

07MIAR_Proyecto_Programacion Redes Neuronales

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1 07MIAR - Redes Neuronales y Deep Learning: Proyecto de programación “*Deep Vision in classification tasks*”

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1.1 Enunciado

En esta actividad, el alumno debe **evaluar y comparar dos estrategias** para la **clasificación de imágenes** empleando el **dataset asignado**. Los alumnos deberá resolver el reto proponiendo una solución válida **basada en aprendizaje profundo**, más concretamente en redes neuronales convolucionales (**CNNs**). Será indispensable que la solución propuesta siga el **pipeline visto en clase** para resolver este tipo de tareas de inteligencia artificial:

1. **Carga** del conjunto de datos
2. **Inspección** del conjunto de datos
3. **Acondicionamiento** del conjunto de datos
4. Desarrollo de la **arquitectura** de red neuronal y **entrenamiento** de la solución
5. **Monitorización** del proceso de **entrenamiento** para la toma de decisiones
6. **Evaluación** del modelo predictivo y planteamiento de la siguiente prueba experimental

1.1.1 Estrategia 1: Entrenar desde cero o *from scratch*

La primera estrategia a comparar será una **red neuronal profunda** que el **alumno debe diseñar, entrenar y optimizar**. Se debe **justificar empíricamente** las decisiones que llevaron a la selección de la **arquitectura e hiperparámetros final**. Se espera que el alumno utilice todas las **técnicas de regularización** mostradas en clase de forma justificada para la mejora del rendimiento de la red neuronal (*weight regularization, dropout, batch normalization, data augmentation, etc.*).

1.1.2 Estrategia 2: Red pre-entrenada

La segunda estrategia a comparar debe incluir la utilización de una **red preentrenada** con el dataset ImageNet, llevando a cabo tareas de **transfer learning** y **fine-tuning** para resolver la tarea de clasificación asignada. Deben **compararse al menos dos tipos de arquitecturas**

(VGGs, ResNet50, Xception, InceptionV3, InceptionResNetV2, MobileNetV2, DenseNet, ResNet) y se debe **seleccionar la que mayor precisión proporcione** (información sobre las arquitecturas disponibles en <https://keras.io/applications/>). Se espera el uso de todas las **técnicas de regularización** mostradas en clase de forma justificada para la mejora del rendimiento de la red neuronal (*weight regularization, dropout, batch normalization, data augmentation, etc.*).

1.2 Normas a seguir

- Será **indispensable** realizar el **trabajo por parejas**. Dichas parejas de alumnxs se generarán **de manera automática** teniendo en cuenta el pais de residencia con el objetivo de facilitar el trabajo en equipo.
- Se debe entregar un **ÚNICO FICHERO PDF POR ALUMNO** que incluya las instrucciones presentes en el Colab Noteboook y su **EJECUCIÓN!!!**. Debe aparecer todo el proceso llevado a cabo en cada estrategia (i.e. carga de datos, inspección de datos, acondicionamiento, proceso de entrenamiento y proceso de validación del modelo).
- **La memoria del trabajo** (el fichero PDF mencionado en el punto anterior) deberá **subirla cada integrante del grupo** (aunque se trate de un documento idéntico) a la actividad que se habilitará **en CampusVIU**.
- Se recomienda trabajar respecto a un directorio base (**BASE_FOLDER**) para facilitar el trabajo en equipo. En este notebook se incluye un ejemplo de cómo almacenar/cargar datos utilizando un directorio base.
- Las **redes propuestas** deben estar **entrenadas** (y **EVIDENCIAR este proceso en el documento PDF**). La entrega de una **red sin entrenar** supondrá **perdida de puntos**.
- Si se desea **evidenciar alguna métrica** del proceso de entrenamiento (precisión, pérdida, etc.), estas deben ser generadas.
- Todos los **gráficos** que se deseen mostrar deberán **generarse en el Colab Notebook** para que tras la conversión aparezcan en el documento PDF.

1.3 *Tips* para realizar la actividad con éxito

- Los **datos** se cargarán directamente **desde** la plataforma **Kaggle** mediante su API (<https://github.com/Kaggle/kaggle-api>). En este Notebook se incluye un ejemplo de como hacerlo. Se recomienda generar una función que aborde esta tarea.
- El **documento PDF a entregar** como solución de la actividad se debe **generar automáticamente desde el fichero “.ipynb”**. En este Notebook se incluye un ejemplo de como hacerlo.
- **Generar secciones y subsecciones en el Colab Notebook** supondrá que el documento **PDF generado** queda totalmente **ordenado** facilitando la evaluación al docente.
- Se recomienda encarecidamente **incluir comentarios concisos pero aclaratorios**.
- Es muy recomendable crear una **última sección** de texto en el Colab Notebook en la que se discutan los diferentes modelos obtenidos y se extraigan las conclusiones pertinentes.

1.4 Criterios de evaluación

- **Seguimiento** de las **normas establecidas** en la actividad (detalladas anteriormente).
- Creación de una **solución que resuelva la tarea de clasificación**, i.e. que las figuras de mérito empleadas para medir la bondad del modelo predictivo evidencien un *performance* superior al rendimiento estocástico.

- **Claridad** en la creación de la solución, en las justificaciones sobre la toma de decisiones llevada a cabo así como en las comparativas y conclusiones finales.
- **Efectividad** al presentar las comparaciones entre métricas de evaluación de ambas estrategias.
- **Demostración** de la utilización de **técnicas de regularización** para mejorar el rendimiento de los modelos.

2 Estratégia 1

1.- CARGA DEL CONJUNTO DE DATOS

más abajo hay una celda para descargar el modelo usando la librería kaggle.

```
[ ]: # Nos aseguramos que tenemos instalada la última versión de la API de Kaggle en Colab
!pip install --upgrade --force-reinstall --no-deps kaggle
```

```
Collecting kaggle
  Downloading kaggle-1.7.4.5-py3-none-any.whl.metadata (16 kB)
  Downloading kaggle-1.7.4.5-py3-none-any.whl (181 kB)
    181.2/181.2 kB
15.0 MB/s eta 0:00:00
Installing collected packages: kaggle
  Attempting uninstall: kaggle
    Found existing installation: kaggle 1.7.4.5
    Uninstalling kaggle-1.7.4.5:
      Successfully uninstalled kaggle-1.7.4.5
Successfully installed kaggle-1.7.4.5
```

```
[ ]: from google.colab import drive
drive.mount('/content/drive')
```

Mounted at /content/drive

```
[ ]: # Crear la carpeta .kaggle si no existe
!mkdir -p ~/.kaggle
```

```
[ ]: # Copiar el archivo desde Drive a la carpeta oculta de Kaggle
# ¡NOTA LAS COMILLAS SIMPLES ALREDEDOR DE LA RUTA DE ORIGEN!
!cp '/content/drive/MyDrive/Colab Notebooks/kaggle.json' ~/.kaggle/
```

```
[ ]: # Dar los permisos de seguridad requeridos (solo lectura para el dueño)
!chmod 600 ~/.kaggle/kaggle.json
```

```
[ ]: !kaggle datasets list
```

ref	size	lastUpdated	downloadCount	voteCount	usabilityRating	title

sadiajavedd/students-academic-performance-dataset				
Students_Academic_Performance_Dataset			8907	2025-10-23
04:16:35.563000	7354	183	1.0	
kainatjamil12/housing				Housing Price
Dataset - Factors Affecting Home		4740	2025-11-08 11:00:08.757000	
1391	27	1.0		
ayeshaimran123/social-media-and-mental-health-balance				Social Media and
Mental Health Balance		5941	2025-10-26 07:51:53.380000	
7080	98	1.0		
shahzadi786/world-smartphone-market-2025				World Smartphone
Market 2025		17795	2025-11-09 04:52:42.650000	
2995	78	1.0		
ayeshasiddiq123/cars-pre				Car Price
Analysis Dataset		46557	2025-11-06 16:38:07.487000	
2445	59	1.0		
minahilfatima12328/performance-trends-in-education				Performance
Trends in Education		96178	2025-11-11 09:34:39.553000	
1012	30	1.0		
nalisha/shopping-behaviour-and-product-ranking-dateset				Shopping
Behaviour and Product Ranking Dateset .		67263	2025-11-12 17:47:25.227000	
1283	52	1.0		
khushikyad001/ai-impact-on-jobs-2030				AI Impact on
Jobs 2030		87410	2025-11-09 17:58:05.410000	
1633	44	1.0		
umerhaddii/shopify-stock-data-2025				Shopify Stock
Data 2025		65437	2025-11-17 09:40:55.917000	
501	29	1.0		
ellimaaac/gpus-specs-from-1986-to-2026				GPUs Specs From
1986 to 2026		217644	2025-11-15 17:00:42.790000	
550	24	1.0		
wardabilal/student-stress-analysis				Student Stress
Analysis		1729	2025-11-01 09:14:39.367000	
2072	44	1.0		
umuttuygurr/e-commerce-customer-behavior-and-sales-analysis-tr				E-Commerce
Customer Behavior & Sales Analysis -TR		584451	2025-11-09 07:40:27.120000	
4775	90	1.0		
ayeshaseherr/student-performance				Student
Performance Factors Dataset		96178	2025-11-12	
05:50:48.240000	1284	30	1.0	
shahzadi786/11111111111111111111111111				Data Developer
Salary in 2024		110754	2025-11-14 13:47:42.313000	
765	28	1.0		
emirhanakku/ai-workforce-and-automation-dataset-20152025				AI Workforce &
Automation Dataset (2015-2025)		7409	2025-11-16 21:41:47.677000	
402	29	0.8235294		
zubairdhuddi/clash-batasets				Clash Royale

```
Cards Data Overview           19338 2025-11-15 09:20:44.713000
466          23  0.88235295
ahmeduzaki/global-earthquake-tsunami-risk-assessment-dataset   Global
Earthquake-Tsunami Risk Assessment Dataset      16151 2025-10-01
16:35:53.273000          20209       672  1.0
ahmadrazakashif/bmw-worldwide-sales-records-20102024          BMW Worldwide
Sales Records (2010-2024)      853348 2025-09-20 14:39:45.280000
26615          511  1.0
dansbecker/melbourne-housing-snapshot          Melbourne
Housing Snapshot          461423 2018-06-05 12:52:24.087000
197907          1701  0.7058824
ayeshasiddiq123/customer-shopping-behavior-dataset          Customer
Shopping Behavior Dataset      72157 2025-11-09 11:12:18.700000
1189          23  1.0
```

```
[ ]: !kaggle datasets download -d gpiosenka/
    ↵butterflies-100-image-dataset-classification
```

```
Dataset URL: https://www.kaggle.com/datasets/gpiosenka/butterflies-100-image-
dataset-classification
License(s): unknown
Downloading butterflies-100-image-dataset-classification.zip to /content
  90% 409M/454M [00:04<00:00, 106MB/s]
  100% 454M/454M [00:04<00:00, 110MB/s]
```

```
[ ]: # Creamos un directorio para descomprimir los datos
!mkdir my_dataset
```

```
mkdir: cannot create directory 'my_dataset': File exists
```

```
[ ]: # Descomprimimos los datos y los dejamos listos para trabajar
!unzip butterflies-100-image-dataset-classification.zip -d my_dataset
```

```
[ ]: # Mostrar el contenido inmediato de la carpeta principal
!ls my_dataset
```

```
# Mostrar el contenido de la carpeta 'train' (donde están las clases)
!ls my_dataset/train | head -n 10
```

```
BUTTERFLIES-97.77.h5 BUTTERFLIES.csv test train valid
ADONIS
AFRICAN GIANT SWALLOWTAIL
AMERICAN SNOOT
AN 88
APPOLLO
ARCIGERA FLOWER MOTH
ATALA
ATLAS MOTH
BANDED ORANGE HELICONIAN
```

BANDED PEACOCK

```
[2]: import kagglehub

# Download latest version
my_dataset = kagglehub.dataset_download("gpiosenka/
↪butterflies-100-image-dataset-classification")

print("Path to dataset files:", my_dataset)
```

Using Colab cache for faster access to the 'butterflies-100-image-dataset-classification' dataset.

Path to dataset files: /kaggle/input/butterflies-100-image-dataset-classification

2.- INSPECCIÓN DEL CONJUNTO DE DATOS

```
[ ]: #Inspección del conjunto de datos
import os
import glob
import pandas as pd
import matplotlib.pyplot as plt

# --- A. Carga e Inspección ---
# La ruta base donde están las carpetas de las clases
DATA_DIR = os.path.join(my_dataset, 'train')

# Recolectar todas las rutas de archivos .jpg de forma recursiva
all_image_paths = glob.glob(os.path.join(DATA_DIR, '**/*.jpg'), recursive=True)

# Crear un DataFrame para manejar las rutas y clases
df = pd.DataFrame({'path': all_image_paths})

# Extraer el nombre de la clase (que es el nombre de la carpeta)
df['class_name'] = df['path'].apply(lambda x: os.path.basename(os.path.
↪dirname(x)))

# Contar la frecuencia de imágenes por clase
class_counts = df['class_name'].value_counts()

# --- B. Resultados en Consola ---
print(f"Total de imágenes encontradas: {len(df)}")
print(f"Total de clases (especies): {class_counts.shape[0]}\n")
print("--- Distribución de las 5 clases MÁS COMUNES ---")
print(class_counts.head())
print("\n--- Distribución de las 5 clases MENOS COMUNES ---")
print(class_counts.tail())
```

```

# --- C. Visualización de la Distribución (Justificación de Regularización) ---
# Usar un gráfico de barras para visualizar el desequilibrio
plt.figure(figsize=(20, 7))
# Mostramos un subconjunto de clases (ej. las 40 principales) para mayor ↴claridad visual
class_counts.head(40).plot(kind='bar', color='skyblue')
plt.title('Distribución de Imágenes por Clase (Top 40)')
plt.xlabel('Especie de Mariposa')
plt.ylabel('Número de Imágenes')
plt.xticks(rotation=70, ha='right', fontsize=9)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
#

```

Total de imágenes encontradas: 12639

Total de clases (especies): 100

--- Distribución de las 5 clases MÁS COMUNES ---

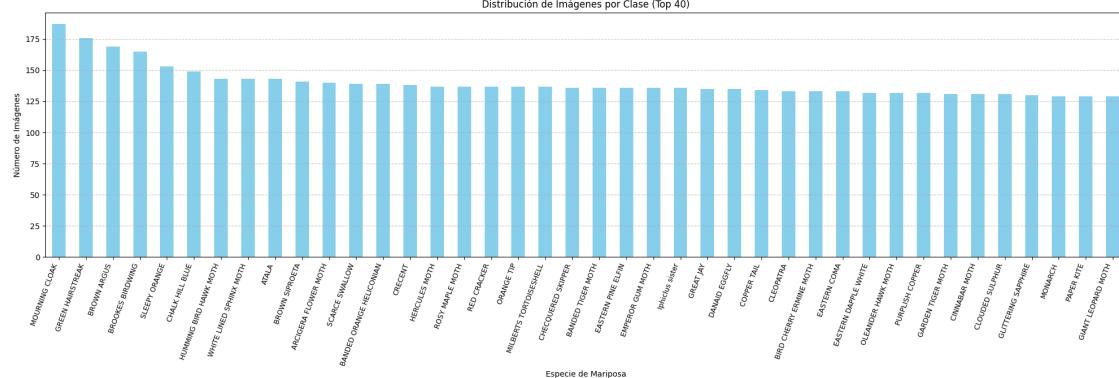
class_name	count
MOURNING CLOAK	187
GREEN HAIRSTREAK	176
BROWN ARGUS	169
BROOKES BIRDWING	165
SLEEPY ORANGE	153

Name: count, dtype: int64

--- Distribución de las 5 clases MENOS COMUNES ---

class_name	count
GOLD BANDED	104
CRIMSON PATCH	103
MALACHITE	103
WOOD SATYR	102
SIXSPOT BURNET MOTH	101

Name: count, dtype: int64



```
[ ]: import os
import glob
import random
from PIL import Image
import matplotlib.pyplot as plt

# La ruta base donde están las carpetas de las clases
DATA_DIR = os.path.join(my_dataset, 'train')

# 1. Obtener todas las carpetas de clases
class_folders = glob.glob(os.path.join(DATA_DIR, '*'))

# 2. Seleccionar una clase (carpeta) al azar
random_class_folder = random.choice(class_folders)
class_name = os.path.basename(random_class_folder)

# 3. Obtener todas las rutas de imágenes dentro de la clase seleccionada
image_paths = glob.glob(os.path.join(random_class_folder, '*.jpg'))

# 4. Seleccionar 6 imágenes al azar (o menos, si la clase tiene menos de 6)
num_samples = 6
sample_images = random.sample(image_paths, min(num_samples, len(image_paths)))

# 5. Mostrar las imágenes
print(f"Mostrando {len(sample_images)} imágenes de la clase seleccionada al azar: {class_name}\n")

plt.figure(figsize=(12, 8))
plt.suptitle(f'Ejemplos de la Clase: {class_name}', fontsize=16, y=1.02)

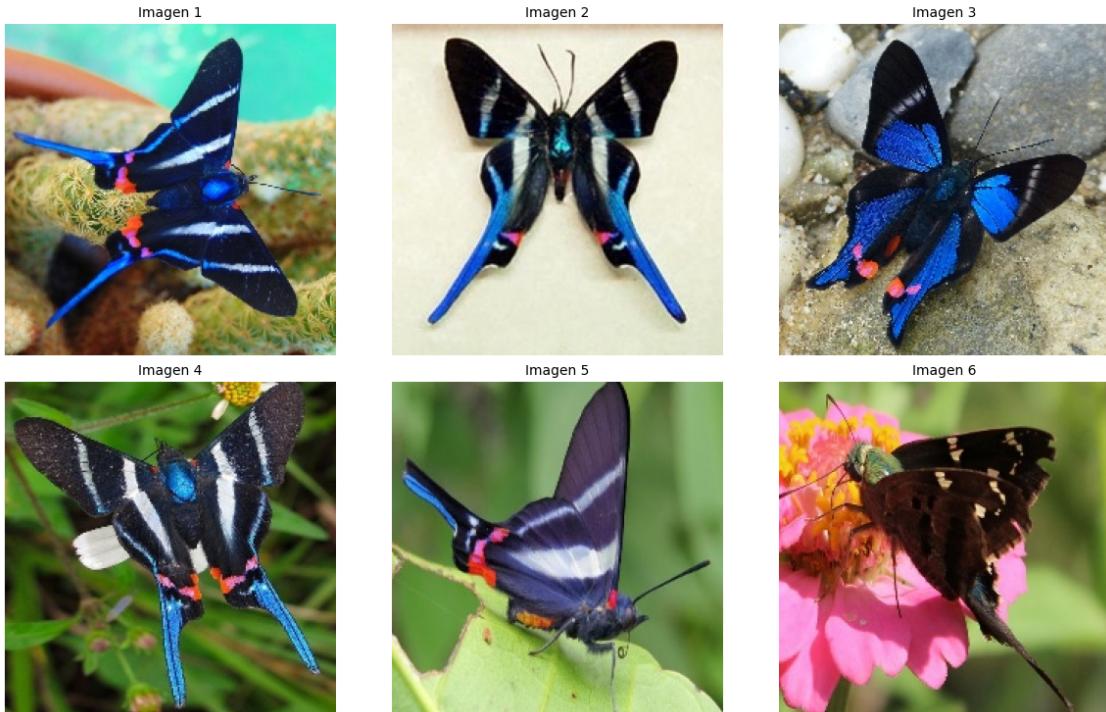
for i, path in enumerate(sample_images):
    # Cargar la imagen
    img = Image.open(path)

    # Crear un subplot de 2 filas y 3 columnas (2x3)
    plt.subplot(2, 3, i + 1)
    plt.imshow(img)
    plt.title(f"Imagen {i + 1}", fontsize=10)
    plt.axis('off')

plt.tight_layout(rect=[0, 0, 1, 0.98]) # Ajustar diseño para incluir el título principal
plt.show()
#
```

Mostrando 6 imágenes de la clase seleccionada al azar: METALMARK

Ejemplos de la Clase: METALMARK



```
[ ]: import os
import glob
import pandas as pd

# La ruta base donde se encuentran las 100 carpetas de clases
DATA_DIR = os.path.join(my_dataset, 'train')

# 1. Recolectar todas las rutas de imágenes
# La búsqueda recursiva encuentra todos los .jpg dentro de las subcarpetas de DATA_DIR
all_image_paths = glob.glob(os.path.join(DATA_DIR, '**/*.jpg'), recursive=True)

# 2. Crear un DataFrame para procesar
df = pd.DataFrame({'path': all_image_paths})

# 3. Extraer el nombre de la clase (nombre de la carpeta)
# os.path.dirname(x) te da la ruta de la carpeta, os.path.basename() extrae el nombre de la clase
```

```

df['class_name'] = df['path'].apply(lambda x: os.path.basename(os.path.
    ↪dirname(x)))

# 4. Contar la frecuencia de imágenes por cada clase (especie)
class_counts = df['class_name'].value_counts().sort_index()

# 5. Mostrar los resultados
print(f"Total de imágenes encontradas en DATA_DIR: {len(df)}")
print(f"Total de clases (especies): {class_counts.shape[0]}\n")

print("--- CONTEO DE IMÁGENES POR CLASE (Top 10 y Últimas 10) ---")
print("Top 10:")
print(class_counts.head(10))
print("\nÚltimas 10:")
print(class_counts.tail(10))

# Muestra la distribución completa si quieras ver las 100 clases (es opcional)
→debido a la longitud
# print("\nDistribución completa de las 100 clases:\n", class_counts)

```

Total de imágenes encontradas en DATA_DIR: 12639

Total de clases (especies): 100

--- CONTEO DE IMÁGENES POR CLASE (Top 10 y Últimas 10) ---

Top 10:

class_name	
ADONIS	126
AFRICAN GIANT SWALLOWTAIL	107
AMERICAN SNOOT	105
AN 88	121
APPOLLO	128
ARCIGERA FLOWER MOTH	140
ATALA	143
ATLAS MOTH	129
BANDED ORANGE HELICONIAN	139
BANDED PEACOCK	119

Name: count, dtype: int64

Últimas 10:

class_name	
SOUTHERN DOGFACE	125
STRAITED QUEEN	124
TROPICAL LEAFWING	118
TWO BARRED FLASHER	109
ULYSES	120
VICEROY	115
WHITE LINED SPHINX MOTH	143

WOOD SATYR	102
YELLOW SWALLOW TAIL	107
ZEBRA LONG WING	108
Name: count, dtype: int64	

3.- ACONDICIONAMIENTO DEL CONJUNTO DE DATOS

```
[ ]: # Acondicionamiento del Conjunto de Datos (Paso 3)
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import os
import glob
import numpy as np

# --- 1. Definición de Parámetros Globales ---
# Estos parámetros deben ser justificados en tu informe:
IMG_SIZE = 128 # Reducción de tamaño para acelerar el entrenamiento (ej. ↵128x128)
BATCH_SIZE = 32 # Tamaño estándar para el procesamiento en lote
DATA_DIR = os.path.join(my_dataset, 'train')

# Contar el número total de imágenes para calcular pasos por época

total_images = len(glob.glob(os.path.join(DATA_DIR, '**/*.jpg')), ↵recursive=True)

# --- 2. Configuración del Aumento de Datos (Regularización) ---
# Justificación: Estas técnicas aumentan la robustez del modelo
# y combaten el sobreajuste (overfitting) debido a la gran cantidad de clases ↵(100).
train_datagen = ImageDataGenerator(
    rescale=1./255,           # Normalización de píxeles (de 0-255 a 0-1) - ↵CRÍTICO
    validation_split=0.2,      # Reservar 20% de los datos para el conjunto de ↵validación

    # Técnicas de Data Augmentation:
    rotation_range=30,        # Rotación hasta 30 grados
    width_shift_range=0.2,     # Desplazamiento horizontal (20% del ancho)
    height_shift_range=0.2,    # Desplazamiento vertical (20% del alto)
    shear_range=0.2,          # Corte o cizallamiento
    zoom_range=0.2,           # Zoom aleatorio
    brightness_range=[0.5, 1.5], # Nuevo: Variación de brillo
    channel_shift_range=30,    # Nuevo: Variación de color
    horizontal_flip=True,     # Volteo horizontal (útil para mariposas)
    vertical_flip=True,       # Volteo vertical (útil para mariposas)
    fill_mode='nearest'       # Estrategia para llenar píxeles nuevos
)
```

```

# --- 3. Creación de Generadores ---

# Generador de Entrenamiento
train_generator = train_datagen.flow_from_directory(
    DATA_DIR,
    target_size=(IMG_SIZE, IMG_SIZE),
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    subset='training', # Utiliza la porción de entrenamiento
    shuffle=True # Mezclar los datos para evitar sesgos
)

# Generador de Validación
validation_generator = train_datagen.flow_from_directory(
    DATA_DIR,
    target_size=(IMG_SIZE, IMG_SIZE),
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    subset='validation', # Utiliza la porción de validación
    shuffle=False # No es necesario mezclar para validación
)

# --- 4. Verificación de Dimensiones y Conteo Final ---
NUM_CLASSES = train_generator.num_classes
STEPS_PER_EPOCH = train_generator.samples // BATCH_SIZE
VALIDATION_STEPS = validation_generator.samples // BATCH_SIZE

print("\n--- Resumen del Acondicionamiento ---")
print(f"Número de Clases (Salida de la Red): {NUM_CLASSES}")
print(f"Imágenes de Entrenamiento: {train_generator.samples}")
print(f"Imágenes de Validación: {validation_generator.samples}")
print(f"Dimensiones de Entrada de la Red: ({IMG_SIZE}, {IMG_SIZE}, 3)")
print(f"Pasos por Época (Train): {STEPS_PER_EPOCH}")
print(f"Pasos por Época (Validation): {VALIDATION_STEPS}")

```

Found 10151 images belonging to 100 classes.

Found 2488 images belonging to 100 classes.

--- Resumen del Acondicionamiento ---
Número de Clases (Salida de la Red): 100
Imágenes de Entrenamiento: 10151
Imágenes de Validación: 2488
Dimensiones de Entrada de la Red: (128, 128, 3)
Pasos por Época (Train): 317
Pasos por Época (Validation): 77

```
[ ]: # Muestra el diccionario de clases: {'BLUE MORPHO': 0, 'GREEN HAIRSTREAK': 1, ...
    ↵.}
print(train_generator.class_indices)
```

```
{'ADONIS': 0, 'AFRICAN GIANT SWALLOWTAIL': 1, 'AMERICAN SNOOT': 2, 'AN 88': 3,
'APOLLO': 4, 'ARCIGERA FLOWER MOTH': 5, 'ATALA': 6, 'ATLAS MOTH': 7, 'BANDED
ORANGE HELICONIAN': 8, 'BANDED PEACOCK': 9, 'BANDED TIGER MOTH': 10, 'BECKERS
WHITE': 11, 'BIRD CHERRY ERMINE MOTH': 12, 'BLACK HAIRSTREAK': 13, 'BLUE
MORPHO': 14, 'BLUE SPOTTED CROW': 15, 'BROOKES BIRDWING': 16, 'BROWN ARGUS': 17,
'BROWN SIPROETA': 18, 'CABBAGE WHITE': 19, 'CAIRNS BIRDWING': 20, 'CHALK HILL
BLUE': 21, 'CHECQUERED SKIPPER': 22, 'CHESTNUT': 23, 'CINNABAR MOTH': 24,
'CLEARWING MOTH': 25, 'CLEOPATRA': 26, 'CLODIUS PARNASSIAN': 27, 'CLOUDED
SULPHUR': 28, 'COMET MOTH': 29, 'COMMON BANDED AWL': 30, 'COMMON WOOD-NYMPH':
31, 'COPPER TAIL': 32, 'CRECENT': 33, 'CRIMSON PATCH': 34, 'DANAID EGGFLY': 35,
'EASTERN COMA': 36, 'EASTERN DAPPLE WHITE': 37, 'EASTERN PINE ELFIN': 38,
'ELBOWED PIERROT': 39, 'EMPEROR GUM MOTH': 40, 'GARDEN TIGER MOTH': 41, 'GIANT
LEOPARD MOTH': 42, 'GLITTERING SAPPHIRE': 43, 'GOLD BANDED': 44, 'GREAT EGGFLY':
45, 'GREAT JAY': 46, 'GREEN CELLED CATTLEHEART': 47, 'GREEN HAIRSTREAK': 48,
'GREY HAIRSTREAK': 49, 'HERCULES MOTH': 50, 'HUMMING BIRD HAWK MOTH': 51, 'INDRA
SWALLOW': 52, 'IO MOTH': 53, 'Iphiclus sister': 54, 'JULIA': 55, 'LARGE MARBLE':
56, 'LUNA MOTH': 57, 'MADAGASCAN SUNSET MOTH': 58, 'MALACHITE': 59, 'MANGROVE
SKIPPER': 60, 'MESTRA': 61, 'METALMARK': 62, 'MILBERTS TORTOISESHELL': 63,
'MONARCH': 64, 'MOURNING CLOAK': 65, 'OLEANDER HAWK MOTH': 66, 'ORANGE OAKLEAF':
67, 'ORANGE TIP': 68, 'ORCHARD SWALLOW': 69, 'PAINTED LADY': 70, 'PAPER KITE':
71, 'PEACOCK': 72, 'PINE WHITE': 73, 'PIPEVINE SWALLOW': 74, 'POLYPHEMUS MOTH':
75, 'POPINJAY': 76, 'PURPLE HAIRSTREAK': 77, 'PURPLISH COPPER': 78, 'QUESTION
MARK': 79, 'RED ADMIRAL': 80, 'RED CRACKER': 81, 'RED POSTMAN': 82, 'RED SPOTTED
PURPLE': 83, 'ROSY MAPLE MOTH': 84, 'SCARCE SWALLOW': 85, 'SILVER SPOT SKIPPER':
86, 'SIXSPOT BURNET MOTH': 87, 'SLEEPY ORANGE': 88, 'SOOTYWING': 89, 'SOUTHERN
DOGFACE': 90, 'STRAITED QUEEN': 91, 'TROPICAL LEAFWING': 92, 'TWO BARRED
FLASHER': 93, 'ULYSES': 94, 'VICEROY': 95, 'WHITE LINED SPHINX MOTH': 96, 'WOOD
SATYR': 97, 'YELLOW SWALLOW TAIL': 98, 'ZEBRA LONG WING': 99}
```

ESTRATEGIA 1: Entrenar desde cero o from scratch

1. MODELO 1

1.1.- DESARROLLO DE LA ARQUITECTURA DE RED NEURONAL Y ENTRENAMIENTO DE LA SOLUCIÓN

```
[ ]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, ↵
    ↵Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.regularizers import l2
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, ↵
    ↵ReduceLROnPlateau
import numpy as np
```

```

# --- 1. Definición y Compilación del Modelo CNN v1 ---
print("Definiendo la arquitectura CNN v1...")

model_v1 = Sequential([
    # Bloque 1
    Conv2D(64, (3, 3), activation='relu', input_shape=(IMG_SIZE, IMG_SIZE, 3)),
    MaxPooling2D((2, 2)),

    # Bloque 2
    Conv2D(128, (3, 3), activation='relu', kernel_regularizer=l2(0.0005)),
    MaxPooling2D((2, 2)),

    # Bloque 3 (Añadido para mayor profundidad)
    Conv2D(256, (3, 3), activation='relu', kernel_regularizer=l2(0.0005)),
    MaxPooling2D((2, 2)),
    # Aplanamiento y Capas Densely Connected
    Flatten(),
    Dense(256, activation='relu'),
    BatchNormalization(),
    # Capa de Salida
    Dense(NUM_CLASSES, activation='softmax')
])

# Compilación
model_v1.compile(
    optimizer=Adam(learning_rate=0.0005), # LR más baja para convergencia fina
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

model_v1.summary()

# --- 2. Entrenamiento con Callbacks Avanzados ---

# Recalcular pasos por época (asegurando que no se corte el entrenamiento)
STEPS_PER_EPOCH = int(np.ceil(train_generator.samples / BATCH_SIZE))
VALIDATION_STEPS = int(np.ceil(validation_generator.samples / BATCH_SIZE))
EPOCHS = 100 # Aumentamos las épocas, EarlyStopping actuará como límite

# Definición de Callbacks
early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=15,
    restore_best_weights=True
)

checkpoint_path = 'best_cnn_from_scratch_v2.keras'

```

```

model_checkpoint = ModelCheckpoint(
    checkpoint_path,
    monitor='val_accuracy',
    save_best_only=True,
    mode='max',
    verbose=1
)

# Estrategia de Decaimiento de Tasa de Aprendizaje
reduce_lr = ReduceLROnPlateau(
    monitor='val_loss',
    factor=0.2,           # Reduce la LR a 1/5
    patience=5,           # Espera 5 épocas sin mejora
    min_lr=0.00001,
    verbose=1
)

print(f"\nIniciando Entrenamiento para {EPOCHS} épocas...")
print(f"Pasos por Época (Train): {STEPS_PER_EPOCH}, Pasos (Validation):"
    f"{VALIDATION_STEPS}")

```

Definiendo la arquitectura CNN v2...

```

/usr/local/lib/python3.12/dist-
packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
    super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model: "sequential"

```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 64)	1,792
max_pooling2d (MaxPooling2D)	(None, 63, 63, 64)	0
conv2d_1 (Conv2D)	(None, 61, 61, 128)	73,856
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_2 (Conv2D)	(None, 28, 28, 256)	295,168
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 256)	0
flatten (Flatten)	(None, 50176)	0

dense (Dense)	(None, 256)	12,845,312
batch_normalization (BatchNormalization)	(None, 256)	1,024
dense_1 (Dense)	(None, 100)	25,700

Total params: 13,242,852 (50.52 MB)

Trainable params: 13,242,340 (50.52 MB)

Non-trainable params: 512 (2.00 KB)

Iniciando Entrenamiento para 100 épocas...
 Pasos por Época (Train): 318, Pasos (Validation): 78

```
[ ]: history_v1 = model_v1.fit(
    train_generator,
    steps_per_epoch=STEPS_PER_EPOCH,
    epochs=EPOCHS,
    validation_data=validation_generator,
    validation_steps=VALIDATION_STEPS,
    callbacks=[early_stopping, model_checkpoint, reduce_lr], # Se usan los 3
    ↪ callbacks
    verbose=1
)

print("\n--- Entrenamiento Finalizado ---")
```

```
/usr/local/lib/python3.12/dist-
packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121:
UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in
its constructor. `**kwargs` can include `workers`, `use_multiprocessing`,
`max_queue_size`. Do not pass these arguments to `fit()`, as they will be
ignored.
    self._warn_if_super_not_called()

Epoch 1/100
318/318          0s 319ms/step -
accuracy: 0.0635 - loss: 4.3563
Epoch 1: val_accuracy improved from -inf to 0.18449, saving model to
best_cnn_from_scratch_v2.keras
318/318          136s 404ms/step -
```

```
accuracy: 0.0637 - loss: 4.3551 - val_accuracy: 0.1845 - val_loss: 3.5247 -
learning_rate: 5.0000e-04
Epoch 2/100
318/318          0s 203ms/step -
accuracy: 0.2355 - loss: 3.2011
Epoch 2: val_accuracy improved from 0.18449 to 0.25764, saving model to
best_cnn_from_scratch_v2.keras
318/318          80s 252ms/step -
accuracy: 0.2356 - loss: 3.2005 - val_accuracy: 0.2576 - val_loss: 2.9711 -
learning_rate: 5.0000e-04
Epoch 3/100
318/318          0s 201ms/step -
accuracy: 0.3805 - loss: 2.5544
Epoch 3: val_accuracy improved from 0.25764 to 0.42886, saving model to
best_cnn_from_scratch_v2.keras
318/318          79s 249ms/step -
accuracy: 0.3806 - loss: 2.5541 - val_accuracy: 0.4289 - val_loss: 2.3668 -
learning_rate: 5.0000e-04
Epoch 4/100
318/318          0s 203ms/step -
accuracy: 0.4741 - loss: 2.1567
Epoch 4: val_accuracy did not improve from 0.42886
318/318          80s 250ms/step -
accuracy: 0.4741 - loss: 2.1565 - val_accuracy: 0.4200 - val_loss: 2.3687 -
learning_rate: 5.0000e-04
Epoch 5/100
318/318          0s 201ms/step -
accuracy: 0.5269 - loss: 1.8857
Epoch 5: val_accuracy improved from 0.42886 to 0.49719, saving model to
best_cnn_from_scratch_v2.keras
318/318          79s 248ms/step -
accuracy: 0.5270 - loss: 1.8855 - val_accuracy: 0.4972 - val_loss: 1.9355 -
learning_rate: 5.0000e-04
Epoch 6/100
318/318          0s 219ms/step -
accuracy: 0.5864 - loss: 1.6551
Epoch 6: val_accuracy improved from 0.49719 to 0.56632, saving model to
best_cnn_from_scratch_v2.keras
318/318          85s 267ms/step -
accuracy: 0.5864 - loss: 1.6550 - val_accuracy: 0.5663 - val_loss: 1.6860 -
learning_rate: 5.0000e-04
Epoch 7/100
318/318          0s 202ms/step -
accuracy: 0.6215 - loss: 1.5222
Epoch 7: val_accuracy improved from 0.56632 to 0.62178, saving model to
best_cnn_from_scratch_v2.keras
318/318          80s 252ms/step -
accuracy: 0.6215 - loss: 1.5222 - val_accuracy: 0.6218 - val_loss: 1.5319 -
```

```
learning_rate: 5.0000e-04
Epoch 8/100
318/318          0s 202ms/step -
accuracy: 0.6470 - loss: 1.3940
Epoch 8: val_accuracy did not improve from 0.62178
318/318          79s 247ms/step -
accuracy: 0.6470 - loss: 1.3940 - val_accuracy: 0.5973 - val_loss: 1.5930 -
learning_rate: 5.0000e-04
Epoch 9/100
318/318          0s 201ms/step -
accuracy: 0.6781 - loss: 1.2875
Epoch 9: val_accuracy improved from 0.62178 to 0.62379, saving model to
best_cnn_from_scratch_v2.keras
318/318          80s 251ms/step -
accuracy: 0.6781 - loss: 1.2875 - val_accuracy: 0.6238 - val_loss: 1.4841 -
learning_rate: 5.0000e-04
Epoch 10/100
318/318          0s 202ms/step -
accuracy: 0.6954 - loss: 1.2247
Epoch 10: val_accuracy did not improve from 0.62379
318/318          81s 248ms/step -
accuracy: 0.6954 - loss: 1.2247 - val_accuracy: 0.6129 - val_loss: 1.5154 -
learning_rate: 5.0000e-04
Epoch 11/100
318/318          0s 204ms/step -
accuracy: 0.7038 - loss: 1.1676
Epoch 11: val_accuracy improved from 0.62379 to 0.65957, saving model to
best_cnn_from_scratch_v2.keras
318/318          80s 253ms/step -
accuracy: 0.7038 - loss: 1.1676 - val_accuracy: 0.6596 - val_loss: 1.3599 -
learning_rate: 5.0000e-04
Epoch 12/100
318/318          0s 206ms/step -
accuracy: 0.7169 - loss: 1.1213
Epoch 12: val_accuracy did not improve from 0.65957
318/318          81s 254ms/step -
accuracy: 0.7169 - loss: 1.1214 - val_accuracy: 0.6559 - val_loss: 1.3804 -
learning_rate: 5.0000e-04
Epoch 13/100
318/318          0s 200ms/step -
accuracy: 0.7455 - loss: 1.0445
Epoch 13: val_accuracy improved from 0.65957 to 0.68770, saving model to
best_cnn_from_scratch_v2.keras
318/318          79s 247ms/step -
accuracy: 0.7455 - loss: 1.0446 - val_accuracy: 0.6877 - val_loss: 1.3163 -
learning_rate: 5.0000e-04
Epoch 14/100
318/318          0s 201ms/step -
```

```
accuracy: 0.7444 - loss: 1.0145
Epoch 14: val_accuracy did not improve from 0.68770
318/318          79s 249ms/step -
accuracy: 0.7444 - loss: 1.0145 - val_accuracy: 0.6326 - val_loss: 1.4999 -
learning_rate: 5.0000e-04
Epoch 15/100
318/318          0s 199ms/step -
accuracy: 0.7475 - loss: 1.0012
Epoch 15: val_accuracy did not improve from 0.68770
318/318          87s 264ms/step -
accuracy: 0.7475 - loss: 1.0013 - val_accuracy: 0.6435 - val_loss: 1.4974 -
learning_rate: 5.0000e-04
Epoch 16/100
318/318          0s 201ms/step -
accuracy: 0.7624 - loss: 0.9632
Epoch 16: val_accuracy improved from 0.68770 to 0.71182, saving model to
best_cnn_from_scratch_v2.keras
318/318          79s 249ms/step -
accuracy: 0.7623 - loss: 0.9633 - val_accuracy: 0.7118 - val_loss: 1.1925 -
learning_rate: 5.0000e-04
Epoch 17/100
318/318          0s 206ms/step -
accuracy: 0.7682 - loss: 0.9468
Epoch 17: val_accuracy did not improve from 0.71182
318/318          80s 251ms/step -
accuracy: 0.7682 - loss: 0.9468 - val_accuracy: 0.7098 - val_loss: 1.2190 -
learning_rate: 5.0000e-04
Epoch 18/100
318/318          0s 202ms/step -
accuracy: 0.7720 - loss: 0.9182
Epoch 18: val_accuracy improved from 0.71182 to 0.73553, saving model to
best_cnn_from_scratch_v2.keras
318/318          79s 250ms/step -
accuracy: 0.7720 - loss: 0.9182 - val_accuracy: 0.7355 - val_loss: 1.1192 -
learning_rate: 5.0000e-04
Epoch 19/100
318/318          0s 203ms/step -
accuracy: 0.7769 - loss: 0.8959
Epoch 19: val_accuracy did not improve from 0.73553
318/318          79s 248ms/step -
accuracy: 0.7769 - loss: 0.8959 - val_accuracy: 0.7090 - val_loss: 1.1943 -
learning_rate: 5.0000e-04
Epoch 20/100
318/318          0s 205ms/step -
accuracy: 0.7839 - loss: 0.8918
Epoch 20: val_accuracy did not improve from 0.73553
318/318          80s 253ms/step -
accuracy: 0.7838 - loss: 0.8918 - val_accuracy: 0.7086 - val_loss: 1.1710 -
```

```
learning_rate: 5.0000e-04
Epoch 21/100
318/318          0s 204ms/step -
accuracy: 0.7928 - loss: 0.8563
Epoch 21: val_accuracy did not improve from 0.73553
318/318          80s 250ms/step -
accuracy: 0.7928 - loss: 0.8563 - val_accuracy: 0.6994 - val_loss: 1.1893 -
learning_rate: 5.0000e-04
Epoch 22/100
318/318          0s 204ms/step -
accuracy: 0.8021 - loss: 0.8152
Epoch 22: val_accuracy did not improve from 0.73553
318/318          80s 252ms/step -
accuracy: 0.8020 - loss: 0.8153 - val_accuracy: 0.7211 - val_loss: 1.1479 -
learning_rate: 5.0000e-04
Epoch 23/100
318/318          0s 202ms/step -
accuracy: 0.7971 - loss: 0.8368
Epoch 23: val_accuracy improved from 0.73553 to 0.73834, saving model to
best_cnn_from_scratch_v2.keras
318/318          80s 250ms/step -
accuracy: 0.7971 - loss: 0.8368 - val_accuracy: 0.7383 - val_loss: 1.0998 -
learning_rate: 5.0000e-04
Epoch 24/100
318/318          0s 206ms/step -
accuracy: 0.7988 - loss: 0.8172
Epoch 24: val_accuracy did not improve from 0.73834
318/318          80s 251ms/step -
accuracy: 0.7988 - loss: 0.8173 - val_accuracy: 0.7106 - val_loss: 1.2146 -
learning_rate: 5.0000e-04
Epoch 25/100
318/318          0s 200ms/step -
accuracy: 0.8083 - loss: 0.7998
Epoch 25: val_accuracy did not improve from 0.73834
318/318          78s 245ms/step -
accuracy: 0.8083 - loss: 0.7998 - val_accuracy: 0.7211 - val_loss: 1.1703 -
learning_rate: 5.0000e-04
Epoch 26/100
318/318          0s 204ms/step -
accuracy: 0.8041 - loss: 0.7944
Epoch 26: val_accuracy did not improve from 0.73834
318/318          79s 250ms/step -
accuracy: 0.8041 - loss: 0.7944 - val_accuracy: 0.7247 - val_loss: 1.1228 -
learning_rate: 5.0000e-04
Epoch 27/100
318/318          0s 201ms/step -
accuracy: 0.8122 - loss: 0.8031
Epoch 27: val_accuracy did not improve from 0.73834
```

```
318/318          78s 246ms/step -
accuracy: 0.8122 - loss: 0.8031 - val_accuracy: 0.7134 - val_loss: 1.2314 -
learning_rate: 5.0000e-04
Epoch 28/100
318/318          0s 203ms/step -
accuracy: 0.8063 - loss: 0.7929
Epoch 28: val_accuracy improved from 0.73834 to 0.74759, saving model to
best_cnn_from_scratch_v2.keras
318/318          80s 252ms/step -
accuracy: 0.8063 - loss: 0.7929 - val_accuracy: 0.7476 - val_loss: 1.0978 -
learning_rate: 5.0000e-04
Epoch 29/100
318/318          0s 201ms/step -
accuracy: 0.8126 - loss: 0.7546
Epoch 29: val_accuracy did not improve from 0.74759
318/318          78s 245ms/step -
accuracy: 0.8126 - loss: 0.7547 - val_accuracy: 0.7343 - val_loss: 1.1447 -
learning_rate: 5.0000e-04
Epoch 30/100
318/318          0s 199ms/step -
accuracy: 0.8148 - loss: 0.7590
Epoch 30: val_accuracy did not improve from 0.74759
318/318          78s 247ms/step -
accuracy: 0.8148 - loss: 0.7590 - val_accuracy: 0.7383 - val_loss: 1.1524 -
learning_rate: 5.0000e-04
Epoch 31/100
318/318          0s 200ms/step -
accuracy: 0.8285 - loss: 0.7236
Epoch 31: val_accuracy did not improve from 0.74759
318/318          78s 245ms/step -
accuracy: 0.8284 - loss: 0.7237 - val_accuracy: 0.7335 - val_loss: 1.1773 -
learning_rate: 5.0000e-04
Epoch 32/100
318/318          0s 199ms/step -
accuracy: 0.8260 - loss: 0.7240
Epoch 32: val_accuracy did not improve from 0.74759
318/318          77s 243ms/step -
accuracy: 0.8260 - loss: 0.7241 - val_accuracy: 0.7138 - val_loss: 1.1997 -
learning_rate: 5.0000e-04
Epoch 33/100
318/318          0s 200ms/step -
accuracy: 0.8203 - loss: 0.7202
Epoch 33: val_accuracy improved from 0.74759 to 0.75482, saving model to
best_cnn_from_scratch_v2.keras
318/318          79s 248ms/step -
accuracy: 0.8203 - loss: 0.7202 - val_accuracy: 0.7548 - val_loss: 1.0772 -
learning_rate: 5.0000e-04
Epoch 34/100
```

```
318/318          0s 200ms/step -
accuracy: 0.8246 - loss: 0.7516
Epoch 34: val_accuracy did not improve from 0.75482
318/318          78s 244ms/step -
accuracy: 0.8246 - loss: 0.7516 - val_accuracy: 0.7400 - val_loss: 1.2100 -
learning_rate: 5.0000e-04
Epoch 35/100
318/318          0s 200ms/step -
accuracy: 0.8308 - loss: 0.7034
Epoch 35: val_accuracy did not improve from 0.75482
318/318          79s 247ms/step -
accuracy: 0.8308 - loss: 0.7034 - val_accuracy: 0.7271 - val_loss: 1.1465 -
learning_rate: 5.0000e-04
Epoch 36/100
318/318          0s 199ms/step -
accuracy: 0.8295 - loss: 0.7192
Epoch 36: val_accuracy did not improve from 0.75482
318/318          81s 244ms/step -
accuracy: 0.8295 - loss: 0.7192 - val_accuracy: 0.7299 - val_loss: 1.1768 -
learning_rate: 5.0000e-04
Epoch 37/100
318/318          0s 201ms/step -
accuracy: 0.8406 - loss: 0.6833
Epoch 37: val_accuracy did not improve from 0.75482
318/318          78s 246ms/step -
accuracy: 0.8405 - loss: 0.6834 - val_accuracy: 0.7436 - val_loss: 1.1912 -
learning_rate: 5.0000e-04
Epoch 38/100
318/318          0s 201ms/step -
accuracy: 0.8304 - loss: 0.6993
Epoch 38: val_accuracy did not improve from 0.75482

Epoch 38: ReduceLROnPlateau reducing learning rate to 0.0001000000474974513.
318/318          78s 245ms/step -
accuracy: 0.8304 - loss: 0.6992 - val_accuracy: 0.7536 - val_loss: 1.1042 -
learning_rate: 5.0000e-04
Epoch 39/100
318/318          0s 202ms/step -
accuracy: 0.8674 - loss: 0.5895
Epoch 39: val_accuracy improved from 0.75482 to 0.80386, saving model to
best_cnn_from_scratch_v2.keras
318/318          80s 251ms/step -
accuracy: 0.8674 - loss: 0.5895 - val_accuracy: 0.8039 - val_loss: 0.8752 -
learning_rate: 1.0000e-04
Epoch 40/100
318/318          0s 203ms/step -
accuracy: 0.8749 - loss: 0.5333
Epoch 40: val_accuracy did not improve from 0.80386
```

```
318/318          79s 248ms/step -
accuracy: 0.8749 - loss: 0.5333 - val_accuracy: 0.7962 - val_loss: 0.8950 -
learning_rate: 1.0000e-04
Epoch 41/100
318/318          0s 208ms/step -
accuracy: 0.8915 - loss: 0.5071
Epoch 41: val_accuracy improved from 0.80386 to 0.81150, saving model to
best_cnn_from_scratch_v2.keras
318/318          82s 257ms/step -
accuracy: 0.8915 - loss: 0.5072 - val_accuracy: 0.8115 - val_loss: 0.8684 -
learning_rate: 1.0000e-04
Epoch 42/100
318/318          0s 207ms/step -
accuracy: 0.8880 - loss: 0.5066
Epoch 42: val_accuracy improved from 0.81150 to 0.81350, saving model to
best_cnn_from_scratch_v2.keras
318/318          82s 257ms/step -
accuracy: 0.8880 - loss: 0.5066 - val_accuracy: 0.8135 - val_loss: 0.8521 -
learning_rate: 1.0000e-04
Epoch 43/100
318/318          0s 204ms/step -
accuracy: 0.8843 - loss: 0.5366
Epoch 43: val_accuracy did not improve from 0.81350
318/318          79s 249ms/step -
accuracy: 0.8843 - loss: 0.5366 - val_accuracy: 0.8027 - val_loss: 0.8888 -
learning_rate: 1.0000e-04
Epoch 44/100
318/318          0s 203ms/step -
accuracy: 0.8841 - loss: 0.5143
Epoch 44: val_accuracy did not improve from 0.81350
318/318          79s 250ms/step -
accuracy: 0.8841 - loss: 0.5143 - val_accuracy: 0.8119 - val_loss: 0.8638 -
learning_rate: 1.0000e-04
Epoch 45/100
318/318          0s 207ms/step -
accuracy: 0.8880 - loss: 0.5102
Epoch 45: val_accuracy did not improve from 0.81350
318/318          80s 253ms/step -
accuracy: 0.8880 - loss: 0.5102 - val_accuracy: 0.8079 - val_loss: 0.8680 -
learning_rate: 1.0000e-04
Epoch 46/100
318/318          0s 210ms/step -
accuracy: 0.8898 - loss: 0.4919
Epoch 46: val_accuracy did not improve from 0.81350
318/318          81s 255ms/step -
accuracy: 0.8898 - loss: 0.4919 - val_accuracy: 0.8031 - val_loss: 0.8642 -
learning_rate: 1.0000e-04
Epoch 47/100
```

```
318/318          0s 201ms/step -
accuracy: 0.8943 - loss: 0.4860
Epoch 47: val_accuracy did not improve from 0.81350

Epoch 47: ReduceLROnPlateau reducing learning rate to 2.0000000949949027e-05.
318/318          85s 266ms/step -
accuracy: 0.8943 - loss: 0.4860 - val_accuracy: 0.8002 - val_loss: 0.8727 -
learning_rate: 1.0000e-04
Epoch 48/100
318/318          0s 201ms/step -
accuracy: 0.9022 - loss: 0.4659
Epoch 48: val_accuracy improved from 0.81350 to 0.82074, saving model to
best_cnn_from_scratch_v2.keras
318/318          79s 249ms/step -
accuracy: 0.9022 - loss: 0.4659 - val_accuracy: 0.8207 - val_loss: 0.8228 -
learning_rate: 2.0000e-05
Epoch 49/100
318/318          0s 209ms/step -
accuracy: 0.8985 - loss: 0.4658
Epoch 49: val_accuracy did not improve from 0.82074
318/318          82s 257ms/step -
accuracy: 0.8985 - loss: 0.4658 - val_accuracy: 0.8203 - val_loss: 0.8076 -
learning_rate: 2.0000e-05
Epoch 50/100
318/318          0s 213ms/step -
accuracy: 0.8998 - loss: 0.4590
Epoch 50: val_accuracy did not improve from 0.82074
318/318          82s 258ms/step -
accuracy: 0.8999 - loss: 0.4590 - val_accuracy: 0.8075 - val_loss: 0.8450 -
learning_rate: 2.0000e-05
Epoch 51/100
318/318          0s 203ms/step -
accuracy: 0.9014 - loss: 0.4573
Epoch 51: val_accuracy improved from 0.82074 to 0.83039, saving model to
best_cnn_from_scratch_v2.keras
318/318          80s 253ms/step -
accuracy: 0.9014 - loss: 0.4573 - val_accuracy: 0.8304 - val_loss: 0.7859 -
learning_rate: 2.0000e-05
Epoch 52/100
318/318          0s 206ms/step -
accuracy: 0.9008 - loss: 0.4648
Epoch 52: val_accuracy did not improve from 0.83039
318/318          80s 251ms/step -
accuracy: 0.9008 - loss: 0.4648 - val_accuracy: 0.8219 - val_loss: 0.8071 -
learning_rate: 2.0000e-05
Epoch 53/100
318/318          0s 207ms/step -
accuracy: 0.9017 - loss: 0.4594
```

```
Epoch 53: val_accuracy did not improve from 0.83039
318/318           80s 253ms/step -
accuracy: 0.9017 - loss: 0.4594 - val_accuracy: 0.8119 - val_loss: 0.8150 -
learning_rate: 2.0000e-05
Epoch 54/100
318/318           0s 204ms/step -
accuracy: 0.9056 - loss: 0.4490
Epoch 54: val_accuracy did not improve from 0.83039
318/318           79s 249ms/step -
accuracy: 0.9056 - loss: 0.4490 - val_accuracy: 0.8232 - val_loss: 0.8234 -
learning_rate: 2.0000e-05
Epoch 55/100
318/318           0s 203ms/step -
accuracy: 0.9114 - loss: 0.4379
Epoch 55: val_accuracy did not improve from 0.83039
318/318           79s 248ms/step -
accuracy: 0.9114 - loss: 0.4379 - val_accuracy: 0.8252 - val_loss: 0.8290 -
learning_rate: 2.0000e-05
Epoch 56/100
318/318           0s 201ms/step -
accuracy: 0.9067 - loss: 0.4340
Epoch 56: val_accuracy did not improve from 0.83039

Epoch 56: ReduceLROnPlateau reducing learning rate to 1e-05.
318/318           78s 246ms/step -
accuracy: 0.9067 - loss: 0.4341 - val_accuracy: 0.8215 - val_loss: 0.8092 -
learning_rate: 2.0000e-05
Epoch 57/100
318/318           0s 203ms/step -
accuracy: 0.9055 - loss: 0.4344
Epoch 57: val_accuracy did not improve from 0.83039
318/318           80s 251ms/step -
accuracy: 0.9055 - loss: 0.4344 - val_accuracy: 0.8159 - val_loss: 0.7868 -
learning_rate: 1.0000e-05
Epoch 58/100
318/318           0s 209ms/step -
accuracy: 0.9075 - loss: 0.4274
Epoch 58: val_accuracy did not improve from 0.83039
318/318           81s 255ms/step -
accuracy: 0.9075 - loss: 0.4274 - val_accuracy: 0.8199 - val_loss: 0.8270 -
learning_rate: 1.0000e-05
Epoch 59/100
318/318           0s 210ms/step -
accuracy: 0.9072 - loss: 0.4386
Epoch 59: val_accuracy did not improve from 0.83039
318/318           81s 255ms/step -
accuracy: 0.9072 - loss: 0.4386 - val_accuracy: 0.8195 - val_loss: 0.8107 -
learning_rate: 1.0000e-05
```

```
Epoch 60/100
318/318           0s 206ms/step -
accuracy: 0.9087 - loss: 0.4383
Epoch 60: val_accuracy did not improve from 0.83039
318/318           81s 254ms/step -
accuracy: 0.9087 - loss: 0.4383 - val_accuracy: 0.8288 - val_loss: 0.8022 -
learning_rate: 1.0000e-05
Epoch 61/100
318/318           0s 205ms/step -
accuracy: 0.9072 - loss: 0.4295
Epoch 61: val_accuracy did not improve from 0.83039
318/318           80s 251ms/step -
accuracy: 0.9072 - loss: 0.4295 - val_accuracy: 0.8248 - val_loss: 0.8099 -
learning_rate: 1.0000e-05
Epoch 62/100
318/318           0s 206ms/step -
accuracy: 0.9105 - loss: 0.4325
Epoch 62: val_accuracy did not improve from 0.83039
318/318           81s 253ms/step -
accuracy: 0.9105 - loss: 0.4325 - val_accuracy: 0.8079 - val_loss: 0.8355 -
learning_rate: 1.0000e-05
Epoch 63/100
318/318           0s 206ms/step -
accuracy: 0.9037 - loss: 0.4465
Epoch 63: val_accuracy did not improve from 0.83039
318/318           80s 252ms/step -
accuracy: 0.9037 - loss: 0.4465 - val_accuracy: 0.8191 - val_loss: 0.8164 -
learning_rate: 1.0000e-05
Epoch 64/100
318/318           0s 212ms/step -
accuracy: 0.9069 - loss: 0.4479
Epoch 64: val_accuracy did not improve from 0.83039
318/318           82s 259ms/step -
accuracy: 0.9069 - loss: 0.4479 - val_accuracy: 0.8187 - val_loss: 0.8116 -
learning_rate: 1.0000e-05
Epoch 65/100
318/318           0s 211ms/step -
accuracy: 0.9063 - loss: 0.4444
Epoch 65: val_accuracy did not improve from 0.83039
318/318           82s 259ms/step -
accuracy: 0.9063 - loss: 0.4444 - val_accuracy: 0.8159 - val_loss: 0.8127 -
learning_rate: 1.0000e-05
Epoch 66/100
318/318           0s 212ms/step -
accuracy: 0.9068 - loss: 0.4352
Epoch 66: val_accuracy did not improve from 0.83039
318/318           83s 260ms/step -
accuracy: 0.9068 - loss: 0.4352 - val_accuracy: 0.8147 - val_loss: 0.8149 -
```

```
learning_rate: 1.0000e-05
```

```
--- Entrenamiento Finalizado ---
```

1.2.- MONITORIZACIÓN DEL PROCESO DE ENTRENAMIENTO PARA LA TOMA DE DECISIONES

```
[ ]: import matplotlib.pyplot as plt
-----
# Lista de Accuracy de Entrenamiento (100 datos)
train_acc = history_v1.history["accuracy"]

# Lista de Accuracy de Validación (100 datos)
val_acc = history_v1.history["val_accuracy"]

# Generamos la lista de épocas (del 1 al 100)
epochs = range(1, len(train_acc)+1)

# -----
# 2. GENERACIÓN DEL GRÁFICO
# -----

plt.figure(figsize=(10, 6)) # Tamaño del gráfico

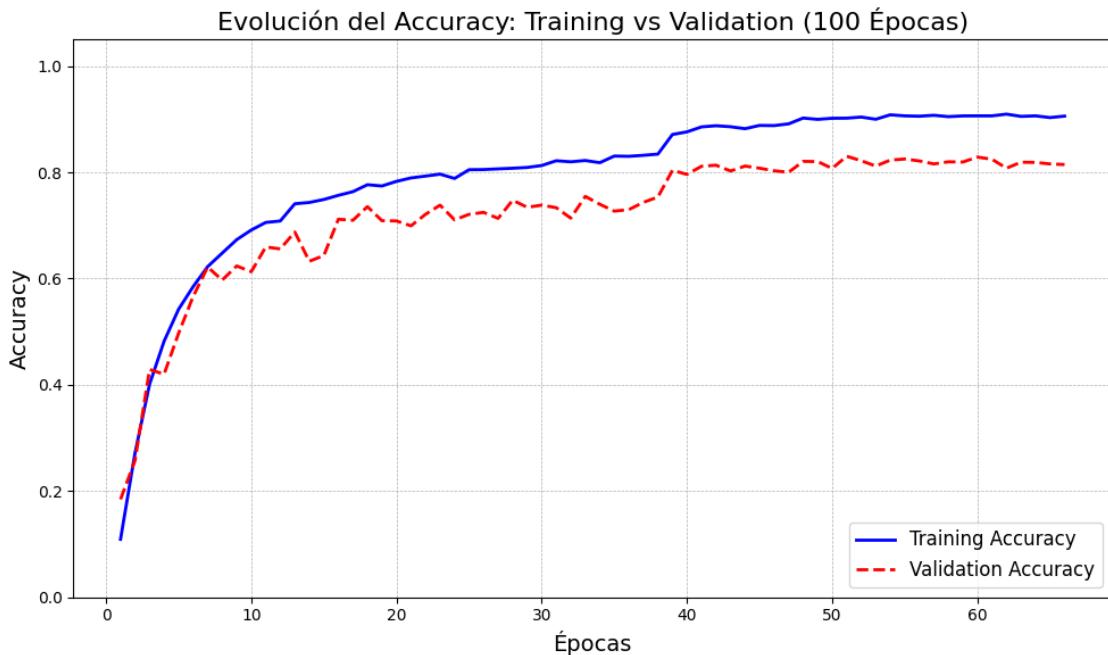
# Dibujar las líneas
plt.plot(epochs, train_acc, 'b-', label='Training Accuracy', linewidth=2)
plt.plot(epochs, val_acc, 'r--', label='Validation Accuracy', linewidth=2)

# Títulos y Etiquetas
plt.title('Evolución del Accuracy: Training vs Validation (100 Épocas)', fontsize=16)
plt.xlabel('Épocas', fontsize=14)
plt.ylabel('Accuracy', fontsize=14)

# Añadir leyenda y rejilla
plt.legend(loc='lower right', fontsize=12)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)

# Ajustar límites (Opcional: asumiendo accuracy de 0 a 1)
plt.ylim(0, 1.05)

# Mostrar gráfico
plt.tight_layout()
plt.show()
```



Interpretación: La curva de entrenamiento (azul, Training Accuracy) está consistentemente por encima de la curva de validación (roja, Validation Accuracy), el diagnóstico es claro: Sobreajuste (Overfitting).

```
[ ]: train_acc = history_v1.history["loss"]
val_acc = history_v1.history["val_loss"]

# Generamos la lista de épocas (del 1 al 100)
epochs = range(1, len(train_acc)+1)

# -----
# 2. GENERACIÓN DEL GRÁFICO
# -----
```

```
plt.figure(figsize=(10, 6)) # Tamaño del gráfico

# Dibujar las líneas
plt.plot(epochs, train_acc, 'b-', label='Training loss', linewidth=2)
plt.plot(epochs, val_acc, 'r--', label='Validation loss', linewidth=2)

# Títulos y Etiquetas
plt.title('Evolución del loss: Training vs Validation (100 Épocas)',
          fontsize=16)
plt.xlabel('Épocas', fontsize=14)
plt.ylabel('Accuracy', fontsize=14)
```

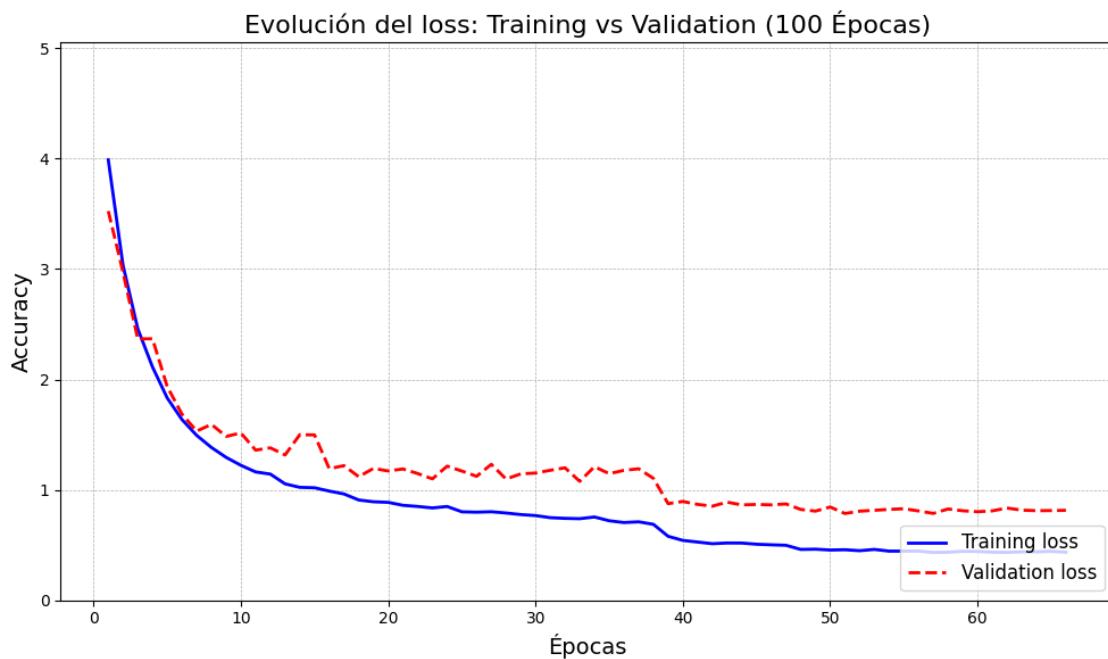
```

# Añadir leyenda y rejilla
plt.legend(loc='lower right', fontsize=12)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)

# Ajustar límites (Opcional: asumiendo accuracy de 0 a 1)
plt.ylim(0, 5.05)

# Mostrar gráfico
plt.tight_layout()
plt.show()

```



Interpretación: El gráfico de pérdidas da la misma conclusión que el gráfico de precisión por lo que se concluye que se requiere más regularización.

1.3.- EVALUACIÓN DEL MODELO PREDICTIVO Y PLANTEAMIENTO DE LA SIGUIENTE PRUEBA EXPERIMENTAL

Este modelo representa una buena línea de base (baseline) para la clasificación multiclase, combinando una arquitectura funcional con estrategias de entrenamiento diseñadas para optimizar la generalización y evitar la inestabilidad. La evaluación del resultado del Modelo v1 muestra un claro caso de sobreajuste (overfitting) y una convergencia estancada, a pesar de las estrategias de entrenamiento avanzadas. El análisis a continuación se centra en la brecha entre las métricas de entrenamiento y validación al final del proceso:

Métrica

Entrenamiento (Train)

Validación (Validation)

Diferencia

Precisión (Accuracy)

~ 90.6%

~ 81.6%

~ 9.0% (Brecha grande)

Pérdida (Loss)

~ 0.44

~ 0.81

~ 0.37 (Brecha significativa)

Tasa de Aprendizaje (LR)

1.0000e⁻⁵

1.0000e⁻⁵

La LR ya está en su valor mínimo.

2. MODELO 2

2.1.- DESARROLLO DE LA ARQUITECTURA DE RED NEURONAL Y ENTRENAMIENTO DE LA SOLUCIÓN

```
[ ]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
    ↪Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.regularizers import l2
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint,
    ↪ReduceLROnPlateau
import numpy as np

# --- 1. Definición y Compilación del Modelo CNN v2 ---
# Este modelo incrementa la capacidad (más filtros, más neuronas densas)
# y la regularización (Dropout, L2, Batch Normalization) para mejorar el
    ↪rendimiento.
# y la regularización (Dropout, L2, Batch Normalization) para mejorar el
    ↪rendimiento.
print("Definiendo la arquitectura CNN v2...")

model_v2 = Sequential([
    # Bloque 1
    Conv2D(64, (3, 3), activation='relu', input_shape=(IMG_SIZE, IMG_SIZE, 3)),
    BatchNormalization(),
    MaxPooling2D((2, 2)),
```

```

# Bloque 2
Conv2D(128, (3, 3), activation='relu', kernel_regularizer=l2(0.0005)),
BatchNormalization(),
MaxPooling2D((2, 2)),

# Bloque 3 (Añadido para mayor profundidad)
Conv2D(256, (3, 3), activation='relu', kernel_regularizer=l2(0.0005)),
BatchNormalization(),
MaxPooling2D((2, 2)),
Dropout(0.4),

# Aplanamiento y Capas Densely Connected
Flatten(),
Dense(1024, activation='relu'),
BatchNormalization(),
Dropout(0.6), # Mayor Dropout para compensar las 1024 neuronas

# Capa de Salida
Dense(NUM_CLASSES, activation='softmax')
])

# Compilación
model_v2.compile(
    optimizer=Adam(learning_rate=0.0005), # LR más baja para convergencia fina
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

model_v2.summary()

# --- 2. Entrenamiento con Callbacks Avanzados ---

# Recalcular pasos por época (asegurando que no se corte el entrenamiento)
STEPS_PER_EPOCH = int(np.ceil(train_generator.samples / BATCH_SIZE))
VALIDATION_STEPS = int(np.ceil(validation_generator.samples / BATCH_SIZE))
EPOCHS = 100 # Aumentamos las épocas, EarlyStopping actuará como límite

# Definición de Callbacks
early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=15,
    restore_best_weights=True
)

checkpoint_path = 'best_cnn_from_scratch_v2.keras'
model_checkpoint = ModelCheckpoint(

```

```

        checkpoint_path,
        monitor='val_accuracy',
        save_best_only=True,
        mode='max',
        verbose=1
    )

# Estrategia de Decaimiento de Tasa de Aprendizaje
reduce_lr = ReduceLROnPlateau(
    monitor='val_loss',
    factor=0.2,           # Reduce la LR a 1/5
    patience=5,           # Espera 5 épocas sin mejora
    min_lr=0.00001,
    verbose=1
)

print(f"\nIniciando Entrenamiento para {EPOCHS} épocas...")
print(f"Pasos por Época (Train): {STEPS_PER_EPOCH}, Pasos (Validation): {VALIDATION_STEPS}")

```

Definiendo la arquitectura CNN v2...

```

/usr/local/lib/python3.12/dist-
packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
    super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model: "sequential"

```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 64)	1,792
batch_normalization (BatchNormalization)	(None, 126, 126, 64)	256
max_pooling2d (MaxPooling2D)	(None, 63, 63, 64)	0
conv2d_1 (Conv2D)	(None, 61, 61, 128)	73,856
batch_normalization_1 (BatchNormalization)	(None, 61, 61, 128)	512
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 128)	0

conv2d_2 (Conv2D)	(None, 28, 28, 256)	295,168
batch_normalization_2 (BatchNormalization)	(None, 28, 28, 256)	1,024
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 256)	0
dropout (Dropout)	(None, 14, 14, 256)	0
flatten (Flatten)	(None, 50176)	0
dense (Dense)	(None, 1024)	51,381,248
batch_normalization_3 (BatchNormalization)	(None, 1024)	4,096
dropout_1 (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 100)	102,500

Total params: 51,860,452 (197.83 MB)

Trainable params: 51,857,508 (197.82 MB)

Non-trainable params: 2,944 (11.50 KB)

Iniciando Entrenamiento para 100 épocas...
Pasos por Época (Train): 318, Pasos (Validation): 78

```
[ ]: history_v2 = model_v2.fit(
    train_generator,
    steps_per_epoch=STEPS_PER_EPOCH,
    epochs=EPOCHS,
    validation_data=validation_generator,
    validation_steps=VALIDATION_STEPS,
    callbacks=[early_stopping, model_checkpoint, reduce_lr], # Se usan los 3
    ↪ callbacks
    verbose=1
)

print("\n--- Entrenamiento Finalizado ---")
```

/usr/local/lib/python3.12/dist-
packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121:

```
UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in
its constructor. `**kwargs` can include `workers`, `use_multiprocessing`,
`max_queue_size`. Do not pass these arguments to `fit()`, as they will be
ignored.
    self._warn_if_super_not_called()

Epoch 1/100
318/318          0s 353ms/step -
accuracy: 0.0550 - loss: 5.5376
Epoch 1: val_accuracy improved from -inf to 0.02532, saving model to
best_cnn_from_scratch_v2.keras
318/318          160s 465ms/step -
accuracy: 0.0551 - loss: 5.5360 - val_accuracy: 0.0253 - val_loss: 7.7071 -
learning_rate: 5.0000e-04
Epoch 2/100
318/318          0s 213ms/step -
accuracy: 0.1526 - loss: 4.0965
Epoch 2: val_accuracy improved from 0.02532 to 0.21785, saving model to
best_cnn_from_scratch_v2.keras
318/318          91s 285ms/step -
accuracy: 0.1527 - loss: 4.0961 - val_accuracy: 0.2178 - val_loss: 3.4367 -
learning_rate: 5.0000e-04
Epoch 3/100
318/318          0s 213ms/step -
accuracy: 0.2279 - loss: 3.4755
Epoch 3: val_accuracy improved from 0.21785 to 0.29180, saving model to
best_cnn_from_scratch_v2.keras
318/318          90s 283ms/step -
accuracy: 0.2279 - loss: 3.4751 - val_accuracy: 0.2918 - val_loss: 3.0124 -
learning_rate: 5.0000e-04
Epoch 4/100
318/318          0s 207ms/step -
accuracy: 0.3076 - loss: 3.0188
Epoch 4: val_accuracy improved from 0.29180 to 0.39068, saving model to
best_cnn_from_scratch_v2.keras
318/318          108s 340ms/step -
accuracy: 0.3076 - loss: 3.0185 - val_accuracy: 0.3907 - val_loss: 2.6124 -
learning_rate: 5.0000e-04
Epoch 5/100
318/318          0s 204ms/step -
accuracy: 0.3810 - loss: 2.5546
Epoch 5: val_accuracy did not improve from 0.39068
318/318          79s 249ms/step -
accuracy: 0.3810 - loss: 2.5545 - val_accuracy: 0.3625 - val_loss: 2.6984 -
learning_rate: 5.0000e-04
Epoch 6/100
318/318          0s 210ms/step -
accuracy: 0.4231 - loss: 2.3756
```

```
Epoch 6: val_accuracy improved from 0.39068 to 0.40635, saving model to
best_cnn_from_scratch_v2.keras
318/318          115s 363ms/step -
accuracy: 0.4231 - loss: 2.3753 - val_accuracy: 0.4064 - val_loss: 2.4194 -
learning_rate: 5.0000e-04
Epoch 7/100
318/318          0s 209ms/step -
accuracy: 0.4642 - loss: 2.1813
Epoch 7: val_accuracy improved from 0.40635 to 0.49477, saving model to
best_cnn_from_scratch_v2.keras
318/318          127s 401ms/step -
accuracy: 0.4642 - loss: 2.1811 - val_accuracy: 0.4948 - val_loss: 2.0467 -
learning_rate: 5.0000e-04
Epoch 8/100
318/318          0s 208ms/step -
accuracy: 0.5107 - loss: 2.0009
Epoch 8: val_accuracy improved from 0.49477 to 0.54783, saving model to
best_cnn_from_scratch_v2.keras
318/318          92s 289ms/step -
accuracy: 0.5107 - loss: 2.0007 - val_accuracy: 0.5478 - val_loss: 1.8434 -
learning_rate: 5.0000e-04
Epoch 9/100
318/318          0s 210ms/step -
accuracy: 0.5625 - loss: 1.7700
Epoch 9: val_accuracy did not improve from 0.54783
318/318          131s 255ms/step -
accuracy: 0.5625 - loss: 1.7700 - val_accuracy: 0.5342 - val_loss: 1.8932 -
learning_rate: 5.0000e-04
Epoch 10/100
318/318          0s 209ms/step -
accuracy: 0.5840 - loss: 1.6726
Epoch 10: val_accuracy improved from 0.54783 to 0.56913, saving model to
best_cnn_from_scratch_v2.keras
318/318          136s 429ms/step -
accuracy: 0.5840 - loss: 1.6727 - val_accuracy: 0.5691 - val_loss: 1.7779 -
learning_rate: 5.0000e-04
Epoch 11/100
318/318          0s 218ms/step -
accuracy: 0.5986 - loss: 1.6126
Epoch 11: val_accuracy improved from 0.56913 to 0.61093, saving model to
best_cnn_from_scratch_v2.keras
318/318          124s 391ms/step -
accuracy: 0.5986 - loss: 1.6126 - val_accuracy: 0.6109 - val_loss: 1.6212 -
learning_rate: 5.0000e-04
Epoch 12/100
318/318          0s 213ms/step -
accuracy: 0.6083 - loss: 1.5746
Epoch 12: val_accuracy improved from 0.61093 to 0.61495, saving model to
```

```
best_cnn_from_scratch_v2.keras
318/318          91s 286ms/step -
accuracy: 0.6083 - loss: 1.5746 - val_accuracy: 0.6150 - val_loss: 1.6357 -
learning_rate: 5.0000e-04
Epoch 13/100
318/318          0s 217ms/step -
accuracy: 0.6337 - loss: 1.4666
Epoch 13: val_accuracy did not improve from 0.61495
318/318          84s 263ms/step -
accuracy: 0.6337 - loss: 1.4667 - val_accuracy: 0.5957 - val_loss: 1.7807 -
learning_rate: 5.0000e-04
Epoch 14/100
318/318          0s 210ms/step -
accuracy: 0.6494 - loss: 1.4267
Epoch 14: val_accuracy did not improve from 0.61495
318/318          82s 258ms/step -
accuracy: 0.6494 - loss: 1.4267 - val_accuracy: 0.5945 - val_loss: 1.7765 -
learning_rate: 5.0000e-04
Epoch 15/100
318/318          0s 216ms/step -
accuracy: 0.6555 - loss: 1.3820
Epoch 15: val_accuracy did not improve from 0.61495
318/318          85s 266ms/step -
accuracy: 0.6555 - loss: 1.3820 - val_accuracy: 0.6009 - val_loss: 1.6765 -
learning_rate: 5.0000e-04
Epoch 16/100
318/318          0s 224ms/step -
accuracy: 0.6670 - loss: 1.3521
Epoch 16: val_accuracy improved from 0.61495 to 0.64469, saving model to
best_cnn_from_scratch_v2.keras
318/318          138s 433ms/step -
accuracy: 0.6670 - loss: 1.3521 - val_accuracy: 0.6447 - val_loss: 1.4724 -
learning_rate: 5.0000e-04
Epoch 17/100
318/318          0s 223ms/step -
accuracy: 0.6793 - loss: 1.3358
Epoch 17: val_accuracy improved from 0.64469 to 0.67042, saving model to
best_cnn_from_scratch_v2.keras
318/318          141s 444ms/step -
accuracy: 0.6793 - loss: 1.3358 - val_accuracy: 0.6704 - val_loss: 1.3996 -
learning_rate: 5.0000e-04
Epoch 18/100
318/318          0s 213ms/step -
accuracy: 0.6919 - loss: 1.2926
Epoch 18: val_accuracy did not improve from 0.67042
318/318          82s 259ms/step -
accuracy: 0.6919 - loss: 1.2926 - val_accuracy: 0.6664 - val_loss: 1.4165 -
learning_rate: 5.0000e-04
```

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Epoch 19/100
318/318           0s 210ms/step -
accuracy: 0.6942 - loss: 1.2582
Epoch 19: val_accuracy did not improve from 0.67042
318/318           82s 258ms/step -
accuracy: 0.6942 - loss: 1.2583 - val_accuracy: 0.6109 - val_loss: 1.7302 -
learning_rate: 5.0000e-04
Epoch 20/100
318/318           0s 210ms/step -
accuracy: 0.7049 - loss: 1.2340
Epoch 20: val_accuracy did not improve from 0.67042
318/318           81s 255ms/step -
accuracy: 0.7049 - loss: 1.2340 - val_accuracy: 0.6636 - val_loss: 1.4754 -
learning_rate: 5.0000e-04
Epoch 21/100
318/318           0s 210ms/step -
accuracy: 0.7176 - loss: 1.1780
Epoch 21: val_accuracy improved from 0.67042 to 0.68810, saving model to
best_cnn_from_scratch_v2.keras
318/318           96s 301ms/step -
accuracy: 0.7176 - loss: 1.1781 - val_accuracy: 0.6881 - val_loss: 1.3661 -
learning_rate: 5.0000e-04
Epoch 22/100
318/318           0s 214ms/step -
accuracy: 0.7223 - loss: 1.1821
Epoch 22: val_accuracy did not improve from 0.68810
318/318           83s 260ms/step -
accuracy: 0.7223 - loss: 1.1821 - val_accuracy: 0.6813 - val_loss: 1.5355 -
learning_rate: 5.0000e-04
Epoch 23/100
318/318           0s 209ms/step -
accuracy: 0.7255 - loss: 1.1498
Epoch 23: val_accuracy improved from 0.68810 to 0.69212, saving model to
best_cnn_from_scratch_v2.keras
318/318           124s 390ms/step -
accuracy: 0.7255 - loss: 1.1499 - val_accuracy: 0.6921 - val_loss: 1.3811 -
learning_rate: 5.0000e-04
Epoch 24/100
318/318           0s 224ms/step -
accuracy: 0.7213 - loss: 1.1570
Epoch 24: val_accuracy did not improve from 0.69212
318/318           86s 271ms/step -
accuracy: 0.7213 - loss: 1.1570 - val_accuracy: 0.5691 - val_loss: 1.9813 -
learning_rate: 5.0000e-04
Epoch 25/100
318/318           0s 210ms/step -
accuracy: 0.7356 - loss: 1.1211
Epoch 25: val_accuracy improved from 0.69212 to 0.70217, saving model to
```

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best_cnn_from_scratch_v2.keras
318/318           127s 401ms/step -
accuracy: 0.7356 - loss: 1.1212 - val_accuracy: 0.7022 - val_loss: 1.3265 -
learning_rate: 5.0000e-04
Epoch 26/100
318/318           0s 217ms/step -
accuracy: 0.7371 - loss: 1.0941
Epoch 26: val_accuracy did not improve from 0.70217
318/318           84s 263ms/step -
accuracy: 0.7371 - loss: 1.0943 - val_accuracy: 0.6359 - val_loss: 1.6320 -
learning_rate: 5.0000e-04
Epoch 27/100
318/318           0s 216ms/step -
accuracy: 0.7312 - loss: 1.1352
Epoch 27: val_accuracy did not improve from 0.70217
318/318           84s 264ms/step -
accuracy: 0.7312 - loss: 1.1352 - val_accuracy: 0.6483 - val_loss: 1.6118 -
learning_rate: 5.0000e-04
Epoch 28/100
318/318           0s 223ms/step -
accuracy: 0.7512 - loss: 1.0721
Epoch 28: val_accuracy improved from 0.70217 to 0.71463, saving model to
best_cnn_from_scratch_v2.keras
318/318           133s 420ms/step -
accuracy: 0.7512 - loss: 1.0721 - val_accuracy: 0.7146 - val_loss: 1.2890 -
learning_rate: 5.0000e-04
Epoch 29/100
318/318           0s 216ms/step -
accuracy: 0.7334 - loss: 1.1166
Epoch 29: val_accuracy improved from 0.71463 to 0.73553, saving model to
best_cnn_from_scratch_v2.keras
318/318           122s 384ms/step -
accuracy: 0.7335 - loss: 1.1166 - val_accuracy: 0.7355 - val_loss: 1.2392 -
learning_rate: 5.0000e-04
Epoch 30/100
318/318           0s 213ms/step -
accuracy: 0.7505 - loss: 1.0527
Epoch 30: val_accuracy did not improve from 0.73553
318/318           83s 260ms/step -
accuracy: 0.7505 - loss: 1.0528 - val_accuracy: 0.7178 - val_loss: 1.2532 -
learning_rate: 5.0000e-04
Epoch 31/100
318/318           0s 211ms/step -
accuracy: 0.7515 - loss: 1.0436
Epoch 31: val_accuracy did not improve from 0.73553
318/318           82s 258ms/step -
accuracy: 0.7515 - loss: 1.0437 - val_accuracy: 0.7203 - val_loss: 1.2508 -
learning_rate: 5.0000e-04
```

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Epoch 32/100
318/318          0s 212ms/step -
accuracy: 0.7507 - loss: 1.0462
Epoch 32: val_accuracy did not improve from 0.73553
318/318          83s 260ms/step -
accuracy: 0.7507 - loss: 1.0463 - val_accuracy: 0.7178 - val_loss: 1.2829 -
learning_rate: 5.0000e-04
Epoch 33/100
318/318          0s 237ms/step -
accuracy: 0.7488 - loss: 1.0627
Epoch 33: val_accuracy did not improve from 0.73553
318/318          93s 292ms/step -
accuracy: 0.7488 - loss: 1.0627 - val_accuracy: 0.7186 - val_loss: 1.2521 -
learning_rate: 5.0000e-04
Epoch 34/100
318/318          0s 218ms/step -
accuracy: 0.7669 - loss: 1.0032
Epoch 34: val_accuracy improved from 0.73553 to 0.74477, saving model to
best_cnn_from_scratch_v2.keras
318/318          92s 289ms/step -
accuracy: 0.7669 - loss: 1.0034 - val_accuracy: 0.7448 - val_loss: 1.1924 -
learning_rate: 5.0000e-04
Epoch 35/100
318/318          0s 214ms/step -
accuracy: 0.7604 - loss: 1.0208
Epoch 35: val_accuracy improved from 0.74477 to 0.74879, saving model to
best_cnn_from_scratch_v2.keras
318/318          126s 397ms/step -
accuracy: 0.7604 - loss: 1.0208 - val_accuracy: 0.7488 - val_loss: 1.1507 -
learning_rate: 5.0000e-04
Epoch 36/100
318/318          0s 208ms/step -
accuracy: 0.7660 - loss: 0.9990
Epoch 36: val_accuracy did not improve from 0.74879
318/318          81s 255ms/step -
accuracy: 0.7660 - loss: 0.9990 - val_accuracy: 0.7391 - val_loss: 1.1741 -
learning_rate: 5.0000e-04
Epoch 37/100
318/318          0s 209ms/step -
accuracy: 0.7778 - loss: 0.9759
Epoch 37: val_accuracy did not improve from 0.74879
318/318          81s 254ms/step -
accuracy: 0.7778 - loss: 0.9760 - val_accuracy: 0.7327 - val_loss: 1.2184 -
learning_rate: 5.0000e-04
Epoch 38/100
318/318          0s 208ms/step -
accuracy: 0.7771 - loss: 0.9792
Epoch 38: val_accuracy did not improve from 0.74879
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318/318          81s 254ms/step -
accuracy: 0.7771 - loss: 0.9792 - val_accuracy: 0.7375 - val_loss: 1.2286 -
learning_rate: 5.0000e-04
Epoch 39/100
318/318          0s 207ms/step -
accuracy: 0.7837 - loss: 0.9547
Epoch 39: val_accuracy did not improve from 0.74879
318/318          81s 253ms/step -
accuracy: 0.7836 - loss: 0.9549 - val_accuracy: 0.7122 - val_loss: 1.3435 -
learning_rate: 5.0000e-04
Epoch 40/100
318/318          0s 209ms/step -
accuracy: 0.7739 - loss: 0.9491
Epoch 40: val_accuracy did not improve from 0.74879

Epoch 40: ReduceLROnPlateau reducing learning rate to 0.0001000000474974513.
318/318          81s 254ms/step -
accuracy: 0.7739 - loss: 0.9491 - val_accuracy: 0.7444 - val_loss: 1.1640 -
learning_rate: 5.0000e-04
Epoch 41/100
318/318          0s 208ms/step -
accuracy: 0.8084 - loss: 0.8659
Epoch 41: val_accuracy improved from 0.74879 to 0.80506, saving model to
best_cnn_from_scratch_v2.keras
318/318          121s 378ms/step -
accuracy: 0.8084 - loss: 0.8659 - val_accuracy: 0.8051 - val_loss: 0.9610 -
learning_rate: 1.0000e-04
Epoch 42/100
318/318          0s 206ms/step -
accuracy: 0.8117 - loss: 0.8451
Epoch 42: val_accuracy did not improve from 0.80506
318/318          80s 252ms/step -
accuracy: 0.8117 - loss: 0.8451 - val_accuracy: 0.8047 - val_loss: 0.9288 -
learning_rate: 1.0000e-04
Epoch 43/100
318/318          0s 206ms/step -
accuracy: 0.8204 - loss: 0.8234
Epoch 43: val_accuracy improved from 0.80506 to 0.80989, saving model to
best_cnn_from_scratch_v2.keras
318/318          129s 406ms/step -
accuracy: 0.8204 - loss: 0.8234 - val_accuracy: 0.8099 - val_loss: 0.9500 -
learning_rate: 1.0000e-04
Epoch 44/100
318/318          0s 206ms/step -
accuracy: 0.8198 - loss: 0.7820
Epoch 44: val_accuracy improved from 0.80989 to 0.81310, saving model to
best_cnn_from_scratch_v2.keras
318/318          122s 385ms/step -
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accuracy: 0.8198 - loss: 0.7820 - val_accuracy: 0.8131 - val_loss: 0.8864 -
learning_rate: 1.0000e-04
Epoch 45/100
318/318          0s 203ms/step -
accuracy: 0.8203 - loss: 0.7775
Epoch 45: val_accuracy did not improve from 0.81310
318/318          79s 248ms/step -
accuracy: 0.8203 - loss: 0.7775 - val_accuracy: 0.8027 - val_loss: 0.9214 -
learning_rate: 1.0000e-04
Epoch 46/100
318/318          0s 218ms/step -
accuracy: 0.8324 - loss: 0.7607
Epoch 46: val_accuracy improved from 0.81310 to 0.81431, saving model to
best_cnn_from_scratch_v2.keras
318/318          135s 425ms/step -
accuracy: 0.8324 - loss: 0.7607 - val_accuracy: 0.8143 - val_loss: 0.8824 -
learning_rate: 1.0000e-04
Epoch 47/100
318/318          0s 210ms/step -
accuracy: 0.8389 - loss: 0.7521
Epoch 47: val_accuracy improved from 0.81431 to 0.82195, saving model to
best_cnn_from_scratch_v2.keras
318/318          130s 409ms/step -
accuracy: 0.8389 - loss: 0.7521 - val_accuracy: 0.8219 - val_loss: 0.8768 -
learning_rate: 1.0000e-04
Epoch 48/100
318/318          0s 207ms/step -
accuracy: 0.8391 - loss: 0.7196
Epoch 48: val_accuracy did not improve from 0.82195
318/318          80s 253ms/step -
accuracy: 0.8390 - loss: 0.7197 - val_accuracy: 0.8135 - val_loss: 0.9191 -
learning_rate: 1.0000e-04
Epoch 49/100
318/318          0s 210ms/step -
accuracy: 0.8436 - loss: 0.7245
Epoch 49: val_accuracy did not improve from 0.82195
318/318          81s 256ms/step -
accuracy: 0.8436 - loss: 0.7245 - val_accuracy: 0.8215 - val_loss: 0.8743 -
learning_rate: 1.0000e-04
Epoch 50/100
318/318          0s 206ms/step -
accuracy: 0.8360 - loss: 0.7322
Epoch 50: val_accuracy improved from 0.82195 to 0.83079, saving model to
best_cnn_from_scratch_v2.keras
318/318          93s 292ms/step -
accuracy: 0.8360 - loss: 0.7322 - val_accuracy: 0.8308 - val_loss: 0.8447 -
learning_rate: 1.0000e-04
Epoch 51/100
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318/318          0s 208ms/step -
accuracy: 0.8500 - loss: 0.6865
Epoch 51: val_accuracy improved from 0.83079 to 0.83360, saving model to
best_cnn_from_scratch_v2.keras
318/318          143s 450ms/step -
accuracy: 0.8500 - loss: 0.6866 - val_accuracy: 0.8336 - val_loss: 0.8557 -
learning_rate: 1.0000e-04
Epoch 52/100
318/318          0s 210ms/step -
accuracy: 0.8421 - loss: 0.7040
Epoch 52: val_accuracy did not improve from 0.83360
318/318          81s 255ms/step -
accuracy: 0.8421 - loss: 0.7040 - val_accuracy: 0.8256 - val_loss: 0.8615 -
learning_rate: 1.0000e-04
Epoch 53/100
318/318          0s 204ms/step -
accuracy: 0.8376 - loss: 0.7143
Epoch 53: val_accuracy did not improve from 0.83360
318/318          80s 251ms/step -
accuracy: 0.8376 - loss: 0.7143 - val_accuracy: 0.8211 - val_loss: 0.8980 -
learning_rate: 1.0000e-04
Epoch 54/100
318/318          0s 206ms/step -
accuracy: 0.8393 - loss: 0.7011
Epoch 54: val_accuracy improved from 0.83360 to 0.83923, saving model to
best_cnn_from_scratch_v2.keras
318/318          115s 362ms/step -
accuracy: 0.8393 - loss: 0.7011 - val_accuracy: 0.8392 - val_loss: 0.8685 -
learning_rate: 1.0000e-04
Epoch 55/100
318/318          0s 207ms/step -
accuracy: 0.8450 - loss: 0.6938
Epoch 55: val_accuracy did not improve from 0.83923
318/318          80s 253ms/step -
accuracy: 0.8449 - loss: 0.6939 - val_accuracy: 0.8284 - val_loss: 0.8345 -
learning_rate: 1.0000e-04
Epoch 56/100
318/318          0s 208ms/step -
accuracy: 0.8489 - loss: 0.6871
Epoch 56: val_accuracy did not improve from 0.83923
318/318          80s 253ms/step -
accuracy: 0.8489 - loss: 0.6871 - val_accuracy: 0.8232 - val_loss: 0.8528 -
learning_rate: 1.0000e-04
Epoch 57/100
318/318          0s 207ms/step -
accuracy: 0.8501 - loss: 0.6760
Epoch 57: val_accuracy did not improve from 0.83923
318/318          81s 254ms/step -
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accuracy: 0.8501 - loss: 0.6759 - val_accuracy: 0.8364 - val_loss: 0.8135 -
learning_rate: 1.0000e-04
Epoch 58/100
318/318          0s 207ms/step -
accuracy: 0.8509 - loss: 0.6600
Epoch 58: val_accuracy did not improve from 0.83923
318/318          80s 252ms/step -
accuracy: 0.8509 - loss: 0.6600 - val_accuracy: 0.8260 - val_loss: 0.8393 -
learning_rate: 1.0000e-04
Epoch 59/100
318/318          0s 209ms/step -
accuracy: 0.8556 - loss: 0.6477
Epoch 59: val_accuracy did not improve from 0.83923
318/318          81s 254ms/step -
accuracy: 0.8556 - loss: 0.6478 - val_accuracy: 0.8276 - val_loss: 0.8270 -
learning_rate: 1.0000e-04
Epoch 60/100
318/318          0s 211ms/step -
accuracy: 0.8594 - loss: 0.6423
Epoch 60: val_accuracy did not improve from 0.83923
318/318          83s 260ms/step -
accuracy: 0.8593 - loss: 0.6423 - val_accuracy: 0.8236 - val_loss: 0.8471 -
learning_rate: 1.0000e-04
Epoch 61/100
318/318          0s 217ms/step -
accuracy: 0.8510 - loss: 0.6504
Epoch 61: val_accuracy did not improve from 0.83923
318/318          84s 263ms/step -
accuracy: 0.8510 - loss: 0.6505 - val_accuracy: 0.8248 - val_loss: 0.8307 -
learning_rate: 1.0000e-04
Epoch 62/100
318/318          0s 207ms/step -
accuracy: 0.8521 - loss: 0.6355
Epoch 62: val_accuracy did not improve from 0.83923

Epoch 62: ReduceLROnPlateau reducing learning rate to 2.0000000949949027e-05.
318/318          80s 252ms/step -
accuracy: 0.8521 - loss: 0.6355 - val_accuracy: 0.8308 - val_loss: 0.8146 -
learning_rate: 1.0000e-04
Epoch 63/100
318/318          0s 210ms/step -
accuracy: 0.8536 - loss: 0.6413
Epoch 63: val_accuracy improved from 0.83923 to 0.84043, saving model to
best_cnn_from_scratch_v2.keras
318/318          128s 404ms/step -
accuracy: 0.8536 - loss: 0.6413 - val_accuracy: 0.8404 - val_loss: 0.7799 -
learning_rate: 2.0000e-05
Epoch 64/100
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318/318          0s 214ms/step -
accuracy: 0.8653 - loss: 0.5989
Epoch 64: val_accuracy did not improve from 0.84043
318/318          83s 261ms/step -
accuracy: 0.8653 - loss: 0.5990 - val_accuracy: 0.8352 - val_loss: 0.7912 -
learning_rate: 2.0000e-05
Epoch 65/100
318/318          0s 210ms/step -
accuracy: 0.8544 - loss: 0.6247
Epoch 65: val_accuracy did not improve from 0.84043
318/318          82s 258ms/step -
accuracy: 0.8544 - loss: 0.6247 - val_accuracy: 0.8360 - val_loss: 0.8041 -
learning_rate: 2.0000e-05
Epoch 66/100
318/318          0s 206ms/step -
accuracy: 0.8714 - loss: 0.5970
Epoch 66: val_accuracy did not improve from 0.84043
318/318          80s 251ms/step -
accuracy: 0.8714 - loss: 0.5971 - val_accuracy: 0.8384 - val_loss: 0.8057 -
learning_rate: 2.0000e-05
Epoch 67/100
318/318          0s 211ms/step -
accuracy: 0.8598 - loss: 0.6119
Epoch 67: val_accuracy improved from 0.84043 to 0.84164, saving model to
best_cnn_from_scratch_v2.keras
318/318          126s 396ms/step -
accuracy: 0.8598 - loss: 0.6119 - val_accuracy: 0.8416 - val_loss: 0.7928 -
learning_rate: 2.0000e-05
Epoch 68/100
318/318          0s 216ms/step -
accuracy: 0.8627 - loss: 0.6034
Epoch 68: val_accuracy did not improve from 0.84164
318/318          84s 265ms/step -
accuracy: 0.8628 - loss: 0.6034 - val_accuracy: 0.8384 - val_loss: 0.7773 -
learning_rate: 2.0000e-05
Epoch 69/100
318/318          0s 215ms/step -
accuracy: 0.8643 - loss: 0.6035
Epoch 69: val_accuracy did not improve from 0.84164
318/318          83s 261ms/step -
accuracy: 0.8643 - loss: 0.6035 - val_accuracy: 0.8368 - val_loss: 0.7876 -
learning_rate: 2.0000e-05
Epoch 70/100
318/318          0s 213ms/step -
accuracy: 0.8631 - loss: 0.6232
Epoch 70: val_accuracy improved from 0.84164 to 0.84204, saving model to
best_cnn_from_scratch_v2.keras
318/318          122s 385ms/step -
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accuracy: 0.8631 - loss: 0.6232 - val_accuracy: 0.8420 - val_loss: 0.7808 -
learning_rate: 2.0000e-05
Epoch 71/100
318/318          0s 214ms/step -
accuracy: 0.8664 - loss: 0.5938
Epoch 71: val_accuracy did not improve from 0.84204
318/318          84s 264ms/step -
accuracy: 0.8664 - loss: 0.5938 - val_accuracy: 0.8324 - val_loss: 0.7910 -
learning_rate: 2.0000e-05
Epoch 72/100
318/318          0s 212ms/step -
accuracy: 0.8728 - loss: 0.5828
Epoch 72: val_accuracy did not improve from 0.84204
318/318          82s 258ms/step -
accuracy: 0.8728 - loss: 0.5828 - val_accuracy: 0.8376 - val_loss: 0.7878 -
learning_rate: 2.0000e-05
Epoch 73/100
318/318          0s 215ms/step -
accuracy: 0.8743 - loss: 0.5822
Epoch 73: val_accuracy did not improve from 0.84204

Epoch 73: ReduceLROnPlateau reducing learning rate to 1e-05.
318/318          83s 261ms/step -
accuracy: 0.8743 - loss: 0.5822 - val_accuracy: 0.8420 - val_loss: 0.7919 -
learning_rate: 2.0000e-05
Epoch 74/100
318/318          0s 212ms/step -
accuracy: 0.8656 - loss: 0.5986
Epoch 74: val_accuracy did not improve from 0.84204
318/318          82s 259ms/step -
accuracy: 0.8656 - loss: 0.5986 - val_accuracy: 0.8364 - val_loss: 0.7694 -
learning_rate: 1.0000e-05
Epoch 75/100
318/318          0s 207ms/step -
accuracy: 0.8638 - loss: 0.6137
Epoch 75: val_accuracy improved from 0.84204 to 0.84365, saving model to
best_cnn_from_scratch_v2.keras
318/318          123s 388ms/step -
accuracy: 0.8639 - loss: 0.6137 - val_accuracy: 0.8436 - val_loss: 0.7590 -
learning_rate: 1.0000e-05
Epoch 76/100
318/318          0s 212ms/step -
accuracy: 0.8645 - loss: 0.5989
Epoch 76: val_accuracy did not improve from 0.84365
318/318          82s 258ms/step -
accuracy: 0.8645 - loss: 0.5988 - val_accuracy: 0.8396 - val_loss: 0.7733 -
learning_rate: 1.0000e-05
Epoch 77/100
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318/318          0s 213ms/step -
accuracy: 0.8631 - loss: 0.6134
Epoch 77: val_accuracy improved from 0.84365 to 0.84486, saving model to
best_cnn_from_scratch_v2.keras
318/318          138s 434ms/step -
accuracy: 0.8631 - loss: 0.6134 - val_accuracy: 0.8449 - val_loss: 0.7666 -
learning_rate: 1.0000e-05
Epoch 78/100
318/318          0s 217ms/step -
accuracy: 0.8728 - loss: 0.5791
Epoch 78: val_accuracy did not improve from 0.84486
318/318          85s 267ms/step -
accuracy: 0.8728 - loss: 0.5791 - val_accuracy: 0.8344 - val_loss: 0.8129 -
learning_rate: 1.0000e-05
Epoch 79/100
318/318          0s 216ms/step -
accuracy: 0.8707 - loss: 0.5799
Epoch 79: val_accuracy did not improve from 0.84486
318/318          83s 262ms/step -
accuracy: 0.8707 - loss: 0.5799 - val_accuracy: 0.8432 - val_loss: 0.7764 -
learning_rate: 1.0000e-05
Epoch 80/100
318/318          0s 205ms/step -
accuracy: 0.8698 - loss: 0.5841
Epoch 80: val_accuracy did not improve from 0.84486
318/318          79s 250ms/step -
accuracy: 0.8698 - loss: 0.5841 - val_accuracy: 0.8396 - val_loss: 0.7921 -
learning_rate: 1.0000e-05
Epoch 81/100
318/318          0s 206ms/step -
accuracy: 0.8627 - loss: 0.6045
Epoch 81: val_accuracy did not improve from 0.84486
318/318          81s 253ms/step -
accuracy: 0.8627 - loss: 0.6045 - val_accuracy: 0.8424 - val_loss: 0.7644 -
learning_rate: 1.0000e-05
Epoch 82/100
318/318          0s 206ms/step -
accuracy: 0.8697 - loss: 0.5915
Epoch 82: val_accuracy did not improve from 0.84486
318/318          80s 251ms/step -
accuracy: 0.8697 - loss: 0.5915 - val_accuracy: 0.8408 - val_loss: 0.8042 -
learning_rate: 1.0000e-05
Epoch 83/100
318/318          0s 209ms/step -
accuracy: 0.8647 - loss: 0.5997
Epoch 83: val_accuracy improved from 0.84486 to 0.84968, saving model to
best_cnn_from_scratch_v2.keras
318/318          125s 394ms/step -
```

```
accuracy: 0.8647 - loss: 0.5997 - val_accuracy: 0.8497 - val_loss: 0.7394 -
learning_rate: 1.0000e-05
Epoch 84/100
318/318          0s 214ms/step -
accuracy: 0.8712 - loss: 0.5850
Epoch 84: val_accuracy did not improve from 0.84968
318/318          83s 263ms/step -
accuracy: 0.8712 - loss: 0.5850 - val_accuracy: 0.8469 - val_loss: 0.7700 -
learning_rate: 1.0000e-05
Epoch 85/100
318/318          0s 215ms/step -
accuracy: 0.8752 - loss: 0.5700
Epoch 85: val_accuracy did not improve from 0.84968
318/318          83s 262ms/step -
accuracy: 0.8752 - loss: 0.5700 - val_accuracy: 0.8360 - val_loss: 0.7926 -
learning_rate: 1.0000e-05
Epoch 86/100
318/318          0s 211ms/step -
accuracy: 0.8637 - loss: 0.6084
Epoch 86: val_accuracy did not improve from 0.84968
318/318          81s 256ms/step -
accuracy: 0.8637 - loss: 0.6084 - val_accuracy: 0.8457 - val_loss: 0.7697 -
learning_rate: 1.0000e-05
Epoch 87/100
318/318          0s 219ms/step -
accuracy: 0.8718 - loss: 0.5878
Epoch 87: val_accuracy did not improve from 0.84968
318/318          84s 265ms/step -
accuracy: 0.8718 - loss: 0.5877 - val_accuracy: 0.8400 - val_loss: 0.7824 -
learning_rate: 1.0000e-05
Epoch 88/100
318/318          0s 218ms/step -
accuracy: 0.8717 - loss: 0.5597
Epoch 88: val_accuracy improved from 0.84968 to 0.85129, saving model to
best_cnn_from_scratch_v2.keras
318/318          127s 400ms/step -
accuracy: 0.8717 - loss: 0.5598 - val_accuracy: 0.8513 - val_loss: 0.7772 -
learning_rate: 1.0000e-05
Epoch 89/100
318/318          0s 215ms/step -
accuracy: 0.8644 - loss: 0.5958
Epoch 89: val_accuracy did not improve from 0.85129
318/318          84s 264ms/step -
accuracy: 0.8645 - loss: 0.5958 - val_accuracy: 0.8477 - val_loss: 0.7827 -
learning_rate: 1.0000e-05
Epoch 90/100
318/318          0s 217ms/step -
accuracy: 0.8730 - loss: 0.5816
```

```
Epoch 90: val_accuracy did not improve from 0.85129
318/318           84s 266ms/step -
accuracy: 0.8730 - loss: 0.5816 - val_accuracy: 0.8477 - val_loss: 0.7590 -
learning_rate: 1.0000e-05
Epoch 91/100
318/318           0s 211ms/step -
accuracy: 0.8673 - loss: 0.5989
Epoch 91: val_accuracy did not improve from 0.85129
318/318           82s 257ms/step -
accuracy: 0.8673 - loss: 0.5989 - val_accuracy: 0.8428 - val_loss: 0.7551 -
learning_rate: 1.0000e-05
Epoch 92/100
318/318           0s 215ms/step -
accuracy: 0.8691 - loss: 0.5972
Epoch 92: val_accuracy did not improve from 0.85129
318/318           83s 262ms/step -
accuracy: 0.8691 - loss: 0.5971 - val_accuracy: 0.8400 - val_loss: 0.7762 -
learning_rate: 1.0000e-05
Epoch 93/100
318/318           0s 213ms/step -
accuracy: 0.8774 - loss: 0.5720
Epoch 93: val_accuracy did not improve from 0.85129
318/318           82s 258ms/step -
accuracy: 0.8774 - loss: 0.5721 - val_accuracy: 0.8396 - val_loss: 0.7793 -
learning_rate: 1.0000e-05
Epoch 94/100
318/318           0s 211ms/step -
accuracy: 0.8689 - loss: 0.5767
Epoch 94: val_accuracy did not improve from 0.85129
318/318           82s 257ms/step -
accuracy: 0.8690 - loss: 0.5767 - val_accuracy: 0.8493 - val_loss: 0.7525 -
learning_rate: 1.0000e-05
Epoch 95/100
318/318           0s 216ms/step -
accuracy: 0.8740 - loss: 0.5640
Epoch 95: val_accuracy did not improve from 0.85129
318/318           83s 262ms/step -
accuracy: 0.8740 - loss: 0.5640 - val_accuracy: 0.8324 - val_loss: 0.7875 -
learning_rate: 1.0000e-05
Epoch 96/100
318/318           0s 215ms/step -
accuracy: 0.8708 - loss: 0.5739
Epoch 96: val_accuracy did not improve from 0.85129
318/318           89s 279ms/step -
accuracy: 0.8708 - loss: 0.5739 - val_accuracy: 0.8445 - val_loss: 0.7917 -
learning_rate: 1.0000e-05
Epoch 97/100
318/318           0s 210ms/step -
```

```

accuracy: 0.8747 - loss: 0.5643
Epoch 97: val_accuracy improved from 0.85129 to 0.85932, saving model to
best_cnn_from_scratch_v2.keras
318/318           137s 430ms/step -
accuracy: 0.8747 - loss: 0.5644 - val_accuracy: 0.8593 - val_loss: 0.7337 -
learning_rate: 1.0000e-05
Epoch 98/100
318/318           0s 214ms/step -
accuracy: 0.8696 - loss: 0.5673
Epoch 98: val_accuracy did not improve from 0.85932
318/318           83s 260ms/step -
accuracy: 0.8696 - loss: 0.5673 - val_accuracy: 0.8493 - val_loss: 0.7381 -
learning_rate: 1.0000e-05
Epoch 99/100
318/318           0s 210ms/step -
accuracy: 0.8762 - loss: 0.5643
Epoch 99: val_accuracy did not improve from 0.85932
318/318           81s 255ms/step -
accuracy: 0.8762 - loss: 0.5643 - val_accuracy: 0.8408 - val_loss: 0.7682 -
learning_rate: 1.0000e-05
Epoch 100/100
318/318           0s 210ms/step -
accuracy: 0.8799 - loss: 0.5568
Epoch 100: val_accuracy did not improve from 0.85932
318/318           82s 256ms/step -
accuracy: 0.8799 - loss: 0.5568 - val_accuracy: 0.8465 - val_loss: 0.7522 -
learning_rate: 1.0000e-05

--- Entrenamiento Finalizado ---

```

2.2.- MONITORIZACIÓN DEL PROCESO DE ENTRENAMIENTO PARA LA TOMA DE DECISIONES

```
[ ]: import json

# Define the filename
history_filename = 'history_v2.json'

# Save the history object to a JSON file
with open(history_filename, 'w') as f:
    json.dump(history_v2.history, f)

print(f"Training history saved to {history_filename}")
```

Training history saved to history_v2.json

```
[ ]: import matplotlib.pyplot as plt
```

```

# -----
# 1. INSERTA TUS DATOS AQUÍ
# Copia y pega tus listas de números dentro de los corchetes
# -----


# Lista de Accuracy de Entrenamiento (100 datos)
train_acc = history_v2.history["accuracy"]

# Lista de Accuracy de Validación (100 datos)
val_acc = history_v2.history["val_accuracy"]

# Generamos la lista de épocas (del 1 al 100)
epochs = range(1, 101)

# -----
# 2. GENERACIÓN DEL GRÁFICO
# -----


plt.figure(figsize=(10, 6)) # Tamaño del gráfico

# Dibujar las líneas
plt.plot(epochs, train_acc, 'b-', label='Training Accuracy', linewidth=2)
plt.plot(epochs, val_acc, 'r--', label='Validation Accuracy', linewidth=2)

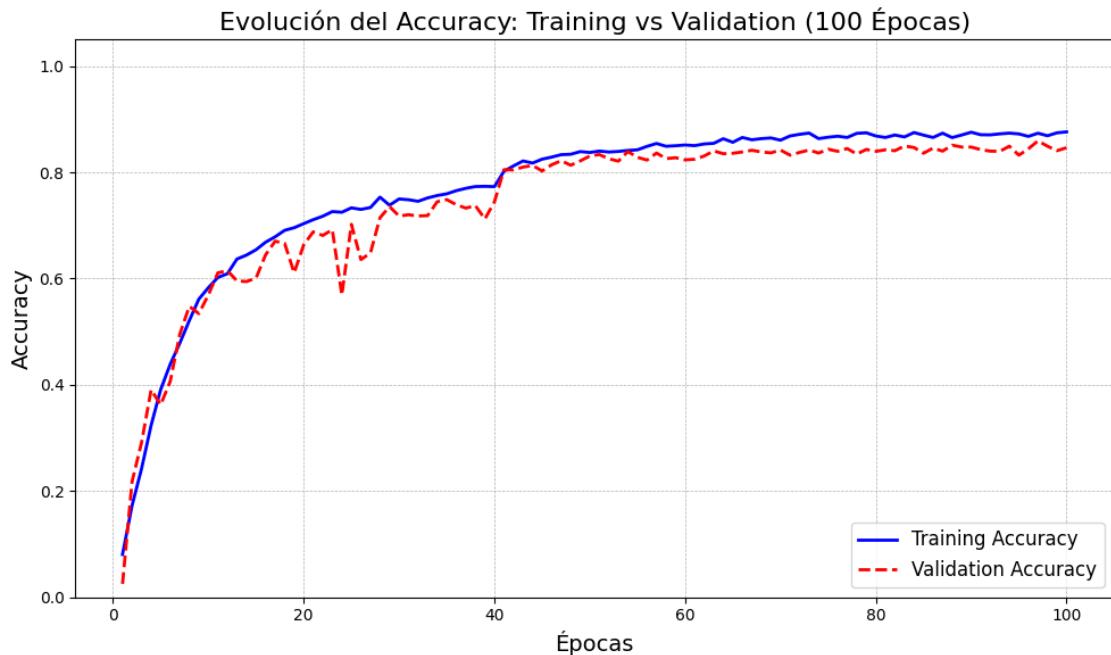
# Títulos y Etiquetas
plt.title('Evolución del Accuracy: Training vs Validation (100 Épocas)', fontsize=16)
plt.xlabel('Épocas', fontsize=14)
plt.ylabel('Accuracy', fontsize=14)

# Añadir leyenda y rejilla
plt.legend(loc='lower right', fontsize=12)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)

# Ajustar límites (Opcional: asumiendo accuracy de 0 a 1)
plt.ylim(0, 1.05)

# Mostrar gráfico
plt.tight_layout()
plt.show()

```



```
[ ]: train_acc =history_v2.history["loss"]
val_acc = history_v2.history["val_loss"]

# Generamos la lista de épocas (del 1 al 100)
epochs = range(1, 101)

# -----
# 2. GENERACIÓN DEL GRÁFICO
# -----


plt.figure(figsize=(10, 6)) # Tamaño del gráfico

# Dibujar las líneas
plt.plot(epochs, train_acc, 'b-', label='Training loss', linewidth=2)
plt.plot(epochs, val_acc, 'r--', label='Validation loss', linewidth=2)

# Títulos y Etiquetas
plt.title('Evolución del loss: Training vs Validation (100 Épocas)', fontweight='bold', fontsize=16)
plt.xlabel('Épocas', fontsize=14)
plt.ylabel('Accuracy', fontsize=14)

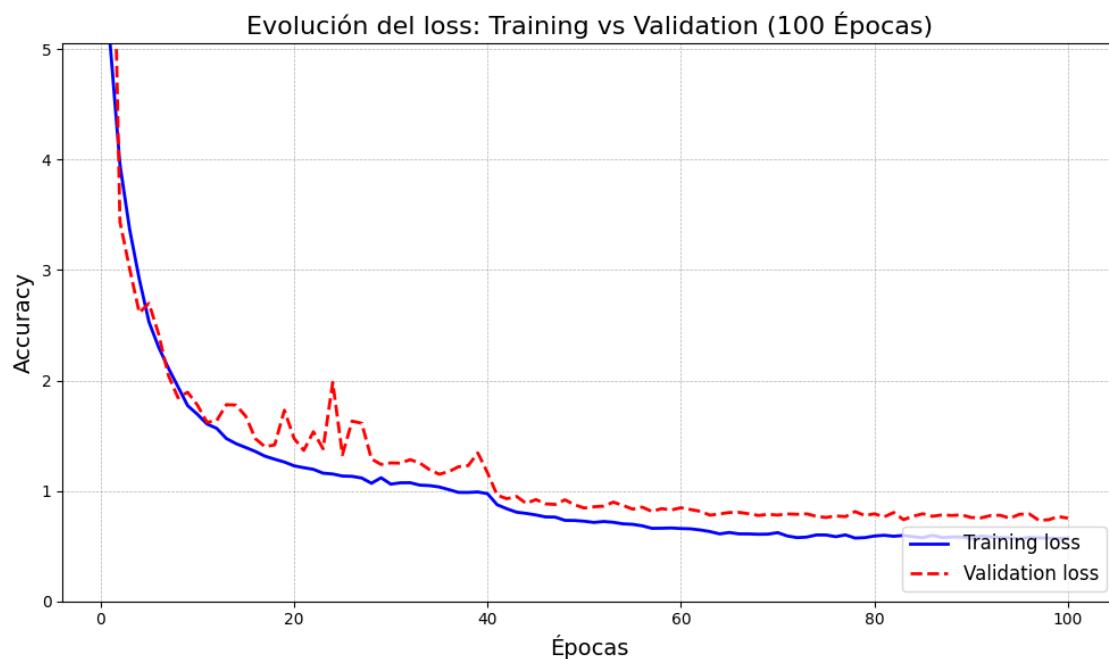
# Añadir leyenda y rejilla
plt.legend(loc='lower right', fontsize=12)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
```

```

# Ajustar límites (Opcional: asumiendo accuracy de 0 a 1)
plt.ylim(0, 5.05)

# Mostrar gráfico
plt.tight_layout()
plt.show()

```



2.3.- EVALUACIÓN DEL MODELO PREDICTIVO Y PLANTEAMIENTO DE LA SIGUIENTE PRUEBA EXPERIMENTAL

El Modelo v2 al final del entrenamiento muestra un rendimiento significativamente mejor que el Modelo v1, ya que logró una mayor precisión de validación, aunque todavía presenta sobreajuste. El Modelo v2 logró un excelente trabajo al controlar el sobreajuste y llevar la precisión a casi el 86%. Sin embargo, la red está estancada en esta arquitectura porque, a pesar de seguir entrenando por más épocas y usar la tasa de aprendizaje más baja, las métricas de validación (val_accuracy y val_loss) dejaron de mejorar consistentemente.

Tabla comparativa del modelo V2 con respecto al V1:

Característica

Modelo v1

Modelo v2

Beneficio de v2

Batch Normalization (BN) en Bloques Conv

Solo al final del Flatten

Añadido después de cada capa Conv2D.

Estabilidad y Convergencia: Acelera el entrenamiento y estabiliza el flujo de gradientes en la red profunda.

Capacidad de Capa Densa

256 neuronas

1024 neuronas.

Mayor Capacidad de Aprendizaje: Permite a la red consolidar las 256 características convolucionales en representaciones mucho más complejas antes de la clasificación final de 100 clases.

Dropout

Ninguno en el cuerpo de la CNN.

Añadido Dropout(0.4) después del Bloque 3 y Dropout(0.6) después de la Capa Densa (1024).

Mejor Regularización: Combate el sobreajuste de manera más agresiva, esencial tras incrementar la capacidad (1024 neuronas). El alto dropout (0.6) evita que la capa densa memorice los datos.

3. MODELO 3

3.1.- DESARROLLO DE LA ARQUITECTURA DE RED NEURONAL Y ENTRENAMIENTO DE LA SOLUCIÓN

```
[ ]: from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, ↴
          ↴Dropout, BatchNormalization
      from tensorflow.keras.optimizers import RMSprop
      from tensorflow.keras.regularizers import l2
      import numpy as np
      from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, ↴
          ↴ReduceLROnPlateau

# Aumentar filtros, reducir regularización y hacer la red más profunda

print("Definiendo la arquitectura CNN v3 (Desde Cero, Mejorada)...")

model_v3 = Sequential([
    # Bloque 1: Mayor número de filtros
    Conv2D(64, (3, 3), activation='relu', kernel_regularizer=l2(0.0001), ↴
        ↴input_shape=(IMG_SIZE, IMG_SIZE, 3)),
    BatchNormalization(),
    MaxPooling2D((2, 2)),

    # Bloque 2
    Conv2D(128, (3, 3), activation='relu', kernel_regularizer=l2(0.0001)),
    BatchNormalization(),
```

```

    MaxPooling2D((2, 2)),

    # Bloque 3: Mayor profundidad
    Conv2D(256, (3, 3), activation='relu', kernel_regularizer=l2(0.0005)),
    BatchNormalization(),
    MaxPooling2D((2, 2)),

    # Bloque 4: Máxima capacidad de extracción de características
    Conv2D(512, (3, 3), activation='relu', kernel_regularizer=l2(0.0005)),
    BatchNormalization(),
    MaxPooling2D((2, 2)), # Esto reduce el tensor a un tamaño manejable

    # Aplanamiento y Capas Densely Connected
    Flatten(),
    # Capa Densa más grande
    Dense(1024, activation='relu', kernel_regularizer=l2(0.0005)),
    BatchNormalization(),
    Dropout(0.5), # Reducir el Dropout del 0.7 al 0.5

    # Capa de Salida
    Dense(NUM_CLASSES, activation='softmax')
)

# Compilación
model_v3.compile(
    # RMSprop a menudo funciona mejor con redes más profundas que Adam
    optimizer=RMSprop(learning_rate=0.0001),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

model_v3.summary()

# --- 2. Entrenamiento con Callbacks Avanzados ---

# Recalcular pasos por época (asegurando que no se corte el entrenamiento)
STEPS_PER_EPOCH = int(np.ceil(train_generator.samples / BATCH_SIZE))
VALIDATION_STEPS = int(np.ceil(validation_generator.samples / BATCH_SIZE))
EPOCHS = 100 # Aumentamos las épocas, EarlyStopping actuará como límite

# Definición de Callbacks
early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=10,
    min_delta=0.001,
    restore_best_weights=True
)

```

```

checkpoint_path = 'best_cnn_from_scratch_v2.keras'
model_checkpoint = ModelCheckpoint(
    checkpoint_path,
    monitor='val_accuracy',
    save_best_only=True,
    mode='max',
    verbose=1
)

# Estrategia de Decaimiento de Tasa de Aprendizaje
reduce_lr = ReduceLROnPlateau(
    monitor='val_loss',
    factor=0.2,           # Reduce la LR a 1/5
    patience=5,          # Espera 5 épocas sin mejora
    min_lr=0.00001,
    verbose=1
)

print(f"\nIniciando Entrenamiento para {EPOCHS} épocas...")
print(f"Pasos por Época (Train): {STEPS_PER_EPOCH}, Pasos (Validation):"
     f"{VALIDATION_STEPS}")

```

Definiendo la arquitectura CNN v3 (Desde Cero, Mejorada)...

```

/usr/local/lib/python3.12/dist-
packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
    super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model: "sequential_2"

```

Layer (type)	Output Shape	Param #
conv2d_7 (Conv2D)	(None, 126, 126, 64)	1,792
batch_normalization_9 (BatchNormalization)	(None, 126, 126, 64)	256
max_pooling2d_7 (MaxPooling2D)	(None, 63, 63, 64)	0
conv2d_8 (Conv2D)	(None, 61, 61, 128)	73,856
batch_normalization_10 (BatchNormalization)	(None, 61, 61, 128)	512

max_pooling2d_8 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_9 (Conv2D)	(None, 28, 28, 256)	295,168
batch_normalization_11 (BatchNormalization)	(None, 28, 28, 256)	1,024
max_pooling2d_9 (MaxPooling2D)	(None, 14, 14, 256)	0
conv2d_10 (Conv2D)	(None, 12, 12, 512)	1,180,160
batch_normalization_12 (BatchNormalization)	(None, 12, 12, 512)	2,048
max_pooling2d_10 (MaxPooling2D)	(None, 6, 6, 512)	0
flatten_2 (Flatten)	(None, 18432)	0
dense_4 (Dense)	(None, 1024)	18,875,392
batch_normalization_13 (BatchNormalization)	(None, 1024)	4,096
dropout_3 (Dropout)	(None, 1024)	0
dense_5 (Dense)	(None, 100)	102,500

Total params: 20,536,804 (78.34 MB)

Trainable params: 20,532,836 (78.33 MB)

Non-trainable params: 3,968 (15.50 KB)

Iniciando Entrenamiento para 100 épocas...
Pasos por Época (Train): 318, Pasos (Validation): 78

```
[ ]: history_v3 = model_v3.fit(
    train_generator,
    steps_per_epoch=STEPS_PER_EPOCH,
    epochs=EPOCHS,
    validation_data=validation_generator,
    validation_steps=VALIDATION_STEPS,
```

```

    callbacks=[early_stopping, model_checkpoint, reduce_lr], # Se usan los 3 callbacks
    verbose=1
)

print("\n--- Entrenamiento Finalizado ---")

```

Epoch 1/100
318/318 0s 226ms/step -
accuracy: 0.0636 - loss: 6.3051
Epoch 1: val_accuracy improved from -inf to 0.01447, saving model to
best_cnn_from_scratch_v2.keras
318/318 100s 290ms/step -
accuracy: 0.0637 - loss: 6.3035 - val_accuracy: 0.0145 - val_loss: 10.8435 -
learning_rate: 1.0000e-04
Epoch 2/100
318/318 0s 216ms/step -
accuracy: 0.1713 - loss: 5.0267
Epoch 2: val_accuracy improved from 0.01447 to 0.22629, saving model to
best_cnn_from_scratch_v2.keras
318/318 85s 266ms/step -
accuracy: 0.1714 - loss: 5.0263 - val_accuracy: 0.2263 - val_loss: 4.5449 -
learning_rate: 1.0000e-04
Epoch 3/100
318/318 0s 219ms/step -
accuracy: 0.2537 - loss: 4.4565
Epoch 3: val_accuracy improved from 0.22629 to 0.35490, saving model to
best_cnn_from_scratch_v2.keras
318/318 86s 269ms/step -
accuracy: 0.2538 - loss: 4.4563 - val_accuracy: 0.3549 - val_loss: 3.8292 -
learning_rate: 1.0000e-04
Epoch 4/100
318/318 0s 213ms/step -
accuracy: 0.3153 - loss: 4.0708
Epoch 4: val_accuracy improved from 0.35490 to 0.41640, saving model to
best_cnn_from_scratch_v2.keras
318/318 141s 266ms/step -
accuracy: 0.3153 - loss: 4.0707 - val_accuracy: 0.4164 - val_loss: 3.5949 -
learning_rate: 1.0000e-04
Epoch 5/100
318/318 0s 214ms/step -
accuracy: 0.3799 - loss: 3.7575
Epoch 5: val_accuracy improved from 0.41640 to 0.43891, saving model to
best_cnn_from_scratch_v2.keras
318/318 85s 268ms/step -
accuracy: 0.3799 - loss: 3.7575 - val_accuracy: 0.4389 - val_loss: 3.5132 -
learning_rate: 1.0000e-04
Epoch 6/100

```
318/318          0s 216ms/step -
accuracy: 0.4083 - loss: 3.5728
Epoch 6: val_accuracy improved from 0.43891 to 0.49437, saving model to
best_cnn_from_scratch_v2.keras
318/318          86s 270ms/step -
accuracy: 0.4083 - loss: 3.5726 - val_accuracy: 0.4944 - val_loss: 3.2303 -
learning_rate: 1.0000e-04
Epoch 7/100
318/318          0s 215ms/step -
accuracy: 0.4583 - loss: 3.3664
Epoch 7: val_accuracy improved from 0.49437 to 0.52130, saving model to
best_cnn_from_scratch_v2.keras
318/318          85s 268ms/step -
accuracy: 0.4584 - loss: 3.3662 - val_accuracy: 0.5213 - val_loss: 3.0908 -
learning_rate: 1.0000e-04
Epoch 8/100
318/318          0s 215ms/step -
accuracy: 0.5097 - loss: 3.1261
Epoch 8: val_accuracy improved from 0.52130 to 0.55506, saving model to
best_cnn_from_scratch_v2.keras
318/318          85s 267ms/step -
accuracy: 0.5097 - loss: 3.1261 - val_accuracy: 0.5551 - val_loss: 2.8969 -
learning_rate: 1.0000e-04
Epoch 9/100
318/318          0s 214ms/step -
accuracy: 0.5288 - loss: 3.0314
Epoch 9: val_accuracy improved from 0.55506 to 0.57677, saving model to
best_cnn_from_scratch_v2.keras
318/318          84s 264ms/step -
accuracy: 0.5288 - loss: 3.0314 - val_accuracy: 0.5768 - val_loss: 2.8680 -
learning_rate: 1.0000e-04
Epoch 10/100
318/318          0s 226ms/step -
accuracy: 0.5666 - loss: 2.8715
Epoch 10: val_accuracy improved from 0.57677 to 0.59285, saving model to
best_cnn_from_scratch_v2.keras
318/318          90s 283ms/step -
accuracy: 0.5665 - loss: 2.8715 - val_accuracy: 0.5928 - val_loss: 2.7673 -
learning_rate: 1.0000e-04
Epoch 11/100
318/318          0s 212ms/step -
accuracy: 0.5891 - loss: 2.7522
Epoch 11: val_accuracy improved from 0.59285 to 0.61937, saving model to
best_cnn_from_scratch_v2.keras
318/318          84s 263ms/step -
accuracy: 0.5891 - loss: 2.7522 - val_accuracy: 0.6194 - val_loss: 2.6581 -
learning_rate: 1.0000e-04
Epoch 12/100
```

```
318/318          0s 208ms/step -
accuracy: 0.6044 - loss: 2.6878
Epoch 12: val_accuracy improved from 0.61937 to 0.63786, saving model to
best_cnn_from_scratch_v2.keras
318/318          83s 260ms/step -
accuracy: 0.6044 - loss: 2.6877 - val_accuracy: 0.6379 - val_loss: 2.5954 -
learning_rate: 1.0000e-04
Epoch 13/100
318/318          0s 218ms/step -
accuracy: 0.6247 - loss: 2.5851
Epoch 13: val_accuracy improved from 0.63786 to 0.65273, saving model to
best_cnn_from_scratch_v2.keras
318/318          85s 268ms/step -
accuracy: 0.6247 - loss: 2.5851 - val_accuracy: 0.6527 - val_loss: 2.4855 -
learning_rate: 1.0000e-04
Epoch 14/100
318/318          0s 216ms/step -
accuracy: 0.6540 - loss: 2.4807
Epoch 14: val_accuracy improved from 0.65273 to 0.65555, saving model to
best_cnn_from_scratch_v2.keras
318/318          85s 267ms/step -
accuracy: 0.6539 - loss: 2.4807 - val_accuracy: 0.6555 - val_loss: 2.4789 -
learning_rate: 1.0000e-04
Epoch 15/100
318/318          0s 214ms/step -
accuracy: 0.6703 - loss: 2.3617
Epoch 15: val_accuracy did not improve from 0.65555
318/318          140s 261ms/step -
accuracy: 0.6703 - loss: 2.3618 - val_accuracy: 0.6547 - val_loss: 2.4754 -
learning_rate: 1.0000e-04
Epoch 16/100
318/318          0s 213ms/step -
accuracy: 0.6832 - loss: 2.3094
Epoch 16: val_accuracy improved from 0.65555 to 0.67162, saving model to
best_cnn_from_scratch_v2.keras
318/318          89s 279ms/step -
accuracy: 0.6832 - loss: 2.3094 - val_accuracy: 0.6716 - val_loss: 2.3565 -
learning_rate: 1.0000e-04
Epoch 17/100
318/318          0s 214ms/step -
accuracy: 0.6949 - loss: 2.2577
Epoch 17: val_accuracy improved from 0.67162 to 0.67765, saving model to
best_cnn_from_scratch_v2.keras
318/318          84s 263ms/step -
accuracy: 0.6949 - loss: 2.2576 - val_accuracy: 0.6777 - val_loss: 2.3420 -
learning_rate: 1.0000e-04
Epoch 18/100
318/318          0s 250ms/step -
```

```
accuracy: 0.7157 - loss: 2.1946
Epoch 18: val_accuracy improved from 0.67765 to 0.69333, saving model to
best_cnn_from_scratch_v2.keras
318/318          95s 299ms/step -
accuracy: 0.7157 - loss: 2.1946 - val_accuracy: 0.6933 - val_loss: 2.2507 -
learning_rate: 1.0000e-04
Epoch 19/100
318/318          0s 217ms/step -
accuracy: 0.7355 - loss: 2.0890
Epoch 19: val_accuracy improved from 0.69333 to 0.71222, saving model to
best_cnn_from_scratch_v2.keras
318/318          86s 269ms/step -
accuracy: 0.7355 - loss: 2.0890 - val_accuracy: 0.7122 - val_loss: 2.1582 -
learning_rate: 1.0000e-04
Epoch 20/100
318/318          0s 216ms/step -
accuracy: 0.7385 - loss: 2.0449
Epoch 20: val_accuracy improved from 0.71222 to 0.72026, saving model to
best_cnn_from_scratch_v2.keras
318/318          85s 266ms/step -
accuracy: 0.7385 - loss: 2.0449 - val_accuracy: 0.7203 - val_loss: 2.1604 -
learning_rate: 1.0000e-04
Epoch 21/100
318/318          0s 213ms/step -
accuracy: 0.7393 - loss: 2.0239
Epoch 21: val_accuracy did not improve from 0.72026
318/318          83s 259ms/step -
accuracy: 0.7393 - loss: 2.0239 - val_accuracy: 0.6965 - val_loss: 2.1755 -
learning_rate: 1.0000e-04
Epoch 22/100
318/318          0s 215ms/step -
accuracy: 0.7544 - loss: 1.9509
Epoch 22: val_accuracy improved from 0.72026 to 0.73312, saving model to
best_cnn_from_scratch_v2.keras
318/318          89s 281ms/step -
accuracy: 0.7545 - loss: 1.9509 - val_accuracy: 0.7331 - val_loss: 2.0927 -
learning_rate: 1.0000e-04
Epoch 23/100
318/318          0s 215ms/step -
accuracy: 0.7647 - loss: 1.9098
Epoch 23: val_accuracy improved from 0.73312 to 0.74598, saving model to
best_cnn_from_scratch_v2.keras
318/318          89s 281ms/step -
accuracy: 0.7647 - loss: 1.9098 - val_accuracy: 0.7460 - val_loss: 2.0129 -
learning_rate: 1.0000e-04
Epoch 24/100
318/318          0s 213ms/step -
accuracy: 0.7730 - loss: 1.8378
```

```
Epoch 24: val_accuracy did not improve from 0.74598
318/318           82s 259ms/step -
accuracy: 0.7730 - loss: 1.8379 - val_accuracy: 0.7420 - val_loss: 1.9955 -
learning_rate: 1.0000e-04
Epoch 25/100
318/318           0s 213ms/step -
accuracy: 0.7796 - loss: 1.8059
Epoch 25: val_accuracy did not improve from 0.74598
318/318           82s 259ms/step -
accuracy: 0.7796 - loss: 1.8059 - val_accuracy: 0.7452 - val_loss: 2.0249 -
learning_rate: 1.0000e-04
Epoch 26/100
318/318           0s 218ms/step -
accuracy: 0.7917 - loss: 1.7441
Epoch 26: val_accuracy improved from 0.74598 to 0.75844, saving model to
best_cnn_from_scratch_v2.keras
318/318           91s 286ms/step -
accuracy: 0.7917 - loss: 1.7441 - val_accuracy: 0.7584 - val_loss: 1.8999 -
learning_rate: 1.0000e-04
Epoch 27/100
318/318           0s 216ms/step -
accuracy: 0.7985 - loss: 1.7123
Epoch 27: val_accuracy improved from 0.75844 to 0.76809, saving model to
best_cnn_from_scratch_v2.keras
318/318           84s 265ms/step -
accuracy: 0.7985 - loss: 1.7123 - val_accuracy: 0.7681 - val_loss: 1.8813 -
learning_rate: 1.0000e-04
Epoch 28/100
318/318           0s 217ms/step -
accuracy: 0.7912 - loss: 1.7133
Epoch 28: val_accuracy improved from 0.76809 to 0.76969, saving model to
best_cnn_from_scratch_v2.keras
318/318           90s 283ms/step -
accuracy: 0.7912 - loss: 1.7133 - val_accuracy: 0.7697 - val_loss: 1.8279 -
learning_rate: 1.0000e-04
Epoch 29/100
318/318           0s 211ms/step -
accuracy: 0.8096 - loss: 1.6280
Epoch 29: val_accuracy did not improve from 0.76969
318/318           82s 256ms/step -
accuracy: 0.8096 - loss: 1.6281 - val_accuracy: 0.7552 - val_loss: 1.8825 -
learning_rate: 1.0000e-04
Epoch 30/100
318/318           0s 213ms/step -
accuracy: 0.8046 - loss: 1.6344
Epoch 30: val_accuracy improved from 0.76969 to 0.77211, saving model to
best_cnn_from_scratch_v2.keras
318/318           88s 277ms/step -
```

```
accuracy: 0.8046 - loss: 1.6343 - val_accuracy: 0.7721 - val_loss: 1.7878 -
learning_rate: 1.0000e-04
Epoch 31/100
318/318          0s 218ms/step -
accuracy: 0.8101 - loss: 1.5880
Epoch 31: val_accuracy did not improve from 0.77211
318/318          84s 265ms/step -
accuracy: 0.8101 - loss: 1.5880 - val_accuracy: 0.7572 - val_loss: 1.8412 -
learning_rate: 1.0000e-04
Epoch 32/100
318/318          0s 212ms/step -
accuracy: 0.8174 - loss: 1.5531
Epoch 32: val_accuracy did not improve from 0.77211
318/318          82s 258ms/step -
accuracy: 0.8174 - loss: 1.5532 - val_accuracy: 0.7713 - val_loss: 1.7952 -
learning_rate: 1.0000e-04
Epoch 33/100
318/318          0s 209ms/step -
accuracy: 0.8266 - loss: 1.5183
Epoch 33: val_accuracy improved from 0.77211 to 0.78497, saving model to
best_cnn_from_scratch_v2.keras
318/318          87s 275ms/step -
accuracy: 0.8266 - loss: 1.5183 - val_accuracy: 0.7850 - val_loss: 1.7402 -
learning_rate: 1.0000e-04
Epoch 34/100
318/318          0s 217ms/step -
accuracy: 0.8280 - loss: 1.4975
Epoch 34: val_accuracy improved from 0.78497 to 0.78577, saving model to
best_cnn_from_scratch_v2.keras
318/318          85s 267ms/step -
accuracy: 0.8280 - loss: 1.4975 - val_accuracy: 0.7858 - val_loss: 1.7040 -
learning_rate: 1.0000e-04
Epoch 35/100
318/318          0s 215ms/step -
accuracy: 0.8284 - loss: 1.4769
Epoch 35: val_accuracy improved from 0.78577 to 0.78778, saving model to
best_cnn_from_scratch_v2.keras
318/318          90s 282ms/step -
accuracy: 0.8284 - loss: 1.4769 - val_accuracy: 0.7878 - val_loss: 1.6726 -
learning_rate: 1.0000e-04
Epoch 36/100
318/318          0s 213ms/step -
accuracy: 0.8352 - loss: 1.4253
Epoch 36: val_accuracy did not improve from 0.78778
318/318          82s 259ms/step -
accuracy: 0.8352 - loss: 1.4253 - val_accuracy: 0.7749 - val_loss: 1.7211 -
learning_rate: 1.0000e-04
Epoch 37/100
```

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318/318          0s 214ms/step -
accuracy: 0.8359 - loss: 1.4203
Epoch 37: val_accuracy did not improve from 0.78778
318/318          83s 261ms/step -
accuracy: 0.8359 - loss: 1.4202 - val_accuracy: 0.7850 - val_loss: 1.6387 -
learning_rate: 1.0000e-04
Epoch 38/100
318/318          0s 211ms/step -
accuracy: 0.8423 - loss: 1.3816
Epoch 38: val_accuracy did not improve from 0.78778
318/318          83s 261ms/step -
accuracy: 0.8423 - loss: 1.3816 - val_accuracy: 0.7830 - val_loss: 1.6635 -
learning_rate: 1.0000e-04
Epoch 39/100
318/318          0s 213ms/step -
accuracy: 0.8395 - loss: 1.3699
Epoch 39: val_accuracy improved from 0.78778 to 0.79582, saving model to
best_cnn_from_scratch_v2.keras
318/318          89s 279ms/step -
accuracy: 0.8395 - loss: 1.3699 - val_accuracy: 0.7958 - val_loss: 1.6057 -
learning_rate: 1.0000e-04
Epoch 40/100
318/318          0s 212ms/step -
accuracy: 0.8490 - loss: 1.3287
Epoch 40: val_accuracy did not improve from 0.79582
318/318          82s 259ms/step -
accuracy: 0.8490 - loss: 1.3287 - val_accuracy: 0.7934 - val_loss: 1.5907 -
learning_rate: 1.0000e-04
Epoch 41/100
318/318          0s 208ms/step -
accuracy: 0.8567 - loss: 1.2906
Epoch 41: val_accuracy improved from 0.79582 to 0.79904, saving model to
best_cnn_from_scratch_v2.keras
318/318          87s 272ms/step -
accuracy: 0.8567 - loss: 1.2906 - val_accuracy: 0.7990 - val_loss: 1.6148 -
learning_rate: 1.0000e-04
Epoch 42/100
318/318          0s 209ms/step -
accuracy: 0.8543 - loss: 1.2939
Epoch 42: val_accuracy did not improve from 0.79904
318/318          81s 255ms/step -
accuracy: 0.8543 - loss: 1.2939 - val_accuracy: 0.7962 - val_loss: 1.5880 -
learning_rate: 1.0000e-04
Epoch 43/100
318/318          0s 206ms/step -
accuracy: 0.8615 - loss: 1.2768
Epoch 43: val_accuracy did not improve from 0.79904
318/318          80s 253ms/step -
```

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accuracy: 0.8614 - loss: 1.2768 - val_accuracy: 0.7914 - val_loss: 1.5675 -
learning_rate: 1.0000e-04
Epoch 44/100
318/318          0s 206ms/step -
accuracy: 0.8684 - loss: 1.2272
Epoch 44: val_accuracy improved from 0.79904 to 0.81230, saving model to
best_cnn_from_scratch_v2.keras
318/318          86s 272ms/step -
accuracy: 0.8684 - loss: 1.2273 - val_accuracy: 0.8123 - val_loss: 1.5114 -
learning_rate: 1.0000e-04
Epoch 45/100
318/318          0s 209ms/step -
accuracy: 0.8660 - loss: 1.2253
Epoch 45: val_accuracy did not improve from 0.81230
318/318          81s 256ms/step -
accuracy: 0.8660 - loss: 1.2253 - val_accuracy: 0.7826 - val_loss: 1.5718 -
learning_rate: 1.0000e-04
Epoch 46/100
318/318          0s 214ms/step -
accuracy: 0.8666 - loss: 1.2089
Epoch 46: val_accuracy did not improve from 0.81230
318/318          84s 265ms/step -
accuracy: 0.8666 - loss: 1.2090 - val_accuracy: 0.8010 - val_loss: 1.5078 -
learning_rate: 1.0000e-04
Epoch 47/100
318/318          0s 210ms/step -
accuracy: 0.8632 - loss: 1.1953
Epoch 47: val_accuracy improved from 0.81230 to 0.81310, saving model to
best_cnn_from_scratch_v2.keras
318/318          87s 274ms/step -
accuracy: 0.8632 - loss: 1.1953 - val_accuracy: 0.8131 - val_loss: 1.4816 -
learning_rate: 1.0000e-04
Epoch 48/100
318/318          0s 211ms/step -
accuracy: 0.8620 - loss: 1.1867
Epoch 48: val_accuracy did not improve from 0.81310
318/318          82s 258ms/step -
accuracy: 0.8620 - loss: 1.1866 - val_accuracy: 0.8083 - val_loss: 1.4824 -
learning_rate: 1.0000e-04
Epoch 49/100
318/318          0s 216ms/step -
accuracy: 0.8721 - loss: 1.1620
Epoch 49: val_accuracy did not improve from 0.81310
318/318          83s 262ms/step -
accuracy: 0.8721 - loss: 1.1620 - val_accuracy: 0.8018 - val_loss: 1.5016 -
learning_rate: 1.0000e-04
Epoch 50/100
318/318          0s 211ms/step -
```

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accuracy: 0.8703 - loss: 1.1536
Epoch 50: val_accuracy improved from 0.81310 to 0.81471, saving model to
best_cnn_from_scratch_v2.keras
318/318          84s 263ms/step -
accuracy: 0.8703 - loss: 1.1536 - val_accuracy: 0.8147 - val_loss: 1.4248 -
learning_rate: 1.0000e-04
Epoch 51/100
318/318          0s 213ms/step -
accuracy: 0.8692 - loss: 1.1190
Epoch 51: val_accuracy did not improve from 0.81471
318/318          141s 262ms/step -
accuracy: 0.8692 - loss: 1.1190 - val_accuracy: 0.8095 - val_loss: 1.4533 -
learning_rate: 1.0000e-04
Epoch 52/100
318/318          0s 214ms/step -
accuracy: 0.8753 - loss: 1.1254
Epoch 52: val_accuracy did not improve from 0.81471
318/318          83s 260ms/step -
accuracy: 0.8753 - loss: 1.1254 - val_accuracy: 0.7942 - val_loss: 1.4707 -
learning_rate: 1.0000e-04
Epoch 53/100
318/318          0s 216ms/step -
accuracy: 0.8762 - loss: 1.0960
Epoch 53: val_accuracy did not improve from 0.81471
318/318          84s 263ms/step -
accuracy: 0.8762 - loss: 1.0960 - val_accuracy: 0.8139 - val_loss: 1.4402 -
learning_rate: 1.0000e-04
Epoch 54/100
318/318          0s 215ms/step -
accuracy: 0.8849 - loss: 1.0669
Epoch 54: val_accuracy did not improve from 0.81471
318/318          83s 260ms/step -
accuracy: 0.8849 - loss: 1.0669 - val_accuracy: 0.7822 - val_loss: 1.4966 -
learning_rate: 1.0000e-04
Epoch 55/100
318/318          0s 211ms/step -
accuracy: 0.8825 - loss: 1.0730
Epoch 55: val_accuracy did not improve from 0.81471
318/318          83s 260ms/step -
accuracy: 0.8825 - loss: 1.0730 - val_accuracy: 0.8063 - val_loss: 1.4065 -
learning_rate: 1.0000e-04
Epoch 56/100
318/318          0s 216ms/step -
accuracy: 0.8929 - loss: 1.0443
Epoch 56: val_accuracy improved from 0.81471 to 0.81953, saving model to
best_cnn_from_scratch_v2.keras
318/318          89s 281ms/step -
accuracy: 0.8929 - loss: 1.0443 - val_accuracy: 0.8195 - val_loss: 1.3656 -
```

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learning_rate: 1.0000e-04
Epoch 57/100
318/318          0s 209ms/step -
accuracy: 0.8889 - loss: 1.0455
Epoch 57: val_accuracy did not improve from 0.81953
318/318          81s 255ms/step -
accuracy: 0.8889 - loss: 1.0455 - val_accuracy: 0.8119 - val_loss: 1.3848 -
learning_rate: 1.0000e-04
Epoch 58/100
318/318          0s 213ms/step -
accuracy: 0.8911 - loss: 1.0240
Epoch 58: val_accuracy did not improve from 0.81953
318/318          83s 260ms/step -
accuracy: 0.8911 - loss: 1.0240 - val_accuracy: 0.8115 - val_loss: 1.3988 -
learning_rate: 1.0000e-04
Epoch 59/100
318/318          0s 211ms/step -
accuracy: 0.8950 - loss: 1.0077
Epoch 59: val_accuracy did not improve from 0.81953
318/318          82s 258ms/step -
accuracy: 0.8950 - loss: 1.0078 - val_accuracy: 0.8067 - val_loss: 1.3816 -
learning_rate: 1.0000e-04
Epoch 60/100
318/318          0s 210ms/step -
accuracy: 0.8928 - loss: 0.9922
Epoch 60: val_accuracy did not improve from 0.81953
318/318          81s 255ms/step -
accuracy: 0.8928 - loss: 0.9923 - val_accuracy: 0.8123 - val_loss: 1.3804 -
learning_rate: 1.0000e-04
Epoch 61/100
318/318          0s 210ms/step -
accuracy: 0.8946 - loss: 1.0056
Epoch 61: val_accuracy did not improve from 0.81953
318/318          82s 257ms/step -
accuracy: 0.8946 - loss: 1.0056 - val_accuracy: 0.8183 - val_loss: 1.3436 -
learning_rate: 1.0000e-04
Epoch 62/100
318/318          0s 208ms/step -
accuracy: 0.8952 - loss: 0.9780
Epoch 62: val_accuracy did not improve from 0.81953
318/318          81s 255ms/step -
accuracy: 0.8952 - loss: 0.9780 - val_accuracy: 0.8071 - val_loss: 1.3691 -
learning_rate: 1.0000e-04
Epoch 63/100
318/318          0s 208ms/step -
accuracy: 0.8963 - loss: 0.9686
Epoch 63: val_accuracy improved from 0.81953 to 0.82637, saving model to
best_cnn_from_scratch_v2.keras
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318/318          86s 272ms/step -
accuracy: 0.8963 - loss: 0.9686 - val_accuracy: 0.8264 - val_loss: 1.3462 -
learning_rate: 1.0000e-04
Epoch 64/100
318/318          0s 208ms/step -
accuracy: 0.9003 - loss: 0.9448
Epoch 64: val_accuracy did not improve from 0.82637
318/318          81s 253ms/step -
accuracy: 0.9002 - loss: 0.9449 - val_accuracy: 0.8227 - val_loss: 1.3009 -
learning_rate: 1.0000e-04
Epoch 65/100
318/318          0s 209ms/step -
accuracy: 0.8916 - loss: 0.9719
Epoch 65: val_accuracy did not improve from 0.82637
318/318          81s 255ms/step -
accuracy: 0.8916 - loss: 0.9719 - val_accuracy: 0.8179 - val_loss: 1.3187 -
learning_rate: 1.0000e-04
Epoch 66/100
318/318          0s 209ms/step -
accuracy: 0.9001 - loss: 0.9409
Epoch 66: val_accuracy did not improve from 0.82637
318/318          82s 257ms/step -
accuracy: 0.9001 - loss: 0.9410 - val_accuracy: 0.8151 - val_loss: 1.3578 -
learning_rate: 1.0000e-04
Epoch 67/100
318/318          0s 208ms/step -
accuracy: 0.8994 - loss: 0.9287
Epoch 67: val_accuracy did not improve from 0.82637
318/318          81s 253ms/step -
accuracy: 0.8994 - loss: 0.9288 - val_accuracy: 0.8163 - val_loss: 1.2917 -
learning_rate: 1.0000e-04
Epoch 68/100
318/318          0s 212ms/step -
accuracy: 0.9013 - loss: 0.9194
Epoch 68: val_accuracy did not improve from 0.82637
318/318          82s 257ms/step -
accuracy: 0.9013 - loss: 0.9194 - val_accuracy: 0.8179 - val_loss: 1.3076 -
learning_rate: 1.0000e-04
Epoch 69/100
318/318          0s 207ms/step -
accuracy: 0.9048 - loss: 0.9187
Epoch 69: val_accuracy improved from 0.82637 to 0.82918, saving model to
best_cnn_from_scratch_v2.keras
318/318          96s 303ms/step -
accuracy: 0.9048 - loss: 0.9187 - val_accuracy: 0.8292 - val_loss: 1.2948 -
learning_rate: 1.0000e-04
Epoch 70/100
318/318          0s 206ms/step -
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accuracy: 0.9079 - loss: 0.8855
Epoch 70: val_accuracy did not improve from 0.82918
318/318          80s 251ms/step -
accuracy: 0.9078 - loss: 0.8856 - val_accuracy: 0.8087 - val_loss: 1.3239 -
learning_rate: 1.0000e-04
Epoch 71/100
318/318          0s 210ms/step -
accuracy: 0.9145 - loss: 0.8779
Epoch 71: val_accuracy did not improve from 0.82918
318/318          82s 257ms/step -
accuracy: 0.9145 - loss: 0.8779 - val_accuracy: 0.8107 - val_loss: 1.3037 -
learning_rate: 1.0000e-04
Epoch 72/100
318/318          0s 209ms/step -
accuracy: 0.9050 - loss: 0.8896
Epoch 72: val_accuracy did not improve from 0.82918
318/318          82s 256ms/step -
accuracy: 0.9050 - loss: 0.8896 - val_accuracy: 0.8240 - val_loss: 1.2727 -
learning_rate: 1.0000e-04
Epoch 73/100
318/318          0s 211ms/step -
accuracy: 0.8996 - loss: 0.9047
Epoch 73: val_accuracy did not improve from 0.82918
318/318          81s 256ms/step -
accuracy: 0.8996 - loss: 0.9048 - val_accuracy: 0.8167 - val_loss: 1.2990 -
learning_rate: 1.0000e-04
Epoch 74/100
318/318          0s 214ms/step -
accuracy: 0.9038 - loss: 0.8789
Epoch 74: val_accuracy did not improve from 0.82918
318/318          83s 261ms/step -
accuracy: 0.9038 - loss: 0.8789 - val_accuracy: 0.8187 - val_loss: 1.3124 -
learning_rate: 1.0000e-04
Epoch 75/100
318/318          0s 212ms/step -
accuracy: 0.9086 - loss: 0.8597
Epoch 75: val_accuracy improved from 0.82918 to 0.83360, saving model to
best_cnn_from_scratch_v2.keras
318/318          89s 279ms/step -
accuracy: 0.9086 - loss: 0.8598 - val_accuracy: 0.8336 - val_loss: 1.2401 -
learning_rate: 1.0000e-04
Epoch 76/100
318/318          0s 211ms/step -
accuracy: 0.9045 - loss: 0.8687
Epoch 76: val_accuracy did not improve from 0.83360
318/318          82s 257ms/step -
accuracy: 0.9045 - loss: 0.8687 - val_accuracy: 0.8240 - val_loss: 1.2418 -
learning_rate: 1.0000e-04
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Epoch 77/100
318/318          0s 207ms/step -
accuracy: 0.9130 - loss: 0.8354
Epoch 77: val_accuracy did not improve from 0.83360
318/318          81s 255ms/step -
accuracy: 0.9130 - loss: 0.8355 - val_accuracy: 0.8256 - val_loss: 1.2350 -
learning_rate: 1.0000e-04
Epoch 78/100
318/318          0s 206ms/step -
accuracy: 0.9140 - loss: 0.8478
Epoch 78: val_accuracy improved from 0.83360 to 0.83722, saving model to
best_cnn_from_scratch_v2.keras
318/318          86s 271ms/step -
accuracy: 0.9139 - loss: 0.8478 - val_accuracy: 0.8372 - val_loss: 1.2144 -
learning_rate: 1.0000e-04
Epoch 79/100
318/318          0s 211ms/step -
accuracy: 0.9123 - loss: 0.8335
Epoch 79: val_accuracy did not improve from 0.83722
318/318          82s 256ms/step -
accuracy: 0.9123 - loss: 0.8336 - val_accuracy: 0.8215 - val_loss: 1.2741 -
learning_rate: 1.0000e-04
Epoch 80/100
318/318          0s 213ms/step -
accuracy: 0.9118 - loss: 0.8455
Epoch 80: val_accuracy improved from 0.83722 to 0.84204, saving model to
best_cnn_from_scratch_v2.keras
318/318          88s 278ms/step -
accuracy: 0.9118 - loss: 0.8455 - val_accuracy: 0.8420 - val_loss: 1.2055 -
learning_rate: 1.0000e-04
Epoch 81/100
318/318          0s 208ms/step -
accuracy: 0.9137 - loss: 0.8362
Epoch 81: val_accuracy did not improve from 0.84204
318/318          81s 253ms/step -
accuracy: 0.9136 - loss: 0.8362 - val_accuracy: 0.8252 - val_loss: 1.2224 -
learning_rate: 1.0000e-04
Epoch 82/100
318/318          0s 210ms/step -
accuracy: 0.9176 - loss: 0.8101
Epoch 82: val_accuracy did not improve from 0.84204
318/318          82s 255ms/step -
accuracy: 0.9176 - loss: 0.8101 - val_accuracy: 0.8244 - val_loss: 1.2712 -
learning_rate: 1.0000e-04
Epoch 83/100
318/318          0s 210ms/step -
accuracy: 0.9096 - loss: 0.8371
Epoch 83: val_accuracy did not improve from 0.84204
```

```
318/318          82s 257ms/step -
accuracy: 0.9096 - loss: 0.8371 - val_accuracy: 0.8260 - val_loss: 1.2110 -
learning_rate: 1.0000e-04
Epoch 84/100
318/318          0s 207ms/step -
accuracy: 0.9185 - loss: 0.8089
Epoch 84: val_accuracy did not improve from 0.84204
318/318          80s 252ms/step -
accuracy: 0.9184 - loss: 0.8090 - val_accuracy: 0.8360 - val_loss: 1.2199 -
learning_rate: 1.0000e-04
Epoch 85/100
318/318          0s 210ms/step -
accuracy: 0.9190 - loss: 0.8032
Epoch 85: val_accuracy did not improve from 0.84204

Epoch 85: ReduceLROnPlateau reducing learning rate to 1.9999999494757503e-05.
318/318          81s 254ms/step -
accuracy: 0.9190 - loss: 0.8032 - val_accuracy: 0.8195 - val_loss: 1.2568 -
learning_rate: 1.0000e-04
Epoch 86/100
318/318          0s 207ms/step -
accuracy: 0.9232 - loss: 0.7864
Epoch 86: val_accuracy improved from 0.84204 to 0.85289, saving model to
best_cnn_from_scratch_v2.keras
318/318          83s 258ms/step -
accuracy: 0.9232 - loss: 0.7863 - val_accuracy: 0.8529 - val_loss: 1.1099 -
learning_rate: 2.0000e-05
Epoch 87/100
318/318          0s 209ms/step -
accuracy: 0.9454 - loss: 0.7065
Epoch 87: val_accuracy improved from 0.85289 to 0.85892, saving model to
best_cnn_from_scratch_v2.keras
318/318          88s 276ms/step -
accuracy: 0.9454 - loss: 0.7065 - val_accuracy: 0.8589 - val_loss: 1.1161 -
learning_rate: 2.0000e-05
Epoch 88/100
318/318          0s 207ms/step -
accuracy: 0.9423 - loss: 0.7065
Epoch 88: val_accuracy did not improve from 0.85892
318/318          80s 252ms/step -
accuracy: 0.9423 - loss: 0.7065 - val_accuracy: 0.8573 - val_loss: 1.0904 -
learning_rate: 2.0000e-05
Epoch 89/100
318/318          0s 208ms/step -
accuracy: 0.9401 - loss: 0.7006
Epoch 89: val_accuracy did not improve from 0.85892
318/318          80s 253ms/step -
accuracy: 0.9401 - loss: 0.7006 - val_accuracy: 0.8525 - val_loss: 1.1303 -
```

```
learning_rate: 2.0000e-05
Epoch 90/100
318/318          0s 206ms/step -
accuracy: 0.9466 - loss: 0.6878
Epoch 90: val_accuracy did not improve from 0.85892
318/318          80s 251ms/step -
accuracy: 0.9466 - loss: 0.6878 - val_accuracy: 0.8573 - val_loss: 1.0895 -
learning_rate: 2.0000e-05
Epoch 91/100
318/318          0s 208ms/step -
accuracy: 0.9451 - loss: 0.6876
Epoch 91: val_accuracy did not improve from 0.85892
318/318          80s 253ms/step -
accuracy: 0.9451 - loss: 0.6876 - val_accuracy: 0.8577 - val_loss: 1.0733 -
learning_rate: 2.0000e-05
Epoch 92/100
318/318          0s 205ms/step -
accuracy: 0.9448 - loss: 0.6767
Epoch 92: val_accuracy improved from 0.85892 to 0.86415, saving model to
best_cnn_from_scratch_v2.keras
318/318          87s 273ms/step -
accuracy: 0.9448 - loss: 0.6768 - val_accuracy: 0.8641 - val_loss: 1.0645 -
learning_rate: 2.0000e-05
Epoch 93/100
318/318          0s 206ms/step -
accuracy: 0.9523 - loss: 0.6482
Epoch 93: val_accuracy did not improve from 0.86415
318/318          80s 251ms/step -
accuracy: 0.9523 - loss: 0.6482 - val_accuracy: 0.8637 - val_loss: 1.0388 -
learning_rate: 2.0000e-05
Epoch 94/100
318/318          0s 209ms/step -
accuracy: 0.9513 - loss: 0.6557
Epoch 94: val_accuracy did not improve from 0.86415
318/318          81s 253ms/step -
accuracy: 0.9513 - loss: 0.6557 - val_accuracy: 0.8601 - val_loss: 1.0638 -
learning_rate: 2.0000e-05
Epoch 95/100
318/318          0s 206ms/step -
accuracy: 0.9508 - loss: 0.6449
Epoch 95: val_accuracy improved from 0.86415 to 0.86656, saving model to
best_cnn_from_scratch_v2.keras
318/318          86s 271ms/step -
accuracy: 0.9508 - loss: 0.6449 - val_accuracy: 0.8666 - val_loss: 1.0478 -
learning_rate: 2.0000e-05
Epoch 96/100
318/318          0s 206ms/step -
accuracy: 0.9539 - loss: 0.6339
```

```

Epoch 96: val_accuracy did not improve from 0.86656
318/318           80s 251ms/step -
accuracy: 0.9539 - loss: 0.6339 - val_accuracy: 0.8662 - val_loss: 1.0316 -
learning_rate: 2.0000e-05
Epoch 97/100
318/318           0s 206ms/step -
accuracy: 0.9563 - loss: 0.6306
Epoch 97: val_accuracy did not improve from 0.86656
318/318           80s 252ms/step -
accuracy: 0.9563 - loss: 0.6306 - val_accuracy: 0.8625 - val_loss: 1.0406 -
learning_rate: 2.0000e-05
Epoch 98/100
318/318           0s 213ms/step -
accuracy: 0.9552 - loss: 0.6199
Epoch 98: val_accuracy did not improve from 0.86656
318/318           82s 259ms/step -
accuracy: 0.9552 - loss: 0.6199 - val_accuracy: 0.8577 - val_loss: 1.0331 -
learning_rate: 2.0000e-05
Epoch 99/100
318/318           0s 212ms/step -
accuracy: 0.9498 - loss: 0.6280
Epoch 99: val_accuracy did not improve from 0.86656
318/318           142s 259ms/step -
accuracy: 0.9498 - loss: 0.6280 - val_accuracy: 0.8581 - val_loss: 1.0174 -
learning_rate: 2.0000e-05
Epoch 100/100
318/318           0s 213ms/step -
accuracy: 0.9533 - loss: 0.6251
Epoch 100: val_accuracy did not improve from 0.86656
318/318           82s 259ms/step -
accuracy: 0.9533 - loss: 0.6251 - val_accuracy: 0.8662 - val_loss: 1.0059 -
learning_rate: 2.0000e-05

--- Entrenamiento Finalizado ---

```

3.2.- MONITORIZACIÓN DEL PROCESO DE ENTRENAMIENTO PARA LA TOMA DE DECISIONES

```

[ ]: import json

# Define the filename
history_filename = 'history_v3.json'

# Save the history object to a JSON file
with open(history_filename, 'w') as f:
    json.dump(history_v3.history, f)

print(f"Training history saved to {history_filename}")

```

```
Training history saved to history_v3.json
```

```
[ ]: train_acc =history_v3.history["accuracy"]

# Lista de Accuracy de Validación (100 datos)
val_acc = history_v3.history["val_accuracy"]

# Generamos la lista de épocas (del 1 al 100)
epochs = range(1, 101)

# -----
# 2. GENERACIÓN DEL GRÁFICO
# -----

plt.figure(figsize=(10, 6)) # Tamaño del gráfico

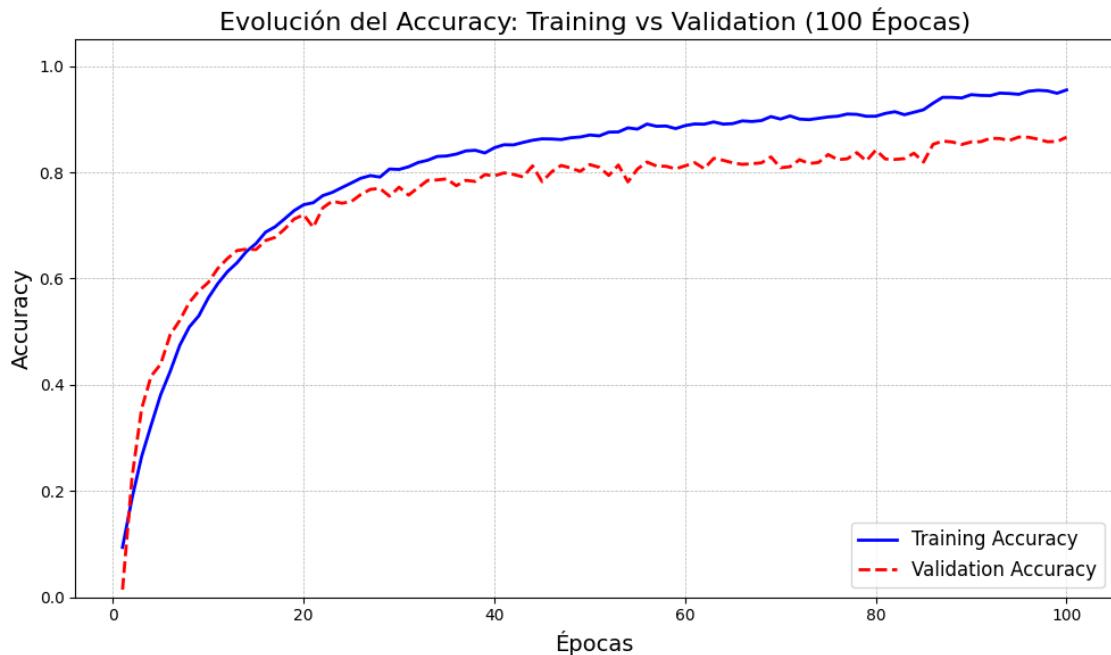
# Dibujar las líneas
plt.plot(epochs, train_acc, 'b-', label='Training Accuracy', linewidth=2)
plt.plot(epochs, val_acc, 'r--', label='Validation Accuracy', linewidth=2)

# Títulos y Etiquetas
plt.title('Evolución del Accuracy: Training vs Validation (100 Épocas)',  
    fontsize=16)
plt.xlabel('Épocas', fontsize=14)
plt.ylabel('Accuracy', fontsize=14)

# Añadir leyenda y rejilla
plt.legend(loc='lower right', fontsize=12)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)

# Ajustar límites (Opcional: asumiendo accuracy de 0 a 1)
plt.ylim(0, 1.05)

# Mostrar gráfico
plt.tight_layout()
plt.show()
```



```
[ ]: train_acc =history_v3.history["loss"]
val_acc = history_v3.history["val_loss"]

# Generamos la lista de épocas (del 1 al 100)
epochs = range(1, 101)

# -----
# 2. GENERACIÓN DEL GRÁFICO
# -----
```

```
plt.figure(figsize=(10, 6)) # Tamaño del gráfico

# Dibujar las líneas
plt.plot(epochs, train_acc, 'b-', label='Training loss', linewidth=2)
plt.plot(epochs, val_acc, 'r--', label='Validation loss', linewidth=2)

# Títulos y Etiquetas
plt.title('Evolución del loss: Training vs Validation (100 Épocas)',
          fontsize=16)
plt.xlabel('Épocas', fontsize=14)
plt.ylabel('Accuracy', fontsize=14)

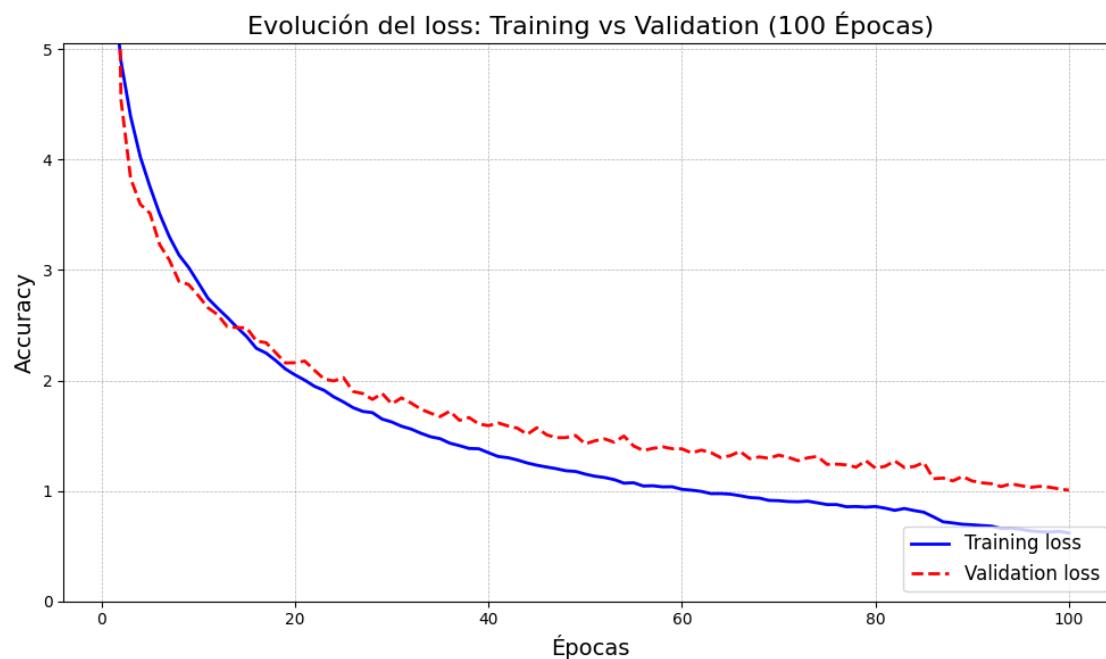
# Añadir leyenda y rejilla
plt.legend(loc='lower right', fontsize=12)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
```

```

# Ajustar límites (Opcional: asumiendo accuracy de 0 a 1)
plt.ylim(0, 5.05)

# Mostrar gráfico
plt.tight_layout()
plt.show()

```



[]:

3.3.- EVALUACIÓN DEL MODELO PREDICTIVO Y PLANTEAMIENTO DE LA SIGUIENTE PRUEBA EXPERIMENTAL

El modelo v3 representa una optimización exhaustiva de la capacidad, profundidad y entrenamiento en comparación con los modelos v1 y v2. Está diseñado para ser la red más potente y mejor regulada de las tres. El modelo v3 eleva significativamente la complejidad de la arquitectura (comparado con v1) y refina los hiperparámetros de entrenamiento (comparado con v2).

Característica

Modelo v1

Modelo v2

Modelo v3 (Mejora)

Profundidad CNN

3 Bloques

3 Bloques

4 Bloques Conv/Pool. (Añade Conv2D(512)).

Máxima Capacidad

256 filtros

256 filtros

512 filtros en el último bloque.

Batch Normalization (BN)

Solo después de Dense

Después de cada Conv2D

Después de cada Conv2D (Mantiene la mejora de v2).

Dropout

Ninguno (solo BN)

0.4 (CNN) y 0.6 (Dense)

Solo 0.5 después de Dense (Regulación más sutil).

Regularización L2

Solo en Bloques 2 y 3

En Bloques 2 y 3

En todos los Bloques Conv y la Capa Densa.

Optimizador

Adam ($LR = 0.0005$)

Adam ($LR = 0.0005$)

RMSprop ($LR = 0.0001$).

Paciencia (EarlyStop)

$P = 15$ (Alta)

$P = 15$ (Alta)

$P = 10$ y $\text{min_delta} = 0.001$ (Detención más estricta).

```
[5]: import tensorflow.keras as keras  
v3_model = keras.models.load_model("model3.keras")
```

```
[7]: import os  
import numpy as np  
import matplotlib.pyplot as plt  
import tensorflow as tf  
from tensorflow.keras.models import load_model
```

```

from sklearn.metrics import accuracy_score

# =====
# 1. CONFIGURACIÓN (¡AJUSTA ESTO!)
TEST_DIR = os.path.join(my_dataset, 'test')                      # Ruta a la carpeta test del dataset
IMG_SIZE = (128, 128)                                            # Debe ser IGUAL al usado en el entrenamiento (ej. 128, 150, 224)
BATCH_SIZE = 32

# =====
# 2. CARGAR DATOS DE TEST
# =====
print(f"Cargando imágenes desde: {TEST_DIR}...")

# IMPORTANTE: shuffle=False es CRUCIAL aquí.
# Necesitamos que las imágenes y las etiquetas mantengan el mismo orden
# para poder compararlas después de la predicción.
test_ds = tf.keras.utils.image_dataset_from_directory(
    TEST_DIR,
    image_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    label_mode='int',   # Devuelve enteros (índices de clase)
    shuffle=False       # ¡NO MEZCLAR! Para que coincida con las predicciones
)

# Obtenemos los nombres de las clases (ej: ['ADONIS', 'JULIA', ...])
class_names = test_ds.class_names
print(f"Clases encontradas: {len(class_names)}")

# =====
# 3. CARGAR MODELO Y PREDICIR
# =====
model = v3_model
print("Realizando predicciones (esto puede tardar un poco)...")
predictions = model.predict(test_ds)

# Convertimos las probabilidades (400, 100) a índices de clase (400,)
y_pred = np.argmax(predictions, axis=1)

# =====
# 4. OBTENER ETIQUETAS REALES (Ground Truth)
# =====
# Como test_ds es un objeto Dataset, necesitamos iterar para sacar las etiquetas reales
y_true = np.concatenate([y for x, y in test_ds], axis=0)

```

```

# =====
# 5. CALCULAR ACCURACY
# =====
acc = accuracy_score(y_true, y_pred)
print(f"\nResultados Finales:")
print(f"-----")
print(f"Imágenes evaluadas: {len(y_true)}")
print(f"ACCURACY DEL MODELO: {acc:.2%}")
print(f"-----")

# =====
# 6. PLOTEAR EJEMPLOS (Real vs Predicho)
# =====
# Vamos a tomar un lote de imágenes para visualizar
# Nota: Tomamos las imágenes originales del dataset para pintarlas
plt.figure(figsize=(15, 15))
images_to_show = 9

# Iteramos sobre el dataset solo para coger imágenes para pintar
for images, labels in test_ds.take(1):
    # Convertimos a numpy
    images = images.numpy().astype("uint8")
    labels = labels.numpy()

    # Solo mostramos las primeras 9 del batch
    for i in range(min(images_to_show, len(images))):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i])

        # Obtenemos nombres
        real_idx = labels[i]
        pred_idx = y_pred[i] # Ojo: y_pred tiene todas, aquí asumimos que es el
        # primer batch

        real_name = class_names[real_idx]
        pred_name = class_names[pred_idx]

        # Color del título: Verde si acertó, Rojo si falló
        color = 'green' if real_idx == pred_idx else 'red'

        plt.title(f"Real: {real_name}\nPred: {pred_name}", color=color, fontweight="bold", fontsize=10)
        plt.axis("off")

plt.suptitle(f"Ejemplos de Predicción (Accuracy Global: {acc:.2%})", fontweight="bold", fontsize=16)

```

```
plt.tight_layout()  
plt.show()
```

Cargando imágenes desde: /kaggle/input/butterflies-100-image-dataset-classification/test...
Found 500 files belonging to 100 classes.

Clases encontradas: 100

Realizando predicciones (esto puede tardar un poco)...

16/16 6s 132ms/step

Resultados Finales:

Imágenes evaluadas: 500

ACCURACY DEL MODELO: 76.20%



```
[3]: import numpy as np
import matplotlib.pyplot as plt
import os

# Supongamos que 'predictions' es tu array (400, 100) que ya obtuviste
# predictions = model.predict(x_test)

# -----
# 1. DEFINIR LAS ETIQUETAS (Nombres de las Mariposas)
# -----
# Si tienes las carpetas del dataset a mano, lo mejor es leerlas directamente
# para asegurar que el orden sea exacto al del entrenamiento.

path_al_dataset = os.path.join(my_dataset, "train")

try:
    # Keras asigna índices en orden alfabético de las carpetas
    class_names = sorted(os.listdir(path_al_dataset))
    print(f"Se encontraron {len(class_names)} especies de mariposas.")
    # Ejemplo: ['ADONIS', 'AFRICAN GIANT SWALLOWTAIL', ... 'ZEBRA LONGWING']
except:
    # Si no tienes la carpeta a mano, tendrías que escribir la lista manual o
    # cargarla
    print("No se encontró la ruta. Asegúrate de apuntar a la carpeta 'train'.")
    class_names = [f"Especie_{i}" for i in range(100)] # Placeholder
```

Se encontraron 100 especies de mariposas.

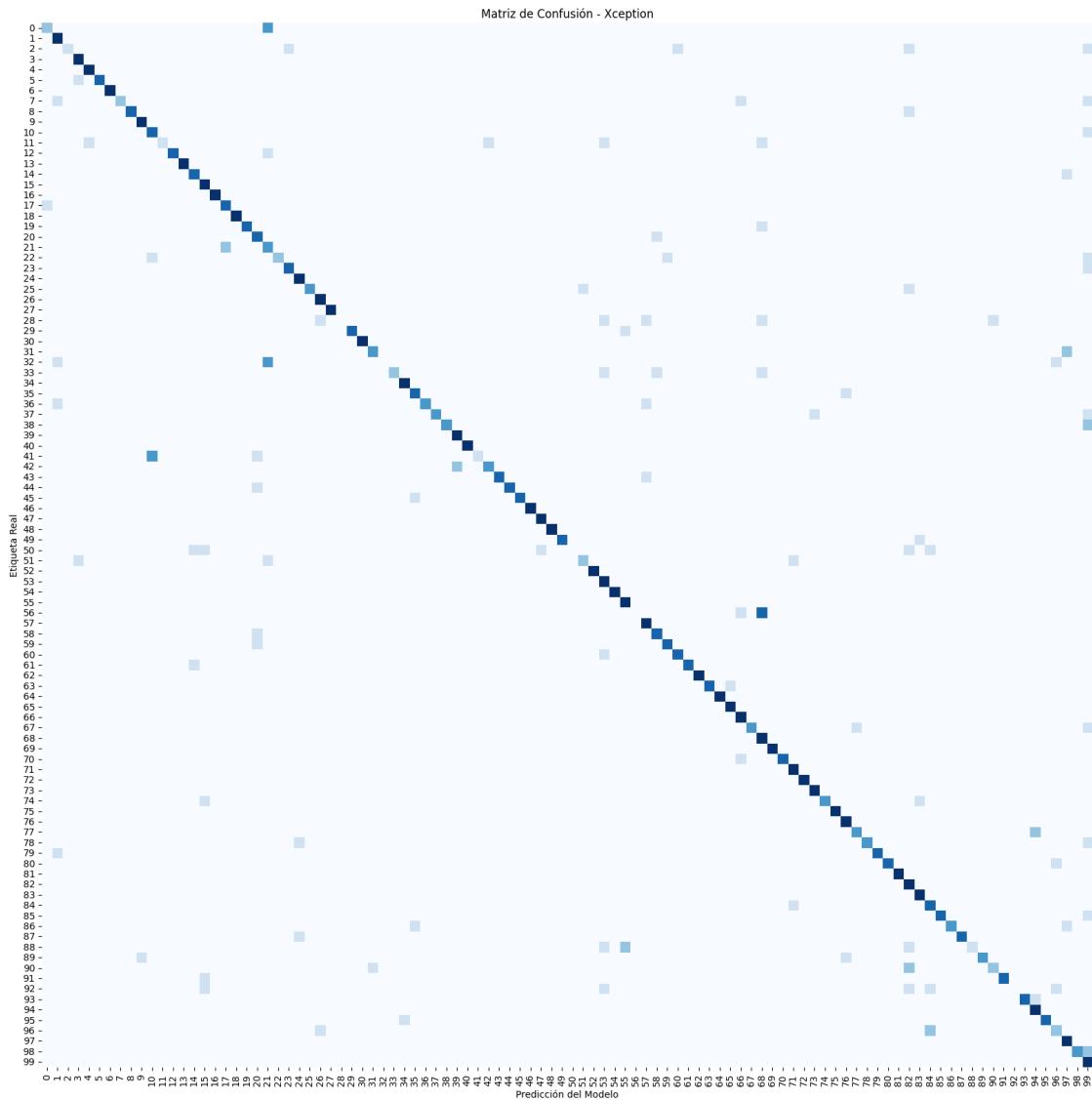
```
[8]: from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns

# --- 4. Matriz de Confusión ---
cm = confusion_matrix(y_true, y_pred)

plt.figure(figsize=(20, 20)) # Tamaño grande porque son 100 clases
sns.heatmap(cm, annot=False, cmap='Blues', cbar=False) # annot=False para no
# saturar
plt.title('Matriz de Confusión - Xception')
plt.ylabel('Etiqueta Real')
plt.xlabel('Predicción del Modelo')
plt.show()

# --- 5. Reporte de Clasificación ---
```

```
# Muestra Precision, Recall y F1-Score por cada clase
print(classification_report(y_true, y_pred, target_names=class_names))
```



		precision	recall	f1-score	support
ADONIS		0.67	0.40	0.50	5
AFRICAN GIANT SWALLOWTAIL		0.56	1.00	0.71	5
AMERICAN SNOOT		1.00	0.20	0.33	5
AN 88		0.71	1.00	0.83	5
APPOLLO		0.83	1.00	0.91	5
ARCIGERA FLOWER MOTH		1.00	0.80	0.89	5
ATALA		1.00	1.00	1.00	5
ATLAS MOTH		1.00	0.40	0.57	5

BANDED ORANGE HELICONIAN	1.00	0.80	0.89	5
BANDED PEACOCK	0.83	1.00	0.91	5
BANDED TIGER MOTH	0.50	0.80	0.62	5
BECKERS WHITE	1.00	0.20	0.33	5
BIRD CHERRY ERMINE MOTH	1.00	0.80	0.89	5
BLACK HAIRSTREAK	1.00	1.00	1.00	5
BLUE MORPHO	0.67	0.80	0.73	5
BLUE SPOTTED CROW	0.56	1.00	0.71	5
BROOKES BIRDWING	1.00	1.00	1.00	5
BROWN ARGUS	0.67	0.80	0.73	5
BROWN SIPROETA	1.00	1.00	1.00	5
CABBAGE WHITE	1.00	0.80	0.89	5
CAIRNS BIRDWING	0.50	0.80	0.62	5
CHALK HILL BLUE	0.27	0.60	0.38	5
CHECQUERED SKIPPER	1.00	0.40	0.57	5
CHESTNUT	0.80	0.80	0.80	5
CINNABAR MOTH	0.71	1.00	0.83	5
CLEARWING MOTH	1.00	0.60	0.75	5
CLEOPATRA	0.71	1.00	0.83	5
CLODIUS PARNASSIAN	1.00	1.00	1.00	5
CLOUDED SULPHUR	0.00	0.00	0.00	5
COMET MOTH	1.00	0.80	0.89	5
COMMON BANDED AWL	1.00	1.00	1.00	5
COMMON WOOD-NYMPH	0.75	0.60	0.67	5
COPPER TAIL	0.00	0.00	0.00	5
CRECENT	1.00	0.40	0.57	5
CRIMSON PATCH	0.83	1.00	0.91	5
DANAID EGGFLY	0.67	0.80	0.73	5
EASTERN COMA	1.00	0.60	0.75	5
EASTERN DAPPLE WHITE	1.00	0.60	0.75	5
EASTERN PINE ELFIN	1.00	0.60	0.75	5
ELBOWED PIERROT	0.71	1.00	0.83	5
EMPEROR GUM MOTH	1.00	1.00	1.00	5
GARDEN TIGER MOTH	1.00	0.20	0.33	5
GIANT LEOPARD MOTH	0.75	0.60	0.67	5
GLITTERING SAPPHIRE	1.00	0.80	0.89	5
GOLD BANDED	1.00	0.80	0.89	5
GREAT EGGFLY	1.00	0.80	0.89	5
GREAT JAY	1.00	1.00	1.00	5
GREEN CELLED CATTLEHEART	0.83	1.00	0.91	5
GREEN HAIRSTREAK	1.00	1.00	1.00	5
GREY HAIRSTREAK	1.00	0.80	0.89	5
HERCULES MOTH	0.00	0.00	0.00	5
HUMMING BIRD HAWK MOTH	0.67	0.40	0.50	5
INDRA SWALLOW	1.00	1.00	1.00	5
IO MOTH	0.45	1.00	0.62	5
Iphiclus sister	1.00	1.00	1.00	5
JULIA	0.62	1.00	0.77	5

LARGE MARBLE	0.00	0.00	0.00	5
LUNA MOTH	0.62	1.00	0.77	5
MADAGASCAN SUNSET MOTH	0.67	0.80	0.73	5
MALACHITE	0.80	0.80	0.80	5
MANGROVE SKIPPER	0.80	0.80	0.80	5
MESTRA	1.00	0.80	0.89	5
METALMARK	1.00	1.00	1.00	5
MILBERTS TORTOISESHELL	1.00	0.80	0.89	5
MONARCH	1.00	1.00	1.00	5
MOURNING CLOAK	0.83	1.00	0.91	5
OLEANDER HAWK MOTH	0.62	1.00	0.77	5
ORANGE OAKLEAF	1.00	0.60	0.75	5
ORANGE TIP	0.38	1.00	0.56	5
ORCHARD SWALLOW	1.00	1.00	1.00	5
PAINTED LADY	1.00	0.80	0.89	5
PAPER KITE	0.71	1.00	0.83	5
PEACOCK	1.00	1.00	1.00	5
PINE WHITE	0.83	1.00	0.91	5
PIPEVINE SWALLOW	1.00	0.60	0.75	5
POLYPHEMUS MOTH	1.00	1.00	1.00	5
POPINJAY	0.71	1.00	0.83	5
PURPLE HAIRSTREAK	0.75	0.60	0.67	5
PURPLISH COPPER	1.00	0.60	0.75	5
QUESTION MARK	1.00	0.80	0.89	5
RED ADMIRAL	1.00	0.80	0.89	5
RED CRACKER	1.00	1.00	1.00	5
RED POSTMAN	0.38	1.00	0.56	5
RED SPOTTED PURPLE	0.71	1.00	0.83	5
ROSY MAPLE MOTH	0.50	0.80	0.62	5
SCARCE SWALLOW	1.00	0.80	0.89	5
SILVER SPOT SKIPPER	1.00	0.60	0.75	5
SIXSPOT BURNET MOTH	1.00	0.80	0.89	5
SLEEPY ORANGE	1.00	0.20	0.33	5
SOOTYWING	1.00	0.60	0.75	5
SOUTHERN DOGFACE	0.67	0.40	0.50	5
STRAITED QUEEN	1.00	0.80	0.89	5
TROPICAL LEAFWING	0.00	0.00	0.00	5
TWO BARRED FLASHER	1.00	0.80	0.89	5
ULYSSES	0.62	1.00	0.77	5
VICEROY	1.00	0.80	0.89	5
WHITE LINED SPHINX MOTH	0.40	0.40	0.40	5
WOOD SATYR	0.56	1.00	0.71	5
YELLOW SWALLOW TAIL	1.00	0.60	0.75	5
ZEBRA LONG WING	0.28	1.00	0.43	5
accuracy			0.76	500
macro avg	0.80	0.76	0.75	500
weighted avg	0.80	0.76	0.75	500

```
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565:  
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels  
with no predicted samples. Use `zero_division` parameter to control this  
behavior.  
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))  
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565:  
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels  
with no predicted samples. Use `zero_division` parameter to control this  
behavior.  
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))  
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565:  
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels  
with no predicted samples. Use `zero_division` parameter to control this  
behavior.  
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

[]:

estrategia_2

November 23, 2025

0.1 Estrategia 2: Red pre-entrenada

1. Carga

```
[ ]: !pip install --upgrade --force-reinstall --no-deps kaggle
```

```
Collecting kaggle
  Downloading kaggle-1.7.4.5-py3-none-any.whl.metadata (16 kB)
  Downloading kaggle-1.7.4.5-py3-none-any.whl (181 kB)
    0.0/181.2 kB
? eta -:--:--
    181.2/181.2 kB
6.1 MB/s eta 0:00:00
Installing collected packages: kaggle
  Attempting uninstall: kaggle
    Found existing installation: kaggle 1.7.4.5
    Uninstalling kaggle-1.7.4.5:
      Successfully uninstalled kaggle-1.7.4.5
Successfully installed kaggle-1.7.4.5
```

```
[ ]: # Seleccionar el API Token personal previamente descargado (fichero kaggle.json)
from google.colab import files
files.upload()
```

```
<IPython.core.display.HTML object>
Saving kaggle.json to kaggle.json
```

```
[ ]: {'kaggle.json':
b'{"username":"rickstark","key":"0956e87b3524fef84e1b1362d030eb43"}'}
```

```
[ ]: # Creamos un directorio en el que copiamos el fichero kaggle.json
!mkdir ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
```

```
[ ]: # Ya podemos listar los datasets disponibles en kaggle para su descarga
!kaggle datasets list
```

ref	size	lastUpdated	title	downloadCount	voteCount	usabilityRating

sadiajavedd/students-academic-performance-dataset			
Students_Academic_Performance_Dataset		8907	2025-10-23
04:16:35.563000	6056	145	1.0
ayeshaimran123/social-media-and-mental-health-balance			Social Media and
Mental Health Balance		5941	2025-10-26 07:51:53.380000
6356	89	1.0	
ayeshasiddiq123/cars-pre			Car Price
Analysis Dataset		46557	2025-11-06 16:38:07.487000
1969	52	1.0	
shahzadi786/world-smartphone-market-2025			World Smartphone
Market 2025		17795	2025-11-09 04:52:42.650000
2495	70	1.0	
shahzadi786/11111111111111111111			Data Developer
Salary in 2024		110754	2025-11-14 13:47:42.313000
466	21	1.0	
nalisha/shopping-behaviour-and-product-ranking-dateset			Shopping
Behaviour and Product Ranking Dateset .		67263	2025-11-12 17:47:25.227000
1016	49	1.0	
wardabilal/student-stress-analysis			Student Stress
Analysis		1729	2025-11-01 09:14:39.367000
1561	40	1.0	
khushikyad001/ai-impact-on-jobs-2030			AI Impact on
Jobs 2030		87410	2025-11-09 17:58:05.410000
1243	37	1.0	
umuttuygurr/e-commerce-customer-behavior-and-sales-analysis-tr			E-Commerce
Customer Behavior & Sales Analysis -TR		584451	2025-11-09 07:40:27.120000
4397	88	1.0	
ahmeduzaki/global-earthquake-tsunami-risk-assessment-dataset			Global
Earthquake-Tsunami Risk Assessment Dataset		16151	2025-10-01
16:35:53.273000	20046	668	1.0
ayeshaseherr/student-performance			Student
Performance Factors Dataset		96178	2025-11-12
05:50:48.240000	1014	29	1.0
minahilfatima12328/performance-trends-in-education			Performance
Trends in Education		96178	2025-11-11 09:34:39.553000
877	29	1.0	
mosapabdelghany/student-performance-factors-dataset			Student
Performance Factors Dataset		96178	2025-10-16
11:31:36.033000	1677	30	1.0
umuttuygurr/city-lifestyle-segmentation-dataset			City Lifestyle
Segmentation Dataset		11274	2025-11-15 10:52:54.243000
518	24	1.0	
ahmadrazakashif/bmw-worldwide-sales-records-20102024			BMW Worldwide
Sales Records (2010-2024)		853348	2025-09-20 14:39:45.280000
26149	506	1.0	
niteshkakkar/clash-royal-cards-data			Clash Royal

```

Cards Data 27543 2025-10-30 06:09:20.800000
386 23 1.0
tan5577/heart-failure-dataset
Heart_Failure_Dataset 8762 2025-10-19
16:54:19.303000 3855 64 1.0
dansbecker/melbourne-housing-snapshot Melbourne
Housing Snapshot 461423 2018-06-05 12:52:24.087000
197729 1701 0.7058824
kainatjamil12/coffe-sale Coffee Shop
Sales Insights 38970 2025-10-19 08:07:33.300000
1033 34 1.0
mubeenshehzadi/global-disaster-2018-2024 Global_disaster
(2018-2024) 1737424 2025-11-10 20:45:06.260000
677 33 1.0

```

```
[ ]: !kaggle datasets download -d gpiosenka/
↳butterflies-100-image-dataset-classification
```

Dataset URL: <https://www.kaggle.com/datasets/gpiosenka/butterflies-100-image-dataset-classification>
 License(s): unknown
 Downloading butterflies-100-image-dataset-classification.zip to /content
 89% 403M/454M [00:02<00:00, 115MB/s]
 100% 454M/454M [00:02<00:00, 176MB/s]

```
[ ]: # Creamos un directorio para descomprimir los datos
!mkdir my_dataset
```

```
[ ]: # Descomprimimos los datos y los dejamos listos para trabajar
!unzip butterflies-100-image-dataset-classification.zip -d my_dataset
```

Se han truncado las últimas 5000 líneas del flujo de salida.

```

inflating: my_dataset/train/MILBERTS TORTOISESHELL/111.jpg
inflating: my_dataset/train/MILBERTS TORTOISESHELL/112.jpg
inflating: my_dataset/train/MILBERTS TORTOISESHELL/113.jpg
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inflating: my_dataset/valid/WHITE LINED SPHINX MOTH/2.jpg
inflating: my_dataset/valid/WHITE LINED SPHINX MOTH/3.jpg
inflating: my_dataset/valid/WHITE LINED SPHINX MOTH/4.jpg
inflating: my_dataset/valid/WHITE LINED SPHINX MOTH/5.jpg
inflating: my_dataset/valid/WOOD SATYR/1.jpg
inflating: my_dataset/valid/WOOD SATYR/2.jpg
inflating: my_dataset/valid/WOOD SATYR/3.jpg
inflating: my_dataset/valid/WOOD SATYR/4.jpg
inflating: my_dataset/valid/WOOD SATYR/5.jpg
inflating: my_dataset/valid/YELLOW SWALLOW TAIL/1.jpg
inflating: my_dataset/valid/YELLOW SWALLOW TAIL/2.jpg
inflating: my_dataset/valid/YELLOW SWALLOW TAIL/3.jpg
inflating: my_dataset/valid/YELLOW SWALLOW TAIL/4.jpg
inflating: my_dataset/valid/YELLOW SWALLOW TAIL/5.jpg
inflating: my_dataset/valid/ZEBRA LONG WING/1.jpg
inflating: my_dataset/valid/ZEBRA LONG WING/2.jpg
inflating: my_dataset/valid/ZEBRA LONG WING/3.jpg
inflating: my_dataset/valid/ZEBRA LONG WING/4.jpg
inflating: my_dataset/valid/ZEBRA LONG WING/5.jpg
```

2. Inspección y Acondicionamiento

```
[ ]: # importar librerias

import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.applications import Xception
```

```
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense, GlobalAveragePooling2D, Dropout, BatchNormalization
from tensorflow.keras.regularizers import l2
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
import matplotlib.pyplot as plt
from tensorflow.keras.applications.resnet50 import preprocess_input
from tensorflow.keras.applications.xception import preprocess_input as preprocess_input_xception
import numpy as np
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
```

[]: # Definir Rutas y Parámetros

```
BASE_DIR = 'my_dataset' # O '/content/my_dataset' en Colab
TRAIN_DIR = f'{BASE_DIR}/train'
VALID_DIR = f'{BASE_DIR}/valid'
TEST_DIR = f'{BASE_DIR}/test'
IMG_SIZE = (224, 224)
BATCH_SIZE = 32

train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    TRAIN_DIR,
    label_mode="categorical",
    image_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    shuffle=True
)

val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    VALID_DIR,
    label_mode="categorical",
    image_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    shuffle=False
)

test_ds = tf.keras.preprocessing.image_dataset_from_directory(
    TEST_DIR,
    label_mode="categorical",
    image_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    shuffle=False
```

```

)

# Nombre de clases
class_names = train_ds.class_names
num_classes = len(class_names)
print("Clases detectadas:", class_names)
print("Número de clases:", num_classes)

# VISUALIZAR ALGUNAS IMÁGENES (REVISIÓN MANUAL)

plt.figure(figsize=(10, 8))
for images, labels in train_ds.take(1):
    for i in range(12):
        plt.subplot(3, 4, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i].numpy().argmax()])
        plt.axis("off")
plt.show()

```

Found 12639 files belonging to 100 classes.
 Found 500 files belonging to 100 classes.
 Found 500 files belonging to 100 classes.
 Clases detectadas: ['ADONIS', 'AFRICAN GIANT SWALLOWTAIL', 'AMERICAN SNOOT', 'AN 88', 'APPOLLO', 'ARCIGERA FLOWER MOTH', 'ATALA', 'ATLAS MOTH', 'BANDED ORANGE HELICONIAN', 'BANDED PEACOCK', 'BANDED TIGER MOTH', 'BECKERS WHITE', 'BIRD CHERRY ERMINE MOTH', 'BLACK HAIRSTREAK', 'BLUE MORPHO', 'BLUE SPOTTED CROW', 'BROOKES BIRDWING', 'BROWN ARGUS', 'BROWN SIPROETA', 'CABBAGE WHITE', 'CAIRNS BIRDWING', 'CHALK HILL BLUE', 'CHECQUERED SKIPPER', 'CHESTNUT', 'CINNABAR MOTH', 'CLEARWING MOTH', 'CLEOPATRA', 'CLODIUS PARNASSIAN', 'CLOUDED SULPHUR', 'COMET MOTH', 'COMMON BANDED AWL', 'COMMON WOOD-NYMPH', 'COPPER TAIL', 'CRECENT', 'CRIMSON PATCH', 'DANAID EGGFLY', 'EASTERN COMA', 'EASTERN DAPPLE WHITE', 'EASTERN PINE ELFIN', 'ELBOWED PIERROT', 'EMPEROR GUM MOTH', 'GARDEN TIGER MOTH', 'GIANT LEOPARD MOTH', 'GLITTERING SAPPHIRE', 'GOLD BANDED', 'GREAT EGGFLY', 'GREAT JAY', 'GREEN CELLED CATTLEHEART', 'GREEN HAIRSTREAK', 'GREY HAIRSTREAK', 'HERCULES MOTH', 'HUMMING BIRD HAWK MOTH', 'INDRA SWALLOW', 'IO MOTH', 'Iphiclus sister', 'JULIA', 'LARGE MARBLE', 'LUNA MOTH', 'MADAGASCAN SUNSET MOTH', 'MALACHITE', 'MANGROVE SKIPPER', 'MESTRA', 'METALMARK', 'MILBERTS TORTOISESHELL', 'MONARCH', 'MOURNING CLOAK', 'OLEANDER HAWK MOTH', 'ORANGE OAKLEAF', 'ORANGE TIP', 'ORCHARD SWALLOW', 'PAINTED LADY', 'PAPER KITE', 'PEACOCK', 'PINE WHITE', 'PIPEVINE SWALLOW', 'POLYPHEMUS MOTH', 'POPINJAY', 'PURPLE HAIRSTREAK', 'PURPLISH COPPER', 'QUESTION MARK', 'RED ADMIRAL', 'RED CRACKER', 'RED POSTMAN', 'RED SPOTTED PURPLE', 'ROSY MAPLE MOTH', 'SCARCE SWALLOW', 'SILVER SPOT SKIPPER', 'SIXSPOT BURNET MOTH', 'SLEEPY ORANGE', 'SOOTYWING', 'SOUTHERN DOGFACE', 'STRAITED QUEEN', 'TROPICAL LEAFWING', 'TWO BARRED FLASHER', 'ULYSSES', 'VICEROY', 'WHITE LINED SPHINX MOTH', 'WOOD SATYR', 'YELLOW SWALLOW TAIL', 'ZEBRA LONG WING']
 Número de clases: 100



Se visualizan algunas imágenes del dataset para entender de manera gráfica el contenido de las mismas. Teniendo en cuenta que las imágenes no necesitan un preprocesamiento diferente a la normalización, procedemos

4. **entrenamiento** de la solución

```
[ ]: # NORMALIZACIÓN AL ESTILO IMAGENET

def preprocess(image, label):
    image = imagenet_utils.preprocess_input(image) # NORMALIZACIÓN EXACTA DE
    ↪IMAGENET
    return image, label

train_ds = train_ds.map(preprocess).prefetch(tf.data.AUTOTUNE)
val_ds = val_ds.map(preprocess).prefetch(tf.data.AUTOTUNE)

print("Pipeline listo. Dataset normalizado.")

# CARGAR UN MODELO PREENTRENADO
```

```

base_model = ResNet50(
    weights='imagenet',
    include_top=False,
    input_shape=(224, 224, 3)
)

base_model.summary()

print("Modelo preentrenado cargado correctamente.")

```

Pipeline listo. Dataset normalizado.

Model: "resnet50"

Layer (type)	Output Shape	Param #
<code>input_layer_1 (InputLayer)</code>	(None, 224, 224, 3)	0 -
<code>conv1_pad (ZeroPadding2D)</code>	(None, 230, 230, 3)	0
<code>conv1_conv (Conv2D)</code>	(None, 112, 112, 64)	9,472
<code>conv1_bn (BatchNormalization)</code>	(None, 112, 112, 64)	256
<code>conv1_relu (Activation)</code>	(None, 112, 112, 64)	0
<code>pool1_pad (ZeroPadding2D)</code>	(None, 114, 114, 64)	0
<code>pool1_pool (MaxPooling2D)</code>	(None, 56, 56, 64)	0
<code>conv2_block1_1_conv (Conv2D)</code>	(None, 56, 56, 64)	4,160
<code>conv2_block1_1_bn (BatchNormalization)</code>	(None, 56, 56, 64)	256

conv2_block1_1_relu	(None, 56, 56, 64)	0 □
↳ conv2_block1_1_bn[0][0]		
(Activation)		□
↳		
conv2_block1_2_conv (Conv2D)	(None, 56, 56, 64)	36,928 □
↳ conv2_block1_1_relu[0][0]		
conv2_block1_2_bn	(None, 56, 56, 64)	256 □
↳ conv2_block1_2_conv[0][0]		
(BatchNormalization)		□
↳		
conv2_block1_2_relu	(None, 56, 56, 64)	0 □
↳ conv2_block1_2_bn[0][0]		
(Activation)		□
↳		
conv2_block1_0_conv (Conv2D)	(None, 56, 56, 256)	16,640 □
↳ pool1_pool[0][0]		
conv2_block1_3_conv (Conv2D)	(None, 56, 56, 256)	16,640 □
↳ conv2_block1_2_relu[0][0]		
conv2_block1_0_bn	(None, 56, 56, 256)	1,024 □
↳ conv2_block1_0_conv[0][0]		
(BatchNormalization)		□
↳		
conv2_block1_3_bn	(None, 56, 56, 256)	1,024 □
↳ conv2_block1_3_conv[0][0]		
(BatchNormalization)		□
↳		
conv2_block1_add (Add)	(None, 56, 56, 256)	0 □
↳ conv2_block1_0_bn[0][0],		
↳ conv2_block1_3_bn[0][0]		□
conv2_block1_out (Activation)	(None, 56, 56, 256)	0 □
↳ conv2_block1_add[0][0]		
conv2_block2_1_conv (Conv2D)	(None, 56, 56, 64)	16,448 □
↳ conv2_block1_out[0][0]		

conv2_block2_1_bn	(None, 56, 56, 64)	256	□
↳ conv2_block2_1_conv[0] [0]			
(BatchNormalization)			□
↳			
conv2_block2_1_relu	(None, 56, 56, 64)	0	□
↳ conv2_block2_1_bn[0] [0]			
(Activation)			□
↳			
conv2_block2_2_conv (Conv2D)	(None, 56, 56, 64)	36,928	□
↳ conv2_block2_1_relu[0] [0]			
conv2_block2_2_bn	(None, 56, 56, 64)	256	□
↳ conv2_block2_2_conv[0] [0]			
(BatchNormalization)			□
↳			
conv2_block2_2_relu	(None, 56, 56, 64)	0	□
↳ conv2_block2_2_bn[0] [0]			
(Activation)			□
↳			
conv2_block2_3_conv (Conv2D)	(None, 56, 56, 256)	16,640	□
↳ conv2_block2_2_relu[0] [0]			
conv2_block2_3_bn	(None, 56, 56, 256)	1,024	□
↳ conv2_block2_3_conv[0] [0]			
(BatchNormalization)			□
↳			
conv2_block2_add (Add)	(None, 56, 56, 256)	0	□
↳ conv2_block1_out[0] [0],			
↳ conv2_block2_3_bn[0] [0]			□
conv2_block2_out (Activation)	(None, 56, 56, 256)	0	□
↳ conv2_block2_add[0] [0]			
conv2_block3_1_conv (Conv2D)	(None, 56, 56, 64)	16,448	□
↳ conv2_block2_out[0] [0]			
conv2_block3_1_bn	(None, 56, 56, 64)	256	□
↳ conv2_block3_1_conv[0] [0]			
(BatchNormalization)			□
↳			

conv2_block3_1_relu	(None, 56, 56, 64)	0 □
↳ conv2_block3_1_bn[0][0]		
(Activation)		□
↳		
conv2_block3_2_conv (Conv2D)	(None, 56, 56, 64)	36,928 □
↳ conv2_block3_1_relu[0][0]		
conv2_block3_2_bn	(None, 56, 56, 64)	256 □
↳ conv2_block3_2_conv[0][0]		
(BatchNormalization)		□
↳		
conv2_block3_2_relu	(None, 56, 56, 64)	0 □
↳ conv2_block3_2_bn[0][0]		
(Activation)		□
↳		
conv2_block3_3_conv (Conv2D)	(None, 56, 56, 256)	16,640 □
↳ conv2_block3_2_relu[0][0]		
conv2_block3_3_bn	(None, 56, 56, 256)	1,024 □
↳ conv2_block3_3_conv[0][0]		
(BatchNormalization)		□
↳		
conv2_block3_add (Add)	(None, 56, 56, 256)	0 □
↳ conv2_block2_out[0][0],		
↳ conv2_block3_3_bn[0][0]		□
conv2_block3_out (Activation)	(None, 56, 56, 256)	0 □
↳ conv2_block3_add[0][0]		
conv3_block1_1_conv (Conv2D)	(None, 28, 28, 128)	32,896 □
↳ conv2_block3_out[0][0]		
conv3_block1_1_bn	(None, 28, 28, 128)	512 □
↳ conv3_block1_1_conv[0][0]		
(BatchNormalization)		□
↳		
conv3_block1_1_relu	(None, 28, 28, 128)	0 □
↳ conv3_block1_1_bn[0][0]		

(Activation)		
↳		
conv3_block1_2_conv (Conv2D) (None, 28, 28, 128)	147,584	□
↳ conv3_block1_1_relu[0] [0]		
conv3_block1_2_bn (None, 28, 28, 128)	512	□
↳ conv3_block1_2_conv[0] [0]		
(BatchNormalization)		
↳		
conv3_block1_2_relu (None, 28, 28, 128)	0	□
↳ conv3_block1_2_bn[0] [0]		
(Activation)		
↳		
conv3_block1_0_conv (Conv2D) (None, 28, 28, 512)	131,584	□
↳ conv2_block3_out[0] [0]		
conv3_block1_3_conv (Conv2D) (None, 28, 28, 512)	66,048	□
↳ conv3_block1_2_relu[0] [0]		
conv3_block1_0_bn (None, 28, 28, 512)	2,048	□
↳ conv3_block1_0_conv[0] [0]		
(BatchNormalization)		
↳		
conv3_block1_3_bn (None, 28, 28, 512)	2,048	□
↳ conv3_block1_3_conv[0] [0]		
(BatchNormalization)		
↳		
conv3_block1_add (Add) (None, 28, 28, 512)	0	□
↳ conv3_block1_0_bn[0] [0],		
↳ conv3_block1_3_bn[0] [0]		
conv3_block1_out (Activation) (None, 28, 28, 512)	0	□
↳ conv3_block1_add[0] [0]		
conv3_block2_1_conv (Conv2D) (None, 28, 28, 128)	65,664	□
↳ conv3_block1_out[0] [0]		
conv3_block2_1_bn (None, 28, 28, 128)	512	□
↳ conv3_block2_1_conv[0] [0]		

(BatchNormalization)		□
↳		
conv3_block2_1_relu	(None, 28, 28, 128)	0 □
↳ conv3_block2_1_bn[0][0]		
(Activation)		□
↳		
conv3_block2_2_conv (Conv2D)	(None, 28, 28, 128)	147,584 □
↳ conv3_block2_1_relu[0][0]		
conv3_block2_2_bn	(None, 28, 28, 128)	512 □
↳ conv3_block2_2_conv[0][0]		
(Activation)		□
↳		
conv3_block2_2_relu	(None, 28, 28, 128)	0 □
↳ conv3_block2_2_bn[0][0]		
(Activation)		□
↳		
conv3_block2_3_conv (Conv2D)	(None, 28, 28, 512)	66,048 □
↳ conv3_block2_2_relu[0][0]		
conv3_block2_3_bn	(None, 28, 28, 512)	2,048 □
↳ conv3_block2_3_conv[0][0]		
(Activation)		□
↳		
conv3_block2_add (Add)	(None, 28, 28, 512)	0 □
↳ conv3_block1_out[0][0],		
↳ conv3_block2_3_bn[0][0]		□
conv3_block2_out (Activation)	(None, 28, 28, 512)	0 □
↳ conv3_block2_add[0][0]		
conv3_block3_1_conv (Conv2D)	(None, 28, 28, 128)	65,664 □
↳ conv3_block2_out[0][0]		
conv3_block3_1_bn	(None, 28, 28, 128)	512 □
↳ conv3_block3_1_conv[0][0]		
(Activation)		□
↳		

conv3_block3_1_relu	(None, 28, 28, 128)	0 □
↳ conv3_block3_1_bn[0][0]		
(Activation)		□
↳		
conv3_block3_2_conv (Conv2D)	(None, 28, 28, 128)	147,584 □
↳ conv3_block3_1_relu[0][0]		
conv3_block3_2_bn	(None, 28, 28, 128)	512 □
↳ conv3_block3_2_conv[0][0]		
(BatchNormalization)		□
↳		
conv3_block3_2_relu	(None, 28, 28, 128)	0 □
↳ conv3_block3_2_bn[0][0]		
(Activation)		□
↳		
conv3_block3_3_conv (Conv2D)	(None, 28, 28, 512)	66,048 □
↳ conv3_block3_2_relu[0][0]		
conv3_block3_3_bn	(None, 28, 28, 512)	2,048 □
↳ conv3_block3_3_conv[0][0]		
(BatchNormalization)		□
↳		
conv3_block3_add (Add)	(None, 28, 28, 512)	0 □
↳ conv3_block2_out[0][0],		
↳ conv3_block3_3_bn[0][0]		□
conv3_block3_out (Activation)	(None, 28, 28, 512)	0 □
↳ conv3_block3_add[0][0]		
conv3_block4_1_conv (Conv2D)	(None, 28, 28, 128)	65,664 □
↳ conv3_block3_out[0][0]		
conv3_block4_1_bn	(None, 28, 28, 128)	512 □
↳ conv3_block4_1_conv[0][0]		
(BatchNormalization)		□
↳		
conv3_block4_1_relu	(None, 28, 28, 128)	0 □
↳ conv3_block4_1_bn[0][0]		
(Activation)		□
↳		

conv3_block4_2_conv (Conv2D) ↳ conv3_block4_1_relu[0] [0]	(None, 28, 28, 128)	147,584 □
conv3_block4_2_bn ↳ conv3_block4_2_conv[0] [0] (BatchNormalization) ↳	(None, 28, 28, 128)	512 □
conv3_block4_2_relu ↳ conv3_block4_2_bn[0] [0] (Activation) ↳	(None, 28, 28, 128)	0 □
conv3_block4_3_conv (Conv2D) ↳ conv3_block4_2_relu[0] [0]	(None, 28, 28, 512)	66,048 □
conv3_block4_3_bn ↳ conv3_block4_3_conv[0] [0] (BatchNormalization) ↳	(None, 28, 28, 512)	2,048 □
conv3_block4_add (Add) ↳ conv3_block3_out[0] [0], ↳ conv3_block4_3_bn[0] [0]	(None, 28, 28, 512)	0 □
conv3_block4_out (Activation) ↳ conv3_block4_add[0] [0]	(None, 28, 28, 512)	0 □
conv4_block1_1_conv (Conv2D) ↳ conv3_block4_out[0] [0]	(None, 14, 14, 256)	131,328 □
conv4_block1_1_bn ↳ conv4_block1_1_conv[0] [0] (BatchNormalization) ↳	(None, 14, 14, 256)	1,024 □
conv4_block1_1_relu ↳ conv4_block1_1_bn[0] [0] (Activation) ↳	(None, 14, 14, 256)	0 □
conv4_block1_2_conv (Conv2D) ↳ conv4_block1_1_relu[0] [0]	(None, 14, 14, 256)	590,080 □

conv4_block1_2_bn	(None, 14, 14, 256)	1,024	□
↳ conv4_block1_2_conv[0] [0]			
(BatchNormalization)			□
↳			
conv4_block1_2_relu	(None, 14, 14, 256)	0	□
↳ conv4_block1_2_bn[0] [0]			
(Activation)			□
↳			
conv4_block1_0_conv (Conv2D)	(None, 14, 14, 1024)	525,312	□
↳ conv3_block4_out[0] [0]			
conv4_block1_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	□
↳ conv4_block1_2_relu[0] [0]			
conv4_block1_0_bn	(None, 14, 14, 1024)	4,096	□
↳ conv4_block1_0_conv[0] [0]			
(BatchNormalization)			□
↳			
conv4_block1_3_bn	(None, 14, 14, 1024)	4,096	□
↳ conv4_block1_3_conv[0] [0]			
(BatchNormalization)			□
↳			
conv4_block1_add (Add)	(None, 14, 14, 1024)	0	□
↳ conv4_block1_0_bn[0] [0],			
↳ conv4_block1_3_bn[0] [0]			□
conv4_block1_out (Activation)	(None, 14, 14, 1024)	0	□
↳ conv4_block1_add[0] [0]			
conv4_block2_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	□
↳ conv4_block1_out[0] [0]			
conv4_block2_1_bn	(None, 14, 14, 256)	1,024	□
↳ conv4_block2_1_conv[0] [0]			
(BatchNormalization)			□
↳			
conv4_block2_1_relu	(None, 14, 14, 256)	0	□
↳ conv4_block2_1_bn[0] [0]			
(Activation)			□
↳			

conv4_block2_2_conv (Conv2D) ↳ conv4_block2_1_relu[0] [0]	(None, 14, 14, 256)	590,080 □
conv4_block2_2_bn ↳ conv4_block2_2_conv[0] [0] (BatchNormalization) ↳	(None, 14, 14, 256)	1,024 □
conv4_block2_2_relu ↳ conv4_block2_2_bn[0] [0] (Activation) ↳	(None, 14, 14, 256)	0 □
conv4_block2_3_conv (Conv2D) ↳ conv4_block2_2_relu[0] [0]	(None, 14, 14, 1024)	263,168 □
conv4_block2_3_bn ↳ conv4_block2_3_conv[0] [0] (BatchNormalization) ↳	(None, 14, 14, 1024)	4,096 □
conv4_block2_add (Add) ↳ conv4_block1_out[0] [0], ↳ conv4_block2_3_bn[0] [0]	(None, 14, 14, 1024)	0 □
conv4_block2_out (Activation) ↳ conv4_block2_add[0] [0]	(None, 14, 14, 1024)	0 □
conv4_block3_1_conv (Conv2D) ↳ conv4_block2_out[0] [0]	(None, 14, 14, 256)	262,400 □
conv4_block3_1_bn ↳ conv4_block3_1_conv[0] [0] (BatchNormalization) ↳	(None, 14, 14, 256)	1,024 □
conv4_block3_1_relu ↳ conv4_block3_1_bn[0] [0] (Activation) ↳	(None, 14, 14, 256)	0 □
conv4_block3_2_conv (Conv2D) ↳ conv4_block3_1_relu[0] [0]	(None, 14, 14, 256)	590,080 □

conv4_block3_2_bn	(None, 14, 14, 256)	1,024	□
↳ conv4_block3_2_conv[0] [0]			
(BatchNormalization)			□
↳			
conv4_block3_2_relu	(None, 14, 14, 256)	0	□
↳ conv4_block3_2_bn[0] [0]			
(Activation)			□
↳			
conv4_block3_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	□
↳ conv4_block3_2_relu[0] [0]			
conv4_block3_3_bn	(None, 14, 14, 1024)	4,096	□
↳ conv4_block3_3_conv[0] [0]			
(BatchNormalization)			□
↳			
conv4_block3_add (Add)	(None, 14, 14, 1024)	0	□
↳ conv4_block2_out[0] [0],			
↳ conv4_block3_3_bn[0] [0]			□
conv4_block3_out (Activation)	(None, 14, 14, 1024)	0	□
↳ conv4_block3_add[0] [0]			
conv4_block4_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	□
↳ conv4_block3_out[0] [0]			
conv4_block4_1_bn	(None, 14, 14, 256)	1,024	□
↳ conv4_block4_1_conv[0] [0]			
(BatchNormalization)			□
↳			
conv4_block4_1_relu	(None, 14, 14, 256)	0	□
↳ conv4_block4_1_bn[0] [0]			
(Activation)			□
↳			
conv4_block4_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	□
↳ conv4_block4_1_relu[0] [0]			
conv4_block4_2_bn	(None, 14, 14, 256)	1,024	□
↳ conv4_block4_2_conv[0] [0]			
(BatchNormalization)			□
↳			

conv4_block4_2_relu	(None, 14, 14, 256)	0 □
↳ conv4_block4_2_bn[0] [0]		
(Activation)		□
↳		
conv4_block4_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168 □
↳ conv4_block4_2_relu[0] [0]		
conv4_block4_3_bn	(None, 14, 14, 1024)	4,096 □
↳ conv4_block4_3_conv[0] [0]		
(BatchNormalization)		□
↳		
conv4_block4_add (Add)	(None, 14, 14, 1024)	0 □
↳ conv4_block3_out[0] [0],		
↳ conv4_block4_3_bn[0] [0]		□
conv4_block4_out (Activation)	(None, 14, 14, 1024)	0 □
↳ conv4_block4_add[0] [0]		
conv4_block5_1_conv (Conv2D)	(None, 14, 14, 256)	262,400 □
↳ conv4_block4_out[0] [0]		
conv4_block5_1_bn	(None, 14, 14, 256)	1,024 □
↳ conv4_block5_1_conv[0] [0]		
(BatchNormalization)		□
↳		
conv4_block5_1_relu	(None, 14, 14, 256)	0 □
↳ conv4_block5_1_bn[0] [0]		
(Activation)		□
↳		
conv4_block5_2_conv (Conv2D)	(None, 14, 14, 256)	590,080 □
↳ conv4_block5_1_relu[0] [0]		
conv4_block5_2_bn	(None, 14, 14, 256)	1,024 □
↳ conv4_block5_2_conv[0] [0]		
(BatchNormalization)		□
↳		
conv4_block5_2_relu	(None, 14, 14, 256)	0 □
↳ conv4_block5_2_bn[0] [0]		

(Activation)		
↳		
conv4_block5_3_conv (Conv2D) (None, 14, 14, 1024)	263,168	□
↳ conv4_block5_2_relu[0] [0]		
conv4_block5_3_bn (None, 14, 14, 1024)	4,096	□
↳ conv4_block5_3_conv[0] [0]		
(BatchNormalization)		
↳		
conv4_block5_add (Add) (None, 14, 14, 1024)	0	□
↳ conv4_block4_out[0] [0],		
↳ conv4_block5_3_bn[0] [0]		
conv4_block5_out (Activation) (None, 14, 14, 1024)	0	□
↳ conv4_block5_add[0] [0]		
conv4_block6_1_conv (Conv2D) (None, 14, 14, 256)	262,400	□
↳ conv4_block5_out[0] [0]		
conv4_block6_1_bn (None, 14, 14, 256)	1,024	□
↳ conv4_block6_1_conv[0] [0]		
(BatchNormalization)		
↳		
conv4_block6_1_relu (None, 14, 14, 256)	0	□
↳ conv4_block6_1_bn[0] [0]		
(Activation)		
↳		
conv4_block6_2_conv (Conv2D) (None, 14, 14, 256)	590,080	□
↳ conv4_block6_1_relu[0] [0]		
conv4_block6_2_bn (None, 14, 14, 256)	1,024	□
↳ conv4_block6_2_conv[0] [0]		
(BatchNormalization)		
↳		
conv4_block6_2_relu (None, 14, 14, 256)	0	□
↳ conv4_block6_2_bn[0] [0]		
(Activation)		
↳		

conv4_block6_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168 □
└ conv4_block6_2_relu[0] [0]		
conv4_block6_3_bn	(None, 14, 14, 1024)	4,096 □
└ conv4_block6_3_conv[0] [0]		
(BatchNormalization)		□
└		
conv4_block6_add (Add)	(None, 14, 14, 1024)	0 □
└ conv4_block5_out[0] [0],		
└ conv4_block6_3_bn[0] [0]		□
conv4_block6_out (Activation)	(None, 14, 14, 1024)	0 □
└ conv4_block6_add[0] [0]		
conv5_block1_1_conv (Conv2D)	(None, 7, 7, 512)	524,800 □
└ conv4_block6_out[0] [0]		
conv5_block1_1_bn	(None, 7, 7, 512)	2,048 □
└ conv5_block1_1_conv[0] [0]		
(BatchNormalization)		□
└		
conv5_block1_1_relu	(None, 7, 7, 512)	0 □
└ conv5_block1_1_bn[0] [0]		
(Activation)		□
└		
conv5_block1_2_conv (Conv2D)	(None, 7, 7, 512)	2,359,808 □
└ conv5_block1_1_relu[0] [0]		
conv5_block1_2_bn	(None, 7, 7, 512)	2,048 □
└ conv5_block1_2_conv[0] [0]		
(BatchNormalization)		□
└		
conv5_block1_2_relu	(None, 7, 7, 512)	0 □
└ conv5_block1_2_bn[0] [0]		
(Activation)		□
└		
conv5_block1_0_conv (Conv2D)	(None, 7, 7, 2048)	2,099,200 □
└ conv4_block6_out[0] [0]		

conv5_block1_3_conv (Conv2D)	(None, 7, 7, 2048)	1,050,624	□
└ conv5_block1_2_relu[0] [0]			
conv5_block1_0_bn	(None, 7, 7, 2048)	8,192	□
└ conv5_block1_0_conv[0] [0]			
(BatchNormalization)			□
└			
conv5_block1_3_bn	(None, 7, 7, 2048)	8,192	□
└ conv5_block1_3_conv[0] [0]			
(BatchNormalization)			□
└			
conv5_block1_add (Add)	(None, 7, 7, 2048)	0	□
└ conv5_block1_0_bn[0] [0],			
└ conv5_block1_3_bn[0] [0]			
conv5_block1_out (Activation)	(None, 7, 7, 2048)	0	□
└ conv5_block1_add[0] [0]			
conv5_block2_1_conv (Conv2D)	(None, 7, 7, 512)	1,049,088	□
└ conv5_block1_out[0] [0]			
conv5_block2_1_bn	(None, 7, 7, 512)	2,048	□
└ conv5_block2_1_conv[0] [0]			
(BatchNormalization)			□
└			
conv5_block2_1_relu	(None, 7, 7, 512)	0	□
└ conv5_block2_1_bn[0] [0]			
(Activation)			□
└			
conv5_block2_2_conv (Conv2D)	(None, 7, 7, 512)	2,359,808	□
└ conv5_block2_1_relu[0] [0]			
conv5_block2_2_bn	(None, 7, 7, 512)	2,048	□
└ conv5_block2_2_conv[0] [0]			
(BatchNormalization)			□
└			
conv5_block2_2_relu	(None, 7, 7, 512)	0	□
└ conv5_block2_2_bn[0] [0]			
(Activation)			□
└			

conv5_block2_3_conv (Conv2D)	(None, 7, 7, 2048)	1,050,624	□
└ conv5_block2_2_relu[0] [0]			
conv5_block2_3_bn	(None, 7, 7, 2048)	8,192	□
└ conv5_block2_3_conv[0] [0]			
(BatchNormalization)			□
└			
conv5_block2_add (Add)	(None, 7, 7, 2048)	0	□
└ conv5_block1_out[0] [0],			
└ conv5_block2_3_bn[0] [0]			□
conv5_block2_out (Activation)	(None, 7, 7, 2048)	0	□
└ conv5_block2_add[0] [0]			
conv5_block3_1_conv (Conv2D)	(None, 7, 7, 512)	1,049,088	□
└ conv5_block2_out[0] [0]			
conv5_block3_1_bn	(None, 7, 7, 512)	2,048	□
└ conv5_block3_1_conv[0] [0]			
(BatchNormalization)			□
└			
conv5_block3_1_relu	(None, 7, 7, 512)	0	□
└ conv5_block3_1_bn[0] [0]			
(Activation)			□
└			
conv5_block3_2_conv (Conv2D)	(None, 7, 7, 512)	2,359,808	□
└ conv5_block3_1_relu[0] [0]			
conv5_block3_2_bn	(None, 7, 7, 512)	2,048	□
└ conv5_block3_2_conv[0] [0]			
(BatchNormalization)			□
└			
conv5_block3_2_relu	(None, 7, 7, 512)	0	□
└ conv5_block3_2_bn[0] [0]			
(Activation)			□
└			
conv5_block3_3_conv (Conv2D)	(None, 7, 7, 2048)	1,050,624	□
└ conv5_block3_2_relu[0] [0]			

```

conv5_block3_3_bn           (None, 7, 7, 2048)      8,192 □
└conv5_block3_3_conv[0][0]
(BatchNormalization)         □
└

conv5_block3_add (Add)       (None, 7, 7, 2048)      0 □
└conv5_block2_out[0][0],     □
└

└conv5_block3_3_bn[0][0]

conv5_block3_out (Activation) (None, 7, 7, 2048)      0 □
└conv5_block3_add[0][0]

```

Total params: 23,587,712 (89.98 MB)

Trainable params: 23,534,592 (89.78 MB)

Non-trainable params: 53,120 (207.50 KB)

Modelo preentrenado cargado correctamente.

En la siguiente celda se congela la ResNet50 preentrenada para usarla como extractor de características y se construye una cabeza de clasificación personalizada. La arquitectura incluye: una entrada compatible con ResNet50, un GlobalAveragePooling2D para reducir los mapas de características, un Dropout del 30% para evitar sobreajuste y una capa Dense con softmax para obtener las probabilidades finales por clase. Luego el modelo se compila con Adam (lr=1e-3) y categorical crossentropy, y se entrena únicamente la parte superior (top classifier) durante 10 épocas para adaptarlo a la nueva tarea manteniendo la red base congelada.

TRANSFER LEARNING MODELO

```
[ ]: base_model.trainable = False
print("Base ResNet50 congelada.")

# CONSTRUIR LA CABEZA DE CLASIFICACIÓN

inputs = layers.Input(shape=(224, 224, 3))
x = base_model(inputs, training=False)
x = layers.GlobalAveragePooling2D()(x)
x = layers.Dropout(0.3)(x)                      # Regularización
outputs = layers.Dense(num_classes, activation='softmax')(x)

model = models.Model(inputs, outputs)
model.summary()
```

```

# COMPIALAR EL MODELO

model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=1e-3),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

# ENTRENAMIENTO DEL "TOP CLASSIFIER"

history = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=10,
    verbose=1
)

print("Entrenamiento inicial completo.")

```

Base ResNet50 congelada.

Model: "functional"

Layer (type)	Output Shape	
Param #		
input_layer_3 (InputLayer)	(None, 224, 224, 3)	
~ 0		
resnet50 (Functional)	(None, 7, 7, 2048)	
~23,587,712		
global_average_pooling2d_1	(None, 2048)	
~ 0		
(GlobalAveragePooling2D)		
dropout_1 (Dropout)	(None, 2048)	
~ 0		
dense_1 (Dense)	(None, 100)	
~204,900		
Total params: 23,792,612 (90.76 MB)		

```
Trainable params: 204,900 (800.39 KB)
```

```
Non-trainable params: 23,587,712 (89.98 MB)
```

```
Epoch 1/10
395/395          4449s 11s/step -
accuracy: 0.6880 - loss: 1.3375 - val_accuracy: 0.9040 - val_loss: 0.3843
Epoch 2/10
395/395          5453s 14s/step -
accuracy: 0.9042 - loss: 0.3616 - val_accuracy: 0.9240 - val_loss: 0.2765
Epoch 3/10
395/395          4303s 11s/step -
accuracy: 0.9373 - loss: 0.2299 - val_accuracy: 0.9320 - val_loss: 0.2618
Epoch 4/10
395/395          4271s 11s/step -
accuracy: 0.9529 - loss: 0.1643 - val_accuracy: 0.9420 - val_loss: 0.2684
Epoch 5/10
395/395          4161s 11s/step -
accuracy: 0.9714 - loss: 0.1146 - val_accuracy: 0.9360 - val_loss: 0.2365
Epoch 6/10
395/395          4134s 10s/step -
accuracy: 0.9706 - loss: 0.1016 - val_accuracy: 0.9520 - val_loss: 0.2258
Epoch 7/10
395/395          4206s 11s/step -
accuracy: 0.9797 - loss: 0.0788 - val_accuracy: 0.9460 - val_loss: 0.2365
Epoch 8/10
395/395          4194s 11s/step -
accuracy: 0.9839 - loss: 0.0660 - val_accuracy: 0.9340 - val_loss: 0.2399
Epoch 9/10
395/395          4191s 11s/step -
accuracy: 0.9858 - loss: 0.0527 - val_accuracy: 0.9460 - val_loss: 0.2560
Epoch 10/10
395/395          4231s 11s/step -
accuracy: 0.9847 - loss: 0.0562 - val_accuracy: 0.9500 - val_loss: 0.2354
Entrenamiento inicial completo.
```

5. Monitorización del proceso de entrenamiento

```
[ ]: # GRAFICAR LOS RESULTADOS

plt.figure(figsize=(16, 6))

# GRÁFICA : LOSS
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], 'b', label='loss')
plt.plot(history.history['val_loss'], 'r', label='val_loss')
plt.title(f'Pérdida - ResNet50')
```

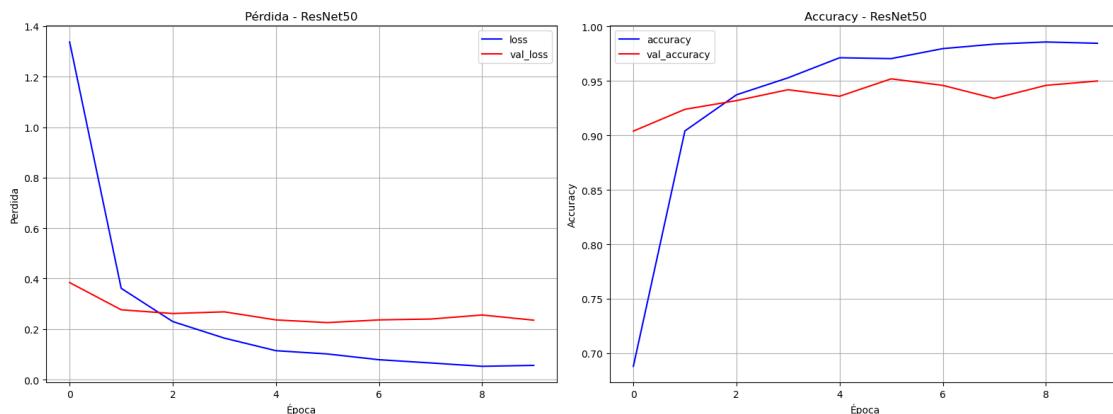
```

plt.xlabel('Época')
plt.ylabel('Perdida')
plt.legend()
plt.grid(True)

# GRÁFICA 2: ACCURACY
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], 'b', label='accuracy')
plt.plot(history.history['val_accuracy'], 'r', label='val_accuracy')
plt.title(f'Accuracy - ResNet50')
plt.xlabel('Época')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

plt.tight_layout()
plt.show()

```



El modelo mostró un aprendizaje súper rápido y estable: la accuracy de entrenamiento subió casi al 95% mientras que la de validación se mantuvo firme alrededor del 90–95%, lo que indica buena capacidad de generalización sin signos fuertes de sobreajuste. Las curvas de pérdida y accuracy confirman este comportamiento: la pérdida baja de forma limpia y la validación se mantiene estable, aunque con pequeñas variaciones normales cuando la red base está congelada. En general, el top classifier aprovechó bien las características de ResNet50, pero para evitar que el modelo se estanque y mejorar aún más su rendimiento, es necesario aplicar data augmentation, ya que aumenta la variedad de imágenes, fortalece la generalización y reduce ese ligero desfase entre entrenamiento y validación que empieza a verse después de varias épocas.

DATA AUGMENTATION Y FINE TUNING

[]: # Generador de Entrenamiento (CON Data Augmentation) ---

```
print("Configurando generador de ENTRENAMIENTO (con Data Augmentation)...")
```

```

train_datagen = ImageDataGenerator(
    preprocessing_function=preprocess_input,
    rotation_range=30,           # Rota
    width_shift_range=0.2,        # Desplaza
    height_shift_range=0.2,
    shear_range=0.2,             # Inclina
    zoom_range=0.2,              # Zoom
    horizontal_flip=True,        # Voltea
    fill_mode='nearest'
)

# Generador de Validación
print("Configurando generador de VALIDACIÓN (solo re-escalado)...")
val_test_datagen = ImageDataGenerator(preprocessing_function=preprocess_input)

# Cargar datos desde los directorios
print("\nCargando datos de ENTRENAMIENTO:")
train_generator = train_datagen.flow_from_directory(
    TRAIN_DIR,
    target_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    seed = 1
)

print("\nCargando datos de VALIDACIÓN:")
validation_generator = val_test_datagen.flow_from_directory(
    VALID_DIR,
    target_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    seed = 1
)

```

Configurando generador de ENTRENAMIENTO (con Data Augmentation)...
Configurando generador de VALIDACIÓN (solo re-escalado)...

Cargando datos de ENTRENAMIENTO:
Found 12639 images belonging to 100 classes.

Cargando datos de VALIDACIÓN:
Found 500 images belonging to 100 classes.

```
[ ]: IMG_SHAPE = (224, 224, 3)
base_model_aug = ResNet50(weights='imagenet',
                           include_top=False,
                           input_shape=IMG_SHAPE)
```

```

base_model_aug.trainable = False

# Construir el Head (con regularización)
x = base_model_aug.output
x = GlobalAveragePooling2D()(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
x = Dense(512, activation='relu', kernel_regularizer=l2(0.01))(x)
outputs = Dense(100, activation='softmax')(x)

model_aug = Model(inputs=base_model_aug.input, outputs=outputs)

# Compilar el Modelo
model_aug.compile(optimizer='adam',
                   loss='categorical_crossentropy',
                   metrics=['accuracy'])

print("\nResumen del Modelo (Fase 1 con Augmentation)")
model_aug.summary()

# Callbacks en caso que no haya mejora en las épocas
early_stopper = EarlyStopping(monitor='val_loss',
                               patience=5,
                               restore_best_weights=True)

# Entrenar
print("\nIniciando entrenamiento (Fase 1 con Augmentation)...")

history_aug = model_aug.fit(
    train_generator,
    epochs=20, # Se agregan 10 épocas más para asegurar que el nuevo procedimiento mejore el resultado
    validation_data=validation_generator,
    callbacks=[early_stopper]
)

print("\nEntrenamiento de Fase 1 (con Augmentation) completado.")

```

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
94765736/94765736 1s
0us/step

Resumen del Modelo (Fase 1 con Augmentation)

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 224, 224, 3)	0	-
conv1_pad (ZeroPadding2D)	(None, 230, 230, 3)	0	input_layer[0] [0]
conv1_conv (Conv2D)	(None, 112, 112, 64)	9,472	conv1_pad[0] [0]
conv1_bn (BatchNormalization)	(None, 112, 112, 64)	256	conv1_conv[0] [0]
conv1_relu (Activation)	(None, 112, 112, 64)	0	conv1_bn[0] [0]
pool1_pad (ZeroPadding2D)	(None, 114, 114, 64)	0	conv1_relu[0] [0]
pool1_pool (MaxPooling2D)	(None, 56, 56, 64)	0	pool1_pad[0] [0]
conv2_block1_1_conv (Conv2D)	(None, 56, 56, 64)	4,160	pool1_pool[0] [0]
conv2_block1_1_bn (BatchNormalization)	(None, 56, 56, 64)	256	conv2_block1_1_c...
conv2_block1_1_relu (Activation)	(None, 56, 56, 64)	0	conv2_block1_1_b...
conv2_block1_2_conv (Conv2D)	(None, 56, 56, 64)	36,928	conv2_block1_1_r...
conv2_block1_2_bn (BatchNormalization)	(None, 56, 56, 64)	256	conv2_block1_2_c...
conv2_block1_2_relu (Activation)	(None, 56, 56, 64)	0	conv2_block1_2_b...
conv2_block1_0_conv (Conv2D)	(None, 56, 56, 256)	16,640	pool1_pool[0] [0]
conv2_block1_3_conv (Conv2D)	(None, 56, 56, 256)	16,640	conv2_block1_2_r...

conv2_block1_0_bn (BatchNormalizatio...)	(None, 56, 56, 256)	1,024	conv2_block1_0_c...
conv2_block1_3_bn (BatchNormalizatio...)	(None, 56, 56, 256)	1,024	conv2_block1_3_c...
conv2_block1_add (Add)	(None, 56, 56, 256)	0	conv2_block1_0_b... conv2_block1_3_b...
conv2_block1_out (Activation)	(None, 56, 56, 256)	0	conv2_block1_add...
conv2_block2_1_conv (Conv2D)	(None, 56, 56, 64)	16,448	conv2_block1_out...
conv2_block2_1_bn (BatchNormalizatio...)	(None, 56, 56, 64)	256	conv2_block2_1_c...
conv2_block2_1_relu (Activation)	(None, 56, 56, 64)	0	conv2_block2_1_b...
conv2_block2_2_conv (Conv2D)	(None, 56, 56, 64)	36,928	conv2_block2_1_r...
conv2_block2_2_bn (BatchNormalizatio...)	(None, 56, 56, 64)	256	conv2_block2_2_c...
conv2_block2_2_relu (Activation)	(None, 56, 56, 64)	0	conv2_block2_2_b...
conv2_block2_3_conv (Conv2D)	(None, 56, 56, 256)	16,640	conv2_block2_2_r...
conv2_block2_3_bn (BatchNormalizatio...)	(None, 56, 56, 256)	1,024	conv2_block2_3_c...
conv2_block2_add (Add)	(None, 56, 56, 256)	0	conv2_block1_out... conv2_block2_3_b...
conv2_block2_out (Activation)	(None, 56, 56, 256)	0	conv2_block2_add...
conv2_block3_1_conv (Conv2D)	(None, 56, 56, 64)	16,448	conv2_block2_out...
conv2_block3_1_bn (BatchNormalizatio...)	(None, 56, 56, 64)	256	conv2_block3_1_c...

conv2_block3_1_relu (Activation)	(None, 56, 56, 64)	0	conv2_block3_1_b...
conv2_block3_2_conv (Conv2D)	(None, 56, 56, 64)	36,928	conv2_block3_1_r...
conv2_block3_2_bn (BatchNormalizatio...)	(None, 56, 56, 64)	256	conv2_block3_2_c...
conv2_block3_2_relu (Activation)	(None, 56, 56, 64)	0	conv2_block3_2_b...
conv2_block3_3_conv (Conv2D)	(None, 56, 56, 256)	16,640	conv2_block3_2_r...
conv2_block3_3_bn (BatchNormalizatio...)	(None, 56, 56, 256)	1,024	conv2_block3_3_c...
conv2_block3_add (Add)	(None, 56, 56, 256)	0	conv2_block2_out... conv2_block3_3_b...
conv2_block3_out (Activation)	(None, 56, 56, 256)	0	conv2_block3_add...
conv3_block1_1_conv (Conv2D)	(None, 28, 28, 128)	32,896	conv2_block3_out...
conv3_block1_1_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block1_1_c...
conv3_block1_1_relu (Activation)	(None, 28, 28, 128)	0	conv3_block1_1_b...
conv3_block1_2_conv (Conv2D)	(None, 28, 28, 128)	147,584	conv3_block1_1_r...
conv3_block1_2_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block1_2_c...
conv3_block1_2_relu (Activation)	(None, 28, 28, 128)	0	conv3_block1_2_b...
conv3_block1_0_conv (Conv2D)	(None, 28, 28, 512)	131,584	conv2_block3_out...
conv3_block1_3_conv (Conv2D)	(None, 28, 28, 512)	66,048	conv3_block1_2_r...

conv3_block1_0_bn (BatchNormalizatio...)	(None, 28, 28, 512)	2,048	conv3_block1_0_c...
conv3_block1_3_bn (BatchNormalizatio...)	(None, 28, 28, 512)	2,048	conv3_block1_3_c...
conv3_block1_add (Add)	(None, 28, 28, 512)	0	conv3_block1_0_b... conv3_block1_3_b...
conv3_block1_out (Activation)	(None, 28, 28, 512)	0	conv3_block1_add...
conv3_block2_1_conv (Conv2D)	(None, 28, 28, 128)	65,664	conv3_block1_out...
conv3_block2_1_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block2_1_c...
conv3_block2_1_relu (Activation)	(None, 28, 28, 128)	0	conv3_block2_1_b...
conv3_block2_2_conv (Conv2D)	(None, 28, 28, 128)	147,584	conv3_block2_1_r...
conv3_block2_2_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block2_2_c...
conv3_block2_2_relu (Activation)	(None, 28, 28, 128)	0	conv3_block2_2_b...
conv3_block2_3_conv (Conv2D)	(None, 28, 28, 512)	66,048	conv3_block2_2_r...
conv3_block2_3_bn (BatchNormalizatio...)	(None, 28, 28, 512)	2,048	conv3_block2_3_c...
conv3_block2_add (Add)	(None, 28, 28, 512)	0	conv3_block1_out... conv3_block2_3_b...
conv3_block2_out (Activation)	(None, 28, 28, 512)	0	conv3_block2_add...
conv3_block3_1_conv (Conv2D)	(None, 28, 28, 128)	65,664	conv3_block2_out...
conv3_block3_1_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block3_1_c...

conv3_block3_1_relu (Activation)	(None, 28, 28, 128)	0	conv3_block3_1_b...
conv3_block3_2_conv (Conv2D)	(None, 28, 28, 128)	147,584	conv3_block3_1_r...
conv3_block3_2_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block3_2_c...
conv3_block3_2_relu (Activation)	(None, 28, 28, 128)	0	conv3_block3_2_b...
conv3_block3_3_conv (Conv2D)	(None, 28, 28, 512)	66,048	conv3_block3_2_r...
conv3_block3_3_bn (BatchNormalizatio...)	(None, 28, 28, 512)	2,048	conv3_block3_3_c...
conv3_block3_add (Add)	(None, 28, 28, 512)	0	conv3_block2_out... conv3_block3_3_b...
conv3_block3_out (Activation)	(None, 28, 28, 512)	0	conv3_block3_add...
conv3_block4_1_conv (Conv2D)	(None, 28, 28, 128)	65,664	conv3_block3_out...
conv3_block4_1_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block4_1_c...
conv3_block4_1_relu (Activation)	(None, 28, 28, 128)	0	conv3_block4_1_b...
conv3_block4_2_conv (Conv2D)	(None, 28, 28, 128)	147,584	conv3_block4_1_r...
conv3_block4_2_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block4_2_c...
conv3_block4_2_relu (Activation)	(None, 28, 28, 128)	0	conv3_block4_2_b...
conv3_block4_3_conv (Conv2D)	(None, 28, 28, 512)	66,048	conv3_block4_2_r...
conv3_block4_3_bn (BatchNormalizatio...)	(None, 28, 28, 512)	2,048	conv3_block4_3_c...

conv3_block4_add (Add)	(None, 28, 28, 512)	0	conv3_block3_out... conv3_block4_3_b...
conv3_block4_out (Activation)	(None, 28, 28, 512)	0	conv3_block4_add...
conv4_block1_1_conv (Conv2D)	(None, 14, 14, 256)	131,328	conv3_block4_out...
conv4_block1_1_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block1_1_c...
conv4_block1_1_relu (Activation)	(None, 14, 14, 256)	0	conv4_block1_1_b...
conv4_block1_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block1_1_r...
conv4_block1_2_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block1_2_c...
conv4_block1_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block1_2_b...
conv4_block1_0_conv (Conv2D)	(None, 14, 14, 1024)	525,312	conv3_block4_out...
conv4_block1_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block1_2_r...
conv4_block1_0_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block1_0_c...
conv4_block1_3_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block1_3_c...
conv4_block1_add (Add)	(None, 14, 14, 1024)	0	conv4_block1_0_b... conv4_block1_3_b...
conv4_block1_out (Activation)	(None, 14, 14, 1024)	0	conv4_block1_add...
conv4_block2_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	conv4_block1_out...
conv4_block2_1_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block2_1_c...

conv4_block2_1_relu (Activation)	(None, 14, 14, 256)	0	conv4_block2_1_b...
conv4_block2_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block2_1_r...
conv4_block2_2_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block2_2_c...
conv4_block2_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block2_2_b...
conv4_block2_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block2_2_r...
conv4_block2_3_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block2_3_c...
conv4_block2_add (Add)	(None, 14, 14, 1024)	0	conv4_block1_out... conv4_block2_3_b...
conv4_block2_out (Activation)	(None, 14, 14, 1024)	0	conv4_block2_add...
conv4_block3_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	conv4_block2_out...
conv4_block3_1_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block3_1_c...
conv4_block3_1_relu (Activation)	(None, 14, 14, 256)	0	conv4_block3_1_b...
conv4_block3_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block3_1_r...
conv4_block3_2_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block3_2_c...
conv4_block3_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block3_2_b...
conv4_block3_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block3_2_r...
conv4_block3_3_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block3_3_c...

conv4_block3_add (Add)	(None, 14, 14, 1024)	0	conv4_block2_out... conv4_block3_3_b...
conv4_block3_out (Activation)	(None, 14, 14, 1024)	0	conv4_block3_add...
conv4_block4_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	conv4_block3_out... conv4_block4_1_c...
conv4_block4_1_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block4_1_c...
conv4_block4_1_relu (Activation)	(None, 14, 14, 256)	0	conv4_block4_1_b...
conv4_block4_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block4_1_r... conv4_block4_2_c...
conv4_block4_2_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block4_2_c...
conv4_block4_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block4_2_b...
conv4_block4_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block4_2_r... conv4_block4_3_c...
conv4_block4_3_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block4_3_c...
conv4_block4_add (Add)	(None, 14, 14, 1024)	0	conv4_block3_out... conv4_block4_3_b...
conv4_block4_out (Activation)	(None, 14, 14, 1024)	0	conv4_block4_add...
conv4_block5_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	conv4_block4_out... conv4_block5_1_c...
conv4_block5_1_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block5_1_c...
conv4_block5_1_relu (Activation)	(None, 14, 14, 256)	0	conv4_block5_1_b...
conv4_block5_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block5_1_r...

conv4_block5_2_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block5_2_c...
conv4_block5_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block5_2_b...
conv4_block5_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block5_2_r...
conv4_block5_3_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block5_3_c...
conv4_block5_add (Add)	(None, 14, 14, 1024)	0	conv4_block4_out... conv4_block5_3_b...
conv4_block5_out (Activation)	(None, 14, 14, 1024)	0	conv4_block5_add...
conv4_block6_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	conv4_block5_out... conv4_block6_1_c...
conv4_block6_1_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block6_1_c...
conv4_block6_1_relu (Activation)	(None, 14, 14, 256)	0	conv4_block6_1_b...
conv4_block6_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block6_1_r... conv4_block6_2_c...
conv4_block6_2_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block6_2_c...
conv4_block6_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block6_2_b...
conv4_block6_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block6_2_r... conv4_block6_3_c...
conv4_block6_3_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block6_3_c...
conv4_block6_add (Add)	(None, 14, 14, 1024)	0	conv4_block5_out... conv4_block6_3_b...
conv4_block6_out (Activation)	(None, 14, 14, 1024)	0	conv4_block6_add...

conv5_block1_1_conv	(None, 7, 7, 512)	524,800	conv4_block6_out...
(Conv2D)			
conv5_block1_1_bn	(None, 7, 7, 512)	2,048	conv5_block1_1_c...
(BatchNormalizatio...			
conv5_block1_1_relu	(None, 7, 7, 512)	0	conv5_block1_1_b...
(Activation)			
conv5_block1_2_conv	(None, 7, 7, 512)	2,359,808	conv5_block1_1_r...
(Conv2D)			
conv5_block1_2_bn	(None, 7, 7, 512)	2,048	conv5_block1_2_c...
(BatchNormalizatio...			
conv5_block1_2_relu	(None, 7, 7, 512)	0	conv5_block1_2_b...
(Activation)			
conv5_block1_0_conv	(None, 7, 7, 2048)	2,099,200	conv4_block6_out...
(Conv2D)			
conv5_block1_3_conv	(None, 7, 7, 2048)	1,050,624	conv5_block1_2_r...
(Conv2D)			
conv5_block1_0_bn	(None, 7, 7, 2048)	8,192	conv5_block1_0_c...
(BatchNormalizatio...			
conv5_block1_3_bn	(None, 7, 7, 2048)	8,192	conv5_block1_3_c...
(BatchNormalizatio...			
conv5_block1_add	(None, 7, 7, 2048)	0	conv5_block1_0_b...
(Add)			conv5_block1_3_b...
conv5_block1_out	(None, 7, 7, 2048)	0	conv5_block1_add...
(Activation)			
conv5_block2_1_conv	(None, 7, 7, 512)	1,049,088	conv5_block1_out...
(Conv2D)			
conv5_block2_1_bn	(None, 7, 7, 512)	2,048	conv5_block2_1_c...
(BatchNormalizatio...			
conv5_block2_1_relu	(None, 7, 7, 512)	0	conv5_block2_1_b...
(Activation)			
conv5_block2_2_conv	(None, 7, 7, 512)	2,359,808	conv5_block2_1_r...
(Conv2D)			

conv5_block2_2_bn	(None, 7, 7, 512) (BatchNormalizatio...)	2,048	conv5_block2_2_c...
conv5_block2_2_relu	(None, 7, 7, 512) (Activation)	0	conv5_block2_2_b...
conv5_block2_3_conv	(None, 7, 7, 2048) (Conv2D)	1,050,624	conv5_block2_2_r...
conv5_block2_3_bn	(None, 7, 7, 2048) (BatchNormalizatio...)	8,192	conv5_block2_3_c...
conv5_block2_add	(None, 7, 7, 2048) (Add)	0	conv5_block1_out... conv5_block2_3_b...
conv5_block2_out	(None, 7, 7, 2048) (Activation)	0	conv5_block2_add...
conv5_block3_1_conv	(None, 7, 7, 512) (Conv2D)	1,049,088	conv5_block2_out...
conv5_block3_1_bn	(None, 7, 7, 512) (BatchNormalizatio...)	2,048	conv5_block3_1_c...
conv5_block3_1_relu	(None, 7, 7, 512) (Activation)	0	conv5_block3_1_b...
conv5_block3_2_conv	(None, 7, 7, 512) (Conv2D)	2,359,808	conv5_block3_1_r...
conv5_block3_2_bn	(None, 7, 7, 512) (BatchNormalizatio...)	2,048	conv5_block3_2_c...
conv5_block3_2_relu	(None, 7, 7, 512) (Activation)	0	conv5_block3_2_b...
conv5_block3_3_conv	(None, 7, 7, 2048) (Conv2D)	1,050,624	conv5_block3_2_r...
conv5_block3_3_bn	(None, 7, 7, 2048) (BatchNormalizatio...)	8,192	conv5_block3_3_c...
conv5_block3_add	(None, 7, 7, 2048) (Add)	0	conv5_block2_out... conv5_block3_3_b...
conv5_block3_out	(None, 7, 7, 2048) (Activation)	0	conv5_block3_add...

global_average_poo...	(None, 2048)	0	conv5_block3_out...
	(GlobalAveragePool...		
batch_normalization	(None, 2048)	8,192	global_average_p...
	(BatchNormalizatio...		
dropout (Dropout)	(None, 2048)	0	batch_normalizat...
dense (Dense)	(None, 512)	1,049,088	dropout[0][0]
dense_1 (Dense)	(None, 100)	51,300	dense[0][0]

Total params: 24,696,292 (94.21 MB)

Trainable params: 1,104,484 (4.21 MB)

Non-trainable params: 23,591,808 (90.00 MB)

Iniciando entrenamiento (Fase 1 con Augmentation)...

```
/usr/local/lib/python3.12/dist-
packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121:
UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in
its constructor. `**kwargs` can include `workers`, `use_multiprocessing`,
`max_queue_size`. Do not pass these arguments to `fit()`, as they will be
ignored.
    self._warn_if_super_not_called()

Epoch 1/20
395/395          184s 430ms/step -
accuracy: 0.5360 - loss: 8.2741 - val_accuracy: 0.8760 - val_loss: 2.5006
Epoch 2/20
395/395          154s 391ms/step -
accuracy: 0.8261 - loss: 2.3485 - val_accuracy: 0.8800 - val_loss: 1.8024
Epoch 3/20
395/395          154s 390ms/step -
accuracy: 0.8269 - loss: 1.9190 - val_accuracy: 0.8840 - val_loss: 1.8060
Epoch 4/20
395/395          154s 391ms/step -
accuracy: 0.8250 - loss: 1.9285 - val_accuracy: 0.8680 - val_loss: 1.8438
Epoch 5/20
395/395          160s 405ms/step -
accuracy: 0.8358 - loss: 1.9185 - val_accuracy: 0.8920 - val_loss: 1.8056
Epoch 6/20
395/395          160s 405ms/step -
```

```
accuracy: 0.8316 - loss: 1.9685 - val_accuracy: 0.8840 - val_loss: 1.7847
Epoch 7/20
395/395          159s 403ms/step -
accuracy: 0.8272 - loss: 1.9554 - val_accuracy: 0.8980 - val_loss: 1.7693
Epoch 8/20
395/395          159s 403ms/step -
accuracy: 0.8303 - loss: 1.9412 - val_accuracy: 0.8860 - val_loss: 1.8092
Epoch 9/20
395/395          160s 405ms/step -
accuracy: 0.8420 - loss: 1.8883 - val_accuracy: 0.8900 - val_loss: 1.7918
Epoch 10/20
395/395          159s 402ms/step -
accuracy: 0.8332 - loss: 1.9038 - val_accuracy: 0.8980 - val_loss: 1.6592
Epoch 11/20
395/395          160s 406ms/step -
accuracy: 0.8402 - loss: 1.8260 - val_accuracy: 0.8840 - val_loss: 1.7443
Epoch 12/20
395/395          160s 405ms/step -
accuracy: 0.8406 - loss: 1.8650 - val_accuracy: 0.8960 - val_loss: 1.7580
Epoch 13/20
395/395          160s 405ms/step -
accuracy: 0.8375 - loss: 1.8465 - val_accuracy: 0.9160 - val_loss: 1.6368
Epoch 14/20
395/395          160s 405ms/step -
accuracy: 0.8372 - loss: 1.8260 - val_accuracy: 0.8860 - val_loss: 1.7018
Epoch 15/20
395/395          160s 406ms/step -
accuracy: 0.8439 - loss: 1.7860 - val_accuracy: 0.8980 - val_loss: 1.6366
Epoch 16/20
395/395          160s 405ms/step -
accuracy: 0.8442 - loss: 1.7727 - val_accuracy: 0.8940 - val_loss: 1.6614
Epoch 17/20
395/395          159s 403ms/step -
accuracy: 0.8415 - loss: 1.7727 - val_accuracy: 0.9000 - val_loss: 1.6393
Epoch 18/20
395/395          160s 406ms/step -
accuracy: 0.8391 - loss: 1.7668 - val_accuracy: 0.9040 - val_loss: 1.6177
Epoch 19/20
395/395          161s 406ms/step -
accuracy: 0.8447 - loss: 1.7424 - val_accuracy: 0.8920 - val_loss: 1.6630
Epoch 20/20
395/395          160s 403ms/step -
accuracy: 0.8467 - loss: 1.7314 - val_accuracy: 0.9060 - val_loss: 1.5714
```

Entrenamiento de Fase 1 (con Augmentation) completado.

Después de entrenar el modelo con data augmentation y aumentar el número de épocas, el desempeño no mejoró: la accuracy de validación se mantuvo alrededor del 90% y la pérdida presentó

fluctuaciones, lo que indica que la cabeza del modelo ya llegó al límite de lo que puede aprender mientras la ResNet50 sigue congelada. El augmentation sí añadió variabilidad útil, pero también hizo más compleja la tarea, y como la red base no pudo adaptarse a esos cambios, el modelo terminó estabilizado e incluso mostrando leves retrocesos en el val_loss. Por eso se vuelve necesario aplicar fine tuning, ya que al descongelar parcialmente las capas superiores de ResNet50 el modelo podrá ajustar pesos más profundos, aprender patrones específicos del dataset y aprovechar realmente las variaciones creadas por el data augmentation, permitiendo superar ese “techo” del 90% donde quedó estancado.

```
[ ]: # Descongelar capas superiores
base_model_aug.trainable = True
#Se descongela apartir de la capa 140 conv4_block6_3_bn
fine_tune_at = 140
for layer in base_model_aug.layers[:fine_tune_at]:
    layer.trainable = False

# Re-compilar con LR bajo
model_aug.compile(optimizer=Adam(learning_rate=1e-5), # 0.00001
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

print("\nResumen del Modelo (Fase 2 con Augmentation)")
model_aug.summary()

# Continuar Entrenamiento
initial_epochs = len(history_aug.history['loss'])
fine_tune_epochs = 20
total_epochs = initial_epochs + fine_tune_epochs

print(f"\nIniciando Fine-Tuning (con Augmentation) desde la época"
      f"{initial_epochs}...")

history_fine_tune_aug = model_aug.fit(
    train_generator,
    epochs=total_epochs,
    initial_epoch=initial_epochs,
    validation_data=validation_generator,
    callbacks=[early_stopper]
)

print("\nEntrenamiento de Fine-Tuning (Fase 2 con Augmentation) completado.")
```

Resumen del Modelo (Fase 2 con Augmentation)

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 224, 224, 3)	0	-
conv1_pad (ZeroPadding2D)	(None, 230, 230, 3)	0	input_layer[0] [0]
conv1_conv (Conv2D)	(None, 112, 112, 64)	9,472	conv1_pad[0] [0]
conv1_bn (BatchNormalization)	(None, 112, 112, 64)	256	conv1_conv[0] [0]
conv1_relu (Activation)	(None, 112, 112, 64)	0	conv1_bn[0] [0]
pool1_pad (ZeroPadding2D)	(None, 114, 114, 64)	0	conv1_relu[0] [0]
pool1_pool (MaxPooling2D)	(None, 56, 56, 64)	0	pool1_pad[0] [0]
conv2_block1_1_conv (Conv2D)	(None, 56, 56, 64)	4,160	pool1_pool[0] [0]
conv2_block1_1_bn (BatchNormalization)	(None, 56, 56, 64)	256	conv2_block1_1_c...
conv2_block1_1_relu (Activation)	(None, 56, 56, 64)	0	conv2_block1_1_b...
conv2_block1_2_conv (Conv2D)	(None, 56, 56, 64)	36,928	conv2_block1_1_r...
conv2_block1_2_bn (BatchNormalization)	(None, 56, 56, 64)	256	conv2_block1_2_c...
conv2_block1_2_relu (Activation)	(None, 56, 56, 64)	0	conv2_block1_2_b...
conv2_block1_0_conv (Conv2D)	(None, 56, 56, 256)	16,640	pool1_pool[0] [0]
conv2_block1_3_conv (Conv2D)	(None, 56, 56, 256)	16,640	conv2_block1_2_r...
conv2_block1_0_bn	(None, 56, 56,	1,024	conv2_block1_0_c...

(BatchNormalizatio...	256)			
conv2_block1_3_bn	(None, 56, 56,	1,024	conv2_block1_3_c...	
(BatchNormalizatio...	256)			
conv2_block1_add	(None, 56, 56,	0	conv2_block1_0_b...	
(Add)	256)		conv2_block1_3_b...	
conv2_block1_out	(None, 56, 56,	0	conv2_block1_add...	
(Activation)	256)			
conv2_block2_1_conv	(None, 56, 56,	16,448	conv2_block1_out...	
(Conv2D)	64)			
conv2_block2_1_bn	(None, 56, 56,	256	conv2_block2_1_c...	
(BatchNormalizatio...	64)			
conv2_block2_1_relu	(None, 56, 56,	0	conv2_block2_1_b...	
(Activation)	64)			
conv2_block2_2_conv	(None, 56, 56,	36,928	conv2_block2_1_r...	
(Conv2D)	64)			
conv2_block2_2_bn	(None, 56, 56,	256	conv2_block2_2_c...	
(BatchNormalizatio...	64)			
conv2_block2_2_relu	(None, 56, 56,	0	conv2_block2_2_b...	
(Activation)	64)			
conv2_block2_3_conv	(None, 56, 56,	16,640	conv2_block2_2_r...	
(Conv2D)	256)			
conv2_block2_3_bn	(None, 56, 56,	1,024	conv2_block2_3_c...	
(BatchNormalizatio...	256)			
conv2_block2_add	(None, 56, 56,	0	conv2_block1_out...	
(Add)	256)		conv2_block2_3_b...	
conv2_block2_out	(None, 56, 56,	0	conv2_block2_add...	
(Activation)	256)			
conv2_block3_1_conv	(None, 56, 56,	16,448	conv2_block2_out...	
(Conv2D)	64)			
conv2_block3_1_bn	(None, 56, 56,	256	conv2_block3_1_c...	
(BatchNormalizatio...	64)			
conv2_block3_1_relu	(None, 56, 56,	0	conv2_block3_1_b...	

(Activation)	64)		
conv2_block3_2_conv (Conv2D)	(None, 56, 56, 64)	36,928	conv2_block3_1_r...
conv2_block3_2_bn (BatchNormalizatio...)	(None, 56, 56, 64)	256	conv2_block3_2_c...
conv2_block3_2_relu (Activation)	(None, 56, 56, 64)	0	conv2_block3_2_b...
conv2_block3_3_conv (Conv2D)	(None, 56, 56, 256)	16,640	conv2_block3_2_r...
conv2_block3_3_bn (BatchNormalizatio...)	(None, 56, 56, 256)	1,024	conv2_block3_3_c...
conv2_block3_add (Add)	(None, 56, 56, 256)	0	conv2_block2_out... conv2_block3_3_b...
conv2_block3_out (Activation)	(None, 56, 56, 256)	0	conv2_block3_add...
conv3_block1_1_conv (Conv2D)	(None, 28, 28, 128)	32,896	conv2_block3_out...
conv3_block1_1_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block1_1_c...
conv3_block1_1_relu (Activation)	(None, 28, 28, 128)	0	conv3_block1_1_b...
conv3_block1_2_conv (Conv2D)	(None, 28, 28, 128)	147,584	conv3_block1_1_r...
conv3_block1_2_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block1_2_c...
conv3_block1_2_relu (Activation)	(None, 28, 28, 128)	0	conv3_block1_2_b...
conv3_block1_0_conv (Conv2D)	(None, 28, 28, 512)	131,584	conv2_block3_out...
conv3_block1_3_conv (Conv2D)	(None, 28, 28, 512)	66,048	conv3_block1_2_r...
conv3_block1_0_bn	(None, 28, 28,	2,048	conv3_block1_0_c...

(BatchNormalizatio...	512)			
conv3_block1_3_bn	(None, 28, 28,	2,048	conv3_block1_3_c...	
(BatchNormalizatio...	512)			
conv3_block1_add	(None, 28, 28,	0	conv3_block1_0_b...	
(Add)	512)		conv3_block1_3_b...	
conv3_block1_out	(None, 28, 28,	0	conv3_block1_add...	
(Activation)	512)			
conv3_block2_1_conv	(None, 28, 28,	65,664	conv3_block1_out...	
(Conv2D)	128)			
conv3_block2_1_bn	(None, 28, 28,	512	conv3_block2_1_c...	
(BatchNormalizatio...	128)			
conv3_block2_1_relu	(None, 28, 28,	0	conv3_block2_1_b...	
(Activation)	128)			
conv3_block2_2_conv	(None, 28, 28,	147,584	conv3_block2_1_r...	
(Conv2D)	128)			
conv3_block2_2_bn	(None, 28, 28,	512	conv3_block2_2_c...	
(BatchNormalizatio...	128)			
conv3_block2_2_relu	(None, 28, 28,	0	conv3_block2_2_b...	
(Activation)	128)			
conv3_block2_3_conv	(None, 28, 28,	66,048	conv3_block2_2_r...	
(Conv2D)	512)			
conv3_block2_3_bn	(None, 28, 28,	2,048	conv3_block2_3_c...	
(BatchNormalizatio...	512)			
conv3_block2_add	(None, 28, 28,	0	conv3_block1_out...	
(Add)	512)		conv3_block2_3_b...	
conv3_block2_out	(None, 28, 28,	0	conv3_block2_add...	
(Activation)	512)			
conv3_block3_1_conv	(None, 28, 28,	65,664	conv3_block2_out...	
(Conv2D)	128)			
conv3_block3_1_bn	(None, 28, 28,	512	conv3_block3_1_c...	
(BatchNormalizatio...	128)			
conv3_block3_1_relu	(None, 28, 28,	0	conv3_block3_1_b...	

(Activation)	128)		
conv3_block3_2_conv (Conv2D)	(None, 28, 28, 128)	147,584	conv3_block3_1_r...
conv3_block3_2_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block3_2_c...
conv3_block3_2_relu (Activation)	(None, 28, 28, 128)	0	conv3_block3_2_b...
conv3_block3_3_conv (Conv2D)	(None, 28, 28, 512)	66,048	conv3_block3_2_r...
conv3_block3_3_bn (BatchNormalizatio...)	(None, 28, 28, 512)	2,048	conv3_block3_3_c...
conv3_block3_add (Add)	(None, 28, 28, 512)	0	conv3_block2_out... conv3_block3_3_b...
conv3_block3_out (Activation)	(None, 28, 28, 512)	0	conv3_block3_add...
conv3_block4_1_conv (Conv2D)	(None, 28, 28, 128)	65,664	conv3_block3_out...
conv3_block4_1_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block4_1_c...
conv3_block4_1_relu (Activation)	(None, 28, 28, 128)	0	conv3_block4_1_b...
conv3_block4_2_conv (Conv2D)	(None, 28, 28, 128)	147,584	conv3_block4_1_r...
conv3_block4_2_bn (BatchNormalizatio...)	(None, 28, 28, 128)	512	conv3_block4_2_c...
conv3_block4_2_relu (Activation)	(None, 28, 28, 128)	0	conv3_block4_2_b...
conv3_block4_3_conv (Conv2D)	(None, 28, 28, 512)	66,048	conv3_block4_2_r...
conv3_block4_3_bn (BatchNormalizatio...)	(None, 28, 28, 512)	2,048	conv3_block4_3_c...
conv3_block4_add	(None, 28, 28,	0	conv3_block3_out...

(Add)	512)		conv3_block4_3_b...
conv3_block4_out (Activation)	(None, 28, 28, 512)	0	conv3_block4_add...
conv4_block1_1_conv (Conv2D)	(None, 14, 14, 256)	131,328	conv3_block4_out...
conv4_block1_1_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block1_1_c...
conv4_block1_1_relu (Activation)	(None, 14, 14, 256)	0	conv4_block1_1_b...
conv4_block1_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block1_1_r...
conv4_block1_2_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block1_2_c...
conv4_block1_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block1_2_b...
conv4_block1_0_conv (Conv2D)	(None, 14, 14, 1024)	525,312	conv3_block4_out...
conv4_block1_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block1_2_r...
conv4_block1_0_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block1_0_c...
conv4_block1_3_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block1_3_c...
conv4_block1_add (Add)	(None, 14, 14, 1024)	0	conv4_block1_0_b... conv4_block1_3_b...
conv4_block1_out (Activation)	(None, 14, 14, 1024)	0	conv4_block1_add...
conv4_block2_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	conv4_block1_out...
conv4_block2_1_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block2_1_c...
conv4_block2_1_relu	(None, 14, 14,	0	conv4_block2_1_b...

(Activation)	256)		
conv4_block2_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block2_1_r...
conv4_block2_2_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block2_2_c...
conv4_block2_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block2_2_b...
conv4_block2_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block2_2_r...
conv4_block2_3_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block2_3_c...
conv4_block2_add (Add)	(None, 14, 14, 1024)	0	conv4_block1_out... conv4_block2_3_b...
conv4_block2_out (Activation)	(None, 14, 14, 1024)	0	conv4_block2_add...
conv4_block3_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	conv4_block2_out...
conv4_block3_1_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block3_1_c...
conv4_block3_1_relu (Activation)	(None, 14, 14, 256)	0	conv4_block3_1_b...
conv4_block3_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block3_1_r...
conv4_block3_2_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block3_2_c...
conv4_block3_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block3_2_b...
conv4_block3_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block3_2_r...
conv4_block3_3_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block3_3_c...
conv4_block3_add	(None, 14, 14,	0	conv4_block2_out...

(Add)	1024)		conv4_block3_3_b...
conv4_block3_out (Activation)	(None, 14, 14, 1024)	0	conv4_block3_add...
conv4_block4_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	conv4_block3_out...
conv4_block4_1_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block4_1_c...
conv4_block4_1_relu (Activation)	(None, 14, 14, 256)	0	conv4_block4_1_b...
conv4_block4_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block4_1_r...
conv4_block4_2_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block4_2_c...
conv4_block4_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block4_2_b...
conv4_block4_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block4_2_r...
conv4_block4_3_bn (BatchNormalizatio...)	(None, 14, 14, 1024)	4,096	conv4_block4_3_c...
conv4_block4_add (Add)	(None, 14, 14, 1024)	0	conv4_block3_out... conv4_block4_3_b...
conv4_block4_out (Activation)	(None, 14, 14, 1024)	0	conv4_block4_add...
conv4_block5_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	conv4_block4_out...
conv4_block5_1_bn (BatchNormalizatio...)	(None, 14, 14, 256)	1,024	conv4_block5_1_c...
conv4_block5_1_relu (Activation)	(None, 14, 14, 256)	0	conv4_block5_1_b...
conv4_block5_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block5_1_r...
conv4_block5_2_bn	(None, 14, 14,	1,024	conv4_block5_2_c...

(BatchNormalizatio...	256)			
conv4_block5_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block5_2_b...	
conv4_block5_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block5_2_r...	
conv4_block5_3_bn (BatchNormalizatio...	(None, 14, 14, 1024)	4,096	conv4_block5_3_c...	
conv4_block5_add (Add)	(None, 14, 14, 1024)	0	conv4_block4_out...	conv4_block5_3_b...
conv4_block5_out (Activation)	(None, 14, 14, 1024)	0	conv4_block5_add...	
conv4_block6_1_conv (Conv2D)	(None, 14, 14, 256)	262,400	conv4_block5_out...	
conv4_block6_1_bn (BatchNormalizatio...	(None, 14, 14, 256)	1,024	conv4_block6_1_c...	
conv4_block6_1_relu (Activation)	(None, 14, 14, 256)	0	conv4_block6_1_b...	
conv4_block6_2_conv (Conv2D)	(None, 14, 14, 256)	590,080	conv4_block6_1_r...	
conv4_block6_2_bn (BatchNormalizatio...	(None, 14, 14, 256)	1,024	conv4_block6_2_c...	
conv4_block6_2_relu (Activation)	(None, 14, 14, 256)	0	conv4_block6_2_b...	
conv4_block6_3_conv (Conv2D)	(None, 14, 14, 1024)	263,168	conv4_block6_2_r...	
conv4_block6_3_bn (BatchNormalizatio...	(None, 14, 14, 1024)	4,096	conv4_block6_3_c...	
conv4_block6_add (Add)	(None, 14, 14, 1024)	0	conv4_block5_out...	conv4_block6_3_b...
conv4_block6_out (Activation)	(None, 14, 14, 1024)	0	conv4_block6_add...	
conv5_block1_1_conv	(None, 7, 7, 512)	524,800	conv4_block6_out...	

(Conv2D)

conv5_block1_1_bn (BatchNormalizatio... (Activation)	(None, 7, 7, 512)	2,048	conv5_block1_1_c...
conv5_block1_1_relu (Activation)	(None, 7, 7, 512)	0	conv5_block1_1_b...
conv5_block1_2_conv (Conv2D)	(None, 7, 7, 512)	2,359,808	conv5_block1_1_r...
conv5_block1_2_bn (BatchNormalizatio... (Activation)	(None, 7, 7, 512)	2,048	conv5_block1_2_c...
conv5_block1_2_relu (Activation)	(None, 7, 7, 512)	0	conv5_block1_2_b...
conv5_block1_0_conv (Conv2D)	(None, 7, 7, 2048)	2,099,200	conv4_block6_out...
conv5_block1_3_conv (Conv2D)	(None, 7, 7, 2048)	1,050,624	conv5_block1_2_r...
conv5_block1_0_bn (BatchNormalizatio... (Activation)	(None, 7, 7, 2048)	8,192	conv5_block1_0_c...
conv5_block1_3_bn (BatchNormalizatio... (Activation)	(None, 7, 7, 2048)	8,192	conv5_block1_3_c...
conv5_block1_add (Add)	(None, 7, 7, 2048)	0	conv5_block1_0_b... conv5_block1_3_b...
conv5_block1_out (Activation)	(None, 7, 7, 2048)	0	conv5_block1_add... conv5_block1_out...
conv5_block2_1_conv (Conv2D)	(None, 7, 7, 512)	1,049,088	conv5_block1_out...
conv5_block2_1_bn (BatchNormalizatio... (Activation)	(None, 7, 7, 512)	2,048	conv5_block2_1_c...
conv5_block2_1_relu (Activation)	(None, 7, 7, 512)	0	conv5_block2_1_b...
conv5_block2_2_conv (Conv2D)	(None, 7, 7, 512)	2,359,808	conv5_block2_1_r...
conv5_block2_2_bn	(None, 7, 7, 512)	2,048	conv5_block2_2_c...

conv5_block2_2_relu	(None, 7, 7, 512)	0	conv5_block2_2_b...
(Activation)			
conv5_block2_3_conv	(None, 7, 7, 2048)	1,050,624	conv5_block2_2_r...
(Conv2D)			
conv5_block2_3_bn	(None, 7, 7, 2048)	8,192	conv5_block2_3_c...
(BatchNormalizatio...			
conv5_block2_add	(None, 7, 7, 2048)	0	conv5_block1_out...
(Add)			conv5_block2_3_b...
conv5_block2_out	(None, 7, 7, 2048)	0	conv5_block2_add...
(Activation)			
conv5_block3_1_conv	(None, 7, 7, 512)	1,049,088	conv5_block2_out...
(Conv2D)			
conv5_block3_1_bn	(None, 7, 7, 512)	2,048	conv5_block3_1_c...
(BatchNormalizatio...			
conv5_block3_1_relu	(None, 7, 7, 512)	0	conv5_block3_1_b...
(Activation)			
conv5_block3_2_conv	(None, 7, 7, 512)	2,359,808	conv5_block3_1_r...
(Conv2D)			
conv5_block3_2_bn	(None, 7, 7, 512)	2,048	conv5_block3_2_c...
(BatchNormalizatio...			
conv5_block3_2_relu	(None, 7, 7, 512)	0	conv5_block3_2_b...
(Activation)			
conv5_block3_3_conv	(None, 7, 7, 2048)	1,050,624	conv5_block3_2_r...
(Conv2D)			
conv5_block3_3_bn	(None, 7, 7, 2048)	8,192	conv5_block3_3_c...
(BatchNormalizatio...			
conv5_block3_add	(None, 7, 7, 2048)	0	conv5_block2_out...
(Add)			conv5_block3_3_b...
conv5_block3_out	(None, 7, 7, 2048)	0	conv5_block3_add...
(Activation)			
global_average_poo...	(None, 2048)	0	conv5_block3_out...

```
(GlobalAveragePool...
batch_normalization (None, 2048)           8,192  global_average_p...
(BatchNormalizatio...
dropout (Dropout) (None, 2048)             0  batch_normalizat...
dense (Dense) (None, 512)                  1,049,088  dropout[0] [0]
dense_1 (Dense) (None, 100)                51,300  dense[0] [0]
```

Total params: 24,696,292 (94.21 MB)

Trainable params: 16,082,532 (61.35 MB)

Non-trainable params: 8,613,760 (32.86 MB)

```
Iniciando Fine-Tuning (con Augmentation) desde la época 20...
Epoch 21/40
395/395          203s 455ms/step -
accuracy: 0.8440 - loss: 1.7211 - val_accuracy: 0.9240 - val_loss: 1.4604
Epoch 22/40
395/395          164s 415ms/step -
accuracy: 0.9008 - loss: 1.5243 - val_accuracy: 0.9340 - val_loss: 1.3871
Epoch 23/40
395/395          163s 413ms/step -
accuracy: 0.9144 - loss: 1.4331 - val_accuracy: 0.9380 - val_loss: 1.3271
Epoch 24/40
395/395          163s 413ms/step -
accuracy: 0.9291 - loss: 1.3367 - val_accuracy: 0.9380 - val_loss: 1.2717
Epoch 25/40
395/395          203s 414ms/step -
accuracy: 0.9354 - loss: 1.2742 - val_accuracy: 0.9480 - val_loss: 1.2277
Epoch 26/40
395/395          163s 414ms/step -
accuracy: 0.9416 - loss: 1.2085 - val_accuracy: 0.9500 - val_loss: 1.1794
Epoch 27/40
395/395          165s 417ms/step -
accuracy: 0.9442 - loss: 1.1596 - val_accuracy: 0.9560 - val_loss: 1.1300
Epoch 28/40
395/395          166s 419ms/step -
accuracy: 0.9520 - loss: 1.0994 - val_accuracy: 0.9580 - val_loss: 1.0845
Epoch 29/40
395/395          166s 420ms/step -
```

```

accuracy: 0.9535 - loss: 1.0468 - val_accuracy: 0.9520 - val_loss: 1.0450
Epoch 30/40
395/395           166s 420ms/step -
accuracy: 0.9584 - loss: 0.9919 - val_accuracy: 0.9580 - val_loss: 0.9946
Epoch 31/40
395/395           164s 416ms/step -
accuracy: 0.9631 - loss: 0.9340 - val_accuracy: 0.9560 - val_loss: 0.9550
Epoch 32/40
395/395           164s 414ms/step -
accuracy: 0.9679 - loss: 0.8850 - val_accuracy: 0.9600 - val_loss: 0.9078
Epoch 33/40
395/395           164s 415ms/step -
accuracy: 0.9684 - loss: 0.8415 - val_accuracy: 0.9560 - val_loss: 0.8674
Epoch 34/40
395/395           165s 416ms/step -
accuracy: 0.9724 - loss: 0.7931 - val_accuracy: 0.9560 - val_loss: 0.8298
Epoch 35/40
395/395           164s 414ms/step -
accuracy: 0.9714 - loss: 0.7594 - val_accuracy: 0.9600 - val_loss: 0.7933
Epoch 36/40
395/395           165s 419ms/step -
accuracy: 0.9706 - loss: 0.7183 - val_accuracy: 0.9600 - val_loss: 0.7537
Epoch 37/40
395/395           165s 417ms/step -
accuracy: 0.9796 - loss: 0.6737 - val_accuracy: 0.9640 - val_loss: 0.7137
Epoch 38/40
395/395           165s 416ms/step -
accuracy: 0.9784 - loss: 0.6395 - val_accuracy: 0.9600 - val_loss: 0.6875
Epoch 39/40
395/395           165s 418ms/step -
accuracy: 0.9802 - loss: 0.5970 - val_accuracy: 0.9620 - val_loss: 0.6601
Epoch 40/40
395/395           163s 414ms/step -
accuracy: 0.9826 - loss: 0.5641 - val_accuracy: 0.9600 - val_loss: 0.6308

```

Entrenamiento de Fine-Tuning (Fase 2 con Augmentation) completado.

```
[ ]: # Combinar historiales
acc_aug = history_aug.history['accuracy'] + history_fine_tune_aug.
    ↵history['accuracy']
val_acc_aug = history_aug.history['val_accuracy'] + history_fine_tune_aug.
    ↵history['val_accuracy']
loss_aug = history_aug.history['loss'] + history_fine_tune_aug.history['loss']
val_loss_aug = history_aug.history['val_loss'] + history_fine_tune_aug.
    ↵history['val_loss']

# Graficar los resultados
```

```

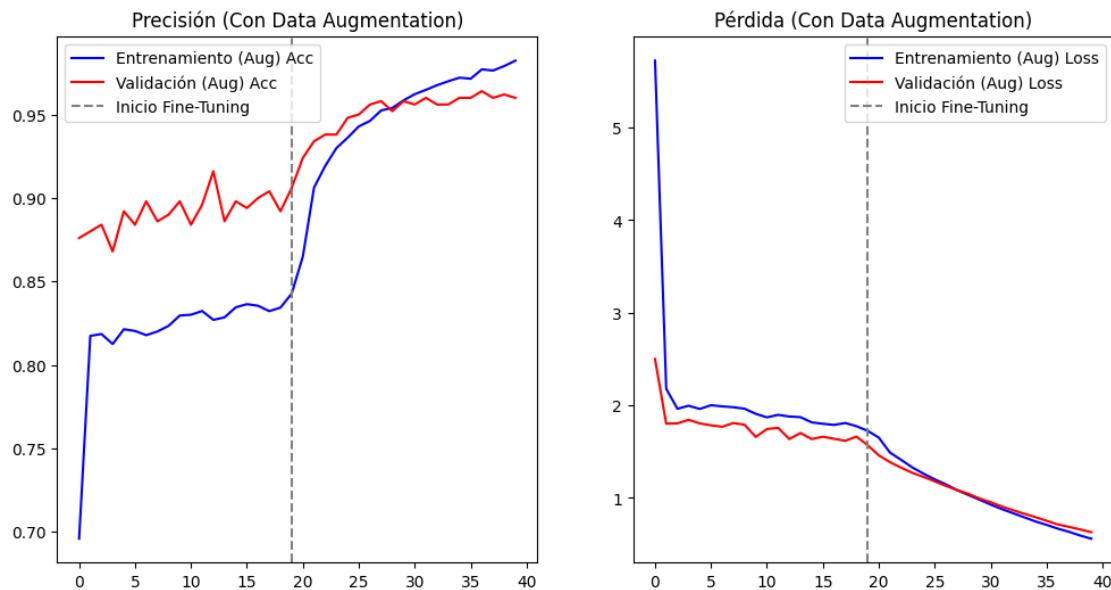
plt.figure(figsize=(12, 6))

# Precisión
plt.subplot(1, 2, 1)
plt.plot(acc_aug, 'b', label='Entrenamiento (Aug) Acc')
plt.plot(val_acc_aug, 'r', label='Validación (Aug) Acc')
plt.axvline(initial_epochs - 1, color='gray', linestyle='--', label='Inicio Fine-Tuning')
plt.title('Precisión (Con Data Augmentation)')
plt.legend()

# Pérdida
plt.subplot(1, 2, 2)
plt.plot(loss_aug, 'b', label='Entrenamiento (Aug) Loss')
plt.plot(val_loss_aug, 'r', label='Validación (Aug) Loss')
plt.axvline(initial_epochs - 1, color='gray', linestyle='--', label='Inicio Fine-Tuning')
plt.title('Pérdida (Con Data Augmentation)')
plt.legend()

plt.show()

```



Tras aplicar fine tuning, el modelo logró romper el estancamiento que tenía con el data augmentation: se observa un salto claro en la precisión justo después del punto donde se descongelan las capas superiores, pasando de una estabilidad cercana al 90% a un ascenso progresivo que supera el 96%. La pérdida también mejora de forma consistente, disminuyendo de valores alrededor de 1.7–2.0 a menos de 0.7 conforme avanzan las épocas, lo que indica que el modelo ahora sí logró aprender patrones más específicos y complejos del dataset. En conjunto, los gráficos muestran que

liberar parte de la ResNet50 permitió que la red adaptara sus características profundas a las transformaciones del augmentation y al dominio real del problema, logrando un rendimiento superior y mucho más estable que en la etapa anterior.

6. Evaluación del modelo predictivo

```
[ ]: # Definir Generador de Test  
# Usamos la función de preprocessamiento  
test_datagen = ImageDataGenerator(  
    preprocessing_function=preprocess_input  
)  
  
print("Cargando datos de TEST...")  
test_generator = test_datagen.flow_from_directory(  
    TEST_DIR,  
    target_size=IMG_SIZE,  
    batch_size=BATCH_SIZE,  
    class_mode='categorical',  
    shuffle=False,  
    seed = 1  
)
```

Cargando datos de TEST...
Found 500 images belonging to 100 classes.

```
[ ]: # Evaluación Rápida  
print("Evaluando modelo ResNet50 en set de Test...")  
results = model_aug.evaluate(test_generator)  
  
print(f"\nLoss del Test: {results[0]:.4f}")  
print(f"Accuracy (Precisión) del Test: {results[1]*100:.2f}%")
```

Evaluando modelo Xception en set de Test...
16/16 2s 96ms/step -
accuracy: 0.9809 - loss: 0.5461

Loss del Test: 0.5567
Accuracy (Precisión) del Test: 97.80%

El modelo acierta casi todas las imágenes del set de test. Es un rendimiento muy alto y muestra que aprendió bien a diferenciar las clases.

```
[ ]: # Generar Predicciones  
  
predictions = model_aug.predict(test_generator)  
  
# Convertir probabilidades a la clase ganadora (índice 0 a 99)  
y_pred = np.argmax(predictions, axis=1)
```

```

# Obtener las etiquetas reales
y_true = test_generator.classes

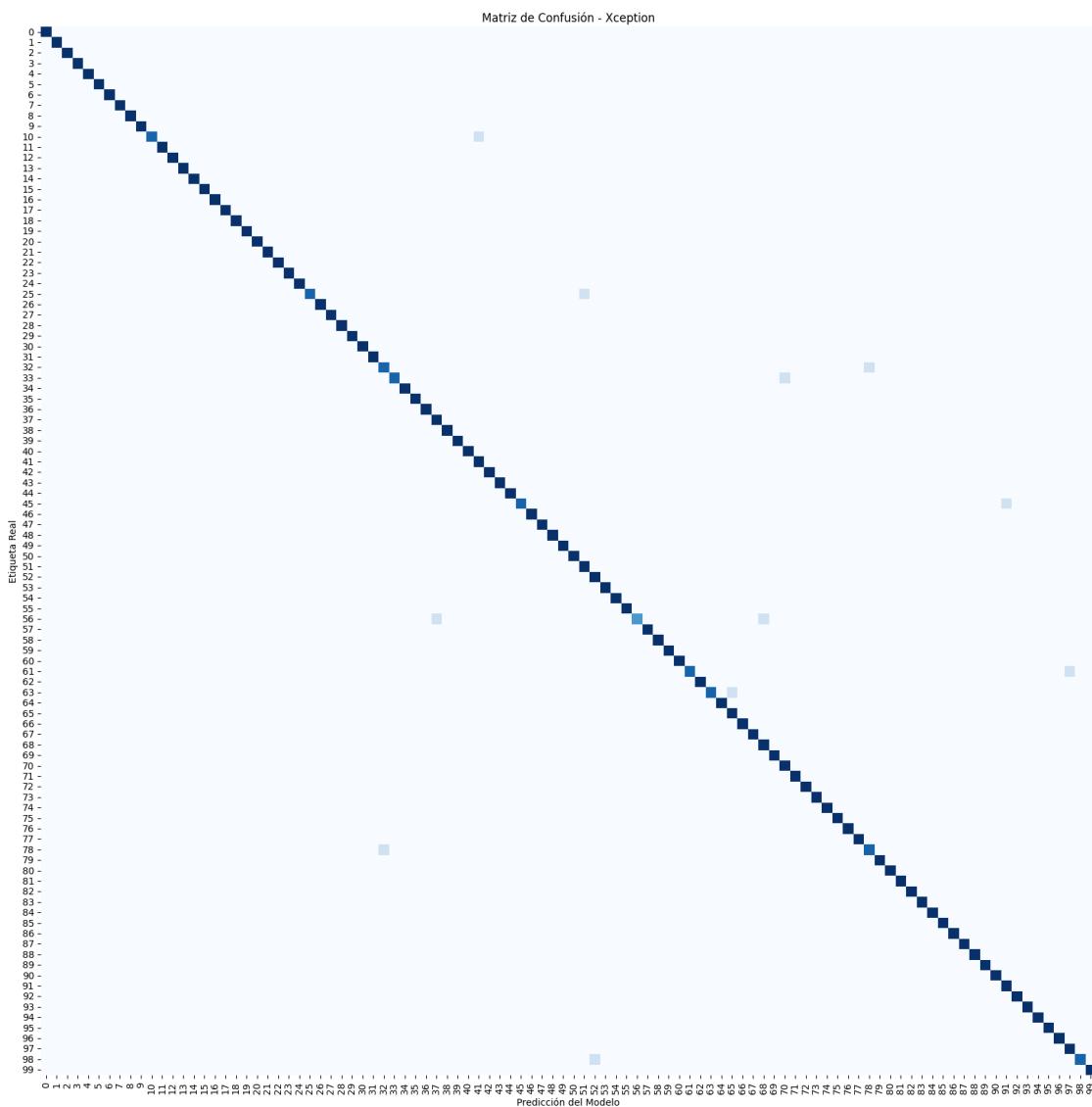
# Matriz de Confusión
cm = confusion_matrix(y_true, y_pred)

plt.figure(figsize=(20, 20)) # Tamaño grande porque son 100 clases
sns.heatmap(cm, annot=False, cmap='Blues', cbar=False) # annot=False para no saturar
plt.title('Matriz de Confusión - RestNet50')
plt.ylabel('Etiqueta Real')
plt.xlabel('Predicción del Modelo')
plt.show()

# --- 5. Reporte de Clasificación ---
# Muestra Precision, Recall y F1-Score por cada clase
class_labels = list(test_generator.class_indices.keys())
print(classification_report(y_true, y_pred, target_names=class_labels))

```

16/16 9s 320ms/step



	precision	recall	f1-score	support
ADONIS	1.00	1.00	1.00	5
AFRICAN GIANT SWALLOWTAIL	1.00	1.00	1.00	5
AMERICAN SNOOT	1.00	1.00	1.00	5
AN 88	1.00	1.00	1.00	5
APOLLO	1.00	1.00	1.00	5
ARCIGERA FLOWER MOTH	1.00	1.00	1.00	5
ATALA	1.00	1.00	1.00	5
ATLAS MOTH	1.00	1.00	1.00	5
BANDED ORANGE HELICONIAN	1.00	1.00	1.00	5
BANDED PEACOCK	1.00	1.00	1.00	5
BANDED TIGER MOTH	1.00	0.80	0.89	5

BECKERS WHITE	1.00	1.00	1.00	5
BIRD CHERRY ERMINE MOTH	1.00	1.00	1.00	5
BLACK HAIRSTREAK	1.00	1.00	1.00	5
BLUE MORPHO	1.00	1.00	1.00	5
BLUE SPOTTED CROW	1.00	1.00	1.00	5
BROOKES BIRDWING	1.00	1.00	1.00	5
BROWN ARGUS	1.00	1.00	1.00	5
BROWN SIPROETA	1.00	1.00	1.00	5
CABBAGE WHITE	1.00	1.00	1.00	5
CAIRNS BIRDWING	1.00	1.00	1.00	5
CHALK HILL BLUE	1.00	1.00	1.00	5
CHECQUERED SKIPPER	1.00	1.00	1.00	5
CHESTNUT	1.00	1.00	1.00	5
CINNABAR MOTH	1.00	1.00	1.00	5
CLEARWING MOTH	1.00	0.80	0.89	5
CLEOPATRA	1.00	1.00	1.00	5
CLODIUS PARNASSIAN	1.00	1.00	1.00	5
CLOUDED SULPHUR	1.00	1.00	1.00	5
COMET MOTH	1.00	1.00	1.00	5
COMMON BANDED AWL	1.00	1.00	1.00	5
COMMON WOOD-NYMPH	1.00	1.00	1.00	5
COPPER TAIL	0.80	0.80	0.80	5
CRECENT	1.00	0.80	0.89	5
CRIMSON PATCH	1.00	1.00	1.00	5
DANAID EGGFLY	1.00	1.00	1.00	5
EASTERN COMA	1.00	1.00	1.00	5
EASTERN DAPPLE WHITE	0.83	1.00	0.91	5
EASTERN PINE ELFIN	1.00	1.00	1.00	5
ELBOWED PIERROT	1.00	1.00	1.00	5
EMPEROR GUM MOTH	1.00	1.00	1.00	5
GARDEN TIGER MOTH	0.83	1.00	0.91	5
GIANT LEOPARD MOTH	1.00	1.00	1.00	5
GLITTERING SAPPHIRE	1.00	1.00	1.00	5
GOLD BANDED	1.00	1.00	1.00	5
GREAT EGGFLY	1.00	0.80	0.89	5
GREAT JAY	1.00	1.00	1.00	5
GREEN CELLED CATTLEHEART	1.00	1.00	1.00	5
GREEN HAIRSTREAK	1.00	1.00	1.00	5
GREY HAIRSTREAK	1.00	1.00	1.00	5
HERCULES MOTH	1.00	1.00	1.00	5
HUMMING BIRD HAWK MOTH	0.83	1.00	0.91	5
INDRA SWALLOW	0.83	1.00	0.91	5
IO MOTH	1.00	1.00	1.00	5
Iphiclus sister	1.00	1.00	1.00	5
JULIA	1.00	1.00	1.00	5
LARGE MARBLE	1.00	0.60	0.75	5
LUNA MOTH	1.00	1.00	1.00	5
MADAGASCAN SUNSET MOTH	1.00	1.00	1.00	5

MALACHITE	1.00	1.00	1.00	5
MANGROVE SKIPPER	1.00	1.00	1.00	5
MESTRA	1.00	0.80	0.89	5
METALMARK	1.00	1.00	1.00	5
MILBERTS TORTOISESHELL	1.00	0.80	0.89	5
MONARCH	1.00	1.00	1.00	5
MOURNING CLOAK	0.83	1.00	0.91	5
OLEANDER HAWK MOTH	1.00	1.00	1.00	5
ORANGE OAKLEAF	1.00	1.00	1.00	5
ORANGE TIP	0.83	1.00	0.91	5
ORCHARD SWALLOW	1.00	1.00	1.00	5
PAINTED LADY	0.83	1.00	0.91	5
PAPER KITE	1.00	1.00	1.00	5
PEACOCK	1.00	1.00	1.00	5
PINE WHITE	1.00	1.00	1.00	5
PIPEVINE SWALLOW	1.00	1.00	1.00	5
POLYPHEMUS MOTH	1.00	1.00	1.00	5
POPINJAY	1.00	1.00	1.00	5
PURPLE HAIRSTREAK	1.00	1.00	1.00	5
PURPLISH COPPER	0.80	0.80	0.80	5
QUESTION MARK	1.00	1.00	1.00	5
RED ADMIRAL	1.00	1.00	1.00	5
RED CRACKER	1.00	1.00	1.00	5
RED POSTMAN	1.00	1.00	1.00	5
RED SPOTTED PURPLE	1.00	1.00	1.00	5
ROSY MAPLE MOTH	1.00	1.00	1.00	5
SCARCE SWALLOW	1.00	1.00	1.00	5
SILVER SPOT SKIPPER	1.00	1.00	1.00	5
SIXSPOT BURNET MOTH	1.00	1.00	1.00	5
SLEEPY ORANGE	1.00	1.00	1.00	5
SOOTYWING	1.00	1.00	1.00	5
SOUTHERN DOGFACE	1.00	1.00	1.00	5
STRAITED QUEEN	0.83	1.00	0.91	5
TROPICAL LEAFWING	1.00	1.00	1.00	5
TWO BARRED FLASHER	1.00	1.00	1.00	5
ULYSES	1.00	1.00	1.00	5
VICEROY	1.00	1.00	1.00	5
WHITE LINED SPHINX MOTH	1.00	1.00	1.00	5
WOOD SATYR	0.83	1.00	0.91	5
YELLOW SWALLOW TAIL	1.00	0.80	0.89	5
ZEBRA LONG WING	1.00	1.00	1.00	5
accuracy			0.98	500
macro avg	0.98	0.98	0.98	500
weighted avg	0.98	0.98	0.98	500

La matriz de confusión se calcula correctamente, pero como el modelo tiene 100 clases, el gráfico

queda demasiado grande y no ofrece una lectura útil; en cambio, el reporte de clasificación sí muestra información clara y relevante, y allí se evidencia que la mayoría de las clases alcanzan valores de F1 de 1, lo que confirma que el modelo está clasificando de forma muy precisa en prácticamente todas las categorías.

```
[ ]: model_aug.save("deepResNet50.h5")
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.
```

Comparacion con modelos Exception

Es esta parte, procedemos a duplicar las fases anteriores para realizar una comparacion entre los modelos

```
[ ]: # --- 0. Rutas y Parámetros ---
BASE_DIR = 'my_dataset'
TRAIN_DIR = f'{BASE_DIR}/train'
VALID_DIR = f'{BASE_DIR}/valid'
IMG_SIZE = (224, 224) # O (299, 299) si prefieres el nativo de Xception
BATCH_SIZE = 32

# --- 1. NUEVOS Generadores Específicos para Xception ---
print("Configurando generadores específicos para Xception...")

train_datagen_xc = ImageDataGenerator(
    preprocessing_function=preprocess_input_xception,
    rotation_range=30,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

val_test_datagen_xc = ImageDataGenerator(
    preprocessing_function=preprocess_input_xception
)

# Cargar las imágenes con los nuevos generadores
train_generator_xc = train_datagen_xc.flow_from_directory(
    TRAIN_DIR,
    target_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='categorical',
```

```

    seed = 1
)

validation_generator_xc = val_test_datagen_xc.flow_from_directory(
    VALID_DIR,
    target_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    seed = 1
)

# --- 2. Cargar Modelo Base: XCEPTION ---
print("\nCargando Xception...")
IMG_SHAPE = (224, 224, 3)

base_model_xc = Xception(weights='imagenet',
                           include_top=False,
                           input_shape=IMG_SHAPE)

base_model_xc.trainable = False # Congelamos primero

# --- 3. Construir el Head ---
x = base_model_xc.output
x = GlobalAveragePooling2D()(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
x = Dense(512, activation='relu', kernel_regularizer=l2(0.01))(x)
outputs = Dense(100, activation='softmax')(x)

model_xc = Model(inputs=base_model_xc.input, outputs=outputs)

# --- 4. Compilar y Entrenar FASE 1 (Solo Head) ---
model_xc.compile(optimizer='adam',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

# Definir Early Stopping si no estaba definido
early_stopper = EarlyStopping(monitor='val_loss', patience=5,
                             restore_best_weights=True)

print("\nIniciando Fase 1 con Xception...")
history_xc = model_xc.fit(
    train_generator_xc, # Usamos el generador NUEVO (_xc)
    epochs=20,
    validation_data=validation_generator_xc, # Usamos el generador NUEVO (_xc)
    callbacks=[early_stopper]
)

```

```

# --- 5. FASE 2: Fine-Tuning Xception ---
print("\nDescongelando para Fine-Tuning Xception...")
base_model_xc.trainable = True

# Xception tiene 132 capas. Descongelemos desde la 100.
fine_tune_at = 100
for layer in base_model_xc.layers[:fine_tune_at]:
    layer.trainable = False

model_xc.compile(optimizer=Adam(learning_rate=1e-5), # LR bajo
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

# Calcular épocas totales
initial_epochs_xc = len(history_xc.history['loss'])
total_epochs_xc = initial_epochs_xc + 20

print(f"\nIniciando Fase 2 con Xception...")
history_fine_xc = model_xc.fit(
    train_generator_xc,
    epochs=total_epochs_xc,
    initial_epoch=initial_epochs_xc,
    validation_data=validation_generator_xc,
    callbacks=[early_stopper]
)

```

Configurando generadores específicos para Xception...
 Found 12639 images belonging to 100 classes.
 Found 500 images belonging to 100 classes.

Cargando Xception...
 Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/xception/xception_weights_tf_dim_ordering_tf_kernels_notop.h5
 83683744/83683744 0s
 0us/step

Iniciando Fase 1 con Xception...
 /usr/local/lib/python3.12/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121:
 UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in its constructor. `**kwargs` can include `workers`, `use_multiprocessing`, `max_queue_size`. Do not pass these arguments to `fit()`, as they will be ignored.
 self._warn_if_super_not_called()
 Epoch 1/20
 395/395 237s 522ms/step -

```
accuracy: 0.4556 - loss: 8.5555 - val_accuracy: 0.7500 - val_loss: 3.0648
Epoch 2/20
395/395          166s 421ms/step -
accuracy: 0.7142 - loss: 2.9087 - val_accuracy: 0.7800 - val_loss: 2.1804
Epoch 3/20
395/395          166s 419ms/step -
accuracy: 0.7250 - loss: 2.3703 - val_accuracy: 0.7920 - val_loss: 2.2074
Epoch 4/20
395/395          165s 417ms/step -
accuracy: 0.7369 - loss: 2.2838 - val_accuracy: 0.7780 - val_loss: 2.2140
Epoch 5/20
395/395          165s 418ms/step -
accuracy: 0.7241 - loss: 2.3031 - val_accuracy: 0.7760 - val_loss: 2.1461
Epoch 6/20
395/395          166s 421ms/step -
accuracy: 0.7130 - loss: 2.3362 - val_accuracy: 0.7940 - val_loss: 2.1032
Epoch 7/20
395/395          164s 416ms/step -
accuracy: 0.7286 - loss: 2.2954 - val_accuracy: 0.7800 - val_loss: 2.0452
Epoch 8/20
395/395          163s 413ms/step -
accuracy: 0.7311 - loss: 2.2261 - val_accuracy: 0.8040 - val_loss: 2.0271
Epoch 9/20
395/395          166s 419ms/step -
accuracy: 0.7318 - loss: 2.2474 - val_accuracy: 0.7900 - val_loss: 2.1098
Epoch 10/20
395/395          163s 414ms/step -
accuracy: 0.7296 - loss: 2.2235 - val_accuracy: 0.7700 - val_loss: 2.0511
Epoch 11/20
395/395          163s 413ms/step -
accuracy: 0.7266 - loss: 2.1933 - val_accuracy: 0.7840 - val_loss: 2.0765
Epoch 12/20
395/395          164s 415ms/step -
accuracy: 0.7328 - loss: 2.1963 - val_accuracy: 0.7860 - val_loss: 2.0166
Epoch 13/20
395/395          168s 426ms/step -
accuracy: 0.7513 - loss: 2.0985 - val_accuracy: 0.8020 - val_loss: 1.9374
Epoch 14/20
395/395          169s 427ms/step -
accuracy: 0.7430 - loss: 2.1092 - val_accuracy: 0.8160 - val_loss: 1.8805
Epoch 15/20
395/395          165s 416ms/step -
accuracy: 0.7346 - loss: 2.1353 - val_accuracy: 0.8180 - val_loss: 1.8915
Epoch 16/20
395/395          167s 421ms/step -
accuracy: 0.7483 - loss: 2.1052 - val_accuracy: 0.7980 - val_loss: 1.9512
Epoch 17/20
395/395          169s 427ms/step -
```

```
accuracy: 0.7544 - loss: 2.0574 - val_accuracy: 0.7960 - val_loss: 1.8093
Epoch 18/20
395/395          168s 424ms/step -
accuracy: 0.7507 - loss: 2.0010 - val_accuracy: 0.8000 - val_loss: 1.8768
Epoch 19/20
395/395          167s 423ms/step -
accuracy: 0.7474 - loss: 2.0306 - val_accuracy: 0.8080 - val_loss: 1.8957
Epoch 20/20
395/395          167s 423ms/step -
accuracy: 0.7480 - loss: 2.0401 - val_accuracy: 0.7960 - val_loss: 1.8978
```

Descongelando para Fine-Tuning Xception...

Iniciando Fase 2 con Xception...

```
Epoch 21/40
395/395          215s 492ms/step -
accuracy: 0.6427 - loss: 2.4936 - val_accuracy: 0.8220 - val_loss: 1.7451
Epoch 22/40
395/395          175s 444ms/step -
accuracy: 0.7917 - loss: 1.8595 - val_accuracy: 0.8620 - val_loss: 1.6297
Epoch 23/40
395/395          175s 443ms/step -
accuracy: 0.8336 - loss: 1.6939 - val_accuracy: 0.8840 - val_loss: 1.5302
Epoch 24/40
395/395          175s 443ms/step -
accuracy: 0.8572 - loss: 1.5790 - val_accuracy: 0.8880 - val_loss: 1.4655
Epoch 25/40
395/395          177s 447ms/step -
accuracy: 0.8711 - loss: 1.4884 - val_accuracy: 0.9100 - val_loss: 1.3968
Epoch 26/40
395/395          174s 440ms/step -
accuracy: 0.8860 - loss: 1.4216 - val_accuracy: 0.9200 - val_loss: 1.3404
Epoch 27/40
395/395          177s 449ms/step -
accuracy: 0.8942 - loss: 1.3504 - val_accuracy: 0.9200 - val_loss: 1.2927
Epoch 28/40
395/395          175s 442ms/step -
accuracy: 0.9053 - loss: 1.2879 - val_accuracy: 0.9240 - val_loss: 1.2410
Epoch 29/40
395/395          177s 447ms/step -
accuracy: 0.8983 - loss: 1.2517 - val_accuracy: 0.9380 - val_loss: 1.1878
Epoch 30/40
395/395          179s 454ms/step -
accuracy: 0.9106 - loss: 1.1812 - val_accuracy: 0.9340 - val_loss: 1.1481
Epoch 31/40
395/395          177s 448ms/step -
accuracy: 0.9136 - loss: 1.1338 - val_accuracy: 0.9400 - val_loss: 1.1004
Epoch 32/40
```

```

395/395           176s 446ms/step -
accuracy: 0.9211 - loss: 1.0818 - val_accuracy: 0.9420 - val_loss: 1.0572
Epoch 33/40
395/395           178s 451ms/step -
accuracy: 0.9250 - loss: 1.0332 - val_accuracy: 0.9440 - val_loss: 1.0106
Epoch 34/40
395/395           176s 444ms/step -
accuracy: 0.9318 - loss: 0.9878 - val_accuracy: 0.9440 - val_loss: 0.9783
Epoch 35/40
395/395           176s 446ms/step -
accuracy: 0.9349 - loss: 0.9454 - val_accuracy: 0.9540 - val_loss: 0.9359
Epoch 36/40
395/395           176s 444ms/step -
accuracy: 0.9392 - loss: 0.8969 - val_accuracy: 0.9500 - val_loss: 0.9012
Epoch 37/40
395/395           176s 445ms/step -
accuracy: 0.9385 - loss: 0.8655 - val_accuracy: 0.9520 - val_loss: 0.8672
Epoch 38/40
395/395           179s 454ms/step -
accuracy: 0.9417 - loss: 0.8228 - val_accuracy: 0.9500 - val_loss: 0.8346
Epoch 39/40
395/395           178s 451ms/step -
accuracy: 0.9454 - loss: 0.7919 - val_accuracy: 0.9540 - val_loss: 0.8052
Epoch 40/40
395/395           176s 445ms/step -
accuracy: 0.9482 - loss: 0.7602 - val_accuracy: 0.9460 - val_loss: 0.7801

```

```

[ ]: # --- 1. Definir Generador de Test para XCEPTION ---
# Usamos la función de preprocesamiento de Xception
TEST_DIR = f'{BASE_DIR}/test'
test_datagen_xc = ImageDataGenerator(
    preprocessing_function=preprocess_input_xception
)

print("Cargando datos de TEST...")
test_generator_xc = test_datagen_xc.flow_from_directory(
    TEST_DIR,
    target_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    shuffle=False,
    seed = 1
)

```

Cargando datos de TEST...
Found 500 images belonging to 100 classes.

```
[ ]: # --- 2. Evaluación Rápida ---
print("Evaluando modelo Xception en set de Test...")
results = model_xc.evaluate(test_generator_xc)

print(f"\nLoss del Test: {results[0]:.4f}")
print(f"Accuracy (Precisión) del Test: {results[1]*100:.2f}%")
```

Evaluando modelo Xception en set de Test...

16/16 2s 120ms/step -

accuracy: 0.9686 - loss: 0.6825

Loss del Test: 0.6879

Accuracy (Precisión) del Test: 96.60%

Este segundo modelo muestra una curva de aprendizaje estable y progresiva: la accuracy de entrenamiento sube hasta ~75–95% y la de validación se mantiene entre 94% y 95%, con una pérdida que baja de manera constante hasta ~0.78. Es un modelo que claramente aprende bien, sin saltos bruscos ni señales fuertes de inestabilidad, pero aun así no alcanza el rendimiento del modelo ResNet50 con fine tuning, que logró llegar a una precisión real de prueba cercana al 98% y un F1 casi perfecto en la mayoría de las clases. En comparación directa, este modelo es bueno y consistente, pero se queda un poco atrás tanto en capacidad de generalización como en precisión global. Por eso, el modelo ResNet50 sigue siendo la mejor opción entre los dos: converge más alto, clasifica mejor y demuestra un entendimiento más fino de las 100 clases del dataset.

```
[ ]: # --- 3. Generar Predicciones ---
# Esto puede tardar un poco dependiendo de cuántas imágenes de test tengas
predictions = model_xc.predict(test_generator_xc)

# Convertir probabilidades a la clase ganadora (índice 0 a 99)
y_pred = np.argmax(predictions, axis=1)

# Obtener las etiquetas reales
y_true = test_generator_xc.classes

# --- 4. Matriz de Confusión ---
cm = confusion_matrix(y_true, y_pred)

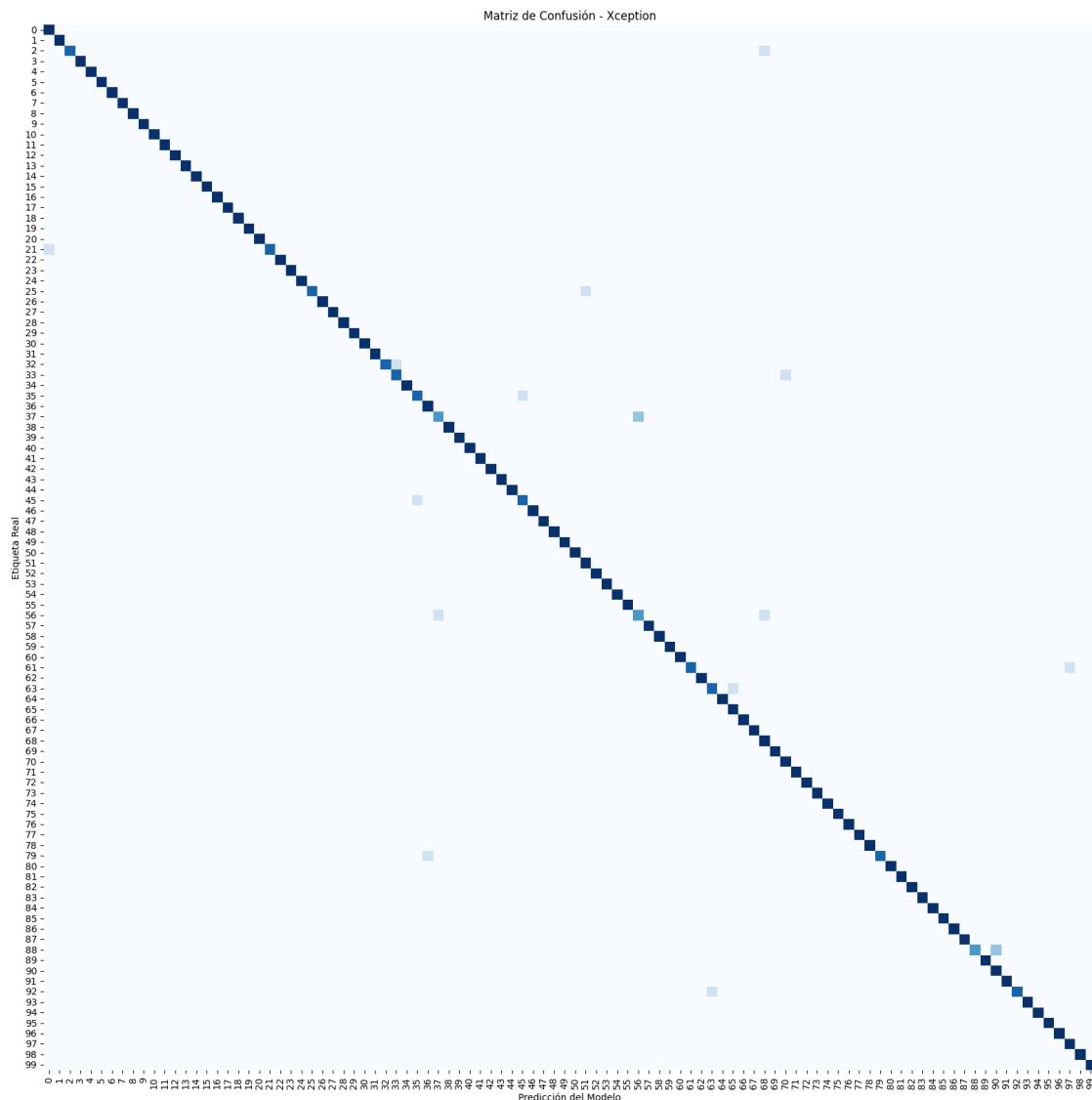
plt.figure(figsize=(20, 20)) # Tamaño grande porque son 100 clases
sns.heatmap(cm, annot=False, cmap='Blues', cbar=False) # annot=False para no saturar
plt.title('Matriz de Confusión - Xception')
plt.ylabel('Etiqueta Real')
plt.xlabel('Predicción del Modelo')
plt.show()

# --- 5. Reporte de Clasificación ---
```

```
# Muestra Precision, Recall y F1-Score por cada clase
class_labels = list(test_generator_xc.class_indices.keys())
print(classification_report(y_true, y_pred, target_names=class_labels))
```

16/16

10s 380ms/step



	precision	recall	f1-score	support
ADONIS	0.83	1.00	0.91	5
AFRICAN GIANT SWALLOWTAIL	1.00	1.00	1.00	5
AMERICAN SNOOT	1.00	0.80	0.89	5
AN 88	1.00	1.00	1.00	5
APOLLO	1.00	1.00	1.00	5

ARCIGERA FLOWER MOTH	1.00	1.00	1.00	5
ATALA	1.00	1.00	1.00	5
ATLAS MOTH	1.00	1.00	1.00	5
BANDED ORANGE HELICONIAN	1.00	1.00	1.00	5
BANDED PEACOCK	1.00	1.00	1.00	5
BANDED TIGER MOTH	1.00	1.00	1.00	5
BECKERS WHITE	1.00	1.00	1.00	5
BIRD CHERRY ERMINE MOTH	1.00	1.00	1.00	5
BLACK HAIRSTREAK	1.00	1.00	1.00	5
BLUE MORPHO	1.00	1.00	1.00	5
BLUE SPOTTED CROW	1.00	1.00	1.00	5
BROOKES BIRDWING	1.00	1.00	1.00	5
BROWN ARGUS	1.00	1.00	1.00	5
BROWN SIPROETA	1.00	1.00	1.00	5
CABBAGE WHITE	1.00	1.00	1.00	5
CAIRNS BIRDWING	1.00	1.00	1.00	5
CHALK HILL BLUE	1.00	0.80	0.89	5
CHECQUERED SKIPPER	1.00	1.00	1.00	5
CHESTNUT	1.00	1.00	1.00	5
CINNABAR MOTH	1.00	1.00	1.00	5
CLEARWING MOTH	1.00	0.80	0.89	5
CLEOPATRA	1.00	1.00	1.00	5
CLODIUS PARNASSTIAN	1.00	1.00	1.00	5
CLOUDED SULPHUR	1.00	1.00	1.00	5
COMET MOTH	1.00	1.00	1.00	5
COMMON BANDED AWL	1.00	1.00	1.00	5
COMMON WOOD-NYMPH	1.00	1.00	1.00	5
COPPER TAIL	1.00	0.80	0.89	5
CRECENT	0.80	0.80	0.80	5
CRIMSON PATCH	1.00	1.00	1.00	5
DANAID EGGFLY	0.80	0.80	0.80	5
EASTERN COMA	0.83	1.00	0.91	5
EASTERN DAPPLE WHITE	0.75	0.60	0.67	5
EASTERN PINE ELFIN	1.00	1.00	1.00	5
ELBOWED PIERROT	1.00	1.00	1.00	5
EMPEROR GUM MOTH	1.00	1.00	1.00	5
GARDEN TIGER MOTH	1.00	1.00	1.00	5
GIANT LEOPARD MOTH	1.00	1.00	1.00	5
GLITTERING SAPPHIRE	1.00	1.00	1.00	5
GOLD BANDED	1.00	1.00	1.00	5
GREAT EGGFLY	0.80	0.80	0.80	5
GREAT JAY	1.00	1.00	1.00	5
GREEN CELLED CATTLEHEART	1.00	1.00	1.00	5
GREEN HAIRSTREAK	1.00	1.00	1.00	5
GREY HAIRSTREAK	1.00	1.00	1.00	5
HERCULES MOTH	1.00	1.00	1.00	5
HUMMING BIRD HAWK MOTH	0.83	1.00	0.91	5
INDRA SWALLOW	1.00	1.00	1.00	5

IO MOTH	1.00	1.00	1.00	5
Iphiclus sister	1.00	1.00	1.00	5
JULIA	1.00	1.00	1.00	5
LARGE MARBLE	0.60	0.60	0.60	5
LUNA MOTH	1.00	1.00	1.00	5
MADAGASCAN SUNSET MOTH	1.00	1.00	1.00	5
MALACHITE	1.00	1.00	1.00	5
MANGROVE SKIPPER	1.00	1.00	1.00	5
MESTRA	1.00	0.80	0.89	5
METALMARK	1.00	1.00	1.00	5
MILBERTS TORTOISESHELL	0.80	0.80	0.80	5
MONARCH	1.00	1.00	1.00	5
MOURNING CLOAK	0.83	1.00	0.91	5
OLEANDER HAWK MOTH	1.00	1.00	1.00	5
ORANGE OAKLEAF	1.00	1.00	1.00	5
ORANGE TIP	0.71	1.00	0.83	5
ORCHARD SWALLOW	1.00	1.00	1.00	5
PAINTED LADY	0.83	1.00	0.91	5
PAPER KITE	1.00	1.00	1.00	5
PEACOCK	1.00	1.00	1.00	5
PINE WHITE	1.00	1.00	1.00	5
PIPEVINE SWALLOW	1.00	1.00	1.00	5
POLYPHEMUS MOTH	1.00	1.00	1.00	5
POPINJAY	1.00	1.00	1.00	5
PURPLE HAIRSTREAK	1.00	1.00	1.00	5
PURPLISH COPPER	1.00	1.00	1.00	5
QUESTION MARK	1.00	0.80	0.89	5
RED ADMIRAL	1.00	1.00	1.00	5
RED CRACKER	1.00	1.00	1.00	5
RED POSTMAN	1.00	1.00	1.00	5
RED SPOTTED PURPLE	1.00	1.00	1.00	5
ROSY MAPLE MOTH	1.00	1.00	1.00	5
SCARCE SWALLOW	1.00	1.00	1.00	5
SILVER SPOT SKIPPER	1.00	1.00	1.00	5
SIXSPOT BURNET MOTH	1.00	1.00	1.00	5
SLEEPY ORANGE	1.00	0.60	0.75	5
SOOTYWING	1.00	1.00	1.00	5
SOUTHERN DOGFACE	0.71	1.00	0.83	5
STRAITED QUEEN	1.00	1.00	1.00	5
TROPICAL LEAFWING	1.00	0.80	0.89	5
TWO BARRED FLASHER	1.00	1.00	1.00	5
ULYES	1.00	1.00	1.00	5
VICEROY	1.00	1.00	1.00	5
WHITE LINED SPHINX MOTH	1.00	1.00	1.00	5
WOOD SATYR	0.83	1.00	0.91	5
YELLOW SWALLOW TAIL	1.00	1.00	1.00	5
ZEBRA LONG WING	1.00	1.00	1.00	5

accuracy		0.97	0.97	500
macro avg	0.97	0.97	0.97	500
weighted avg	0.97	0.97	0.97	500

```
[ ]: model_xc.save("deepXception.h5")
```

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

- validacion del modelo con imagenes nuevas

```
[ ]: # IMPORTANTE: Traemos las dos funciones de preprocesamiento para normalizar las nuevas imagenes

from tensorflow.keras.applications.xception import preprocess_input as pre_xception
from tensorflow.keras.applications.resnet50 import preprocess_input as pre_resnet

mapa_etiquetas = {v: k for k, v in train_generator_xc.class_indices.items()}

def probar_imagen(ruta_imagen, modelo, funcion_preprocess):

    try:
        # Cargar imagen (224x224 funciona para ambos en este caso)
        img = keras_image.load_img(ruta_imagen, target_size=(224, 224))

        # Convertir a Array
        img_array = keras_image.img_to_array(img)

        # Expandir dimensiones (de 3D a 4D)
        img_batch = np.expand_dims(img_array, axis=0)

        # Usamos la función que recibimos como argumento
        img_preprocessed = funcion_preprocess(img_batch)

        # Predecir
        prediccion = modelo.predict(img_preprocessed)

        # Resultados
        indice_ganador = np.argmax(prediccion)
        probabilidad = np.max(prediccion)
        nombre_clase = mapa_etiquetas[indice_ganador]
```

```

# Mostrar
plt.figure(figsize=(6, 6))
plt.imshow(img)
plt.axis('off')
titulo = f"Modelo: {modelo.name}\nPredicción: {nombre_clase} con {probabilidad*100:.2f}% de confianza."
print(f"--> Resultado: {nombre_clase} con {probabilidad*100:.2f}% de confianza.")

except Exception as e:
    print(f"Error: {e}")

```

[]: probar_imagen('/content/add_2.jpg', modelo_xc, preprocess_input_xception)

1/1 0s 59ms/step

Modelo: functional_1
Predicción: ADONIS (99.94%)

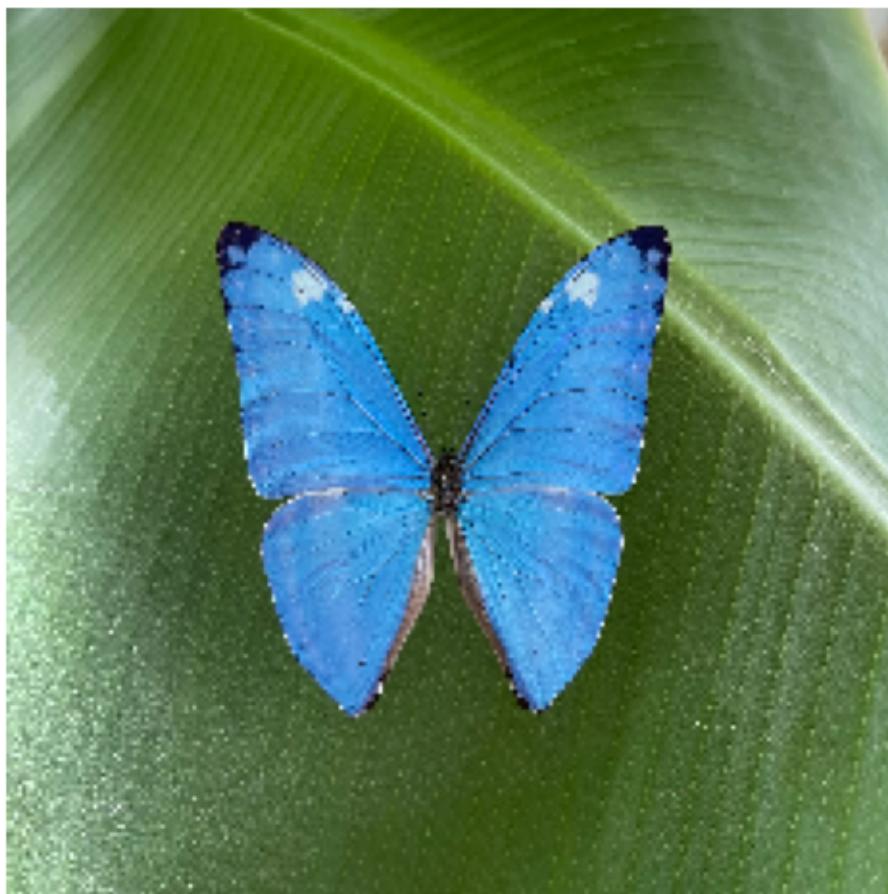


--> Resultado: ADONIS con 99.94% de confianza.

```
[ ]: probar_imagen('/content/add_1.jpg', model_aug, preprocess_input)
```

1/1 0s 70ms/step

Modelo: functional
Predicción: ADONIS (40.65%)



--> Resultado: ADONIS con 40.65% de confianza.

En esta imagen se evidencia un bajo porcentaje de confianza sin embargo, podria estar asociado a la baja resolucion de la misma

```
[ ]: probar_imagen('/content/add_2.jpg', model_aug, preprocess_input)
```

1/1 0s 68ms/step

Predicción: ADONIS
Confianza: 99.94%

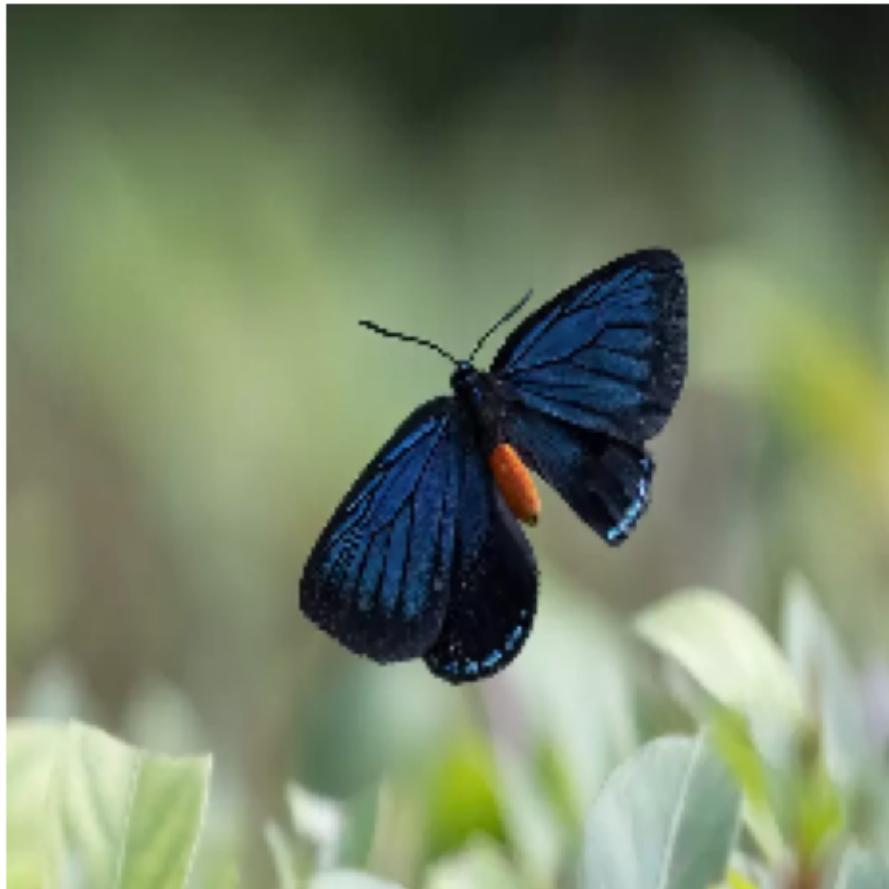


--> El modelo cree que es: ADONIS (99.94%)

[]: probar_imagen('/content/add_3.jpg', model_aug)

1/1 0s 64ms/step

Predicción: ATALA
Confianza: 92.55%



--> El modelo cree que es: ATALA (92.55%)

Además de las evaluaciones formales, también se probó el modelo con un conjunto de imágenes externas que no pertenecían ni al entrenamiento ni al test, simplemente para ver cómo respondía ante ejemplos completamente nuevos. Los resultados fueron sólidos: todas las predicciones superaron el 92% de confianza, lo que muestra que el modelo no solo recuerda patrones del dataset, sino que realmente generaliza bien. La única excepción fue una imagen cuya predicción quedó alrededor del 40%, pero era evidente que tenía una resolución muy baja y muy poco detalle, así que era esperable que el modelo dudara. Aun así, incluso en ese caso, la clase sugerida coincidía con la especie correcta según referencias de internet. En resumen, las pruebas externas confirmaron que el modelo mantiene coherencia y precisión incluso fuera de los datos originales.

Conclusiones estrategia 1 Hemos conseguido un modelo final que llegó a 90% de accuracy en validación pero no superó los 80% en el test. El tiempo de entrenar un modelo utilizando Collab es muy grande, más de 2 horas, lo que es otro factor a tener en consideración. Seguramente las técnicas de regularización utilizadas, como capas BatchNormalization y Dropout ayudan, pero parece que encontramos el límite que podíamos con los recursos computacionales disponibles.

Conclusiones estrategia 2 El proceso inició con la implementación de un modelo base mediante *transfer learning*, cuyas métricas iniciales fueron correctas pero mostraban espacio claro de mejora, especialmente frente al riesgo de sobreajuste y la limitada robustez ante variabilidad del dataset. A partir de allí se aplicaron técnicas de *data augmentation* —rotaciones, variaciones de brillo, flips y escalados— para incrementar la diversidad de imágenes. Posteriormente, el *fine-tuning* permitió desbloquear capas superiores del modelo y ajustar pesos pre-entrenados para adaptarlos a las características específicas del dataset. Cada ajuste mejoró gradualmente la generalización del modelo y redujo la pérdida en validación.

En este proceso comparativo, **ResNet50** destacó con un rendimiento sobresaliente: obtuvo **97.6% de accuracy en el conjunto de test**, una pérdida estable y un comportamiento consistente entre *train*, *validation* y *test*, lo que evidenció un aprendizaje sólido y sin señales de sobreajuste crítico. Además, las pruebas adicionales con imágenes externas —no presentes en entrenamiento ni test— confirmaron su capacidad de generalización, logrando más del **92% de confianza** en casi todas, excepto una de baja resolución que alcanzó cerca del **40%**, lo que se explica por la mala calidad visual. Estos resultados, sumados a la estabilidad del modelo y la coherencia entre predicciones y especies verificadas en fuentes externas, consolidan a **ResNet50 como el mejor modelo del experimento**.

0.1.1 Conclusión General

A lo largo del proceso se implementaron y compararon dos enfoques complementarios para resolver la tarea de clasificación multiclase. En la **Estrategia 1**, se construyó una red neuronal desde cero, ajustando arquitectura, hiperparámetros y técnicas de regularización con base en experimentación. Aunque este modelo logró aprender patrones relevantes del dataset, su rendimiento final fue moderado y no alcanzó las métricas obtenidas con los modelos preentrenados. Esto es esperado: un modelo creado *desde cero* parte sin conocimiento previo, requiere una cantidad de datos significativamente mayor para generalizar bien y suele presentar mayores dificultades para optimizar parámetros de manera estable cuando se trabaja con datasets de tamaño medio.

En contraste, la **Estrategia 2**, basada en *transfer learning* y *fine-tuning*, permitió aprovechar el conocimiento previamente adquirido por arquitecturas entrenadas sobre ImageNet, lo cual se tradujo en un salto considerable en desempeño. La comparación sistemática entre modelos como Xception y ResNet50 demostró que **ResNet50** fue la arquitectura con mejor precisión en el conjunto de test (**97.6%**), manteniendo estabilidad y buena capacidad de generalización incluso frente a imágenes externas al dataset. Esto evidencia que partir de un modelo preentrenado no solo acelera el desarrollo, sino que mejora significativamente la calidad de las predicciones, ya que las capas profundas ya contienen representaciones visuales altamente optimizadas y aplicables a nuevas tareas.

En síntesis, los resultados muestran que **descargar un modelo preentrenado y aplicar fine-tuning es superior a construir una red desde cero** cuando se trabaja con datasets limitados en tamaño o variabilidad. El modelo preentrenado parte desde un punto de conocimiento mucho más avanzado, reduce el riesgo de sobreajuste y permite alcanzar niveles de precisión difíciles de lograr con arquitecturas diseñadas desde cero bajo las mismas condiciones. Por ello, la Estrategia 2 no solo fue más eficiente, sino claramente más efectiva para este proyecto.