical_accu
Epoch 42/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.2868 - sparse_categorical_accu
Epoch 43/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.2695 - sparse_categorical_accu
```

```
Epoch 44/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.2494 - sparse_categorical_accu
Epoch 45/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.2371 - sparse_categorical_accu
Epoch 46/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.2062 - sparse_categorical_accu
Epoch 47/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.1841 - sparse_categorical_accu
Epoch 48/50
51/51 [==============================] - 0s 8ms/sample - loss: 4.1558 - sparse_categorical_accu
Epoch 49/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.1301 - sparse_categorical_accu
Epoch 50/50
51/51 [==============================] - 0s 9ms/sample - loss: 4.0937 - sparse_categorical_accu
```

One more time, we plot some examples picked from the test set along with ground truth and predictions. The model does pretty well. We will try to use this architecture as the encoder for our seq2seq model.

In [38]:
```
# Select some random images from the training set
random_indices = [random.randint(0, len(test_images) - 1) for i in range(0,9)]

# Predict the labels
random_images = np.array([test_images[idx] for idx in random_indices])
random_images = np.expand_dims(random_images,axis=4)
predictions = k_conv_model.predict(random_images)

# Get the label of the highest confidence predictions
max_prediction_labels = []
for prediction in predictions:
    max_prediction = np.max(prediction)
    index_of_max = np.where(prediction == np.max(prediction))[0][0]
    max_prediction_labels.append(unique_labels[index_of_max])

# Plot some sample predictions
plot_indices(random_indices, test_images, test_labels, unique_labels, metadata=max_pre
```

```
/Users/erikbeerepoot/.virtualenvs/ml-tf1/lib/python3.7/site-packages/ipykernel_launcher.py:6: 
```


gt_label=x
meta=\alpha
gt_label=1
meta=\pi
gt_label=+
meta=\pi
gt_label=r
meta=\pi
gt_label=(
meta=\pi
gt_label=3
meta=\pi
gt_label=1
meta=\pi
gt_label=-
meta=\pi
gt_label=+
meta=\pi
0
20
40
60
80
100
120