# **Title - Landmark Detection**

# **ABSTRACT**

What is Landmark Detection?

The mechanism of detecting the famous human-made sculptures, buildings, and monuments inside an image is defined as Landmark Detection. You can simply compare it with the famous application of Google known as Google Landmark Detection, which is used by Google Maps.

At the end of this project, you will be able to create your own landmark detector like Google using the Keras library of Deep learning.

Dataset

We choose Kaggle's dataset for our deep learning project. The dataset consists of image URLs that are publicly available online. The dataset contains three CSV files including test images, training images, and index images. The test images are for the purpose of image recognition and landmark labelling predicted by the deep learning model. The training images are already defined and associated with landmark labels that are used to train models for accurate landmark recognition. The use of index images is found in the image retrieval task. You can download the dataset from

URL: for dataset(105gb)

https://www.kaggle.com/competitions/landmark-recognition-2020/data.

#### **OBJECTIVE**

Our task is to build neural networks to recognize the landmarks inside the images using the Python programming language. The most critical task for any project is to choose an appropriate dataset for model training.

This technology can predict landmark labels directly from image pixels, to help people better understand and organize their photo collections.

# **INTRODUCTION**

Object recognition is one of the fundamental problems widely studied in computer vision. The problem that we will be investigating falls into this very category: we want to recognize landmarks (e.g. White House, Great Wall of China etc.) present in an image directly from the image pixels. Landmark recognition is interesting because it can help people better understand and organize their digital photo collections. Despite being a straightforward objective, i.e. identifying landmark presented in a given image, the task itself is challenging especially as we increase the number of distinct landmarks. Our proposed landmark recognition problem can be best described as an instance-level recognition problem. It differs from categorical recognition problem in that instead of recognizing general entities such as mountains and buildings. Landmark recognition also differs from what we have seen in the ImageNet classification challenge. For example, since landmarks are generally rigid,

immobilized, one-of-the-kind objects, the intra-class variation is very small (in other words, a landmark's appearance does not change that much across different images of it). As a result, variations only arise due to image capture conditions, such as foreground/background clutter, occlusions, different viewpoints, weather and illumination, making this distinct from other image recognition datasets where images of a particular class (such as a cat) can vary much more in shape and appearance. These characteristics are also shared with other instance-level recognition problems, such as artwork recognition — ideally with mild modification, our solution to landmark recognition problem can be applied to research for other image recognition problems as well. In this project. landmark recognition problem.

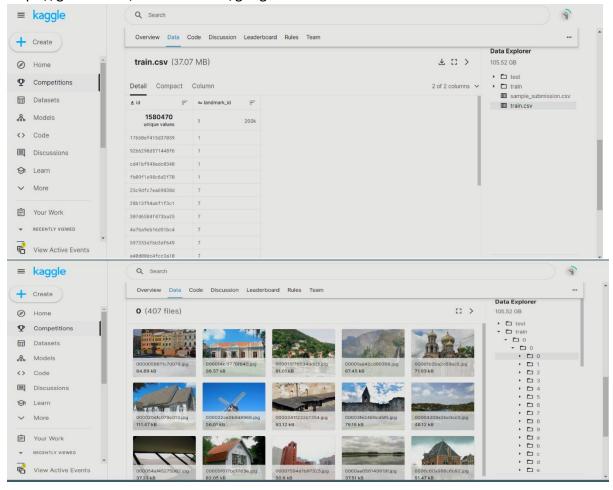
#### **METHODOLOGY**

#### **Data Collection**

Data collection is the process of gathering and measuring information on variables of interest, in an established systematic fashion that enables one to answer stated research questions, test hypotheses, and evaluate outcomes.

Data collected from

https://github.com/cvdfoundation/google-landmark



# **Preprocessing**

Data preprocessing, a component of data preparation, describes any type of processing performed on raw data to prepare it for another data processing procedure. It has traditionally been an important preliminary step for the data mining process.

- Resizing images
- Normalization- the process of organizing data in a database. This includes creating tables and establishing relationships between those tables according to rules designed both to protect the data and to make the database more flexible by eliminating redundancy and inconsistent dependency

# augmentation

Data augmentation is a technique of artificially increasing the training set by creating modified copies of a dataset using existing data. It includes making minor changes to the dataset or using deep learning to generate new data points.

- Rotating
- Flipping
- Scaling
- Encoding

#### Model creation

- Import Python Libraries
- Read the Dataset
- Explore the Dataset
- Feature Selection
- Build the Model
- Evaluate the Model's Performance

# Sequential model

Keras documentation the Sequential model is a linear stack of layers. You can create a Sequential model by passing a list of layer instances to the constructor: from keras. models import Sequential from keras. layers import Dense, Activation model = Sequential ([Dense(32, input\_shape=(,)). we have the following declaration in it

- Input layer
- output layer
- hidden layer
- CNN

A CNN can be instantiated as a Sequential model because each layer has exactly one input and output and is stacked together to form the entire network

full connected layers

# **Fitting**

Data fitting is the process of fitting models to data and analyzing the accuracy of the fit. Engineers and scientists use data fitting techniques, including mathematical equations and nonparametric methods, to model acquired data.

MATLAB lets you import and visualize your data, and perform basic fitting techniques such as polynomial and spline interpolation. You can perform data fitting interactively using the MATLAB Basic Fitting tool, or programmatically using MATLAB functions for fitting.

# Split the data

Data splitting is when data is divided into two or more subsets. Typically, with a two-part split, one part is used to evaluate or test the data and the other to train the model. Data splitting is an important aspect of data science, particularly for creating models based on data A commonly used ratio is 80:20, which means 80% of the data is for training and 20% for testing. We used 70:30 ie uses the first 70 percent of your data for training and the remaining 30 percent of the data for evaluation.

# train model with data

The process of training an ML model involves providing an ML algorithm (that is, the *learning algorithm*) with training data to learn from. The term *ML model* refers to the model artifact that is created by the training process.

The training data must contain the correct answer, which is known as a *target* or *target attribute*. The learning algorithm finds patterns in the training data that map the input data attributes to the target (the answer that you want to predict), and it outputs an ML model that captures these patterns.

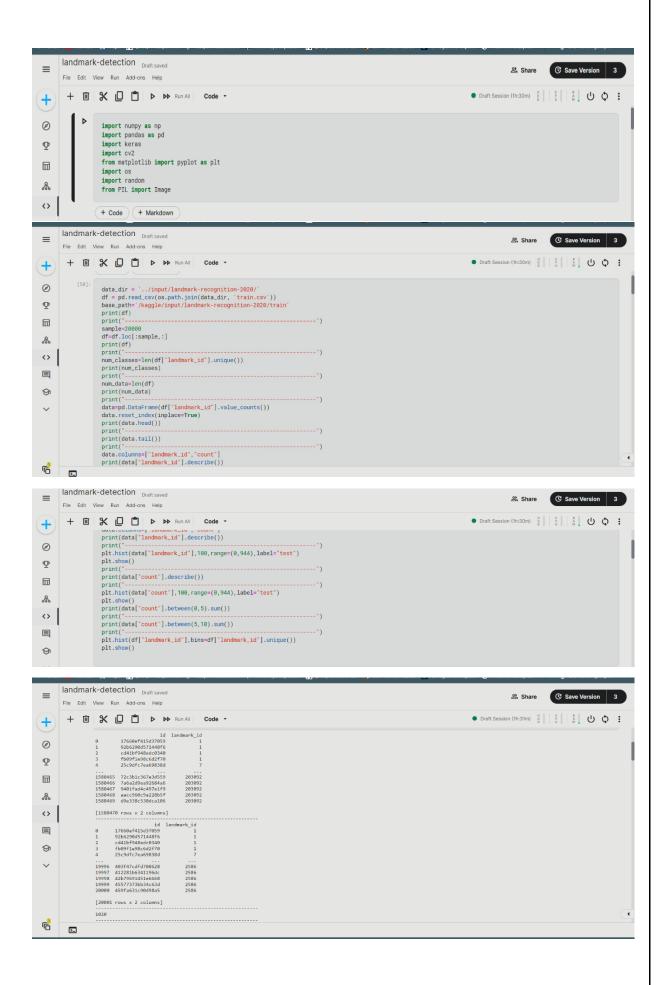
# test the model-metric accuracy, 11 score

You build a model, get feedback from metrics, make improvements, and continue until you achieve a desirable classification accuracy. Evaluation metrics explain the performance of the model. An important aspect of evaluation metrics is their capability to discriminate among model results.

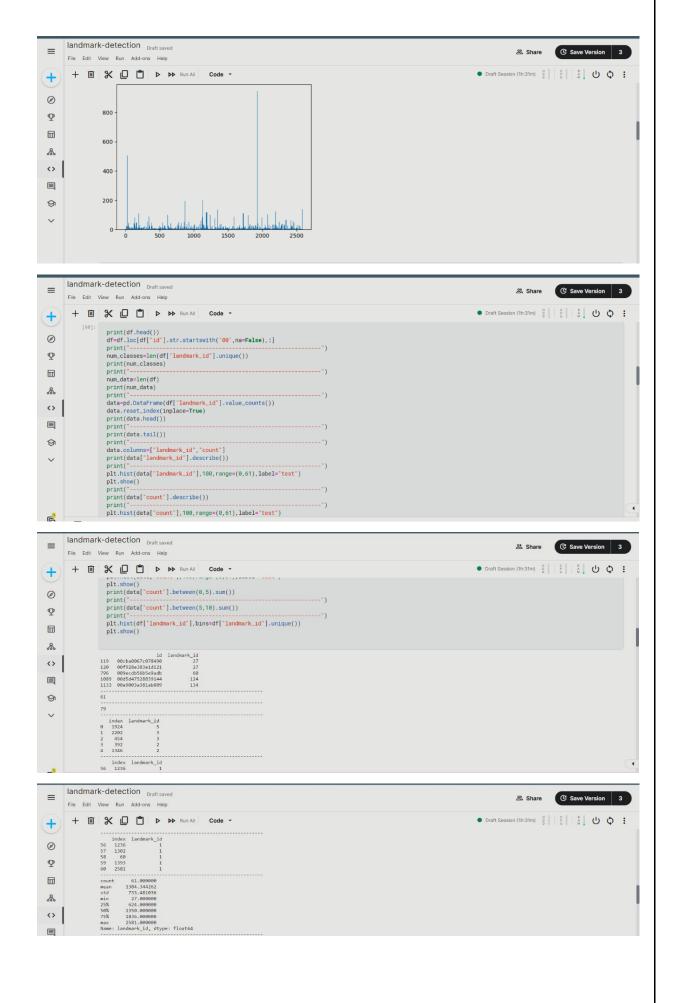
We perform prediction on the model. We can expect the output as show below

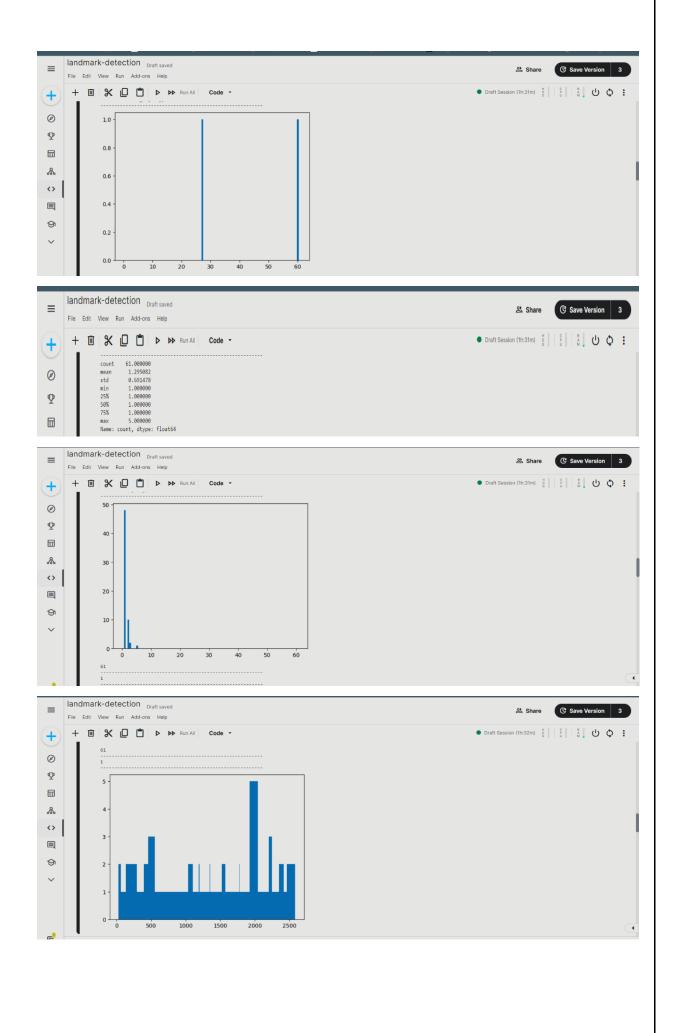
# CODE

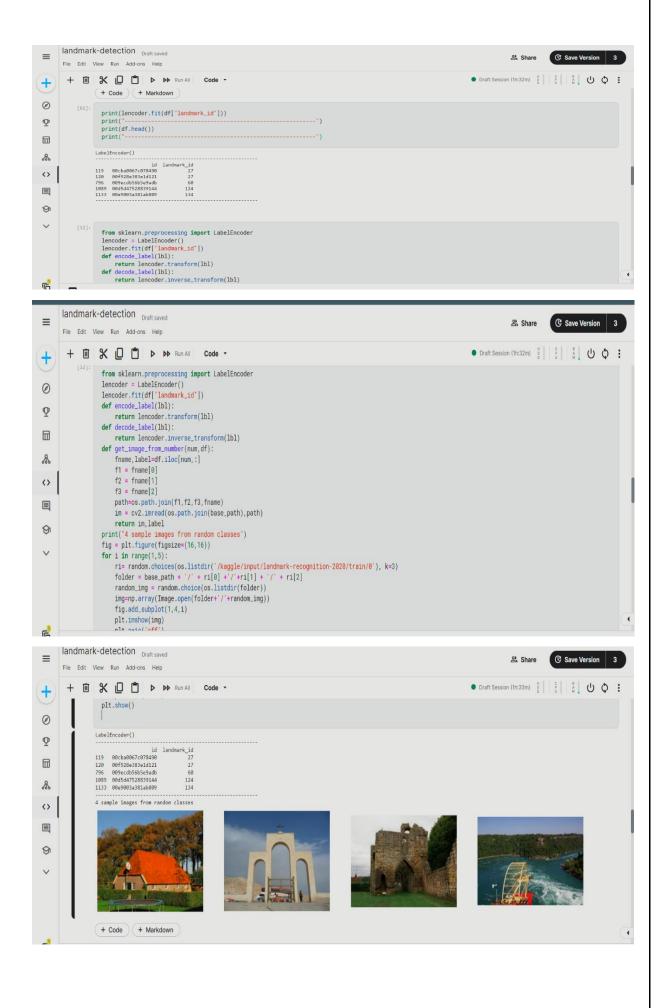
https://www.kaggle.com/code/poornimamarini/landmark-detection

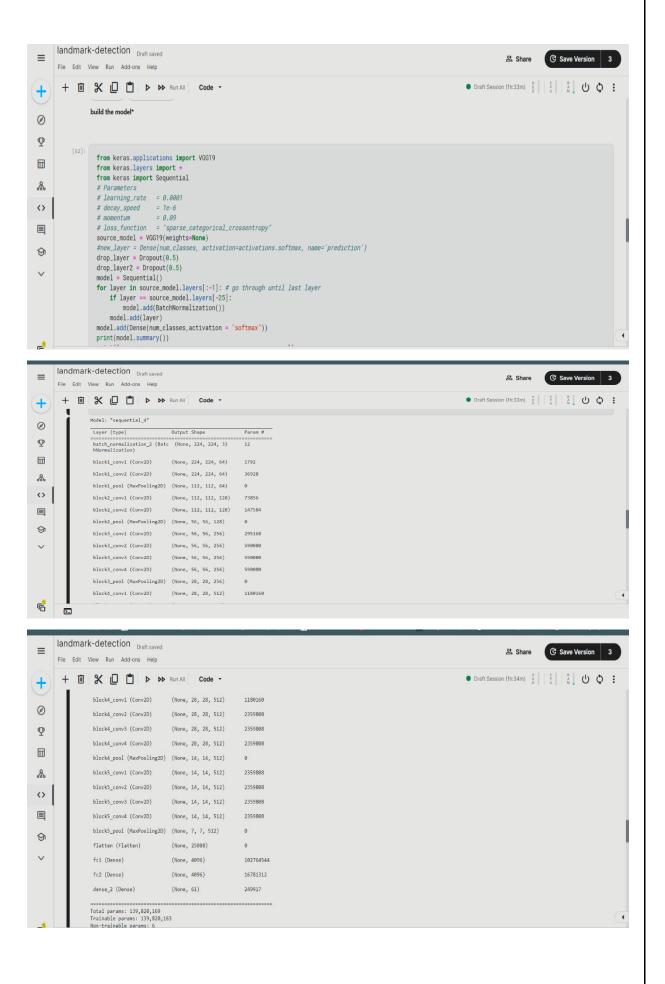


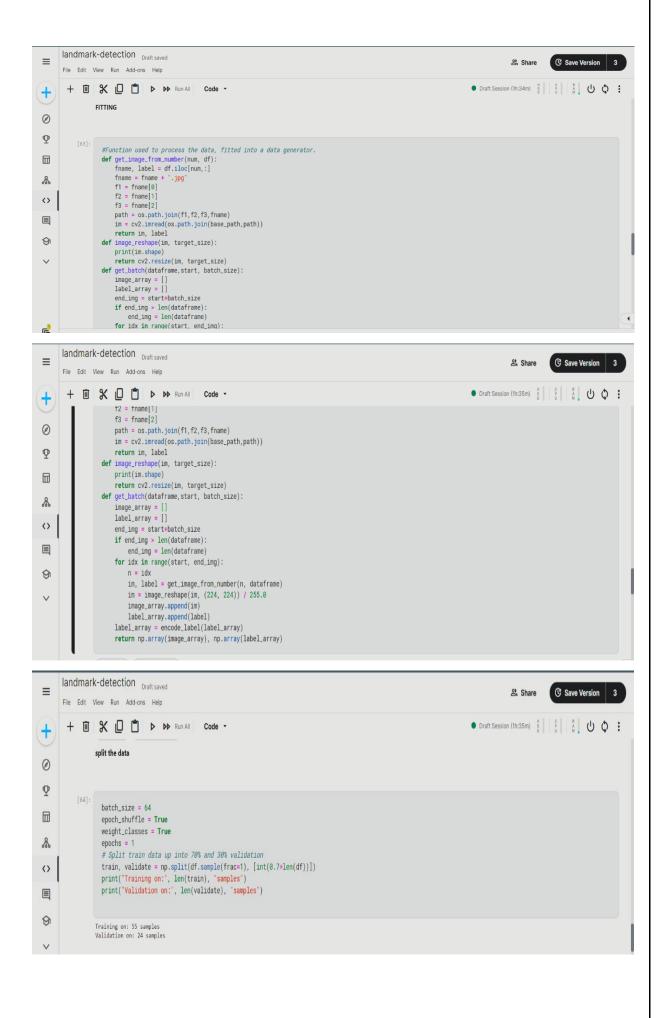












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                   for e in range(epochs):
    print("Epoch: ", str(e+1) + "/" + str(epochs))
    if epoch_shuffle:
        train = train.sample(frac = 1)
    for it in range(int(np.ceil(len(train)/batch_size))):
        X_train, y_train = get_batch(train, it*batch_size, 100)
Φ
&
                             model.train_on_batch(X_train, y_train)
                    model.save("Model")
<>
                  Epoch: 1/1
(880, 800, 3)
(680, 880, 3)
(680, 880, 3)
(482, 646, 3)
(482, 646, 3)
(482, 680, 533, 3)
(680, 880, 3)
(581, 890, 3)
(531, 800, 3)
(531, 800, 3)
(548, 800, 3)
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(548, 800, 3)
(560, 800, 3)
(680, 600, 3)
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                                                                                                                                                      TEST
(P)
Φ
                    ### Test on the training set
batch_size = 16
                   ፠
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                                                               Confidence:", np.round(res[cla[idx]],2), "- GT:", y_train[idx])
```







good\_preds.append([batch\_size\*it + idx, cla[idx], res[cla[idx]]])
print("Errors: ", errors, "Acc:", np.round(100\*(len(validate)-errors)/len(validate),2))
#60od predictions







# CONCLUSION You can see the model output, how images are classified depending on the classes and labels. It uses the Keras library of deep learning to create a convolutional network which in turn trains the model. We perform good predictions results the above as Expected output for prediction. As the data has large memory(105gb) run it in Kaggle. we tackled the problem of Landmark recognition using transfer learning and data augmentation.