nutri-v2.1–3

October 9, 2025

1 Food-101: v2.2 - Objetivo 80% Accuracy

Mejoras: Arquitectura profunda + BatchNorm + Mixup/CutMix + LR Scheduler + Regularización agresiva

[15]:
```
# Imports
import tensorflow as tf
import tensorflow_datasets as tfds
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, classification_report
import pandas as pd
```

[16]:
```
# Mixed precision DESACTIVADO (causa inestabilidad numérica)
# tf.keras.mixed_precision.set_global_policy('mixed_float16')
print('Mixed Precision: DESACTIVADO (float32 para estabilidad)')
```

```
Mixed Precision: DESACTIVADO (float32 para estabilidad)
```

[17]:
```
# Configuración
IMG_SIZE = 224
BATCH_SIZE = 64
NUM_CLASSES_TO_USE = 5
AUTOTUNE = tf.data.AUTOTUNE

print(f'IMG_SIZE: {IMG_SIZE} | BATCH_SIZE: {BATCH_SIZE} | CLASES:␣
 ↪{NUM_CLASSES_TO_USE}')
```

```
IMG_SIZE: 224 | BATCH_SIZE: 64 | CLASES: 5
```

[18]:
```
# Cargar dataset
(train_ds, val_ds), info = tfds.load(
    'food101',
    split=['train', 'validation'],
    with_info=True,
    as_supervised=True
)

class_names = info.features['label'].names
```

```python
print(f'Dataset: {len(class_names)} clases totales')

if NUM_CLASSES_TO_USE < 101:
    train_ds = train_ds.filter(lambda img, label: label < NUM_CLASSES_TO_USE)
    val_ds = val_ds.filter(lambda img, label: label < NUM_CLASSES_TO_USE)
    num_classes = NUM_CLASSES_TO_USE
    class_names = class_names[:NUM_CLASSES_TO_USE]
else:
    num_classes = len(class_names)

print(f'Usando: {num_classes} clases - {class_names}')
```

```
Dataset: 101 clases totales
Usando: 5 clases - ['apple_pie', 'baby_back_ribs', 'baklava', 'beef_carpaccio',
'beef_tartare']
```

[19]:

```python
# Funciones de preprocessing y augmentation SIMPLIFICADO
def preprocess(image, label):
    image = tf.image.resize(image, [IMG_SIZE, IMG_SIZE])
    image = image / 255.0
    return image, label

# Augmentation SIMPLE (solo flip - Mixup/CutMix hace el resto)
data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip('horizontal'),
])

def augment(image, label):
    image = data_augmentation(image, training=True)
    return image, label

# Mixup
def mixup(image, label, alpha=0.2):
    batch_size = tf.shape(image)[0]
    dist = tf.compat.v1.distributions.Beta(alpha, alpha)
    lam = dist.sample(1)[0]

    indices = tf.random.shuffle(tf.range(batch_size))
    mixed_image = lam * image + (1 - lam) * tf.gather(image, indices)

    label_a = tf.one_hot(label, NUM_CLASSES_TO_USE)
    label_b = tf.one_hot(tf.gather(label, indices), NUM_CLASSES_TO_USE)
    mixed_label = lam * label_a + (1 - lam) * label_b

    return mixed_image, mixed_label

# CutMix
```

```python
def cutmix(image, label, alpha=1.0):
    batch_size = tf.shape(image)[0]
    image_height, image_width = IMG_SIZE, IMG_SIZE

    dist = tf.compat.v1.distributions.Beta(alpha, alpha)
    lam = dist.sample(1)[0]

    cut_ratio = tf.sqrt(1.0 - lam)
    cut_h = tf.cast(image_height * cut_ratio, tf.int32)
    cut_w = tf.cast(image_width * cut_ratio, tf.int32)

    cy = tf.random.uniform([], 0, image_height, dtype=tf.int32)
    cx = tf.random.uniform([], 0, image_width, dtype=tf.int32)

    y1 = tf.clip_by_value(cy - cut_h // 2, 0, image_height)
    y2 = tf.clip_by_value(cy + cut_h // 2, 0, image_height)
    x1 = tf.clip_by_value(cx - cut_w // 2, 0, image_width)
    x2 = tf.clip_by_value(cx + cut_w // 2, 0, image_width)

    indices = tf.random.shuffle(tf.range(batch_size))
    shuffled_image = tf.gather(image, indices)

    mask = tf.concat([
        tf.zeros([batch_size, y1, image_width, 3]),
        tf.concat([
            tf.zeros([batch_size, y2-y1, x1, 3]),
            tf.ones([batch_size, y2-y1, x2-x1, 3]),
            tf.zeros([batch_size, y2-y1, image_width-x2, 3])
        ], axis=2),
        tf.zeros([batch_size, image_height-y2, image_width, 3])
    ], axis=1)

    mixed_image = image * (1 - mask) + shuffled_image * mask

    area = tf.cast((x2 - x1) * (y2 - y1), tf.float32)
    total_area = tf.cast(image_height * image_width, tf.float32)
    lam_adjusted = 1.0 - (area / total_area)

    label_a = tf.one_hot(label, NUM_CLASSES_TO_USE)
    label_b = tf.one_hot(tf.gather(label, indices), NUM_CLASSES_TO_USE)
    mixed_label = lam_adjusted * label_a + (1 - lam_adjusted) * label_b

    return mixed_image, mixed_label

print('Augmentation SIMPLIFICADO: Solo RandomFlip + Mixup/CutMix')
```

```
Augmentation SIMPLIFICADO: Solo RandomFlip + Mixup/CutMix
```

[20]:
```python
# Pipeline con mixup/cutmix
train_dataset = (
    train_ds
    .map(preprocess, num_parallel_calls=AUTOTUNE)
    .cache()
    .shuffle(1000)
    .map(augment, num_parallel_calls=AUTOTUNE)
    .batch(BATCH_SIZE)
    .prefetch(AUTOTUNE)
)

def apply_mixup_cutmix(images, labels):
    # Cast images to float32 to avoid type mismatch with mixup/cutmix operations
    images = tf.cast(images, tf.float32)
    choice = tf.random.uniform([], 0, 1)
    if choice < 0.25:
        return mixup(images, labels, alpha=0.2)
    elif choice < 0.5:
        return cutmix(images, labels, alpha=1.0)
    else:
        return images, tf.one_hot(labels, NUM_CLASSES_TO_USE)

train_dataset = train_dataset.map(apply_mixup_cutmix,␣
 ↪num_parallel_calls=AUTOTUNE)

val_dataset = (
    val_ds
    .map(preprocess, num_parallel_calls=AUTOTUNE)
    .cache()
    .batch(BATCH_SIZE)
    .map(lambda x, y: (x, tf.one_hot(y, NUM_CLASSES_TO_USE)))
    .prefetch(AUTOTUNE)
)

print('Pipeline: Mixup 25% | CutMix 25% | Normal 50%')
```

```
Pipeline: Mixup 25% | CutMix 25% | Normal 50%
```

[21]:
```python
# Arquitectura BALANCEADA: Dropout solo en bloques profundos
model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(IMG_SIZE, IMG_SIZE, 3)),

    # Bloque 1: 32 filtros - SIN dropout (deja aprender features básicas)
    tf.keras.layers.Conv2D(32, 3, activation='relu', padding='same'),
    tf.keras.layers.Conv2D(32, 3, activation='relu', padding='same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D(2),
```

```
    # Bloque 2: 64 filtros - SIN dropout
    tf.keras.layers.Conv2D(64, 3, activation='relu', padding='same'),
    tf.keras.layers.Conv2D(64, 3, activation='relu', padding='same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D(2),

    # Bloque 3: 128 filtros - Dropout 0.2 (regularización moderada)
    tf.keras.layers.Conv2D(128, 3, activation='relu', padding='same'),
    tf.keras.layers.Conv2D(128, 3, activation='relu', padding='same'),
    tf.keras.layers.Conv2D(128, 3, activation='relu', padding='same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D(2),
    tf.keras.layers.Dropout(0.2),

    # Bloque 4: 256 filtros - Dropout 0.2
    tf.keras.layers.Conv2D(256, 3, activation='relu', padding='same'),
    tf.keras.layers.Conv2D(256, 3, activation='relu', padding='same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D(2),
    tf.keras.layers.Dropout(0.2),

    # Clasificador - Dropout 0.3 (no 0.5)
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(256, activation='relu', kernel_regularizer=tf.keras.
  ↪regularizers.l2(0.0001)),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(num_classes, activation='softmax')
])

model.summary()
total_params = model.count_params()
print(f'\nParams: {total_params:,} | Dropout BALANCEADO: bloques 3-4 (0.2),␣
  ↪Dense (0.3)')
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
conv2d_9 (Conv2D)	(None, 224, 224, 32)	896
conv2d_10 (Conv2D)	(None, 224, 224, 32)	9,248
batch_normalization_4 (BatchNormalization)	(None, 224, 224, 32)	128

max_pooling2d_4 (MaxPooling2D)	(None, 112, 112, 32)	0
conv2d_11 (Conv2D)	(None, 112, 112, 64)	18,496
conv2d_12 (Conv2D)	(None, 112, 112, 64)	36,928
batch_normalization_5 (BatchNormalization)	(None, 112, 112, 64)	256
max_pooling2d_5 (MaxPooling2D)	(None, 56, 56, 64)	0
conv2d_13 (Conv2D)	(None, 56, 56, 128)	73,856
conv2d_14 (Conv2D)	(None, 56, 56, 128)	147,584
conv2d_15 (Conv2D)	(None, 56, 56, 128)	147,584
batch_normalization_6 (BatchNormalization)	(None, 56, 56, 128)	512
max_pooling2d_6 (MaxPooling2D)	(None, 28, 28, 128)	0
dropout_6 (Dropout)	(None, 28, 28, 128)	0
conv2d_16 (Conv2D)	(None, 28, 28, 256)	295,168
conv2d_17 (Conv2D)	(None, 28, 28, 256)	590,080
batch_normalization_7 (BatchNormalization)	(None, 28, 28, 256)	1,024
max_pooling2d_7 (MaxPooling2D)	(None, 14, 14, 256)	0
dropout_7 (Dropout)	(None, 14, 14, 256)	0
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 256)	0
dropout_8 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 256)	65,792
dropout_9 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 5)	1,285

Total params: 1,388,837 (5.30 MB)

Trainable params: 1,387,877 (5.29 MB)

Non-trainable params: 960 (3.75 KB)

```
Params: 1,388,837 | Dropout BALANCEADO: bloques 3-4 (0.2), Dense (0.3)
```

[22]:

```python
# Compilar SIN label smoothing (Mixup/CutMix ya suavizan labels)
model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=0.0005),  # LR reducido
    loss=tf.keras.losses.CategoricalCrossentropy(),  # SIN label_smoothing
    metrics=['accuracy']
)

print('Optimizer: Adam (LR 0.0005) | Loss: CategoricalCrossentropy (sin label␣
↪smoothing)')
```

```
Optimizer: Adam (LR 0.0005) | Loss: CategoricalCrossentropy (sin label
smoothing)
```

[23]:

```python
# LR Scheduler AJUSTADO: Warmup + Cosine Annealing con LR más bajo
class WarmupCosineDecay(tf.keras.callbacks.Callback):
    def __init__(self, max_lr=0.0005, min_lr=0.00001, warmup_epochs=5,␣
↪total_epochs=60):
        super().__init__()
        self.max_lr = max_lr
        self.min_lr = min_lr
        self.warmup_epochs = warmup_epochs
        self.total_epochs = total_epochs

    def on_epoch_begin(self, epoch, logs=None):
        if epoch < self.warmup_epochs:
            lr = self.max_lr * (epoch + 1) / self.warmup_epochs
        else:
            progress = (epoch - self.warmup_epochs) / (self.total_epochs - self.
↪warmup_epochs)
            lr = self.min_lr + 0.5 * (self.max_lr - self.min_lr) * (1 + tf.
↪cos(np.pi * progress))

        optimizer = self.model.optimizer
        if hasattr(optimizer, 'learning_rate'):
            optimizer.learning_rate.assign(lr)

        if epoch < 5 or epoch % 10 == 0:
```

```
            print(f'Epoch {epoch+1}: LR = {lr:.6f}')

lr_scheduler = WarmupCosineDecay(max_lr=0.0005, min_lr=0.00001,␣
 ↪warmup_epochs=5, total_epochs=60)
print('LR Scheduler: Warmup 0→0.0005 (epochs 1-5) + Cosine 0.0005→0.00001␣
 ↪(epochs 6-60)')
```

```
LR Scheduler: Warmup 0→0.0005 (epochs 1-5) + Cosine 0.0005→0.00001 (epochs 6-60)
```

[24]:

```
# Callbacks y entrenamiento
early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss',
    patience=15,  # Más tolerante (antes era 10)
    restore_best_weights=True,
    verbose=1
)

model_checkpoint = tf.keras.callbacks.ModelCheckpoint(
    'best_model_v2.3.keras',  # Nueva versión balanceada
    monitor='val_accuracy',
    save_best_only=True,
    verbose=1
)

EPOCHS = 60

print(f'\nv2.3 BALANCEADA - Entrenamiento: {EPOCHS} epochs, early stopping␣
 ↪patience=15')
print('Cambios vs v2.2:')
print('    Mixed precision: DESACTIVADO')
print('    Label smoothing: ELIMINADO')
print('    Augmentation: SIMPLIFICADO (solo flip)')
print('    Dropout: REDUCIDO (bloques 3-4: 0.2, Dense: 0.3)')
print('    LR: REDUCIDO (0.0005 vs 0.001)')
print('\nEsperado: 60-75% accuracy\n')

history = model.fit(
    train_dataset,
    validation_data=val_dataset,
    epochs=EPOCHS,
    callbacks=[early_stopping, lr_scheduler, model_checkpoint],
    verbose=1
)
```

```

v2.3 BALANCEADA - Entrenamiento: 60 epochs, early stopping patience=15
Cambios vs v2.2:
    Mixed precision: DESACTIVADO
```

```
    Label smoothing: ELIMINADO
    Augmentation: SIMPLIFICADO (solo flip)
    Dropout: REDUCIDO (bloques 3-4: 0.2, Dense: 0.3)
    LR: REDUCIDO (0.0005 vs 0.001)

Esperado: 60-75% accuracy

Epoch 1: LR = 0.000100
Epoch 1/60
     59/Unknown 296s 5s/step - accuracy: 0.2474 - loss: 2.1411

/opt/homebrew/anaconda3/envs/ml_env/lib/python3.9/site-
packages/keras/src/trainers/epoch_iterator.py:160: UserWarning: Your input ran
out of data; interrupting training. Make sure that your dataset or generator can
generate at least `steps_per_epoch * epochs` batches. You may need to use the
`.repeat()` function when building your dataset.
  self._interrupted_warning()


Epoch 1: val_accuracy improved from -inf to 0.20000, saving model to
best_model_v2.3.keras
59/59            315s 5s/step -
accuracy: 0.2483 - loss: 2.1373 - val_accuracy: 0.2000 - val_loss: 1.7284
Epoch 2: LR = 0.000200
Epoch 2/60
59/59            0s 3s/step -
accuracy: 0.4245 - loss: 1.5606
Epoch 2: val_accuracy did not improve from 0.20000
59/59            164s 3s/step -
accuracy: 0.4243 - loss: 1.5604 - val_accuracy: 0.2000 - val_loss: 2.0163
Epoch 3: LR = 0.000300
Epoch 3/60
59/59            0s 3s/step -
accuracy: 0.4333 - loss: 1.5103
Epoch 3: val_accuracy did not improve from 0.20000
59/59            175s 3s/step -
accuracy: 0.4334 - loss: 1.5095 - val_accuracy: 0.2000 - val_loss: 2.5297
Epoch 4: LR = 0.000400
Epoch 4/60
59/59            0s 3s/step -
accuracy: 0.4605 - loss: 1.3875
Epoch 4: val_accuracy did not improve from 0.20000
59/59            170s 3s/step -
accuracy: 0.4605 - loss: 1.3878 - val_accuracy: 0.2000 - val_loss: 2.9423
Epoch 5: LR = 0.000500
Epoch 5/60
59/59            0s 3s/step -
accuracy: 0.4645 - loss: 1.3959
Epoch 5: val_accuracy improved from 0.20000 to 0.20080, saving model to
```

```
best_model_v2.3.keras
59/59            167s 3s/step -
accuracy: 0.4649 - loss: 1.3950 - val_accuracy: 0.2008 - val_loss: 3.2559
Epoch 6/60
59/59            0s 3s/step -
accuracy: 0.4903 - loss: 1.3422
Epoch 6: val_accuracy improved from 0.20080 to 0.20720, saving model to
best_model_v2.3.keras
59/59            181s 3s/step -
accuracy: 0.4903 - loss: 1.3423 - val_accuracy: 0.2072 - val_loss: 2.4967
Epoch 7/60
59/59            0s 3s/step -
accuracy: 0.4444 - loss: 1.4320
Epoch 7: val_accuracy did not improve from 0.20720
59/59            167s 3s/step -
accuracy: 0.4449 - loss: 1.4310 - val_accuracy: 0.2000 - val_loss: 2.8392
Epoch 8/60
59/59            0s 3s/step -
accuracy: 0.4931 - loss: 1.3750
Epoch 8: val_accuracy improved from 0.20720 to 0.39120, saving model to
best_model_v2.3.keras
59/59            169s 3s/step -
accuracy: 0.4931 - loss: 1.3747 - val_accuracy: 0.3912 - val_loss: 1.5338
Epoch 9/60
59/59            0s 3s/step -
accuracy: 0.5110 - loss: 1.3280
Epoch 9: val_accuracy improved from 0.39120 to 0.48240, saving model to
best_model_v2.3.keras
59/59            165s 3s/step -
accuracy: 0.5109 - loss: 1.3278 - val_accuracy: 0.4824 - val_loss: 1.3236
Epoch 10/60
59/59            0s 3s/step -
accuracy: 0.5168 - loss: 1.2505
Epoch 10: val_accuracy did not improve from 0.48240
59/59            167s 3s/step -
accuracy: 0.5168 - loss: 1.2513 - val_accuracy: 0.4032 - val_loss: 1.3934
Epoch 11: LR = 0.000490
Epoch 11/60
59/59            0s 3s/step -
accuracy: 0.4962 - loss: 1.3324
Epoch 11: val_accuracy did not improve from 0.48240
59/59            179s 3s/step -
accuracy: 0.4964 - loss: 1.3318 - val_accuracy: 0.4720 - val_loss: 1.4269
Epoch 12/60
59/59            0s 3s/step -
accuracy: 0.5366 - loss: 1.2375
Epoch 12: val_accuracy did not improve from 0.48240
59/59            175s 3s/step -
```

```
accuracy: 0.5365 - loss: 1.2380 - val_accuracy: 0.3272 - val_loss: 1.9440
Epoch 13/60
59/59            0s 3s/step -
accuracy: 0.5034 - loss: 1.3140
Epoch 13: val_accuracy improved from 0.48240 to 0.52160, saving model to
best_model_v2.3.keras
59/59            180s 3s/step -
accuracy: 0.5035 - loss: 1.3139 - val_accuracy: 0.5216 - val_loss: 1.2830
Epoch 14/60
59/59            0s 3s/step -
accuracy: 0.5059 - loss: 1.2875
Epoch 14: val_accuracy did not improve from 0.52160
59/59            183s 3s/step -
accuracy: 0.5059 - loss: 1.2878 - val_accuracy: 0.2072 - val_loss: 4.9405
Epoch 15/60
59/59            0s 3s/step -
accuracy: 0.5315 - loss: 1.2811
Epoch 15: val_accuracy improved from 0.52160 to 0.54560, saving model to
best_model_v2.3.keras
59/59            180s 3s/step -
accuracy: 0.5315 - loss: 1.2815 - val_accuracy: 0.5456 - val_loss: 1.1684
Epoch 16/60
59/59            0s 3s/step -
accuracy: 0.5010 - loss: 1.3406
Epoch 16: val_accuracy improved from 0.54560 to 0.55280, saving model to
best_model_v2.3.keras
59/59            168s 3s/step -
accuracy: 0.5012 - loss: 1.3401 - val_accuracy: 0.5528 - val_loss: 1.2045
Epoch 17/60
59/59            0s 3s/step -
accuracy: 0.5319 - loss: 1.2828
Epoch 17: val_accuracy did not improve from 0.55280
59/59            170s 3s/step -
accuracy: 0.5320 - loss: 1.2825 - val_accuracy: 0.4512 - val_loss: 1.2473
Epoch 18/60
59/59            0s 3s/step -
accuracy: 0.5592 - loss: 1.2143
Epoch 18: val_accuracy improved from 0.55280 to 0.58800, saving model to
best_model_v2.3.keras
59/59            172s 3s/step -
accuracy: 0.5590 - loss: 1.2150 - val_accuracy: 0.5880 - val_loss: 1.0577
Epoch 19/60
59/59            0s 3s/step -
accuracy: 0.4736 - loss: 1.3566
Epoch 19: val_accuracy did not improve from 0.58800
59/59            173s 3s/step -
accuracy: 0.4740 - loss: 1.3561 - val_accuracy: 0.3504 - val_loss: 1.9208
Epoch 20/60
```

```
59/59            0s 3s/step -
accuracy: 0.5452 - loss: 1.2782
Epoch 20: val_accuracy did not improve from 0.58800
59/59            179s 3s/step -
accuracy: 0.5450 - loss: 1.2780 - val_accuracy: 0.2648 - val_loss: 3.2457
Epoch 21: LR = 0.000415
Epoch 21/60
59/59            0s 3s/step -
accuracy: 0.5169 - loss: 1.3122
Epoch 21: val_accuracy did not improve from 0.58800
59/59            173s 3s/step -
accuracy: 0.5171 - loss: 1.3120 - val_accuracy: 0.3736 - val_loss: 2.3501
Epoch 22/60
59/59            0s 3s/step -
accuracy: 0.5102 - loss: 1.3483
Epoch 22: val_accuracy did not improve from 0.58800
59/59            158s 3s/step -
accuracy: 0.5105 - loss: 1.3472 - val_accuracy: 0.5560 - val_loss: 1.1261
Epoch 23/60
59/59            0s 3s/step -
accuracy: 0.5663 - loss: 1.1748
Epoch 23: val_accuracy improved from 0.58800 to 0.59120, saving model to
best_model_v2.3.keras
59/59            160s 3s/step -
accuracy: 0.5661 - loss: 1.1756 - val_accuracy: 0.5912 - val_loss: 1.0062
Epoch 24/60
59/59            0s 3s/step -
accuracy: 0.5784 - loss: 1.1823
Epoch 24: val_accuracy did not improve from 0.59120
59/59            170s 3s/step -
accuracy: 0.5784 - loss: 1.1821 - val_accuracy: 0.4744 - val_loss: 1.5456
Epoch 25/60
59/59            0s 3s/step -
accuracy: 0.5706 - loss: 1.1583
Epoch 25: val_accuracy did not improve from 0.59120
59/59            162s 3s/step -
accuracy: 0.5706 - loss: 1.1587 - val_accuracy: 0.5744 - val_loss: 1.1010
Epoch 26/60
59/59            0s 3s/step -
accuracy: 0.5754 - loss: 1.2027
Epoch 26: val_accuracy did not improve from 0.59120
59/59            164s 3s/step -
accuracy: 0.5752 - loss: 1.2028 - val_accuracy: 0.4280 - val_loss: 2.0358
Epoch 27/60
59/59            0s 3s/step -
accuracy: 0.5794 - loss: 1.2183
Epoch 27: val_accuracy did not improve from 0.59120
59/59            164s 3s/step -
```

```
accuracy: 0.5793 - loss: 1.2182 - val_accuracy: 0.5880 - val_loss: 1.0262
Epoch 28/60
59/59            0s 3s/step -
accuracy: 0.5744 - loss: 1.1331
Epoch 28: val_accuracy did not improve from 0.59120
59/59            164s 3s/step -
accuracy: 0.5747 - loss: 1.1331 - val_accuracy: 0.4288 - val_loss: 1.6073
Epoch 29/60
59/59            0s 3s/step -
accuracy: 0.6030 - loss: 1.1441
Epoch 29: val_accuracy did not improve from 0.59120
59/59            163s 3s/step -
accuracy: 0.6028 - loss: 1.1441 - val_accuracy: 0.5024 - val_loss: 1.2370
Epoch 30/60
59/59            0s 3s/step -
accuracy: 0.6089 - loss: 1.0730
Epoch 30: val_accuracy improved from 0.59120 to 0.59520, saving model to
best_model_v2.3.keras
59/59            178s 3s/step -
accuracy: 0.6088 - loss: 1.0733 - val_accuracy: 0.5952 - val_loss: 0.9621
Epoch 31: LR = 0.000290
Epoch 31/60
59/59            0s 3s/step -
accuracy: 0.6124 - loss: 1.0760
Epoch 31: val_accuracy improved from 0.59520 to 0.61600, saving model to
best_model_v2.3.keras
59/59            173s 3s/step -
accuracy: 0.6125 - loss: 1.0758 - val_accuracy: 0.6160 - val_loss: 0.9091
Epoch 32/60
59/59            0s 3s/step -
accuracy: 0.5994 - loss: 1.0554
Epoch 32: val_accuracy improved from 0.61600 to 0.67040, saving model to
best_model_v2.3.keras
59/59            171s 3s/step -
accuracy: 0.5996 - loss: 1.0559 - val_accuracy: 0.6704 - val_loss: 0.8771
Epoch 33/60
59/59            0s 3s/step -
accuracy: 0.6508 - loss: 1.0182
Epoch 33: val_accuracy did not improve from 0.67040
59/59            173s 3s/step -
accuracy: 0.6506 - loss: 1.0185 - val_accuracy: 0.6208 - val_loss: 0.9521
Epoch 34/60
59/59            0s 3s/step -
accuracy: 0.6349 - loss: 1.0131
Epoch 34: val_accuracy did not improve from 0.67040
59/59            174s 3s/step -
accuracy: 0.6347 - loss: 1.0138 - val_accuracy: 0.6208 - val_loss: 1.0065
Epoch 35/60
```

```
59/59            0s 3s/step -
accuracy: 0.6096 - loss: 1.0941
Epoch 35: val_accuracy did not improve from 0.67040
59/59            181s 3s/step -
accuracy: 0.6097 - loss: 1.0941 - val_accuracy: 0.6560 - val_loss: 0.8637
Epoch 36/60
59/59            0s 3s/step -
accuracy: 0.6068 - loss: 1.1407
Epoch 36: val_accuracy did not improve from 0.67040
59/59            167s 3s/step -
accuracy: 0.6070 - loss: 1.1400 - val_accuracy: 0.5792 - val_loss: 1.0162
Epoch 37/60
59/59            0s 3s/step -
accuracy: 0.6261 - loss: 1.0916
Epoch 37: val_accuracy did not improve from 0.67040
59/59            161s 3s/step -
accuracy: 0.6261 - loss: 1.0919 - val_accuracy: 0.6528 - val_loss: 0.8784
Epoch 38/60
59/59            0s 3s/step -
accuracy: 0.6708 - loss: 0.9508
Epoch 38: val_accuracy improved from 0.67040 to 0.70240, saving model to
best_model_v2.3.keras
59/59            161s 3s/step -
accuracy: 0.6705 - loss: 0.9517 - val_accuracy: 0.7024 - val_loss: 0.7942
Epoch 39/60
59/59            0s 3s/step -
accuracy: 0.6717 - loss: 0.9679
Epoch 39: val_accuracy did not improve from 0.70240
59/59            161s 3s/step -
accuracy: 0.6715 - loss: 0.9683 - val_accuracy: 0.6520 - val_loss: 0.8448
Epoch 40/60
59/59            0s 3s/step -
accuracy: 0.6685 - loss: 0.9591
Epoch 40: val_accuracy improved from 0.70240 to 0.71440, saving model to
best_model_v2.3.keras
59/59            169s 3s/step -
accuracy: 0.6685 - loss: 0.9591 - val_accuracy: 0.7144 - val_loss: 0.7485
Epoch 41: LR = 0.000153
Epoch 41/60
59/59            0s 3s/step -
accuracy: 0.7058 - loss: 0.8630
Epoch 41: val_accuracy improved from 0.71440 to 0.73760, saving model to
best_model_v2.3.keras
59/59            173s 3s/step -
accuracy: 0.7055 - loss: 0.8644 - val_accuracy: 0.7376 - val_loss: 0.7023
Epoch 42/60
59/59            0s 3s/step -
accuracy: 0.6707 - loss: 1.0250
```

```
Epoch 42: val_accuracy did not improve from 0.73760
59/59            167s 3s/step -
accuracy: 0.6709 - loss: 1.0247 - val_accuracy: 0.7144 - val_loss: 0.7447
Epoch 43/60
59/59            0s 2s/step -
accuracy: 0.6556 - loss: 1.0144
Epoch 43: val_accuracy did not improve from 0.73760
59/59            155s 3s/step -
accuracy: 0.6557 - loss: 1.0140 - val_accuracy: 0.7056 - val_loss: 0.7695
Epoch 44/60
59/59            0s 3s/step -
accuracy: 0.6885 - loss: 0.9915
Epoch 44: val_accuracy improved from 0.73760 to 0.77120, saving model to
best_model_v2.3.keras
59/59            168s 3s/step -
accuracy: 0.6885 - loss: 0.9910 - val_accuracy: 0.7712 - val_loss: 0.6623
Epoch 45/60
59/59            0s 3s/step -
accuracy: 0.6634 - loss: 0.9925
Epoch 45: val_accuracy did not improve from 0.77120
59/59            163s 3s/step -
accuracy: 0.6636 - loss: 0.9922 - val_accuracy: 0.6456 - val_loss: 0.9086
Epoch 46/60
59/59            0s 3s/step -
accuracy: 0.6935 - loss: 0.9099
Epoch 46: val_accuracy improved from 0.77120 to 0.78160, saving model to
best_model_v2.3.keras
59/59            162s 3s/step -
accuracy: 0.6938 - loss: 0.9095 - val_accuracy: 0.7816 - val_loss: 0.6416
Epoch 47/60
59/59            0s 3s/step -
accuracy: 0.7151 - loss: 0.8753
Epoch 47: val_accuracy did not improve from 0.78160
59/59            165s 3s/step -
accuracy: 0.7151 - loss: 0.8749 - val_accuracy: 0.7656 - val_loss: 0.6568
Epoch 48/60
59/59            0s 3s/step -
accuracy: 0.7337 - loss: 0.7999
Epoch 48: val_accuracy did not improve from 0.78160
59/59            160s 3s/step -
accuracy: 0.7336 - loss: 0.8002 - val_accuracy: 0.7736 - val_loss: 0.6527
Epoch 49/60
59/59            0s 3s/step -
accuracy: 0.7140 - loss: 0.9003
Epoch 49: val_accuracy improved from 0.78160 to 0.78240, saving model to
best_model_v2.3.keras
59/59            161s 3s/step -
accuracy: 0.7138 - loss: 0.9007 - val_accuracy: 0.7824 - val_loss: 0.6644
```

```
Epoch 50/60
59/59            0s 3s/step -
accuracy: 0.7054 - loss: 0.9572
Epoch 50: val_accuracy did not improve from 0.78240
59/59            172s 3s/step -
accuracy: 0.7053 - loss: 0.9569 - val_accuracy: 0.7560 - val_loss: 0.6813
Epoch 51: LR = 0.000049
Epoch 51/60
59/59            0s 3s/step -
accuracy: 0.7352 - loss: 0.8411
Epoch 51: val_accuracy improved from 0.78240 to 0.78960, saving model to
best_model_v2.3.keras
59/59            168s 3s/step -
accuracy: 0.7350 - loss: 0.8416 - val_accuracy: 0.7896 - val_loss: 0.6509
Epoch 52/60
59/59            0s 3s/step -
accuracy: 0.7388 - loss: 0.7986
Epoch 52: val_accuracy improved from 0.78960 to 0.79200, saving model to
best_model_v2.3.keras
59/59            162s 3s/step -
accuracy: 0.7387 - loss: 0.7995 - val_accuracy: 0.7920 - val_loss: 0.6170
Epoch 53/60
59/59            0s 3s/step -
accuracy: 0.7351 - loss: 0.8076
Epoch 53: val_accuracy improved from 0.79200 to 0.79760, saving model to
best_model_v2.3.keras
59/59            168s 3s/step -
accuracy: 0.7353 - loss: 0.8076 - val_accuracy: 0.7976 - val_loss: 0.6063
Epoch 54/60
59/59            0s 3s/step -
accuracy: 0.7653 - loss: 0.7679
Epoch 54: val_accuracy improved from 0.79760 to 0.80000, saving model to
best_model_v2.3.keras
59/59            164s 3s/step -
accuracy: 0.7650 - loss: 0.7687 - val_accuracy: 0.8000 - val_loss: 0.6079
Epoch 55/60
59/59            0s 3s/step -
accuracy: 0.7514 - loss: 0.8179
Epoch 55: val_accuracy did not improve from 0.80000
59/59            166s 3s/step -
accuracy: 0.7513 - loss: 0.8180 - val_accuracy: 0.7888 - val_loss: 0.6154
Epoch 56/60
59/59            0s 3s/step -
accuracy: 0.7099 - loss: 0.9015
Epoch 56: val_accuracy did not improve from 0.80000
59/59            166s 3s/step -
accuracy: 0.7100 - loss: 0.9012 - val_accuracy: 0.7960 - val_loss: 0.6072
Epoch 57/60
```

```
59/59              0s 3s/step -
accuracy: 0.7326 - loss: 0.8857
Epoch 57: val_accuracy did not improve from 0.80000
59/59              165s 3s/step -
accuracy: 0.7326 - loss: 0.8853 - val_accuracy: 0.7920 - val_loss: 0.6058
Epoch 58/60
59/59              0s 3s/step -
accuracy: 0.7607 - loss: 0.7775
Epoch 58: val_accuracy did not improve from 0.80000
59/59              169s 3s/step -
accuracy: 0.7605 - loss: 0.7781 - val_accuracy: 0.7896 - val_loss: 0.6021
Epoch 59/60
59/59              0s 3s/step -
accuracy: 0.7451 - loss: 0.7776
Epoch 59: val_accuracy did not improve from 0.80000
59/59              169s 3s/step -
accuracy: 0.7454 - loss: 0.7770 - val_accuracy: 0.7968 - val_loss: 0.5955
Epoch 60/60
59/59              0s 3s/step -
accuracy: 0.7420 - loss: 0.8476
Epoch 60: val_accuracy improved from 0.80000 to 0.80960, saving model to
best_model_v2.3.keras
59/59              164s 3s/step -
accuracy: 0.7417 - loss: 0.8476 - val_accuracy: 0.8096 - val_loss: 0.5920
Restoring model weights from the end of the best epoch: 60.
```

[25]:

```python
# Evaluación
test_loss, test_acc = model.evaluate(val_dataset)
print(f'\nValidation Loss: {test_loss:.4f} | Validation Accuracy: {test_acc:.
 ↪4f} ({test_acc*100:.1f}%)')
```

```
20/20              9s 434ms/step -
accuracy: 0.8232 - loss: 0.5667

Validation Loss: 0.5920 | Validation Accuracy: 0.8096 (81.0%)
```

[26]:

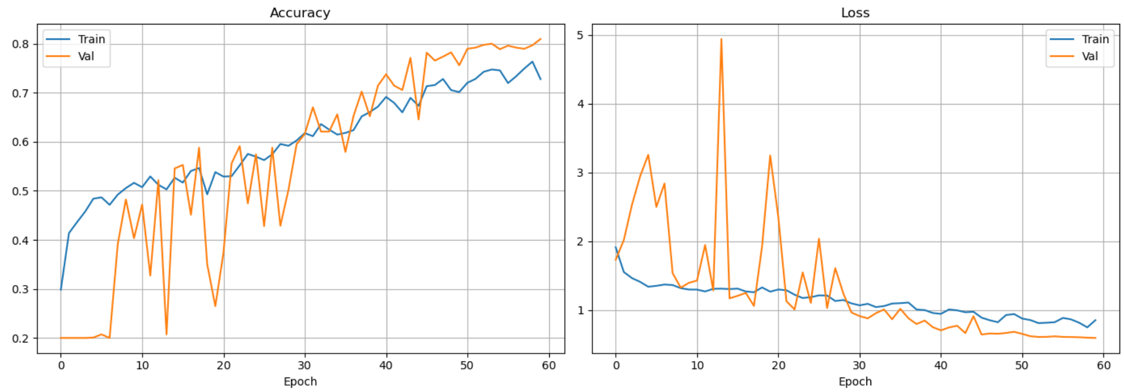
```python
# Gráficas de entrenamiento
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 5))

ax1.plot(history.history['accuracy'], label='Train')
ax1.plot(history.history['val_accuracy'], label='Val')
ax1.set_title('Accuracy')
ax1.set_xlabel('Epoch')
ax1.legend()
ax1.grid(True)

ax2.plot(history.history['loss'], label='Train')
ax2.plot(history.history['val_loss'], label='Val')
```

```
ax2.set_title('Loss')
ax2.set_xlabel('Epoch')
ax2.legend()
ax2.grid(True)

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



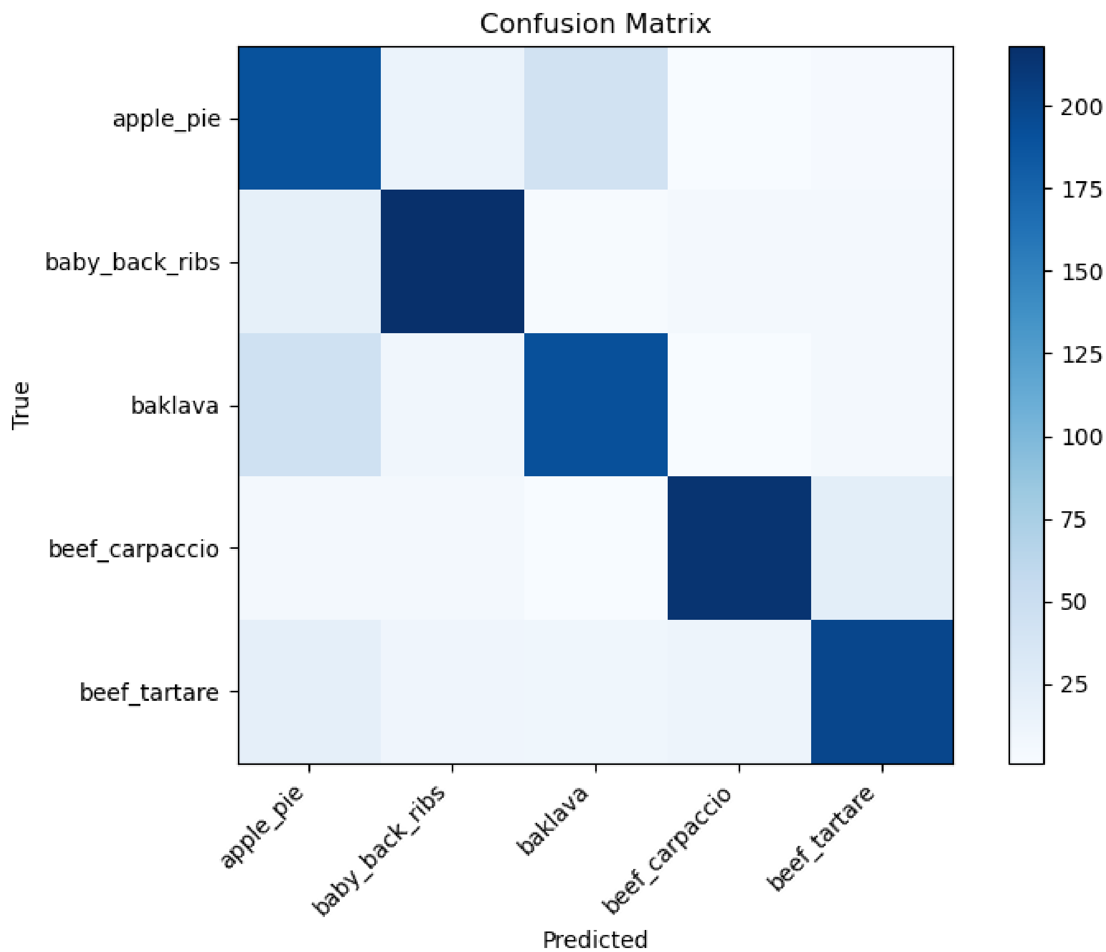
[27]:
```
# Matriz de confusión y reporte
y_true = []
y_pred = []

for images, labels_onehot in val_dataset:
    predictions = model.predict(images, verbose=0)
    y_true.extend(tf.argmax(labels_onehot, axis=1).numpy())
    y_pred.extend(np.argmax(predictions, axis=1))

y_true = np.array(y_true)
y_pred = np.array(y_pred)

# Confusion matrix
cm = confusion_matrix(y_true, y_pred)
plt.figure(figsize=(8, 6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(num_classes)
plt.xticks(tick_marks, class_names, rotation=45, ha='right')
plt.yticks(tick_marks, class_names)
plt.ylabel('True')
plt.xlabel('Predicted')
plt.tight_layout()
plt.show()
```

```python
# Classification report
print('\nClassification Report:')
print(classification_report(y_true, y_pred, target_names=class_names, digits=3))
```




```
Classification Report:
                precision    recall  f1-score   support

     apple_pie      0.679     0.760     0.717       250
baby_back_ribs      0.852     0.872     0.862       250
       baklava      0.780     0.764     0.772       250
beef_carpaccio      0.915     0.856     0.884       250
  beef_tartare      0.847     0.796     0.821       250

      accuracy                          0.810      1250
     macro avg      0.814     0.810     0.811      1250
```

```
  weighted avg      0.814     0.810     0.811      1250
```

[28]:
```
print(f'\n=== RESULTADOS v2.3 BALANCEADA ({num_classes} clases) ===')
print(f'Train: {history.history["accuracy"][-1]:.3f} | Val: {test_acc:.3f}')
print(f'Overfitting gap: {(history.history["accuracy"][-1] - test_acc)*100:.
↪1f}%')
print(f'\nv2.0: 20% | v2.1: 38% | v2.2: 20% (colapsó) | v2.3: {test_acc*100:.
↪1f}%')
print(f'Objetivo 80%: {"  ALCANZADO" if test_acc >= 0.80 else f"Faltan {(0.
↪80-test_acc)*100:.1f} puntos"}')
```

```
=== RESULTADOS v2.3 BALANCEADA (5 clases) ===
Train: 0.728 | Val: 0.810
Overfitting gap: -8.2%

v2.0: 20% | v2.1: 38% | v2.2: 20% (colapsó) | v2.3: 81.0%
Objetivo 80%:   ALCANZADO
```