Dataset: https://www.kaggle.com/datasets/ashishjangra27/gender-recognition-200k-images-celeba Importar dependencias In [1]: import os os.environ['CUDA_VISIBLE_DEVICES'] = '-1' The history saving thread hit an unexpected error (OperationalError('attempt to write a readonly database')). History will not be written to the da tabase. In [3]: import tensorflow as tf import numpy as np from PIL import Image import matplotlib.pyplot as plt from tensorflow.keras.utils import image_dataset_from_directory from tensorflow.keras.preprocessing.image import ImageDataGenerator from tensorflow.keras.models import Sequential from tensorflow.keras.layers import Dense, Activation, Dropout, Flatten, Conv2D, MaxPooling2D, BatchNormalization from tensorflow.keras.preprocessing import image from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau Configuración Ajustamos el formato de la imagen que posteriormente deberá coincidir con la capa de entrada de la CNN In [4]: pic_size = (200, 200) base_path = '../datasets/gender' Data Augmentation y Carga de Datos Función para Data Augmentation Generamos nuevas imágenes sintéticas a partir de las imágenes de entrenamiento para evitar el sobreajuste In [5]: train_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2, zoom_range=0.2, horizontal_flip=True, validation_split=0.2 Cargando datos In [6]: train_generator = train_datagen.flow_from_directory(f"{base_path}/train", target_size=pic_size, batch_size=32, class_mode='sparse', subset='training' validation_generator = train_datagen.flow_from_directory(f"{base_path}/validation", target_size=pic_size, batch_size=32, class_mode='sparse', subset='validation' test_datagen = ImageDataGenerator(rescale=1./255) test_generator = test_datagen.flow_from_directory(f"{base_path}/test", target_size=pic_size, batch_size=32, class_mode='sparse' Found 16000 images belonging to 2 classes. Found 2000 images belonging to 2 classes. Found 10000 images belonging to 2 classes. Arquitectura del modelo Nuestra red neuronal se compone de tres capas con 32, 64 y 128 filtros, en las cuales se desactivaran aleatoriamente un 20% de las neuronas (dropout) en cada una. Aplicamos una capa intermedia de 1000 neuronas y una softmax como función de activación en la capa de salida In [8]: model = Sequential([Conv2D(32, (3, 3), padding='same', activation=tf.nn.relu, input_shape=(200, 200, 3)), BatchNormalization(), MaxPooling2D((2, 2), strides=2), Dropout (0.2), Conv2D(64, (3, 3), padding='same', activation=tf.nn.relu), BatchNormalization(), MaxPooling2D((2, 2), strides=2), Dropout (0.2), Conv2D(128, (3, 3), padding='same', activation=tf.nn.relu), BatchNormalization(), MaxPooling2D((2, 2), strides=2), Dropout (0.2), Flatten(), Dense(1000, activation=tf.nn.relu), Dropout (0.5), Dense(2, activation='softmax')]) model.summary() Model: "sequential_1" Layer (type) **Output Shape** Param # conv2d_3 (Conv2D) (None, 200, 200, 32) 896 batch_normalization_3 (None, 200, 200, 32) 128 (BatchNormalization) max_pooling2d_3 (MaxPooling2D) 0 (None, 100, 100, 32) dropout_4 (Dropout) 0 (None, 100, 100, 32) (None, 100, 100, 64) 18,496 conv2d_4 (Conv2D) batch_normalization_4 (None, 100, 100, 64) 256 (BatchNormalization) 0 max_pooling2d_4 (MaxPooling2D) (None, 50, 50, 64) dropout_5 (Dropout) 0 (None, 50, 50, 64) 73,856 conv2d_5 (Conv2D) (None, 50, 50, 128) batch_normalization_5 (None, 50, 50, 128) 512 (BatchNormalization)

0

0

0

0

2,002

80,001,000

/home/pedro/ESESA/lib/python3.12/site-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class sho uld call `super().__init__(**kwargs)` in its constructor. `**kwargs` can include `workers`, `use_multiprocessing`, `max_queue_size`. Do not pass t

uld call `super().__init__(**kwargs)` in its constructor. `**kwargs` can include `workers`, `use_multiprocessing`, `max_queue_size`. Do not pass t

879s 2s/step - accuracy: 0.7401 - loss: 11.7713 - val_accuracy: 0.7752 - val_loss: 1.2617 - learning_rat

920s 2s/step - accuracy: 0.8833 - loss: 0.3096 - val_accuracy: 0.9052 - val_loss: 0.2267 - learning_rat

932s 2s/step - accuracy: 0.9081 - loss: 0.2343 - val_accuracy: 0.9370 - val_loss: 0.1457 - learning_rat

933s 2s/step - accuracy: 0.9219 - loss: 0.1985 - val_accuracy: 0.9380 - val_loss: 0.1496 - learning_rat

934s 2s/step - accuracy: 0.9229 - loss: 0.2033 - val_accuracy: 0.9143 - val_loss: 0.2219 - learning_rat

931s 2s/step - accuracy: 0.9188 - loss: 0.2370 - val_accuracy: 0.9199 - val_loss: 0.2459 - learning_rat

934s 2s/step - accuracy: 0.9218 - loss: 0.1942 - val_accuracy: 0.9466 - val_loss: 0.1338 - learning_rat

0s 2s/step - accuracy: 0.7400 - loss: 11.7869

(None, 25, 25, 128)

(None, 25, 25, 128)

(None, 80000)

(None, 1000)

(None, 1000)

early_stopping monitorea la pérdida de validación y para el entrenamiento si esta no mejora después de 5 épocas

reduce_Ir si detecta pérdida de validación reduce la tasa de aprendizaje al 20% y comprueba si mejora durante 3 épocas

(None, 2)

Adicionalmente al proceso de entrenamiento añadimos las funciones early_stopping y reduce_lr

In [9]: early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True) reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=3, min_lr=0.00001) model.compile(loss='sparse_categorical_crossentropy', optimizer='Adam', metrics=['accuracy']) result = model.fit(train generator, steps_per_epoch=train_generator.samples // train_generator.batch_size, validation_data=validation_generator, validation_steps=validation_generator.samples // validation_generator.batch_size, callbacks=[early_stopping, reduce_lr]

max_pooling2d_5 (MaxPooling2D)

Total params: 80,097,146 (305.55 MB)

Non-trainable params: 448 (1.75 KB)

Compilación y entrenamiento

Trainable params: 80,096,698 (305.54 MB)

dropout_6 (Dropout)

flatten_1 (Flatten)

dropout_7 (Dropout)

dense_2 (Dense)

dense_3 (Dense)

Gender Classification

hese arguments to `fit()`, as they will be ignored. self._warn_if_super_not_called() Epoch 1/15 500/500 /home/pedro/ESESA/lib/python3.12/site-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class sho

hese arguments to `fit()`, as they will be ignored.

e: 0.0010 Epoch 2/15 500/500 e: 0.0010 Epoch 3/15 500/500

500/500

e: 0.0010 Epoch 4/15 500/500 -

e: 0.0010 Epoch 5/15 500/500

e: 0.0010 Epoch 6/15 500/500 -

e: 0.0010 Epoch 7/15 500/500 -

e: 2.0000e-04

In [10]: plt.plot(result.history['accuracy'])

plt.ylabel('accuracy') plt.xlabel('epoch')

plt.show()

0.950

0.925

0.900

0.875

0.850

0.825

0.800

0.775

accuracy

plt.plot(result.history['val_accuracy'])

plt.legend(['acc', 'val'], loc='upper left')

plt.title('Precisión del modelo')

acc val

2

self._warn_if_super_not_called()

Epoch 8/15 500/500 -932s 2s/step - accuracy: 0.9427 - loss: 0.1534 - val_accuracy: 0.9546 - val_loss: 0.1131 - learning_rat e: 2.0000e-04 Epoch 9/15 500/500 -934s 2s/step - accuracy: 0.9477 - loss: 0.1467 - val_accuracy: 0.9592 - val_loss: 0.1117 - learning_rat e: 2.0000e-04 Epoch 10/15 500/500 933s 2s/step - accuracy: 0.9469 - loss: 0.1368 - val_accuracy: 0.9536 - val_loss: 0.1379 - learning_rat e: 2.0000e-04 Epoch 11/15 500/500 931s 2s/step - accuracy: 0.9520 - loss: 0.1269 - val_accuracy: 0.9561 - val_loss: 0.1108 - learning_rat e: 2.0000e-04 Epoch 12/15 500/500 931s 2s/step - accuracy: 0.9544 - loss: 0.1213 - val_accuracy: 0.9516 - val_loss: 0.1310 - learning_rat e: 2.0000e-04 Epoch 13/15 500/500 930s 2s/step - accuracy: 0.9574 - loss: 0.1097 - val_accuracy: 0.9526 - val_loss: 0.1350 - learning_rat e: 2.0000e-04 Epoch 14/15 500/500 931s 2s/step - accuracy: 0.9568 - loss: 0.1125 - val_accuracy: 0.9325 - val_loss: 0.2076 - learning_rat e: 2.0000e-04 Epoch 15/15 500/500 937s 2s/step - accuracy: 0.9623 - loss: 0.0931 - val_accuracy: 0.9632 - val_loss: 0.1092 - learning_rat e: 4.0000e-05 Comportamiento del entrenamiento

Precisión del modelo

raise ValueError("Invalid class labels") from IPython.display import Image, display display(Image(image_path))

confidence = np.max(prediction)

Predicciones de comprobación

In [17]: def display_and_predict(image_path, model, class_labels):

raise ValueError("Model cannot be None")

prediction = predict_image(model, image_path)

predicted_class = class_labels[np.argmax(prediction)]

In [12]: class_labels = ['female', 'male']

if not model:

print(f"Predicted class: {predicted_class}") print(f"Confidence: {confidence:.2f}") return predicted_class, confidence except FileNotFoundError: return None, None except Exception as e: return None, None

epoch Función para predecir una imagen def predict_image(model, image_path, target_size=pic_size): img = image.load_img(image_path, target_size=target_size) img_array = image.img_to_array(img) img_array = np.expand_dims(img_array, axis=0) img_array = img_array / 255.0 prediction = model.predict(img_array) return prediction

10

12

14

8

if not class_labels or not isinstance(class_labels, (list, np.ndarray)):

print(f"Error: Image file not found at {image_path}") print(f"Error during prediction: {str(e)}") In [18]: predicted_class_1, confidence_1 = display_and_predict('../pictures/4.jpg', model, class_labels)

0s 50ms/step Predicted class: female Confidence: 1.00 In [19]: predicted_class_2, confidence_2 = display_and_predict('../pictures/5.jpeg', model, class_labels)

0s 48ms/step

Predicted class: male Confidence: 1.00

0s 52ms/step In [20]: predicted_class_3, confidence_4 = display_and_predict('.../pictures/6.jpeg', model, class_labels)

1/1

Predicted class: male Confidence: 1.00