# sign\_language\_cnn\_le\_net

## May 5, 2020

```
In [10]: 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, De
         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[10]:
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      62
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```

[5 rows x 785 columns]

## 1 Data Processing

```
In [11]: 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 [12]: # 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 wid
             height_shift_range=0.1, # randomly shift images vertically (fraction of total height
             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 [13]: 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 [14]: X_test.shape
Out[14]: (7171, 28, 28, 1)
In [15]: # LeNet
         model = create_le_net()
In [16]: #keras.utils.plot_model(model, "my_mnist_model.png", show_shapes=True)
In [17]: model.compile(loss="sparse_categorical_crossentropy",
                       optimizer="adam",
                       metrics=["accuracy"])
```

## 3 Model Training

In [18]: from keras.callbacks import EarlyStopping, ModelCheckpoint

```
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,
                   y_train,
                   batch_size = 128,
                   subset="validation")
   history = model.fit(train_generator,
            epochs=500,
            validation_data=validation_generator,
            validation_steps=400,
            callbacks=[early_stopping, mcp_save])
Epoch 1/500
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Epoch 3/500
Epoch 4/500
Epoch 5/500
Epoch 6/500
Epoch 7/500
Epoch 8/500
Epoch 9/500
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Epoch 13/500
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Epoch 33/500
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Epoch 81/500
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Epoch 82/500											
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0486	_	acc:	0.9860	_	val_loss
Epoch 83/500			. 1								_
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0461	_	acc:	0.9863	_	val_loss
Epoch 84/500											_
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0490	_	acc:	0.9861	_	val_loss
Epoch 85/500											_
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0444	_	acc:	0.9870	_	val_loss
Epoch 86/500			-								
172/172 [==========]	-	10s	60ms/step	_	loss:	0.0466	-	acc:	0.9865	-	val_loss
Epoch 87/500											
172/172 [=========]	-	10s	61ms/step	_	loss:	0.0454	-	acc:	0.9862	-	val_loss
Epoch 88/500											
172/172 [=========]	-	10s	60 ms/step	-	loss:	0.0480	-	acc:	0.9849	-	val_loss
Epoch 89/500											
172/172 [========]	-	10s	60ms/step	-	loss:	0.0471	-	acc:	0.9851	-	val_loss
Epoch 90/500											
172/172 [========]	-	10s	60ms/step	-	loss:	0.0459	-	acc:	0.9863	-	val_loss
Epoch 91/500											
172/172 [====================================	-	10s	60ms/step	-	loss:	0.0428	-	acc:	0.9870	-	val_loss
Epoch 92/500											
172/172 [====================================	-	10s	60ms/step	-	loss:	0.0406	-	acc:	0.9883	-	val_loss
Epoch 93/500					_						
172/172 [====================================	-	10s	60ms/step	-	loss:	0.0453	-	acc:	0.9860	-	val_loss
Epoch 94/500					_						
172/172 [====================================	-	10s	60ms/step	-	loss:	0.0500	-	acc:	0.9844	-	val_loss
Epoch 95/500		4.0	00 / 1		-	0.0456			0.0000		
172/172 [====================================	-	10s	60ms/step	-	loss:	0.0456	-	acc:	0.9866	-	val_loss
Epoch 96/500		100	61mg/g+on		1.000.	0 0402			0 0074		] ]
172/172 [====================================	-	108	olms/step	-	loss:	0.0403	_	acc:	0.9874	-	val_loss
172/172 [====================================		10g	60mg/gton		loggi	0 0365		2661	0 0800		wal logg
Epoch 98/500	-	105	ooms/scep	_	TOSS.	0.0303	_	acc.	0.9090	_	Val_1055
172/172 [====================================	_	10g	60mg/gtan	_	1000.	0 0439	_	acc.	0 9872	_	wal logg
Epoch 99/500		105	ooms, step	_	1055.	0.0400	_	acc.	0.3012		Var_1055
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0447	_	acc:	0.9858	_	val loss
Epoch 100/500		100	oome, boop		1000.	0.011		acc.	0.0000		V41_1000
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0397	_	acc:	0.9878	_	val loss
Epoch 101/500			, , , , , , , , , , , , , , , , , , ,								
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0393	_	acc:	0.9881	_	val_loss
Epoch 102/500			. 1								_
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0371	_	acc:	0.9892	_	val_loss
Epoch 103/500			. 1								_ "
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0374	_	acc:	0.9887	_	val_loss
Epoch 104/500			•								
172/172 [==========]	-	10s	60ms/step	_	loss:	0.0412	_	acc:	0.9871	-	val_loss
Epoch 105/500			_								
172/172 [========]	-	10s	61ms/step	_	loss:	0.0409	_	acc:	0.9880	-	val_loss

Epoch 106/500											
172/172 [========]	_	10s	61mg/sten	_	1088.	0 0384	_	acc.	0 9890	_	val loss
Epoch 107/500		105	Olms/Step	_	TOBB.	0.0004	_	acc.	0.3030	_	Vai_1055
172/172 [========]		10a	61mg/g+on		1000.	0 0207		2001	0 0077		,,,,, logg
	_	108	61ms/scep	-	TOSS:	0.0397	-	acc:	0.9011	-	val_1088
Epoch 108/500		4.0	co / .		,	0.000			0.000		
172/172 [====================================	-	108	60ms/step	-	loss:	0.0383	-	acc:	0.9883	-	val_loss
Epoch 109/500					_						
172/172 [====================================	-	10s	60ms/step	-	loss:	0.0403	-	acc:	0.9878	-	val_loss
Epoch 110/500			/		_						
172/172 [====================================	-	10s	60ms/step	-	loss:	0.0377	-	acc:	0.9887	-	val_loss
Epoch 111/500											
172/172 [=======]	-	10s	60ms/step	-	loss:	0.0334	-	acc:	0.9909	-	val_loss
Epoch 112/500											
172/172 [=========]	-	10s	60ms/step	-	loss:	0.0363	-	acc:	0.9889	-	val_loss
Epoch 113/500											
172/172 [========]	_	10s	60ms/step	-	loss:	0.0379	-	acc:	0.9880	-	val_loss
Epoch 114/500											
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0346	-	acc:	0.9889	_	val_loss
Epoch 115/500			_								
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0339	_	acc:	0.9900	_	val_loss
Epoch 116/500											_
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0279	_	acc:	0.9914	_	val loss
Epoch 117/500											· · · ·
172/172 [========]	_	10s	60ms/step	_	loss:	0.0357	_	acc:	0.9893	_	val loss
Epoch 118/500		100	come, ecop		TODE.	0.0001		acc.	0.0000		VGI_1000
172/172 [========]	_	10g	60mg/sten	_	1000.	0 0341	_	acc.	0 9901	_	wal logg
Epoch 119/500	_	105	ooms/scep	Ī	TOSS.	0.0041	_	acc.	0.9901	_	Val_1055
172/172 [========]		10a	61mg/g+on		1000.	0 0200		2001	0 0000		,,,,, logg
	_	108	oms/scep	-	TOSS.	0.0326	-	acc.	0.9090	-	Val_1088
Epoch 120/500		10-	60/		1	0 0276			0.000		
172/172 [====================================	-	108	60ms/step	-	loss:	0.0376	-	acc:	0.9880	-	val_loss
Epoch 121/500		4.0	co / .		,	0.0000			0 0004		
172/172 [====================================	-	10s	60ms/step	-	loss:	0.0332	-	acc:	0.9904	-	val_loss
Epoch 122/500			/		_						
172/172 [====================================	-	10s	60ms/step	-	loss:	0.0311	-	acc:	0.9907	-	val_loss
Epoch 123/500											
172/172 [=========]	-	10s	60ms/step	-	loss:	0.0327	-	acc:	0.9896	-	val_loss
Epoch 124/500											
172/172 [========]	-	10s	60ms/step	-	loss:	0.0381	-	acc:	0.9879	-	val_loss
Epoch 125/500											
172/172 [=========]	-	10s	60ms/step	-	loss:	0.0316	-	acc:	0.9891	-	val_loss
Epoch 126/500											
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0260	-	acc:	0.9926	_	val_loss
Epoch 127/500			•								
172/172 [====================================	_	10s	60ms/step	_	loss:	0.0288	_	acc:	0.9911	_	val_loss
Epoch 128/500											= '
172/172 [========]	_	10s	60ms/sten	_	loss:	0.0339	_	acc:	0.9896	_	val loss
Epoch 129/500			, _оор								
172/172 [========]	_	10s	60ms/sten	_	loss	0.0346	_	acc.	0.9893	_	val loss
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Epoch 200/500
Epoch 201/500
```

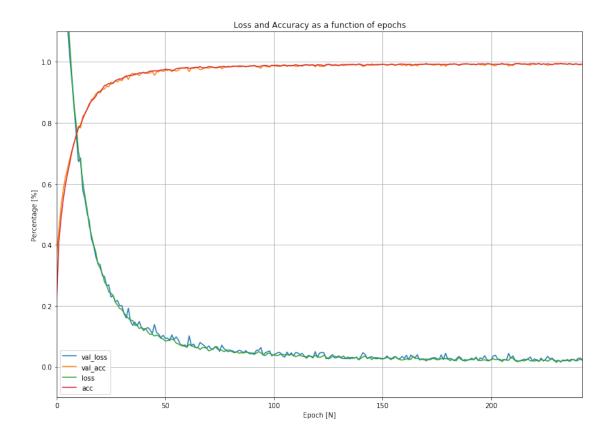
```
Epoch 202/500
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Epoch 242/500
Epoch 243/500
```

## 4 Model Evaluation

```
plt.gca().set_ylim(-0.1, 1.1)
plt.xlabel("Epoch [N]")
plt.ylabel("Percentage [%]")
plt.title("Loss and Accuracy as a function of epochs")
plt.show()
```

7171/7171 [=========] - 0s 31us/step Model evaluation: [0.06010350688544694, 0.983544833356575]



```
In [20]: import math
    num_rows = 3
    num_cols = 3

X_new = X_test[:num_rows*num_cols]

y_pred = model.predict_classes(X_new)

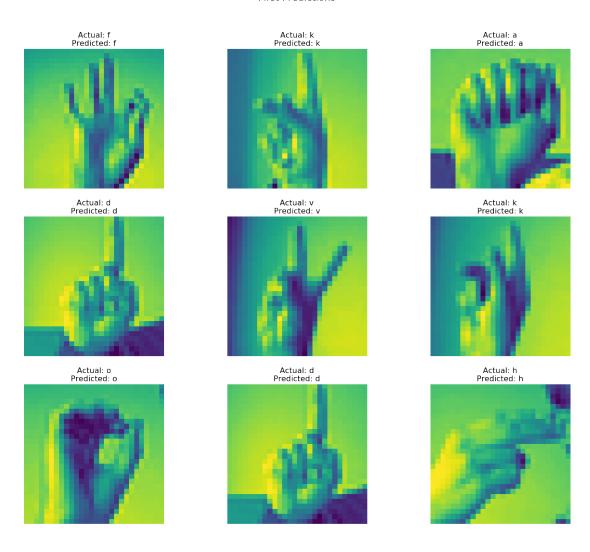
fig, ax = plt.subplots(num_rows, num_cols, figsize=(18, 16))
    for index, image in enumerate(X_new):
        ax[math.floor(index/num_rows), index%num_rows].imshow(image.reshape((28,28)))
```

```
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)
```

#### First Predictions

fig.show()



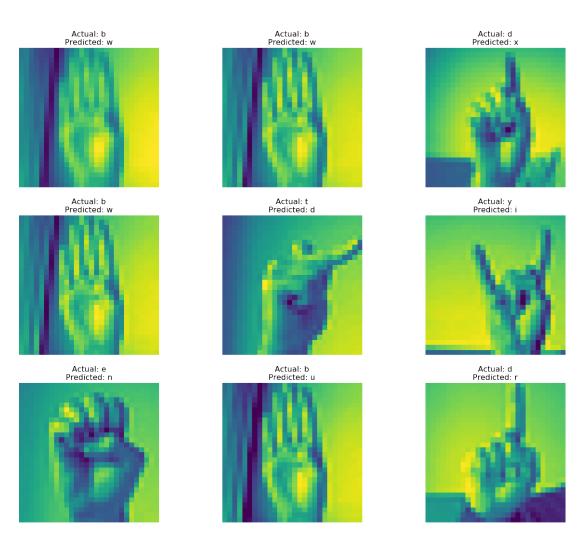
```
y_pred_confusion = y_pred[confusion_indices]
y_test_confusion = y_test[confusion_indices]

fig, ax = plt.subplots(num_rows, num_cols, figsize=(18, 16))
for index, image in enumerate(X_confusion[:num_rows*num_cols]):
    ax[math.floor(index/num_rows), index%num_rows].imshow(image.reshape((28,28)), inter
    ax[math.floor(index/num_rows), index%num_rows].set_title(
        f"Actual: {class_names[y_test_confusion[index]]}\nPredicted: {class_names[y_prefontsize=16)}
    ax[int(index/num_rows), index%num_rows].axis('off')

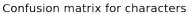
fig.tight_layout()
fig.suptitle('Incorrect Predictions', fontsize=20)
fig.subplots_adjust(top=0.88)
```

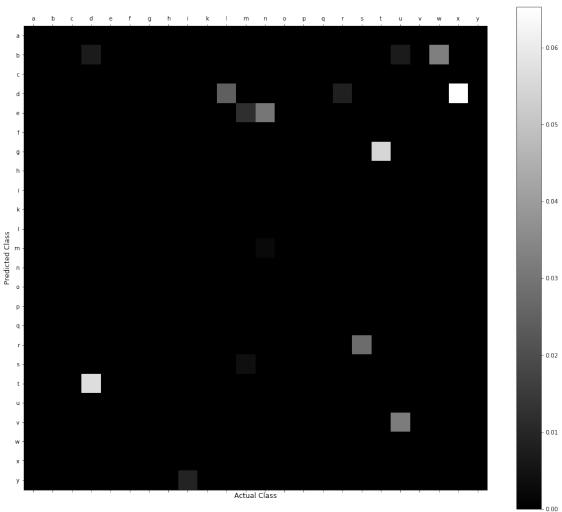
#### **Incorrect Predictions**

fig.show()



```
In [22]: 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()
```





# 5 Comparison with no Image Generation

```
Train on 21963 samples, validate on 5491 samples
Epoch 1/500
Epoch 2/500
Epoch 3/500
Epoch 4/500
Epoch 5/500
Epoch 6/500
Epoch 7/500
Epoch 8/500
Epoch 9/500
Epoch 10/500
Epoch 11/500
Epoch 12/500
Epoch 13/500
Epoch 14/500
Epoch 15/500
Epoch 16/500
Epoch 17/500
Epoch 18/500
Epoch 19/500
Epoch 20/500
```

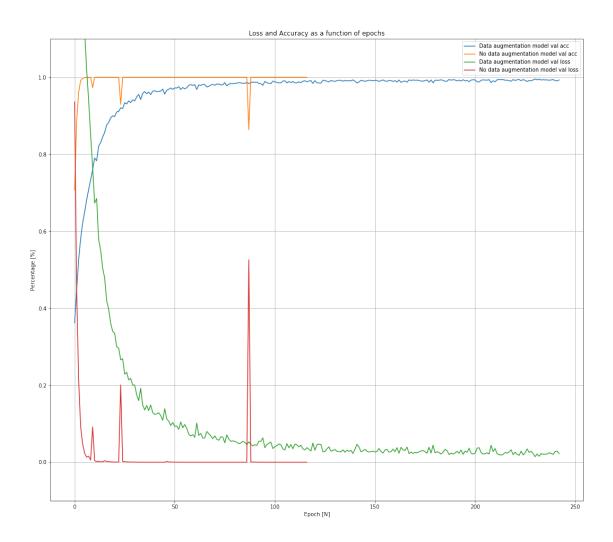
```
Epoch 21/500
Epoch 22/500
Epoch 23/500
Epoch 24/500
Epoch 25/500
Epoch 26/500
Epoch 27/500
Epoch 28/500
Epoch 29/500
Epoch 30/500
Epoch 31/500
Epoch 32/500
Epoch 33/500
Epoch 34/500
Epoch 35/500
Epoch 36/500
Epoch 37/500
Epoch 38/500
Epoch 39/500
Epoch 40/500
Epoch 41/500
Epoch 42/500
Epoch 43/500
Epoch 44/500
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Epoch 45/500
Epoch 46/500
Epoch 47/500
Epoch 48/500
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Epoch 66/500
Epoch 67/500
Epoch 68/500
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Epoch 69/500
Epoch 70/500
Epoch 71/500
Epoch 72/500
Epoch 73/500
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Epoch 86/500
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Epoch 88/500
Epoch 89/500
Epoch 90/500
Epoch 91/500
Epoch 92/500
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Epoch 93/500
Epoch 94/500
Epoch 95/500
Epoch 96/500
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Epoch 108/500
Epoch 109/500
Epoch 110/500
Epoch 111/500
Epoch 112/500
Epoch 113/500
Epoch 114/500
Epoch 115/500
Epoch 116/500
```

```
Epoch 117/500
In [25]: 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 a
        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 22us/step
Model evaluation: [0.7251484119123586, 0.8899735043926927]
Out[25]: Text(0.5, 1.0, 'Loss and Accuracy as a function of epochs')
```



```
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

y\_labels = np.array([class\_names[y] for y in y\_test])

