Instruções

objetivo geral: criar uma rede neural para classificação de imagens do dataset fashion mnist e exploração de todas as características da rede neural, uma por vez.

O melhor resultado de cada questão/etapa é utilizado nas próximas

QUESTÃO 01: exploração inicial

- Dataset fashion mnist
- função de ativação
- 5 testes com inicialização aleatória: diferenças de convergencia, estabilidade e desempenho
- dataset de treino
- métricas: medida de desempenho(accuracy), função de perda (entropia cruzada/loss), curva de convergência
- otimizador: Adam
- arquitetura: quantas camadas e neurônios por camada
- funcoes de ativação: ReLU, Sigmoid ou Tanh
- quantas épocas
- taxa de aprendizado
- indícios de under/overfitting

QUESTÃO 02: exploração de hiperparâmetros

- taxa de aprendizado x termo momento x velocidade de convergência
- Grid search para encontrar a melhor combinação: erro de treinamento x taxa de aprendizado x momento
- taxa de aprendizado menor e momento intermediário
- dataset de treino e (opcionalmente) dataset de validação
- métricas: função de perda, velocidade de convergência, curva de convergência e (opcional) estabilidade
- critério de parada
- combinação com melhor equilíbrio entre velocidadee estabilidade
- tendências observadas(ex: maior taxa de aprendizado leva a maior velocidade, mas menor estabilidade)

QUESTÃO 03: topologia de rede neural

- dataset de treino e (opcionalmente) dataset de validação

- impacto do número de camadas ocultas e neurônios por camada e teste de variação desses números
- métricas: função de perda, curva de convergência(under e overfitting), tempo de treinamento, generalização(medida F), precisão, revocação
- gráfico de perda mostrando diferença entre topologias

QUESTÃO 04: qualidade dos dados

- influência do número e qualidade dos dados, ruído, etc sobre a capacidade de generalização
- dividir o dataset em subsets de acordo com o rótulo -> manter proporcionalidade
- faixas do dataset: 10%, 30%, 50%, 70%, 100%
- métrica: função de perda, acurácia,
- identificar saturação no aprendizado
- curvas de generalização: tamanho do conjunto X desempenho
- tempo de treinamento e custo computacional
- Estratégia de amostragem(estratificada, aleatória ou outra)

QUESTÃO 05:

- escolher 4 melhores modelos e usar modelo de testes neles
- treinamento como referência comparativa
- ajustes de otimização
- métricas: perda(entropia cruzada categórica), acurácia, curva de validação(treinamento x teste), F1 score, precisão, revocação
- escolha da configuração final do modelo

QUESTÃO 06: validação cruzada k-fold

divisão do dataset em k-subconjuntos e teste em todos eles

- métricas: média de todas as partições de perda: acurácia e F1.
- para cada partição: curvas de validação e variância(dispersão) dos resultados
- justificativa do tamanho de k
- identificação de flutuações

In [2]:
```
import numpy as np
import matplotlib.pyplot as plt
#from tensorflow import kerasimpor
from tensorflow import keras
from sklearn.model_selection import train_test_split
import secrets
```

Divisão do dataset

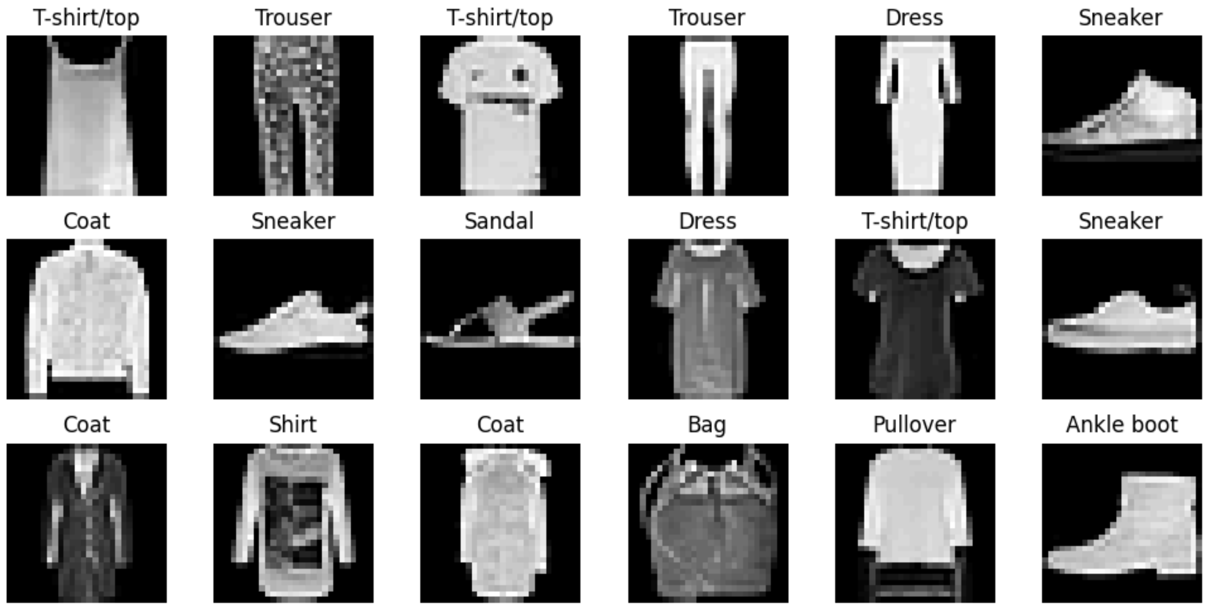
In [3]:
```
#dataset já dividido em treino e teste
(x_train, y_train), (x_test, y_test) = keras.datasets.fashion_mnist.load_dat
#split de treino entre 80% treino e 20% validação
x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test_siz
# Normalização (0-1) para visualização e futura modelagem
x_train = x_train.astype("float32")/255.0
x_test = x_test.astype("float32")/255.0
x_val = x_val.astype("float32")/255.0
"""
converte inteiro discreto de 0 a 255 para contínuo float de 0.0 a 1.0
redes neurais funcionam melhor com entradas contínuas e escala pequena e pró
float representa melhor valores intermediários entre 2 as cores possíveis (p
y é inteiro de 0 a 9, sendo o número sua classe, não precisa de normalização
"""
```

Out[3]:
```
'\nconverte inteiro discreto de 0 a 255 para contínuo float de 0.0 a 1.0\nr
edes neurais funcionam melhor com entradas contínuas e escala pequena e pró
xima\nfloat representa melhor valores intermediários entre 2 as cores possí
veis (preto e branco)\ny é inteiro de 0 a 9, sendo o número sua classe, não
precisa de normalização\n'
```

vizualização do dataset Fashion-MNIST

In [4]:
```
labels = [
    "T-shirt/top","Trouser","Pullover","Dress","Coat","Sandal","Shirt","Snea
]

print(f"Treino: {x_train.shape}, Validação: {x_val.shape}, Teste: {x_test.sh
print("Exemplo de rótulos (0-9):", labels)

# Grid de amostras aleatórias do conjunto de treino
fig, axes = plt.subplots(3, 6, figsize=(10, 5))
for i, ax in enumerate(axes.ravel()):
    idx = np.random.randint(0, len(x_train))
    ax.imshow(x_train[idx], cmap="gray")
    ax.set_title(labels[y_train[idx]])
    ax.axis("off")
plt.tight_layout()
plt.show()
```

```
Treino: (48000, 28, 28), Validação: (12000, 28, 28), Teste: (10000, 28, 28)
Exemplo de rótulos (0-9): ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Co
at', 'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']
```



Questão 01: Rede neural simples

Modelo

In [5]:
```
"""
configuração padrão:
    camada de entrada com 784 neurônios(cada pixel da imagem 28x28)
    2 camadas ocultas (64 e 32 neurônios)
    camada de saída com 10 neurônios (10 classes)
"""

def build_model(learning_rate=1e-3, beta1=0.9, activation_hidden = 'relu', a

    layers = [
        keras.layers.InputLayer(shape=(28, 28)),  # imagens 28x28 pixels, ca
        keras.layers.Flatten()  # transforma matriz 2D 28x28 em vetor 1D com
    ]
    # adiciona dinamicamente as camadas ocultas conforme num_hidden_layers
    for i in range(num_hidden_layers):
        layers.append(keras.layers.Dense(neurons_per_layer[i], activation_hi

    # camada de saída
    layers.append(keras.layers.Dense(10, activation_output))  # 10 saídas (c

    # modelo sequencial -> "clássico" com uma camada após a outra
    model = keras.Sequential(layers)

    optimizer = keras.optimizers.Adam(learning_rate, beta1)
    model.compile(
        optimizer = optimizer,  # aprendizado adaptativo
        loss='sparse_categorical_crossentropy',  # ideal para classificação
        metrics=['accuracy']  # medida de desempenho simples
```

```
    )
    return model
```

gerador de seeds

In [6]:
```
PRIME_STEP = 2654435761  # grande e usado em hashing
MASK32 = 0xFFFFFFFF
base = secrets.randbits(32)

# ===== Método para "espaçar" mais as seeds =====
# Ideia: usar uma base aleatória de 32 bits e aplicar um incremento grande e
# (ex: 2654435761 = constante de Knuth) gerando progressão pseudo-dispersada
# Depois aplicamos uma mistura (hash simples) para minimizar correlação line
def spaced_seeds(n, base_seed, step):
    seeds = []
    for i in range(n):
        raw = (base_seed + i * step) & MASK32
        # Mistura extra: multiplicação + xor + shift (barato, evita sequênci
        mixed = (raw * 0x9E3779B1) & MASK32
        mixed ^= (mixed >> 16)
        seeds.append(mixed)
    return seeds

seeds = spaced_seeds(5, base, PRIME_STEP)
```

treinamento

In [7]:
```
histories = []
final_metrics = []
log_lines = []

for i, seed in enumerate(seeds, start=1):
    keras.utils.set_random_seed(seed)
    model = build_model()
    h = model.fit(
        x_train, y_train,
        epochs=5,
        batch_size=128,
        verbose=0
    )
    histories.append(h)
    final_metrics.append({
        'run': i,
        'seed': seed,
        'final_train_loss': h.history['loss'][-1],
        'final_train_acc': h.history['accuracy'][-1]
    })
    log_lines.append(
        f"=== Treinamento {i}/5 (seed={seed}) ===\n"
        f"Train - Loss: {h.history['loss'][-1]:.4f}, accuracy: {h.history['a
    )

print("\n".join(log_lines))
```

```
=== Treinamento 1/5 (seed=481108300) ===
Train - Loss: 0.3472, accuracy: 0.8774
=== Treinamento 2/5 (seed=479467222) ===
Train - Loss: 0.3410, accuracy: 0.8779
=== Treinamento 3/5 (seed=477809369) ===
Train - Loss: 0.3470, accuracy: 0.8748
=== Treinamento 4/5 (seed=476168037) ===
Train - Loss: 0.3420, accuracy: 0.8772
=== Treinamento 5/5 (seed=474510125) ===
Train - Loss: 0.3446, accuracy: 0.8769
```

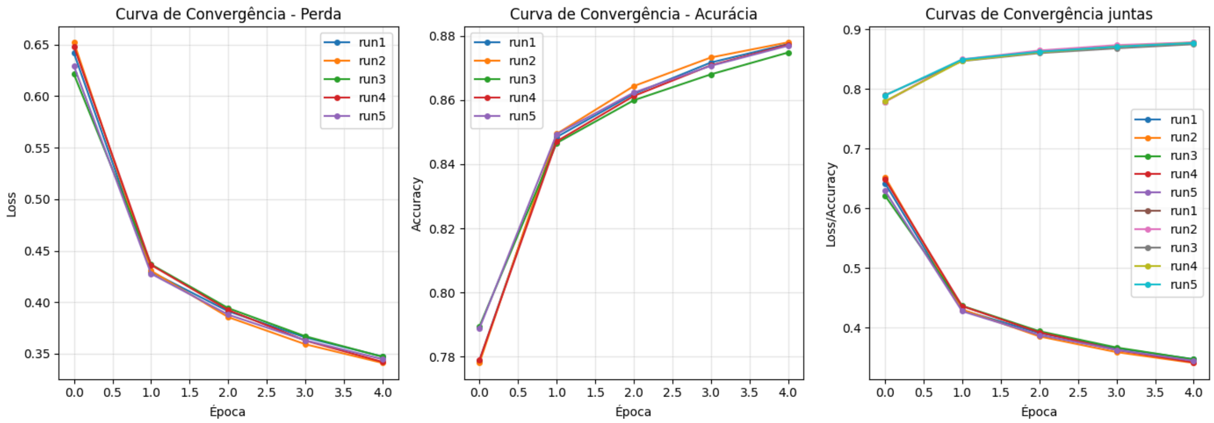
visualização

In [ ]:

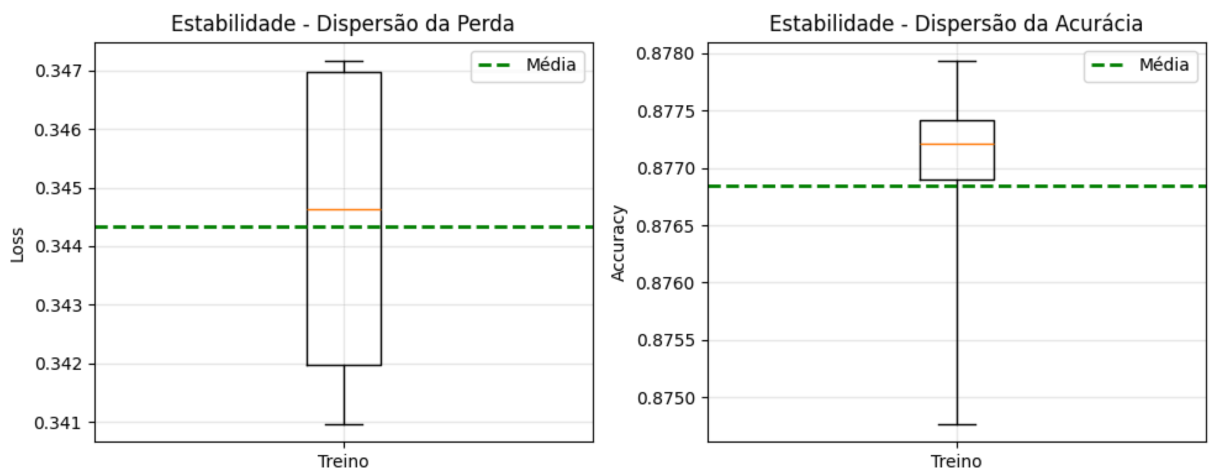
```python
# ========== CURVAS DE CONVERGÊNCIA ==========
fig, axes = plt.subplots(1, 3, figsize=(14, 5))

print(f"estrutura das histories: {histories[-1].history}")
print("é possível adicionar mais informações no dicionário history, como f1,

#perda
for i, h in enumerate(histories, start=1):
    axes[0].plot(h.history['loss'], label=f'run{i}', marker='o', markersize=
axes[0].set_title('Curva de Convergência - Perda')
axes[0].set_xlabel('Época')
axes[0].set_ylabel('Loss')
axes[0].legend()
axes[0].grid(True, alpha=0.3)

#acurácia
for i, h in enumerate(histories, start=1):
    axes[1].plot(h.history['accuracy'], label=f'run{i}', marker='o', markers
axes[1].set_title('Curva de Convergência - Acurácia')
axes[1].set_xlabel('Época')
axes[1].set_ylabel('Accuracy')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

#as duas(análise de over/underfitting)
for i, h in enumerate(histories, start=1):
    axes[2].plot(h.history['loss'], label=f'run{i}', marker='o', markersize=
for i, h in enumerate(histories, start=1):
    axes[2].plot(h.history['accuracy'], label=f'run{i}', marker='o', markers
axes[2].set_title('Curvas de Convergência juntas')
axes[2].set_xlabel('Época')
axes[2].set_ylabel('Loss/Accuracy')
axes[2].legend()
axes[2].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()
#loss continua alta, accuracy continua baixa -> underfitting
#loss continua caindo mesmo com accuracy estagnada -> overfitting
# ========== ESTABILIDADE ==========
train_losses = [m['final_train_loss'] for m in final_metrics]
train_accuracies = [m['final_train_acc'] for m in final_metrics]
```

```
print("\n========== ESTABILIDADE ==========")
print(f"Loss - média: {np.mean(train_losses):.4f}")
print(f"Loss - desvio padrão: {np.std(train_losses):.4f}")
print(f"accuracy  - média: {np.mean(train_accuracies):.4f}")
print(f"accuracy  - desvio padrão: {np.std(train_accuracies):.4f}")

fig, axes = plt.subplots(1, 2, figsize=(10, 4))
#5 seeds divididas entre bigode superior(máximo), limite superior da caixa,
axes[0].boxplot(train_losses, whis=(0, 100))
axes[0].set_title('Estabilidade - Dispersão da Perda')
axes[0].set_ylabel('Loss')
axes[0].set_xticklabels(['Treino'])
#axes[0].scatter([1]*len(train_losses), train_losses, color='red', zorder=2)
axes[0].axhline(y=np.mean(train_losses), color='green', linestyle='--', line
axes[0].legend()
axes[0].grid(True, alpha=0.3)

axes[1].boxplot(train_accuracies, whis=(0, 100))
axes[1].set_title('Estabilidade - Dispersão da Acurácia')
axes[1].set_ylabel('Accuracy')
axes[1].set_xticklabels(['Treino'])
#axes[1].scatter([1]*len(train_accuracies), train_accuracies, color='red', z
axes[1].axhline(y=np.mean(train_accuracies), color='green', linestyle='--',
axes[1].legend()
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# ========== DESEMPENHO ==========
print("\n========== DESEMPENHO por seed ==========")
for m in final_metrics:
    print(f"Run {m['run']} (seed={m['seed']}): Loss={m['final_train_loss']:.

fig, axes = plt.subplots(1, 2, figsize=(12, 4))
x = np.arange(1, 6)

axes[0].bar(x, train_losses, alpha=0.7, color='steelblue')
axes[0].set_title('Desempenho - Perda Final por Seed')
axes[0].set_xlabel('Run')
axes[0].set_ylabel('Loss')
axes[0].set_xticks(x)
axes[0].grid(True, alpha=0.3, axis='y')

axes[1].bar(x, train_accuracies, alpha=0.7, color='coral')
axes[1].set_title('Desempenho - Acurácia Final por Seed')
axes[1].set_xlabel('Run')
axes[1].set_ylabel('Accuracy')
axes[1].set_xticks(x)
axes[1].grid(True, alpha=0.3, axis='y')

plt.tight_layout()
plt.show()

print("\nSeeds usadas:", seeds)
```

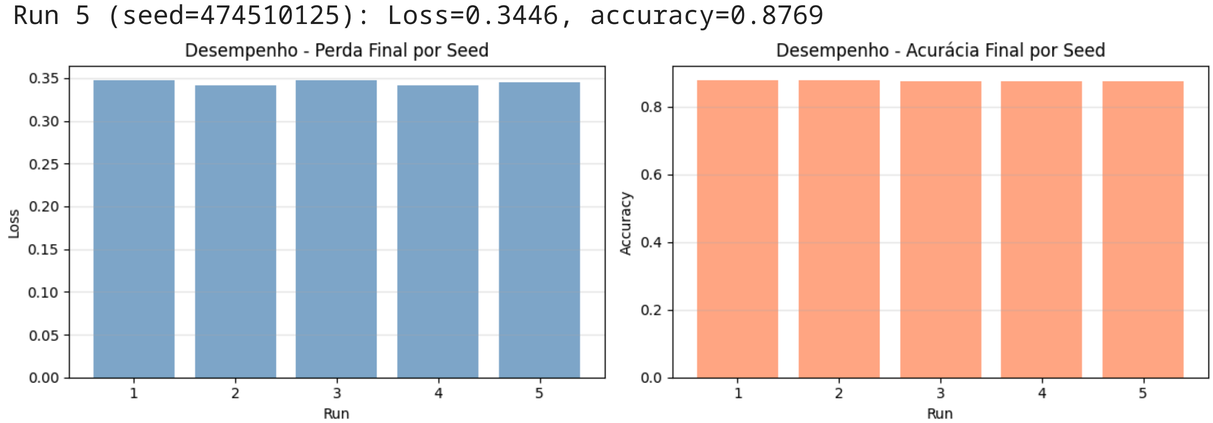
```
estrutura das histories: {'accuracy': [0.788895845413208, 0.8493333458900452, 0.862291693687439, 0.8706458210945129, 0.8768958449363708], 'loss': [0.629216194152832, 0.4276357889175415, 0.3878442645072937, 0.3628866374492645, 0.34462350606918335]}
```




```
========== ESTABILIDADE ==========
Loss - média: 0.3443
Loss - desvio padrão: 0.0025
accuracy  - média: 0.8768
accuracy  - desvio padrão: 0.0011
```




```
========== DESEMPENHO por seed ==========
Run 1 (seed=481108300): Loss=0.3472, accuracy=0.8774
Run 2 (seed=479467222): Loss=0.3410, accuracy=0.8779
Run 3 (seed=477809369): Loss=0.3470, accuracy=0.8748
Run 4 (seed=476168037): Loss=0.3420, accuracy=0.8772
Run 5 (seed=474510125): Loss=0.3446, accuracy=0.8769
```




```
Seeds usadas: [481108300, 479467222, 477809369, 476168037, 474510125]
```

escolha de função de ativação

In [9]:
```
activation_function_hidden_layer_options = ['relu', 'sigmoid', 'tanh']
```

treinamento

In [10]:
```
#TODO
#TODO
seeds_q1 = spaced_seeds(1, base, PRIME_STEP)
results_q1 = []

for activation_function_hidden_layer in activation_function_hidden_layer_opt
    run_losses = []
    run_accuracies = []

    for s in seeds_q1:
        keras.utils.set_random_seed(s)
        model = build_model(activation_hidden=activation_function_hidden_lay
        h = model.fit(x_train, y_train, verbose=1)
        run_losses.append(h.history['loss'][-1])
        run_accuracies.append(h.history['accuracy'][-1])
    results_q1.append({
        'activation_function_hidden_layer': activation_function_hidden_layer
        'loss_mean': float(np.mean(run_losses)),
        'loss_std': float(np.std(run_losses)),
        'accuracy_mean': float(np.mean(run_accuracies)),
        'accuracy_std': float(np.std(run_accuracies))
    })
```

```
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 2s 990us/step - accuracy: 0.8078 - loss: 0.543
8
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 2s 990us/step - accuracy: 0.8078 - loss: 0.543
8
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 2s 963us/step - accuracy: 0.7541 - loss: 0.806
9
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 2s 963us/step - accuracy: 0.7541 - loss: 0.806
9
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.8164 - loss: 0.5236
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.8164 - loss: 0.5236
```

ordenação

In [11]:
```
# Ordena por melhor equilíbrio: alta acurácia média, baixa perda média e bai
# Score simples: accuracy_mean - loss_mean - (loss_std + accuracy_std)
sorted_results_q1 = sorted(
    results_q1,
    key=lambda sorted_result: (-(sorted_result['accuracy_mean']), sorted_res
)

print("Funções de ativação(melhor pra pior):")
for i,sorted_result in enumerate(sorted_results_q1[:3]):
    print(
```

```
        f"{i+1}. activation_function_hidden_layer={sorted_result['activation
    )
```

```
Funções de ativação(melhor pra pior):
1. activation_function_hidden_layer=tanh
2. activation_function_hidden_layer=relu
3. activation_function_hidden_layer=sigmoid
```

Questão 02: hiperparâmetros

parâmetros ajustados

In [12]:
```
#TODO: mais opções de hiperparâmetros para teste exaustivo final
num_epochs_grid = [5, 10, 20]
learning_rates = [1e-4, 1e-3, 1e-2]
batch_sizes = [64, 128, 256]
momentums_beta1 = [0.7, 0.9, 0.99]
```

treinamento

In [13]:
```
#TODO: aumentar número de seeds para teste exaustivo final
#TODO: treino e validação
import time

seeds_q2 = spaced_seeds(1, base, PRIME_STEP)
results_q2 = []  # lista de dicts com hiperparâmetros e métricas agregadas
histories_q2 = []

for epochs in num_epochs_grid:
    for learning_rate in learning_rates:
        for batch_size in batch_sizes:
            for beta1 in momentums_beta1:
                run_losses = []
                run_accuracies = []
                run_times = []

                for s in seeds_q2:
                    keras.utils.set_random_seed(s)
                    model = build_model(learning_rate=learning_rate, beta1=b

                    # Mede tempo de treinamento
                    start_time = time.time()
                    h = model.fit(x_train, y_train, epochs=epochs, batch_siz
                    training_time = time.time() - start_time

                    histories_q2.append(h)
                    run_losses.append(h.history['loss'][-1])
                    run_accuracies.append(h.history['accuracy'][-1])
                    run_times.append(training_time)

                results_q2.append({
                    'epochs': epochs,
```

```
                    'learning_rate': learning_rate,
                    'batch_size': batch_size,
                    'beta1': beta1,
                    'loss_mean': float(np.mean(run_losses)),
                    'loss_std': float(np.std(run_losses)),
                    'accuracy_mean': float(np.mean(run_accuracies)),
                    'accuracy_std': float(np.std(run_accuracies)),
                    'time_mean': float(np.mean(run_times)),
                    'time_std': float(np.std(run_times))
                })

print(f"\n✓ Treinamento Q2 concluído: {len(results_q2)} combinações testadas
```

```
Epoch 1/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6837 - loss: 0.9813
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6837 - loss: 0.9813
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8121 - loss: 0.5791
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8121 - loss: 0.5791
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8322 - loss: 0.5077
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8322 - loss: 0.5077
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8416 - loss: 0.4711
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8416 - loss: 0.4711
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8481 - loss: 0.4477
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8481 - loss: 0.4477
Epoch 1/5
Epoch 1/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6748 - loss: 0.9979
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6748 - loss: 0.9979
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8116 - loss: 0.5780
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8116 - loss: 0.5780
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8323 - loss: 0.5060
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8323 - loss: 0.5060
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8419 - loss: 0.4703
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8419 - loss: 0.4703
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8482 - loss: 0.4471
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8482 - loss: 0.4471
Epoch 1/5
Epoch 1/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6323 - loss: 1.0701
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6323 - loss: 1.0701
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7973 - loss: 0.6077
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7973 - loss: 0.6077
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8245 - loss: 0.5241
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8245 - loss: 0.5241
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8370 - loss: 0.4835
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8370 - loss: 0.4835
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Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8441 - loss: 0.4589
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8441 - loss: 0.4589
Epoch 1/5
Epoch 1/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6241 - loss: 1.1816
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6241 - loss: 1.1816
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7885 - loss: 0.6632
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7885 - loss: 0.6632
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8180 - loss: 0.5629
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8180 - loss: 0.5629
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8311 - loss: 0.5150
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8311 - loss: 0.5150
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8393 - loss: 0.4852
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8393 - loss: 0.4852
Epoch 1/5
Epoch 1/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6098 - loss: 1.2116
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6098 - loss: 1.2116
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7849 - loss: 0.6708
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7849 - loss: 0.6708
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8170 - loss: 0.5646
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8170 - loss: 0.5646
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8306 - loss: 0.5160
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8306 - loss: 0.5160
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8383 - loss: 0.4859
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8383 - loss: 0.4859
Epoch 1/5
Epoch 1/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5543 - loss: 1.3111
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5543 - loss: 1.3111
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7510 - loss: 0.7195
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7510 - loss: 0.7195
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8012 - loss: 0.6011
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8012 - loss: 0.6011
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Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8201 - loss: 0.5423
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8201 - loss: 0.5423
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8300 - loss: 0.5075
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8300 - loss: 0.5075
Epoch 1/5
Epoch 1/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5318 - loss: 1.4596
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5318 - loss: 1.4596
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7406 - loss: 0.8180
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7406 - loss: 0.8180
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7902 - loss: 0.6622
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7902 - loss: 0.6622
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8116 - loss: 0.5893
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8116 - loss: 0.5893
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8228 - loss: 0.5464
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8228 - loss: 0.5464
Epoch 1/5
Epoch 1/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.5100 - loss: 1.5057
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.5100 - loss: 1.5057
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7343 - loss: 0.8268
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7343 - loss: 0.8268
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7868 - loss: 0.6676
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7868 - loss: 0.6676
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8102 - loss: 0.5887
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8102 - loss: 0.5887
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8227 - loss: 0.5444
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8227 - loss: 0.5444
Epoch 1/5
Epoch 1/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.4453 - loss: 1.6274
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.4453 - loss: 1.6274
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6911 - loss: 0.9137
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6911 - loss: 0.9137
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Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7457 - loss: 0.7244
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7457 - loss: 0.7244
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7868 - loss: 0.6358
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7868 - loss: 0.6358
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8074 - loss: 0.5810
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8074 - loss: 0.5810
Epoch 1/5
Epoch 1/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8014 - loss: 0.5740
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8014 - loss: 0.5740
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8540 - loss: 0.4091
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8540 - loss: 0.4091
Epoch 3/5
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8671 - loss: 0.3695
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8671 - loss: 0.3695
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8760 - loss: 0.3437
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8760 - loss: 0.3437
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8819 - loss: 0.3241
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8819 - loss: 0.3241
Epoch 1/5
Epoch 1/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7966 - loss: 0.5808
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7966 - loss: 0.5808
Epoch 2/5
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8550 - loss: 0.4100
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8550 - loss: 0.4100
Epoch 3/5
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8675 - loss: 0.3697
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8675 - loss: 0.3697
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8761 - loss: 0.3450
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8761 - loss: 0.3450
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8821 - loss: 0.3256
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8821 - loss: 0.3256
Epoch 1/5
Epoch 1/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7813 - loss: 0.6209
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7813 - loss: 0.6209
Epoch 2/5
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  1/750 ━━━━━━━━━━━━━━━━━━━━ 14s 20ms/step - accuracy: 0.8594 - loss: 0.4245E
poch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8475 - loss: 0.4348
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8475 - loss: 0.4348
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8604 - loss: 0.3938
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8604 - loss: 0.3938
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8684 - loss: 0.3678
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8684 - loss: 0.3678
Epoch 5/5
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8731 - loss: 0.3527
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8731 - loss: 0.3527
Epoch 1/5
Epoch 1/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7819 - loss: 0.6342
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7819 - loss: 0.6342
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8460 - loss: 0.4383
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8460 - loss: 0.4383
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8591 - loss: 0.3976
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8591 - loss: 0.3976
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8696 - loss: 0.3702
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8696 - loss: 0.3702
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8755 - loss: 0.3484
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8755 - loss: 0.3484
Epoch 1/5
Epoch 1/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7789 - loss: 0.6418
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7789 - loss: 0.6418
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8484 - loss: 0.4295
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8484 - loss: 0.4295
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8619 - loss: 0.3911
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8619 - loss: 0.3911
Epoch 4/5
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8717 - loss: 0.3657
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8717 - loss: 0.3657
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8774 - loss: 0.3472
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8774 - loss: 0.3472
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Epoch 1/5
Epoch 1/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7507 - loss: 0.6988
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7507 - loss: 0.6988
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8413 - loss: 0.4498
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8413 - loss: 0.4498
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.4035
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.4035
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8649 - loss: 0.3760
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8649 - loss: 0.3760
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8706 - loss: 0.3578
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8706 - loss: 0.3578
Epoch 1/5
Epoch 1/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7519 - loss: 0.7279
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7519 - loss: 0.7279
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8402 - loss: 0.4613
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8402 - loss: 0.4613
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8534 - loss: 0.4181
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8534 - loss: 0.4181
Epoch 4/5
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8614 - loss: 0.3920
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8614 - loss: 0.3920
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8676 - loss: 0.3722
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8676 - loss: 0.3722
Epoch 1/5
Epoch 1/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7382 - loss: 0.7560
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7382 - loss: 0.7560
Epoch 2/5
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8393 - loss: 0.4607
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8393 - loss: 0.4607
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8556 - loss: 0.4085
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8556 - loss: 0.4085
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8650 - loss: 0.3800
Epoch 5/5
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188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8650 - loss: 0.3800
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8714 - loss: 0.3598
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8714 - loss: 0.3598
Epoch 1/5
Epoch 1/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7139 - loss: 0.8085
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7139 - loss: 0.8085
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8257 - loss: 0.4988
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8257 - loss: 0.4988
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8459 - loss: 0.4337
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8459 - loss: 0.4337
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8576 - loss: 0.3995
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8576 - loss: 0.3995
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8639 - loss: 0.3799
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8639 - loss: 0.3799
Epoch 1/5
Epoch 1/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7964 - loss: 0.5529
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7964 - loss: 0.5529
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8420 - loss: 0.4283
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8420 - loss: 0.4283
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8526 - loss: 0.4026
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8526 - loss: 0.4026
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8574 - loss: 0.3867
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8574 - loss: 0.3867
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8626 - loss: 0.3735
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8626 - loss: 0.3735
Epoch 1/5
Epoch 1/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8028 - loss: 0.5428
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8028 - loss: 0.5428
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8446 - loss: 0.4228
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8446 - loss: 0.4228
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.3992
Epoch 4/5
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750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.3992
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8616 - loss: 0.3805
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8616 - loss: 0.3805
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8635 - loss: 0.3751
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8635 - loss: 0.3751
Epoch 1/5
Epoch 1/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7857 - loss: 0.5834
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7857 - loss: 0.5834
Epoch 2/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 995us/step - accuracy: 0.8462 - loss: 0.4265
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 995us/step - accuracy: 0.8462 - loss: 0.4265
Epoch 3/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8554 - loss: 0.4034
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8554 - loss: 0.4034
Epoch 4/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 984us/step - accuracy: 0.8564 - loss: 0.3981
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 984us/step - accuracy: 0.8564 - loss: 0.3981
Epoch 5/5
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.3914
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.3914
Epoch 1/5
Epoch 1/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7980 - loss: 0.5555
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7980 - loss: 0.5555
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8461 - loss: 0.4204
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8461 - loss: 0.4204
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8586 - loss: 0.3841
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8586 - loss: 0.3841
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8651 - loss: 0.3629
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8651 - loss: 0.3629
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8697 - loss: 0.3510
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8697 - loss: 0.3510
Epoch 1/5
Epoch 1/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7985 - loss: 0.5525
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7985 - loss: 0.5525
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8487 - loss: 0.4128
Epoch 3/5
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375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8487 - loss: 0.4128
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8602 - loss: 0.3847
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8602 - loss: 0.3847
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8668 - loss: 0.3643
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8668 - loss: 0.3643
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8721 - loss: 0.3531
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8721 - loss: 0.3531
Epoch 1/5
Epoch 1/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7810 - loss: 0.5940
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7810 - loss: 0.5940
Epoch 2/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8480 - loss: 0.4235
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8480 - loss: 0.4235
Epoch 3/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8575 - loss: 0.3926
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8575 - loss: 0.3926
Epoch 4/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8641 - loss: 0.3709
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8641 - loss: 0.3709
Epoch 5/5
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8654 - loss: 0.3636
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8654 - loss: 0.3636
Epoch 1/5
Epoch 1/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7770 - loss: 0.6170
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7770 - loss: 0.6170
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8468 - loss: 0.4227
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8468 - loss: 0.4227
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8607 - loss: 0.3803
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8607 - loss: 0.3803
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8675 - loss: 0.3598
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8675 - loss: 0.3598
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8744 - loss: 0.3439
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8744 - loss: 0.3439
Epoch 1/5
Epoch 1/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7793 - loss: 0.6110
Epoch 2/5
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188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7793 - loss: 0.6110
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8506 - loss: 0.4133
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8506 - loss: 0.4133
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8635 - loss: 0.3735
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8635 - loss: 0.3735
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8733 - loss: 0.3499
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8733 - loss: 0.3499
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8770 - loss: 0.3346
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8770 - loss: 0.3346
Epoch 1/5
Epoch 1/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7491 - loss: 0.6867
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7491 - loss: 0.6867
Epoch 2/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8377 - loss: 0.4589
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8377 - loss: 0.4589
Epoch 3/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8554 - loss: 0.4008
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8554 - loss: 0.4008
Epoch 4/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8626 - loss: 0.3774
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8626 - loss: 0.3774
Epoch 5/5
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8716 - loss: 0.3503
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8716 - loss: 0.3503
Epoch 1/10
Epoch 1/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6837 - loss: 0.9813
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6837 - loss: 0.9813
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8121 - loss: 0.5791
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8121 - loss: 0.5791
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8322 - loss: 0.5077
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8322 - loss: 0.5077
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 995us/step - accuracy: 0.8416 - loss: 0.4711
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 995us/step - accuracy: 0.8416 - loss: 0.4711
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8481 - loss: 0.4477
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8481 - loss: 0.4477
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Epoch 6/10
  1/750 ━━━━━━━━━━━━━━━━━━━━ 14s 20ms/step - accuracy: 0.9062 - loss: 0.3626E
poch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 992us/step - accuracy: 0.8529 - loss: 0.4306
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 992us/step - accuracy: 0.8529 - loss: 0.4306
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8566 - loss: 0.4174
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8566 - loss: 0.4174
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 995us/step - accuracy: 0.8601 - loss: 0.4065
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 995us/step - accuracy: 0.8601 - loss: 0.4065
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8628 - loss: 0.3972
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8628 - loss: 0.3972
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8655 - loss: 0.3892
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8655 - loss: 0.3892
Epoch 1/10
Epoch 1/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6748 - loss: 0.9979
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6748 - loss: 0.9979
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8116 - loss: 0.5780
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8116 - loss: 0.5780
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8323 - loss: 0.5060
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8323 - loss: 0.5060
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8419 - loss: 0.4703
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8419 - loss: 0.4703
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 990us/step - accuracy: 0.8482 - loss: 0.4471
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 990us/step - accuracy: 0.8482 - loss: 0.4471
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8538 - loss: 0.4302
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8538 - loss: 0.4302
Epoch 7/10
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 976us/step - accuracy: 0.8579 - loss: 0.4170
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 976us/step - accuracy: 0.8579 - loss: 0.4170
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8608 - loss: 0.4062
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8608 - loss: 0.4062
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1000us/step - accuracy: 0.8638 - loss: 0.3970
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Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1000us/step - accuracy: 0.8638 - loss: 0.3970
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8664 - loss: 0.3889
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8664 - loss: 0.3889
Epoch 1/10
Epoch 1/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6323 - loss: 1.0701
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6323 - loss: 1.0701
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7973 - loss: 0.6077
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7973 - loss: 0.6077
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8245 - loss: 0.5241
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8245 - loss: 0.5241
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8370 - loss: 0.4835
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8370 - loss: 0.4835
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8441 - loss: 0.4589
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8441 - loss: 0.4589
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8499 - loss: 0.4412
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8499 - loss: 0.4412
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.4273
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.4273
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8570 - loss: 0.4160
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8570 - loss: 0.4160
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8602 - loss: 0.4064
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8602 - loss: 0.4064
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8630 - loss: 0.3980
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8630 - loss: 0.3980
Epoch 1/10
Epoch 1/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6241 - loss: 1.1816
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6241 - loss: 1.1816
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7885 - loss: 0.6632
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7885 - loss: 0.6632
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8180 - loss: 0.5629
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Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8180 - loss: 0.5629
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8311 - loss: 0.5150
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8311 - loss: 0.5150
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8393 - loss: 0.4852
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8393 - loss: 0.4852
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8443 - loss: 0.4639
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8443 - loss: 0.4639
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8490 - loss: 0.4477
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8490 - loss: 0.4477
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8525 - loss: 0.4349
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8525 - loss: 0.4349
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8565 - loss: 0.4242
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8565 - loss: 0.4242
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8593 - loss: 0.4150
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8593 - loss: 0.4150
Epoch 1/10
Epoch 1/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6098 - loss: 1.2116
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6098 - loss: 1.2116
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7849 - loss: 0.6708
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7849 - loss: 0.6708
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8170 - loss: 0.5646
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8170 - loss: 0.5646
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8306 - loss: 0.5160
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8306 - loss: 0.5160
Epoch 5/10
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8383 - loss: 0.4859
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8383 - loss: 0.4859
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8444 - loss: 0.4646
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8444 - loss: 0.4646
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8487 - loss: 0.4485
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Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8487 - loss: 0.4485
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8525 - loss: 0.4356
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8525 - loss: 0.4356
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8565 - loss: 0.4249
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8565 - loss: 0.4249
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8589 - loss: 0.4159
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8589 - loss: 0.4159
Epoch 1/10
Epoch 1/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.5543 - loss: 1.3111
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.5543 - loss: 1.3111
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7510 - loss: 0.7195
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7510 - loss: 0.7195
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8012 - loss: 0.6011
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8012 - loss: 0.6011
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8201 - loss: 0.5423
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8201 - loss: 0.5423
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8300 - loss: 0.5075
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8300 - loss: 0.5075
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8361 - loss: 0.4830
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8361 - loss: 0.4830
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8419 - loss: 0.4653
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8419 - loss: 0.4653
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8454 - loss: 0.4514
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8454 - loss: 0.4514
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8492 - loss: 0.4399
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8492 - loss: 0.4399
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8529 - loss: 0.4302
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8529 - loss: 0.4302
Epoch 1/10
Epoch 1/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5318 - loss: 1.4596
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Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5318 - loss: 1.4596
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7406 - loss: 0.8180
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7406 - loss: 0.8180
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7902 - loss: 0.6622
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7902 - loss: 0.6622
Epoch 4/10
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8116 - loss: 0.5893
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8116 - loss: 0.5893
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8228 - loss: 0.5464
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8228 - loss: 0.5464
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8308 - loss: 0.5173
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8308 - loss: 0.5173
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8364 - loss: 0.4957
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8364 - loss: 0.4957
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8410 - loss: 0.4786
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8410 - loss: 0.4786
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8453 - loss: 0.4645
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8453 - loss: 0.4645
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8479 - loss: 0.4527
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8479 - loss: 0.4527
Epoch 1/10
Epoch 1/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.5100 - loss: 1.5057
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.5100 - loss: 1.5057
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7343 - loss: 0.8268
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7343 - loss: 0.8268
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7868 - loss: 0.6676
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7868 - loss: 0.6676
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8102 - loss: 0.5887
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8102 - loss: 0.5887
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8227 - loss: 0.5444
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Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8227 - loss: 0.5444
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8315 - loss: 0.5148
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8315 - loss: 0.5148
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8372 - loss: 0.4931
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8372 - loss: 0.4931
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8412 - loss: 0.4764
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8412 - loss: 0.4764
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8447 - loss: 0.4629
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8447 - loss: 0.4629
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8480 - loss: 0.4516
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8480 - loss: 0.4516
Epoch 1/10
Epoch 1/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.4453 - loss: 1.6274
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.4453 - loss: 1.6274
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.6911 - loss: 0.9137
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.6911 - loss: 0.9137
Epoch 3/10
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7457 - loss: 0.7244
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7457 - loss: 0.7244
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7868 - loss: 0.6358
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7868 - loss: 0.6358
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8074 - loss: 0.5810
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8074 - loss: 0.5810
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8189 - loss: 0.5453
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8189 - loss: 0.5453
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8274 - loss: 0.5195
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8274 - loss: 0.5195
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8336 - loss: 0.4995
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8336 - loss: 0.4995
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8378 - loss: 0.4834
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Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8378 - loss: 0.4834
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8416 - loss: 0.4701
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8416 - loss: 0.4701
Epoch 1/10
Epoch 1/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8014 - loss: 0.5740
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8014 - loss: 0.5740
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.4091
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.4091
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8671 - loss: 0.3695
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8671 - loss: 0.3695
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8760 - loss: 0.3437
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8760 - loss: 0.3437
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8819 - loss: 0.3241
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8819 - loss: 0.3241
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8881 - loss: 0.3085
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8881 - loss: 0.3085
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8922 - loss: 0.2951
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8922 - loss: 0.2951
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8960 - loss: 0.2846
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8960 - loss: 0.2846
Epoch 9/10
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9000 - loss: 0.2739
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9000 - loss: 0.2739
Epoch 10/10
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9028 - loss: 0.2645
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9028 - loss: 0.2645
Epoch 1/10
Epoch 1/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7966 - loss: 0.5808
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7966 - loss: 0.5808
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8550 - loss: 0.4100
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8550 - loss: 0.4100
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8675 - loss: 0.3697
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Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8675 - loss: 0.3697
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8761 - loss: 0.3450
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8761 - loss: 0.3450
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8821 - loss: 0.3256
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8821 - loss: 0.3256
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8862 - loss: 0.3104
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8862 - loss: 0.3104
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8911 - loss: 0.2971
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8911 - loss: 0.2971
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8952 - loss: 0.2859
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8952 - loss: 0.2859
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8990 - loss: 0.2760
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8990 - loss: 0.2760
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9018 - loss: 0.2679
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9018 - loss: 0.2679
Epoch 1/10
Epoch 1/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7813 - loss: 0.6209
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7813 - loss: 0.6209
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8475 - loss: 0.4348
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8475 - loss: 0.4348
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8604 - loss: 0.3938
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8604 - loss: 0.3938
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8684 - loss: 0.3678
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8684 - loss: 0.3678
Epoch 5/10
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8731 - loss: 0.3527
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8731 - loss: 0.3527
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8772 - loss: 0.3385
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8772 - loss: 0.3385
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8825 - loss: 0.3226
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Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8825 - loss: 0.3226
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8873 - loss: 0.3109
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8873 - loss: 0.3109
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8912 - loss: 0.2999
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8912 - loss: 0.2999
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8938 - loss: 0.2910
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8938 - loss: 0.2910
Epoch 1/10
Epoch 1/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.7819 - loss: 0.6342
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.7819 - loss: 0.6342
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8460 - loss: 0.4383
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8460 - loss: 0.4383
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8591 - loss: 0.3976
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8591 - loss: 0.3976
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8696 - loss: 0.3702
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8696 - loss: 0.3702
Epoch 5/10
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8755 - loss: 0.3484
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8755 - loss: 0.3484
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8807 - loss: 0.3308
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8807 - loss: 0.3308
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8853 - loss: 0.3171
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8853 - loss: 0.3171
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8895 - loss: 0.3049
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8895 - loss: 0.3049
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8934 - loss: 0.2947
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8934 - loss: 0.2947
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8968 - loss: 0.2852
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8968 - loss: 0.2852
Epoch 1/10
Epoch 1/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7789 - loss: 0.6418
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Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7789 - loss: 0.6418
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8484 - loss: 0.4295
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8484 - loss: 0.4295
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8619 - loss: 0.3911
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8619 - loss: 0.3911
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8717 - loss: 0.3657
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8717 - loss: 0.3657
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8774 - loss: 0.3472
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8774 - loss: 0.3472
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8827 - loss: 0.3315
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8827 - loss: 0.3315
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8865 - loss: 0.3183
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8865 - loss: 0.3183
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8899 - loss: 0.3061
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8899 - loss: 0.3061
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8932 - loss: 0.2952
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8932 - loss: 0.2952
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8965 - loss: 0.2862
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8965 - loss: 0.2862
Epoch 1/10
Epoch 1/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7507 - loss: 0.6988
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7507 - loss: 0.6988
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8413 - loss: 0.4498
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8413 - loss: 0.4498
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.4035
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.4035
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8649 - loss: 0.3760
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8649 - loss: 0.3760
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8706 - loss: 0.3578
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Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8706 - loss: 0.3578
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8759 - loss: 0.3411
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8759 - loss: 0.3411
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8799 - loss: 0.3287
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8799 - loss: 0.3287
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8849 - loss: 0.3187
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8849 - loss: 0.3187
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8877 - loss: 0.3079
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8877 - loss: 0.3079
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8914 - loss: 0.2982
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8914 - loss: 0.2982
Epoch 1/10
Epoch 1/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7519 - loss: 0.7279
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7519 - loss: 0.7279
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8402 - loss: 0.4613
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8402 - loss: 0.4613
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8534 - loss: 0.4181
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8534 - loss: 0.4181
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8614 - loss: 0.3920
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8614 - loss: 0.3920
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8676 - loss: 0.3722
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8676 - loss: 0.3722
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8738 - loss: 0.3559
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8738 - loss: 0.3559
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8790 - loss: 0.3419
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8790 - loss: 0.3419
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8824 - loss: 0.3300
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8824 - loss: 0.3300
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8858 - loss: 0.3196
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Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8858 - loss: 0.3196
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8883 - loss: 0.3104
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8883 - loss: 0.3104
Epoch 1/10
Epoch 1/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7382 - loss: 0.7560
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7382 - loss: 0.7560
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8393 - loss: 0.4607
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8393 - loss: 0.4607
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8556 - loss: 0.4085
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8556 - loss: 0.4085
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8650 - loss: 0.3800
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8650 - loss: 0.3800
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8714 - loss: 0.3598
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8714 - loss: 0.3598
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8755 - loss: 0.3443
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8755 - loss: 0.3443
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8796 - loss: 0.3322
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8796 - loss: 0.3322
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8835 - loss: 0.3215
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8835 - loss: 0.3215
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8871 - loss: 0.3121
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8871 - loss: 0.3121
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8902 - loss: 0.3034
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8902 - loss: 0.3034
Epoch 1/10
Epoch 1/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7139 - loss: 0.8085
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7139 - loss: 0.8085
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8257 - loss: 0.4988
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8257 - loss: 0.4988
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8459 - loss: 0.4337
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Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8459 - loss: 0.4337
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8576 - loss: 0.3995
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8576 - loss: 0.3995
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8639 - loss: 0.3799
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8639 - loss: 0.3799
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8681 - loss: 0.3644
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8681 - loss: 0.3644
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8728 - loss: 0.3526
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8728 - loss: 0.3526
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8785 - loss: 0.3389
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8785 - loss: 0.3389
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8822 - loss: 0.3270
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8822 - loss: 0.3270
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8848 - loss: 0.3179
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8848 - loss: 0.3179
Epoch 1/10
Epoch 1/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7964 - loss: 0.5529
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7964 - loss: 0.5529
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8420 - loss: 0.4283
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8420 - loss: 0.4283
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8526 - loss: 0.4026
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8526 - loss: 0.4026
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8574 - loss: 0.3867
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8574 - loss: 0.3867
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8626 - loss: 0.3735
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8626 - loss: 0.3735
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8665 - loss: 0.3648
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8665 - loss: 0.3648
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8691 - loss: 0.3576
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Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8691 - loss: 0.3576
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8717 - loss: 0.3507
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8717 - loss: 0.3507
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8738 - loss: 0.3437
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8738 - loss: 0.3437
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8765 - loss: 0.3394
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8765 - loss: 0.3394
Epoch 1/10
Epoch 1/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8028 - loss: 0.5428
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8028 - loss: 0.5428
Epoch 2/10
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8446 - loss: 0.4228
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8446 - loss: 0.4228
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.3992
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.3992
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8616 - loss: 0.3805
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8616 - loss: 0.3805
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8635 - loss: 0.3751
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8635 - loss: 0.3751
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8646 - loss: 0.3679
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8646 - loss: 0.3679
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8689 - loss: 0.3614
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8689 - loss: 0.3614
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8684 - loss: 0.3629
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8684 - loss: 0.3629
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8729 - loss: 0.3501
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8729 - loss: 0.3501
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8724 - loss: 0.3489
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8724 - loss: 0.3489
Epoch 1/10
Epoch 1/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.7857 - loss: 0.5834
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Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.7857 - loss: 0.5834
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8462 - loss: 0.4265
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8462 - loss: 0.4265
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8554 - loss: 0.4034
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8554 - loss: 0.4034
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8564 - loss: 0.3981
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8564 - loss: 0.3981
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.3914
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.3914
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8593 - loss: 0.3878
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8593 - loss: 0.3878
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8629 - loss: 0.3776
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8629 - loss: 0.3776
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8591 - loss: 0.3820
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8591 - loss: 0.3820
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8643 - loss: 0.3745
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8643 - loss: 0.3745
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8701 - loss: 0.3554
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8701 - loss: 0.3554
Epoch 1/10
Epoch 1/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7980 - loss: 0.5555
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7980 - loss: 0.5555
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8461 - loss: 0.4204
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8461 - loss: 0.4204
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8586 - loss: 0.3841
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8586 - loss: 0.3841
Epoch 4/10
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8651 - loss: 0.3629
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8651 - loss: 0.3629
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8697 - loss: 0.3510
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Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8697 - loss: 0.3510
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8741 - loss: 0.3413
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8741 - loss: 0.3413
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8761 - loss: 0.3313
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8761 - loss: 0.3313
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8803 - loss: 0.3262
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8803 - loss: 0.3262
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8813 - loss: 0.3248
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8813 - loss: 0.3248
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8845 - loss: 0.3116
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8845 - loss: 0.3116
Epoch 1/10
Epoch 1/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7985 - loss: 0.5525
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7985 - loss: 0.5525
Epoch 2/10
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8487 - loss: 0.4128
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8487 - loss: 0.4128
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8602 - loss: 0.3847
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8602 - loss: 0.3847
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8668 - loss: 0.3643
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8668 - loss: 0.3643
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8721 - loss: 0.3531
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8721 - loss: 0.3531
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8733 - loss: 0.3453
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8733 - loss: 0.3453
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8761 - loss: 0.3363
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8761 - loss: 0.3363
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8784 - loss: 0.3282
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8784 - loss: 0.3282
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8816 - loss: 0.3187
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Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8816 - loss: 0.3187
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8811 - loss: 0.3183
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8811 - loss: 0.3183
Epoch 1/10
Epoch 1/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7810 - loss: 0.5940
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7810 - loss: 0.5940
Epoch 2/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8480 - loss: 0.4235
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8480 - loss: 0.4235
Epoch 3/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8575 - loss: 0.3926
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8575 - loss: 0.3926
Epoch 4/10
Epoch 4/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8641 - loss: 0.3709
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8641 - loss: 0.3709
Epoch 5/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8654 - loss: 0.3636
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8654 - loss: 0.3636
Epoch 6/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8706 - loss: 0.3484
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8706 - loss: 0.3484
Epoch 7/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8752 - loss: 0.3391
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8752 - loss: 0.3391
Epoch 8/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8734 - loss: 0.3404
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8734 - loss: 0.3404
Epoch 9/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8741 - loss: 0.3382
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8741 - loss: 0.3382
Epoch 10/10
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8788 - loss: 0.3278
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8788 - loss: 0.3278
Epoch 1/10
Epoch 1/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.7770 - loss: 0.6170
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.7770 - loss: 0.6170
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8468 - loss: 0.4227
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8468 - loss: 0.4227
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8607 - loss: 0.3803
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Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8607 - loss: 0.3803
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8675 - loss: 0.3598
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8675 - loss: 0.3598
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8744 - loss: 0.3439
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8744 - loss: 0.3439
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8764 - loss: 0.3311
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8764 - loss: 0.3311
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8796 - loss: 0.3219
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8796 - loss: 0.3219
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8826 - loss: 0.3146
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8826 - loss: 0.3146
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8850 - loss: 0.3078
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8850 - loss: 0.3078
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8881 - loss: 0.2991
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8881 - loss: 0.2991
Epoch 1/10
Epoch 1/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7793 - loss: 0.6110
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7793 - loss: 0.6110
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8506 - loss: 0.4133
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8506 - loss: 0.4133
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8635 - loss: 0.3735
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8635 - loss: 0.3735
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8733 - loss: 0.3499
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8733 - loss: 0.3499
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8770 - loss: 0.3346
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8770 - loss: 0.3346
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8801 - loss: 0.3290
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8801 - loss: 0.3290
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8827 - loss: 0.3159
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Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8827 - loss: 0.3159
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8865 - loss: 0.3063
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8865 - loss: 0.3063
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8869 - loss: 0.3064
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8869 - loss: 0.3064
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8923 - loss: 0.2925
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8923 - loss: 0.2925
Epoch 1/10
Epoch 1/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7491 - loss: 0.6867
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7491 - loss: 0.6867
Epoch 2/10
Epoch 2/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8377 - loss: 0.4589
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8377 - loss: 0.4589
Epoch 3/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8554 - loss: 0.4008
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8554 - loss: 0.4008
Epoch 4/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8626 - loss: 0.3774
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8626 - loss: 0.3774
Epoch 5/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8716 - loss: 0.3503
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8716 - loss: 0.3503
Epoch 6/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8737 - loss: 0.3462
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8737 - loss: 0.3462
Epoch 7/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8764 - loss: 0.3361
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8764 - loss: 0.3361
Epoch 8/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8788 - loss: 0.3266
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8788 - loss: 0.3266
Epoch 9/10
Epoch 9/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8800 - loss: 0.3248
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8800 - loss: 0.3248
Epoch 10/10
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8809 - loss: 0.3221
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8809 - loss: 0.3221
Epoch 1/20
Epoch 1/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.6837 - loss: 0.9813
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750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.6837 - loss: 0.9813
Epoch 2/20
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8121 - loss: 0.5791
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8121 - loss: 0.5791
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8322 - loss: 0.5077
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8322 - loss: 0.5077
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8416 - loss: 0.4711
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8416 - loss: 0.4711
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8481 - loss: 0.4477
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8481 - loss: 0.4477
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8529 - loss: 0.4306
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8529 - loss: 0.4306
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8566 - loss: 0.4174
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8566 - loss: 0.4174
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8601 - loss: 0.4065
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8601 - loss: 0.4065
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8628 - loss: 0.3972
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8628 - loss: 0.3972
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8655 - loss: 0.3892
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8655 - loss: 0.3892
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8678 - loss: 0.3819
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8678 - loss: 0.3819
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8700 - loss: 0.3754
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8700 - loss: 0.3754
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8722 - loss: 0.3695
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8722 - loss: 0.3695
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8741 - loss: 0.3641
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8741 - loss: 0.3641
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8756 - loss: 0.3591
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Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8756 - loss: 0.3591
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8771 - loss: 0.3543
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8771 - loss: 0.3543
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8789 - loss: 0.3498
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8789 - loss: 0.3498
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8802 - loss: 0.3457
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8802 - loss: 0.3457
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8812 - loss: 0.3417
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8812 - loss: 0.3417
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8825 - loss: 0.3380
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8825 - loss: 0.3380
Epoch 1/20
Epoch 1/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.6748 - loss: 0.9979
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.6748 - loss: 0.9979
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8116 - loss: 0.5780
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8116 - loss: 0.5780
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8323 - loss: 0.5060
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8323 - loss: 0.5060
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8419 - loss: 0.4703
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8419 - loss: 0.4703
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8482 - loss: 0.4471
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8482 - loss: 0.4471
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8538 - loss: 0.4302
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8538 - loss: 0.4302
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8579 - loss: 0.4170
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8579 - loss: 0.4170
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8608 - loss: 0.4062
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8608 - loss: 0.4062
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8638 - loss: 0.3970
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Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8638 - loss: 0.3970
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8664 - loss: 0.3889
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8664 - loss: 0.3889
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8689 - loss: 0.3818
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8689 - loss: 0.3818
Epoch 12/20
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8706 - loss: 0.3753
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8706 - loss: 0.3753
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8725 - loss: 0.3695
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8725 - loss: 0.3695
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8741 - loss: 0.3641
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8741 - loss: 0.3641
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8760 - loss: 0.3590
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8760 - loss: 0.3590
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8773 - loss: 0.3543
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8773 - loss: 0.3543
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8786 - loss: 0.3499
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8786 - loss: 0.3499
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8800 - loss: 0.3457
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8800 - loss: 0.3457
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8811 - loss: 0.3419
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8811 - loss: 0.3419
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8823 - loss: 0.3381
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8823 - loss: 0.3381
Epoch 1/20
Epoch 1/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6323 - loss: 1.0701
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6323 - loss: 1.0701
Epoch 2/20
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7973 - loss: 0.6077
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7973 - loss: 0.6077
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8245 - loss: 0.5241
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Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8245 - loss: 0.5241
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8370 - loss: 0.4835
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8370 - loss: 0.4835
Epoch 5/20
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8441 - loss: 0.4589
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8441 - loss: 0.4589
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8499 - loss: 0.4412
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8499 - loss: 0.4412
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.4273
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.4273
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8570 - loss: 0.4160
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8570 - loss: 0.4160
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8602 - loss: 0.4064
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8602 - loss: 0.4064
Epoch 10/20
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8630 - loss: 0.3980
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8630 - loss: 0.3980
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8651 - loss: 0.3906
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8651 - loss: 0.3906
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8674 - loss: 0.3839
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8674 - loss: 0.3839
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8687 - loss: 0.3778
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8687 - loss: 0.3778
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8703 - loss: 0.3721
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8703 - loss: 0.3721
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8717 - loss: 0.3668
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8717 - loss: 0.3668
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8734 - loss: 0.3619
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8734 - loss: 0.3619
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8751 - loss: 0.3572
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Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8751 - loss: 0.3572
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8763 - loss: 0.3526
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8763 - loss: 0.3526
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8776 - loss: 0.3483
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8776 - loss: 0.3483
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8790 - loss: 0.3442
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8790 - loss: 0.3442
Epoch 1/20
Epoch 1/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.6241 - loss: 1.1816
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.6241 - loss: 1.1816
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7885 - loss: 0.6632
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7885 - loss: 0.6632
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8180 - loss: 0.5629
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8180 - loss: 0.5629
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8311 - loss: 0.5150
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8311 - loss: 0.5150
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8393 - loss: 0.4852
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8393 - loss: 0.4852
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8443 - loss: 0.4639
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8443 - loss: 0.4639
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8490 - loss: 0.4477
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8490 - loss: 0.4477
Epoch 8/20
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8525 - loss: 0.4349
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8525 - loss: 0.4349
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8565 - loss: 0.4242
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8565 - loss: 0.4242
Epoch 10/20
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8593 - loss: 0.4150
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8593 - loss: 0.4150
Epoch 11/20
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8614 - loss: 0.4068
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Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8614 - loss: 0.4068
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8634 - loss: 0.3996
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8634 - loss: 0.3996
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8653 - loss: 0.3932
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8653 - loss: 0.3932
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8668 - loss: 0.3873
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8668 - loss: 0.3873
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8681 - loss: 0.3820
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8681 - loss: 0.3820
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8696 - loss: 0.3770
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8696 - loss: 0.3770
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8712 - loss: 0.3724
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8712 - loss: 0.3724
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8729 - loss: 0.3681
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8729 - loss: 0.3681
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8742 - loss: 0.3640
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8742 - loss: 0.3640
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8754 - loss: 0.3601
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8754 - loss: 0.3601
Epoch 1/20
Epoch 1/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6098 - loss: 1.2116
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6098 - loss: 1.2116
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7849 - loss: 0.6708
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7849 - loss: 0.6708
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8170 - loss: 0.5646
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8170 - loss: 0.5646
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8306 - loss: 0.5160
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8306 - loss: 0.5160
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8383 - loss: 0.4859
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375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8383 - loss: 0.4859
Epoch 6/20
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8444 - loss: 0.4646
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8444 - loss: 0.4646
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8487 - loss: 0.4485
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8487 - loss: 0.4485
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8525 - loss: 0.4356
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8525 - loss: 0.4356
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8565 - loss: 0.4249
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8565 - loss: 0.4249
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8589 - loss: 0.4159
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8589 - loss: 0.4159
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8615 - loss: 0.4079
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8615 - loss: 0.4079
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8634 - loss: 0.4006
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8634 - loss: 0.4006
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8651 - loss: 0.3941
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8651 - loss: 0.3941
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8665 - loss: 0.3883
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8665 - loss: 0.3883
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8681 - loss: 0.3829
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8681 - loss: 0.3829
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8698 - loss: 0.3780
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8698 - loss: 0.3780
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8710 - loss: 0.3735
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8710 - loss: 0.3735
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8726 - loss: 0.3692
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8726 - loss: 0.3692
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8737 - loss: 0.3652
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Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8737 - loss: 0.3652
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8750 - loss: 0.3615
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8750 - loss: 0.3615
Epoch 1/20
Epoch 1/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5543 - loss: 1.3111
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5543 - loss: 1.3111
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7510 - loss: 0.7195
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7510 - loss: 0.7195
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8012 - loss: 0.6011
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8012 - loss: 0.6011
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8201 - loss: 0.5423
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8201 - loss: 0.5423
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8300 - loss: 0.5075
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8300 - loss: 0.5075
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8361 - loss: 0.4830
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8361 - loss: 0.4830
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8419 - loss: 0.4653
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8419 - loss: 0.4653
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8454 - loss: 0.4514
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8454 - loss: 0.4514
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8492 - loss: 0.4399
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8492 - loss: 0.4399
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8529 - loss: 0.4302
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8529 - loss: 0.4302
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8556 - loss: 0.4217
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8556 - loss: 0.4217
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8571 - loss: 0.4143
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8571 - loss: 0.4143
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8585 - loss: 0.4075
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Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8585 - loss: 0.4075
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8611 - loss: 0.4013
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8611 - loss: 0.4013
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8631 - loss: 0.3958
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8631 - loss: 0.3958
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8646 - loss: 0.3906
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8646 - loss: 0.3906
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8662 - loss: 0.3857
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8662 - loss: 0.3857
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8676 - loss: 0.3815
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8676 - loss: 0.3815
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8688 - loss: 0.3775
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8688 - loss: 0.3775
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8697 - loss: 0.3734
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8697 - loss: 0.3734
Epoch 1/20
Epoch 1/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5318 - loss: 1.4596
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5318 - loss: 1.4596
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7406 - loss: 0.8180
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7406 - loss: 0.8180
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7902 - loss: 0.6622
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7902 - loss: 0.6622
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8116 - loss: 0.5893
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8116 - loss: 0.5893
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8228 - loss: 0.5464
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8228 - loss: 0.5464
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8308 - loss: 0.5173
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8308 - loss: 0.5173
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8364 - loss: 0.4957
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Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8364 - loss: 0.4957
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8410 - loss: 0.4786
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8410 - loss: 0.4786
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8453 - loss: 0.4645
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8453 - loss: 0.4645
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8479 - loss: 0.4527
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8479 - loss: 0.4527
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8506 - loss: 0.4427
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8506 - loss: 0.4427
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8535 - loss: 0.4341
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8535 - loss: 0.4341
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8559 - loss: 0.4265
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8559 - loss: 0.4265
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8578 - loss: 0.4197
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8578 - loss: 0.4197
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8595 - loss: 0.4135
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8595 - loss: 0.4135
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8611 - loss: 0.4077
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8611 - loss: 0.4077
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8624 - loss: 0.4024
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8624 - loss: 0.4024
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8640 - loss: 0.3975
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8640 - loss: 0.3975
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8652 - loss: 0.3931
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8652 - loss: 0.3931
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8660 - loss: 0.3889
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8660 - loss: 0.3889
Epoch 1/20
Epoch 1/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5100 - loss: 1.5057
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Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5100 - loss: 1.5057
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7343 - loss: 0.8268
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7343 - loss: 0.8268
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7868 - loss: 0.6676
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7868 - loss: 0.6676
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8102 - loss: 0.5887
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8102 - loss: 0.5887
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8227 - loss: 0.5444
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8227 - loss: 0.5444
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8315 - loss: 0.5148
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8315 - loss: 0.5148
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8372 - loss: 0.4931
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8372 - loss: 0.4931
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8412 - loss: 0.4764
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8412 - loss: 0.4764
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8447 - loss: 0.4629
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8447 - loss: 0.4629
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8480 - loss: 0.4516
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8480 - loss: 0.4516
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8510 - loss: 0.4420
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8510 - loss: 0.4420
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8535 - loss: 0.4336
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8535 - loss: 0.4336
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8553 - loss: 0.4261
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8553 - loss: 0.4261
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8571 - loss: 0.4194
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8571 - loss: 0.4194
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8588 - loss: 0.4133
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Epoch 16/20
188/188 0s 2ms/step - accuracy: 0.8588 - loss: 0.4133
Epoch 16/20
188/188 0s 2ms/step - accuracy: 0.8604 - loss: 0.4077
Epoch 17/20
188/188 0s 2ms/step - accuracy: 0.8604 - loss: 0.4077
Epoch 17/20
188/188 0s 2ms/step - accuracy: 0.8622 - loss: 0.4024
188/188 0s 2ms/step - accuracy: 0.8622 - loss: 0.4024
Epoch 18/20
Epoch 18/20
188/188 0s 2ms/step - accuracy: 0.8636 - loss: 0.3975
Epoch 19/20
188/188 0s 2ms/step - accuracy: 0.8636 - loss: 0.3975
Epoch 19/20
188/188 0s 2ms/step - accuracy: 0.8650 - loss: 0.3930
Epoch 20/20
188/188 0s 2ms/step - accuracy: 0.8650 - loss: 0.3930
Epoch 20/20
188/188 0s 2ms/step - accuracy: 0.8662 - loss: 0.3887
188/188 0s 2ms/step - accuracy: 0.8662 - loss: 0.3887
Epoch 1/20
Epoch 1/20
188/188 1s 2ms/step - accuracy: 0.4453 - loss: 1.6274
Epoch 2/20
188/188 1s 2ms/step - accuracy: 0.4453 - loss: 1.6274
Epoch 2/20
188/188 0s 2ms/step - accuracy: 0.6911 - loss: 0.9137
Epoch 3/20
188/188 0s 2ms/step - accuracy: 0.6911 - loss: 0.9137
Epoch 3/20
188/188 0s 2ms/step - accuracy: 0.7457 - loss: 0.7244
Epoch 4/20
188/188 0s 2ms/step - accuracy: 0.7457 - loss: 0.7244
Epoch 4/20
188/188 0s 2ms/step - accuracy: 0.7868 - loss: 0.6358
Epoch 5/20
188/188 0s 2ms/step - accuracy: 0.7868 - loss: 0.6358
Epoch 5/20
188/188 0s 2ms/step - accuracy: 0.8074 - loss: 0.5810
Epoch 6/20
188/188 0s 2ms/step - accuracy: 0.8074 - loss: 0.5810
Epoch 6/20
188/188 0s 2ms/step - accuracy: 0.8189 - loss: 0.5453
Epoch 7/20
188/188 0s 2ms/step - accuracy: 0.8189 - loss: 0.5453
Epoch 7/20
188/188 0s 2ms/step - accuracy: 0.8274 - loss: 0.5195
Epoch 8/20
188/188 0s 2ms/step - accuracy: 0.8274 - loss: 0.5195
Epoch 8/20
188/188 0s 2ms/step - accuracy: 0.8336 - loss: 0.4995
Epoch 9/20
188/188 0s 2ms/step - accuracy: 0.8336 - loss: 0.4995
Epoch 9/20
188/188 0s 2ms/step - accuracy: 0.8378 - loss: 0.4834
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Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8378 - loss: 0.4834
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8416 - loss: 0.4701
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8416 - loss: 0.4701
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8448 - loss: 0.4592
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8448 - loss: 0.4592
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8472 - loss: 0.4498
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8472 - loss: 0.4498
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8491 - loss: 0.4416
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8491 - loss: 0.4416
Epoch 14/20
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8518 - loss: 0.4343
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8518 - loss: 0.4343
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8537 - loss: 0.4278
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8537 - loss: 0.4278
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8558 - loss: 0.4218
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8558 - loss: 0.4218
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8573 - loss: 0.4164
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8573 - loss: 0.4164
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8594 - loss: 0.4113
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8594 - loss: 0.4113
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8604 - loss: 0.4067
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8604 - loss: 0.4067
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8620 - loss: 0.4023
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8620 - loss: 0.4023
Epoch 1/20
Epoch 1/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.8014 - loss: 0.5740
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.8014 - loss: 0.5740
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.4091
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.4091
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8671 - loss: 0.3695
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Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8671 - loss: 0.3695
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8760 - loss: 0.3437
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8760 - loss: 0.3437
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8819 - loss: 0.3241
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8819 - loss: 0.3241
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8881 - loss: 0.3085
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8881 - loss: 0.3085
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8922 - loss: 0.2951
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8922 - loss: 0.2951
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8960 - loss: 0.2846
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8960 - loss: 0.2846
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9000 - loss: 0.2739
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9000 - loss: 0.2739
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9028 - loss: 0.2645
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9028 - loss: 0.2645
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9054 - loss: 0.2562
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9054 - loss: 0.2562
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9082 - loss: 0.2487
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9082 - loss: 0.2487
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9115 - loss: 0.2413
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9115 - loss: 0.2413
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9139 - loss: 0.2348
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9139 - loss: 0.2348
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9160 - loss: 0.2290
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9160 - loss: 0.2290
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9177 - loss: 0.2235
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9177 - loss: 0.2235
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9202 - loss: 0.2162
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Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9202 - loss: 0.2162
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.9216 - loss: 0.2117
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.9216 - loss: 0.2117
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.9239 - loss: 0.2048
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.9239 - loss: 0.2048
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9257 - loss: 0.1998
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9257 - loss: 0.1998
Epoch 1/20
Epoch 1/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.7966 - loss: 0.5808
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.7966 - loss: 0.5808
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8550 - loss: 0.4100
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8550 - loss: 0.4100
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8675 - loss: 0.3697
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8675 - loss: 0.3697
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8761 - loss: 0.3450
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8761 - loss: 0.3450
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8821 - loss: 0.3256
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8821 - loss: 0.3256
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8862 - loss: 0.3104
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8862 - loss: 0.3104
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8911 - loss: 0.2971
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8911 - loss: 0.2971
Epoch 8/20
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8952 - loss: 0.2859
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8952 - loss: 0.2859
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8990 - loss: 0.2760
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8990 - loss: 0.2760
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9018 - loss: 0.2679
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9018 - loss: 0.2679
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9046 - loss: 0.2607
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Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9046 - loss: 0.2607
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9072 - loss: 0.2533
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9072 - loss: 0.2533
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9096 - loss: 0.2450
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9096 - loss: 0.2450
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9118 - loss: 0.2400
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9118 - loss: 0.2400
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9134 - loss: 0.2336
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9134 - loss: 0.2336
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9156 - loss: 0.2281
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9156 - loss: 0.2281
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9172 - loss: 0.2212
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9172 - loss: 0.2212
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9194 - loss: 0.2169
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9194 - loss: 0.2169
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9213 - loss: 0.2122
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9213 - loss: 0.2122
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9231 - loss: 0.2071
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9231 - loss: 0.2071
Epoch 1/20
Epoch 1/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7813 - loss: 0.6209
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7813 - loss: 0.6209
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8475 - loss: 0.4348
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8475 - loss: 0.4348
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8604 - loss: 0.3938
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8604 - loss: 0.3938
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8684 - loss: 0.3678
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8684 - loss: 0.3678
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8731 - loss: 0.3527
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Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8731 - loss: 0.3527
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8772 - loss: 0.3385
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8772 - loss: 0.3385
Epoch 7/20
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8825 - loss: 0.3226
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8825 - loss: 0.3226
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8873 - loss: 0.3109
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8873 - loss: 0.3109
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8912 - loss: 0.2999
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8912 - loss: 0.2999
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8938 - loss: 0.2910
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8938 - loss: 0.2910
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8963 - loss: 0.2821
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8963 - loss: 0.2821
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8982 - loss: 0.2765
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8982 - loss: 0.2765
Epoch 13/20
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8981 - loss: 0.2746
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8981 - loss: 0.2746
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9006 - loss: 0.2704
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9006 - loss: 0.2704
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9017 - loss: 0.2658
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9017 - loss: 0.2658
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9046 - loss: 0.2584
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9046 - loss: 0.2584
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9075 - loss: 0.2514
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9075 - loss: 0.2514
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9088 - loss: 0.2452
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9088 - loss: 0.2452
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9129 - loss: 0.2364
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Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9129 - loss: 0.2364
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9162 - loss: 0.2299
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9162 - loss: 0.2299
Epoch 1/20
Epoch 1/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7819 - loss: 0.6342
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7819 - loss: 0.6342
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8460 - loss: 0.4383
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8460 - loss: 0.4383
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8591 - loss: 0.3976
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8591 - loss: 0.3976
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8696 - loss: 0.3702
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8696 - loss: 0.3702
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8755 - loss: 0.3484
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8755 - loss: 0.3484
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8807 - loss: 0.3308
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8807 - loss: 0.3308
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8853 - loss: 0.3171
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8853 - loss: 0.3171
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8895 - loss: 0.3049
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8895 - loss: 0.3049
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8934 - loss: 0.2947
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8934 - loss: 0.2947
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8968 - loss: 0.2852
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8968 - loss: 0.2852
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8987 - loss: 0.2768
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8987 - loss: 0.2768
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9014 - loss: 0.2693
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9014 - loss: 0.2693
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9036 - loss: 0.2627
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Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9036 - loss: 0.2627
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9061 - loss: 0.2559
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9061 - loss: 0.2559
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9083 - loss: 0.2499
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9083 - loss: 0.2499
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9104 - loss: 0.2446
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9104 - loss: 0.2446
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9126 - loss: 0.2391
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9126 - loss: 0.2391
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9142 - loss: 0.2335
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9142 - loss: 0.2335
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9161 - loss: 0.2283
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9161 - loss: 0.2283
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9177 - loss: 0.2242
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9177 - loss: 0.2242
Epoch 1/20
Epoch 1/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7789 - loss: 0.6418
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7789 - loss: 0.6418
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8484 - loss: 0.4295
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8484 - loss: 0.4295
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8619 - loss: 0.3911
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8619 - loss: 0.3911
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8717 - loss: 0.3657
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8717 - loss: 0.3657
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8774 - loss: 0.3472
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8774 - loss: 0.3472
Epoch 6/20
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8827 - loss: 0.3315
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8827 - loss: 0.3315
Epoch 7/20
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8865 - loss: 0.3183
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Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8865 - loss: 0.3183
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8899 - loss: 0.3061
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8899 - loss: 0.3061
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8932 - loss: 0.2952
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8932 - loss: 0.2952
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8965 - loss: 0.2862
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8965 - loss: 0.2862
Epoch 11/20
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8993 - loss: 0.2783
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8993 - loss: 0.2783
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9014 - loss: 0.2708
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9014 - loss: 0.2708
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9055 - loss: 0.2631
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9055 - loss: 0.2631
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9073 - loss: 0.2570
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9073 - loss: 0.2570
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9095 - loss: 0.2505
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9095 - loss: 0.2505
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9112 - loss: 0.2447
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9112 - loss: 0.2447
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9129 - loss: 0.2389
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9129 - loss: 0.2389
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9149 - loss: 0.2342
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9149 - loss: 0.2342
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9159 - loss: 0.2293
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9159 - loss: 0.2293
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9184 - loss: 0.2241
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9184 - loss: 0.2241
Epoch 1/20
Epoch 1/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7507 - loss: 0.6988
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Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7507 - loss: 0.6988
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8413 - loss: 0.4498
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8413 - loss: 0.4498
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.4035
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.4035
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8649 - loss: 0.3760
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8649 - loss: 0.3760
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8706 - loss: 0.3578
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8706 - loss: 0.3578
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8759 - loss: 0.3411
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8759 - loss: 0.3411
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8799 - loss: 0.3287
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8799 - loss: 0.3287
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8849 - loss: 0.3187
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8849 - loss: 0.3187
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8877 - loss: 0.3079
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8877 - loss: 0.3079
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8914 - loss: 0.2982
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8914 - loss: 0.2982
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8938 - loss: 0.2903
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8938 - loss: 0.2903
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8963 - loss: 0.2838
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8963 - loss: 0.2838
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8981 - loss: 0.2810
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8981 - loss: 0.2810
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8991 - loss: 0.2770
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8991 - loss: 0.2770
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9024 - loss: 0.2710
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Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9024 - loss: 0.2710
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9018 - loss: 0.2698
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9018 - loss: 0.2698
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9016 - loss: 0.2701
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9016 - loss: 0.2701
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9039 - loss: 0.2600
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9039 - loss: 0.2600
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9050 - loss: 0.2581
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9050 - loss: 0.2581
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9060 - loss: 0.2554
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9060 - loss: 0.2554
Epoch 1/20
Epoch 1/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7519 - loss: 0.7279
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7519 - loss: 0.7279
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8402 - loss: 0.4613
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8402 - loss: 0.4613
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8534 - loss: 0.4181
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8534 - loss: 0.4181
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8614 - loss: 0.3920
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8614 - loss: 0.3920
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8676 - loss: 0.3722
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8676 - loss: 0.3722
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8738 - loss: 0.3559
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8738 - loss: 0.3559
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8790 - loss: 0.3419
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8790 - loss: 0.3419
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8824 - loss: 0.3300
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8824 - loss: 0.3300
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8858 - loss: 0.3196
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Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8858 - loss: 0.3196
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8883 - loss: 0.3104
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8883 - loss: 0.3104
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8911 - loss: 0.3020
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8911 - loss: 0.3020
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8929 - loss: 0.2951
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8929 - loss: 0.2951
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8957 - loss: 0.2880
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8957 - loss: 0.2880
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8988 - loss: 0.2818
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8988 - loss: 0.2818
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9004 - loss: 0.2757
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9004 - loss: 0.2757
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9029 - loss: 0.2705
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9029 - loss: 0.2705
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9048 - loss: 0.2652
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9048 - loss: 0.2652
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9064 - loss: 0.2604
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9064 - loss: 0.2604
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9083 - loss: 0.2553
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9083 - loss: 0.2553
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9094 - loss: 0.2509
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9094 - loss: 0.2509
Epoch 1/20
Epoch 1/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7382 - loss: 0.7560
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7382 - loss: 0.7560
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8393 - loss: 0.4607
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8393 - loss: 0.4607
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8556 - loss: 0.4085
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Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8556 - loss: 0.4085
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8650 - loss: 0.3800
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8650 - loss: 0.3800
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8714 - loss: 0.3598
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8714 - loss: 0.3598
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8755 - loss: 0.3443
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8755 - loss: 0.3443
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8796 - loss: 0.3322
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8796 - loss: 0.3322
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8835 - loss: 0.3215
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8835 - loss: 0.3215
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8871 - loss: 0.3121
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8871 - loss: 0.3121
Epoch 10/20
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8902 - loss: 0.3034
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8902 - loss: 0.3034
Epoch 11/20
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8924 - loss: 0.2958
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8924 - loss: 0.2958
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8948 - loss: 0.2887
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8948 - loss: 0.2887
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8975 - loss: 0.2827
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8975 - loss: 0.2827
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8996 - loss: 0.2766
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8996 - loss: 0.2766
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9016 - loss: 0.2708
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9016 - loss: 0.2708
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9031 - loss: 0.2653
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9031 - loss: 0.2653
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9049 - loss: 0.2599
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Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9049 - loss: 0.2599
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9066 - loss: 0.2543
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9066 - loss: 0.2543
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9085 - loss: 0.2495
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9085 - loss: 0.2495
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9105 - loss: 0.2446
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9105 - loss: 0.2446
Epoch 1/20
Epoch 1/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7139 - loss: 0.8085
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7139 - loss: 0.8085
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8257 - loss: 0.4988
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8257 - loss: 0.4988
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8459 - loss: 0.4337
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8459 - loss: 0.4337
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8576 - loss: 0.3995
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8576 - loss: 0.3995
Epoch 5/20
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8639 - loss: 0.3799
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8639 - loss: 0.3799
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8681 - loss: 0.3644
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8681 - loss: 0.3644
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8728 - loss: 0.3526
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8728 - loss: 0.3526
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8785 - loss: 0.3389
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8785 - loss: 0.3389
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8822 - loss: 0.3270
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8822 - loss: 0.3270
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8848 - loss: 0.3179
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8848 - loss: 0.3179
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8878 - loss: 0.3102
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Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8878 - loss: 0.3102
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8914 - loss: 0.3025
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8914 - loss: 0.3025
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8939 - loss: 0.2950
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8939 - loss: 0.2950
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8955 - loss: 0.2893
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8955 - loss: 0.2893
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8969 - loss: 0.2838
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8969 - loss: 0.2838
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8984 - loss: 0.2794
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8984 - loss: 0.2794
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9007 - loss: 0.2734
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9007 - loss: 0.2734
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9022 - loss: 0.2685
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9022 - loss: 0.2685
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9034 - loss: 0.2632
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9034 - loss: 0.2632
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9051 - loss: 0.2590
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9051 - loss: 0.2590
Epoch 1/20
Epoch 1/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.7964 - loss: 0.5529
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.7964 - loss: 0.5529
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8420 - loss: 0.4283
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8420 - loss: 0.4283
Epoch 3/20
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8526 - loss: 0.4026
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8526 - loss: 0.4026
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8574 - loss: 0.3867
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8574 - loss: 0.3867
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8626 - loss: 0.3735
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750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8626 - loss: 0.3735
Epoch 6/20
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8665 - loss: 0.3648
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8665 - loss: 0.3648
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8691 - loss: 0.3576
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8691 - loss: 0.3576
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8717 - loss: 0.3507
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8717 - loss: 0.3507
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8738 - loss: 0.3437
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8738 - loss: 0.3437
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8765 - loss: 0.3394
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8765 - loss: 0.3394
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8803 - loss: 0.3273
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8803 - loss: 0.3273
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8785 - loss: 0.3335
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8785 - loss: 0.3335
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8811 - loss: 0.3270
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8811 - loss: 0.3270
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8823 - loss: 0.3223
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8823 - loss: 0.3223
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8840 - loss: 0.3166
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8840 - loss: 0.3166
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8845 - loss: 0.3165
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8845 - loss: 0.3165
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8857 - loss: 0.3106
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8857 - loss: 0.3106
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8871 - loss: 0.3094
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8871 - loss: 0.3094
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8882 - loss: 0.3100
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Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8882 - loss: 0.3100
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8902 - loss: 0.3018
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8902 - loss: 0.3018
Epoch 1/20
Epoch 1/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.8028 - loss: 0.5428
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.8028 - loss: 0.5428
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8446 - loss: 0.4228
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8446 - loss: 0.4228
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.3992
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8540 - loss: 0.3992
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8616 - loss: 0.3805
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8616 - loss: 0.3805
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8635 - loss: 0.3751
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8635 - loss: 0.3751
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8646 - loss: 0.3679
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8646 - loss: 0.3679
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8689 - loss: 0.3614
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8689 - loss: 0.3614
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8684 - loss: 0.3629
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8684 - loss: 0.3629
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8729 - loss: 0.3501
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8729 - loss: 0.3501
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8724 - loss: 0.3489
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8724 - loss: 0.3489
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8730 - loss: 0.3459
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8730 - loss: 0.3459
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8753 - loss: 0.3420
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8753 - loss: 0.3420
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8784 - loss: 0.3328
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Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8784 - loss: 0.3328
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8801 - loss: 0.3301
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8801 - loss: 0.3301
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8804 - loss: 0.3267
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8804 - loss: 0.3267
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8816 - loss: 0.3248
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8816 - loss: 0.3248
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8830 - loss: 0.3225
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8830 - loss: 0.3225
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8821 - loss: 0.3236
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8821 - loss: 0.3236
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8839 - loss: 0.3181
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8839 - loss: 0.3181
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8857 - loss: 0.3162
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8857 - loss: 0.3162
Epoch 1/20
Epoch 1/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.7857 - loss: 0.5834
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.7857 - loss: 0.5834
Epoch 2/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8462 - loss: 0.4265
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8462 - loss: 0.4265
Epoch 3/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8554 - loss: 0.4034
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8554 - loss: 0.4034
Epoch 4/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8564 - loss: 0.3981
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8564 - loss: 0.3981
Epoch 5/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.3914
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8568 - loss: 0.3914
Epoch 6/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8593 - loss: 0.3878
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8593 - loss: 0.3878
Epoch 7/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8629 - loss: 0.3776
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Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8629 - loss: 0.3776
Epoch 8/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8591 - loss: 0.3820
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8591 - loss: 0.3820
Epoch 9/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8643 - loss: 0.3745
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8643 - loss: 0.3745
Epoch 10/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8701 - loss: 0.3554
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8701 - loss: 0.3554
Epoch 11/20
Epoch 11/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8724 - loss: 0.3475
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8724 - loss: 0.3475
Epoch 12/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8725 - loss: 0.3444
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8725 - loss: 0.3444
Epoch 13/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8714 - loss: 0.3561
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8714 - loss: 0.3561
Epoch 14/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8751 - loss: 0.3392
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8751 - loss: 0.3392
Epoch 15/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8789 - loss: 0.3353
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8789 - loss: 0.3353
Epoch 16/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8775 - loss: 0.3404
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8775 - loss: 0.3404
Epoch 17/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8792 - loss: 0.3332
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8792 - loss: 0.3332
Epoch 18/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8802 - loss: 0.3290
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8802 - loss: 0.3290
Epoch 19/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8792 - loss: 0.3354
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8792 - loss: 0.3354
Epoch 20/20
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8808 - loss: 0.3257
750/750 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8808 - loss: 0.3257
Epoch 1/20
Epoch 1/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7980 - loss: 0.5555
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Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7980 - loss: 0.5555
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8461 - loss: 0.4204
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8461 - loss: 0.4204
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8586 - loss: 0.3841
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8586 - loss: 0.3841
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8651 - loss: 0.3629
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8651 - loss: 0.3629
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8697 - loss: 0.3510
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8697 - loss: 0.3510
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8741 - loss: 0.3413
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8741 - loss: 0.3413
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8761 - loss: 0.3313
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8761 - loss: 0.3313
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8803 - loss: 0.3262
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8803 - loss: 0.3262
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8813 - loss: 0.3248
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8813 - loss: 0.3248
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8845 - loss: 0.3116
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8845 - loss: 0.3116
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8849 - loss: 0.3114
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8849 - loss: 0.3114
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8868 - loss: 0.3092
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8868 - loss: 0.3092
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8885 - loss: 0.3040
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8885 - loss: 0.3040
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8889 - loss: 0.2956
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8889 - loss: 0.2956
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8899 - loss: 0.2979
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Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8899 - loss: 0.2979
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8908 - loss: 0.2939
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8908 - loss: 0.2939
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8938 - loss: 0.2894
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8938 - loss: 0.2894
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8964 - loss: 0.2792
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8964 - loss: 0.2792
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8973 - loss: 0.2784
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8973 - loss: 0.2784
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8969 - loss: 0.2762
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8969 - loss: 0.2762
Epoch 1/20
Epoch 1/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7985 - loss: 0.5525
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7985 - loss: 0.5525
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8487 - loss: 0.4128
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8487 - loss: 0.4128
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8602 - loss: 0.3847
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8602 - loss: 0.3847
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8668 - loss: 0.3643
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8668 - loss: 0.3643
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8721 - loss: 0.3531
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8721 - loss: 0.3531
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8733 - loss: 0.3453
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8733 - loss: 0.3453
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8761 - loss: 0.3363
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8761 - loss: 0.3363
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8784 - loss: 0.3282
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8784 - loss: 0.3282
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8816 - loss: 0.3187
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Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8816 - loss: 0.3187
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8811 - loss: 0.3183
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8811 - loss: 0.3183
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8832 - loss: 0.3159
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8832 - loss: 0.3159
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8868 - loss: 0.3059
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8868 - loss: 0.3059
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8875 - loss: 0.3020
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8875 - loss: 0.3020
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8890 - loss: 0.3030
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8890 - loss: 0.3030
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8906 - loss: 0.2943
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8906 - loss: 0.2943
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8913 - loss: 0.2928
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8913 - loss: 0.2928
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8907 - loss: 0.2952
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8907 - loss: 0.2952
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8929 - loss: 0.2847
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8929 - loss: 0.2847
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8929 - loss: 0.2888
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8929 - loss: 0.2888
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8962 - loss: 0.2780
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8962 - loss: 0.2780
Epoch 1/20
Epoch 1/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.7810 - loss: 0.5940
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.7810 - loss: 0.5940
Epoch 2/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8480 - loss: 0.4235
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8480 - loss: 0.4235
Epoch 3/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8575 - loss: 0.3926
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Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8575 - loss: 0.3926
Epoch 4/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8641 - loss: 0.3709
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8641 - loss: 0.3709
Epoch 5/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8654 - loss: 0.3636
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8654 - loss: 0.3636
Epoch 6/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8706 - loss: 0.3484
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8706 - loss: 0.3484
Epoch 7/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8752 - loss: 0.3391
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8752 - loss: 0.3391
Epoch 8/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8734 - loss: 0.3404
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8734 - loss: 0.3404
Epoch 9/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8741 - loss: 0.3382
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8741 - loss: 0.3382
Epoch 10/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8788 - loss: 0.3278
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8788 - loss: 0.3278
Epoch 11/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8837 - loss: 0.3153
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8837 - loss: 0.3153
Epoch 12/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8830 - loss: 0.3134
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8830 - loss: 0.3134
Epoch 13/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8804 - loss: 0.3209
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8804 - loss: 0.3209
Epoch 14/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8795 - loss: 0.3260
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8795 - loss: 0.3260
Epoch 15/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8836 - loss: 0.3190
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8836 - loss: 0.3190
Epoch 16/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8820 - loss: 0.3188
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8820 - loss: 0.3188
Epoch 17/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8870 - loss: 0.3097
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Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8870 - loss: 0.3097
Epoch 18/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8895 - loss: 0.3048
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8895 - loss: 0.3048
Epoch 19/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8896 - loss: 0.3031
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8896 - loss: 0.3031
Epoch 20/20
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8901 - loss: 0.3011
375/375 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8901 - loss: 0.3011
Epoch 1/20
Epoch 1/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7770 - loss: 0.6170
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7770 - loss: 0.6170
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8468 - loss: 0.4227
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8468 - loss: 0.4227
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8607 - loss: 0.3803
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8607 - loss: 0.3803
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8675 - loss: 0.3598
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8675 - loss: 0.3598
Epoch 5/20
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8744 - loss: 0.3439
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8744 - loss: 0.3439
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8764 - loss: 0.3311
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8764 - loss: 0.3311
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8796 - loss: 0.3219
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8796 - loss: 0.3219
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8826 - loss: 0.3146
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8826 - loss: 0.3146
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8850 - loss: 0.3078
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8850 - loss: 0.3078
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8881 - loss: 0.2991
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8881 - loss: 0.2991
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8897 - loss: 0.2953
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Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8897 - loss: 0.2953
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8924 - loss: 0.2873
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8924 - loss: 0.2873
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8920 - loss: 0.2891
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8920 - loss: 0.2891
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8928 - loss: 0.2849
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8928 - loss: 0.2849
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8943 - loss: 0.2806
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8943 - loss: 0.2806
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8966 - loss: 0.2749
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8966 - loss: 0.2749
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8959 - loss: 0.2745
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8959 - loss: 0.2745
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8952 - loss: 0.2793
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8952 - loss: 0.2793
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8963 - loss: 0.2768
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8963 - loss: 0.2768
Epoch 20/20
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8984 - loss: 0.2698
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8984 - loss: 0.2698
Epoch 1/20
Epoch 1/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7793 - loss: 0.6110
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7793 - loss: 0.6110
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8506 - loss: 0.4133
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8506 - loss: 0.4133
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8635 - loss: 0.3735
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8635 - loss: 0.3735
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8733 - loss: 0.3499
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8733 - loss: 0.3499
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8770 - loss: 0.3346
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Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8770 - loss: 0.3346
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8801 - loss: 0.3290
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8801 - loss: 0.3290
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8827 - loss: 0.3159
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8827 - loss: 0.3159
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8865 - loss: 0.3063
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8865 - loss: 0.3063
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8869 - loss: 0.3064
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8869 - loss: 0.3064
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8923 - loss: 0.2925
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8923 - loss: 0.2925
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8925 - loss: 0.2904
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8925 - loss: 0.2904
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8924 - loss: 0.2884
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8924 - loss: 0.2884
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8949 - loss: 0.2827
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8949 - loss: 0.2827
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8954 - loss: 0.2846
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8954 - loss: 0.2846
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8937 - loss: 0.2831
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8937 - loss: 0.2831
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8961 - loss: 0.2773
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8961 - loss: 0.2773
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8981 - loss: 0.2740
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8981 - loss: 0.2740
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9005 - loss: 0.2696
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9005 - loss: 0.2696
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9018 - loss: 0.2673
```

```
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9018 - loss: 0.2673
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9017 - loss: 0.2654
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9017 - loss: 0.2654
Epoch 1/20
Epoch 1/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7491 - loss: 0.6867
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7491 - loss: 0.6867
Epoch 2/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8377 - loss: 0.4589
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8377 - loss: 0.4589
Epoch 3/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8554 - loss: 0.4008
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8554 - loss: 0.4008
Epoch 4/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8626 - loss: 0.3774
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8626 - loss: 0.3774
Epoch 5/20
Epoch 5/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8716 - loss: 0.3503
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8716 - loss: 0.3503
Epoch 6/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8737 - loss: 0.3462
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8737 - loss: 0.3462
Epoch 7/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8764 - loss: 0.3361
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8764 - loss: 0.3361
Epoch 8/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8788 - loss: 0.3266
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8788 - loss: 0.3266
Epoch 9/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8800 - loss: 0.3248
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8800 - loss: 0.3248
Epoch 10/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8809 - loss: 0.3221
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8809 - loss: 0.3221
Epoch 11/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8820 - loss: 0.3170
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8820 - loss: 0.3170
Epoch 12/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8817 - loss: 0.3189
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8817 - loss: 0.3189
Epoch 13/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8846 - loss: 0.3081
```

```
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8846 - loss: 0.3081
Epoch 14/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8871 - loss: 0.3038
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8871 - loss: 0.3038
Epoch 15/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8896 - loss: 0.2984
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8896 - loss: 0.2984
Epoch 16/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8922 - loss: 0.2922
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8922 - loss: 0.2922
Epoch 17/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8922 - loss: 0.2884
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8922 - loss: 0.2884
Epoch 18/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8962 - loss: 0.2798
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8962 - loss: 0.2798
Epoch 19/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8954 - loss: 0.2811
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8954 - loss: 0.2811
Epoch 20/20
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8937 - loss: 0.2836
188/188 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8937 - loss: 0.2836

✓ Treinamento Q2 concluído: 81 combinações testadas

✓ Treinamento Q2 concluído: 81 combinações testadas
```

ordenação

In [14]:

```
# Ordena por melhor equilíbrio: alta acurácia média, baixa perda média e bai
# Score simples: accuracy_mean - loss_mean - (loss_std + accuracy_std)
sorted_results_q2 = sorted(
    results_q2,
    key=lambda sorted_result: (-(sorted_result['accuracy_mean']), sorted_res
)

print("Top 10 melhores combinações (melhor pro pior):")
for i,sorted_result in enumerate(sorted_results_q2[:10]):
    print(
        f"{i+1}. epochs={sorted_result['epochs']}, learning_rate={sorted_res
        f" batch={sorted_result['batch_size']}, beta1={sorted_result['beta1'
        f"loss_mean={sorted_result['loss_mean']:.4f} (±{sorted_result['loss_
        f"accuracy_mean={sorted_result['accuracy_mean']:.4f} (±{sorted_resul
    )

print("\n\nTop 10 piores combinações (melhor pro pior):")
for i,sorted_result in enumerate(sorted_results_q2[-10:-1]):
    print(
```

```
        f"{i+1}. epochs={sorted_result['epochs']}, learning_rate={sorted_res
        f" batch={sorted_result['batch_size']}, beta1={sorted_result['beta1'
        f"loss_mean={sorted_result['loss_mean']:.4f} (±{sorted_result['loss_
        f"accuracy_mean={sorted_result['accuracy_mean']:.4f} (±{sorted_resul
    )
```

```
Top 10 melhores combinações (melhor pro pior):
1. epochs=20, learning_rate=0.001, batch=64, beta1=0.7 | loss_mean=0.1998
(±0.0000), accuracy_mean=0.9257 (±0.0000)
2. epochs=20, learning_rate=0.001, batch=64, beta1=0.9 | loss_mean=0.2071
(±0.0000), accuracy_mean=0.9231 (±0.0000)
3. epochs=20, learning_rate=0.001, batch=128, beta1=0.9 | loss_mean=0.2241
(±0.0000), accuracy_mean=0.9184 (±0.0000)
4. epochs=20, learning_rate=0.001, batch=128, beta1=0.7 | loss_mean=0.2242
(±0.0000), accuracy_mean=0.9177 (±0.0000)
5. epochs=20, learning_rate=0.001, batch=64, beta1=0.99 | loss_mean=0.2299
(±0.0000), accuracy_mean=0.9162 (±0.0000)
6. epochs=20, learning_rate=0.001, batch=256, beta1=0.9 | loss_mean=0.2446
(±0.0000), accuracy_mean=0.9105 (±0.0000)
7. epochs=20, learning_rate=0.001, batch=256, beta1=0.7 | loss_mean=0.2509
(±0.0000), accuracy_mean=0.9094 (±0.0000)
8. epochs=20, learning_rate=0.001, batch=128, beta1=0.99 | loss_mean=0.2554
(±0.0000), accuracy_mean=0.9060 (±0.0000)
9. epochs=20, learning_rate=0.001, batch=256, beta1=0.99 | loss_mean=0.2590
(±0.0000), accuracy_mean=0.9051 (±0.0000)
10. epochs=10, learning_rate=0.001, batch=64, beta1=0.7 | loss_mean=0.2645
(±0.0000), accuracy_mean=0.9028 (±0.0000)


Top 10 piores combinações (melhor pro pior):
1. epochs=10, learning_rate=0.0001, batch=256, beta1=0.9 | loss_mean=0.4516
(±0.0000), accuracy_mean=0.8480 (±0.0000)
2. epochs=10, learning_rate=0.0001, batch=256, beta1=0.7 | loss_mean=0.4527
(±0.0000), accuracy_mean=0.8479 (±0.0000)
3. epochs=5, learning_rate=0.0001, batch=64, beta1=0.99 | loss_mean=0.4589
(±0.0000), accuracy_mean=0.8441 (±0.0000)
4. epochs=10, learning_rate=0.0001, batch=256, beta1=0.99 | loss_mean=0.4701
(±0.0000), accuracy_mean=0.8416 (±0.0000)
5. epochs=5, learning_rate=0.0001, batch=128, beta1=0.7 | loss_mean=0.4852
(±0.0000), accuracy_mean=0.8393 (±0.0000)
6. epochs=5, learning_rate=0.0001, batch=128, beta1=0.9 | loss_mean=0.4859
(±0.0000), accuracy_mean=0.8383 (±0.0000)
7. epochs=5, learning_rate=0.0001, batch=128, beta1=0.99 | loss_mean=0.5075
(±0.0000), accuracy_mean=0.8300 (±0.0000)
8. epochs=5, learning_rate=0.0001, batch=256, beta1=0.7 | loss_mean=0.5464
(±0.0000), accuracy_mean=0.8228 (±0.0000)
9. epochs=5, learning_rate=0.0001, batch=256, beta1=0.9 | loss_mean=0.5444
(±0.0000), accuracy_mean=0.8227 (±0.0000)
```

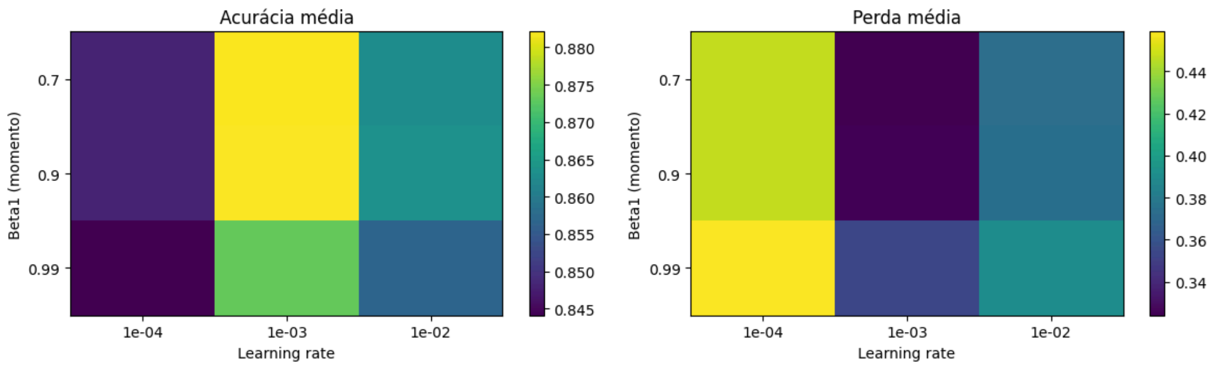
comparações

In [15]:

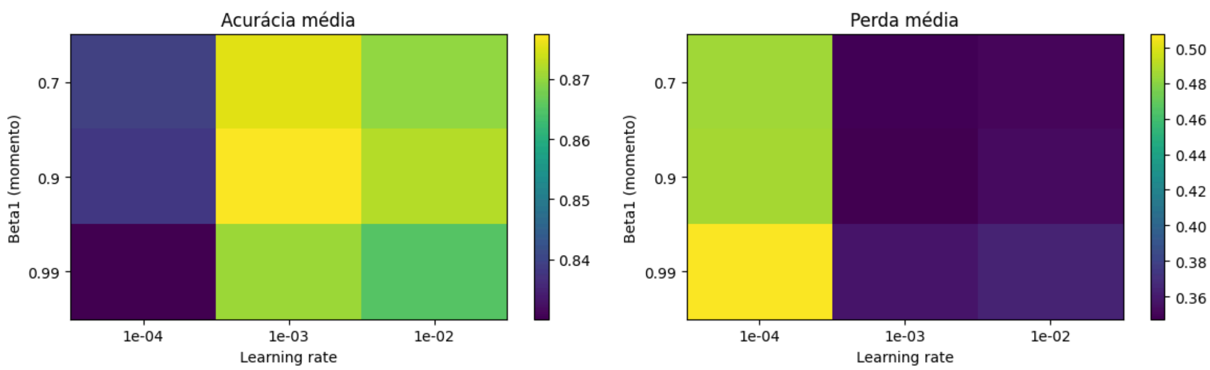
```
# Loop sobre epochs e batch_size: para cada combinação, gera mapas de calor
# usando as métricas agregadas em `results`.

# Conjuntos ordenados de parâmetros disponíveis em `results`
```

```python
unique_epochs = sorted(list({r['epochs'] for r in results_q2}))
unique_batch_sizes = sorted(list({r['batch_size'] for r in results_q2}))
unique_beta1s = sorted(list({r['beta1'] for r in results_q2}))
unique_learning_rates = sorted(list({r['learning_rate'] for r in results_q2}

# Para cada (epochs, batch_size), monta matrizes 2D [beta1 x lr] de acurácia
for epochs in unique_epochs:
    for batch_size in unique_batch_sizes:
        # Filtra resultados referentes à combinação fixa (epochs, batch_size
        subset = [r for r in results_q2 if r['epochs'] == epochs and r['batc
        if not subset:
            continue
        # Índices para mapeamento beta1 x lr
        b1_index = {b1: i for i, b1 in enumerate(unique_beta1s)}
        lr_index = {lr: j for j, lr in enumerate(unique_learning_rates)}

        accuracy_matrix = np.full((len(unique_beta1s), len(unique_learning_r
        loss_matrix = np.full((len(unique_beta1s), len(unique_learning_rates

        for r in subset:
            i = b1_index[r['beta1']]
            j = lr_index[r['learning_rate']]
            accuracy_matrix[i, j] = r['accuracy_mean']
            loss_matrix[i, j] = r['loss_mean']

        # Visualização dos mapas de calor
        fig, axes = plt.subplots(1, 2, figsize=(12, 4))
        fig.suptitle(f"Epochs={epochs}, Batch={batch_size}")

        im0 = axes[0].imshow(accuracy_matrix, cmap='viridis', aspect='auto')
        axes[0].set_title('Acurácia média')
        axes[0].set_xticks(range(len(unique_learning_rates)))
        axes[0].set_xticklabels([f"{lr:.0e}" for lr in unique_learning_rates
        axes[0].set_yticks(range(len(unique_beta1s)))
        axes[0].set_yticklabels([str(b1) for b1 in unique_beta1s])
        axes[0].set_xlabel('Learning rate')
        axes[0].set_ylabel('Beta1 (momento)')
        plt.colorbar(im0, ax=axes[0])

        im1 = axes[1].imshow(loss_matrix, cmap='viridis', aspect='auto')
        axes[1].set_title('Perda média')
        axes[1].set_xticks(range(len(unique_learning_rates)))
        axes[1].set_xticklabels([f"{lr:.0e}" for lr in unique_learning_rates
        axes[1].set_yticks(range(len(unique_beta1s)))
        axes[1].set_yticklabels([str(b1) for b1 in unique_beta1s])
        axes[1].set_xlabel('Learning rate')
        axes[1].set_ylabel('Beta1 (momento)')
        plt.colorbar(im1, ax=axes[1])

        plt.tight_layout()
        plt.show()
#esperado: loss com cores invertidas de accuracy -> equilibrados
```

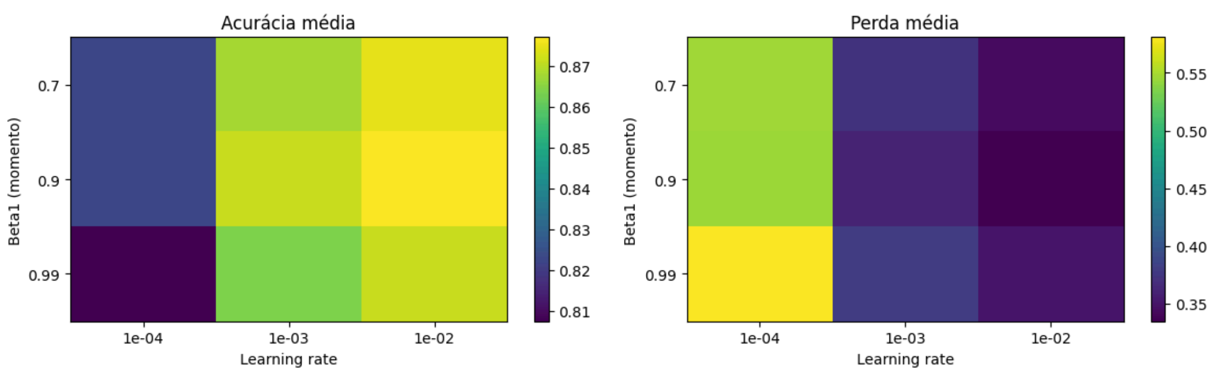
Epochs=5, Batch=64



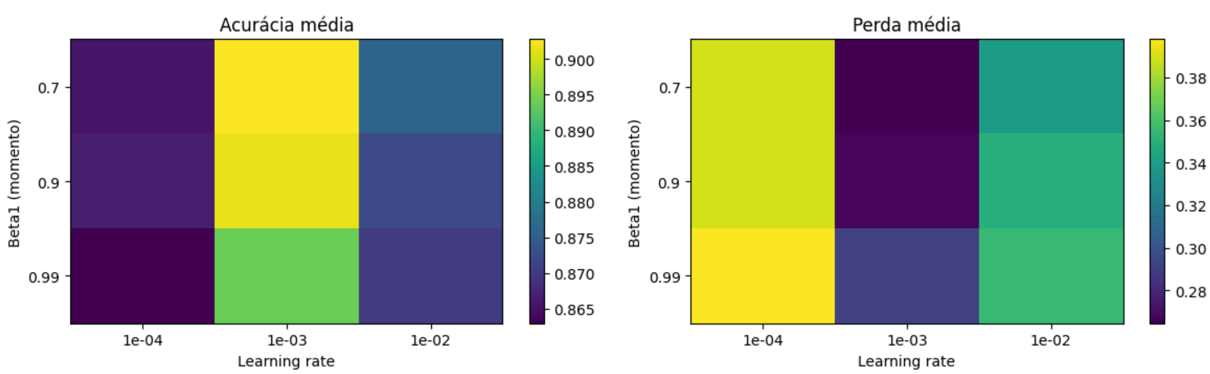
Epochs=5, Batch=128

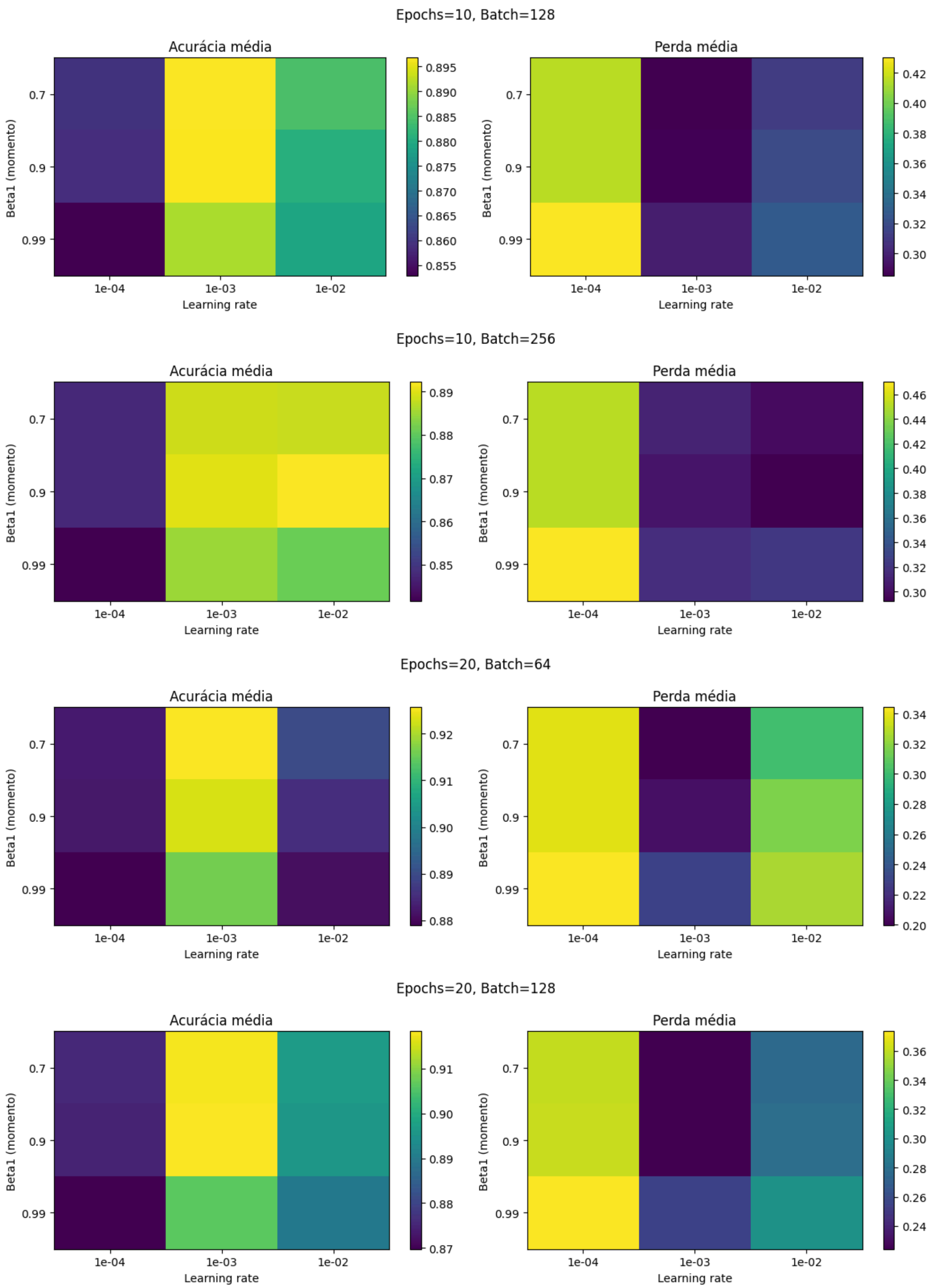


Epochs=5, Batch=256

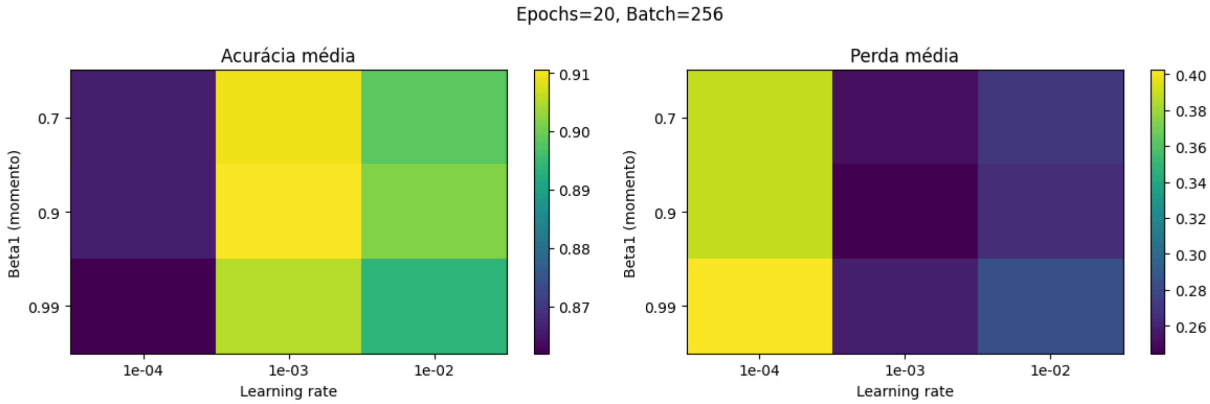


Epochs=10, Batch=64





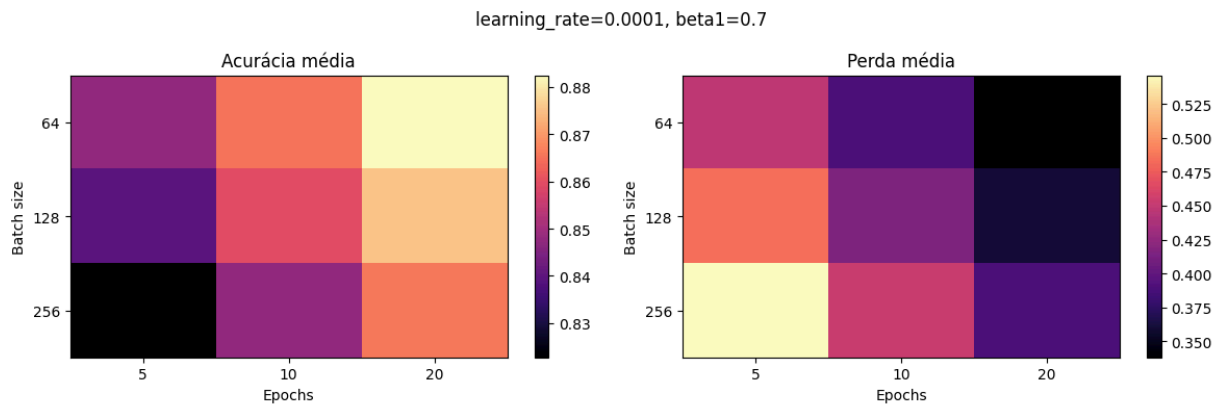
Epochs=10, Batch=128
Acurácia média
Perda média
Epochs=10, Batch=256
Acurácia média
Perda média
Epochs=20, Batch=64
Acurácia média
Perda média
Epochs=20, Batch=128
Acurácia média
Perda média
Beta1 (momento)
0.7
0.9
0.99
1e-04
1e-03
1e-02
Learning rate
0.855
0.860
0.865
0.870
0.875
0.880
0.885
0.890
0.895
0.30
0.32
0.34
0.36
0.38
0.40
0.42
0.44
0.46
0.85
0.86
0.87
0.88
0.89
0.90
0.91
0.92
0.20
0.22
0.24
0.26
0.28

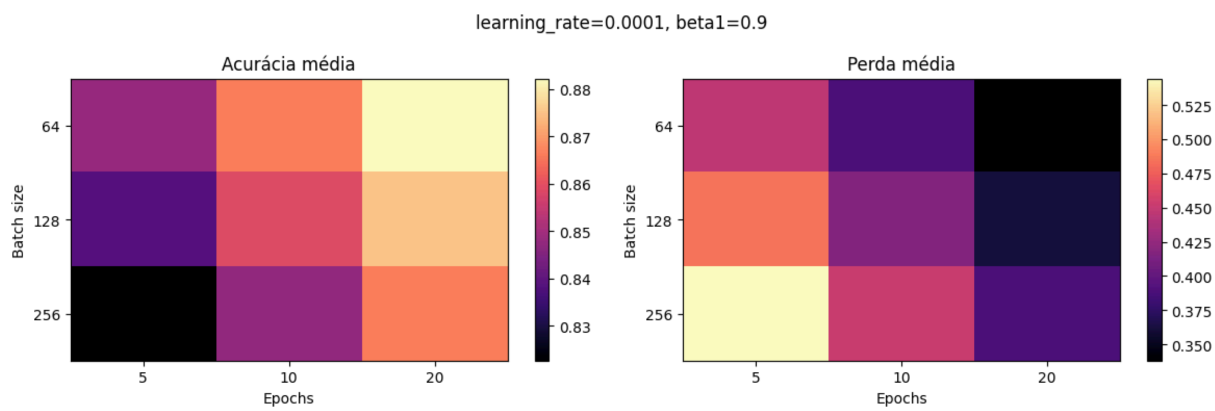


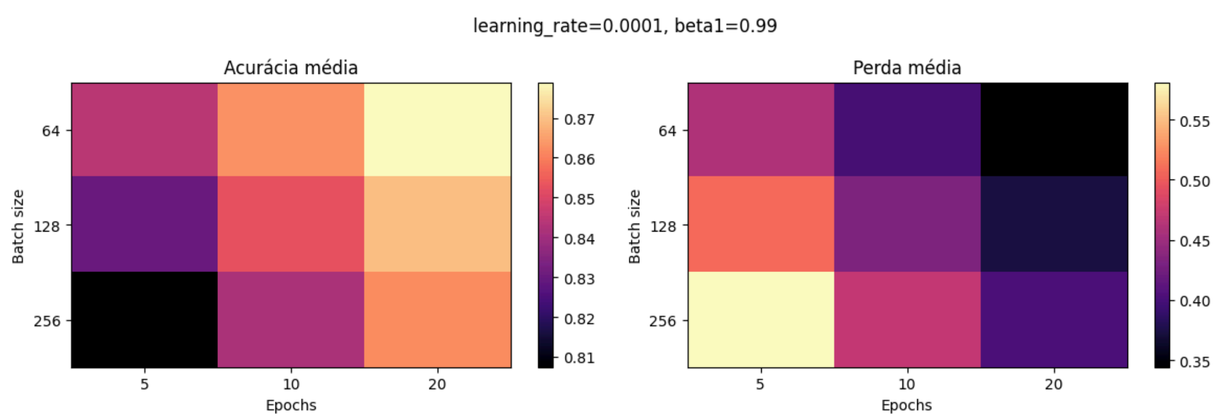
visualização alternativa

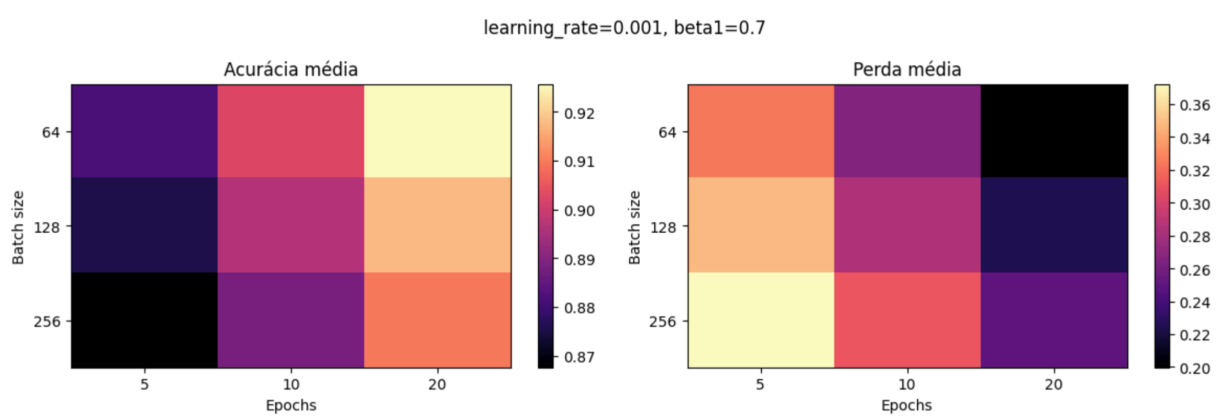
In [16]:
```
# Para cada (lr, beta1), monta matrizes 2D [epoch x batch_size] de acurácia
for learning_rate in unique_learning_rates:
    for beta1 in unique_beta1s:
        # Filtra resultados referentes à combinação fixa (epochs, batch_size
        subset = [r for r in results_q2 if r['learning_rate'] == learning_ra
        if not subset:
            continue
        # Índices para mapeamento beta1 x lr
        ba_index = {ba: i for i, ba in enumerate(unique_batch_sizes)}
        ep_index = {ep: j for j, ep in enumerate(unique_epochs)}

        accuracy_matrix = np.full((len(unique_batch_sizes), len(unique_epoch
        loss_matrix = np.full((len(unique_batch_sizes), len(unique_epochs)),

        for r in subset:
            i = ba_index[r['batch_size']]
            j = ep_index[r['epochs']]
            accuracy_matrix[i, j] = r['accuracy_mean']
            loss_matrix[i, j] = r['loss_mean']

        # Visualização dos mapas de calor
        fig, axes = plt.subplots(1, 2, figsize=(12, 4))
        fig.suptitle(f"learning_rate={learning_rate}, beta1={beta1}")

        im0 = axes[0].imshow(accuracy_matrix, cmap='magma', aspect='auto')
        axes[0].set_title('Acurácia média')
        axes[0].set_xticks(range(len(unique_epochs)))
        axes[0].set_xticklabels([str(ep) for ep in unique_epochs])
        axes[0].set_yticks(range(len(unique_batch_sizes)))
        axes[0].set_yticklabels([str(b) for b in unique_batch_sizes])
        axes[0].set_xlabel('Epochs')
        axes[0].set_ylabel('Batch size')
        plt.colorbar(im0, ax=axes[0])

        im1 = axes[1].imshow(loss_matrix, cmap='magma', aspect='auto')
        axes[1].set_title('Perda média')
        axes[1].set_xticks(range(len(unique_epochs)))
        axes[1].set_xticklabels([str(ep) for ep in unique_epochs])
        axes[1].set_yticks(range(len(unique_batch_sizes)))
        axes[1].set_yticklabels([str(b) for b in unique_batch_sizes])
```

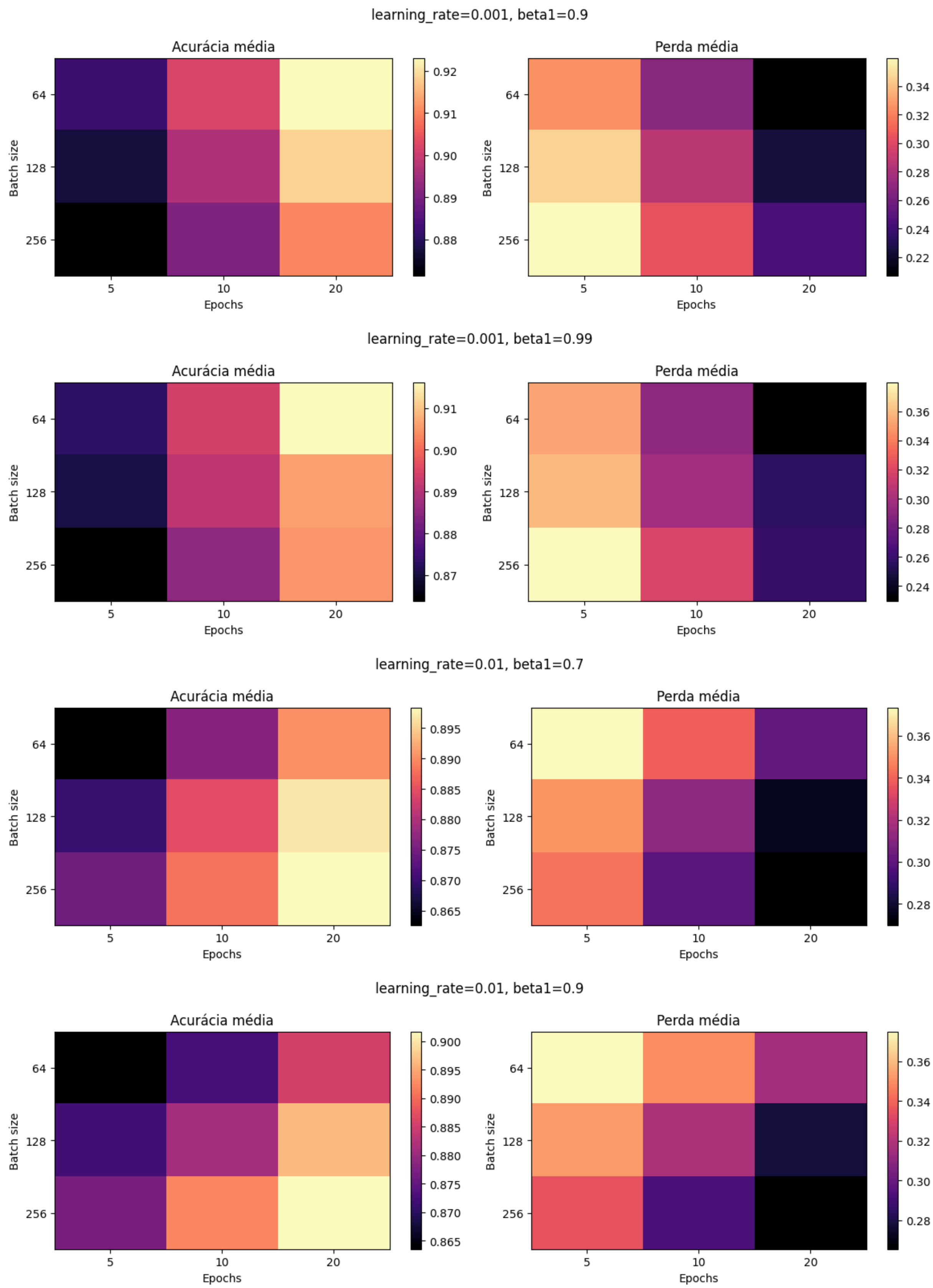
```
    axes[1].set_xlabel('Epochs')
    axes[1].set_ylabel('Batch size')
    plt.colorbar(im1, ax=axes[1])

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



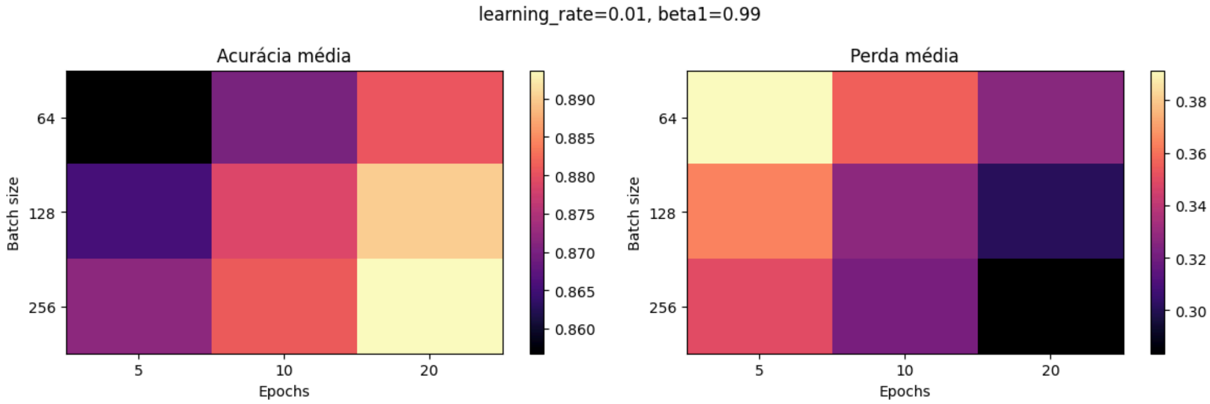








learning_rate=0.001, beta1=0.9
Acurácia média
Perda média
learning_rate=0.001, beta1=0.99
Acurácia média
Perda média
learning_rate=0.01, beta1=0.7
Acurácia média
Perda média
learning_rate=0.01, beta1=0.9
Acurácia média
Perda média
Batch size
64
128
256
Epochs
5
10
20



métricas

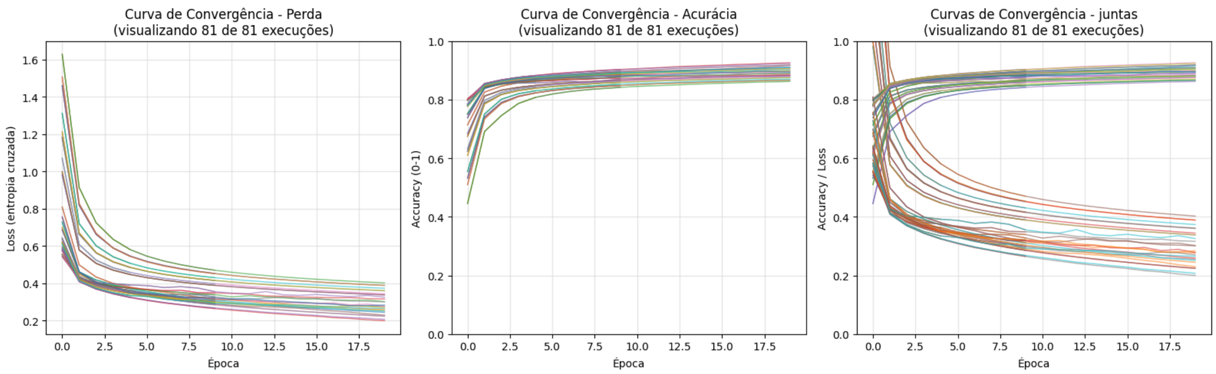
In [40]:

```
print(f"Total de combinações testadas: {len(results_q2)}")


print("========== CURVAS DE CONVERGÊNCIA ==========")
sample_step = 1 # mostra modelos 1 a 1, ajuste para visualização menos polui
sample_indices = list(range(0, len(histories_q2), sample_step)) #start, stop

fig, axes = plt.subplots(1, 3, figsize=(16, 5))

#perda
for idx in sample_indices:
    h = histories_q2[idx]
    axes[0].plot(h.history['loss'], alpha=0.6, linewidth=1)
axes[0].set_title(f'Curva de Convergência - Perda\n(visualizando {len(sample
axes[0].set_xlabel('Época')
axes[0].set_ylabel('Loss (entropia cruzada)')
axes[0].grid(True, alpha=0.3)

#acurácia
for idx in sample_indices:
    h = histories_q2[idx]
    axes[1].plot(h.history['accuracy'], alpha=0.6, linewidth=1)
axes[1].set_title(f'Curva de Convergência - Acurácia\n(visualizando {len(sam
axes[1].set_xlabel('Época')
axes[1].set_ylabel('Accuracy (0-1)')
axes[1].grid(True, alpha=0.3)
axes[1].set_ylim([0, 1])

#as duas
for idx in sample_indices:
    h = histories_q2[idx]
    axes[2].plot(h.history['accuracy'], alpha=0.6, linewidth=1)
    axes[2].plot(h.history['loss'], alpha=0.6, linewidth=1)
axes[2].set_title(f'Curvas de Convergência - juntas\n(visualizando {len(samp
axes[2].set_xlabel('Época')
axes[2].set_ylabel('Accuracy / Loss')
axes[2].grid(True, alpha=0.3)
axes[2].set_ylim([0, 1])

plt.tight_layout()
```

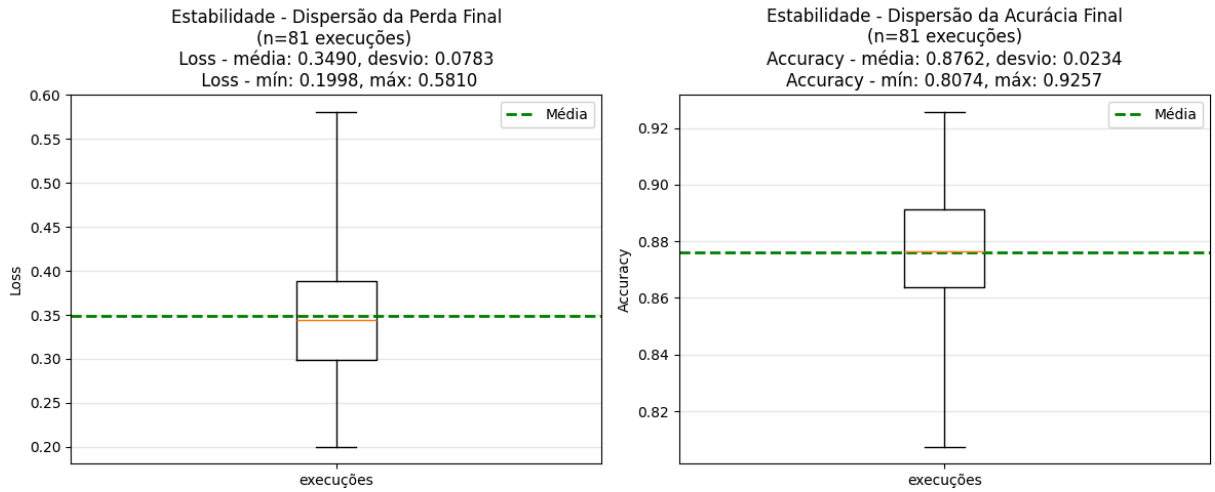
```
plt.show()


print(f"\n========== ESTABILIDADE (n={len(train_losses)}) ==========")
train_losses = [h.history['loss'][-1] for h in histories_q2]
train_accuracies = [h.history['accuracy'][-1] for h in histories_q2]


fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Boxplot de Loss
axes[0].boxplot(train_losses, whis=(0, 100))
axes[0].set_title(f'Estabilidade - Dispersão da Perda Final\n(n={len(train_l
                  f'\n Loss - média: {np.mean(train_losses):.4f}, desvio: {n
                  f'\n Loss - mín: {np.min(train_losses):.4f}, máx: {np.max(
axes[0].set_ylabel('Loss')
axes[0].set_xticklabels(['execuções'])
axes[0].axhline(y=np.mean(train_losses), color='green', linestyle='--', line
#pontos individuais
#axes[0].scatter([1]*len(train_losses), train_losses, color='red', zorder=2)
axes[0].legend()
axes[0].grid(True, alpha=0.3, axis='y')

# Boxplot de Accuracy
axes[1].boxplot(train_accuracies, whis=(0, 100))
axes[1].set_title(f'Estabilidade - Dispersão da Acurácia Final\n(n={len(trai
                  f'\nAccuracy - média: {np.mean(train_accuracies):.4f}, des
                  f'\nAccuracy - mín: {np.min(train_accuracies):.4f}, máx: {
axes[1].set_ylabel('Accuracy')
axes[1].set_xticklabels(['execuções'])
axes[1].axhline(y=np.mean(train_accuracies), color='green', linestyle='--',
#pontos individuais
#axes[1].scatter([1]*len(train_accuracies), train_accuracies, color='red', z
axes[1].legend()
axes[1].grid(True, alpha=0.3, axis='y')

plt.tight_layout()
plt.show()


print("\n========== TEMPO DE TREINAMENTO ==========")

all_times = [r['time_mean'] for r in results_q2]
all_time_stds = [r['time_std'] for r in results_q2]
#média e desvio do tempo de execução do mesmo modelo para todas as seeds

print(f"Tempo médio geral: {np.mean(all_times):.2f}s (±{np.std(all_times):.2
print(f"Tempo mínimo: {np.min(all_times):.2f}s")
print(f"Tempo máximo: {np.max(all_times):.2f}s")

#tempo por quantidade total de épocas do modelo
time_by_epochs = {}
for r in results_q2:
    ep = r['epochs']
    if ep not in time_by_epochs:
        time_by_epochs[ep] = []
```

```
    time_by_epochs[ep].append(r['time_mean'])

print("\nTempo médio por número de épocas:")
for ep in sorted(time_by_epochs.keys()):
    print(f"  {ep} épocas: {np.mean(time_by_epochs[ep]):.2f}s (±{np.std(time

# Gráfico de tempo por épocas
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

epochs_list = sorted(time_by_epochs.keys())
mean_times = [np.mean(time_by_epochs[ep]) for ep in epochs_list]
std_times = [np.std(time_by_epochs[ep]) for ep in epochs_list]

axes[0].set_title('Tempo de Treinamento vs Número de Épocas')
axes[0].bar(epochs_list, mean_times, yerr=std_times, alpha=0.7, capsize=10,
axes[0].set_xlabel('Número de Épocas')
axes[0].set_ylabel('Tempo Médio de Treinamento (s)')
axes[0].grid(True, alpha=0.3, axis='y')


axes[1].set_title('Distribuição dos Tempos de Treinamento')
axes[1].hist(all_times, bins=25, alpha=0.7, color='teal', edgecolor='black')
axes[1].axvline(np.mean(all_times), color='red', linestyle='--', linewidth=2
axes[1].set_xlabel('Tempo de Treinamento (s)')
axes[1].set_ylabel('Frequência')
axes[1].legend()
axes[1].grid(True, alpha=0.3, axis='y')

plt.tight_layout()
plt.show()


print("\n========== TOP 5 COMBINAÇÕES MAIS RÁPIDAS ==========")
sorted_by_time = sorted(results_q2, key=lambda x: x['time_mean'])
for i, r in enumerate(sorted_by_time[:5], 1):
    print(f"{i}. Tempo: {r['time_mean']:.2f}s | epochs={r['epochs']}, lr={r[
          f"batch={r['batch_size']}, beta1={r['beta1']}")
    print(f"   Loss: {r['loss_mean']:.4f}, Acc: {r['accuracy_mean']:.4f}")

print("\n========== TOP 5 COMBINAÇÕES MAIS LENTAS ==========")
for i, r in enumerate(sorted_by_time[-5:], 1):
    print(f"{i}. Tempo: {r['time_mean']:.2f}s | epochs={r['epochs']}, lr={r[
          f"batch={r['batch_size']}, beta1={r['beta1']}")
    print(f"   Loss: {r['loss_mean']:.4f}, Acc: {r['accuracy_mean']:.4f}")
```

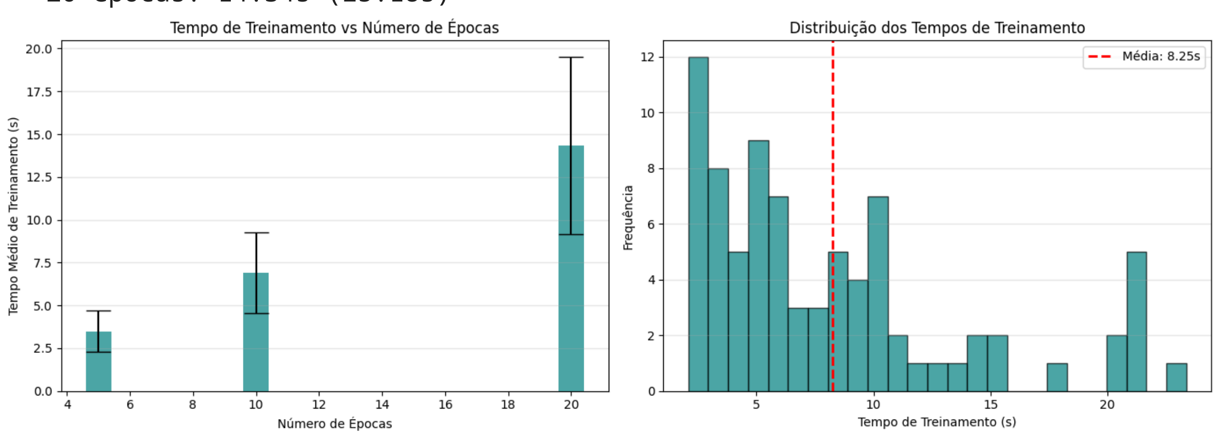
```
Total de combinações testadas: 81
========== CURVAS DE CONVERGÊNCIA ==========
```




```
========== ESTABILIDADE (n=81) ==========
```




```
========== TEMPO DE TREINAMENTO ==========
Tempo médio geral: 8.25s (±5.64s)
Tempo mínimo: 2.09s
Tempo máximo: 23.35s

Tempo médio por número de épocas:
  5 épocas: 3.49s (±1.20s)
  10 épocas: 6.93s (±2.36s)
  20 épocas: 14.34s (±5.18s)
```



```
========== TOP 5 COMBINAÇÕES MAIS RÁPIDAS ==========
1. Tempo: 2.09s | epochs=5, lr=0.01, batch=256, beta1=0.7
   Loss: 0.3439, Acc: 0.8744
2. Tempo: 2.15s | epochs=5, lr=0.0001, batch=256, beta1=0.9
   Loss: 0.5444, Acc: 0.8227
3. Tempo: 2.21s | epochs=5, lr=0.0001, batch=256, beta1=0.99
   Loss: 0.5810, Acc: 0.8074
4. Tempo: 2.22s | epochs=5, lr=0.0001, batch=256, beta1=0.7
   Loss: 0.5464, Acc: 0.8228
5. Tempo: 2.23s | epochs=5, lr=0.001, batch=256, beta1=0.9
   Loss: 0.3598, Acc: 0.8714

========== TOP 5 COMBINAÇÕES MAIS LENTAS ==========
1. Tempo: 20.98s | epochs=20, lr=0.0001, batch=64, beta1=0.99
   Loss: 0.3442, Acc: 0.8790
2. Tempo: 21.25s | epochs=20, lr=0.0001, batch=64, beta1=0.7
   Loss: 0.3380, Acc: 0.8825
3. Tempo: 21.39s | epochs=20, lr=0.01, batch=64, beta1=0.99
   Loss: 0.3257, Acc: 0.8808
4. Tempo: 21.39s | epochs=20, lr=0.001, batch=64, beta1=0.9
   Loss: 0.2071, Acc: 0.9231
5. Tempo: 23.35s | epochs=20, lr=0.001, batch=64, beta1=0.7
   Loss: 0.1998, Acc: 0.9257
```

Questão 03: topologia

Parâmetros ajustados

In [18]:
```python
num_hidden_layers_options = [1, 2, 3]
neurons_per_layer_options = {
    1: [[64], [128], [256]],
    2: [[64, 32], [128, 64], [256, 128]],
    3: [[128, 64, 32], [256, 128, 64], [512, 256, 128]]
}
```

treinamento

In [41]:
```python
#TODO: aumentar número de seeds para teste exaustivo final
#TODO: treino e validação
import time
from sklearn.metrics import f1_score, precision_score, recall_score

seeds_q3 = spaced_seeds(1, base, PRIME_STEP)
results_q3 = []
histories_q3 = []

for num_hidden_layers in num_hidden_layers_options:
    for neurons_per_layer in neurons_per_layer_options[num_hidden_layers]:
        run_losses = []
        run_accuracies = []
        run_times = []
        run_f1_scores = []
```

```
        run_precisions = []
        run_recalls = []

        for s in seeds_q3:
            keras.utils.set_random_seed(s)
            model = build_model(learning_rate=0.001, beta1=0.7, num_hidden_l

            start_time = time.time()
            h = model.fit(x_train, y_train, epochs=20, batch_size=64, verbos
            training_time = time.time() - start_time

            #predição necessária para métricas adicionai
            y_pred = model.predict(x_train, verbose=0)
            y_pred_classes = np.argmax(y_pred, axis=1)

            f1 = f1_score(y_train, y_pred_classes, average='weighted')
            precision = precision_score(y_train, y_pred_classes, average='we
            recall = recall_score(y_train, y_pred_classes, average='weighted

            run_losses.append(h.history['loss'][-1])
            run_accuracies.append(h.history['accuracy'][-1])
            run_times.append(training_time)
            run_f1_scores.append(f1)
            run_precisions.append(precision)
            run_recalls.append(recall)
            #TODO
            histories_q3.append({
                'history': h,
                'num_hidden_layers': num_hidden_layers,
                'neurons_per_layer': neurons_per_layer
            })

        results_q3.append({
            'number of hidden layers': num_hidden_layers,
            'neurons per layer': neurons_per_layer,
            'loss_mean': float(np.mean(run_losses)),
            'loss_std': float(np.std(run_losses)),
            'accuracy_mean': float(np.mean(run_accuracies)),
            'accuracy_std': float(np.std(run_accuracies)),
            'time_mean': float(np.mean(run_times)),
            'time_std': float(np.std(run_times)),
            'f1_mean': float(np.mean(run_f1_scores)),
            'f1_std': float(np.std(run_f1_scores)),
            'precision_mean': float(np.mean(run_precisions)),
            'precision_std': float(np.std(run_precisions)),
            'recall_mean': float(np.mean(run_recalls)),
            'recall_std': float(np.std(run_recalls))
        })
```

```
✓ Treinamento Q3 concluído: 9 configurações testadas
```

Ordenação

In [60]:

```
# Ordena por melhor equilíbrio: alta acurácia média, baixa perda média e bai
# Score simples: accuracy_mean - loss_mean - (loss_std + accuracy_std)
```

```python
#9 combinações possíveis
sorted_results_q3 = sorted(
    results_q3,
    key=lambda sorted_result_q3: (-(sorted_result_q3['accuracy_mean']), sort
)

print("Top combinações (ordem decrescente):")
for i,sorted_result_q3 in enumerate(sorted_results_q3):
    print(
        f"\n{i+1}.number of hidden layers={sorted_result_q3['number of hidde
        f" | neurons per layer={sorted_result_q3['neurons per layer']}"
        f"\n    loss_mean={sorted_result_q3['loss_mean']:.4f} (±{sorted_resu
        f"\n    accuracy_mean={sorted_result_q3['accuracy_mean']:.4f} (±{sor
        "\n----------Não considerados para ordenação----------"
        f"\n    time_mean={sorted_result_q3['time_mean']:.2f}s (±{sorted_res
        f"\n    F1={sorted_result_q3['f1_mean']:.4f} (±{sorted_result_q3['f1
        f"\n    Precision={sorted_result_q3['precision_mean']:.4f} (±{sorted
        f"\n    Recall={sorted_result_q3['recall_mean']:.4f} (±{sorted_resul
    )
```

```
Top combinações (ordem decrescente):

1.number of hidden layers=2 | neurons per layer=[256, 128]
    loss_mean=0.1318 (±0.0000),
    accuracy_mean=0.9493 (±0.0000)
----------Não considerados para ordenação----------
    time_mean=32.13s (±0.00s)
    F1=0.9338 (±0.0000)
    Precision=0.9339 (±0.0000)
    Recall=0.9338 (±0.0000)

2.number of hidden layers=1 | neurons per layer=[256]
    loss_mean=0.1445 (±0.0000),
    accuracy_mean=0.9475 (±0.0000)
----------Não considerados para ordenação----------
    time_mean=25.57s (±0.00s)
    F1=0.9284 (±0.0000)
    Precision=0.9303 (±0.0000)
    Recall=0.9284 (±0.0000)

3.number of hidden layers=3 | neurons per layer=[512, 256, 128]
    loss_mean=0.1416 (±0.0000),
    accuracy_mean=0.9452 (±0.0000)
----------Não considerados para ordenação----------
    time_mean=68.81s (±0.00s)
    F1=0.9242 (±0.0000)
    Precision=0.9272 (±0.0000)
    Recall=0.9242 (±0.0000)

4.number of hidden layers=3 | neurons per layer=[256, 128, 64]
    loss_mean=0.1449 (±0.0000),
    accuracy_mean=0.9435 (±0.0000)
----------Não considerados para ordenação----------
    time_mean=32.14s (±0.00s)
    F1=0.9320 (±0.0000)
    Precision=0.9331 (±0.0000)
    Recall=0.9319 (±0.0000)

5.number of hidden layers=2 | neurons per layer=[128, 64]
    loss_mean=0.1602 (±0.0000),
    accuracy_mean=0.9405 (±0.0000)
----------Não considerados para ordenação----------
    time_mean=20.93s (±0.00s)
    F1=0.9278 (±0.0000)
    Precision=0.9282 (±0.0000)
    Recall=0.9279 (±0.0000)

6.number of hidden layers=1 | neurons per layer=[128]
    loss_mean=0.1725 (±0.0000),
    accuracy_mean=0.9371 (±0.0000)
----------Não considerados para ordenação----------
    time_mean=21.87s (±0.00s)
    F1=0.9274 (±0.0000)
    Precision=0.9285 (±0.0000)
    Recall=0.9276 (±0.0000)
```

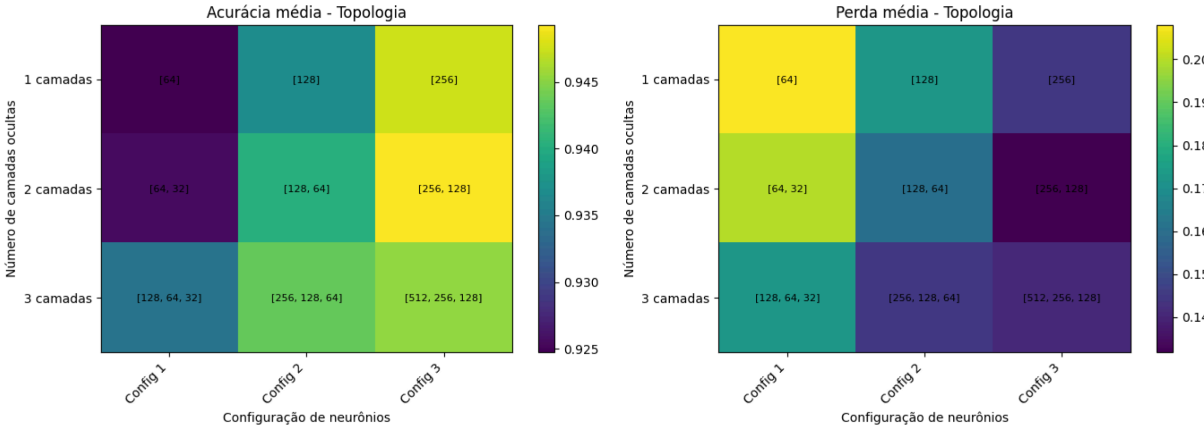
```
7.number of hidden layers=3 | neurons per layer=[128, 64, 32]
    loss_mean=0.1721 (±0.0000),
    accuracy_mean=0.9344 (±0.0000)
----------Não considerados para ordenação----------
    time_mean=23.40s (±0.00s)
    F1=0.9202 (±0.0000)
    Precision=0.9216 (±0.0000)
    Recall=0.9205 (±0.0000)

8.number of hidden layers=2 | neurons per layer=[64, 32]
    loss_mean=0.1998 (±0.0000),
    accuracy_mean=0.9257 (±0.0000)
----------Não considerados para ordenação----------
    time_mean=17.86s (±0.00s)
    F1=0.9200 (±0.0000)
    Precision=0.9215 (±0.0000)
    Recall=0.9208 (±0.0000)

9.number of hidden layers=1 | neurons per layer=[64]
    loss_mean=0.2080 (±0.0000),
    accuracy_mean=0.9247 (±0.0000)
----------Não considerados para ordenação----------
    time_mean=17.15s (±0.00s)
    F1=0.9194 (±0.0000)
    Precision=0.9203 (±0.0000)
    Recall=0.9201 (±0.0000)
```

comparação

In [ ]:

```
unique_num_hidden_layers = sorted(list({r['number of hidden layers'] for r i

# Para cada número de camadas, ordena as configurações de neurônios
# Como temos 3 opções por número de camadas, indexamos sequencialmente
configs_per_layers = {nh: [] for nh in unique_num_hidden_layers}
for r in results_q3:
    nh = r['number of hidden layers']
    nn = r['neurons per layer']
    if nn not in configs_per_layers[nh]:
        configs_per_layers[nh].append(nn)

# Ordena cada lista por tamanho crescente (total de neurônios)
for nh in configs_per_layers:
    configs_per_layers[nh].sort(key=lambda x: sum(x))

# Número máximo de configurações por número de camadas
max_configs = max(len(configs_per_layers[nh]) for nh in unique_num_hidden_la

# Matrizes para os mapas de calor
accuracy_matrix = np.full((len(unique_num_hidden_layers), max_configs), np.n
loss_matrix = np.full((len(unique_num_hidden_layers), max_configs), np.nan)


for i, nh in enumerate(unique_num_hidden_layers):
    for j, nn in enumerate(configs_per_layers[nh]):
        match = [r for r in results_q3 if r['number of hidden layers'] == nh
```

```python
        if match:
            accuracy_matrix[i, j] = match[0]['accuracy_mean']
            loss_matrix[i, j] = match[0]['loss_mean']

#Labels dos gráficos
col_labels = []
for nh in unique_num_hidden_layers:
    for nn in configs_per_layers[nh]:
        col_labels.append(str(nn))

config_labels = [f"Config {j+1}" for j in range(max_configs)]

# Visualização dos mapas de calor
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

im0 = axes[0].imshow(accuracy_matrix, cmap='viridis', aspect='auto')
axes[0].set_title('Acurácia média - Topologia')
axes[0].set_xticks(range(max_configs))
axes[0].set_xticklabels(config_labels, rotation=45, ha='right')
axes[0].set_yticks(range(len(unique_num_hidden_layers)))
axes[0].set_yticklabels([f"{nh} camadas" for nh in unique_num_hidden_layers]
axes[0].set_xlabel('Configuração de neurônios')
axes[0].set_ylabel('Número de camadas ocultas')

# Anota cada célula com a configuração real dentro do mapa
for i, nh in enumerate(unique_num_hidden_layers):
    for j, nn in enumerate(configs_per_layers[nh]):
        text = axes[0].text(j, i, str(nn), ha="center", va="center",
                            color="white" if accuracy_matrix[i, j] < 0.5 else
                            fontsize=8)

plt.colorbar(im0, ax=axes[0])

im1 = axes[1].imshow(loss_matrix, cmap='viridis', aspect='auto')
axes[1].set_title('Perda média - Topologia')
axes[1].set_xticks(range(max_configs))
axes[1].set_xticklabels(config_labels, rotation=45, ha='right')
axes[1].set_yticks(range(len(unique_num_hidden_layers)))
axes[1].set_yticklabels([f"{nh} camadas" for nh in unique_num_hidden_layers]
axes[1].set_xlabel('Configuração de neurônios')
axes[1].set_ylabel('Número de camadas ocultas')

# Anota cada célula com a configuração real
for i, nh in enumerate(unique_num_hidden_layers):
    for j, nn in enumerate(configs_per_layers[nh]):
        text = axes[1].text(j, i, str(nn), ha="center", va="center",
                            color="white" if loss_matrix[i, j] > 0.5 else "bl
                            fontsize=8)

plt.colorbar(im1, ax=axes[1])

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



Métricas

In [56]:
```
# Métricas da Questão 03: análise de todas as topologias testadas
# Métricas: função de perda, curva de convergência, tempo de treinamento, ge

print("========== ANÁLISE DE TODAS AS TOPOLOGIAS Q3 ==========\n")

# Organiza os resultados por número de camadas
results_by_layers = {}
for r in results_q3:
    nh = r['number of hidden layers']
    if nh not in results_by_layers:
        results_by_layers[nh] = []
    results_by_layers[nh].append(r)

# Ordena cada grupo por soma de neurônios
for nh in results_by_layers:
    results_by_layers[nh].sort(key=lambda x: sum(x['neurons per layer']))

colors_map = {1: 'blue', 2: 'red', 3: 'green'}
markers_map = {1: 'o', 2: 's', 3: '^'}

# Prepara dados agregados
all_configs = []
all_losses = []
all_loss_stds = []
all_accuracies = []
all_acc_stds = []
all_times = []
all_time_stds = []
all_f1 = []
all_f1_stds = []
all_precision = []
all_precision_stds = []
all_recall = []
all_recall_stds = []
colors_list = []

for nh in sorted(results_by_layers.keys()):
    for r in results_by_layers[nh]:
        config_label = f"{nh}L: {r['neurons per layer']}"
```

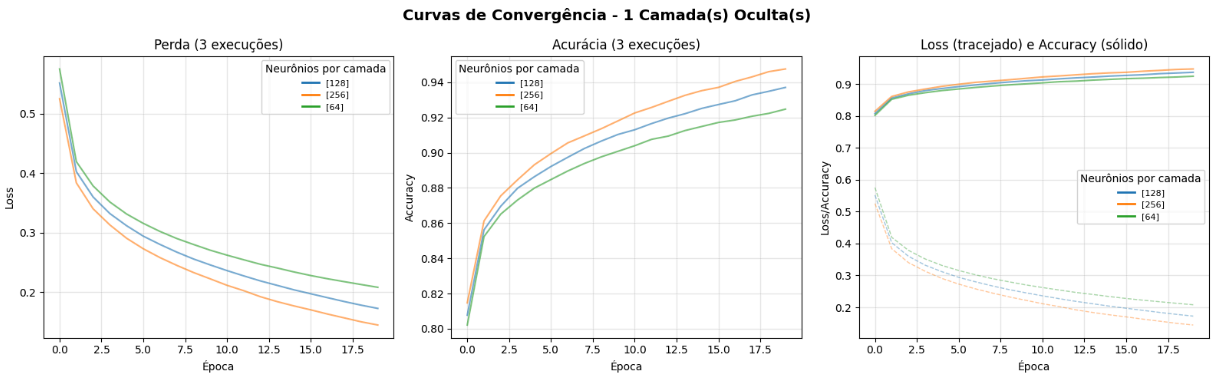
```
        all_configs.append(config_label)
        all_losses.append(r['loss_mean'])
        all_loss_stds.append(r['loss_std'])
        all_accuracies.append(r['accuracy_mean'])
        all_acc_stds.append(r['accuracy_std'])
        all_times.append(r['time_mean'])
        all_time_stds.append(r['time_std'])
        all_f1.append(r['f1_mean'])
        all_f1_stds.append(r['f1_std'])
        all_precision.append(r['precision_mean'])
        all_precision_stds.append(r['precision_std'])
        all_recall.append(r['recall_mean'])
        all_recall_stds.append(r['recall_std'])
        colors_list.append(colors_map[nh])

x_pos = np.arange(len(all_configs))

# Legenda comum
from matplotlib.patches import Patch
legend_elements = [Patch(facecolor=colors_map[nh], label=f'{nh} camada(s)')
                   for nh in sorted(colors_map.keys())]

# ========== 2. CURVAS DE CONVERGÊNCIA - POR NÚMERO DE CAMADAS ==========
print("\n2. CURVAS DE CONVERGÊNCIA - Separadas por número de camadas")

# Define cores distintas para cada configuração de neurônios
colors_neurons = plt.cm.tab10(np.linspace(0, 1, 10))

# Para cada número de camadas, cria um conjunto de 3 subplots
for num_layers in sorted(set([h['num_hidden_layers'] for h in histories_q3])
    # Filtra históricos desta configuração de camadas
    layer_histories = [h for h in histories_q3 if h['num_hidden_layers'] ==

    # Organiza por configuração única de neurônios
    unique_configs = {}
    for h in layer_histories:
        config_key = str(h['neurons_per_layer'])
        if config_key not in unique_configs:
            unique_configs[config_key] = []
        unique_configs[config_key].append(h['history'])

    fig, axes = plt.subplots(1, 3, figsize=(16, 5))
    fig.suptitle(f'Curvas de Convergência - {num_layers} Camada(s) Oculta(s)


    axes[0].set_title(f'Perda ({len(layer_histories)} execuções)')
    color_idx = 0
    for config_key, histories_list in sorted(unique_configs.items()):
        color = colors_neurons[color_idx % len(colors_neurons)]
        for h in histories_list:
            axes[0].plot(h.history['loss'], alpha=0.6, linewidth=1.5, color=
        # Adiciona label apenas uma vez por configuração
        axes[0].plot([], [], color=color, linewidth=2, label=config_key)
        color_idx += 1

    axes[0].set_xlabel('Época')
```

```
    axes[0].set_ylabel('Loss')
    axes[0].legend(title='Neurônios por camada', fontsize=8, loc='best')
    axes[0].grid(True, alpha=0.3)


    axes[1].set_title(f'Acurácia ({len(layer_histories)} execuções)')
    color_idx = 0
    for config_key, histories_list in sorted(unique_configs.items()):
        color = colors_neurons[color_idx % len(colors_neurons)]
        for h in histories_list:
            axes[1].plot(h.history['accuracy'], alpha=0.6, linewidth=1.5, co
        # Adiciona label apenas uma vez por configuração
        axes[1].plot([], [], color=color, linewidth=2, label=config_key)
        color_idx += 1

    axes[1].set_xlabel('Época')
    axes[1].set_ylabel('Accuracy')
    axes[1].legend(title='Neurônios por camada', fontsize=8, loc='best')
    axes[1].grid(True, alpha=0.3)


    axes[2].set_title('Loss (tracejado) e Accuracy (sólido)')
    color_idx = 0
    for config_key, histories_list in sorted(unique_configs.items()):
        color = colors_neurons[color_idx % len(colors_neurons)]
        for h in histories_list:
            axes[2].plot(h.history['loss'], alpha=0.4, linewidth=1, color=co
            axes[2].plot(h.history['accuracy'], alpha=0.6, linewidth=1.5, co
        # Adiciona labels
        axes[2].plot([], [], color=color, linewidth=2, label=config_key)
        color_idx += 1

    axes[2].set_xlabel('Época')
    axes[2].set_ylabel('Loss/Accuracy')
    axes[2].legend(title='Neurônios por camada', fontsize=8, loc='best')
    axes[2].grid(True, alpha=0.3)

    plt.tight_layout()
    plt.show()

    print(f"\n{num_layers} camada(s): {len(layer_histories)} execuções")
    for config_key in sorted(unique_configs.keys()):
        print(f"  Configuração {config_key}: {len(unique_configs[config_key]

print("\n2.5. CURVAS DE CONVERGÊNCIA - Todas as Topologias")
fig, axes = plt.subplots(1, 3, figsize=(16, 5))
# Perda
for r in results_q3:
    config_key = f"{r['number of hidden layers']}L: {r['neurons per layer']}
    color = colors_map[r['number of hidden layers']]
    matching_histories = [h for h in histories_q3 if h['num_hidden_layers']
    for h in matching_histories:
        axes[0].plot(h['history'].history['loss'], alpha=0.4, linewidth=1, c
    axes[0].plot([], [], color=color, linewidth=2, label=config_key)
axes[0].set_title(f'Perda ({len(histories_q3)} execuções)')
axes[0].set_xlabel('Época')
```

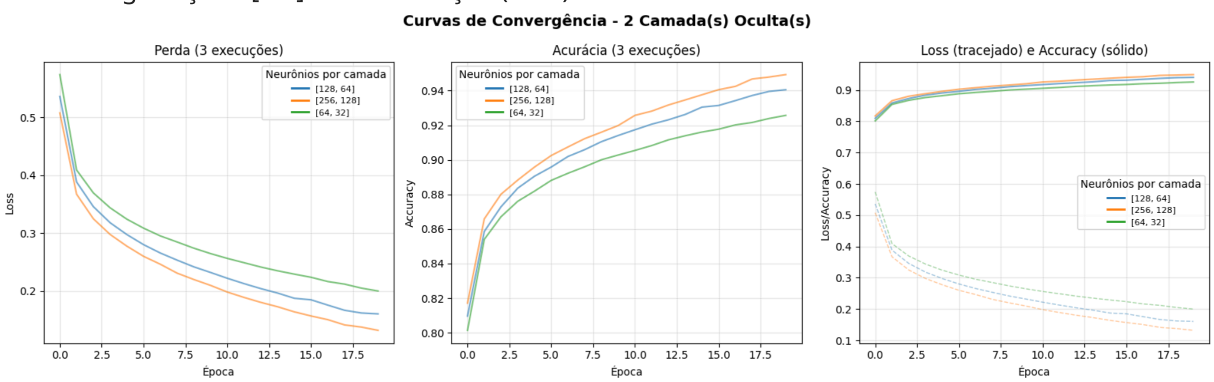
```
axes[0].set_ylabel('Loss')
axes[0].legend(title='Configuração', fontsize=8, loc='best')
axes[0].grid(True, alpha=0.3)
# Acurácia
for r in results_q3:
    config_key = f"{r['number of hidden layers']}L: {r['neurons per layer']}
    color = colors_map[r['number of hidden layers']]
    matching_histories = [h for h in histories_q3 if h['num_hidden_layers']
    for h in matching_histories:
        axes[1].plot(h['history'].history['accuracy'], alpha=0.4, linewidth=
    axes[1].plot([], [], color=color, linewidth=2, label=config_key)
axes[1].set_title(f'Acurácia ({len(histories_q3)} execuções)')
axes[1].set_xlabel('Época')
axes[1].set_ylabel('Accuracy')
axes[1].legend(title='Configuração', fontsize=8, loc='best')
axes[1].grid(True, alpha=0.3)
# Ambas
for r in results_q3:
    config_key = f"{r['number of hidden layers']}L: {r['neurons per layer']}
    color = colors_map[r['number of hidden layers']]
    matching_histories = [h for h in histories_q3 if h['num_hidden_layers']
    for h in matching_histories:
        axes[2].plot(h['history'].history['loss'], alpha=0.3, linewidth=1, c
        axes[2].plot(h['history'].history['accuracy'], alpha=0.4, linewidth=
    axes[2].plot([], [], color=color, linewidth=2, label=config_key)
axes[2].set_title('Loss (tracejado) e Accuracy (sólido)')
axes[2].set_xlabel('Época')
axes[2].set_ylabel('Loss/Accuracy')
axes[2].legend(title='Configuração', fontsize=8, loc='best')
axes[2].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# ========== 3. TEMPO DE TREINAMENTO ==========
print("\n3. TEMPO DE TREINAMENTO")
fig, ax = plt.subplots(figsize=(14, 6))

bars = ax.bar(x_pos, all_times, yerr=all_time_stds, alpha=0.7, capsize=3)
for i, bar in enumerate(bars):
    bar.set_color(colors_list[i])

ax.set_xticks(x_pos)
ax.set_xticklabels(all_configs, rotation=45, ha='right', fontsize=9)
ax.set_ylabel('Tempo de Treinamento (segundos)')
ax.set_title('Tempo de Treinamento - Todas as Topologias')
ax.grid(True, alpha=0.3, axis='y')
ax.legend(handles=legend_elements, loc='upper left')

plt.tight_layout()
plt.show()

for nh in sorted(results_by_layers.keys()):
    print(f"\n{nh} camada(s):")
    for r in results_by_layers[nh]:
        print(f"  {r['neurons per layer']}: Tempo = {r['time_mean']:.2f}s (±
```

```python
# ========== 4. GENERALIZAÇÃO (F1, PRECISÃO, REVOCAÇÃO) ==========
print("\n4. GENERALIZAÇÃO - Medida F1, Precisão e Revocação")
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# F1 Score
bars0 = axes[0].bar(x_pos, all_f1, yerr=all_f1_stds, alpha=0.7, capsize=3)
for i, bar in enumerate(bars0):
    bar.set_color(colors_list[i])
axes[0].set_xticks(x_pos)
axes[0].set_xticklabels(all_configs, rotation=45, ha='right', fontsize=8)
axes[0].set_ylabel('F1 Score (weighted)')
axes[0].set_title('F1 Score - Todas as Topologias')
axes[0].grid(True, alpha=0.3, axis='y')
axes[0].set_ylim([min(all_f1) - 0.01, 1.0])
axes[0].legend(handles=legend_elements, loc='lower right', fontsize=8)

# Precisão
bars1 = axes[1].bar(x_pos, all_precision, yerr=all_precision_stds, alpha=0.7
for i, bar in enumerate(bars1):
    bar.set_color(colors_list[i])
axes[1].set_xticks(x_pos)
axes[1].set_xticklabels(all_configs, rotation=45, ha='right', fontsize=8)
axes[1].set_ylabel('Precisão (weighted)')
axes[1].set_title('Precisão - Todas as Topologias')
axes[1].grid(True, alpha=0.3, axis='y')
axes[1].set_ylim([min(all_precision) - 0.01, 1.0])

# Revocação
bars2 = axes[2].bar(x_pos, all_recall, yerr=all_recall_stds, alpha=0.7, caps
for i, bar in enumerate(bars2):
    bar.set_color(colors_list[i])
axes[2].set_xticks(x_pos)
axes[2].set_xticklabels(all_configs, rotation=45, ha='right', fontsize=8)
axes[2].set_ylabel('Revocação (weighted)')
axes[2].set_title('Revocação (Recall) - Todas as Topologias')
axes[2].grid(True, alpha=0.3, axis='y')
axes[2].set_ylim([min(all_recall) - 0.01, 1.0])

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

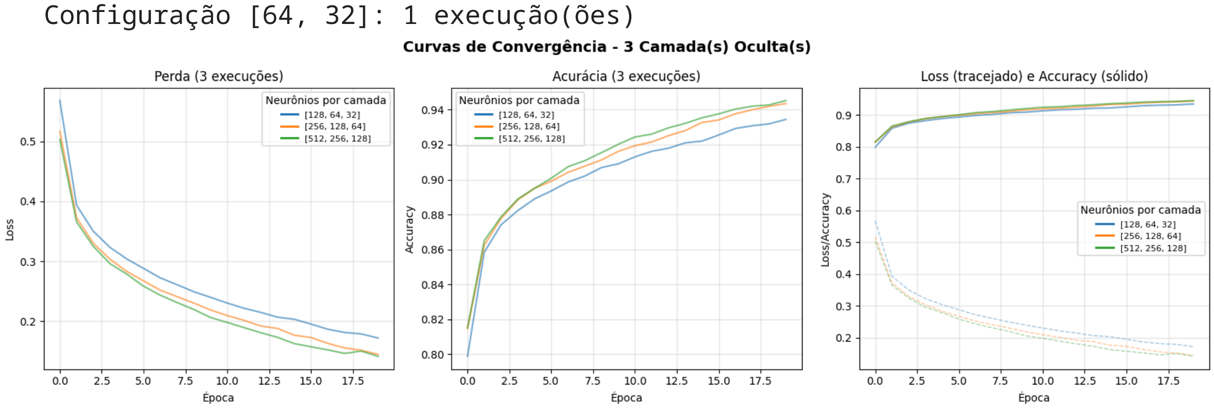
```
========== ANÁLISE DE TODAS AS TOPOLOGIAS Q3 ==========


2. CURVAS DE CONVERGÊNCIA - Separadas por número de camadas
```



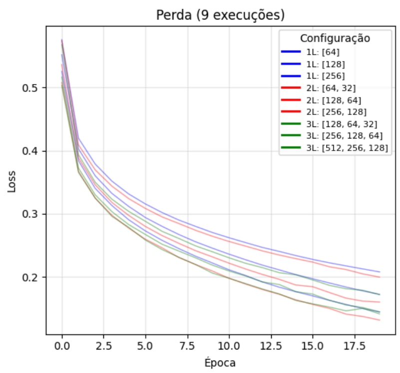

```
1 camada(s): 3 execuções
  Configuração [128]: 1 execução(ões)
  Configuração [256]: 1 execução(ões)
  Configuração [64]: 1 execução(ões)
```

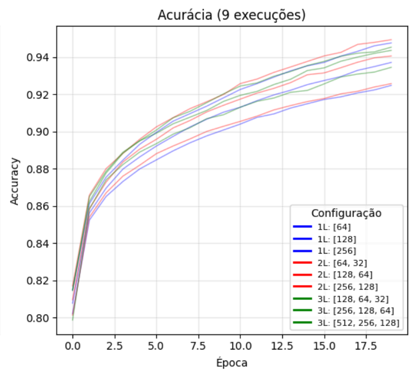


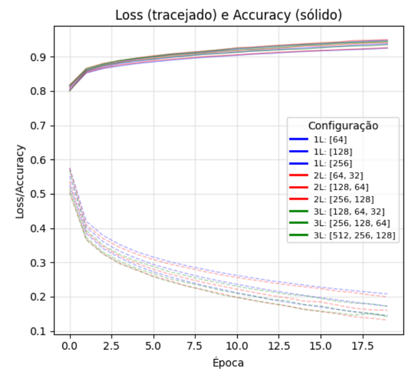

```
2 camada(s): 3 execuções
  Configuração [128, 64]: 1 execução(ões)
  Configuração [256, 128]: 1 execução(ões)
  Configuração [64, 32]: 1 execução(ões)
```



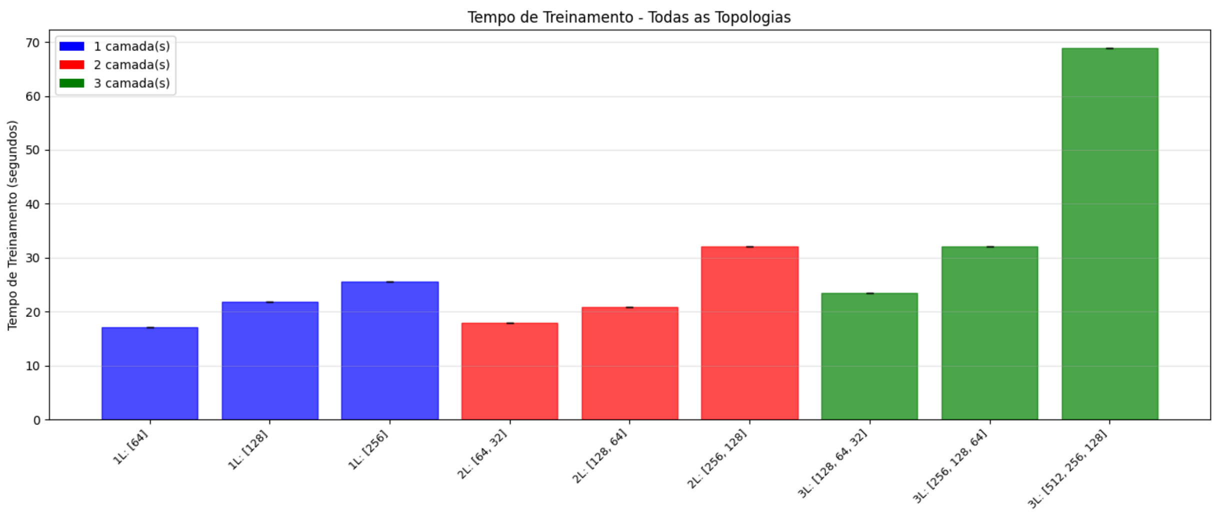

```
3 camada(s): 3 execuções
  Configuração [128, 64, 32]: 1 execução(ões)
  Configuração [256, 128, 64]: 1 execução(ões)
  Configuração [512, 256, 128]: 1 execução(ões)

2.5. CURVAS DE CONVERGÊNCIA - Todas as Topologias
```





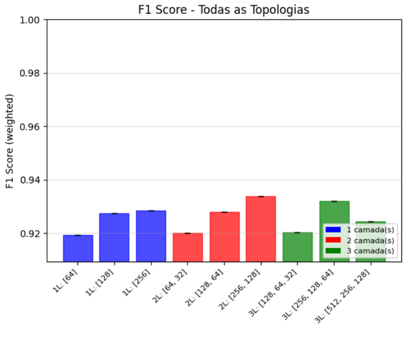


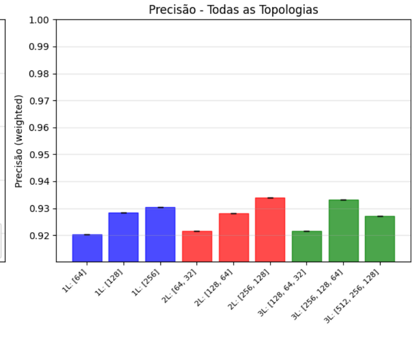
3. TEMPO DE TREINAMENTO

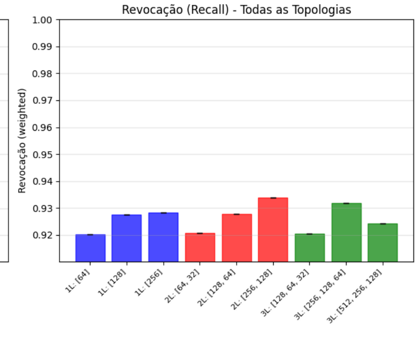



```
1 camada(s):
  [64]: Tempo = 17.15s (±0.00s)
  [128]: Tempo = 21.87s (±0.00s)
  [256]: Tempo = 25.57s (±0.00s)

2 camada(s):
  [64, 32]: Tempo = 17.86s (±0.00s)
  [128, 64]: Tempo = 20.93s (±0.00s)
  [256, 128]: Tempo = 32.13s (±0.00s)

3 camada(s):
  [128, 64, 32]: Tempo = 23.40s (±0.00s)
  [256, 128, 64]: Tempo = 32.14s (±0.00s)
  [512, 256, 128]: Tempo = 68.81s (±0.00s)
```

4. GENERALIZAÇÃO - Medida F1, Precisão e Revocação







Questão 04

melhor modelo até o momento(desconsiderando velocidade de convergência):

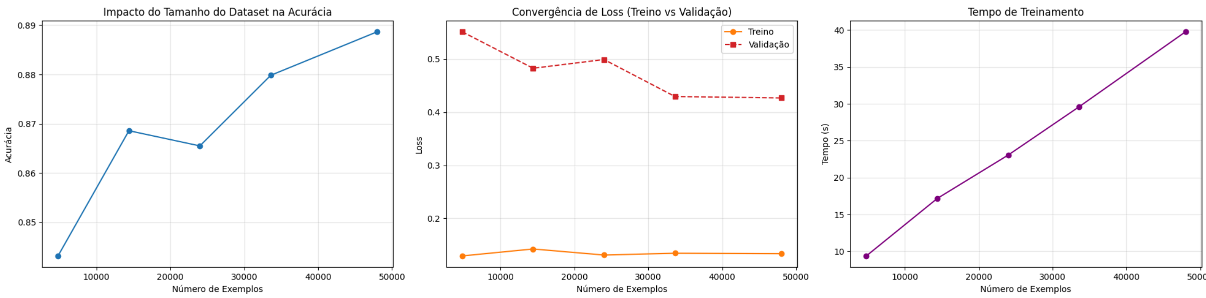
- 2 camadas ocultas, com 256 e 128 neurônios
- batch size: 64
- beta1: 0.7
- learning rate: 0.001
- epochs: 20
- função de ativação: tanh

In [32]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import f1_score
import time
import matplotlib.pyplot as plt
import numpy as np
from tensorflow import keras

# ============================================================================
# CONFIGURAÇÃO DA MELHOR TOPOLOGIA (Da Questão 3)
# ============================================================================
MELHOR_NUM_CAMADAS = 2
MELHOR_NEURONIOS = [256, 128]
MELHOR_LR = 0.001       # Valor padrão que obteve bom desempenho (Loss ~0.13
MELHOR_BETA1 = 0.7
EPOCHS_FIXAS = 20       # Fixo para garantir convergência nessa análise

# ============================================================================
# QUESTÃO 04: Influência da Quantidade de Dados
# ============================================================================

# Frações do dataset para teste (10% a 100%)
fractions = [0.1, 0.3, 0.5, 0.7, 1.0]
results_q4 = []

print(f"=== INICIANDO QUESTÃO 4 ===")
print(f"Topologia Fixa: {MELHOR_NUM_CAMADAS} camadas ocultas {MELHOR_NEURONI
print(f"Hiperparâmetros: LR={MELHOR_LR}, Beta1={MELHOR_BETA1}, Epochs={EPOCH
print(f"Testando frações: {fractions}\n")

for frac in fractions:
    # 1. Amostragem Estratificada
    if frac == 1.0:
        x_subset, y_subset = x_train, y_train
    else:
        # Mantém a proporção das classes mesmo cortando os dados
        x_subset, _, y_subset, _ = train_test_split(
            x_train, y_train,
            train_size=frac,
            stratify=y_train,
            random_state=42
```

```python
        )

    n_samples = len(x_subset)
    print(f"> Treinando com {int(frac * 100)}% dos dados ({n_samples} amostr

    # 2. Construir modelo (resetando pesos a cada iteração)
    keras.utils.set_random_seed(42)
    model = build_model(
        learning_rate=MELHOR_LR,
        beta1=MELHOR_BETA1,
        num_hidden_layers=MELHOR_NUM_CAMADAS,
        neurons_per_layer=MELHOR_NEURONIOS
    )

    # 3. Treinar e medir tempo
    start_time = time.time()
    history = model.fit(
        x_subset, y_subset,
        epochs=EPOCHS_FIXAS,
        batch_size=64,
        validation_data=(x_val, y_val), # Validação sempre com 100% dos dado
        verbose=0
    )
    elapsed_time = time.time() - start_time

    # 4. Coletar Métricas
    loss_train = history.history['loss'][-1]
    loss_val, acc_val = model.evaluate(x_val, y_val, verbose=0)
    loss_test, acc_test = model.evaluate(x_test, y_test, verbose=0)

    # F1 Score na validação
    y_val_pred = np.argmax(model.predict(x_val, verbose=0), axis=1)
    f1_val = f1_score(y_val, y_val_pred, average='weighted')

    results_q4.append({
        'fraction': frac,
        'samples': n_samples,
        'time': elapsed_time,
        'train_loss': loss_train,
        'val_loss': loss_val,
        'val_acc': acc_val,
        'val_f1': f1_val,
        'test_acc': acc_test
    })

    print(f"  Tempo: {elapsed_time:.1f}s | Val Acc: {acc_val:.4f} | Val Loss

# =============================================================================
# VISUALIZAÇÃO DOS RESULTADOS
# =============================================================================

sizes = [r['samples'] for r in results_q4]
val_accs = [r['val_acc'] for r in results_q4]
train_losses = [r['train_loss'] for r in results_q4]
val_losses = [r['val_loss'] for r in results_q4]
times = [r['time'] for r in results_q4]
```

```python
fig, ax = plt.subplots(1, 3, figsize=(20, 5))

# 1. Curva de Aprendizado (Acurácia x Dados)
ax[0].plot(sizes, val_accs, 'o-', label='Validação', color='tab:blue')
ax[0].set_title('Impacto do Tamanho do Dataset na Acurácia')
ax[0].set_xlabel('Número de Exemplos')
ax[0].set_ylabel('Acurácia')
ax[0].grid(True, alpha=0.3)

# 2. Curva de Loss (Treino vs Validação) - Mostra Overfitting em poucos dado
ax[1].plot(sizes, train_losses, 'o-', label='Treino', color='tab:orange')
ax[1].plot(sizes, val_losses, 's--', label='Validação', color='tab:red')
ax[1].set_title('Convergência de Loss (Treino vs Validação)')
ax[1].set_xlabel('Número de Exemplos')
ax[1].set_ylabel('Loss')
ax[1].legend()
ax[1].grid(True, alpha=0.3)

# 3. Custo Computacional
ax[2].plot(sizes, times, 'o-', color='purple')
ax[2].set_title('Tempo de Treinamento')
ax[2].set_xlabel('Número de Exemplos')
ax[2].set_ylabel('Tempo (s)')
ax[2].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Tabela Final
print("\nRESUMO DOS RESULTADOS (QUESTÃO 4):")
print(f"{'Dados(%)':<10} | {'Amostras':<10} | {'Tempo(s)':<10} | {'Val Acc':
print("-" * 65)
for r in results_q4:
    print(f"{r['fraction']*100:<10.0f} | {r['samples']:<10} | {r['time']:<10
```

```
=== INICIANDO QUESTÃO 4 ===
Topologia Fixa: 2 camadas ocultas [256, 128]
Hiperparâmetros: LR=0.001, Beta1=0.7, Epochs=20
Testando frações: [0.1, 0.3, 0.5, 0.7, 1.0]

> Treinando com 10% dos dados (4800 amostras)...
  Tempo: 9.4s | Val Acc: 0.8432 | Val Loss: 0.5515
> Treinando com 30% dos dados (14400 amostras)...
  Tempo: 17.2s | Val Acc: 0.8686 | Val Loss: 0.4828
> Treinando com 50% dos dados (24000 amostras)...
  Tempo: 23.1s | Val Acc: 0.8655 | Val Loss: 0.4992
> Treinando com 70% dos dados (33600 amostras)...
  Tempo: 29.6s | Val Acc: 0.8798 | Val Loss: 0.4295
> Treinando com 100% dos dados (48000 amostras)...
  Tempo: 39.8s | Val Acc: 0.8887 | Val Loss: 0.4268
```




```
RESUMO DOS RESULTADOS (QUESTÃO 4):
Dados(%)    | Amostras    | Tempo(s)    | Val Acc     | Val F1
-----------------------------------------------------------------
10          | 4800        | 9.38        | 0.8432      | 0.8453
30          | 14400       | 17.17       | 0.8686      | 0.8645
50          | 24000       | 23.06       | 0.8655      | 0.8651
70          | 33600       | 29.60       | 0.8798      | 0.8812
100         | 48000       | 39.77       | 0.8887      | 0.8893
```

In [ ]:

```python
# Questão 5
```

In [34]:

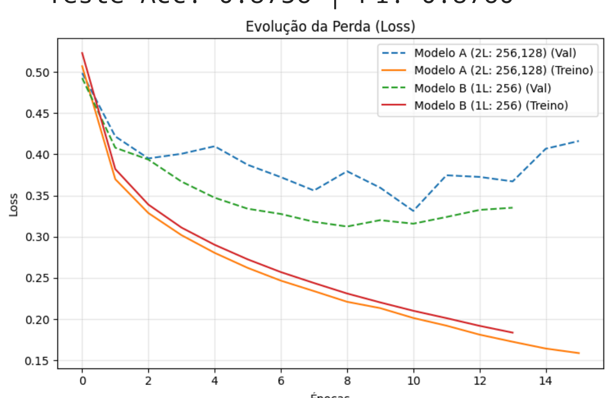
```python
from sklearn.metrics import classification_report
from tensorflow.keras.callbacks import EarlyStopping

# ==============================================================================
# CONFIGURAÇÃO DA QUESTÃO 5
# ==============================================================================

# Recupera as 4 melhores topologias da Questão 3
top_4_configs = []

# Verifica se a lista ordenada existe no contexto global (foi gerada na célu
if 'sorted_results_q3' in globals() and len(sorted_results_q3) > 0:
    print(f">>> Conectando dados: Recuperando os {min(4, len(sorted_results_

    # Os 4 melhores resultados
    for i, res in enumerate(sorted_results_q3[:4]):

        # Prepara os dados para o formato que a Questão 5 espera
        n_layers = res['number of hidden layers']
        neurons_list = res['neurons per layer']

        # Gera o nome do modelo. ("Modelo A (2L: 256,128)")
        neurons_str = ",".join(str(n) for n in neurons_list)
        model_name = f"Modelo {chr(65+i)} ({n_layers}L: {neurons_str})"

        # Dicionário de configuração
        config = {
            'layers': n_layers,
            'neurons': neurons_list,
            'name': model_name
        }
        top_4_configs.append(config)

        # Feedback visual para confirmar quais modelos foram pegos
        print(f"   [{i+1}° Lugar] Selecionado: {model_name} | Acurácia Q3: {
```

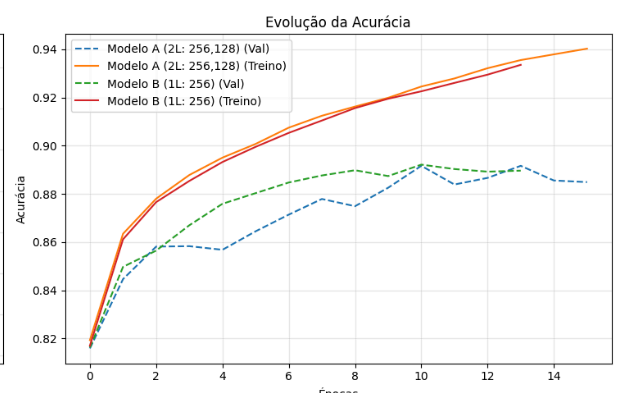
```python
else:
    # Fallback apenas se a célula anterior não tiver sido rodada
    print(">>> AVISO: 'sorted_results_q3' não encontrado.")
    sys.exit()

# Melhores parâmetros fixos
LR_FINAL = 0.001       # Da Q2
BETA1_FINAL = 0.7      # Da Q2
MAX_EPOCHS = 50        # 50 é alto, mas o Early Stopping corta antes

print(f"\n\n=== INICIANDO QUESTÃO 5: Treinamento Final e Teste ===")
print(f"Usando 100% dos dados de treino ({len(x_train)} amostras)")
print(f"Estratégia: Early Stopping (paciência=5 épocas)")

final_results = []
histories_q5 = []

for config in top_4_configs:
    print(f"\n> Treinando {config['name']}...")

    # 1. Construir modelo
    keras.utils.set_random_seed(42) # Seed fixa para comparação justa
    model = build_model(
        learning_rate=LR_FINAL,
        beta1=BETA1_FINAL,
        num_hidden_layers=config['layers'],
        neurons_per_layer=config['neurons']
    )

    # 2. Callback de Early Stopping
    # Para de treinar se a 'val_loss' não melhorar por 5 épocas seguidas
    # restore_best_weights=True garante que o modelo final é o da melhor épo
    es = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=

    # 3. Treinamento
    start_time = time.time()
    history = model.fit(
        x_train, y_train,
        epochs=MAX_EPOCHS,
        batch_size=64,
        validation_data=(x_val, y_val),
        callbacks=[es],
        verbose=0 # Mude para 1 se quiser ver a barra de progresso
    )
    elapsed_time = time.time() - start_time

    # 4. Avaliação final no teste
    y_test_pred_prob = model.predict(x_test, verbose=0)
    y_test_pred = np.argmax(y_test_pred_prob, axis=1)

    # Métricas detalhadas
    report = classification_report(y_test, y_test_pred, output_dict=True)

    # Salva resultados
    res = {
        'name': config['name'],
```

```
        'config': config,
        'time': elapsed_time,
        'epochs_run': len(history.history['loss']),
        'test_acc': report['accuracy'],
        'test_f1': report['weighted avg']['f1-score'],
        'test_precision': report['weighted avg']['precision'],
        'test_recall': report['weighted avg']['recall'],
        'val_loss_final': min(history.history['val_loss']) # A melhor valida
    }
    final_results.append(res)
    histories_q5.append(history)

    print(f"  Terminou em {res['epochs_run']} épocas ({elapsed_time:.1f}s)")
    print(f"  Teste Acc: {res['test_acc']:.4f} | F1: {res['test_f1']:.4f}")

# ============================================================================
# ANÁLISE E VISUALIZAÇÃO
# ============================================================================

# Gráfico das curvas de aprendizado dos dois melhores modelos
best_2 = sorted(final_results, key=lambda x: x['test_acc'], reverse=True)[:2
fig, ax = plt.subplots(1, 2, figsize=(15, 5))

for i, res in enumerate(best_2):
    # Encontra o history correspondente
    # Não é ideal, mas funciona pq a ordem de inserção é a mesma
    hist = next(h for h, r in zip(histories_q5, final_results) if r['name']

    ax[0].plot(hist.history['val_loss'], label=f"{res['name']} (Val)", lines
    ax[0].plot(hist.history['loss'], label=f"{res['name']} (Treino)")

    ax[1].plot(hist.history['val_accuracy'], label=f"{res['name']} (Val)", l
    ax[1].plot(hist.history['accuracy'], label=f"{res['name']} (Treino)")

ax[0].set_title('Evolução da Perda (Loss)')
ax[0].set_xlabel('Épocas')
ax[0].set_ylabel('Loss')
ax[0].legend()
ax[0].grid(True, alpha=0.3)

ax[1].set_title('Evolução da Acurácia')
ax[1].set_xlabel('Épocas')
ax[1].set_ylabel('Acurácia')
ax[1].legend()
ax[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Tabela final de decisão
print("\n" + "="*100)
print(f"{'MODELO':<25} | {'ACC (Teste)':<12} | {'F1 (Teste)':<12} | {'Épocas
print("="*100)
# Ordena por F1 Score no teste (critério de desempate comum)
final_results.sort(key=lambda x: x['test_f1'], reverse=True)
```

```
for r in final_results:
    print(f"{r['name']:<25} | {r['test_acc']:.4f}       | {r['test_f1']:.4f}
print("="*100)

print(f"\n>>> RESULTADO: O modelo '{final_results[0]['name']}' parece ser a
```

```
>>> Conectando dados: Recuperando os 4 melhores modelos da memória...
   [1º Lugar] Selecionado: Modelo A (2L: 256,128) | Acurácia Q3: 0.9490
   [2º Lugar] Selecionado: Modelo B (1L: 256) | Acurácia Q3: 0.9469
   [3º Lugar] Selecionado: Modelo C (3L: 512,256,128) | Acurácia Q3: 0.9460
   [4º Lugar] Selecionado: Modelo D (3L: 256,128,64) | Acurácia Q3: 0.9433
=== INICIANDO QUESTÃO 5: Treinamento Final e Teste ===
Usando 100% dos dados de treino (48000 amostras)
Estratégia: Early Stopping (paciência=5 épocas)

> Treinando Modelo A (2L: 256,128)...
Epoch 16: early stopping
Restoring model weights from the end of the best epoch: 11.
  Terminou em 16 épocas (32.4s)
  Teste Acc: 0.8845 | F1: 0.8851

> Treinando Modelo B (1L: 256)...
Epoch 14: early stopping
Restoring model weights from the end of the best epoch: 9.
  Terminou em 14 épocas (24.6s)
  Teste Acc: 0.8763 | F1: 0.8770

> Treinando Modelo C (3L: 512,256,128)...
Epoch 14: early stopping
Restoring model weights from the end of the best epoch: 9.
  Terminou em 14 épocas (51.5s)
  Teste Acc: 0.8761 | F1: 0.8770

> Treinando Modelo D (3L: 256,128,64)...
Epoch 14: early stopping
Restoring model weights from the end of the best epoch: 9.
  Terminou em 14 épocas (30.6s)
  Teste Acc: 0.8756 | F1: 0.8760
```





```
================================================================================
=======================
MODELO                     | ACC (Teste)   | F1 (Teste)    | Épocas    | Tempo
================================================================================
=======================
Modelo A (2L: 256,128)     | 0.8845        | 0.8851        | 16        | 32.4s
Modelo C (3L: 512,256,128) | 0.8761        | 0.8770        | 14        | 51.5s
Modelo B (1L: 256)         | 0.8763        | 0.8770        | 14        | 24.6s
Modelo D (3L: 256,128,64)  | 0.8756        | 0.8760        | 14        | 30.6s
================================================================================
=======================

>>> RESULTADO: O modelo 'Modelo A (2L: 256,128)' parece ser a melhor escolha
para a Q6.
```

In [ ]:

```
# Questão 6
```

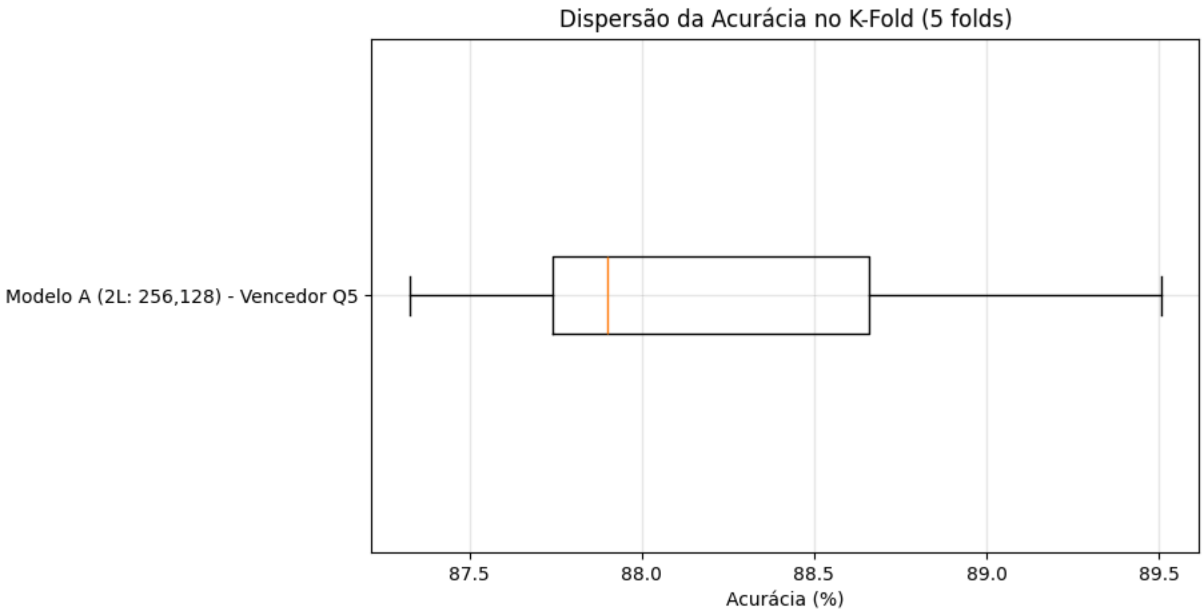
In [35]:

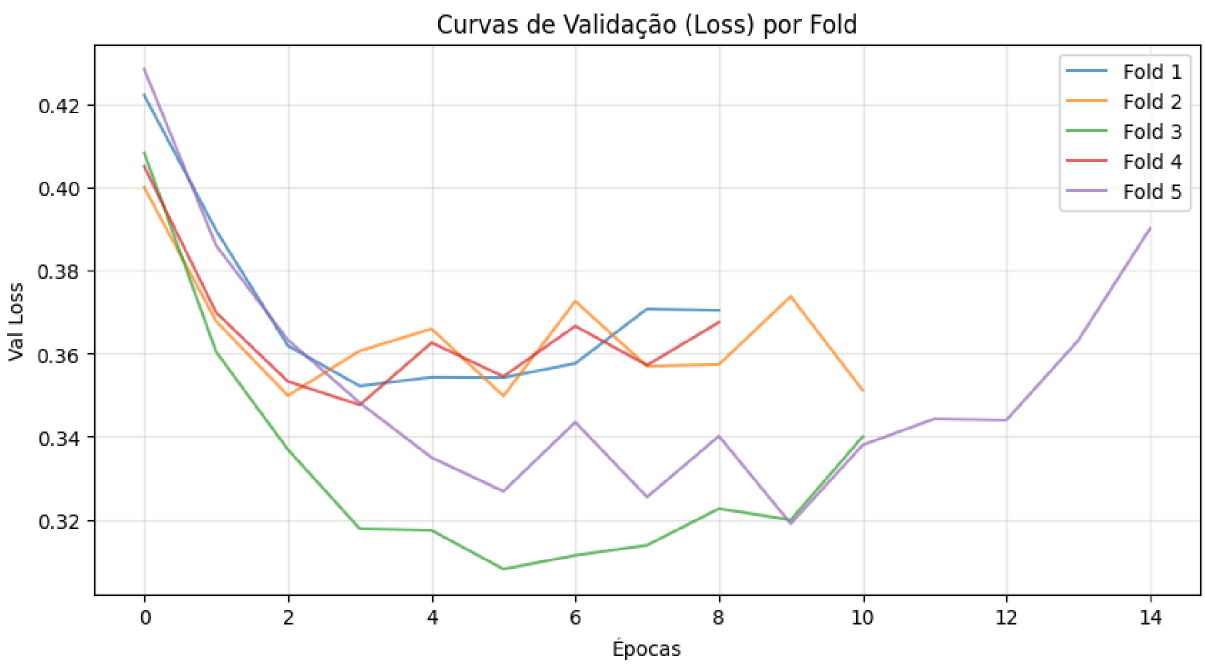
```
from sklearn.model_selection import KFold
import numpy as np
import matplotlib.pyplot as plt
from tensorflow import keras
from tensorflow.keras.callbacks import EarlyStopping

# ============================================================================
# QUESTÃO 06: VALIDAÇÃO CRUZADA K-FOLD
# ============================================================================
# Divisão do dataset em k-subconjuntos e teste em todos eles.

# --- Configuração ---
# Recuperando a melhor configuração da Questão 5 (Modelo B)
BEST_CONFIG_Q6 = {
    'layers': 2,
    'neurons': [256, 128],
    'name': 'Modelo A (2L: 256,128) - Vencedor Q5'
}

# Parâmetros de treino
K_FOLDS = 5
BATCH_SIZE = 64
MAX_EPOCHS = 50
LR_FINAL = 0.001     # Melhor Learning Rate da Q2
BETA1_FINAL = 0.7

# O K-Fold faz suas próprias divisões de treino/validação
X_FULL = np.concatenate((x_train, x_val), axis=0)
Y_FULL = np.concatenate((y_train, y_val), axis=0)

print(f"=== INICIANDO QUESTÃO 6: Validação Cruzada (K={K_FOLDS}) ===")
print(f"Modelo Avaliado: {BEST_CONFIG_Q6['name']}")
print(f"Total de dados para rodízio: {len(X_FULL)} amostras")

# Listas para armazenar métricas de cada fold
fold_accuracies = []
fold_losses = []
fold_histories = []
```

```
# K-Fold
# shuffle=True garante que as classes estejam misturadas
kfold = KFold(n_splits=K_FOLDS, shuffle=True, random_state=42)

fold_no = 1

for train_index, val_index in kfold.split(X_FULL, Y_FULL):
    print(f"\n> Rodando Fold {fold_no}/{K_FOLDS}...")

    # 1. Separando dados do Fold atual
    X_train_fold = X_FULL[train_index]
    Y_train_fold = Y_FULL[train_index]
    X_val_fold = X_FULL[val_index]
    Y_val_fold = Y_FULL[val_index]

    # 2. Constroi Modelo (Resetando pesos a cada fold)
    keras.utils.set_random_seed(42) # Fixa a seed para padronizar
    model = build_model(
        learning_rate=LR_FINAL,
        beta1=BETA1_FINAL,
        num_hidden_layers=BEST_CONFIG_Q6['layers'],
        neurons_per_layer=BEST_CONFIG_Q6['neurons']
    )

    # 3. Early Stopping (para evitar overfitting em cada fold)
    es = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=

    # 4. Treinamento
    history = model.fit(
        X_train_fold, Y_train_fold,
        batch_size=BATCH_SIZE,
        epochs=MAX_EPOCHS,
        validation_data=(X_val_fold, Y_val_fold),
        callbacks=[es],
        verbose=0 # 0 desativa barra de progresso
    )

    # 5. Avaliação no conjunto de validação deste fold
    scores = model.evaluate(X_val_fold, Y_val_fold, verbose=0)
    acc_percent = scores[1] * 100

    print(f"  Concluído em {len(history.history['loss'])} épocas.")
    print(f"  Acurácia do Fold {fold_no}: {acc_percent:.2f}% | Loss: {scores

    fold_accuracies.append(acc_percent)
    fold_losses.append(scores[0])
    fold_histories.append(history)

    fold_no += 1

# ============================================================================
# ANÁLISE E VISUALIZAÇÃO Q6
# ============================================================================

print("\n" + "="*60)
print("RELATÓRIO FINAL - VALIDAÇÃO CRUZADA K-FOLD")
```

```
print("="*60)

mean_acc = np.mean(fold_accuracies)
std_acc = np.std(fold_accuracies)
mean_loss = np.mean(fold_losses)

print(f"Modelo: {BEST_CONFIG_Q6['name']}")
print(f"Média de Acurácia: {mean_acc:.2f}% (+/- {std_acc:.2f}%)")
print(f"Média de Perda:    {mean_loss:.4f}")
print("-" * 60)
print("Detalhamento por Fold:")
for i, acc in enumerate(fold_accuracies):
    print(f"  Fold {i+1}: {acc:.2f}%")
print("="*60)

# Boxplot para visualizar a variância
plt.figure(figsize=(8, 5))
plt.boxplot(fold_accuracies, vert=False)
plt.title(f'Dispersão da Acurácia no K-Fold ({K_FOLDS} folds)')
plt.xlabel('Acurácia (%)')
plt.yticks([1], [BEST_CONFIG_Q6['name']])
plt.grid(True, alpha=0.3)
plt.show()

# Curvas de aprendizado de todos os folds para ver se houve divergencia
plt.figure(figsize=(10, 5))
for i, h in enumerate(fold_histories):
    plt.plot(h.history['val_loss'], label=f'Fold {i+1}', alpha=0.7)
plt.title('Curvas de Validação (Loss) por Fold')
plt.xlabel('Épocas')
plt.ylabel('Val Loss')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()

# Conclusão Automática
if std_acc < 1.5:
    print(f"\n>>> CONCLUSÃO Q6: O modelo é robusto (std={std_acc:.2f}% < 1.5
    print("O desempenho se manteve estável em diferentes subconjuntos de dad
    print("confirmando que a escolha da Questão 5 é válida, e não por acaso.
else:
    print(f"\n>>> CONCLUSÃO Q6: O modelo apresenta VARIÂNCIA MODERADA/ALTA (
    print("Pode have um problema com os dados de treino. Considere mais dado
```

```
=== INICIANDO QUESTÃO 6: Validação Cruzada (K=5) ===
Modelo Avaliado: Modelo A (2L: 256,128) - Vencedor Q5
Total de dados para rodízio: 60000 amostras

> Rodando Fold 1/5...
  Concluído em 9 épocas.
  Acurácia do Fold 1: 87.33% | Loss: 0.3522

> Rodando Fold 2/5...
  Concluído em 11 épocas.
  Acurácia do Fold 2: 87.74% | Loss: 0.3498

> Rodando Fold 3/5...
  Concluído em 11 épocas.
  Acurácia do Fold 3: 88.66% | Loss: 0.3080

> Rodando Fold 4/5...
  Concluído em 9 épocas.
  Acurácia do Fold 4: 87.90% | Loss: 0.3477

> Rodando Fold 5/5...
  Concluído em 15 épocas.
  Acurácia do Fold 5: 89.51% | Loss: 0.3190

============================================================
RELATÓRIO FINAL - VALIDAÇÃO CRUZADA K-FOLD
============================================================
Modelo: Modelo A (2L: 256,128) - Vencedor Q5
Média de Acurácia: 88.23% (+/- 0.77%)
Média de Perda:    0.3353
------------------------------------------------------------
Detalhamento por Fold:
  Fold 1: 87.33%
  Fold 2: 87.74%
  Fold 3: 88.66%
  Fold 4: 87.90%
  Fold 5: 89.51%
============================================================
```






```
>>> CONCLUSÃO Q6: O modelo é robusto (std=0.77% < 1.5%).
O desempenho se manteve estável em diferentes subconjuntos de dados,
confirmando que a escolha da Questão 5 é válida, e não por acaso.
```

In [ ]: