

# RPS CNN Training

March 28, 2021

```
[1]: from os import getcwd, listdir
import numpy as np
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import datasets, layers, models
from tensorflow.keras.models import load_model
from tensorflow.keras.utils import plot_model
from tensorflow.keras.preprocessing import image
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix
```

```
[2]: DATASET = getcwd() + "/dataset/rps-cv-images/"
CLASSES = 3
IMG_WIDTH = 300
IMG_HEIGHT = 200
BATCH_SIZE = 16
NB_TRAIN_SAMPLES = 1751
NB_VALIDATION_SAMPLES = 437
EPOCHS = 50
```

```
[3]: DATASET
```

```
[3]: '/home/amogh/Documents/Study/PiRockPaperScissors/notebooks/dataset/rps-cv-
images/'
```

```
[37]: train_datagen = ImageDataGenerator(
    rescale=1.0 / 255,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    validation_split=0.2,
)

test_datagen = ImageDataGenerator(rescale=1.0 / 255, validation_split=0.2)

train_generator = train_datagen.flow_from_directory(
    DATASET,
    target_size=(IMG_WIDTH, IMG_HEIGHT),
```

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        batch_size=BATCH_SIZE,
        class_mode="categorical",
        subset="training",
    )

    validation_generator = test_datagen.flow_from_directory(
        DATASET,
        target_size=(IMG_WIDTH, IMG_HEIGHT),
        batch_size=BATCH_SIZE,
        class_mode="categorical",
        subset="validation",
        shuffle=False
    )

```

Found 1751 images belonging to 3 classes.  
 Found 437 images belonging to 3 classes.

```

[5]: model = models.Sequential()
    model.add(
        layers.Conv2D(32, (3, 3), activation="relu", input_shape=(IMG_WIDTH,
        ↪ IMG_HEIGHT, 3))
    )
    model.add(layers.MaxPooling2D((2, 2)))
    model.add(layers.Conv2D(64, (3, 3), activation="relu"))
    model.add(layers.MaxPooling2D((2, 2)))
    model.add(layers.Conv2D(64, (3, 3), activation="relu"))
    model.add(layers.Flatten())
    model.add(layers.Dense(512, activation="relu"))
    model.add(layers.Dense(CLASSES, activation="softmax"))
    model.summary()

```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 298, 198, 32)	896
max_pooling2d (MaxPooling2D)	(None, 149, 99, 32)	0
conv2d_1 (Conv2D)	(None, 147, 97, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 73, 48, 64)	0
conv2d_2 (Conv2D)	(None, 71, 46, 64)	36928
flatten (Flatten)	(None, 209024)	0
dense (Dense)	(None, 512)	107020800

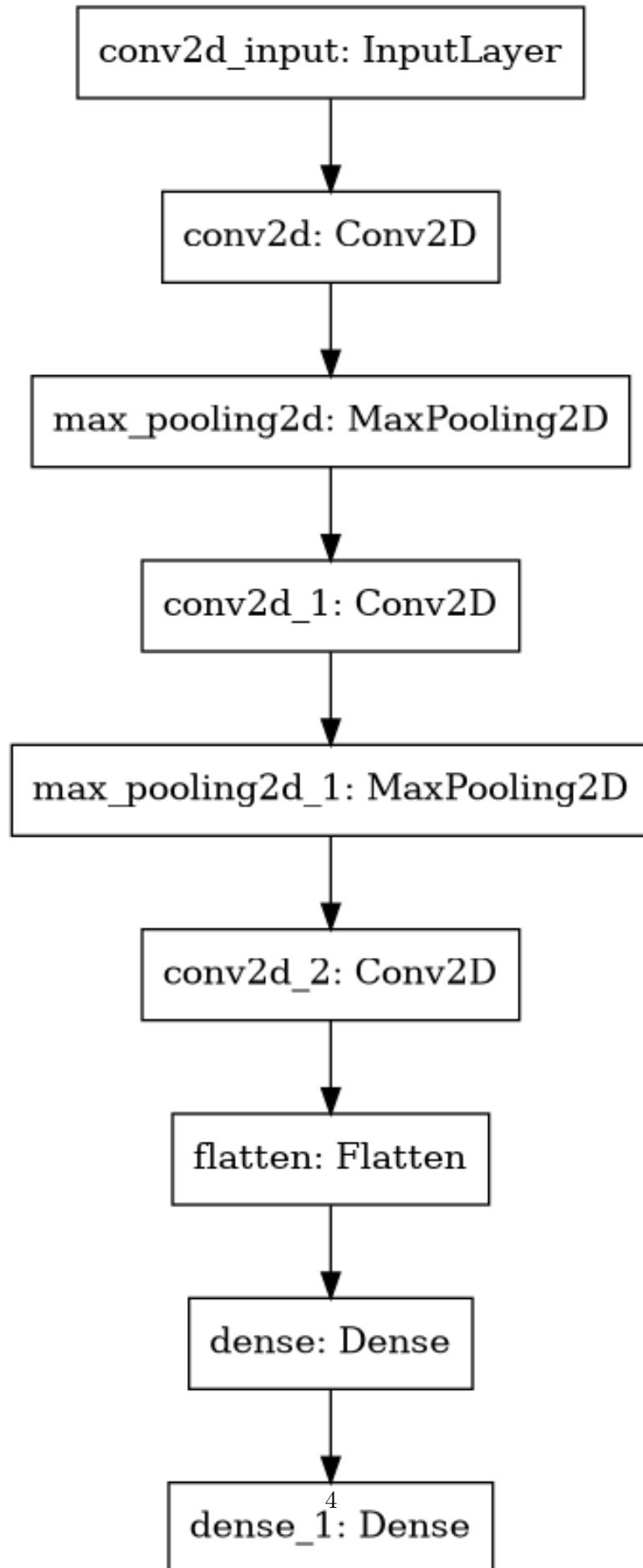
```
-----  
dense_1 (Dense)                (None, 3)                1539  
=====
```

Total params: 107,078,659  
Trainable params: 107,078,659  
Non-trainable params: 0

```
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```

```
[6]: plot_model(model)
```

```
[6]:
```



```
[7]: earlystop = tf.keras.callbacks.EarlyStopping(
    monitor="val_loss", min_delta=0, patience=5, verbose=1,
    ↪restore_best_weights=True
)

callbacks = [earlystop]

model.compile(
    optimizer="adam",
    loss=tf.keras.losses.CategoricalCrossentropy(),
    metrics=["accuracy"],
)

history = model.fit(
    train_generator,
    steps_per_epoch=NB_TRAIN_SAMPLES // BATCH_SIZE,
    epochs=EPOCHS,
    callbacks=callbacks,
    validation_data=validation_generator,
    validation_steps=NB_VALIDATION_SAMPLES // BATCH_SIZE,
)
```

Epoch 1/50

109/109 [=====] - 19s 173ms/step - loss: 1.0308 -  
accuracy: 0.5948 - val\_loss: 0.6890 - val\_accuracy: 0.7593

Epoch 2/50

109/109 [=====] - 17s 159ms/step - loss: 0.4613 -  
accuracy: 0.8225 - val\_loss: 0.3221 - val\_accuracy: 0.8889

Epoch 3/50

109/109 [=====] - 17s 157ms/step - loss: 0.3131 -  
accuracy: 0.8807 - val\_loss: 0.2772 - val\_accuracy: 0.9051

Epoch 4/50

109/109 [=====] - 17s 156ms/step - loss: 0.2557 -  
accuracy: 0.9118 - val\_loss: 0.2102 - val\_accuracy: 0.9398

Epoch 5/50

109/109 [=====] - 17s 155ms/step - loss: 0.2179 -  
accuracy: 0.9170 - val\_loss: 0.2233 - val\_accuracy: 0.9306

Epoch 6/50

109/109 [=====] - 17s 154ms/step - loss: 0.2050 -  
accuracy: 0.9262 - val\_loss: 0.2498 - val\_accuracy: 0.9051

Epoch 7/50

109/109 [=====] - 17s 154ms/step - loss: 0.1545 -  
accuracy: 0.9441 - val\_loss: 0.1428 - val\_accuracy: 0.9537

Epoch 8/50

109/109 [=====] - 17s 154ms/step - loss: 0.1335 -

```

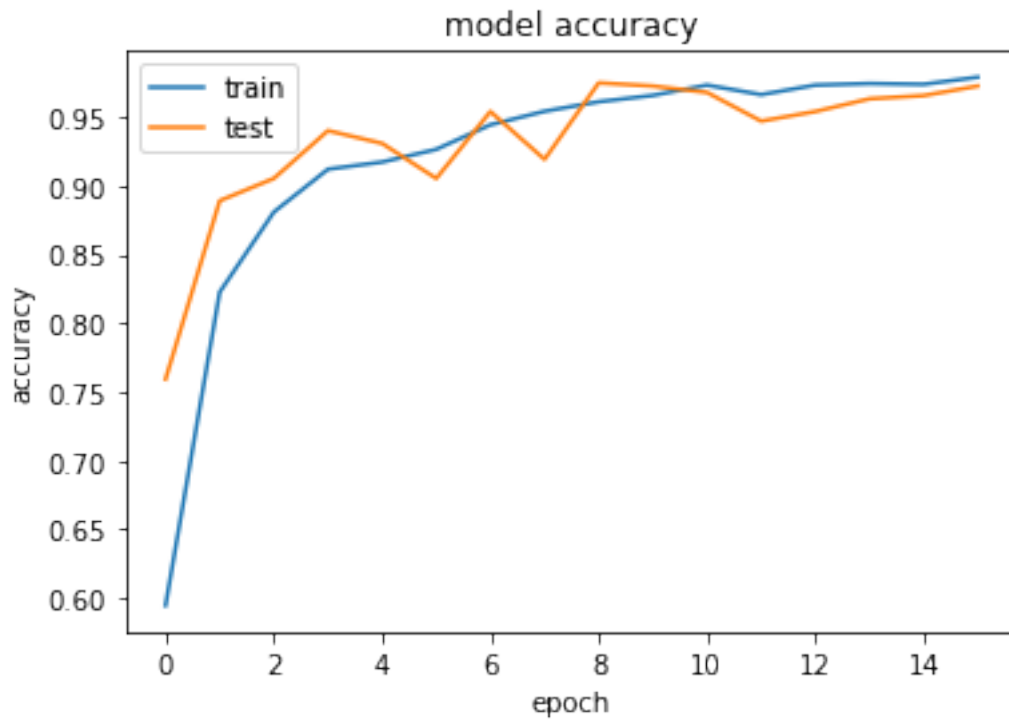
accuracy: 0.9539 - val_loss: 0.2359 - val_accuracy: 0.9190
Epoch 9/50
109/109 [=====] - 17s 155ms/step - loss: 0.1091 -
accuracy: 0.9608 - val_loss: 0.1305 - val_accuracy: 0.9745
Epoch 10/50
109/109 [=====] - 17s 155ms/step - loss: 0.0879 -
accuracy: 0.9654 - val_loss: 0.1198 - val_accuracy: 0.9722
Epoch 11/50
109/109 [=====] - 17s 157ms/step - loss: 0.0853 -
accuracy: 0.9729 - val_loss: 0.1064 - val_accuracy: 0.9676
Epoch 12/50
109/109 [=====] - 17s 153ms/step - loss: 0.0905 -
accuracy: 0.9660 - val_loss: 0.1630 - val_accuracy: 0.9468
Epoch 13/50
109/109 [=====] - 17s 155ms/step - loss: 0.0646 -
accuracy: 0.9729 - val_loss: 0.1241 - val_accuracy: 0.9537
Epoch 14/50
109/109 [=====] - 17s 153ms/step - loss: 0.0637 -
accuracy: 0.9741 - val_loss: 0.1110 - val_accuracy: 0.9630
Epoch 15/50
109/109 [=====] - 17s 153ms/step - loss: 0.0856 -
accuracy: 0.9735 - val_loss: 0.1486 - val_accuracy: 0.9653
Epoch 16/50
109/109 [=====] - ETA: 0s - loss: 0.0593 - accuracy:
0.9787Restoring model weights from the end of the best epoch.
109/109 [=====] - 17s 156ms/step - loss: 0.0593 -
accuracy: 0.9787 - val_loss: 0.1108 - val_accuracy: 0.9722
Epoch 00016: early stopping

```

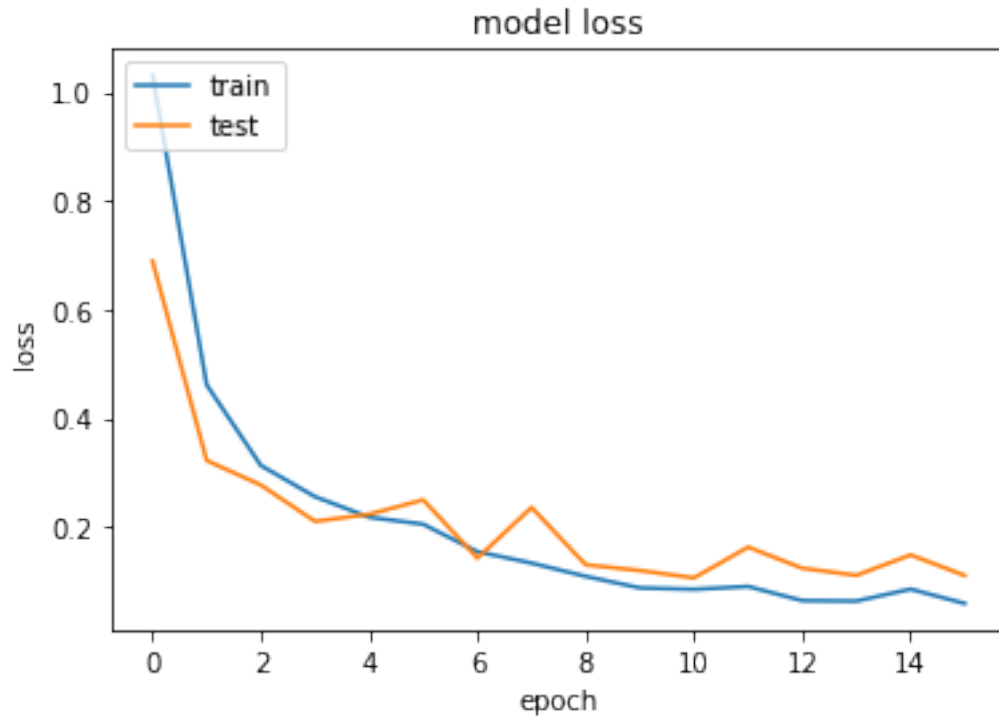
```

[8]: plt.plot(history.history["accuracy"])
plt.plot(history.history["val_accuracy"])
plt.title("model accuracy")
plt.ylabel("accuracy")
plt.xlabel("epoch")
plt.legend(["train", "test"], loc="upper left")
plt.show()

```



```
[9]: plt.plot(history.history["loss"])
plt.plot(history.history["val_loss"])
plt.title("model loss")
plt.ylabel("loss")
plt.xlabel("epoch")
plt.legend(["train", "test"], loc="upper left")
plt.show()
```



```
[10]: model.save("rps-cnn.h5")
```

```
[11]: model.save_weights("rps-cnn-weights.h5")
```

```
[13]: loaded_model = load_model(getcwd() + "/rps-cnn.h5")
```

```
[38]: Y_pred = loaded_model.predict_generator(
        validation_generator, NB_VALIDATION_SAMPLES // BATCH_SIZE + 1
    )
    y_pred = np.argmax(Y_pred, axis=1)

    class_labels = {v: k for k, v in validation_generator.class_indices.items()}

    print("Confusion Matrix")
    print(confusion_matrix(validation_generator.classes, y_pred))

    print("Classification Report")
    target_names = list(class_labels.values())
    print(
        classification_report(
            validation_generator.classes, y_pred, target_names=target_names
        )
    )
```



Confusion Matrix

```
[[133  5  4]
 [ 1 144  0]
 [ 3  1 146]]
```

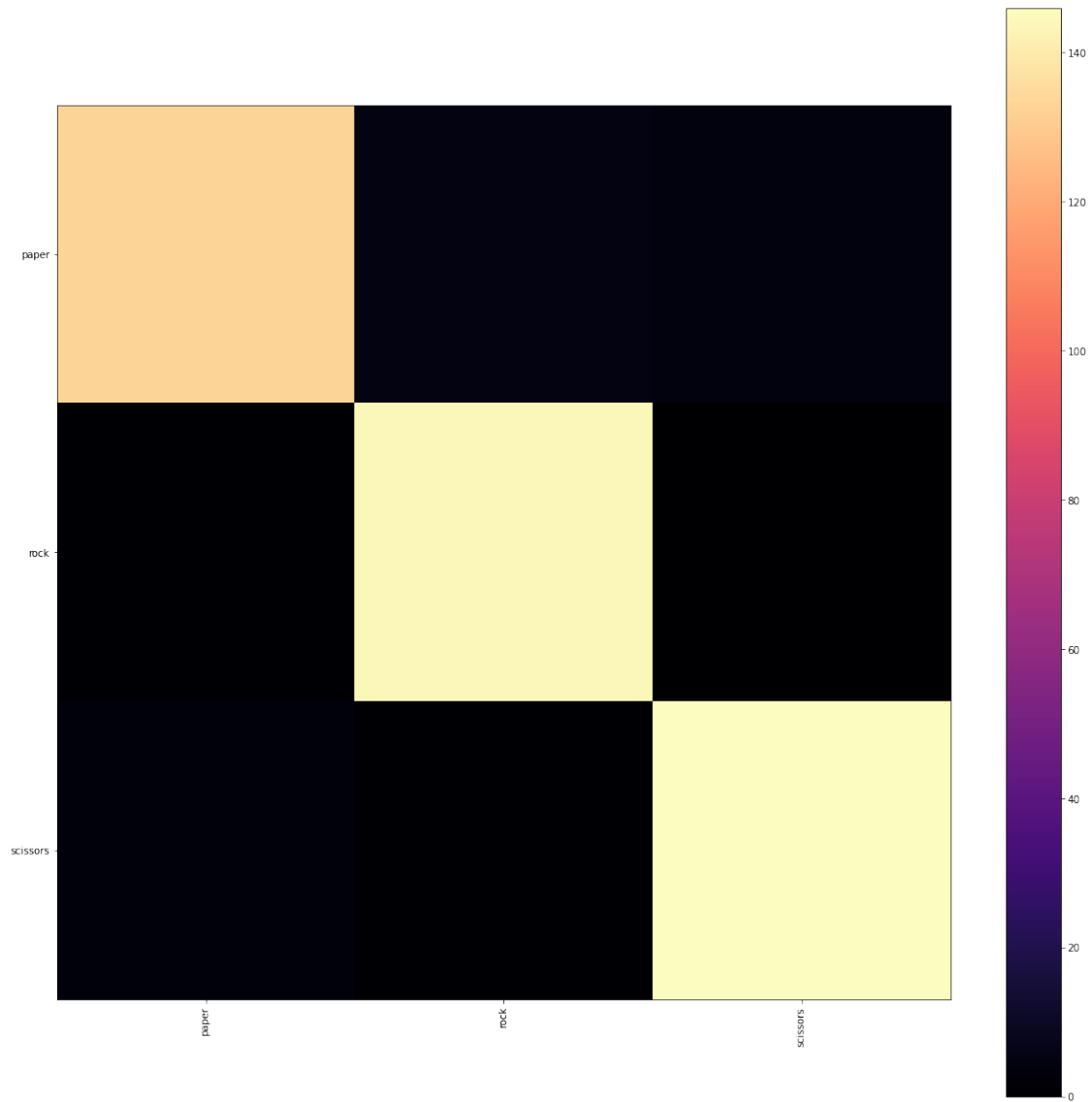
Classification Report

	precision	recall	f1-score	support
paper	0.97	0.94	0.95	142
rock	0.96	0.99	0.98	145
scissors	0.97	0.97	0.97	150
accuracy			0.97	437
macro avg	0.97	0.97	0.97	437
weighted avg	0.97	0.97	0.97	437

```
[39]: plt.figure(figsize=(20,20))
cnf_matrix = confusion_matrix(validation_generator.classes, y_pred)
plt.imshow(cnf_matrix, interpolation='nearest', cmap = "magma")
plt.colorbar()

classes = list(class_labels.values())

tick_marks = np.arange(len(classes))
_ = plt.xticks(tick_marks, classes, rotation=90)
_ = plt.yticks(tick_marks, classes)
```



```
[36]: path = DATASET

fig = plt.figure(figsize=(20, 8))

def predictedLabelColor(original, predicted):
    if original == predicted:
        return "green"
    else:
        return "red"
```

```

for i in range(50):
    rps_names = listdir(path)
    rps_names_folders = listdir(path)
    random_rps_index = np.random.randint(0, len(rps_names))
    rps_name = rps_names_folders[random_rps_index]

    rps_images_path = path + "/" + rps_name
    rps_images = listdir(rps_images_path)
    random_rps_image_index = np.random.randint(0, len(rps_images))
    rps_image = rps_images[random_rps_image_index]
    rps_image_path = rps_images_path + "/" + rps_image

    result_image_array = image.img_to_array(
        image.load_img(rps_image_path, target_size=(IMG_WIDTH, IMG_HEIGHT))
    )
    normalized_result = result_image_array * 1.0 / 255
    expanded_result = np.expand_dims(normalized_result, axis=0)
    classes = loaded_model.predict_classes(expanded_result, batch_size=10)
    predicted_label = class_labels[classes[0]]

    ax = fig.add_subplot(5, 10, 1 + i, xticks=[], yticks=[])
    ax.set_title(
        "Predicted: {}".format(predicted_label),
        color=predictedLabelColor(rps_name, predicted_label),
    )
    plt.imshow(normalized_result)

plt.show()

```

