sign_language_cnn

May 5, 2020

```
In [245]: import matplotlib.pyplot as plt
          import numpy as np
          import tensorflow as tf
          import pandas as pd
          from tensorflow import keras
          from tensorflow.keras.layers import Conv2D, Flatten, MaxPooling2D, AveragePooling2D, D
          from keras.preprocessing.image import ImageDataGenerator
          import string
          from libitmal import kernelfuns as itmalkernelfuns
          itmalkernelfuns.EnableGPU()
          %matplotlib inline
          def get_mnist_dataset():
              test_pd = pd.read_csv("./SignLanguageData/sign_mnist_test.csv",
                  skiprows=1)
              train_pd = pd.read_csv("./SignLanguageData/sign_mnist_train.csv",
                  skiprows=1)
              return train_pd, test_pd
          train_pd, test_pd = get_mnist_dataset()
          X_train, X_test = train_pd.values[:,1:], test_pd.values[:,1:]
          y_train, y_test = train_pd.values[:,0], test_pd.values[:,0]
          class_names = list(string.ascii_lowercase)
          train_pd.head()
Out [245]:
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[5 rows x 785 columns]

1 Data Processing

In [246]: X_train = X_train / 255

```
X_{test} = X_{test} / 255
          X_train = X_train.reshape(*X_train.shape[:1], 28, 28)
          X_test = X_test.reshape(*X_test.shape[:1], 28, 28)
         X_train = X_train.reshape(X_train.shape[0], 28, 28, 1)
         X_test = X_test.reshape(X_test.shape[0], 28, 28, 1)
          batch_size, height, width, channel = X_train.shape
         print(X_train.shape)
(27454, 28, 28, 1)
In [247]: # Datageneration form https://www.kagqle.com/madz2000/cnn-using-keras-99-7-accuracy
          datagen = ImageDataGenerator(
              featurewise_center=False, # set input mean to 0 over the dataset
              samplewise_center=False, # set each sample mean to 0
              featurewise_std_normalization=False, # divide inputs by std of the dataset
              samplewise_std_normalization=False, # divide each input by its std
              zca_whitening=False, # apply ZCA whitening
              rotation_range=10, # randomly rotate images in the range (degrees, 0 to 180)
              zoom_range = 0.1, # Randomly zoom image
              width_shift_range=0.1, # randomly shift images horizontally (fraction of total wi
             height_shift_range=0.1, # randomly shift images vertically (fraction of total her
              horizontal_flip=False, # randomly flip images
              vertical_flip=False, # randomly flip images,
              validation_split=0.2 #20 % validation split
          )
          datagen.fit(X_train)
```

2 Model Creation

```
In [248]: def create_le_net():
              model = keras.models.Sequential([
                  ZeroPadding2D(input_shape=X_train.shape[1:], padding=(3, 3)),
                  Conv2D(filters=6, kernel_size=(5, 5), strides=1, activation="tanh"),
                  AveragePooling2D(pool_size=6, strides=2, padding="same"),
                  Conv2D(filters=16, kernel_size=(5, 5), strides=1, activation="tanh"),
                  AveragePooling2D(pool_size=6, strides=2, padding="same"),
                  Conv2D(filters=120, kernel_size=(5, 5), strides=1, activation="tanh"),
                  Flatten(),
                  Dense(84, activation="tanh"),
                  Dense(len(class_names), activation="softmax")
              ])
              return model
          def create_model():
              model = keras.models.Sequential([
                  ZeroPadding2D(input_shape=X_train.shape[1:], padding=(3, 3)),
                  Conv2D(filters=16, kernel_size=(3, 3), activation="relu"),
                  AveragePooling2D(),
                  Conv2D(filters=32, kernel_size=(3, 3), activation="relu"),
                  AveragePooling2D(),
                  Flatten(),
                  Dense(256, activation="relu"),
                  Dense(512, activation="relu"),
                  Dense(128, activation="relu"),
                  Dense(64, activation="relu"),
                  Dense(len(class_names), activation="softmax")
              ])
              return model
In [249]: X_test.shape
Out[249]: (7171, 28, 28, 1)
In [250]: # LeNet
          model = create_model()
In [251]: #keras.utils.plot_model(model, "my_mnist_model.png", show_shapes=True)
In [252]: model.compile(loss="sparse_categorical_crossentropy",
                        optimizer="adam",
                        metrics=["accuracy"])
```

3 Model Training

In [253]: from keras.callbacks import EarlyStopping, ModelCheckpoint

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early_stopping = EarlyStopping(monitor='loss',
                patience=30,
                verbose=0,
                mode='min')
    mcp_save = ModelCheckpoint('cnn_model_checkpoint.h5',
               save_best_only=True,
               monitor='val_loss',
               mode='min')
    train_generator = datagen.flow(X_train,
                 y_train,
                 batch_size = 128,
                 subset="training")
    validation_generator = datagen.flow(X_train,
                   batch_size = 128,
                   subset="validation")
    history = model.fit(train_generator,
            epochs=500,
            validation_data=validation_generator,
            validation_steps=800,
            callbacks=[early_stopping, mcp_save])
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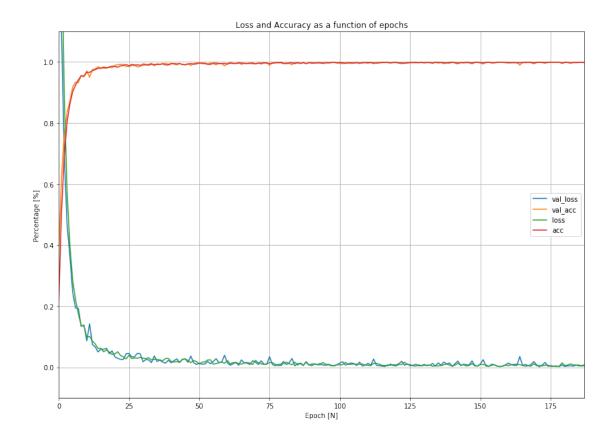
Epoch 106/500											
172/172 [====================================	_	18s	105ms/step	_	loss:	0.0107	_	acc:	0.9967	_	val_los
Epoch 107/500											
172/172 [====================================	_	18s	105ms/step	_	loss:	0.0100	_	acc:	0.9974	_	val los
Epoch 108/500											_
172/172 [====================================	_	18s	105ms/step	_	loss:	0.0094	_	acc:	0.9969	_	val_los
Epoch 109/500											_
172/172 [====================================	_	18s	106ms/step	_	loss:	0.0105	_	acc:	0.9969	_	val_los
Epoch 110/500			•								
172/172 [====================================	_	18s	105ms/step	_	loss:	0.0071	-	acc:	0.9979	_	val_los
Epoch 111/500											
172/172 [=========]	_	18s	105ms/step	-	loss:	0.0067	-	acc:	0.9979	-	val_los
Epoch 112/500											
172/172 [========]	-	18s	105ms/step	-	loss:	0.0054	-	acc:	0.9982	-	val_los
Epoch 113/500											
172/172 [========]	_	18s	105ms/step	-	loss:	0.0128	-	acc:	0.9968	-	val_los
Epoch 114/500											
172/172 [====================================	-	18s	105ms/step	-	loss:	0.0123	-	acc:	0.9963	-	val_los
Epoch 115/500											
172/172 [====================================	-	18s	105ms/step	-	loss:	0.0102	-	acc:	0.9970	-	val_los
Epoch 116/500											
172/172 [====================================	-	18s	106ms/step	-	loss:	0.0063	-	acc:	0.9980	-	val_los
Epoch 117/500					_						
172/172 [====================================	-	18s	106ms/step	-	loss:	0.0060	-	acc:	0.9980	-	val_los
Epoch 118/500		40	100 / .		-	0 0040			0 0007		
172/172 [====================================	-	188	106ms/step	-	loss:	0.0046	-	acc:	0.9987	-	val_los
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172/172 [=========] Epoch 120/500	_	Ios	105ms/step	-	loss:	0.0105	-	acc:	0.9967	-	val_los
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172/172 [=======]	_	18e	105mg/gtan	_	1000.	0 0044	_	acc.	n 9988	_	wal log
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172/172 [========]	_	18s	105ms/step	_	loss:	0.0091	_	acc:	0.9969	_	val los
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172/172 [=========]	_	18s	105ms/step	_	loss:	0.0089	_	acc:	0.9972	_	val_los
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172/172 [====================================	_	18s	105ms/step	_	loss:	0.0165	-	acc:	0.9954	_	val_los
Epoch 125/500			_								
172/172 [=========]	_	18s	105ms/step	-	loss:	0.0089	-	acc:	0.9977	-	val_los
Epoch 126/500											
172/172 [========]	-	18s	105ms/step	-	loss:	0.0087	-	acc:	0.9975	-	val_los
Epoch 127/500											
172/172 [=======]	-	18s	105ms/step	-	loss:	0.0050	-	acc:	0.9980	-	val_los
Epoch 128/500											
172/172 [=======]	-	18s	105ms/step	-	loss:	0.0036	-	acc:	0.9989	-	val_los
Epoch 129/500											
172/172 [========]	-	18s	105ms/step	-	loss:	0.0078	-	acc:	0.9975	-	val_los

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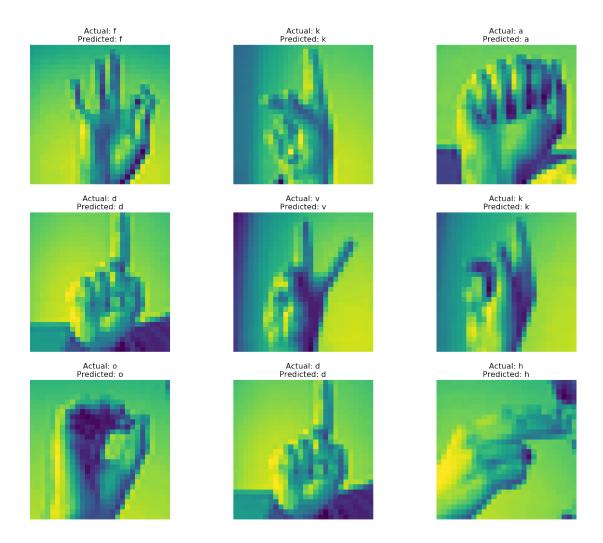
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Epoch 188/500
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4 Model Evaluation



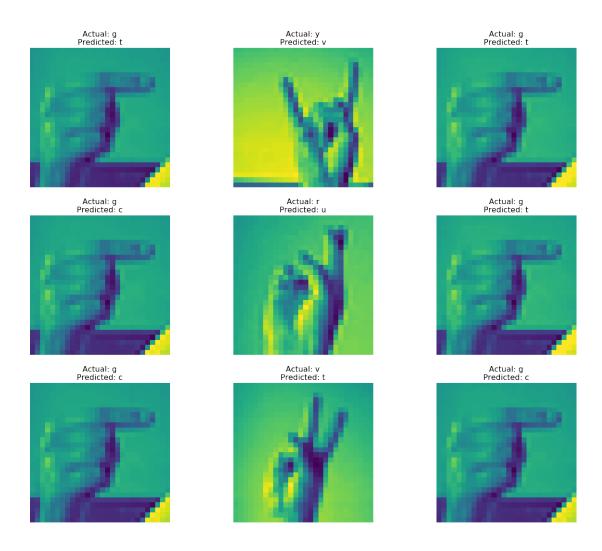
```
In [255]: import math
          num\_rows = 3
         num\_cols = 3
         X_new = X_test[:num_rows*num_cols]
          y_pred = model.predict_classes(X_new)
          fig, ax = plt.subplots(num_rows, num_cols, figsize=(18, 16))
          for index, image in enumerate(X_new):
              ax[math.floor(index/num_rows), index%num_rows].imshow(image.reshape((28,28)))
              ax[math.floor(index/num_rows), index%num_rows].set_title(
                  f"Actual: {class_names[y_test[index]]}\nPredicted: {class_names[y_pred[index]]
                  fontsize=16)
              ax[int(index/num_rows), index%num_rows].axis('off')
          fig.tight_layout()
          fig.suptitle(f'First Predictions', fontsize=20)
          fig.subplots_adjust(top=0.88)
          fig.show()
```

First Predictions



```
fig.tight_layout()
fig.suptitle('Incorrect Predictions', fontsize=20)
fig.subplots_adjust(top=0.88)
fig.show()
```

Incorrect Predictions



In [257]: import sklearn.metrics as metrics

```
confusion_matrix = metrics.confusion_matrix(y_test, y_pred)
row_sum = confusion_matrix.sum(axis=1, keepdims=True)
norm_confusion_matrix = confusion_matrix / row_sum
```

Becausse j and z aren't possible we cant include them in confusion matrix

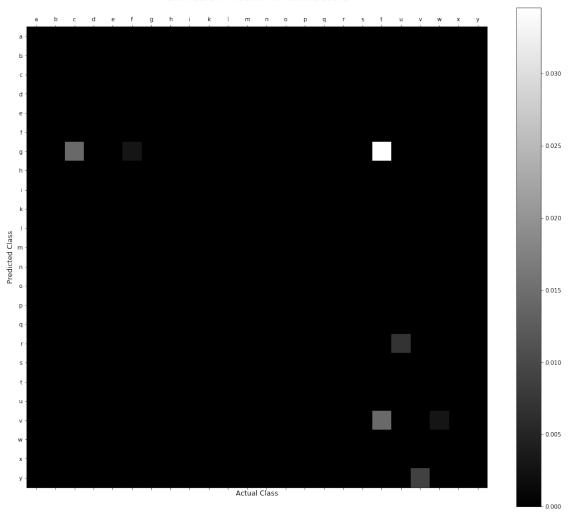
```
class_names_clean = class_names.copy()
class_names_clean.remove('j')
class_names_clean.remove('z')

np.fill_diagonal(norm_confusion_matrix, 0)

fig, ax = plt.subplots(figsize=(18, 16))

mat_ax = ax.matshow(norm_confusion_matrix, interpolation='nearest', cmap=plt.cm.gray)
fig.colorbar(mat_ax)
ax.set_title('Confusion matrix for characters', fontsize=20)
ax.set_xlabel('Actual Class', fontsize=12)
ax.set_ylabel('Predicted Class', fontsize=12)
ax.set_xticks(ticks=np.arange(0, len(class_names_clean)))
ax.set_xticklabels(class_names_clean)
ax.set_yticks(ticks=np.arange(0, len(class_names_clean)))
ax.set_yticklabels(class_names_clean)
fig.show()
```

Confusion matrix for characters



5 Comparison with no Image Generation

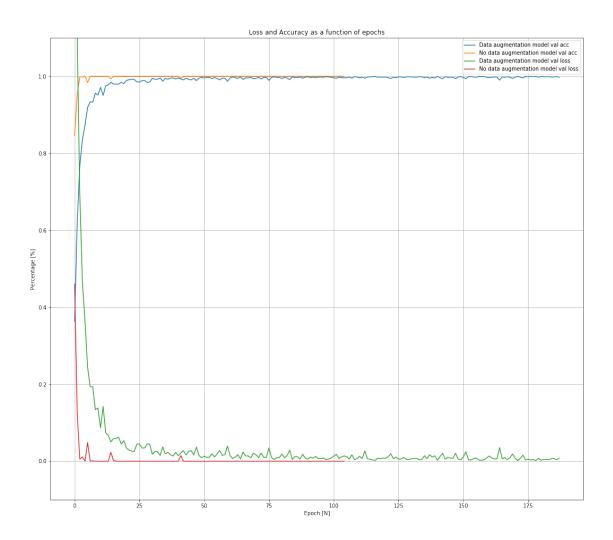
```
In [83]: # Fit model without data augmentation
  no_data_aug_model = create_model()
  no_data_aug_model.compile(loss="sparse_categorical_crossentropy",
       optimizer="adam",
       metrics=["accuracy"])
  history_no_data_aug = no_data_aug_model.fit(X_train,
         y_train,
         epochs=500,
         validation_split=0.2,
         callbacks=[early_stopping])
Train on 21963 samples, validate on 5491 samples
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Epoch 88/500
In [291]: fig, ax = plt.subplots(figsize=(18, 16))
      evaluation = no_data_aug_model.evaluate(X_test, y_test)
      print(f'Model evaluation: {evaluation}')
      ax.plot(history.history['val_acc'], label='Data augmentation model val acc')
      ax.plot(history_no_data_aug.history['val_acc'], label='No data augmentation model val
      ax.plot(history.history['val_loss'], label='Data augmentation model val loss')
      ax.plot(history_no_data_aug.history['val_loss'], label='No data augmentation model val
      ax.legend(loc="upper right")
      ax.grid(True)
      fig.gca().set_ylim(-0.1, 1.1)
      ax.set_xlabel("Epoch [N]")
      ax.set_ylabel("Percentage [%]")
      ax.set_title("Loss and Accuracy as a function of epochs")
7171/7171 [=========== ] - Os 30us/step
Model evaluation: [1.0886914953212061, 0.8923441639938642]
Out[291]: Text(0.5, 1.0, 'Loss and Accuracy as a function of epochs')
```



```
X_new_indeces = []
y_labels = np.array([class_names[y] for y in y_test])
for c in word_to_predict:
    index = np.where(y_labels==c)[0][2]
    X_new_indeces.append(index)
X_new_indeces = np.array(X_new_indeces)
y_pred = model.predict_classes(X_test[X_new_indeces])
fig, ax = plt.subplots(num_rows, int(len(word_to_predict)/num_rows), figsize=(18, 10))
for index, val in enumerate(X_new_indeces):
    ax[math.floor(index/num_cols_pr_row), index%num_cols_pr_row].imshow(X_test[val].res
    ax[math.floor(index/num_cols_pr_row), index%num_cols_pr_row].set_title(
        f"Actual: {class_names[y_test[val]]}\nPredicted: {class_names[y_pred[index]]}",
        fontsize=16)
    ax[math.floor(index/num_cols_pr_row), index%num_cols_pr_row].axis('off')
fig.tight_layout()
fig.suptitle(f'Prediction of {word_to_predict}', fontsize=20)
fig.subplots_adjust(top=0.88)
fig.show()
```

Prediction of helloworld

