# Laboratorio 4: Clasificación de Imágenes con CNN (CIFAR-10)

**Integrantes**

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**Objetivo general**
Implementar y comparar un modelo base ANN y una CNN para clasificar el dataset CIFAR-10,evaluando desempeño, curvas de aprendizaje y errores comunes. También se incluye un ejercicio opcional de Data Augmentation.

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# Parte 1: Preparación del Conjunto de Datos

1. Cargamos el dataset CIFAR-10 directamente desde `keras.datasets`.
   - Son 60,000 imágenes de tamaño 32x32x3 (RGB).
   - Se dividen en 50,000 de entrenamiento y 10,000 de prueba.
2. Normalizamos los valores de píxeles, dividiéndolos entre 255, de modo que los valores queden en el rango [0,1]. Cómo las imagenes son arrays entre 0 y 255 de la intensidad de cada pixel.
3. Definimos los nombres de las clases (avión, coche, perro, etc.).
4. Mostramos 10 imágenes de entrenamiento con sus etiquetas para confirmar que los datos están bien cargados.

In [1]:
```
from matplotlib import pyplot as plt
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.datasets import cifar10

(x_train, y_train), (x_test, y_test) = cifar10.load_data() # Carga de CIFAR-10 data

class_names = ['airplane','automobile','bird','cat','deer',
               'dog','frog','horse','ship','truck'] # Definir los nombres de las cl

# Mostrar las formas de los conjuntos de datos
print("Shapes -> x_train:", x_train.shape, "y_train:", y_train.shape)
print("Shapes -> x_test:", x_test.shape, "y_test:", y_test.shape)

# Normalización [0,1]
x_train = x_train.astype("float32") / 255.0
x_test  = x_test.astype("float32") / 255.0
```

```
# Visualización de 10 ejemplos
def show_grid(images, labels, n=10):
    plt.figure(figsize=(8,8))
    idx = np.random.choice(len(images), n, replace=False)
    for i, j in enumerate(idx):
        plt.subplot(5,5,i+1)
        plt.imshow(images[j])
        plt.title(class_names[labels[j][0]])
        plt.axis("off")
    plt.tight_layout()
    plt.show()

show_grid(x_train, y_train)
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 44s 0us/step
Shapes -> x_train: (50000, 32, 32, 3) y_train: (50000, 1)
Shapes -> x_test: (10000, 32, 32, 3) y_test: (10000, 1)
```


## Parte 2: Modelo Base ANN

Se define una función `build_ann` qué implementa una red neuronal artificial densa (ANN):

- Se aplana la imagen (32×32×3 → 3072 neuronas).
- Dos capas densas ocultas con activación ReLU.
- Capa final Dense(10) con activación Softmax para clasificar las 10 clases.

Se compila el modelo con:

- **Optimizer:** Adam.
- **Loss:** categorical_crossentropy.
- **Métrica:** Accuracy.

Luego lo entrenamos, medimos tiempo de entrenamiento y evaluamos el rendimiento en el set de prueba.

In [2]:
```
import time
from tensorflow.keras.utils import to_categorical

# One-hot encoding
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)

# Función para construir el modelo ANN
def build_ann(input_shape=(32,32,3), num_classes=10):
    model = keras.Sequential([
        layers.Flatten(input_shape=input_shape), # Aplanar la imagen 32x32x3 a un v
        layers.Dense(512, activation="relu"), # Capa oculta con 512 neuronas y acti
        layers.Dense(256, activation="relu"), # Capa oculta con 256 neuronas y acti
        layers.Dense(num_classes, activation="softmax") # Capa de salida con activa
    ])
    model.compile(optimizer='adam',
                  loss='categorical_crossentropy', # Función de pérdida para clasificac
                  metrics=['accuracy']) # Métrica de precisión
    return model

# Construcción del modelo ANN
ann = build_ann()
# Mostrar resumen del modelo
ann.summary()
```

```
C:\Users\JM\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p
0\LocalCache\local-packages\Python311\site-packages\keras\src\layers\reshaping\flatt
en.py:37: 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 lay
er in the model instead.
  super().__init__(**kwargs)
```

**Model: "sequential"**

| **Layer (type)** | **Output Shape** | **Param #** |
|---|---|---:|
| flatten (Flatten) | (None, 3072) | 0 |
| dense (Dense) | (None, 512) | 1,573,376 |
| dense_1 (Dense) | (None, 256) | 131,328 |
| dense_2 (Dense) | (None, 10) | 2,570 |

**Total params:** 1,707,274 (6.51 MB)

**Trainable params:** 1,707,274 (6.51 MB)

**Non-trainable params:** 0 (0.00 B)

## Entrenamiento del modelo ANN

En este bloque de código se entrena el modelo(ANN): Se define:

- `batch_size = 64` que va a ser el tamaño del lote

- `epochs = 10` que van a ser las epocas que va a recorrer el modelo

Para el entrenamiento se le pasan los parametros a la función para entrenar el modelo:

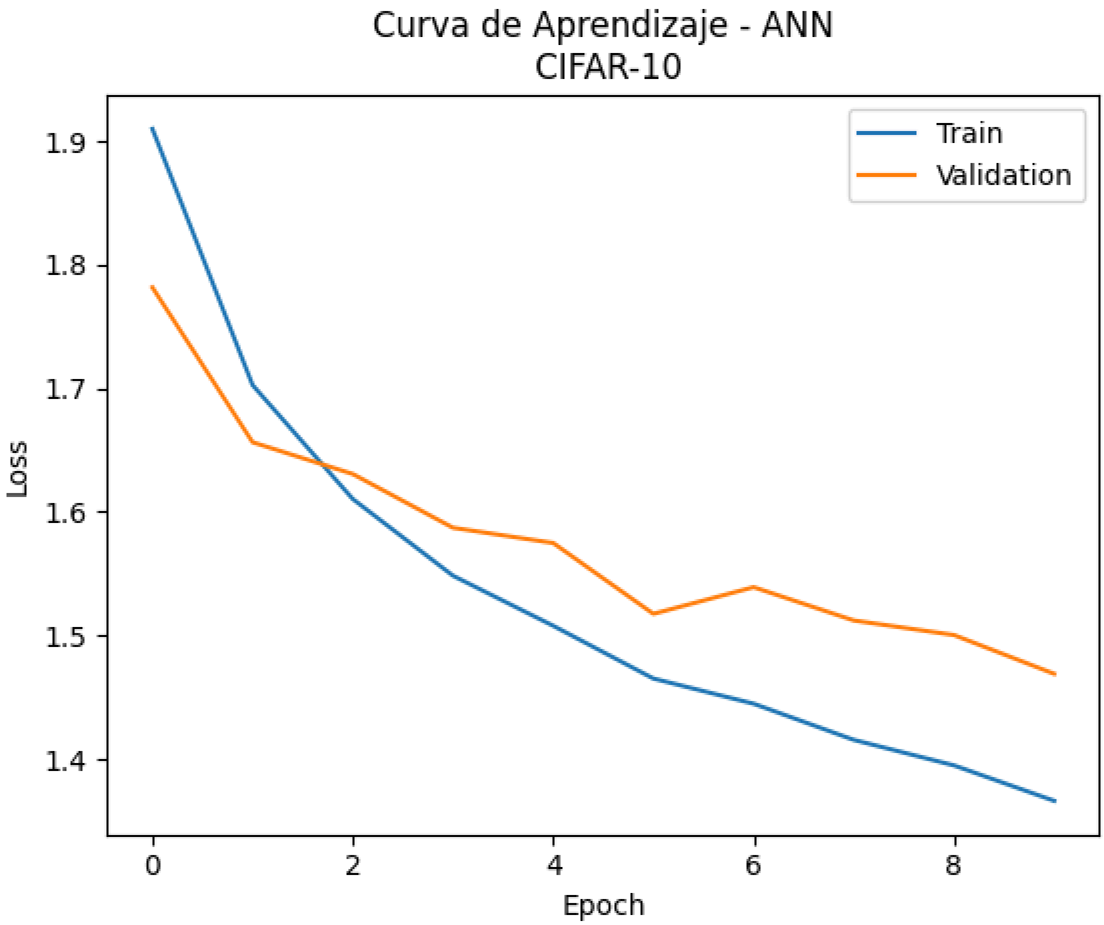
- Se le mandan los conjuntos de entrenamiento
- El `validation_split=0.2` para usar 20% de los datos de entrenamiento para validación
- El `batch_size` y `epochs`
- El `verbose=2` para mostrar información detallada durante el entrenamiento

In [ ]:
```
# Entrenamiento ANN
ann = build_ann()
batch_size = 64
epochs = 10

start = time.time() # Inicio del temporizador
hist_ann = ann.fit(
    x_train, y_train,
    validation_split=0.2, # Usar 20% de los datos de entrenamiento para validación
    batch_size=batch_size,
    epochs=epochs,
    verbose=2 # Mostrar información detallada durante el entrenamiento
)
t_train_ann = time.time() - start # fin del temporizador
# Mostrar tiempo de entrenamiento
print(f"Tiempo de entrenamiento ANN: {t_train_ann:.2f} s")

# Evaluación del modelo en test
test_loss_ann, test_acc_ann = ann.evaluate(x_test, y_test, verbose=0)
print(f"[ANN] Test Acc: {test_acc_ann:.4f} | Test Loss: {test_loss_ann:.4f}")
```

```
Epoch 1/10
625/625 - 18s - 28ms/step - accuracy: 0.3171 - loss: 1.9101 - val_accuracy: 0.3634 -
val_loss: 1.7818
Epoch 2/10
625/625 - 16s - 26ms/step - accuracy: 0.3871 - loss: 1.7027 - val_accuracy: 0.4085 -
val_loss: 1.6564
Epoch 3/10
625/625 - 16s - 26ms/step - accuracy: 0.4251 - loss: 1.6105 - val_accuracy: 0.4203 -
val_loss: 1.6307
Epoch 4/10
625/625 - 16s - 26ms/step - accuracy: 0.4449 - loss: 1.5484 - val_accuracy: 0.4392 -
val_loss: 1.5872
Epoch 5/10
625/625 - 16s - 25ms/step - accuracy: 0.4602 - loss: 1.5079 - val_accuracy: 0.4412 -
val_loss: 1.5749
Epoch 6/10
625/625 - 16s - 25ms/step - accuracy: 0.4768 - loss: 1.4652 - val_accuracy: 0.4671 -
val_loss: 1.5175
Epoch 7/10
625/625 - 16s - 25ms/step - accuracy: 0.4835 - loss: 1.4448 - val_accuracy: 0.4629 -
val_loss: 1.5391
Epoch 8/10
625/625 - 16s - 25ms/step - accuracy: 0.4943 - loss: 1.4155 - val_accuracy: 0.4673 -
val_loss: 1.5122
Epoch 9/10
625/625 - 16s - 25ms/step - accuracy: 0.5017 - loss: 1.3949 - val_accuracy: 0.4751 -
val_loss: 1.5004
Epoch 10/10
625/625 - 16s - 25ms/step - accuracy: 0.5098 - loss: 1.3662 - val_accuracy: 0.4787 -
val_loss: 1.4690
Tiempo de entrenamiento ANN: 161.29 s
[ANN] Test Acc: 0.4809 | Test Loss: 1.4493
```

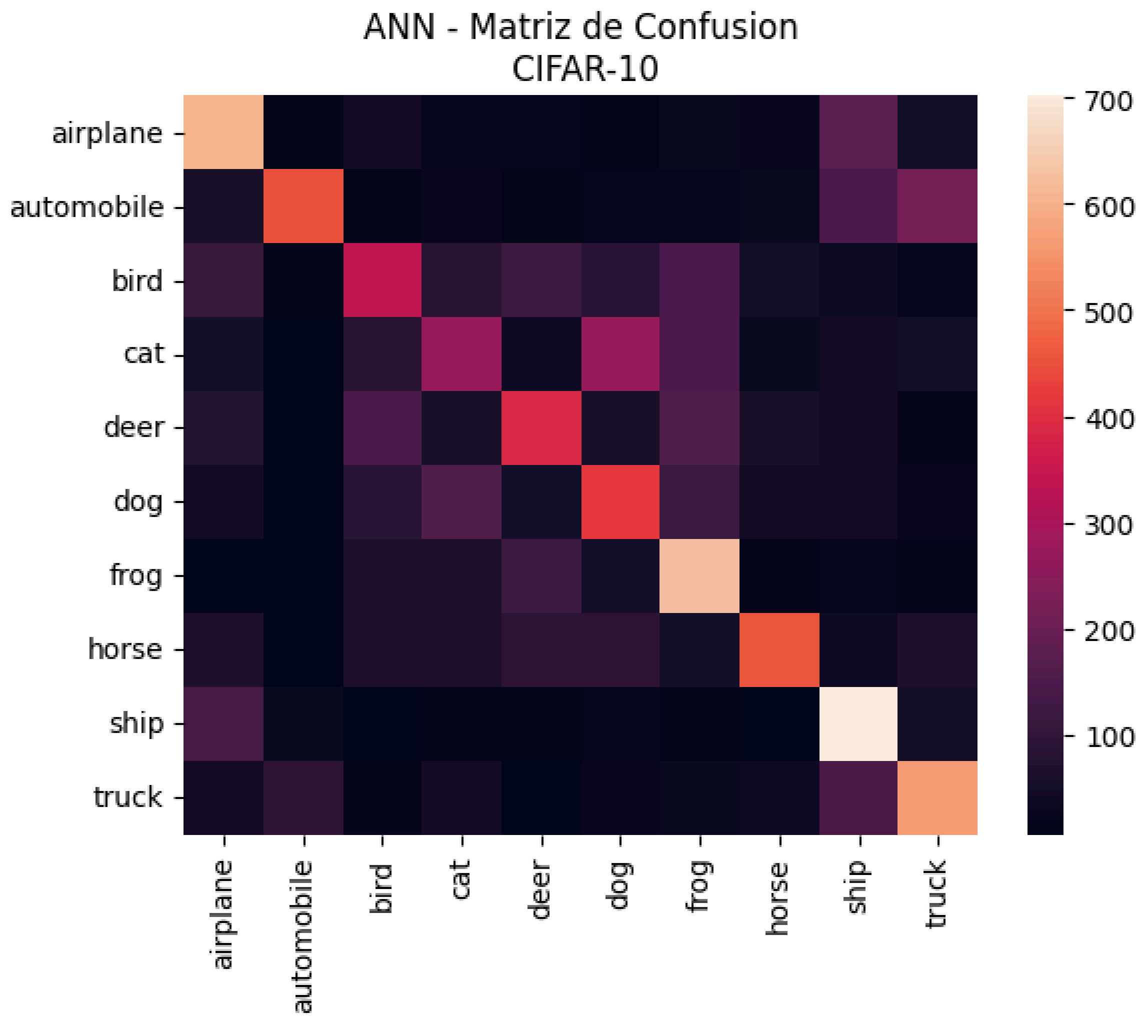
In [47]:

```python
from matplotlib import pyplot as plt
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
# Learning Curve
plt.title("Curva de Aprendizaje - ANN\n CIFAR-10")
plt.plot(np.arange(0,epochs), hist_ann.history["loss"], label="Train")
plt.plot(np.arange(0,epochs), hist_ann.history["val_loss"], label="Validation")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.show()

# Confusion Matrix
pred_start = time.time()
y_pred_prob = ann.predict(x_test)
print(f"Tiempo de prediccion {time.time() -pred_start}")

y_pred_class = np.argmax(y_pred_prob,axis=1)
y_test_class = np.argmax(y_test, axis=1)
print(classification_report(y_test_class, y_pred_class))
cm = confusion_matrix(y_test_class, y_pred_class)
sns.heatmap(cm, xticklabels=class_names, yticklabels=class_names)
plt.title("ANN - Matriz de Confusion\n CIFAR-10")
```




```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
Tiempo de prediccion 1.0924034118652344
              precision    recall  f1-score   support

           0       0.50      0.60      0.55      1000
           1       0.70      0.45      0.55      1000
           2       0.39      0.33      0.36      1000
           3       0.33      0.27      0.30      1000
           4       0.45      0.38      0.41      1000
           5       0.39      0.42      0.40      1000
           6       0.46      0.63      0.53      1000
           7       0.62      0.46      0.53      1000
           8       0.50      0.70      0.59      1000
           9       0.53      0.57      0.55      1000

    accuracy                           0.48     10000
   macro avg       0.49      0.48      0.48     10000
weighted avg       0.49      0.48      0.48     10000
```

Out[47]: `Text(0.5, 1.0, 'ANN - Matriz de Confusion\n CIFAR-10')`




## Parte 3: Implementación de CNN

Se define una función `build_cnn` para diseñar una red neuronal convolucional (CNN):

- Varias capas Conv2D con filtros (32, 64, 128).
- Capas de MaxPooling2D para reducir la dimensión espacial.
- Dropout en puntos estratégicos para reducir sobreajuste.
- Al final, una capa densa y salida Softmax de 10 clases.

Luego se registra el tiempo de entrenamiento y se evalúa con los datos de prueba.

In [43]:
```
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping

# Función para construir el modelo CNN
def build_cnn(input_shape=(32,32,3), num_classes=10, dropout_rate=0.3):
    model = keras.Sequential([
        Conv2D(32, (3,3), activation='relu', padding='same', input_shape=input_shap
        MaxPooling2D((2,2)), # Capa de max pooling 1
        Dropout(dropout_rate),
        Conv2D(64, (3,3), activation='relu', padding='same'), # Capa convolucional
```

```
        MaxPooling2D((2,2)), # Capa de max pooling 2
        Dropout(dropout_rate),
        Conv2D(128, (3,3), activation='relu', padding='same'), # Capa convolucional
        MaxPooling2D((2,2)), # Capa de max pooling 3
        Dropout(dropout_rate),
        Flatten(), # Aplanar las características extraídas
        Dense(256, activation='relu'), # Capa densa oculta con 256 neuronas y activ
        Dropout(dropout_rate),
        Dense(num_classes, activation='softmax')  # Capa de salida con activación s
    ])
    model.compile( # Compilación del modelo
        optimizer='adam',
        loss="categorical_crossentropy", # Función de pérdida para clasificación mu
        metrics=["accuracy"] # Métrica de precisión
    )
    return model

# Construcción del modelo CNN
cnn = build_cnn()
# Mostrar resumen del modelo
cnn.summary()
```

```
C:\Users\JM\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p
0\LocalCache\local-packages\Python311\site-packages\keras\src\layers\convolutional\b
ase_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 fi
rst layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

**Model: "sequential_1"**

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d (Conv2D) | (None, 32, 32, 32) | 896 |
| max_pooling2d (MaxPooling2D) | (None, 16, 16, 32) | 0 |
| dropout (Dropout) | (None, 16, 16, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 16, 16, 64) | 18,496 |
| max_pooling2d_1 (MaxPooling2D) | (None, 8, 8, 64) | 0 |
| dropout_1 (Dropout) | (None, 8, 8, 64) | 0 |
| conv2d_2 (Conv2D) | (None, 8, 8, 128) | 73,856 |
| max_pooling2d_2 (MaxPooling2D) | (None, 4, 4, 128) | 0 |
| dropout_2 (Dropout) | (None, 4, 4, 128) | 0 |
| flatten_1 (Flatten) | (None, 2048) | 0 |
| dense_3 (Dense) | (None, 256) | 524,544 |
| dropout_3 (Dropout) | (None, 256) | 0 |
| dense_4 (Dense) | (None, 10) | 2,570 |

**Total params:** 620,362 (2.37 MB)

**Trainable params:** 620,362 (2.37 MB)

**Non-trainable params:** 0 (0.00 B)

## Entrenamiento del modelo CNN

En este bloque de código se entrena el modelo(ANN):

Se llama a la función para entrenar el modelo:

- Se mandan los conjuntos de entrenamiento, `epochs = 10` , `validation_split=0.2` , `batch_size = 64` , `verbose=2` que es exactamente lo mismo que se le mandó al modelo ann
- Solo se le agrega `callbacks=[early]`
  - Entrenamos el modelo usando validación y `EarlyStopping` para detener si no mejora la accuracy en validación.

In [44]:
```
early = keras.callbacks.EarlyStopping( # Callback para detener el entrenamiento tem
    monitor="val_accuracy", # Monitorear la precisión en el conjunto de validación
    patience=5, # Paciencia para detener el entrenamiento
    restore_best_weights=True # Restaurar los mejores pesos al detener el entrenami
)
```

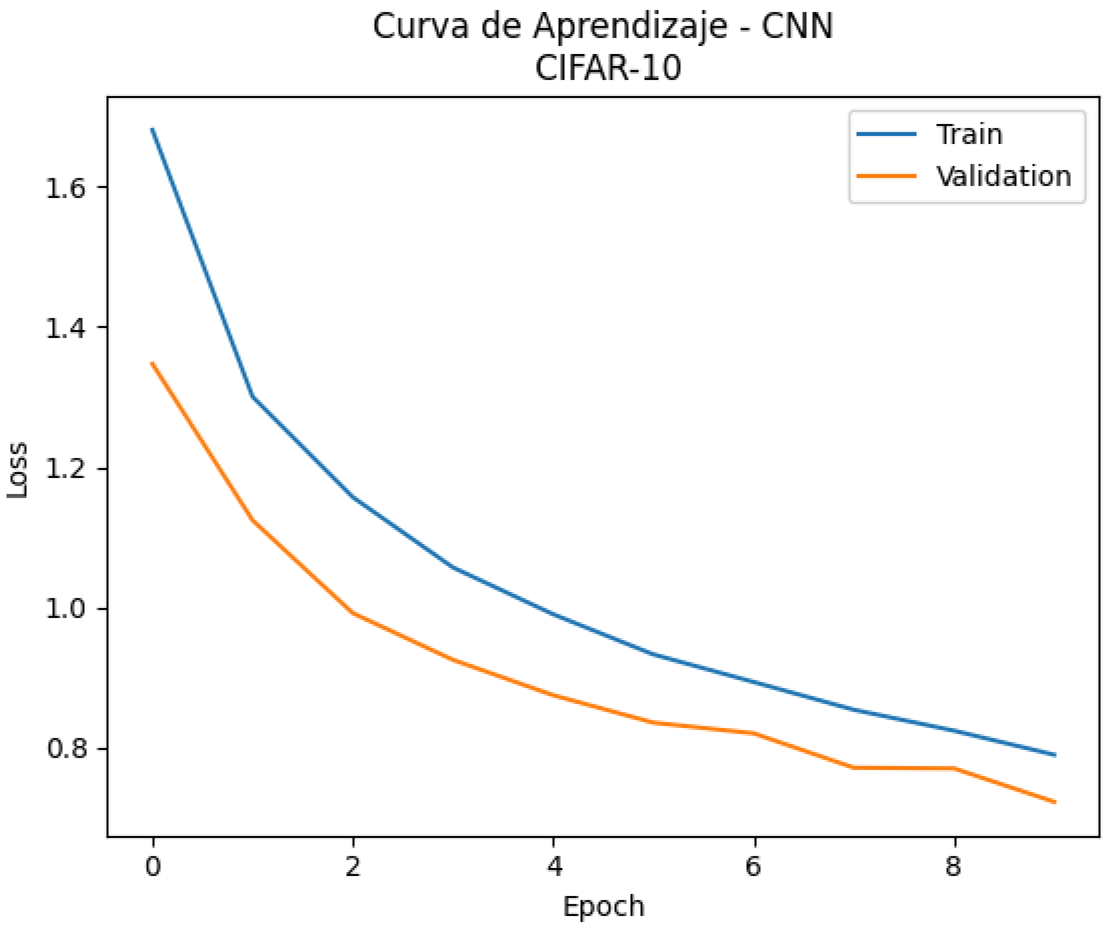
```python
start = time.time() # Inicio del temporizador
# Entrenamiento del modelo CNN
hist_cnn = cnn.fit(
    x_train, y_train, # Datos de entrenamiento
    validation_split=0.2, # Usar 20% de los datos de entrenamiento para validación
    batch_size=64, # Tamaño del lote
    epochs=10, #
    callbacks=[early],
    verbose=2
)
t_train_cnn = time.time() - start # Tiempo de entrenamiento
print(f"Tiempo de entrenamiento CNN: {t_train_cnn:.2f} s")

test_loss_cnn, test_acc_cnn = cnn.evaluate(x_test, y_test, verbose=0)
print(f"[CNN] Test Acc: {test_acc_cnn:.4f} | Test Loss: {test_loss_cnn:.4f}")
```

```
Epoch 1/10
625/625 - 28s - 45ms/step - accuracy: 0.3816 - loss: 1.6806 - val_accuracy: 0.5168 -
val_loss: 1.3471
Epoch 2/10
625/625 - 26s - 41ms/step - accuracy: 0.5312 - loss: 1.3001 - val_accuracy: 0.6029 -
val_loss: 1.1240
Epoch 3/10
625/625 - 29s - 47ms/step - accuracy: 0.5871 - loss: 1.1570 - val_accuracy: 0.6512 -
val_loss: 0.9917
Epoch 4/10
625/625 - 29s - 47ms/step - accuracy: 0.6246 - loss: 1.0568 - val_accuracy: 0.6769 -
val_loss: 0.9250
Epoch 5/10
625/625 - 28s - 45ms/step - accuracy: 0.6486 - loss: 0.9901 - val_accuracy: 0.6976 -
val_loss: 0.8747
Epoch 6/10
625/625 - 29s - 47ms/step - accuracy: 0.6687 - loss: 0.9328 - val_accuracy: 0.7092 -
val_loss: 0.8355
Epoch 7/10
625/625 - 28s - 45ms/step - accuracy: 0.6877 - loss: 0.8935 - val_accuracy: 0.7095 -
val_loss: 0.8203
Epoch 8/10
625/625 - 29s - 46ms/step - accuracy: 0.6971 - loss: 0.8539 - val_accuracy: 0.7348 -
val_loss: 0.7713
Epoch 9/10
625/625 - 29s - 47ms/step - accuracy: 0.7085 - loss: 0.8241 - val_accuracy: 0.7346 -
val_loss: 0.7703
Epoch 10/10
625/625 - 29s - 47ms/step - accuracy: 0.7199 - loss: 0.7898 - val_accuracy: 0.7492 -
val_loss: 0.7227
Tiempo de entrenamiento CNN: 286.61 s
[CNN] Test Acc: 0.7476 | Test Loss: 0.7378
```

In [48]:

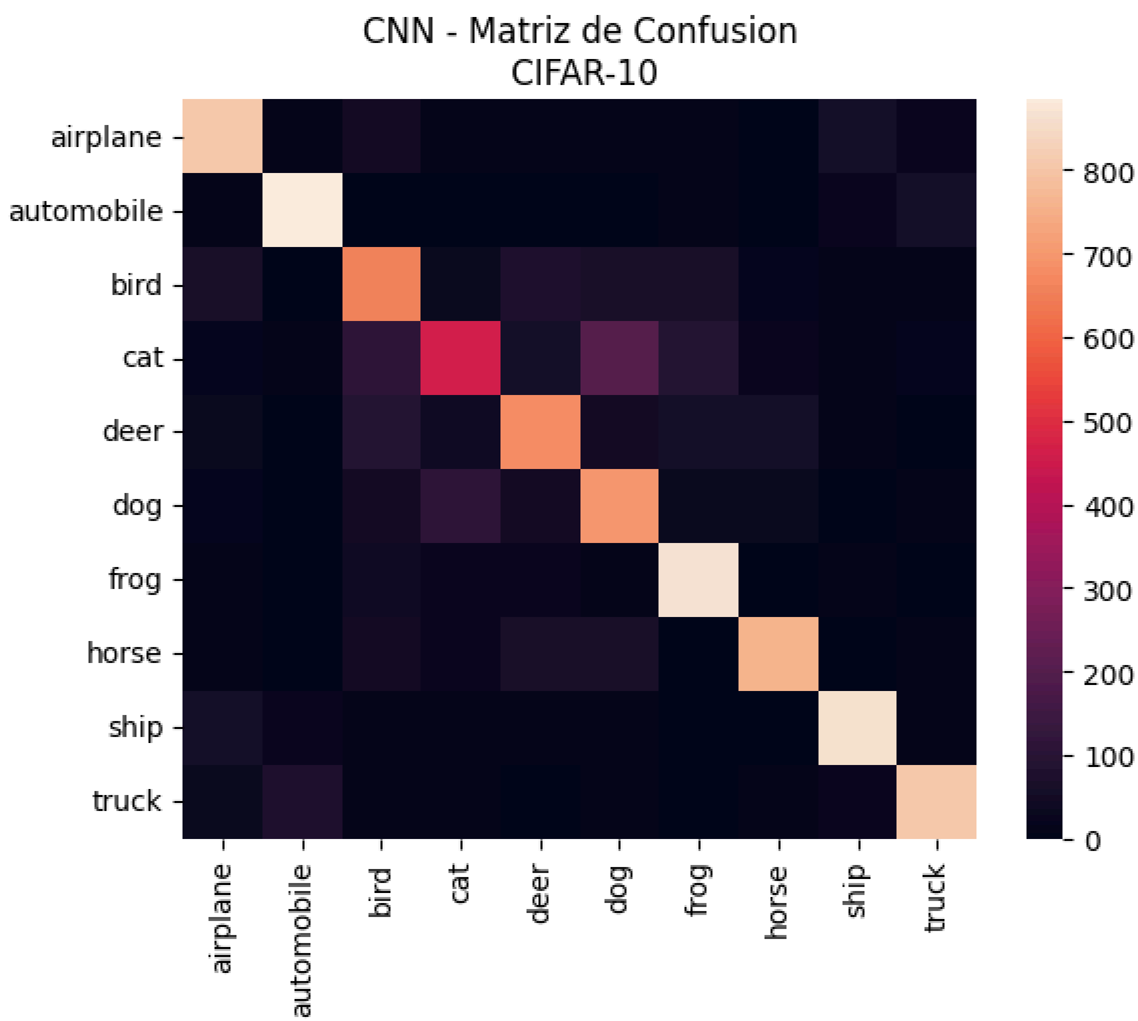
```python
# Learning curve
plt.title("Curva de Aprendizaje - CNN\n CIFAR-10")
plt.plot(np.arange(0,epochs), hist_cnn.history["loss"], label="Train")
plt.plot(np.arange(0,epochs), hist_cnn.history["val_loss"], label="Validation")
plt.xlabel("Epoch")
plt.ylabel("Loss")
```

```
plt.legend()
plt.show()

# Confusion Matrix
pred_start = time.time()
y_pred_prob = cnn.predict(x_test)
print(f"Tiempo de prediccion {time.time() -pred_start}")
y_pred_class = np.argmax(y_pred_prob,axis=1)
y_test_class = np.argmax(y_test, axis=1)
print(classification_report(y_test_class, y_pred_class))
cm = confusion_matrix(y_test_class, y_pred_class)
sns.heatmap(cm, xticklabels=class_names, yticklabels=class_names)
plt.title("CNN - Matriz de Confusion\n CIFAR-10")
```



```
313/313 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step
Tiempo de prediccion 2.1732585430145264
              precision    recall  f1-score   support

           0       0.76      0.81      0.78      1000
           1       0.86      0.88      0.87      1000
           2       0.62      0.66      0.64      1000
           3       0.63      0.46      0.53      1000
           4       0.69      0.68      0.69      1000
           5       0.62      0.70      0.66      1000
           6       0.75      0.87      0.81      1000
           7       0.84      0.76      0.80      1000
           8       0.85      0.86      0.86      1000
           9       0.85      0.81      0.83      1000

    accuracy                           0.75     10000
   macro avg       0.75      0.75      0.75     10000
weighted avg       0.75      0.75      0.75     10000
```

Out[48]: `Text(0.5, 1.0, 'CNN - Matriz de Confusion\n CIFAR-10')`

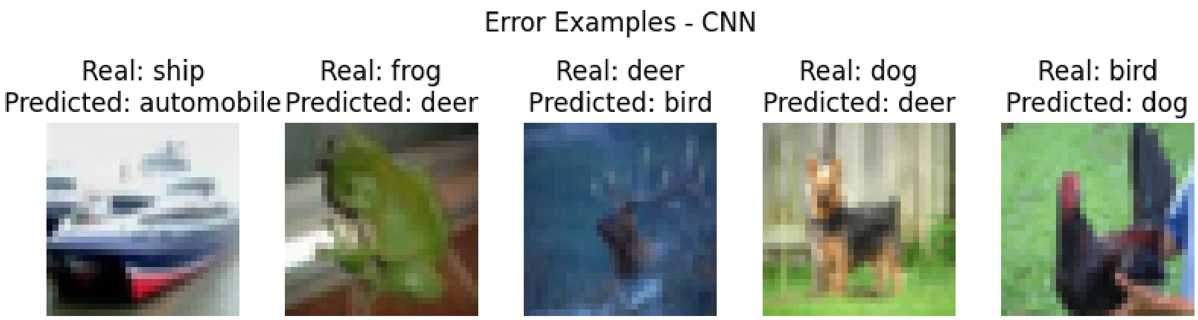



# Parte 4: Ejemplificacion de errores

In [94]:
```
def show_prediction_errors(model, model_name, wrong_count):
    # Init
    wrong_images = []
    wrong_labels = []
    correct_labels = []
    counter = 0

    # Find error examples
    while(len(wrong_labels) < wrong_count):
        x_single = np.expand_dims(x_test[counter], axis=0)
        pred_prob = model.predict(x_single, verbose=0)
        pred_class = np.argmax(pred_prob)


        real_class = np.argmax(y_test[counter])

        if(pred_class!= real_class):
            wrong_images.append(np.squeeze(x_single, axis=0) )
            wrong_labels.append(pred_class)
            correct_labels.append(real_class)
        counter+=1

    # Show error examples
    plt.figure(figsize=(8,8))
    plt.suptitle(f"Error Examples - {model_name}")
    for i in range(wrong_count):
        plt.subplot(5,5,i+1)
        plt.imshow(wrong_images[i])
        plt.title(
        f"Real: {class_names[correct_labels[i]]}\nPredicted: {class_names[wrong_lab
        )
        plt.axis("off")
    plt.tight_layout()
    plt.show()
```

In [ ]:
```
# Para ANN
show_prediction_errors(ann, "ANN", 5)
```


In [ ]:
```
# Para CNN
show_prediction_errors(cnn, "CNN", 5)
```




# Puntos Extra: Data Augmentation

In [107…

```python
from tensorflow.keras.layers import RandomFlip, RandomRotation, RandomZoom



def build_cnn_augmented(input_shape=(32,32,3), num_classes=10, dropout_rate=0.3):
    model = keras.Sequential([
        # Data augmentation
        RandomFlip("horizontal_and_vertical", input_shape=input_shape),
        RandomZoom(0.1),
        RandomRotation(0.1),

        # Convolutional layers
        Conv2D(32, (3,3), activation='relu', padding='same', input_shape=input_shap
        MaxPooling2D((2,2)), # Capa de max pooling 1
        Dropout(dropout_rate),
        Conv2D(64, (3,3), activation='relu', padding='same'), # Capa convolucional
        MaxPooling2D((2,2)), # Capa de max pooling 2
        Dropout(dropout_rate),
        Conv2D(128, (3,3), activation='relu', padding='same'), # Capa convolucional
        MaxPooling2D((2,2)), # Capa de max pooling 3
        Dropout(dropout_rate),

        # Fully Connected layers
        Flatten(), # Aplanar las características extraídas
        Dense(256, activation='relu'), # Capa densa oculta con 256 neuronas y activ
        Dropout(dropout_rate),
        Dense(num_classes, activation='softmax')  # Capa de salida con activación s
    ])
    model.compile( # Compilación del modelo
        optimizer='adam',
        loss="categorical_crossentropy", # Función de pérdida para clasificación mu
        metrics=["accuracy"] # Métrica de precisión
    )
    return model

# Construcción del modelo CNN
cnn_aug = build_cnn_augmented()
# Mostrar resumen del modelo
cnn_aug.summary()
```

```
C:\Users\JM\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p
0\LocalCache\local-packages\Python311\site-packages\keras\src\layers\preprocessing\t
f_data_layer.py:19: UserWarning: Do not pass an `input_shape`/`input_dim` argument t
o a layer. When using Sequential models, prefer using an `Input(shape)` object as th
e first layer in the model instead.
  super().__init__(**kwargs)
C:\Users\JM\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p
0\LocalCache\local-packages\Python311\site-packages\keras\src\layers\convolutional\b
ase_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 fi
rst layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

**Model: "sequential_12"**

| **Layer (type)** | **Output Shape** | **Param #** |
|---|---|---:|
| random_flip_6 (RandomFlip) | (None, 32, 32, 3) | 0 |
| random_zoom_5 (RandomZoom) | (None, 32, 32, 3) | 0 |
| random_rotation_5 (RandomRotation) | (None, 32, 32, 3) | 0 |
| conv2d_21 (Conv2D) | (None, 32, 32, 32) | 896 |
| max_pooling2d_21 (MaxPooling2D) | (None, 16, 16, 32) | 0 |
| dropout_28 (Dropout) | (None, 16, 16, 32) | 0 |
| conv2d_22 (Conv2D) | (None, 16, 16, 64) | 18,496 |
| max_pooling2d_22 (MaxPooling2D) | (None, 8, 8, 64) | 0 |
| dropout_29 (Dropout) | (None, 8, 8, 64) | 0 |
| conv2d_23 (Conv2D) | (None, 8, 8, 128) | 73,856 |
| max_pooling2d_23 (MaxPooling2D) | (None, 4, 4, 128) | 0 |
| dropout_30 (Dropout) | (None, 4, 4, 128) | 0 |
| flatten_8 (Flatten) | (None, 2048) | 0 |
| dense_17 (Dense) | (None, 256) | 524,544 |
| dropout_31 (Dropout) | (None, 256) | 0 |
| dense_18 (Dense) | (None, 10) | 2,570 |

**Total params:** 620,362 (2.37 MB)

**Trainable params:** 620,362 (2.37 MB)

**Non-trainable params:** 0 (0.00 B)

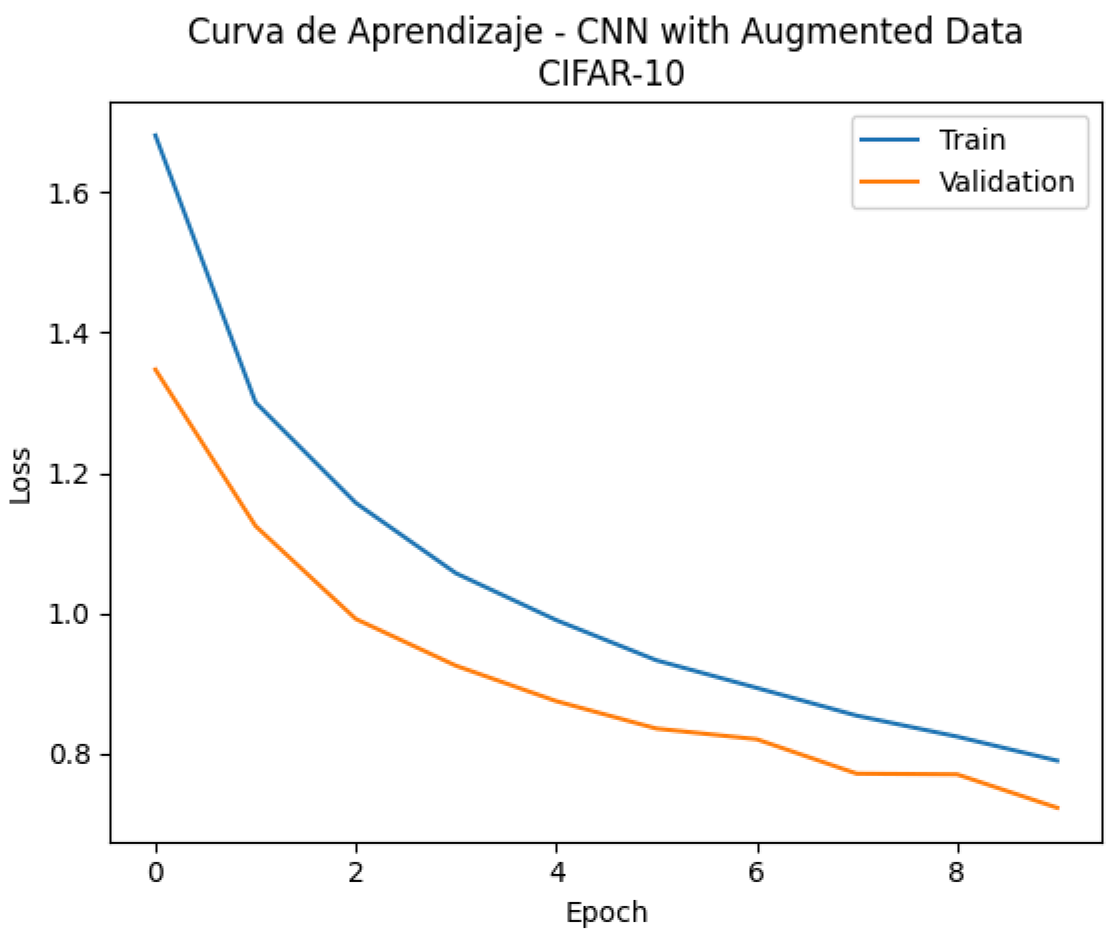
In [108…

```
early = keras.callbacks.EarlyStopping( # Callback para detener el entrenamiento tem
    monitor="val_accuracy", # Monitorear la precisión en el conjunto de validación
    patience=5, # Paciencia para detener el entrenamiento
    restore_best_weights=True # Restaurar los mejores pesos al detener el entrenami
)

start = time.time() # Inicio del temporizador
# Entrenamiento del modelo CNN
hist_cnn_aug = cnn_aug.fit(
    x_train, y_train, # Datos de entrenamiento
    validation_split=0.2, # Usar 20% de los datos de entrenamiento para validación
    batch_size=64, # Tamaño del lote
    epochs=10, #
    callbacks=[early],
    verbose=2
)
t_train_cnn = time.time() - start # Tiempo de entrenamiento
print(f"Tiempo de entrenamiento CNN: {t_train_cnn:.2f} s")

test_loss_cnn, test_acc_cnn = cnn_aug.evaluate(x_test, y_test, verbose=0)
print(f"[CNN] Test Acc: {test_acc_cnn:.4f} | Test Loss: {test_loss_cnn:.4f}")
```

```
Epoch 1/10
625/625 - 36s - 58ms/step - accuracy: 0.2925 - loss: 1.8875 - val_accuracy: 0.4099 -
val_loss: 1.6239
Epoch 2/10
625/625 - 33s - 52ms/step - accuracy: 0.4114 - loss: 1.6090 - val_accuracy: 0.4784 -
val_loss: 1.4227
Epoch 3/10
625/625 - 33s - 53ms/step - accuracy: 0.4447 - loss: 1.5240 - val_accuracy: 0.4923 -
val_loss: 1.3913
Epoch 4/10
625/625 - 34s - 54ms/step - accuracy: 0.4676 - loss: 1.4725 - val_accuracy: 0.5059 -
val_loss: 1.3575
Epoch 5/10
625/625 - 35s - 57ms/step - accuracy: 0.4843 - loss: 1.4275 - val_accuracy: 0.5449 -
val_loss: 1.2801
Epoch 6/10
625/625 - 37s - 58ms/step - accuracy: 0.4971 - loss: 1.3910 - val_accuracy: 0.5346 -
val_loss: 1.2944
Epoch 7/10
625/625 - 35s - 56ms/step - accuracy: 0.5070 - loss: 1.3751 - val_accuracy: 0.5292 -
val_loss: 1.2855
Epoch 8/10
625/625 - 36s - 58ms/step - accuracy: 0.5185 - loss: 1.3428 - val_accuracy: 0.5584 -
val_loss: 1.2218
Epoch 9/10
625/625 - 36s - 58ms/step - accuracy: 0.5256 - loss: 1.3169 - val_accuracy: 0.5528 -
val_loss: 1.2357
Epoch 10/10
625/625 - 36s - 58ms/step - accuracy: 0.5311 - loss: 1.3043 - val_accuracy: 0.5566 -
val_loss: 1.2300
Tiempo de entrenamiento CNN: 351.83 s
[CNN] Test Acc: 0.5594 | Test Loss: 1.2195
```

In [109…

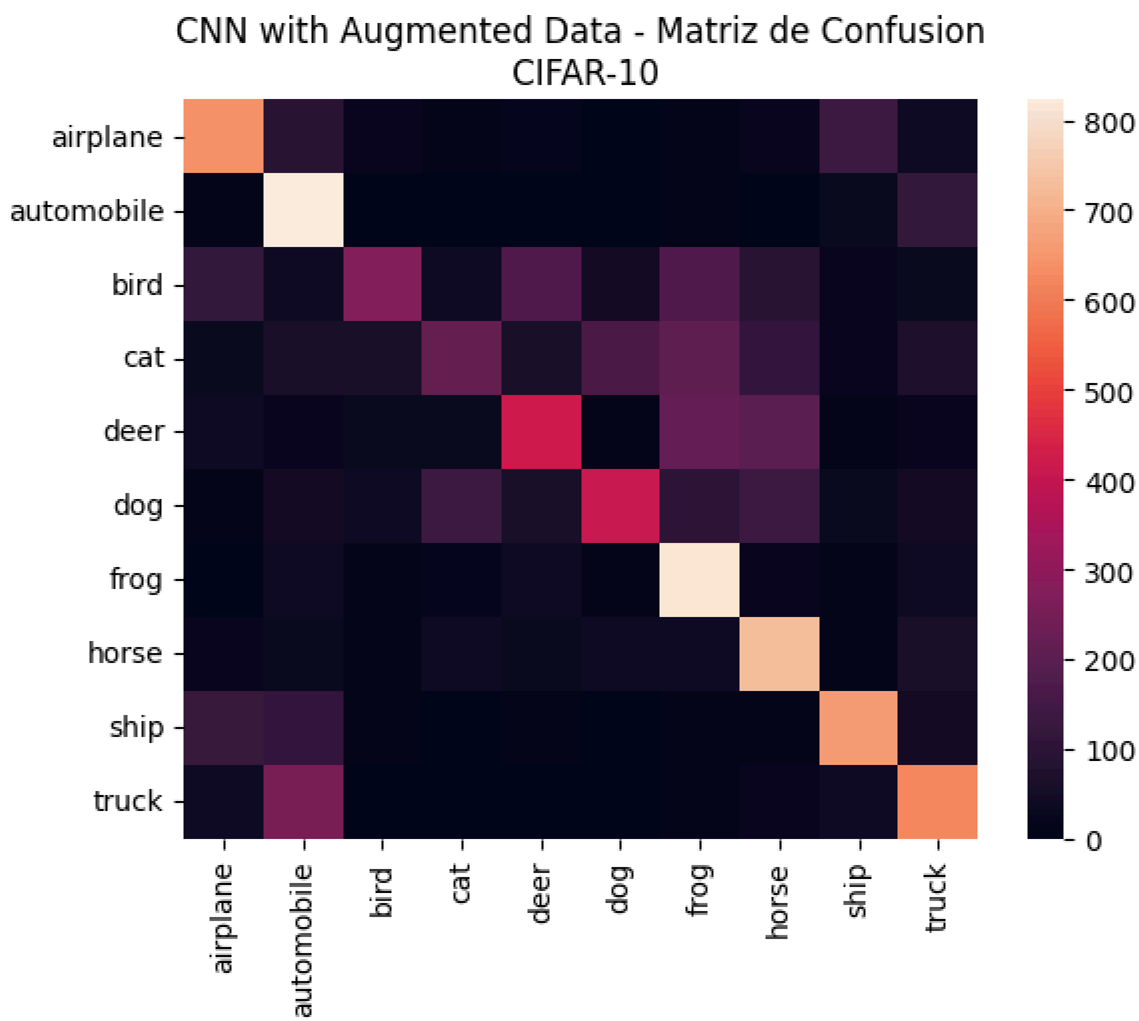
```
# Learning curve
plt.title("Curva de Aprendizaje - CNN with Augmented Data\n CIFAR-10")
plt.plot(np.arange(0,epochs), hist_cnn.history["loss"], label="Train")
plt.plot(np.arange(0,epochs), hist_cnn.history["val_loss"], label="Validation")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.show()

# Confusion Matrix
pred_start = time.time()
y_pred_prob = cnn_aug.predict(x_test)
print(f"Tiempo de prediccion {time.time() -pred_start}")
y_pred_class = np.argmax(y_pred_prob,axis=1)
y_test_class = np.argmax(y_test, axis=1)
print(classification_report(y_test_class, y_pred_class))
cm = confusion_matrix(y_test_class, y_pred_class)
sns.heatmap(cm, xticklabels=class_names, yticklabels=class_names)
plt.title("CNN with Augmented Data - Matriz de Confusion\n CIFAR-10")
```



```
313/313 ━━━━━━━━━━━━━━━━━━━━ 3s 9ms/step
Tiempo de prediccion 3.0713276863098145
              precision    recall  f1-score   support

           0       0.61      0.64      0.63      1000
           1       0.54      0.82      0.65      1000
           2       0.59      0.27      0.37      1000
           3       0.44      0.22      0.29      1000
           4       0.51      0.42      0.46      1000
           5       0.59      0.41      0.48      1000
           6       0.51      0.81      0.63      1000
           7       0.54      0.72      0.62      1000
           8       0.68      0.66      0.67      1000
           9       0.57      0.62      0.60      1000

    accuracy                           0.56     10000
   macro avg       0.56      0.56      0.54     10000
weighted avg       0.56      0.56      0.54     10000
```

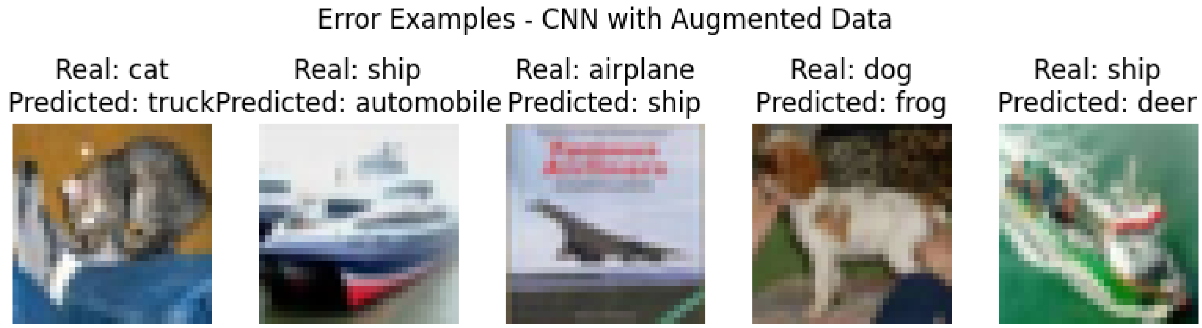
Out[109…

```
Text(0.5, 1.0, 'CNN with Augmented Data - Matriz de Confusion\n CIFAR-10')
```




In [110…

```python
show_prediction_errors(cnn_aug, "CNN with Augmented Data", 5)
```


Error Examples - CNN with Augmented Data
Real: cat
Predicted: truck
Real: ship
Predicted: automobile
Real: airplane
Predicted: ship
Real: dog
Predicted: frog
Real: ship
Predicted: deer