

# fhtabxpa9

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

inputs = keras.Input(shape=(IMG_SIZE, IMG_SIZE, 3))
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='sgd',
    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_SGDOptimizer.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 1092s

869ms/step - accuracy: 0.4040 - loss: 1.9449 - val\_accuracy: 0.5251 - val\_loss: 1.3241 - learning\_rate: 0.0100

Epoch 2/30

1250/1250 1091s

873ms/step - accuracy: 0.5952 - loss: 1.1380 - val\_accuracy: 0.6099 - val\_loss: 1.1089 - learning\_rate: 0.0100

Epoch 3/30

1250/1250 1131s

905ms/step - accuracy: 0.6770 - loss: 0.9113 - val\_accuracy: 0.6040 - val\_loss: 1.1744 - learning\_rate: 0.0100

Epoch 4/30

1250/1250 1199s

933ms/step - accuracy: 0.7436 - loss: 0.7177 - val\_accuracy: 0.6360 - val\_loss: 1.0946 - learning\_rate: 0.0100

Epoch 5/30

1250/1250 1165s

932ms/step - accuracy: 0.8082 - loss: 0.5436 - val\_accuracy: 0.6662 - val\_loss: 1.0878 - learning\_rate: 0.0100

Epoch 6/30

1250/1250 1149s

919ms/step - accuracy: 0.8600 - loss: 0.3930 - val\_accuracy: 0.6546 - val\_loss: 1.2478 - learning\_rate: 0.0100

Epoch 7/30

1250/1250 906s 725ms/step

- accuracy: 0.9039 - loss: 0.2750 - val\_accuracy: 0.6658 - val\_loss: 1.2213 - learning\_rate: 0.0100

Epoch 8/30

1250/1250 542s 434ms/step

- accuracy: 0.9402 - loss: 0.1761 - val\_accuracy: 0.7045 - val\_loss: 1.1164 - learning\_rate: 0.0020

Epoch 9/30

1250/1250 535s 428ms/step

- accuracy: 0.9619 - loss: 0.1190 - val\_accuracy: 0.7054 - val\_loss: 1.1198 - learning\_rate: 0.0020

Epoch 10/30

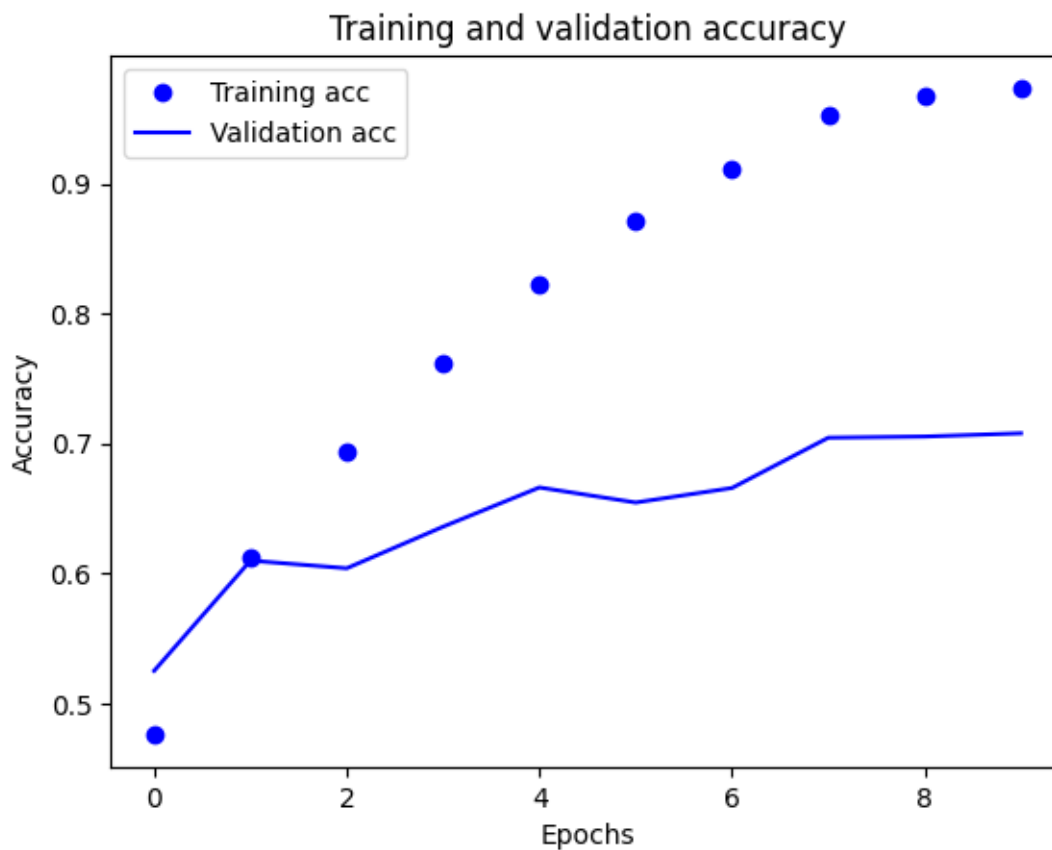
1250/1250 552s 442ms/step

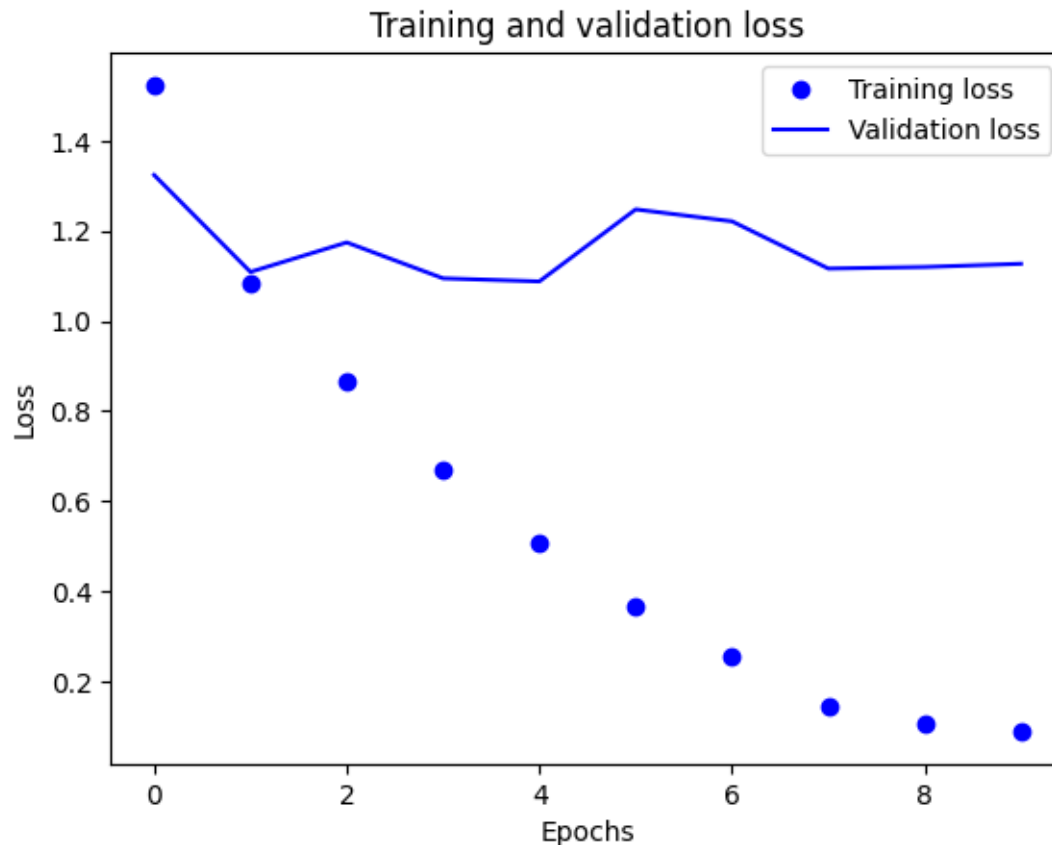
- accuracy: 0.9696 - loss: 0.0996 - val\_accuracy: 0.7079 - val\_loss: 1.1270 -

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          21s 67ms/step -
accuracy: 0.6692 - loss: 1.0758
Validation Accuracy: 0.6661999821662903
```

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

```
313/313          21s 67ms/step -
accuracy: 0.6583 - loss: 1.0930
Loss: 1.0986255407333374, Accuracy: 0.654699981212616
```

```
[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          0s 140ms/step
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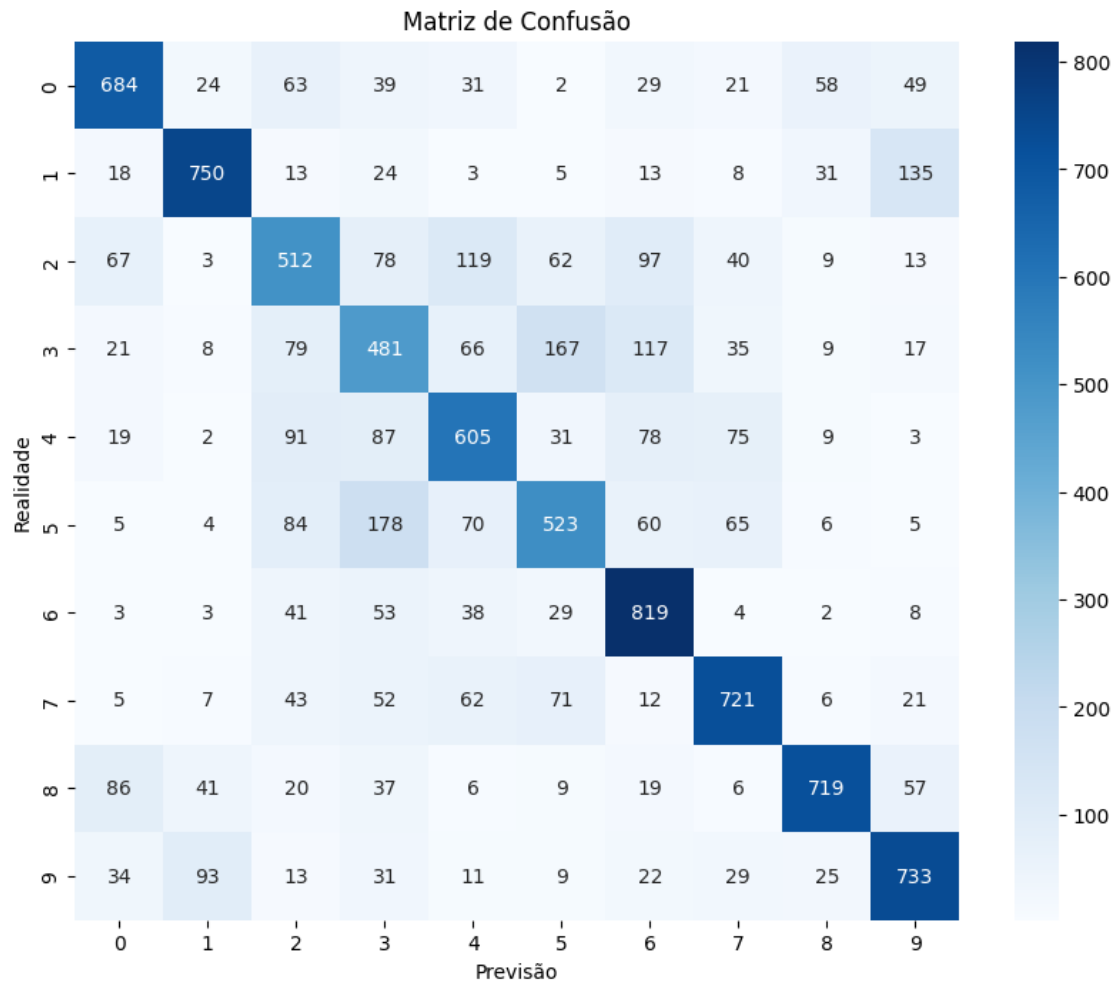
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1/1	0s 75ms/step
1/1	0s 68ms/step
1/1	0s 70ms/step
1/1	0s 98ms/step



	precision	recall	f1-score	support
0	0.73	0.68	0.70	1000
1	0.80	0.75	0.78	1000
2	0.53	0.51	0.52	1000
3	0.45	0.48	0.47	1000
4	0.60	0.60	0.60	1000
5	0.58	0.52	0.55	1000
6	0.65	0.82	0.72	1000
7	0.72	0.72	0.72	1000
8	0.82	0.72	0.77	1000
9	0.70	0.73	0.72	1000
accuracy			0.65	10000
macro avg	0.66	0.65	0.65	10000
weighted avg	0.66	0.65	0.65	10000

