

```

10         break
17 plt.show()
18 concat_image = np.concatenate(concat_image, axis=1)
19 plt.figure(figsize=(16,16))
20 plt.imshow(concat_image)
21 plt.show()
22
23

```



## ▼ 5.7 Entrenamiento con Data Augmentation.

[inicio](#)

### ▼ 5.7.1 Preparamos los datos y el modelo

```

1 # crear subconjunto de datos
2 print("Creando conjunto de datos ...")
3 samples_per_class=100
4 data_subset, labels_subset = crear_subset(x_data, processed_y, samples_per_class=samples_per_class, number_of_classes=102, verb
5
6 # crear nuevos set de train, validate y test
7 print("Creando sets de train, validate y test ...")
8 X_train, y_train, X_validate, y_validate, X_test, y_test = crear_sets_tvt(data_subset=data_subset, labels_subset=labels_subse
9
10 # crea el modelo según la opción
11 print("Creando el modelo ...")
12 final_model_to_test = create_model_gec(opcion_modelo=4, optimizador="None")
13 final_model_to_test.compile(loss='categorical_crossentropy',
14                             optimizer=Adam(lr=.0001),
15                             metrics=['accuracy'])
16
17
18

```

### ▼ 5.7.2 Entrenamiento y evaluación del modelo

```

1 ### entrenar utilizando el generador de data
2 # Compute quantities required for feature-wise normalization
3 # (std, mean, and principal components if ZCA whitening is applied).
4 # datagen.fit(x_train)
5
6 print("Entrenando ...")
7 start_time = timeit.default_timer()
8
9 # es necesario especificar el numero de steps cuando se usa un generator (para saber cuando dejar de generar datos en una epo
10 batch_size = 32
11 num_samples = X_train.shape[0] * 30 # multiplicar por 10 el numero de ejemplos
12
13 # Fit the model on the batches generated by datagen.flow().
14 history_augmentation = final_model_to_test.fit_generator(datagen.flow(X_train, y_train, batch_size=batch_size),
15                                                         epochs=18,
16                                                         validation_data=(X_test, y_test),
17                                                         workers=4,
18                                                         steps_per_epoch=num_samples//batch_size)
19
20 # guardamos los pesos
21 nombre_archivo_modelo = BASE_FOLDER + "modelo_0_final_1.hdf5"
22 final_model_to_test.save(nombre_archivo_modelo)
23 print("Modelo guardado en:" + nombre_archivo_modelo)

```

```

23 print("Modelo guardado en: ", nombre_archivo_modelo,
24
25 print("Tiempo de ejecución del experimento:",round(timeit.default_timer() - start_time,0))
26
27 plot_results_gec(history_augmentation)
28
29 print("\nEvaluando ...")
30 loss_val, acc_val = final_model_to_test.evaluate(X_validate, y_validate, verbose=0)
31 loss_test, acc_test = final_model_to_test.evaluate(X_test, y_test, verbose=0)
32 loss_all, acc_all = final_model_to_test.evaluate(x_data, y_cat, verbose=0)
33 print("Exactitud validate:",round((acc_val*100),4),"%", Loss:"round(loss_val,4))
34 print("Exactitud test:",round((acc_test*100),4),"%", Loss:"round(loss_test,4))
35 print("Exactitud todo el dataset:",round((acc_all*100),4),"%", Loss:"round(loss_all,4))
36
37 # epochs 9: 65%
38 # experimento batch 32, epochs 18, imagenes 30 74% validation
39
40
41

```

```

Epoch 1/18
6000/6000 [=====] - 435s 73ms/step - loss: 2.2670 - acc: 0.4761 - val_loss: 1.5920 - val_acc: 0.617
Epoch 2/18
6000/6000 [=====] - 412s 69ms/step - loss: 1.3154 - acc: 0.6533 - val_loss: 1.3522 - val_acc: 0.671
Epoch 3/18
6000/6000 [=====] - 411s 69ms/step - loss: 0.9527 - acc: 0.7329 - val_loss: 1.2777 - val_acc: 0.704
Epoch 4/18
6000/6000 [=====] - 408s 68ms/step - loss: 0.7354 - acc: 0.7873 - val_loss: 1.4373 - val_acc: 0.691
Epoch 5/18
6000/6000 [=====] - 418s 70ms/step - loss: 0.5940 - acc: 0.8227 - val_loss: 1.3330 - val_acc: 0.721
Epoch 6/18
6000/6000 [=====] - 406s 68ms/step - loss: 0.4896 - acc: 0.8515 - val_loss: 1.3749 - val_acc: 0.716
Epoch 7/18
6000/6000 [=====] - 402s 67ms/step - loss: 0.4115 - acc: 0.8746 - val_loss: 1.3774 - val_acc: 0.716
Epoch 8/18
6000/6000 [=====] - 412s 69ms/step - loss: 0.3641 - acc: 0.8881 - val_loss: 1.4022 - val_acc: 0.734
Epoch 9/18
6000/6000 [=====] - 399s 66ms/step - loss: 0.3199 - acc: 0.9006 - val_loss: 1.4676 - val_acc: 0.731
Epoch 10/18
6000/6000 [=====] - 407s 68ms/step - loss: 0.2955 - acc: 0.9087 - val_loss: 1.4016 - val_acc: 0.733
Epoch 11/18
6000/6000 [=====] - 405s 67ms/step - loss: 0.2544 - acc: 0.9199 - val_loss: 1.5844 - val_acc: 0.725
Epoch 12/18
6000/6000 [=====] - 406s 68ms/step - loss: 0.2453 - acc: 0.9234 - val_loss: 1.5697 - val_acc: 0.731
Epoch 13/18
6000/6000 [=====] - 405s 68ms/step - loss: 0.2263 - acc: 0.9288 - val_loss: 1.4761 - val_acc: 0.732
Epoch 14/18
6000/6000 [=====] - 409s 68ms/step - loss: 0.2113 - acc: 0.9335 - val_loss: 1.5127 - val_acc: 0.744
Epoch 15/18
6000/6000 [=====] - 406s 68ms/step - loss: 0.1981 - acc: 0.9385 - val_loss: 1.5575 - val_acc: 0.736
Epoch 16/18
6000/6000 [=====] - 404s 67ms/step - loss: 0.1911 - acc: 0.9396 - val_loss: 1.6264 - val_acc: 0.723
Epoch 17/18
6000/6000 [=====] - 411s 69ms/step - loss: 0.1748 - acc: 0.9445 - val_loss: 1.7610 - val_acc: 0.722
Epoch 18/18
6000/6000 [=====] - 422s 70ms/step - loss: 0.1680 - acc: 0.9466 - val_loss: 1.5964 - val_acc: 0.744

```

```

1 # vemos los resultados # 61% best test 66%
2 plot_results(history_augmentation)
3
4 # predecimos para verificar la exactitud conseguida
5 #predict_sample(X_test,y_test,model=test_model)
6 print("Exactitud en subconjunto de test:")
7 predict_accuracy(X_test, y_test, model,verbose=True)
8
9 print("\nExactitud en todo el dataset:")
10 predict_accuracy(x_data, y_cat, model,verbose=True)
11

```

↗