Testando o Modelo ResNet-50

Nesse documento, encontra-se o conteúdo acerca das testagens do modelo ResNet-50 para classificação de imagens.

Primeiro Teste

Modelagem

Modelo Base:

```
base_model = ResNet50(weights="imagenet", include_top=False, input_shape=(480, 480, 3))

base_model.trainable = False
```

Camada Superior:

```
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(512, activation="relu", kernel_regularizer=l2(0.01))(x)
x = Dropout(0.5)(x)
output_layer = Dense(2, activation="softmax")(x)
```

Modelo Final:

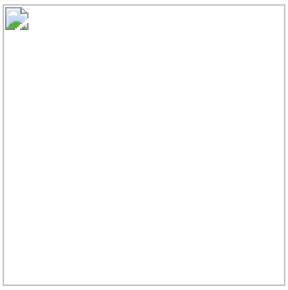
```
model = Model(inputs=base_model.input, outputs=output_layer)

model.compile(
    optimizer=Adam(learning_rate=0.0001),
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"]
)
```

Completo:

```
# Modelo Base
base_model = ResNet50(weights="imagenet", include_top=False, input_shape=(480, 480, 3))

base_model.trainable = False

# Camada superior
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(512, activation="relu", kernel_regularizer=l2(0.01))(x)
x = Dropout(0.5)(x)
output_layer = Dense(2, activation="softmax")(x)

model = Model(inputs=base_model.input, outputs=output_layer)

# Compilando
model.compile(
    optimizer=Adam(learning_rate=0.0001),
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"]
)
```

Treinamento

```
# Treinando o modelo com os dados de treino e validar com os dados de validação
history = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=10
)
```



	accuracy	loss	val_accuracy	val_loss
0	0.805066	0.4268	0.855556	0.322229
1	0.957048	0.169792	0.911111	0.207207
2	0.986784	0.0886557	0.916667	0.20116
3	0.990088	0.0603779	0.922222	0.203695
4	0.996696	0.0428907	0.927778	0.199241
5	0.995595	0.0338027	0.927778	0.200289
6	0.997797	0.0260448	0.933333	0.204704
7	0.997797	0.0227316	0.938889	0.204688
8	0.998899	0.0167188	0.938889	0.230109
9	0.998899	0.0149863	0.938889	0.213935

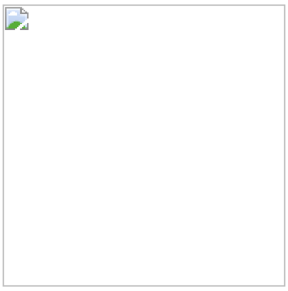
Validação com Teste

```
test_loss, test_acc = model.evaluate(test_ds)
print(f"Acurácia no conjunto de teste: {test_acc * 100:.2f}%")
```

```
11/11 ━━━━━━━━━━━━━━━━━━━━ 9s 846ms/step - accuracy: 0.3737 - loss: 1.5854
```

Acurácia no conjunto de teste: \(64.57\%\)

Gradcam:



Segundo Teste

No segundo teste, vou aplicar métodos para evitar overfitting e melhorar a generalização da seguinte forma:

- Adicionando penalizadores
- Reajustando a arquitetura
- Diminuindo taxa de aprendizagem
- Fine Tuning

Modelo SEM Fine-Tuning

Modelagem

Módulos:

```
import tensorflow as tf
import numpy as np
import cv2
import matplotlib.pyplot as plt
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Dropout, GlobalAveragePooling2D
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.regularizers import l2
from tensorflow.keras.callbacks import ReduceLROnPlateau
from tensorflow.keras.preprocessing import image_dataset_from_directory
```

Modelo Base:

```
base_model = ResNet50(weights="imagenet", include_top=False, input_shape=(480, 480, 3))
base_model.trainable = False
```

Camada Superior:

```
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(512, activation="relu", kernel_regularizer=l2(0.01))(x)  # Regularização L2
x = Dropout(0.5)(x)
output_layer = Dense(2, activation="softmax")(x)
```

Modelo Final:

```
model = Model(inputs=base_model.input, outputs=output_layer)

model.compile(optimizer=Adam(learning_rate=0.0001), loss="sparse_categorical_crossentropy", metrics=["accuracy"])
```

Completo:

```
base_model = ResNet50(weights="imagenet", include_top=False, input_shape=(480, 480, 3))
base_model.trainable = False

x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(512, activation="relu", kernel_regularizer=l2(0.01))(x)  # Regularização L2
x = Dropout(0.5)(x)
output_layer = Dense(2, activation="softmax")(x)

model = Model(inputs=base_model.input, outputs=output_layer)

model.compile(optimizer=Adam(learning_rate=0.0001), loss="sparse_categorical_crossentropy", metrics=["accuracy"])
```

Treinamento

```
# Callback para reduzir a taxa de aprendizado automaticamente
lr_scheduler = ReduceLROnPlateau(monitor="val_loss", factor=0.5, patience=3, verbose=1)

history = model.fit(train_ds, validation_data=val_ds, epochs=15, callbacks=[lr_scheduler])
```

	accuracy	loss	val_accuracy	val_loss	learning_rate
0	0.786344	7.66283	0.883333	6.52977	0.0001
1	0.935022	5.66489	0.922222	4.95051	0.0001
2	0.97467	4.26733	0.927778	3.7962	0.0001
3	0.986784	3.24993	0.922222	2.93257	0.0001
4	0.990088	2.48994	0.927778	2.3087	0.0001
5	0.992291	1.93818	0.927778	1.84245	0.0001
6	0.997797	1.5242	0.938889	1.50236	0.0001
7	0.997797	1.22271	0.938889	1.24341	0.0001
8	0.997797	1.00043	0.938889	1.05268	0.0001
9	0.997797	0.835094	0.916667	0.908606	0.0001
10	0.995595	0.711198	0.938889	0.820028	0.0001
11	0.996696	0.613841	0.938889	0.742791	0.0001
12	0.998899	0.538765	0.938889	0.664574	0.0001
13	0.997797	0.476076	0.938889	0.624237	0.0001
14	0.996696	0.430458	0.938889	0.568388	0.0001

Validação com Teste

```
test_loss, test_acc = model.evaluate(test_ds)
print(f"Acurácia no conjunto de teste com regularização e sem fine-tuning: {test_acc * 100:.2f}%")
```

```
11/11 ━━━━━━━━━━━━━━━━━━━━ 3s 316ms/step - accuracy: 0.3493 - loss: 1.8019
```

Acurácia no conjunto de teste com regularização e sem fine-tuning: 62.29%

GradCam:

Modelo COM Fine-Tuning

A modelagem base permanece a mesma.

Modelo Final:

```
# Modelo para fine-tuning
model_finetuning = Model(inputs=base_model.input, outputs=output_layer)

# Deixar treináveis as 10 últimas camadas
for layer in base_model.layers[-10:]:
    layer.trainable = True

# Compilado com taxa de aprendizado menor
model_finetuning.compile(optimizer=Adam(learning_rate=0.00001), loss="sparse_categorical_crossentropy", metrics=["accuracy"])

# Treino
history_finetune = model_finetuning.fit(train_ds, validation_data=val_ds, epochs=10, callbacks=[lr_scheduler])
```

Completo:

```
base_model = ResNet50(weights="imagenet", include_top=False, input_shape=(480, 480, 3))
base_model.trainable = False

x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(512, activation="relu", kernel_regularizer=l2(0.01))(x)  # Regularização L2
x = Dropout(0.5)(x)
output_layer = Dense(2, activation="softmax")(x)

model_finetuning = Model(inputs=base_model.input, outputs=output_layer)

for layer in base_model.layers[-10:]:
    layer.trainable = True

model_finetuning.compile(optimizer=Adam(learning_rate=0.00001), loss="sparse_categorical_crossentropy", metrics=["accuracy"])
```

Treinamento

```
history_finetune = model_finetuning.fit(train_ds, validation_data=val_ds, epochs=10, callbacks=[lr_scheduler])
```

	accuracy	loss	val_accuracy	val_loss	learning_rate
0	0.997797	0.388907	0.938889	0.643104	1e-05
1	0.998899	0.371528	0.938889	0.675099	1e-05
2	0.997797	0.362334	0.933333	0.639913	1e-05
3	1	0.347455	0.922222	0.582716	1e-05
4	1	0.336777	0.938889	0.568633	1e-05
5	1	0.327655	0.938889	0.517056	1e-05
6	1	0.316483	0.938889	0.508146	1e-05
7	1	0.307381	0.944444	0.46344	1e-05
8	1	0.296128	0.938889	0.466465	1e-05
9	1	0.28635	0.938889	0.464206	1e-05

Validação com Teste

```
test_loss, test_acc = model_finetuning.evaluate(test_ds)
print(f"Acurácia no conjunto de teste: {test_acc * 100:.2f}%")
```

```
11/11 ━━━━━━━━━━━━━━━━━━━━ 3s 303ms/step - accuracy: 0.4709 - loss: 2.0168
```

Acurácia no conjunto de teste com Fine-Tuning: 72.57%

GradCam: