

nqnzbeasz

June 19, 2024

```
[1]: import os, shutil
train_dir = 'C:/Users/flavi/Desktop/Projeto-20240530/train'
validation_dir = 'C:/Users/flavi/Desktop/Projeto-20240530/validation'
test_dir = 'C:/Users/flavi/Desktop/Projeto-20240530/test'
```

```
[2]: from keras.utils import image_dataset_from_directory
IMG_SIZE = 150
train_dataset = image_dataset_from_directory(
train_dir,
image_size=(IMG_SIZE, IMG_SIZE),
batch_size=32)
validation_dataset = image_dataset_from_directory(
validation_dir,
image_size=(IMG_SIZE, IMG_SIZE),
batch_size=32)
test_dataset = image_dataset_from_directory(
test_dir,
image_size=(IMG_SIZE, IMG_SIZE),
batch_size=32)
```

Found 40000 files belonging to 10 classes.

Found 10000 files belonging to 10 classes.

Found 10000 files belonging to 10 classes.

```
[3]: from tensorflow import keras
from keras import layers
from keras import models
from keras.preprocessing import image

data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal_and_vertical"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),
    ]
)

inputs = keras.Input(shape=(IMG_SIZE, IMG_SIZE, 3))
```

```

x = data_augmentation(inputs)
x = layers.Rescaling(1./255)(inputs)

x = layers.Conv2D(filters=32, kernel_size=3, activation="relu",
padding='same')(x)
x = layers.BatchNormalization()(x)
x = layers.MaxPooling2D(pool_size=2)(x)

x = layers.Conv2D(filters=64, kernel_size=3, activation="relu",
padding='same')(x)
x = layers.BatchNormalization()(x)
x = layers.MaxPooling2D(pool_size=2)(x)

x = layers.Conv2D(filters=128, kernel_size=3, activation="relu",
padding='same')(x)
x = layers.BatchNormalization()(x)
x = layers.MaxPooling2D(pool_size=2)(x)

x = layers.Flatten()(x)
x = layers.Dropout(0.5)(x)
x = layers.Dense(512, activation="relu")(x)
outputs = layers.Dense(10, activation="softmax")(x)
model = keras.Model(inputs=inputs, outputs=outputs)

```

```

[4]: model.compile(
    optimizer='adam',
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

```

```

[5]: from keras.callbacks import ReduceLROnPlateau

reduce_lr = ReduceLROnPlateau(
    monitor='val_loss',
    factor=0.2,
    patience=2,
    min_lr=0.001
)

```

```

[6]: from keras.callbacks import EarlyStopping

early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=5,
    restore_best_weights=True
)

```

```
[7]: from keras.callbacks import ModelCheckpoint

model_checkpoint = ModelCheckpoint(
    filepath='C:/Users/flavi/Desktop/projetoClassificacaoDeImagens/
    dl_project_2201707_2211044/ModelosS/ModelS_AdamOptimizerComData.keras',
    save_best_only=True,
    monitor='val_loss'
)
```

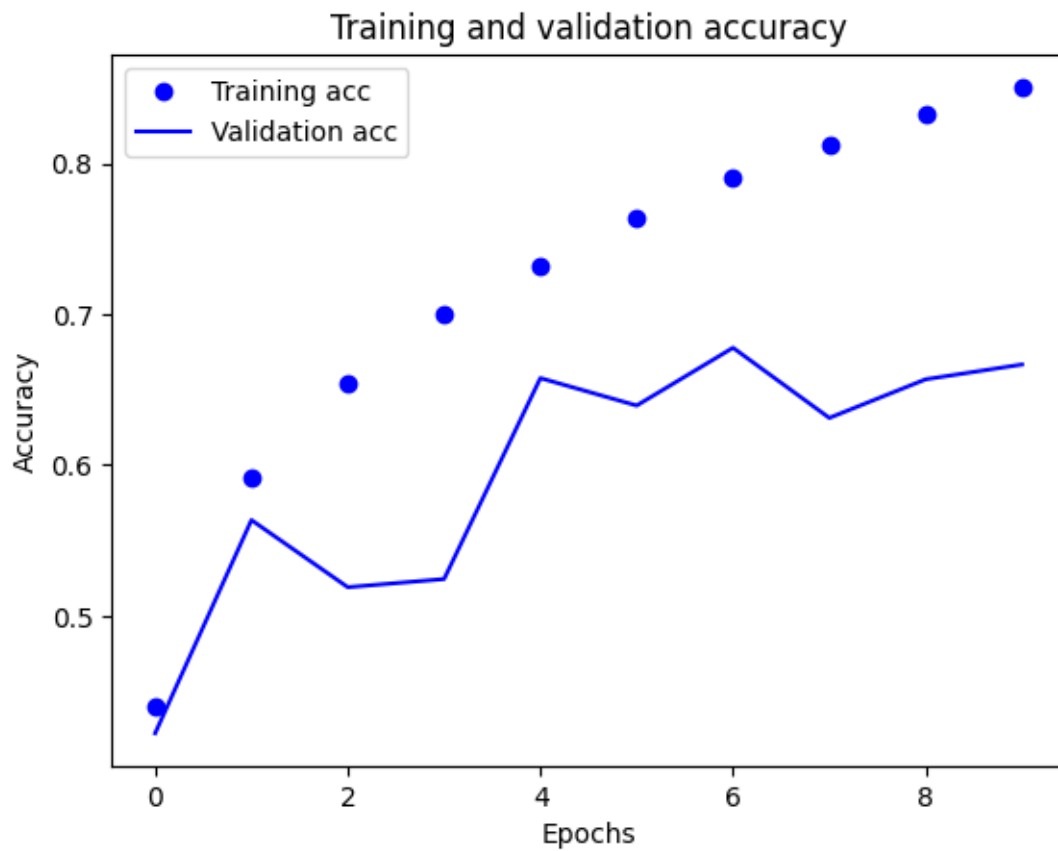
```
[8]: callbacks = [reduce_lr, early_stopping, model_checkpoint]
history = model.fit(
    train_dataset,
    epochs=30,
    validation_data=validation_dataset,
    callbacks=callbacks
)
```

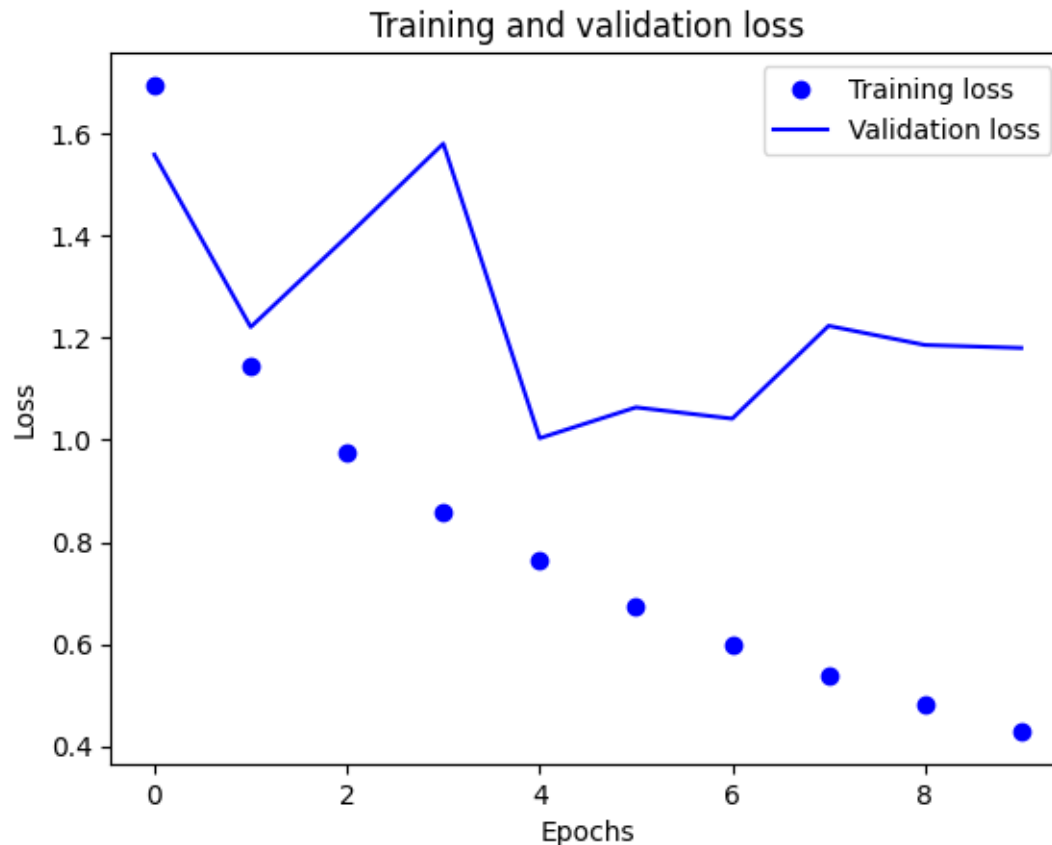
```
Epoch 1/30
1250/1250          1441s 1s/step -
accuracy: 0.3599 - loss: 2.6228 - val_accuracy: 0.4222 - val_loss: 1.5588 -
learning_rate: 0.0010
Epoch 2/30
1250/1250          1221s
977ms/step - accuracy: 0.5683 - loss: 1.2108 - val_accuracy: 0.5635 - val_loss:
1.2211 - learning_rate: 0.0010
Epoch 3/30
1250/1250          752s 601ms/step
- accuracy: 0.6369 - loss: 1.0144 - val_accuracy: 0.5190 - val_loss: 1.3985 -
learning_rate: 0.0010
Epoch 4/30
1250/1250          680s 544ms/step
- accuracy: 0.6869 - loss: 0.8906 - val_accuracy: 0.5244 - val_loss: 1.5803 -
learning_rate: 0.0010
Epoch 5/30
1250/1250          1091s
873ms/step - accuracy: 0.7235 - loss: 0.7926 - val_accuracy: 0.6576 - val_loss:
1.0033 - learning_rate: 0.0010
Epoch 6/30
1250/1250          1241s
993ms/step - accuracy: 0.7566 - loss: 0.6982 - val_accuracy: 0.6394 - val_loss:
1.0638 - learning_rate: 0.0010
Epoch 7/30
1250/1250          1244s
995ms/step - accuracy: 0.7805 - loss: 0.6307 - val_accuracy: 0.6777 - val_loss:
1.0417 - learning_rate: 0.0010
Epoch 8/30
1250/1250          1240s
```

992ms/step - accuracy: 0.8055 - loss: 0.5612 - val\_accuracy: 0.6312 - val\_loss: 1.2235 - learning\_rate: 0.0010  
Epoch 9/30  
1250/1250 1227s  
982ms/step - accuracy: 0.8270 - loss: 0.5035 - val\_accuracy: 0.6568 - val\_loss: 1.1859 - learning\_rate: 0.0010  
Epoch 10/30  
1250/1250 1244s  
995ms/step - accuracy: 0.8421 - loss: 0.4559 - val\_accuracy: 0.6666 - val\_loss: 1.1801 - learning\_rate: 0.0010

```
[9]: import matplotlib.pyplot as plt
plt.plot(history.history['accuracy'], 'bo', label='Training acc')
plt.plot(history.history['val_accuracy'], 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

plt.plot(history.history['loss'], 'bo', label='Training loss')
plt.plot(history.history['val_loss'], 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```





```
[10]: val_loss, val_acc = model.evaluate(validation_dataset)
      print('Validation Accuracy:', val_acc)
```

```
313/313          52s 166ms/step -
accuracy: 0.6562 - loss: 0.9955
Validation Accuracy: 0.6575999855995178
```

```
[11]: loss, accuracy = model.evaluate(test_dataset)
      print(f"Loss: {loss}, Accuracy: {accuracy}")
```

```
313/313          52s 166ms/step -
accuracy: 0.6516 - loss: 1.0232
Loss: 1.0121647119522095, Accuracy: 0.6565999984741211
```

```
[12]: import numpy as np
      from sklearn.metrics import confusion_matrix, classification_report
      import seaborn as sns
      import matplotlib.pyplot as plt

      # Function to evaluate the model and get true and predicted labels
```

```

def evaluate_model(model, dataset):
    all_labels = []
    all_predictions = []

    for images, labels in dataset:
        predictions = model.predict(images)
        predicted_labels = np.argmax(predictions, axis=1)
        true_labels = labels.numpy() # Convert to numpy array if not already

        all_labels.extend(true_labels)
        all_predictions.extend(predicted_labels)

    return np.array(all_labels), np.array(all_predictions)

# Get true and predicted labels for the test dataset
true_labels, predicted_labels = evaluate_model(model, test_dataset)

# Compute the confusion matrix
conf_matrix = confusion_matrix(true_labels, predicted_labels)

# Plot the confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues",
            xticklabels=range(10), yticklabels=range(10))
plt.title('Matriz de Confusão')
plt.xlabel('Previsão')
plt.ylabel('Realidade')
plt.show()

# Print classification report
class_names = [str(i) for i in range(10)] # Define class names based on your
dataset
print(classification_report(true_labels, predicted_labels,
                             target_names=class_names))

# Extract precision, recall, and F1-score for each class from classification
report
report = classification_report(true_labels, predicted_labels,
                              target_names=class_names, output_dict=True)

metrics = {'precision': [], 'recall': [], 'f1-score': []}
for cls in class_names:
    metrics['precision'].append(report[cls]['precision'])
    metrics['recall'].append(report[cls]['recall'])
    metrics['f1-score'].append(report[cls]['f1-score'])

# Plot precision, recall, and F1-score

```

```

plt.figure(figsize=(10, 6))
bar_width = 0.2
index = np.arange(len(class_names))

plt.bar(index, metrics['precision'], bar_width, label='Precision')
plt.bar(index + bar_width, metrics['recall'], bar_width, label='Recall')
plt.bar(index + 2*bar_width, metrics['f1-score'], bar_width, label='F1-score')

plt.xlabel('Class')
plt.ylabel('Scores')
plt.title('Precision, Recall e F1-score para cada classe')
plt.xticks(index + bar_width, class_names)
plt.legend()

plt.tight_layout()
plt.show()

```

```

1/1          1s 685ms/step
1/1          0s 209ms/step
1/1          0s 248ms/step
1/1          0s 261ms/step
1/1          0s 219ms/step
1/1          0s 169ms/step
1/1          0s 227ms/step
1/1          0s 286ms/step
1/1          0s 218ms/step
1/1          0s 194ms/step
1/1          0s 222ms/step
1/1          0s 293ms/step
1/1          0s 228ms/step
1/1          0s 222ms/step
1/1          0s 227ms/step
1/1          0s 305ms/step
1/1          0s 323ms/step
1/1          0s 269ms/step
1/1          0s 217ms/step
1/1          0s 190ms/step
1/1          0s 231ms/step
1/1          0s 284ms/step
1/1          0s 299ms/step
1/1          0s 244ms/step
1/1          0s 180ms/step
1/1          0s 137ms/step
1/1          0s 296ms/step
1/1          0s 245ms/step
1/1          0s 242ms/step
1/1          0s 243ms/step

```



1/1	0s 185ms/step
1/1	0s 231ms/step
1/1	0s 237ms/step
1/1	0s 166ms/step
1/1	0s 266ms/step
1/1	0s 290ms/step
1/1	0s 250ms/step
1/1	0s 160ms/step
1/1	0s 296ms/step
1/1	0s 257ms/step
1/1	0s 164ms/step
1/1	0s 243ms/step
1/1	0s 244ms/step
1/1	0s 298ms/step
1/1	0s 218ms/step
1/1	0s 207ms/step
1/1	0s 167ms/step
1/1	0s 223ms/step
1/1	0s 291ms/step
1/1	0s 247ms/step
1/1	0s 195ms/step
1/1	0s 252ms/step
1/1	0s 295ms/step
1/1	0s 235ms/step
1/1	0s 225ms/step
1/1	0s 241ms/step
1/1	0s 258ms/step
1/1	0s 248ms/step
1/1	0s 191ms/step
1/1	0s 211ms/step
1/1	0s 301ms/step
1/1	0s 273ms/step
1/1	0s 217ms/step
1/1	0s 209ms/step
1/1	0s 168ms/step
1/1	0s 234ms/step
1/1	0s 298ms/step
1/1	0s 231ms/step
1/1	0s 186ms/step
1/1	0s 245ms/step
1/1	0s 295ms/step
1/1	0s 294ms/step
1/1	0s 276ms/step
1/1	0s 259ms/step
1/1	0s 175ms/step
1/1	0s 214ms/step
1/1	0s 290ms/step
1/1	0s 220ms/step

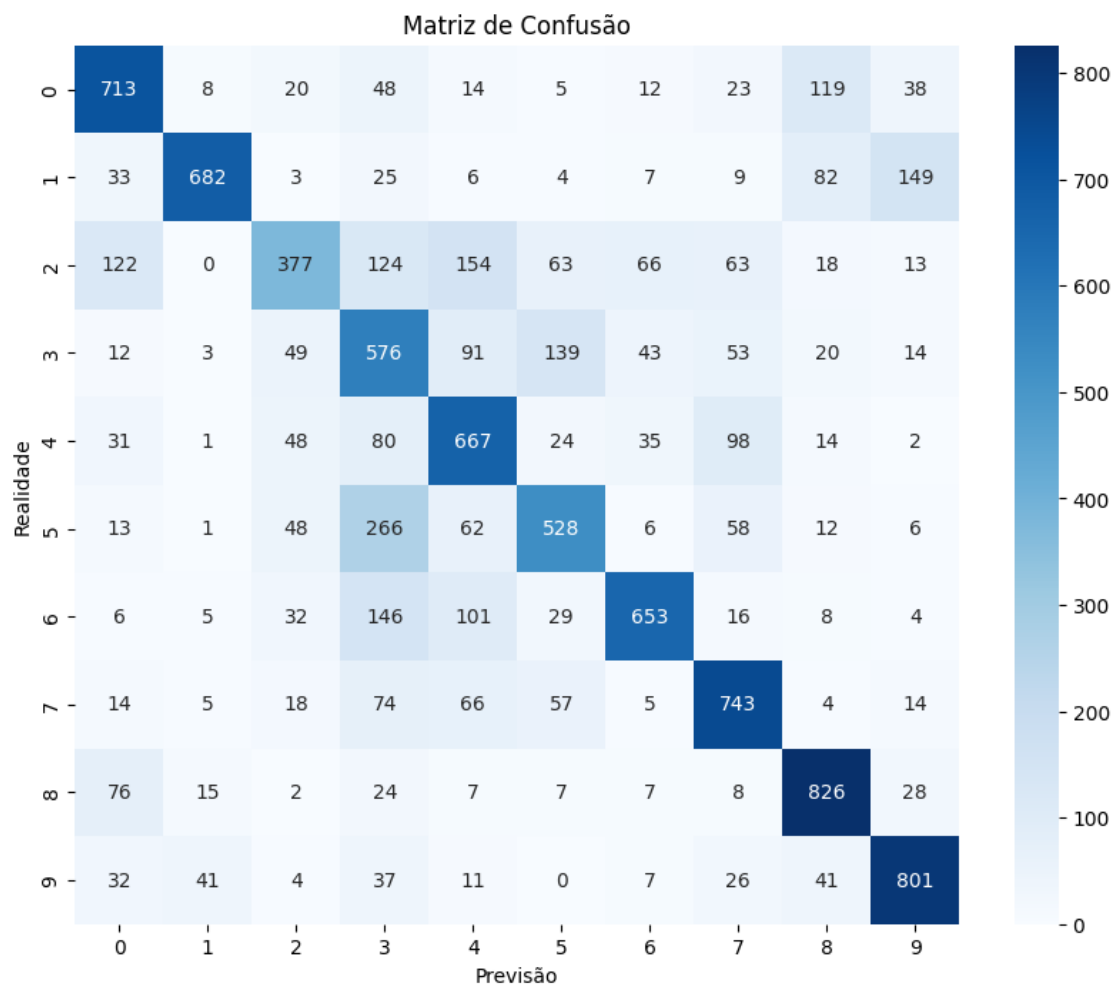
1/1	0s 210ms/step
1/1	0s 165ms/step
1/1	0s 272ms/step
1/1	0s 289ms/step
1/1	0s 301ms/step
1/1	0s 270ms/step
1/1	0s 257ms/step
1/1	0s 198ms/step
1/1	0s 246ms/step
1/1	0s 287ms/step
1/1	0s 222ms/step
1/1	0s 241ms/step
1/1	0s 183ms/step
1/1	0s 225ms/step
1/1	0s 248ms/step
1/1	0s 250ms/step
1/1	0s 227ms/step
1/1	0s 170ms/step
1/1	0s 350ms/step
1/1	0s 281ms/step
1/1	0s 221ms/step
1/1	0s 307ms/step
1/1	0s 185ms/step
1/1	0s 217ms/step
1/1	0s 181ms/step
1/1	0s 248ms/step
1/1	0s 157ms/step
1/1	0s 298ms/step
1/1	0s 292ms/step
1/1	0s 248ms/step
1/1	0s 171ms/step
1/1	0s 222ms/step
1/1	0s 212ms/step
1/1	0s 178ms/step
1/1	0s 235ms/step
1/1	0s 144ms/step
1/1	0s 252ms/step
1/1	0s 217ms/step
1/1	0s 203ms/step
1/1	0s 187ms/step
1/1	0s 241ms/step
1/1	0s 231ms/step
1/1	0s 264ms/step
1/1	0s 254ms/step
1/1	0s 158ms/step
1/1	0s 245ms/step
1/1	0s 288ms/step
1/1	0s 233ms/step

1/1	0s 164ms/step
1/1	0s 250ms/step
1/1	0s 269ms/step
1/1	0s 281ms/step
1/1	0s 176ms/step
1/1	0s 227ms/step
1/1	0s 217ms/step
1/1	0s 300ms/step
1/1	0s 244ms/step
1/1	0s 214ms/step
1/1	0s 223ms/step
1/1	0s 297ms/step
1/1	0s 265ms/step
1/1	0s 283ms/step
1/1	0s 207ms/step
1/1	0s 261ms/step
1/1	0s 293ms/step
1/1	0s 296ms/step
1/1	0s 250ms/step
1/1	0s 202ms/step
1/1	0s 219ms/step
1/1	0s 187ms/step
1/1	0s 199ms/step
1/1	0s 203ms/step
1/1	0s 195ms/step
1/1	0s 236ms/step
1/1	0s 302ms/step
1/1	0s 234ms/step
1/1	0s 224ms/step
1/1	0s 171ms/step
1/1	0s 209ms/step
1/1	0s 281ms/step
1/1	0s 237ms/step
1/1	0s 251ms/step
1/1	0s 179ms/step
1/1	0s 217ms/step
1/1	0s 256ms/step
1/1	0s 249ms/step
1/1	0s 178ms/step
1/1	0s 219ms/step
1/1	0s 164ms/step
1/1	0s 226ms/step
1/1	0s 317ms/step
1/1	0s 216ms/step
1/1	0s 224ms/step
1/1	0s 292ms/step
1/1	0s 239ms/step
1/1	0s 162ms/step

1/1	0s 256ms/step
1/1	0s 287ms/step
1/1	0s 271ms/step
1/1	0s 241ms/step
1/1	0s 178ms/step
1/1	0s 274ms/step
1/1	0s 225ms/step
1/1	0s 158ms/step
1/1	0s 239ms/step
1/1	0s 202ms/step
1/1	0s 193ms/step
1/1	0s 182ms/step
1/1	0s 286ms/step
1/1	0s 228ms/step
1/1	0s 161ms/step
1/1	0s 224ms/step
1/1	0s 304ms/step
1/1	0s 307ms/step
1/1	0s 184ms/step
1/1	0s 256ms/step
1/1	0s 205ms/step
1/1	0s 278ms/step
1/1	0s 236ms/step
1/1	0s 216ms/step
1/1	0s 274ms/step
1/1	0s 294ms/step
1/1	0s 344ms/step
1/1	0s 241ms/step
1/1	0s 148ms/step
1/1	0s 235ms/step
1/1	0s 241ms/step
1/1	0s 246ms/step
1/1	0s 173ms/step
1/1	0s 159ms/step
1/1	0s 228ms/step
1/1	0s 195ms/step
1/1	0s 192ms/step
1/1	0s 193ms/step
1/1	0s 244ms/step
1/1	0s 203ms/step
1/1	0s 258ms/step
1/1	0s 141ms/step
1/1	0s 240ms/step
1/1	0s 252ms/step
1/1	0s 248ms/step
1/1	0s 233ms/step
1/1	0s 261ms/step
1/1	0s 211ms/step

1/1	0s 243ms/step
1/1	0s 235ms/step
1/1	0s 201ms/step
1/1	0s 300ms/step
1/1	0s 229ms/step
1/1	0s 215ms/step
1/1	0s 234ms/step
1/1	0s 207ms/step
1/1	0s 251ms/step
1/1	0s 215ms/step
1/1	0s 244ms/step
1/1	0s 229ms/step
1/1	0s 249ms/step
1/1	0s 226ms/step
1/1	0s 203ms/step
1/1	0s 173ms/step
1/1	0s 264ms/step
1/1	0s 239ms/step
1/1	0s 252ms/step
1/1	0s 200ms/step
1/1	0s 235ms/step
1/1	0s 278ms/step
1/1	0s 240ms/step
1/1	0s 213ms/step
1/1	0s 204ms/step
1/1	0s 284ms/step
1/1	0s 243ms/step
1/1	0s 193ms/step
1/1	0s 189ms/step
1/1	0s 216ms/step
1/1	0s 210ms/step
1/1	0s 181ms/step
1/1	0s 172ms/step
1/1	0s 283ms/step
1/1	0s 375ms/step
1/1	0s 308ms/step
1/1	0s 295ms/step
1/1	0s 239ms/step
1/1	0s 212ms/step
1/1	0s 208ms/step
1/1	0s 296ms/step
1/1	0s 251ms/step
1/1	0s 260ms/step
1/1	0s 205ms/step
1/1	0s 211ms/step
1/1	0s 297ms/step
1/1	0s 347ms/step
1/1	0s 284ms/step

1/1	0s 205ms/step
1/1	0s 177ms/step
1/1	0s 175ms/step
1/1	0s 232ms/step
1/1	0s 226ms/step
1/1	0s 195ms/step
1/1	0s 218ms/step
1/1	0s 229ms/step
1/1	0s 268ms/step
1/1	0s 265ms/step
1/1	0s 266ms/step
1/1	0s 219ms/step
1/1	0s 201ms/step
1/1	0s 289ms/step
1/1	0s 223ms/step
1/1	0s 242ms/step
1/1	0s 210ms/step
1/1	0s 230ms/step
1/1	0s 300ms/step
1/1	0s 299ms/step
1/1	0s 248ms/step
1/1	0s 188ms/step
1/1	0s 241ms/step
1/1	0s 330ms/step
1/1	0s 293ms/step
1/1	0s 231ms/step
1/1	0s 216ms/step
1/1	0s 250ms/step
1/1	0s 149ms/step
1/1	0s 244ms/step
1/1	0s 187ms/step
1/1	0s 173ms/step
1/1	0s 174ms/step
1/1	0s 222ms/step
1/1	0s 280ms/step
1/1	0s 249ms/step
1/1	0s 257ms/step
1/1	0s 173ms/step
1/1	0s 172ms/step
1/1	0s 231ms/step
1/1	0s 228ms/step
1/1	0s 266ms/step
1/1	1s 525ms/step



	precision	recall	f1-score	support
0	0.68	0.71	0.69	1000
1	0.90	0.68	0.77	1000
2	0.63	0.38	0.47	1000
3	0.41	0.58	0.48	1000
4	0.57	0.67	0.61	1000
5	0.62	0.53	0.57	1000
6	0.78	0.65	0.71	1000
7	0.68	0.74	0.71	1000
8	0.72	0.83	0.77	1000
9	0.75	0.80	0.77	1000
accuracy			0.66	10000
macro avg	0.67	0.66	0.66	10000
weighted avg	0.67	0.66	0.66	10000

