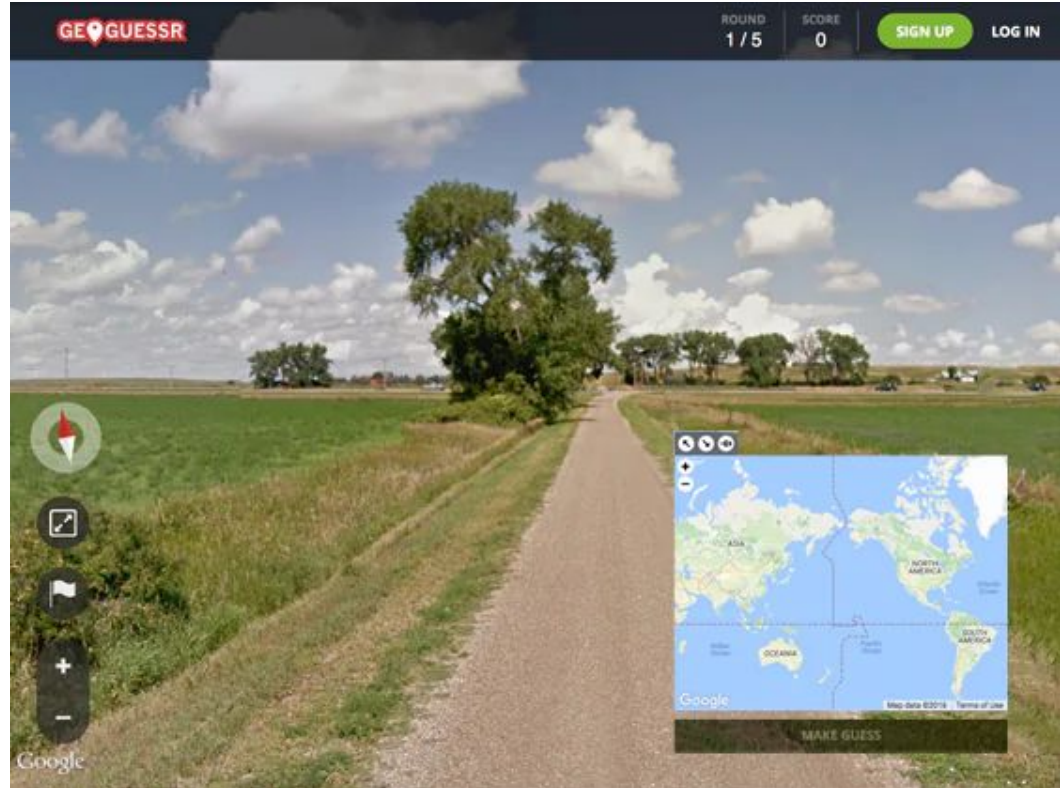


[www.geoguessr.com](http://www.geoguessr.com)

# GeoGuessr

- Popular Online Game
- Guess location of “random” Street View image
- Really fun but also quite difficult



## **Initial Idea for Project:**

Guess location based on GeoGuessr Image

Try to base recognition on human player approach:

- Position of sun
- Road markings
- Position of Street View car (left- or right-hand traffic)
- Vegetation

Decided against, this idea and approaches because it is really difficult and extensive pre-processing required

# Our more realistic Idea:

## Distinguish between Europe and Asia









# Goal

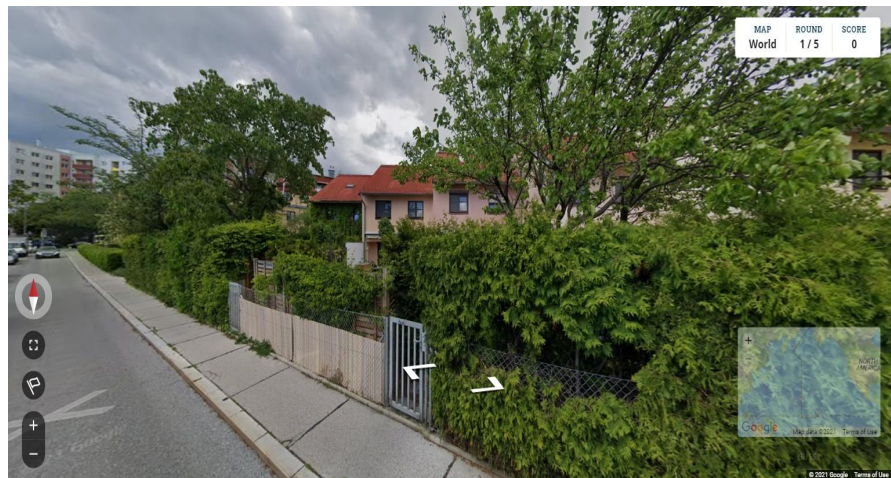
- Successfully distinguish between Asia and Europe countries
- Better accuracy than dummy classifier (0.5)
- Evaluate different model architectures and model setups

# **Dataset and Pre-Processing**

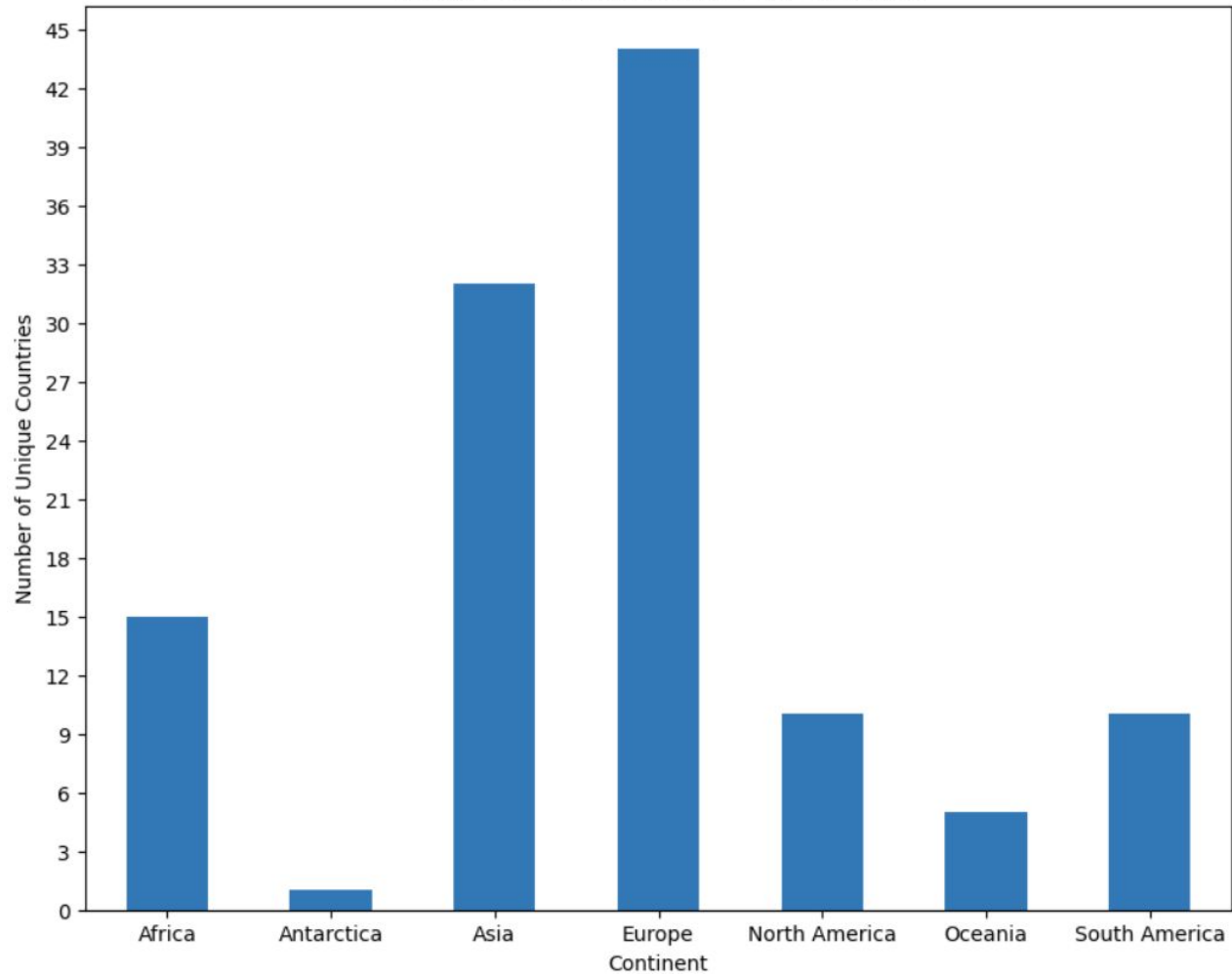
# Dataset

- 50k Images  
[GeoLocation - Geoguessr Images \(50K\) \(kaggle.com\)](https://www.kaggle.com/geo-location-geoguessr-images-50k)
- Split into individual countries
- Data scraped from GeoGuessr
- Strong class imbalance, since amount of Street View images is highly dependent on country

 Australia 1704 files	 Austria 347 files	 Bangladesh 106 files
 Bermuda 3 files	 Bhutan 20 files	 Bolivia 116 files

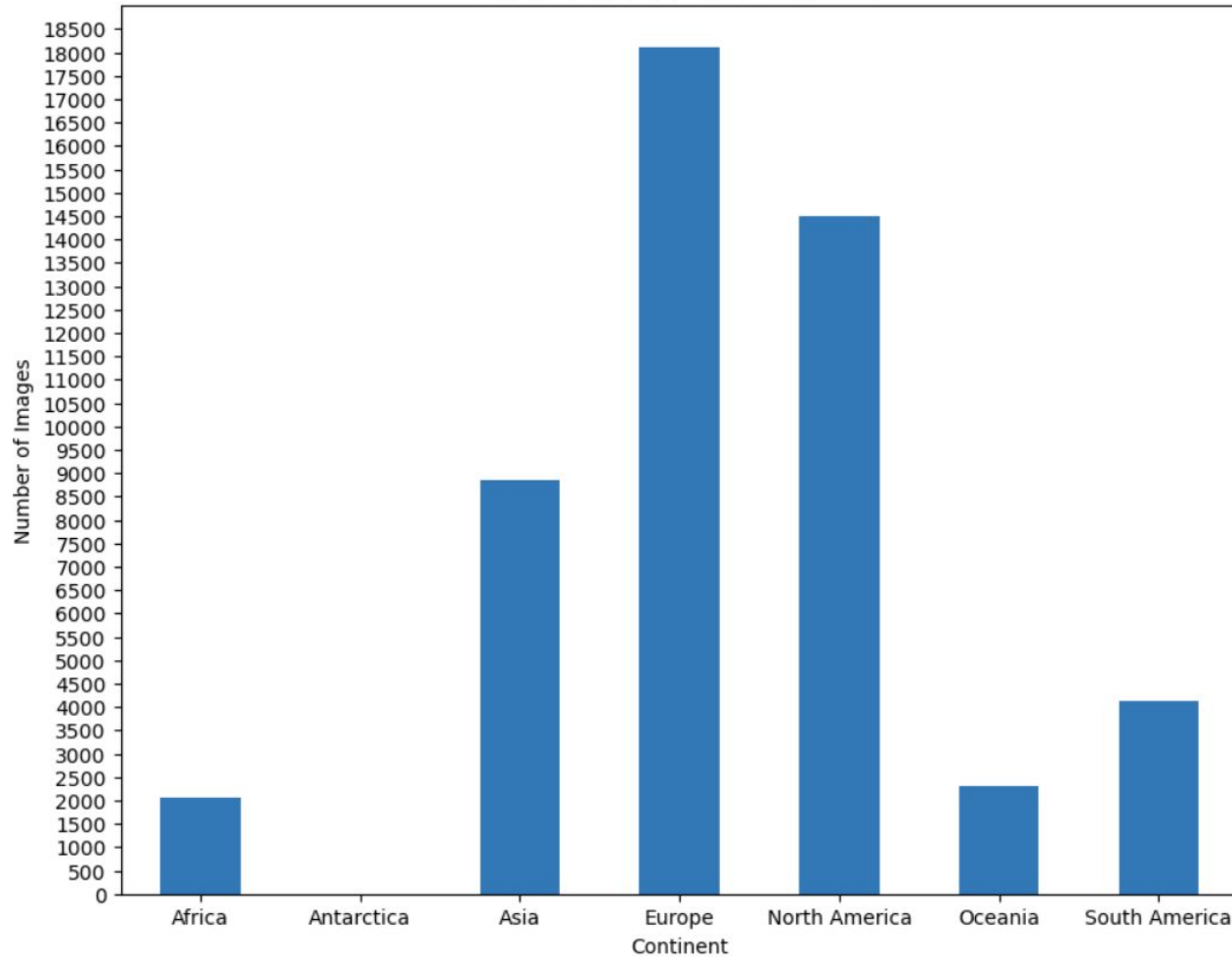


Number of Unique Countries per Continent





Number of Images per Continent



Max. amount  
we used for  
training



# Data Preparation

1. Group countries into continents
2. Resize images to 224x224
3. (Non) Crop
4. Split into three sets
  - a. 70% Train
  - b. 20% Validation
  - c. 10% Test



Sample non cropped



Sample center  
cropped



Simple. Flexible. Powerful.

# Model Architectures

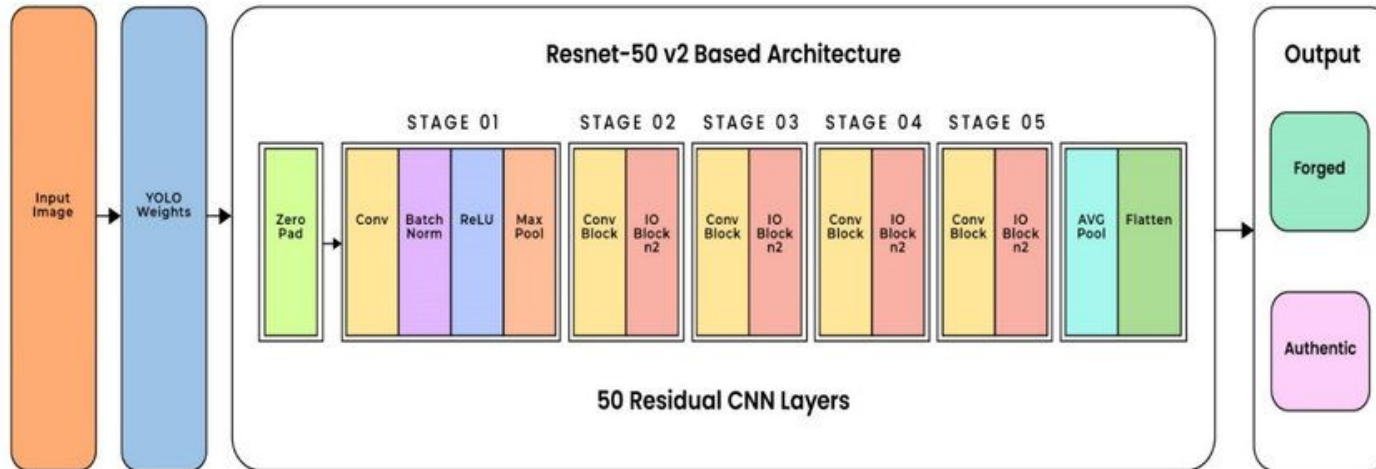
# A Note on Preprocessing

- Each model architecture required its own preprocessing
  - Keras provides a function, mostly scaling between  $[0,1]$  or  $[-1,1]$
  - sometimes includes data centering
- Data augmentation could be performed in augmentation layers
  - Horizontal flips, stretching, rotating etc.

Note: each Keras Application expects a specific kind of input preprocessing. For ResNet, call `keras.applications.resnet_v2.preprocess_input` on your inputs before passing them to the model. `resnet_v2.preprocess_input` will scale input pixels between -1 and 1.

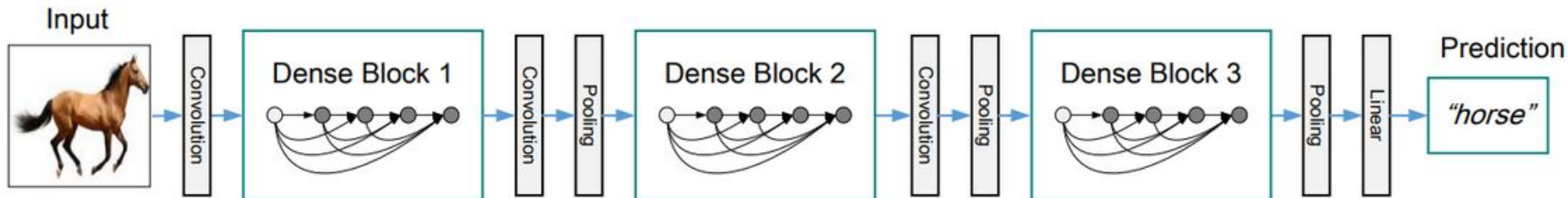
# ResNet50(v2)

- Residual Network with 50 layers
- CNN Architecture
- reduce vanishing gradient problem in deep neural networks by using residual connections or skip connections



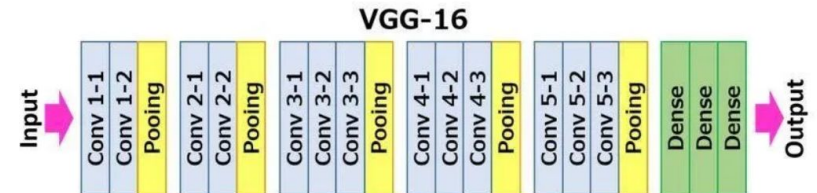
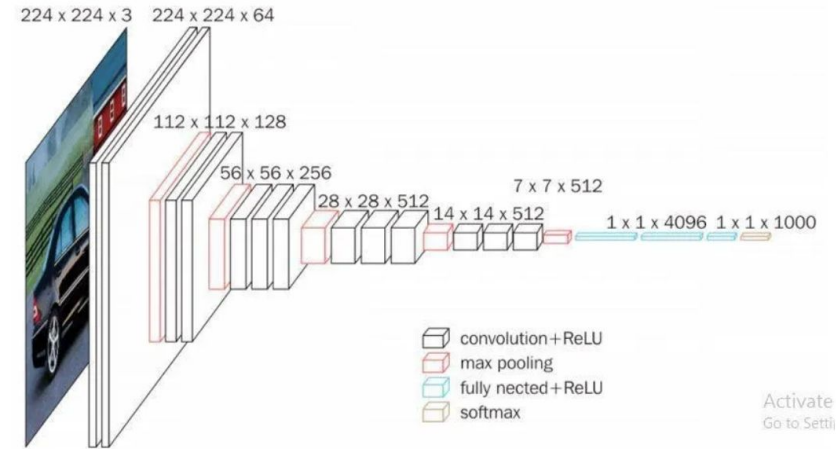
# DenseNet121 - Densely Connected Convolutional Network

- Connects each layer to every other layer in a feed-forward fashion
- Each layer uses feature-maps of all preceding layers as inputs:
  - consequently its own feature-maps are used as inputs into all subsequent layers.
- **Advantages:**
  - strong feature propagation and feature reuse:
    - reduces the total number of parameters



# VGG16 - Very Deep Convolutional Network

- By the Visual Geometry Group, Oxford
- 16 layers that have trainable weights, 21 total
- 13 convolutional layers
- small 3x3 convolution kernel to avoid too many parameters



# Training



# Training

- Use 8000 images per continent
- Utilized EarlyStopper and Checkpoints
- Lots of trial and error in terms of applying learning rates and regularization

# Training duration

CPU based training (DenseNet121) time roughly 300 seconds per epoch

Tried to use GPU for learning on two local machines -> could not get it to work

Bought Google Colab Pro in hope to improve training time and make Collaboration easier

# Evaluation

# Dense121 - center cropped images

DenseNet121 : 36.51%



Epoch 11/30

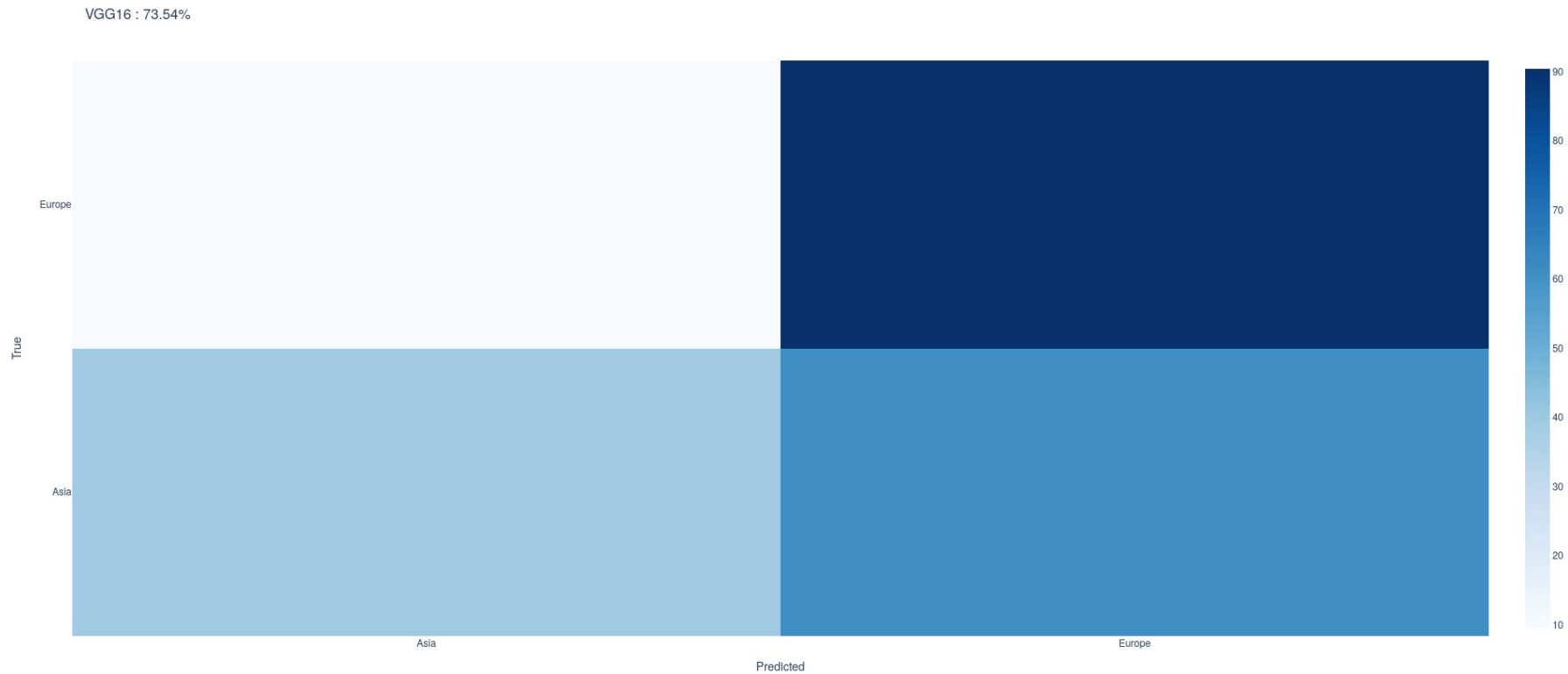
350/350 [=====] - ETA: 0s - loss: 0.4756 - accuracy: 0.7760

Epoch 00011: val\_loss improved from 0.52002 to 0.48650, saving model to models/dense2\_model\_best\_adam.hdf5

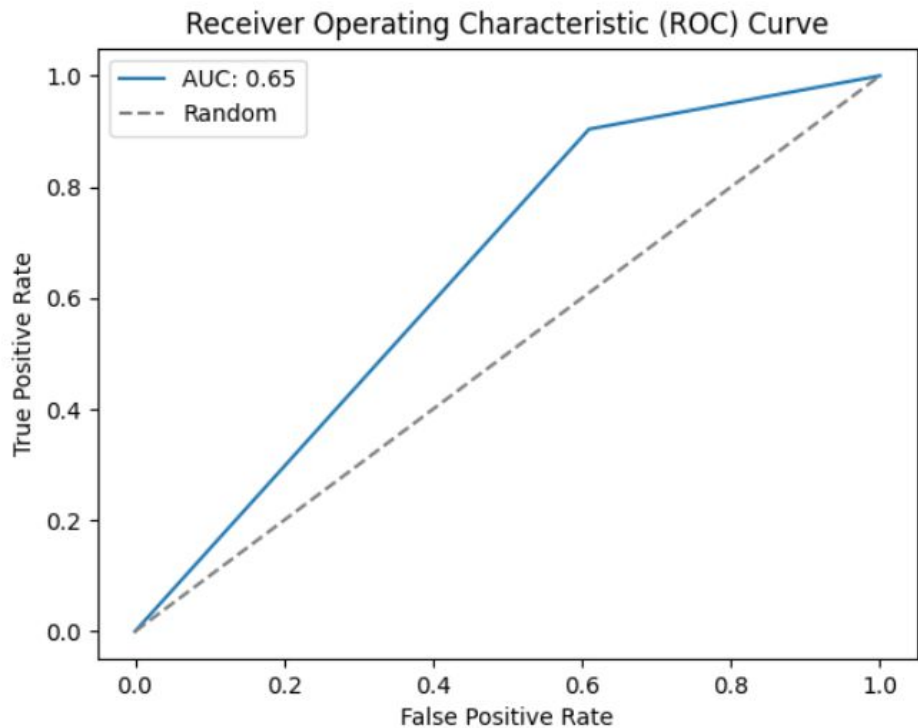
350/350 [=====] - 25s 73ms/step - loss: 0.4756 - accuracy: 0.7760 - val\_loss: 0.4865 - val\_accuracy: 0.7716



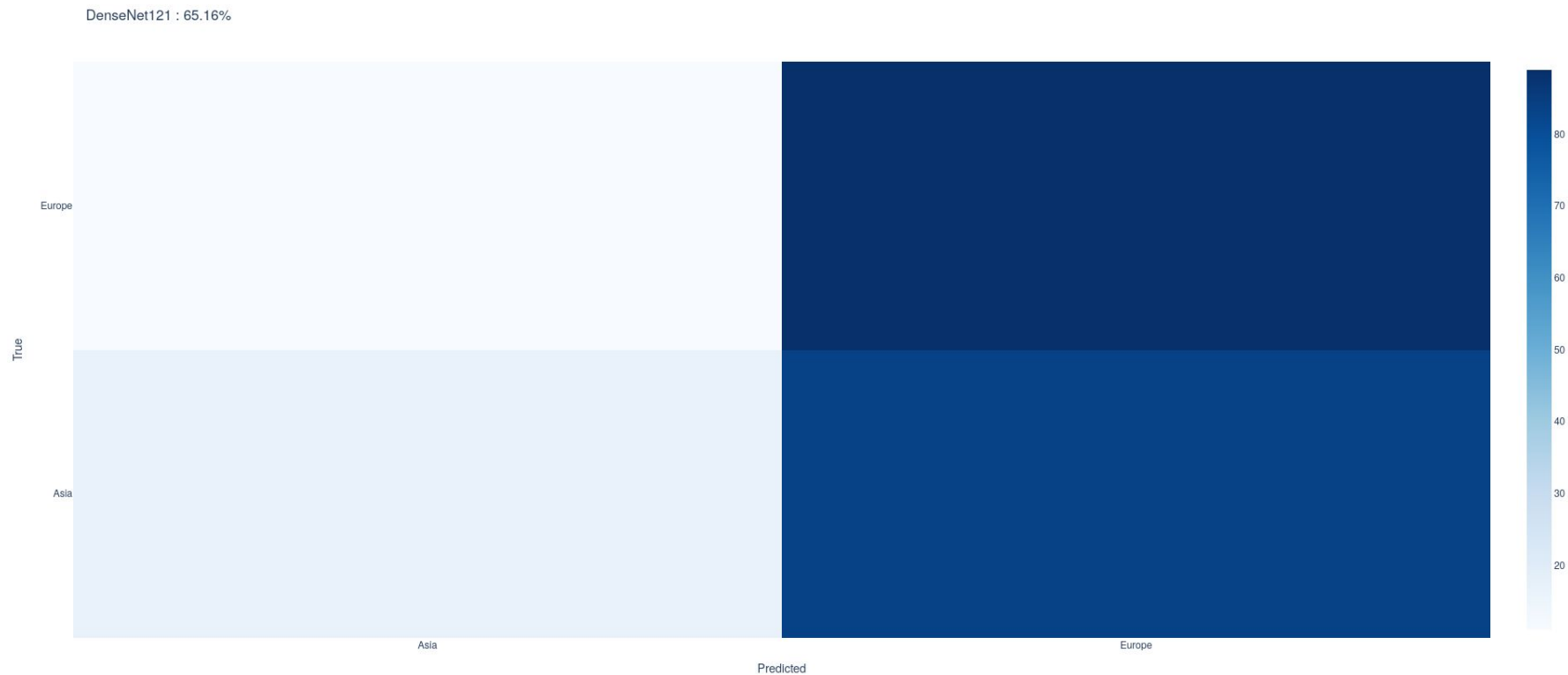
# VGG - center cropped images



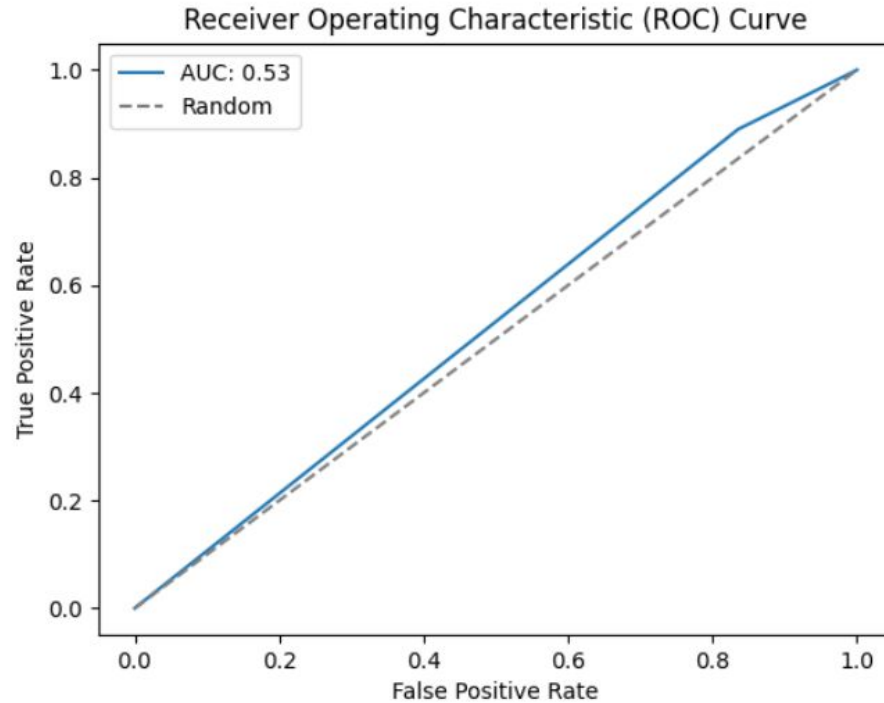
# VGG - center cropped images



# Dense - non cropped images



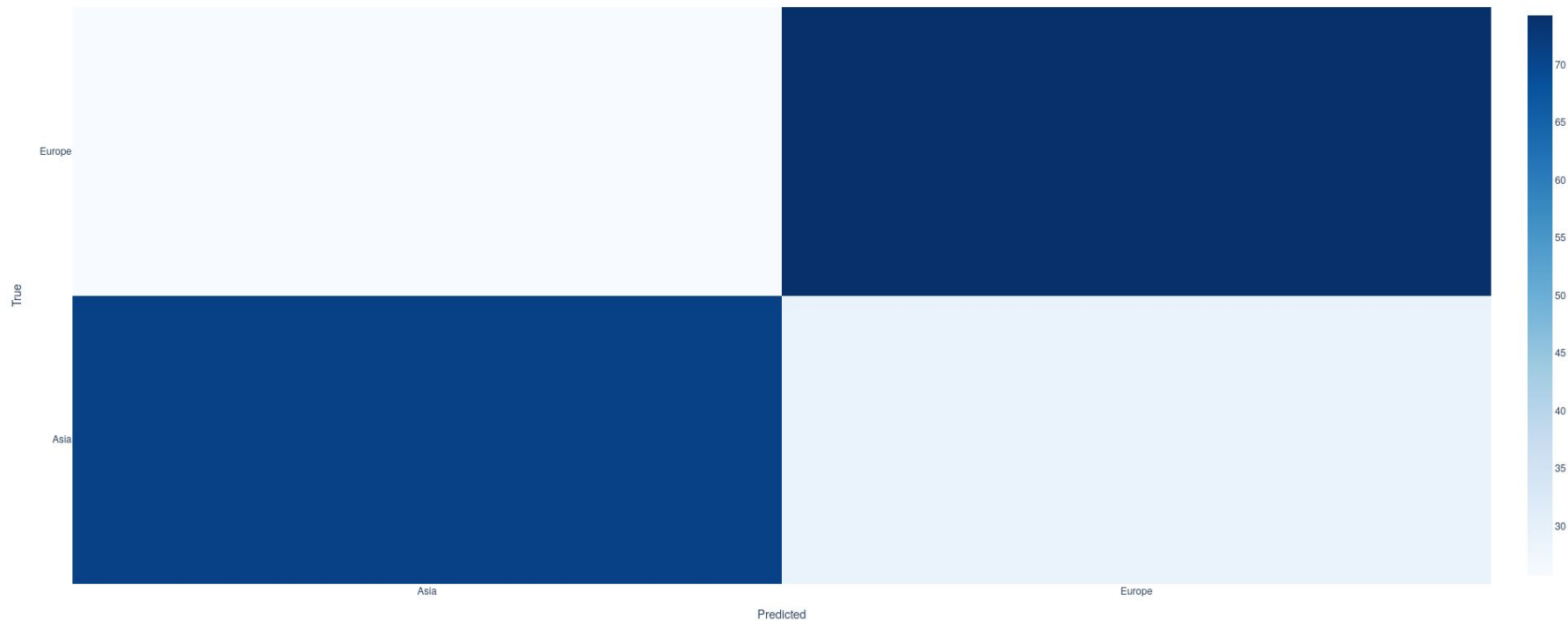
# Dense - non cropped images



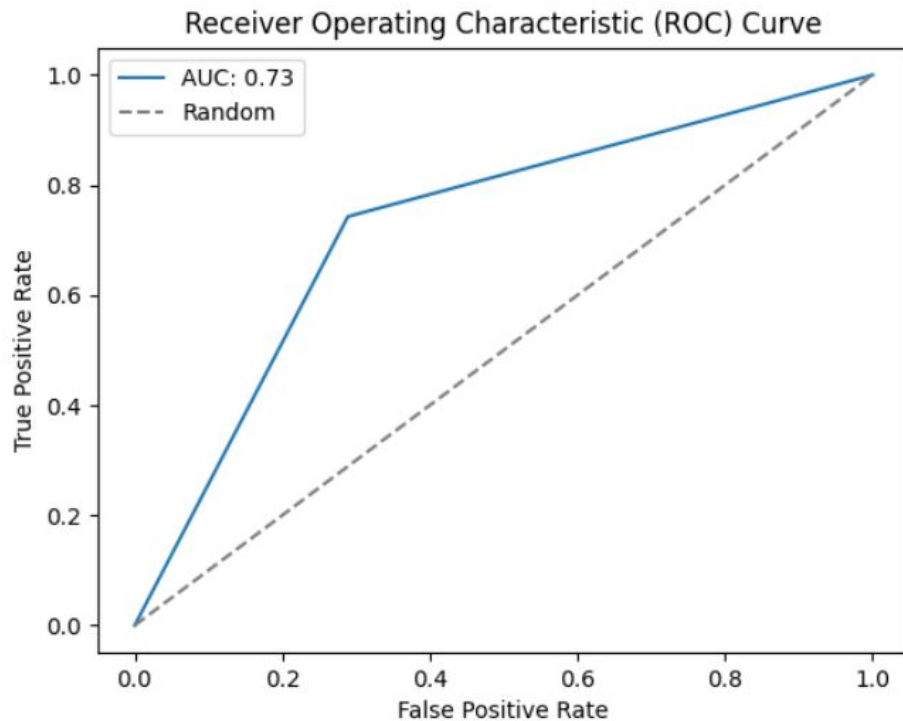


# VGG - non cropped images

VGG16 : 73.24%

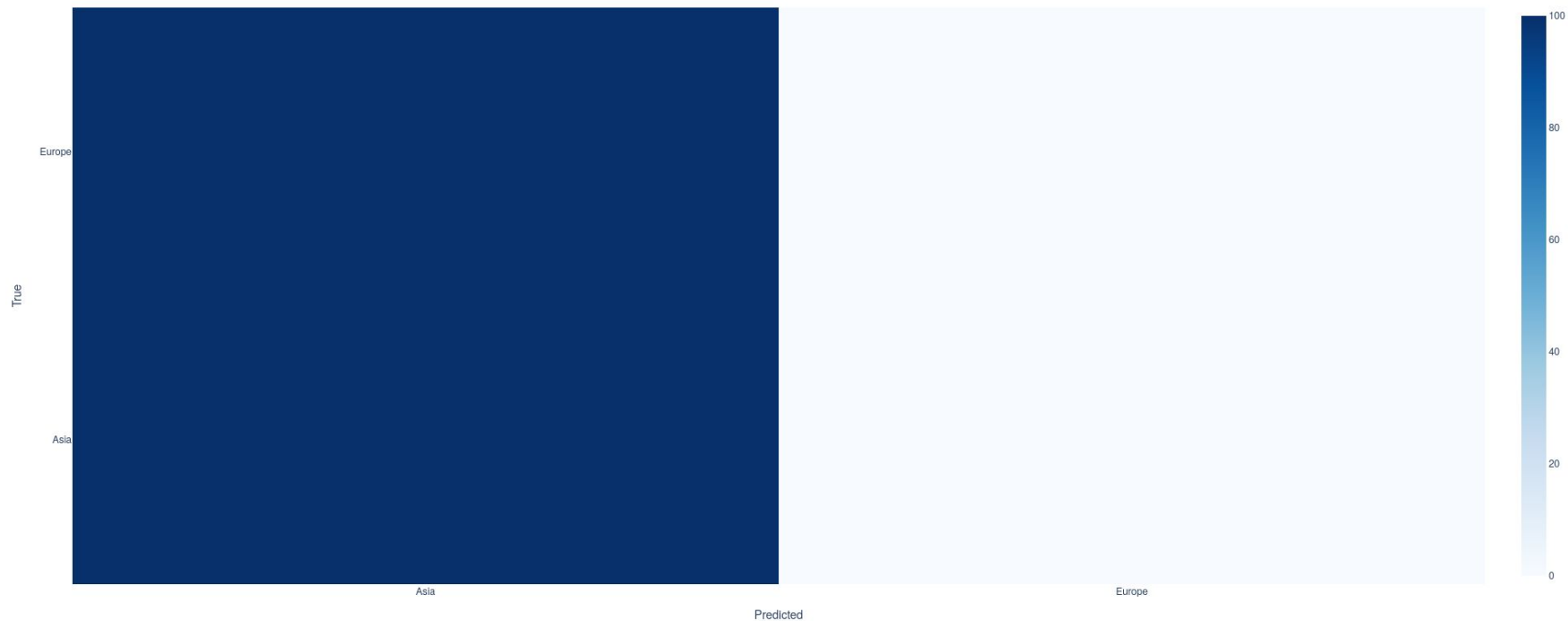


# VGG - non cropped images



# ResNet

ResNet50 : 32.84%



# **Lessons learned**

# Lessons Learned

- Transfer learning is its own science
- We were lacking both compute and more images
- Overfitting is tough to avoid with complex network architectures

# What we would have done differently?

- Accumulated more data in the beginning
- Capture panorama (3 images) to better determine one position
- More research about transfer learning and preventing overfitting
- Limit the scope to a more specific part of the image

# What could be added to the approach?

## Filtering:

Filtering with Places365 dataset (Scene Recognition)

Filtering with YOLO for cropping to areas of interest

- ex. trees, foliage, houses

## Further data augmentation