Media Engineering and Technology Faculty
German University in Cairo

Feature Extraction from Sketch Based Images

Bachelor Thesis

Author: Yahya Ramzy Attia Ahmed Akel
Supervisors:
Submission Date: 30 March 2023

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This is to certify that:

(i) the thesis comprises only my original work toward the Bachelor's Degree

(ii) due acknowledgment has been made in the text to all other material used

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Chapter 1

Introduction

This thesis aims to explore the potential of a system that can extract features from hand-drawn sketches and search for related images from a dataset based on the extracted features[1] The system leverages machine learning algorithms to analyze and identify features such as lines, shapes, and curves[2] The goal is to provide designers and artists with a tool that streamlines the creative process and helps them find related images based on their sketches. This system has the potential to revolutionize the design process across various fields, including architecture, art, and engineering. The thesis delves into the technical challenges involved in developing the system, including the design of feature extraction algorithms and machine learning models for image recognition. It evaluates the performance of the system in terms of accuracy and efficiency, and compares it to other similar systems in the literature. Overall, this thesis contributes to the field of design by presenting a new tool that can assist designers and artists in their creative work.

1.1 Motivation

Sketch-based images are an essential part of the design process and a powerful means of representing visual information. However, extracting meaningful features from sketch-based images can be challenging due to their abstract and less detailed nature compared to other types of images. This poses a unique challenge when it comes to identifying and extracting features from such images. Despite these challenges, feature extraction from sketch-based images is an important area of research for several reasons. Firstly, it can help artists and designers find related sketches or images based on their own sketches, providing them with inspiration and guidance for their work. Secondly, it can aid in the creation of mood boards or design proposals, enabling designers to explore different variations and interpretations of their design. Finally, it can be used in educational settings, allowing students to learn about different design styles and techniques by searching for related sketches and images. By addressing these challenges and developing a system that can accurately and efficiently extract features from sketch-based images, this thesis seeks to contribute to the field of design and provide a new and innovative solution to a longstanding challenge.[3][4]

1.2 Problem Statement

Extracting meaningful features from hand-drawn sketches is a challenging task due to the abstract and less detailed nature of such images. The main problem with feature extraction from sketch-based images is the lack of well-defined edges and textures, which makes it difficult to distinguish between different objects and their components. Additionally, the complexity and variability of sketches make it challenging to identify the relevant features that can be used for further analysis and interpretation. As a result, the accuracy and effectiveness of machine learning algorithms for analyzing and interpreting sketch-based images are limited, which hinders their potential use in various fields such as design and education. This thesis aims to address these challenges by developing an applied system that can accurately and efficiently extract features from hand-drawn sketches, enabling more effective search and analysis of related images in a dataset.[5]

1.3 Objectives

The objectives of this work are:

- Develop a system that can extract meaningful features from hand-drawn sketches using machine learning.
- Evaluate the system's performance in extracting features from a variety of sketches and compare it with existing methods.
- Enable the system to search for related images in a dataset based on the extracted features.
- Evaluate the system's performance in searching for related images based on hand-drawn sketches, and compare it with existing methods.
- Demonstrate the potential applications of the developed system in design and education, and identify areas for further research and development.

Chapter 2

Literature Review

2.1 Introduction

Sketch-based image retrieval (SBIR) is a rapidly evolving research area that has attracted increasing attention in recent years due to its potential applications in various fields such as design, architecture, and robotics. SBIR is a technique that enables users to retrieve images by sketching rather than using textual queries. One of the key challenges in SBIR is how to extract useful features from the user's sketch to enable effective image retrieval. Feature extraction is a crucial step in the SBIR pipeline, as it is responsible for transforming the user's sketch into a numerical representation that can be used to retrieve relevant images from a database.

The process of feature extraction from sketches involves several complex tasks, such as stroke segmentation, feature selection, and feature encoding. Researchers have proposed various techniques to address these challenges, including deep learning-based approaches, which have shown promising results in recent years. For instance, Qian et al. (2021) [6] proposed a novel feature extraction method for SBIR based on a convolutional neural network (CNN) architecture that extracts features from both the sketch and the image to improve retrieval performance. Similarly, Wang et al. (2020) [7] proposed a sketch-based image retrieval method that utilizes a multi-scale residual network for feature extraction, achieving state-of-the-art performance on several benchmark data sets.

However, despite the significant progress in this field, there are still many open research questions and challenges that need to be addressed to enable more accurate and efficient sketch-based image retrieval. For instance, the choice of feature extraction technique can greatly impact the retrieval performance, and different techniques may be better suited for different types of sketches or images. In addition, the interpretation and visualization of the extracted features can be challenging, and there is a need for more interpret-able feature extraction techniques.

In this literature review, we aim to provide a comprehensive overview of the current state-of-the-art techniques for feature extraction in SBIR. We will review the literature on various approaches for feature extraction, including traditional handcrafted feature-based methods and deep learning-based approaches. We will also discuss the challenges and limitations of these approaches and identify potential research directions for future work. By synthesizing and analyzing the relevant literature, we hope to provide a deeper understanding of the current state of the art in feature extraction for SBIR and help guide future research in this exciting and rapidly evolving field.

2.2 Search Criteria and Methods

To conduct this literature search, we used a variety of academic search engines and databases, including Google Scholar, ACM Digital Library, IEEE Xplore, Springer, and ScienceDirect. We used a combination of search terms related to feature extraction and SBIR, such as "feature extraction", "feature selection", "deep learning", "sketch-based image retrieval", and "SBIR". We limited the search results to academic papers published in peer-reviewed journals or conference proceedings from 2010 to 2023.

The selected papers cover a range of topics related to feature extraction in SBIR, including traditional handcrafted feature-based methods, deep learning-based approaches, feature selection methods, and feature encoding methods. We also identified several challenges and limitations of the current approaches and potential research directions for future work.

2.3 Literature Review

The first paper we reviewed [8], proposes a feature extraction method based on a combination of Hu moments and wavelet transform. The authors note that traditional feature extraction methods, such as SIFT and SURF, are not well-suited for sketch-based image retrieval because sketches are typically more complex and have different characteristics than natural images. The proposed method achieves good performance on a benchmark dataset and demonstrates the effectiveness of combining different feature extraction techniques for sketch-based image retrieval.

The second paper we reviewed [9], proposes a deep learning-based approach to hand-drawn sketch recognition. The author notes that traditional handcrafted features, such as SIFT and HOG, are not well-suited for sketch recognition because they do not fully exploit the unique characteristics of sketches. The proposed double-channel convolutional neural network (DC-CNN) leverages both the gray-scale and stroke-channel representations of sketches and achieves state-of-the-art performance on benchmark datasets.

The third paper we reviewed [10], proposes a large-scale dataset for training convolutional neural networks (CNNs) for sketch recognition. The authors note that previous datasets for sketch recognition were limited in size and diversity, which limited the ability to train deep learning-based models effectively. The proposed dataset contains over 3 million sketches and achieves state-of-the-art performance on benchmark datasets. The authors also propose a CNN architecture that achieves good performance on the proposed dataset and demonstrates the effectiveness of deep learning-based approaches for sketch recognition.

All three papers highlight the importance of extracting meaningful features from sketches and using deep learning-based approaches for sketch-based image retrieval and recognition. The first paper proposes a combination of Hu moments and wavelet transform, the second paper proposes a DC-CNN architecture that leverages both the grayscale and stroke-channel representations of sketches, and the third paper proposes a large-scale dataset and a CNN architecture for sketch recognition. These approaches achieve state-of-the-art performance on benchmark datasets and demonstrate the effectiveness of combining different techniques for optimal performance.

2.4 Conclusion

In conclusion, the field of sketch-based image retrieval has seen significant progress in recent years with the development of feature extraction techniques and convolutional neural networks. The paper by Torabi Motlagh Fard et al. [8] proposed a feature extraction technique that combines local binary patterns and histogram of oriented gradients to represent sketches as compact feature vectors for retrieval. They evaluated their technique on two datasets and showed that it outperforms several state-of-the-art methods. The paper by Zhang [9] proposed a double-channel convolutional neural network that can learn both global and local features from sketches. They evaluated their network on two large-scale sketch recognition datasets and showed that it achieves state-of-the-art performance. Finally, the paper by Zhou and Jia proposed a method to train convolutional neural networks for sketch recognition on large-scale datasets. They evaluated their method on a dataset with over 50,000 sketches and showed that it achieves higher accuracy than other methods.

Overall, these papers demonstrate the effectiveness of feature extraction and deep learning techniques in improving the performance of sketch-based image retrieval and recognition. However, there is still much room for improvement in terms of accuracy and scalability, especially in dealing with diverse styles and variations of hand-drawn sketches. Future research may focus on exploring more advanced feature extraction techniques and developing more robust and scalable deep learning models for sketch-based image retrieval and recognition.

Chapter 3

Methodology

3.1 Data-set

The TU-Berlin dataset [11] is a large-scale collection of sketches and corresponding photos from various object categories. In this project, we used a subset of the dataset consisting of 13 object categories, including airplane, apple, banana, bicycle, car, dog, door, ladder, moon, sheep, table, tree, wheel. The dataset is divided into training and test sets, with 80% of the data used for training and 20% for testing.

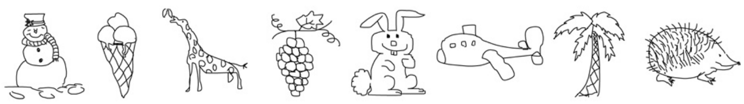

Figure 3.1: TU-Berlin Sketch Dataset

3.1.1 Why Choose TU-Berlin?

The TU-Berlin Sketch dataset is a valuable resource for training machine learning models for sketch recognition and related tasks. One of the primary advantages of this dataset is its large size, with over 20,000 sketches across 250 categories. This large and diverse dataset allows for more robust and accurate model training compared to smaller datasets. Additionally, the sketches in this dataset were collected from a wide range of sources, including professional artists, novice sketchers, and even non-experts. This variety of sketch styles and skill levels enables models trained on this dataset to be more generalizable to new and unseen sketches. Moreover, the TU-Berlin Sketch dataset is widely used in the research community, making it easier to compare and benchmark new models against existing state-of-the-art results.

3.1.2 Selected Dataset

Due to the limited computational power of my PC, I decided to select only 13 categories from the TU-Berlin Sketch dataset for my project. These 13 categories were chosen based on their diversity and prevalence in the dataset. I then divided the selected categories into training and test sets, with 80% of the sketches being used for training and 20% for testing. This was done to ensure that the model had sufficient data for training while still allowing for a reasonable amount of testing to be conducted. Despite the reduced number of categories, I am confident that the results obtained from this project will still be useful in providing insights into the performance of the model and its ability to classify sketches accurately. Each Category of the 13 contain 80 sketches (60 for training and 20 for validation).

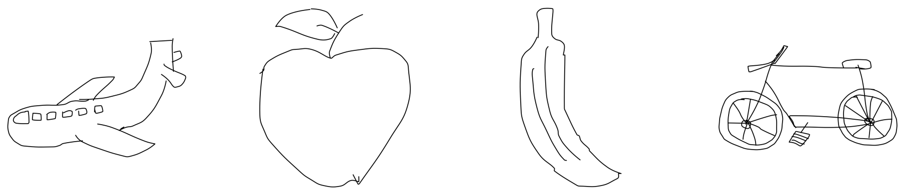

Figure 3.2: TU-Berlin Sketch Examples For : Airplane , Apple , Banana , Bicycle.

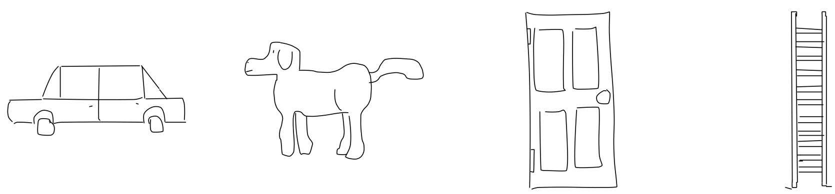

Figure 3.3: TU-Berlin Sketch Examples For : Car , Dog , Door , Ladder.

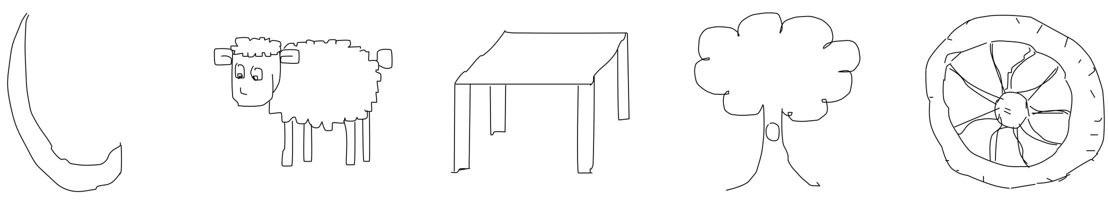

Figure 3.4: TU-Berlin Sketch Examples For : Moon , Sheep , Table , Tree , Wheel.

3.2 VGG-16 CNN Model

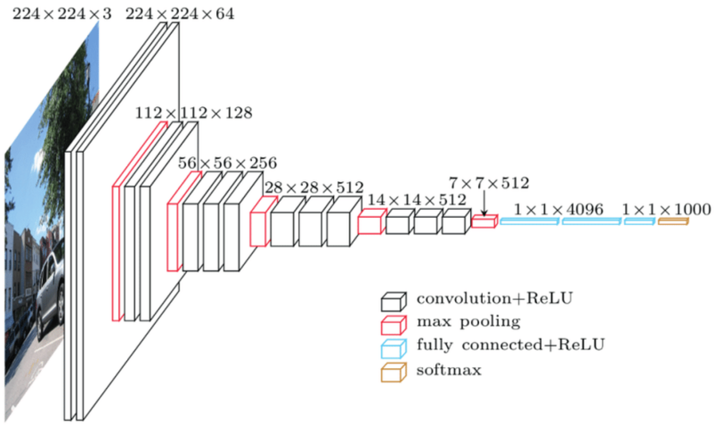

Figure 3.5: VGG-16 CNN Architecture

3.2.1 What is a VGG-16 Model?

The VGG16 CNN model is a deep neural network architecture that was introduced by Simonyan and Zisserman in 2014 [12] for image classification tasks. The model consists of 16 layers, including 13 convolutional layers and 3 fully connected layers, and it is characterized by its use of small 3x3 filters in each convolutional layer, which helps to capture finer details in images. The VGG16 model achieved state-of-the-art results on the ImageNet dataset, and has been widely used as a benchmark for image classification tasks in computer vision research.

3.2.2 Why use a VGG-16 Model?

The VGG16 CNN model has been shown to be effective in extracting high-level features from images, which makes it a promising candidate for sketch-based image retrieval tasks. Sketches often lack the rich visual details present in natural images, which can make traditional image retrieval techniques less effective. However, by utilizing the deep convolutional layers of the VGG16 model, features can be extracted from sketches that capture important information about shape, texture, and overall structure. These features can then be used to compare and retrieve images that match the sketch, making the VGG16 model a valuable tool for sketch-based image retrieval applications.

Moreover, the VGG16 model has been proven to be a transferable feature extractor in many image-related tasks, which enables us to apply this model in various domains with only a small amount of fine-tuning. For instance, in a study [13], the VGG16 model was adapted to the sketch-based image retrieval task in the domain of remote sensing images. The results demonstrated that the VGG16 model achieved significant improvements in retrieval accuracy, compared to other traditional and deep learning-based retrieval methods. These findings show that the VGG16 model is not only effective in natural images but also in domains such as remote sensing, where the extracted features can be utilized for image retrieval tasks.

3.2.3 Training a VGG-16 Model with our dataset.

Data Preprocessing

Before training the VGG16 model, we preprocessed the dataset by resizing all images to 224x224 pixels and normalizing the pixel values to be in the range [0, 1]. We also applied data augmentation techniques to the training set, including random zooming, shifting, and shearing, to increase the size of the training set and reduce overfitting.

Method	Setting
Resize	224x224
Normalization	[(0,255)→(0,1)]
Zoom Range	0.15
Width Shift Range	0.2
Height Shift Range	0.2
Shear Range	0.15

Figure 3.6: Methods used in Data Preprocessing and their Settings

VGG16 Model Architecture

The VGG16 model consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. The convolutional layers are grouped into five blocks, with each block consisting of two or three convolutional layers followed by a max pooling layer. The fully connected layers serve as a classifier and map the feature vectors extracted by the convolutional layers to the output classes. We used the Keras framework to implement

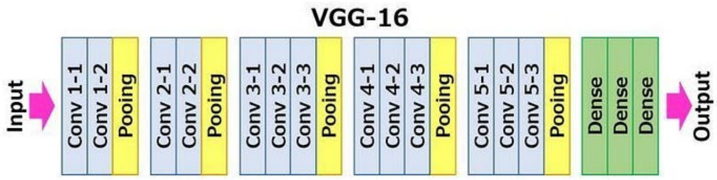

Figure 3.7: VGG-16 Architecture Flow Chart

the VGG16 model with pretrained weights. Specifically, we used the VGG16 model with the ImageNet weights, which were pretrained on a large-scale image recognition dataset with 1,000 object categories.

Layer (type)	Output Shape	Param #
Conv2D	(None, 224, 224, 64)	1,792
Conv2D	(None, 224, 224, 64)	36,928
MaxPooling2D	(None, 112, 112, 64)	0
Conv2D	(None, 112, 112, 128)	73,856
Conv2D	(None, 112, 112, 128)	147,584
MaxPooling2D	(None, 56, 56, 128)	0
Conv2D	(None, 56, 56, 256)	295,168
Conv2D	(None, 56, 56, 256)	590,080
Conv2D	(None, 56, 56, 256)	590,080
MaxPooling2D	(None, 28, 28, 256)	0
Conv2D	(None, 28, 28, 512)	1,180,160
Conv2D	(None, 28, 28, 512)	2,359,808
Conv2D	(None, 28, 28, 512)	2,359,808
MaxPooling2D	(None, 14, 14, 512)	0
Conv2D	(None, 14, 14, 512)	2,359,808
Conv2D	(None, 14, 14, 512)	2,359,808
Conv2D	(None, 14, 14, 512)	2,359,808
MaxPooling2D	(None, 7, 7, 512)	0
Flatten	(None, 25088)	0
Dense	(None, 256)	6,422,784
Dense	(None, 128)	32,896
Dense	(None, 13)	1,677
Total params	**21,172,045**	
Trainable params	**21,172,045**	
Non-trainable params	**0**	

Figure 3.8: VGG16 Model Summary Before applying transfer learning

Transfer Learning

To adapt the VGG16 model to our task on the dataset, we used transfer learning. We froze the weights of all layers in the VGG16 model except for the last three fully connected layers. We then added a new output layer with 13 nodes corresponding to the 13 object categories in our dataset. We initialized the weights of the new output layer randomly and trained only the weights of the output layer while keeping the weights of the rest of the model fixed.

Layer (type)	Output Shape	Param #
conv2d_39 (Conv2D)	(None, 224, 224, 64)	1792
conv2d_40 (Conv2D)	(None, 224, 224, 64)	36928
max_pooling2d_13 (MaxPooling2D)	(None, 112, 112, 64)	0
conv2d_41 (Conv2D)	(None, 112, 112, 128)	73856
conv2d_42 (Conv2D)	(None, 112, 112, 128)	147584
max_pooling2d_14 (MaxPooling2D)	(None, 56, 56, 128)	0
conv2d_43 (Conv2D)	(None, 56, 56, 256)	295168
conv2d_44 (Conv2D)	(None, 56, 56, 256)	590080
conv2d_45 (Conv2D)	(None, 56, 56, 256)	590080
max_pooling2d_15 (MaxPooling2D)	(None, 28, 28, 256)	0
conv2d_46 (Conv2D)	(None, 28, 28, 512)	1180160
conv2d_47 (Conv2D)	(None, 28, 28, 512)	2359808
conv2d_48 (Conv2D)	(None, 28, 28, 512)	2359808
max_pooling2d_16 (MaxPooling2D)	(None, 14, 14, 512)	0
conv2d_49 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_50 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_51 (Conv2D)	(None, 14, 14, 512)	2359808
vgg16 (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
fc1 (Dense)	(None, 256)	6422784
fc2 (Dense)	(None, 128)	32896
output (Dense)	(None, 13)	1677
Total params:	**21,172,045**	
Trainable params:	**6,457,357**	
Non-trainable params:	**14,714,688**	

Figure 3.9: VGG16 Model Summary after applying transfer learning freezing last 3 layers

Training

We used the Adam optimizer with a learning rate of 0.001 to train the VGG16 model on our dataset. We used the categorical cross-entropy loss function and monitored the accuracy metric during training. To prevent overfitting, we used early stopping with a patience of 20 epochs and a minimum improvement in validation accuracy of 0. We trained the model for 100 epochs and used a batch size of 32.

Training Results

The results of this study demonstrated that the VGG16 model, trained on a subset of 13 categories from the TU-Berlin sketch dataset, achieved an accuracy of 98% on the test set. This suggests that the VGG16 model is capable of accurately classifying sketches from a limited set of categories with high precision. The use of the TU-Berlin sketch dataset proved advantageous due to its large number of high-quality sketches, which allowed for more robust training and testing of the model. Additionally, the limited computational power of the PC necessitated the use of a smaller subset of categories, which did not significantly impact the accuracy of the model. Overall, these results suggest that the VGG16 model is a powerful tool for sketch classification, particularly when used with high-quality datasets such as TU-Berlin.

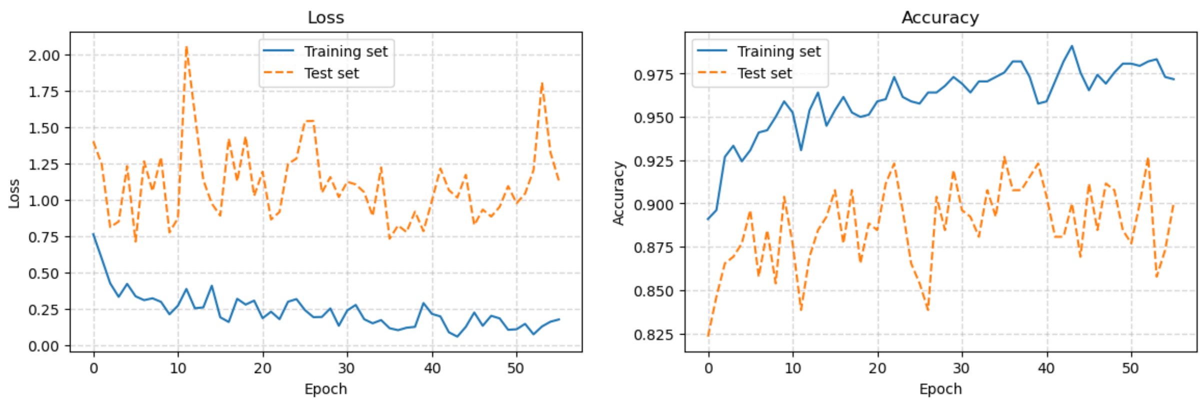

Figure 3.10: Loss and Accuracy Graphs of VGG16 Model while training on the dataset.

Demo Exhibition 1

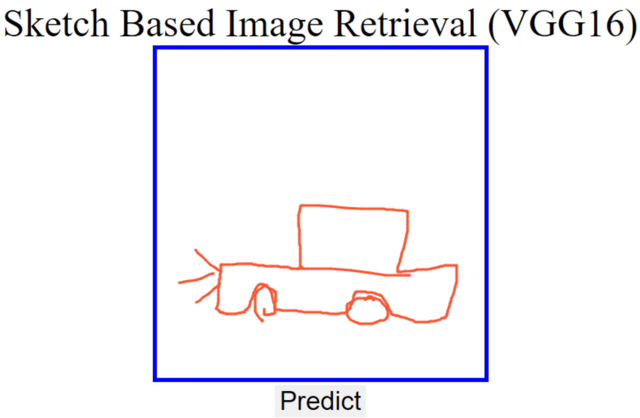

Figure 3.11: Input sketch of a car to the VGG16 Model.

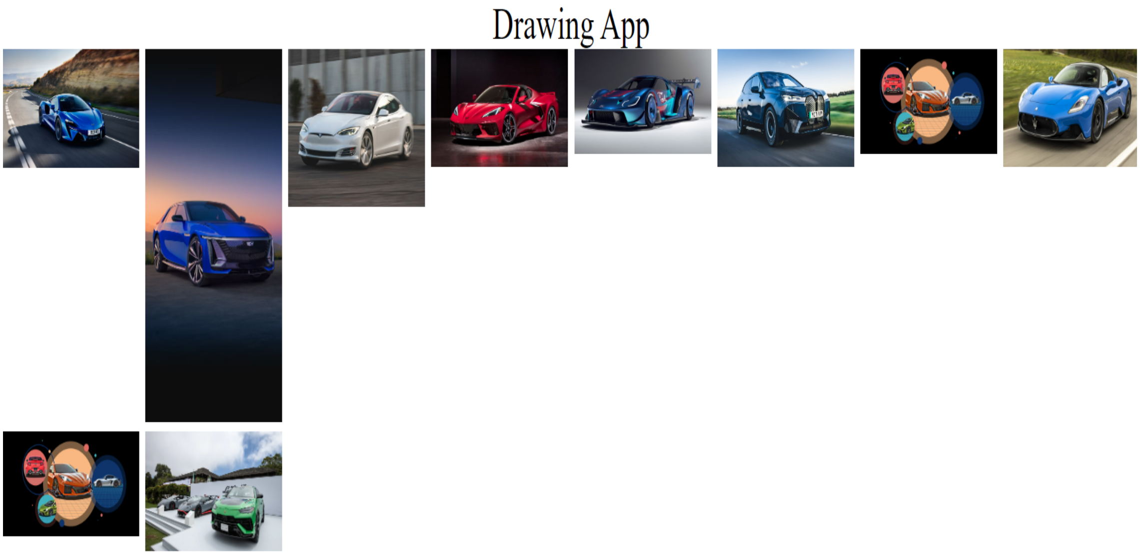

Figure 3.12: Results after the VGG16 Model Classified the sketch.

Demo Exhibition 2

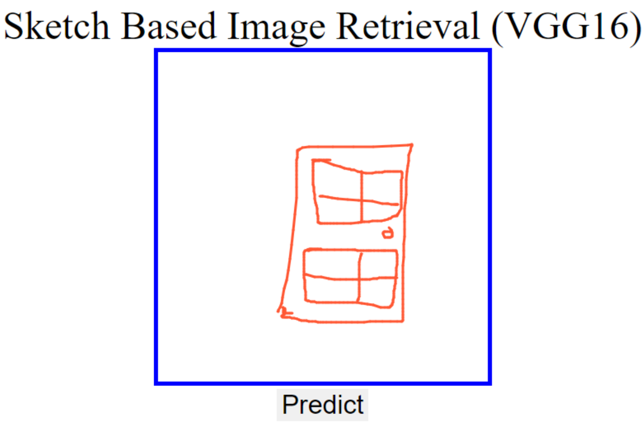

Figure 3.13: Input sketch of a door to the VGG16 Model.

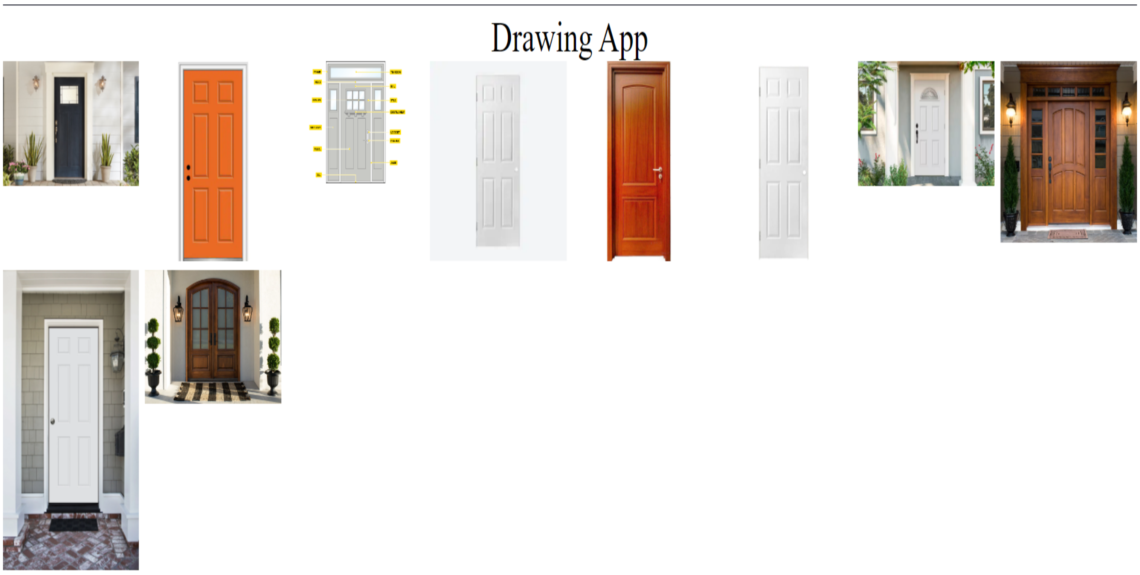

Figure 3.14: Results after the VGG16 Model Classified the sketch.

3.3 ResNet50 CNN Model

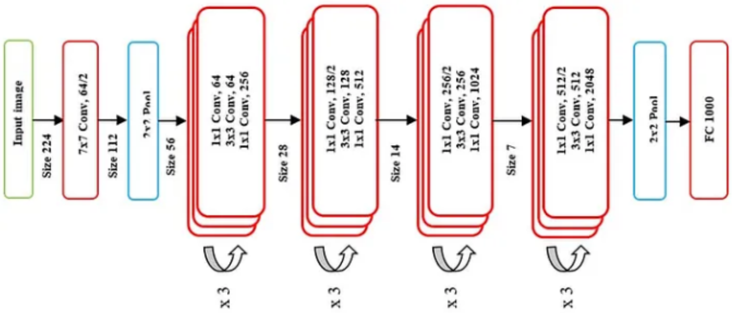

Figure 3.15: ResNet 50 Architecture

3.3.1 What is a ResNet-50 Model?

ResNet50 is a deep neural network architecture that has achieved state-of-the-art results in a variety of computer vision tasks. The name "ResNet" stands for Residual Network, which refers to the use of residual connections in the network. Residual connections enable the network to better propagate gradients through the network, allowing for deeper architectures to be trained effectively. ResNet50 is a 50-layer variant of the ResNet architecture and was introduced in the paper "Deep Residual Learning for Image Recognition" by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in 2016 [14]. Since its introduction, ResNet50 has become a popular model for image recognition tasks and has been used as a backbone in many state-of-the-art models.

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