FYP Final Report

by Xin Qi Lim

Submission date: 12-Feb-2020 11:29AM (UTC+0800)
Submission ID: 1255895012
File name: jacklyn_report.pdf (1.58M)
Word count: 8289
Character count: 42278

CHAPTER 1

INTRODUCTION

1.1 Preface

Every city in the world is shaped by different elements which give the city a character. A city streetscape affects humans in various psychological ways, including well-being, behaviour as well as their mental health. This is why along the years the urban planners, sociologists and policymakers strive to carry out researches on understanding urban perception on city streetscapes for better city development. There is no definitive meaning for the term "Urban Perception", but it mainly means the perception of humans on the contrast of city streetscapes. Urban perception can be looked into through different perceptual attributes.

1.2 Problem Statement

To better understand the human perception on city streetscapes, studies have been carried out to measure different attributes (e.g., Lively (De Nadai et al., 2016), Safety (Ordonez & Berg, 2014), Poverty (Piaggesi et al., 2019) etc.) that describe the city. However, most of the studies to quantify the perception have been carried out manually such as surveys and questionnaires. The targeted participants for the studies are also

arguably biased due to the limitation on the location proximity. Furthermore, studies have to be conducted from time to time since human perception varies to a certain extent over time. Manual social studies on city streetscapes are not only time consuming but also limiting in the sense of reachability and having low throughout.

1.3 Research Objectives

In the past decade, we can see a rise on the computed studies on urban perception. Moreover, nowadays with the breakthrough of big data technology on Computer Vision, we can carry out the studies in a more efficient and generic way based off visually perceived information of streetscapes. In a research study, the MIT Media Lab has built a crowdsourced dataset of Google Street View (GSV) images by getting random people around the Internet to pick a winner in a pairwise GSV images comparison given a certain urban perceptual attribute. There are 6 different perceptual attributes being looked into by the MIT Media Lab in this study, namely "Beautiful", "Boring", "Depressing", "Lively", "Wealthy" and "Safety". By utilising the dataset, the research objectives of this research are to

- Identify and train a suitable deep learning model for a multilabelled classification task to predict the labels of a location given the GSV image of that certain location.
- Present a city-level visualisation on the predicted perceptual attributes.

1.4 Research Scope

In the first part, the research focuses on identifying and training a deep learning model for a multilabelled classification task. The deep learning model will be trained on GSV images to predict the labels of a given GSV image. The visualisation on the perceptual attributes will be done by averaging predicted scores of perceptual attributes in given coordinate-based locations in certain neighbourhoods in Kuala Lumpur, Malaysia. The covered neighbourhoods are visualised in Chapter 5.2a.

CHAPTER 2

LITERATURE REVIEW

The literature review will be divided into three main parts: Early Work on Urban Perception, Urban Perception Prediction and Visualisation of Perceptual Attributes.

2.1 Urban Perception of Cities

In the first sub-section of the literature review, urban perception of cities will be discussed.

2.1.1 Earlier Work on Urban Perception

A classic literature on urban studies, Lynch (1960) studied about human visual perception of cities in three American cities by getting research participants to draw mental images of the cities. The focus was on “legibility" of a city in which legibility is defined as how easily a particular city view can be perceived and categorised into a pattern. Lynch emphasized on the importance of visual sense of a city and induced that the mental images contain five elements: paths, edges, districts, nodes and landmarks. This study inspired the usage of GSV as it covers all the elements presented by the mental images.

Nasar (1990) conducted a survey on the likability of areas in two American cities. The respondents were divided into two categories: the residents and the visitors. The respondents were asked to verbally describe the areas based on the likability. Nasar then came up with an evaluation map which describes the area based on likability. This approach is similar to extracting semantic information from an image for further processing. From the survey, it is found out that residents and visitors had different preferences in the areas. It is also suggested in the paper that maps and photograph could be utilised in future works to help the respondents to identify the areas. The shortcoming of the designed survey can be fixed by using a large dataset of GSV images since the different preferences would converge in a large set of data. Nasar also conducted various studies using different methodologies on urban perception in (Nasar, 1982), (Nasar, 1988) and (Nasar & Jones, 1997).

Along the years, researchers started studying urban perception via digital data. Tucker, Ostwald, and Chalup (2004) proposed a method to analyse streetscape using image segmentation and Hough Transform algorithm (Hough, 1962) which detects less obvious boundaries in images. The algorithm requires the user to manually specify a threshold hence it might need to be implemented in some higher level algorithms for it to be able to process bigger sets of data. In Ratti, Frenchman, Pulselli, and Williams's research (2006), they used cell phone usage data to study the intensity of mobile usage at a certain area. The authors suggested to make use of the data to induce the characteristic of an area based on the high intensity of usage on different hours of the

day. However, the induction might not be accurate due to the lack of an actual visual representation of an area. In this case, visual attribute of an area is crucial in telling the urban characteristics.

In an effort to gather a large dataset (Place Pulse 1.0) for urban perception studies, Salesses, Schechtner, and Hidalgo (2013) collected Google Street View (GSV) images and self-captured street view images in 4 different cities. The collected street views were then rated based on collected human perception on preferred city for a particular perceptual attribute in a pairwise comparison. Computational urban perception of an image was then computed in win and loss ratio in pairwise comparison. This research is one of the initial approaches on collecting a large scale of street view data for urban perception studies. However, the street views collected only covers 4 Western cities, hence Place Pulse 2.0 which covers several Asian cities is used for this FYP.

2.2 Urban Perception Prediction

2.2.1 Place Pulse 2.0

Place Pulse 2.0 (Dubey et al., 2016) is a dataset consisting of GSV images of 56 cities from all the continents except for Antartica. In the research, same methodology as in Dubey et al.'s work, pairwise comparison was carried out to collect the human perception of a certain perceptual attribute in a city street view. The paper discussed about the notable ranking methods - Streetscore (Naik, Philipoom, Raskar, & Hidalgo, 2014)

but the model was trained based on Place Pulse 1.0 (Salesses et al., 2013) which only consists of 4 cities. Thus the authors decided to train their own Streetscore model using Microsoft Trueskill (Herbrich, Minka, & Graepel, 2007). For the prediction of urban perception of street view images, Dubey et al. deployed a siamese-like CNN model which accepts an image pair as input and predicts winner in the pairwise comparison. Figure 2.1 shows the architecture of the proposed CNN model.

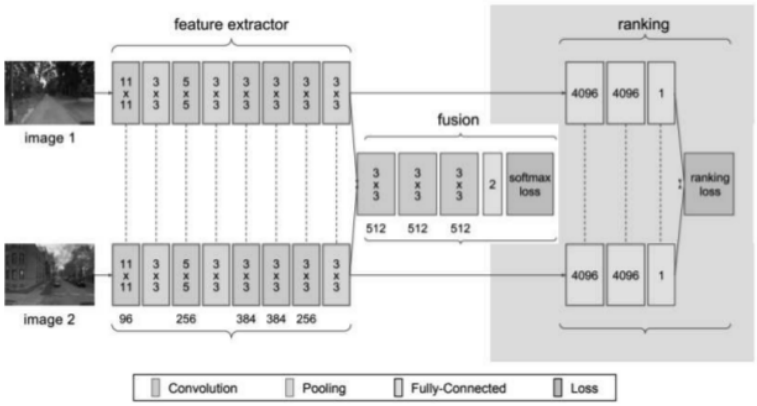


Figure 2.1: Architecture of Siamese-based CNN, reproduced from Dubey et al. (2016)

The model managed to achieve an accuracy of 73.5% for the prediction of urban perception. The limitation of this paper is on the rating methodology since it does not take semantic information of an image into account. Moreover, the GSV images collected by authors only focus on the default GSV angle which only displays the street. Hence information on neighbourhood in a close proximity might be missed out. The research can also be improved by measuring other data types such as audio information of a city, geo-tagged mobile data, social media information etc.

Place Pulse 2.0 has been referenced in numerous papers as the dataset to train machine learning models. Zhang et al. (2018) performed spatial mapping of perceptual attributes to two Chinese cities, namely Beijing and Shanghai. Each perceptual attribute was trained individually on the GSV images in such a way that the perceptual attributes were binarised in +1 as positive and -1 as negative in each image. A SVM classifier was then used to predict the perceptual distribution in the two cities. The authors also studied the relationship between a certain perceptual attribute and the visual elements in the certain image using multivariate regression.

Using the same dataset, Xu et al. (Xu et al., 2019) proposed a double column CNN architecture which takes both semantic features and generic features in the Google Street View (GSV) images as inputs. The authors evaluated the correlation between objects presented in an image and the perceptual attribute. Further studies can look into how the objects affect the perceptual attributes. Aside from these papers, (Ilic, Sawada, & Zarzelli, 2019), (Partridge, 2018) and (Min, Mei, Liu, Wang, & Jiang, 2019) also experimented with the Place Pulse 2.0 Dataset.

2.2.2 Other Street View Imagery

There are also studies that performed data collection via mobile crowdsourcing with the aim of expanding the coverage of inaccessible streets by GSV (Santani et al., 2018). In this study, human urban perception was labelled automatically via low-level features and deep learning features which were extracted using GoogLeNet. The researchers

then built a Random Forest model for the prediction of urban perception. In this paper, the authors proposed a auto-inferred human perception of the streetscape using pre-trained CNN models. However, the maximum of R^2 value between the inferred human perception and predicted perception is only 0.49. Moreover, the reliability of ground truth which is the auto-inferred “human perception" is also questionable since computing it did not involve actual human perception.

Liu, Chen, Zhu, Xu, and Lin (2017) worked on predicting safety scores using multi-instance regression on street views along with crime records as the safety score for each place. Then, the safety scores which were derived from primary instance of each image were predicted using Expectation-Maximization (EM). In evaluating the result, the R^2 value reached 0.84 between predicted score and true score.

2.2.3 Satellite Imagery

Urban perception studies using satellite imagery has also been looked into by the researchers in the domain. Wang et al. (2018) and He et al. (2018) both investigated commercial activeness using satellite images. In both the studies, patches of image regions were used to train the model. Wang et al. (2018) made use of Support Vector Regression (SVR) which accepts features extracted using Bag-of-Features (BOG) as input to predict the commercial activeness. He et al. (2018) implemented a CNN model to extract the feature vectors of the image patches and predicted the commercial activeness using regression. The results were validated using the amount of online

reviews on an area to denote the popularity of an area and thus representing the commercial activeness of the area. The accuracy of Wang et al. (2018) and He et al. (2018) achieved an accuracy of 62.66% and 74.3% respectively.

Piaggesi et al. (2019) looked into city poverty prediction using satellite imagery. The ground truth used was the household income obtained from surveys. Features of each image were extracted using CNN and the prediction was done using regression, which is similar to all the score predictions done in some papers discussed in this section.

Based on the result of these researches, satellite imagery is also a good alternative to be considered to train the model since it covers some secluded areas which are not reachable by GSV.

2.2.4 Multimodal Approach

As a foreword, multimodality in this section is defined as the combination between different types of data or methodologies.

In a neuroscience research, it is proven that human perception is highly influenced by multisensory interaction (Watkins, Shams, Josephs, & Rees, 2007). Thus, multimodal approach which involves other forms of sensory data such as audio and smell data is also worth investigating. As being stressed by Lynch (1960), visual sense plays a crucial part for the legibility of a city. Hence, for a more thorough investigation, visual

data cannot be omitted while training a predictive model. In other words, on top of visual data, different forms of data can also be added as additional measurements.

Verma, Jana, and Ramamritham (2019) collected a time series of visual and audio data. The research focused on classifying the visual and audio data based on their semantic information for further urban perception studies. In the research, CNN was used for objects detection and semantic segmentation. Long Short-Term Memory (LSTM) network as the RNN was used for audio classification.

As another form of multimodal approach which involves visual data and mobile data, De Nadai et al. (2016) investigated the relationship between safe-looking and liveliness in a neighbourhood by using GSV for safe-looking prediction and mobile phone data as a measurement for liveliness. CNN was used to predict the safety score and the population density which denotes the liveliness was derived using the mobile phone data.

2.2.5 Summary of Urban Perception Prediction on Street View Imagery

The methodologies for urban perception prediction on street view images are summarised in Table 2.1. The table includes summarised researches which implemented multimodal approach but the emphasis is given on the the urban perception prediction on the street view imagery in the research papers.

Table 2.1: Urban Perception on Street View Imagery

Authors	Task	Methodology for Urban Perception Prediction
Salesses et al. (2013) (Place Pulse 1.0)	Quantify urban perception on Safety, Class and Uniqueness in 4 cities	Win and loss ratio in pairwise comparison
Dubey et al. (2016) (Place Pulse 2.0)	Predict winner in a pairwise comparison given a perceptual attribute	• Crowdsourced large dataset • Siamese-like CNN model
De Nadai et al. (2016)	Investigate the relationship between social activeness and perception of safety	CNN for safety score prediction and measured it with mobile phone activity data as the social activeness metrics
Liu et al. (2017)	Develop a deep multi-instance regression method to predict weakly supervised GSV images.	Deep hierachical multi-instance regression which made use of Expectation-Maximization (EM)
Xu et al. (2019)	Predict urban perceptual scores of images (Ranking Task)	Double column CNN architecture trained on semantic features and generic features
Santani et al. (2018)	Automatically infer urban perception on outdoor scenes	• Mobile crowdsourced dataset • Random Forest for urban perception prediction
Wang et al. (2018)	Predict commercial activeness from satellite and street view images	• Bag-of-Features (BOG) for feature • Extraction and SVR for commercial activeness prediction
Zhang et al. (2018)	• Binary classification for each perceptual attributes (safe, lively, boring, wealthy, depressing, and beautiful) • Investigate the influence of visual elements on urban perception	• SVM classifier to classify binarised perceptual attributes on each image • Multivariate regression analysis
Verma et al. (2019)	Propose methodology for data collection on visual and audio data based on semantic information	CNN for objects detection and semantic segmentation

2.3 *Visualisation of Perceptual Attributes Score in Cities*

As proposed in the second objective, a city-level visualisation will be constructed. In this sub-section, ways of visualisation are looked into. In scrutinising the research papers that did urban perception in the visual aspect, it is found that most of the findings are visualised using the following three main methods: (i) Geospatial representation, (ii) Graph and (iii) Correlation matrix.

In the Place Pulse 2.0 paper, Dubey et al. (2016) visualised the urban perception using geospatial representation. In Figure 2.2, we can see the safety scores represented geospatially in discrete values. On first look, information is hard to be gathered due to the discrete safety score of all categories being scattered evenly across the maps.

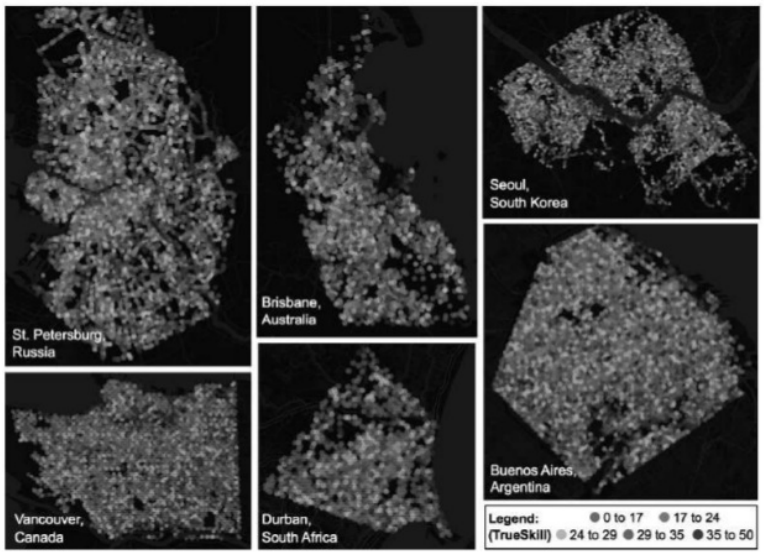


Figure 2.2: Safety scores for 6 cities, reproduced from Dubey et al. (2016)

Ordonez and Berg (2014) visualised the predicted safety score using geospatial representation as well. The authors visualised three different results so they can be compared with each other. Here, the comparisons between predicted scores and ground truth scores can be seen very clearly since all of them were being visualised using the same technique. Another example of clear visualisation is that the safety scores are being presented in gradient form which is more intuitive to the human eyes. Figure 2.3 shows the visualisation result by Ordonez and Berg.

Figure 2.3: Safety scores for ground truth values, predicted values from a model trained from the same city as ground truth and predicted values from a model trained from a different city, reproduced from Ordonez and Berg (2014)

De Nadai et al. (2016) labelled each district with different discrete values which gives an overall representation for each district. This approach is clear in delivering the information but since each district is labelled only one single discrete value, some information might be lost through the representation. Figure 2.4 shows the visualisation of result by De Nadai et al.

Figure 2.4: Safety score for each district for Rome and Milan, reproduced from De Nadai et al. (2016)

2.3.1 Graph

In this domain, graphs are mainly used to compare the actual and predicted values to show the accuracy of the model.

Santani et al. (2018) plotted a comparative histogram to compare the actual and predicted score. While the difference between actual and predicted scores can be seen for each range, we can hardly measure the correlation of the two variables.

He et al. (2018) plotted a scatter plot as shown in Figure 2.6 to investigate the correlation between the actual and predicted value.

It is worth noting that while scatter plot is good at showing correlation between the actual and predicted values, it is hard to pinpoint the exact values to show the difference

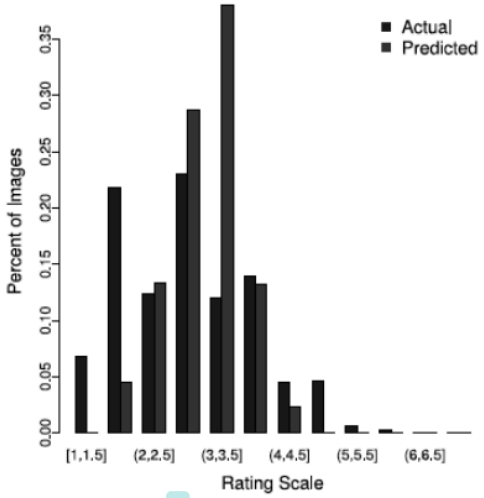


Figure 2.5: Comparative histogram of actual and predicted values for the degree of dangerous in a city, reproduced from Santani et al. (2018)

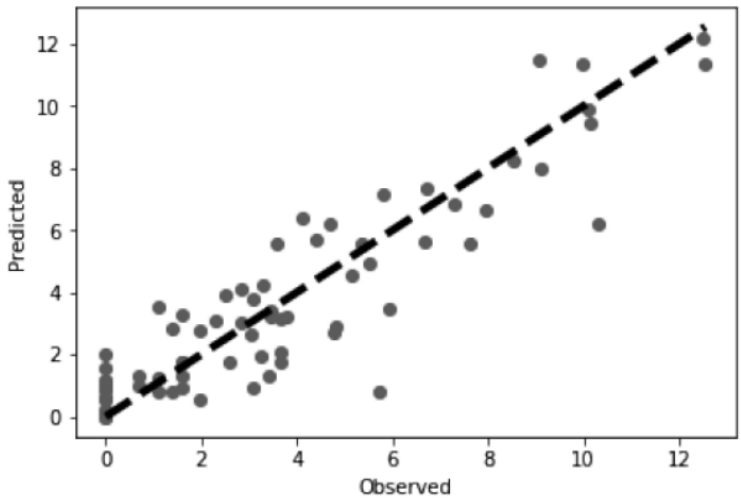


Figure 2.6: Scatter plot of predicted values against observed (actual) values of commercial activeness of a city, reproduced from He et al. (2018)

between the actual and predicted values using scatter plot. Hence, both comparative histogram and scatter plots can be used to analyse the accuracy of the model.

2.3.2 Correlation matrix

Correlation matrix is another way to visualise the correlation between variables. Zhang et al. (2018) and Santani et al. (2018) used correlation matrix to visualise the correlation of different urban perceptions. In an attempt to ensure that semantic information in images is closely related to urban perceptions, Xu et al. (2019) used correlation matrix to visualise correlation between semantic information in images and urban perceptions.

By comparing the presentation of the correlation matrix in all three papers, we can see that Santani et al. (2018)'s visualisation in Figure 2.8 shows the clearest patterns due to arranged rows and columns while in Xu et al. (2019)'s correlation matrix in Figure 2.9, it is relatively harder to find the patterns. However, this can also be caused by how a single semantic element can be correlated to different urban perceptions.

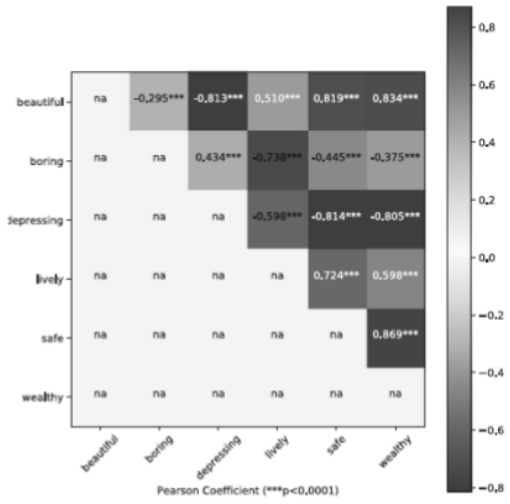


Figure 2.7: Correlation matrix between urban perceptions, reproduced from Zhang et al. (2018)

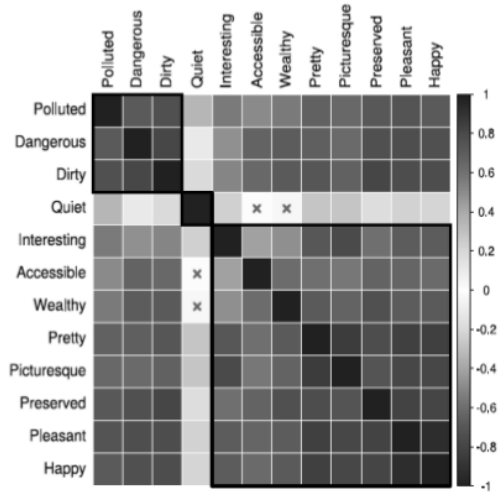


Figure 2.8: Correlation matrix between urban perceptions, reproduced from Santani et al. (2018)

Figure 2.9: Correlation matrix between semantic information and urban perceptions, reproduced from Xu et al. (2019)

CHAPTER 3

THEORETICAL FRAMEWORK

3.1 Street View Images as Dataset

Human visual perception of cities, as described by Lynch (1960), are built on 5 main elements, namely: paths, edges, districts, nodes and landmarks. Built on top of this foundation, urban perception is largely influenced by these 5 elements. Hence, to study about urban perception in the visual way, it is important that our dataset consists of images that contain these 5 elements.

3.1.1 Google Street View Images

Google Street View (GSV) is a service provided by Google for its users to visualise streets on Google Maps. It consists of street-level images captured by Google Street View cars from time to time. Since the images are street-level images, they could capture the city streetscapes very well.

Figure 3.1 shows a few examples of GSV images. As shown in the figure, paths (channels where observers move along, e.g, pathways), edges (boundaries that set apart continuity, e.g., buildings), nodes (strategic meeting points, e.g., junctions) and land-

marks (public reference points relevant to the city, e.g., National Monument) are all present in the images.

Figure 3.1: Examples of Google Street View Image

3.2 Deep Learning Using CNN

In this section, Convolutional Neural network (CNN) will be discussed. CNN is good at recognising spatial patterns. Thus, it outperforms many models in image classification. Similar to the regular Artificial Neural Network, it has hidden layers where a list of weighted inputs are used to produce a set of outputs via an activation function. In addition to that, CNN consists of Convolutional Layers and Pooling Layers which are responsible for the feature extraction part of CNN.

3.2.1 Architecture of CNN

In general, CNN is made up of 3 layers which consist of Convolutional Layer, Pooling Layer and the Fully-connected Layer.

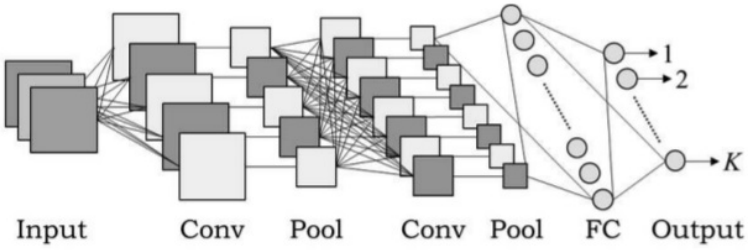


Figure 3.2: An example of CNN architecture, reproduced from Hidaka and Kurita (2017)

3.2.1 (a) Convolutional Layer

In the Convolutional layer, a filter will slide through the input image and a dot product will be produced for each pixel (*CS231n Convolutional Neural Networks for Visual Recognition*, 2017). As the filter successfully slides through the whole input image, a convolved output which is also known as the activation map will be produced. The convolutional layer is used to extract the features from the images. Figure 3.3 shows an example of an activation map.

Figure 3.3: An example of an Activation Map, reproduced from Xu et al. (2019)

3.2.1 (b) Pooling Layer

The pooling layer is used to for spatial size reduction to reduce computation and also reduce overfitting (*CS231n Convolutional Neural Networks for Visual Recognition*, 2017). Usually pooling is carried out by Max Pooling or Average Pooling. Max Pooling is found to perform better than Average Pooling (*CS231n Convolutional Neural Networks for Visual Recognition*, 2017).

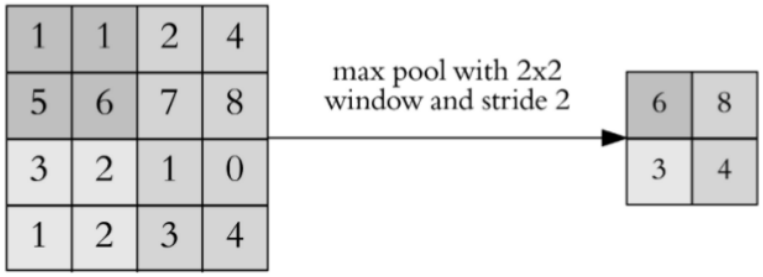


Figure 3.4: An example of Max Pooling, reproduced from Dertat (2017)

3.2.1 (c) Fully-connected Layer

The fully-connected layer is the part where classification is done. This layer holds all the activation information from each dimension in the feature extraction part. Flattening of the multidimensional information will be performed before the information is used for the classification task.

CHAPTER 4

RESEARCH METHODOLOGY

The research methodology is divided into 4 main stages, namely: Data Gathering, Data Pre-Processing, Model Building and Data Visualisation. The task will be subdivided into smaller tasks in each stage.

Figure 4.1 and 4.2 shows the Gannt chart and the tasks that were completed throughout the semester for both FYP 1 and 2.

Figure 4.1: Gannt chart for FYP 1

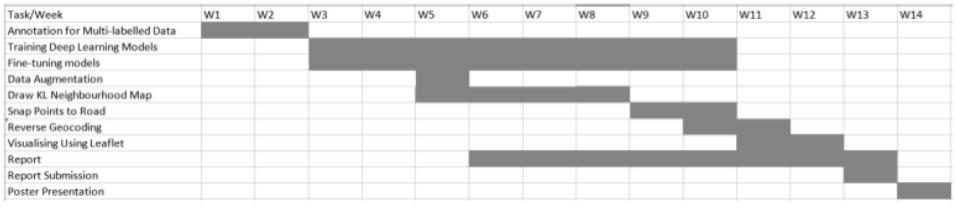


Figure 4.2: Gannt chart for FYP 2

4.0.1 Overall Research Methodology Process

Figure 4.3 shows the overall process framework of the research methodology. Firstly, a CSV file from Place Pulse 2.0 dataset which contains the result of the pairwise comparison between GSV images on different perceptual attributes was downloaded. The CSV file was then inspected to find out the amount of records that are located in Asian cities contained in the dataset.

After inspecting the data, since the amount of records that are located in Asian cities were found out to be high, data selection was done on the CSV file by selecting the records in which they are located in the Asian cities. Then, the selected dataset was checked to find out if the data are balance. Undersampling was carried out after finding out that the dataset is imbalance. Annotation of perceptual attributes were then done for the selected records after undersampling.

GSV images were then downloaded according to the coordinates of the selected data to be used as the training data. After the GSV images were downloaded and annotated with its perceptual attributes, it was used to train a deep transfer learning model. In the model building process, several parameters were fine-tuned and data augmentation was done to try to improve the training outcome.

After the model had been trained, the GSV images for Kuala Lumpur Neighbourhood

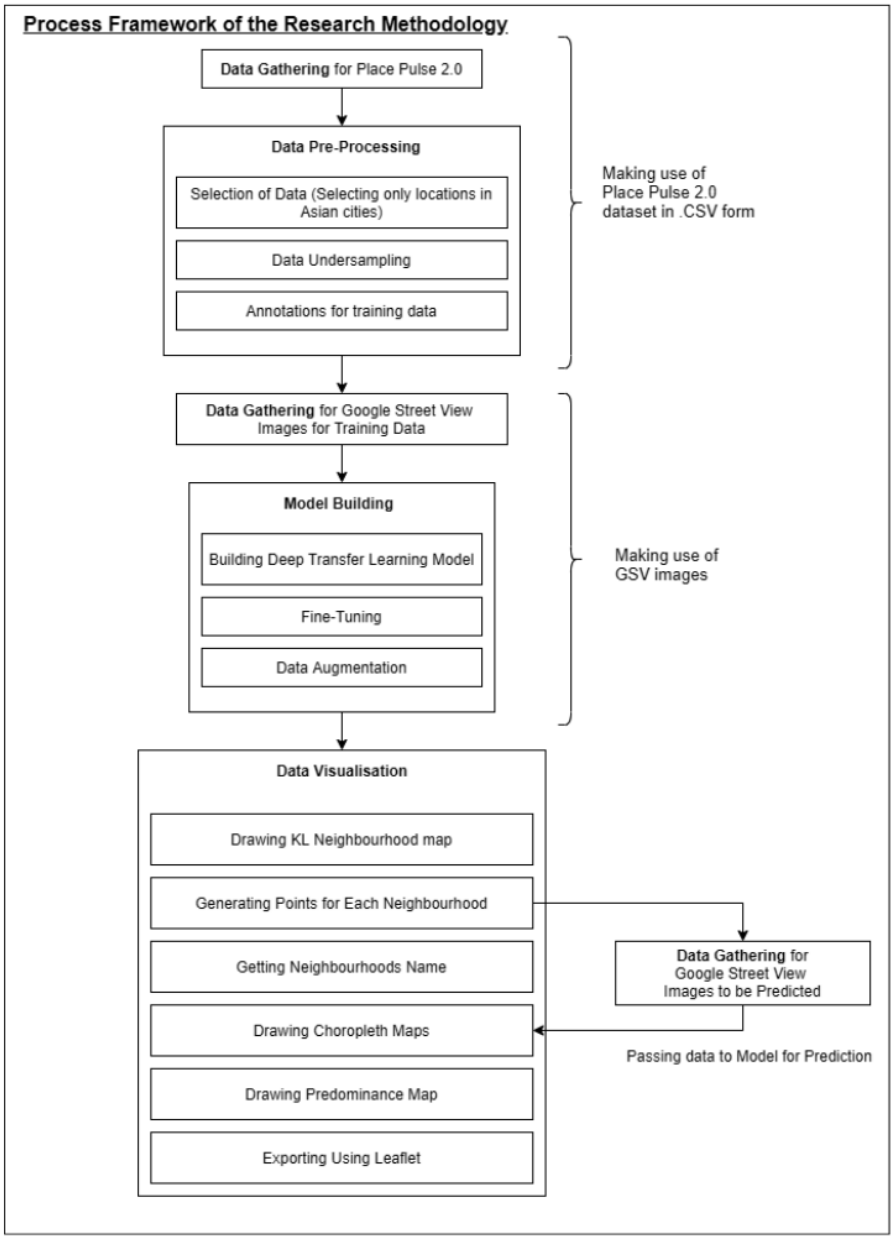


Figure 4.3: Process Framework of the Research Methodology

were downloaded as the data to be predicted. Map visualisation was used to visualise the perceptual attributes of each neighbourhood. Several steps were involved in the the Data visualisation stage. Data visualisation part will be discussed in details in Section 4.5.

4.1 Data Gathering

Data Gathering was carried out in 3 different steps to collect the (i) Place Pulse 2.0 pairwise comparison result which is available in a CSV file, (ii) GSV images in different Asian cities for training data and (iii) GSV images in KL neighbourhoods to be predicted.

4.1.1 Place Pulse 2.0 Pairwise Comparison Result (CSV)

The Place Pulse 2.0 dataset is the result of the pairwise comparison between 2 GSV images on a given perceptual attribute. The dataset is in .CSV form which consists of the coordinates of the 2 GSV images which were used in the pairwise comparison as well as the winner in the pairwise comparison for the given perceptual attributes (i.e.: the city which was perceived to suit the given perceptual attribute more).

The Place Pulse 2.0 dataset was downloaded from the Place Pulse website which is run by the MIT Media Lab. Data Pre-Processing (Section 4.2) was done on the Place Pulse 2.0 dataset to extract relevant data which focus on the Asian cities.

4.1.2 Google Street View Images

Subsequently, GSV images were downloaded using the coordinates provided by the Place Pulse 2.0 dataset. The GSV images for training data were downloaded by querying using the Street View Static API.

GSV images to be predicted were downloaded after the KL neighbourhood map was drawn in the visualisation part (Section 5.2) using Street View Static API as well. The GSV images downloaded for each neighbourhood were used to predict the perceptual attributes for each neighbourhood.

The downloaded image size for the GSV images are 224x224. To preserve the similarity between GSV images in the Place Pulse 2.0 experiment and the GSV images to be downloaded, the heading, pitch and field-of-view (FOV) of GSV were not specified as the authors of Place Pulse 2.0 did not specify them for the experiment.

The GSV images were annotated (will be further discussed in Section 4.2.3) according to their coordinates and if they emerge as a winner in the Place Pulse 2.0 dataset. The shortcoming of querying using the Street View Static API is that there is a limitation on the cost-free query amount which is 28,000 queries per month.

4.2 Data Pre-Processing

The data pre-preprocessing are divided into 3 stages, namely data selection, undersampling and annotations for training data.

4.2.1 Data Selection

Data selection to was carried out so that the training data are more relevant to the GSV images to be predicted in Kuala Lumpur neighbourhoods. From the Place Pulse 2.0 dataset, there are 7 Asian cities that are present in the records, namely: Singapore, Tel Aviv, Hong Kong, Tokyo, Taipei, Bangkok and Kyoto. Since the city streetscapes of Asian cities are more similar to each other than city streetscapes of other continents, the records which are located in the 7 Asian cities were extracted to be the training data.

3 bounding boxes were used to get the records which consist of the coordinates of the GSV images of the mentioned Asian cities. 3 smaller boxes were used instead of one big bounding box to ensure that irrelevant cities would not be included in the rows selected. Figure 4.4 illustrates the bounding boxes drawn to get the coordinates of the GSV images in the 7 different Asian cities.

The following state the cities being enclosed in each box.

- Box 1: Tel Aviv
- Box 2: Bangkok & Singapore

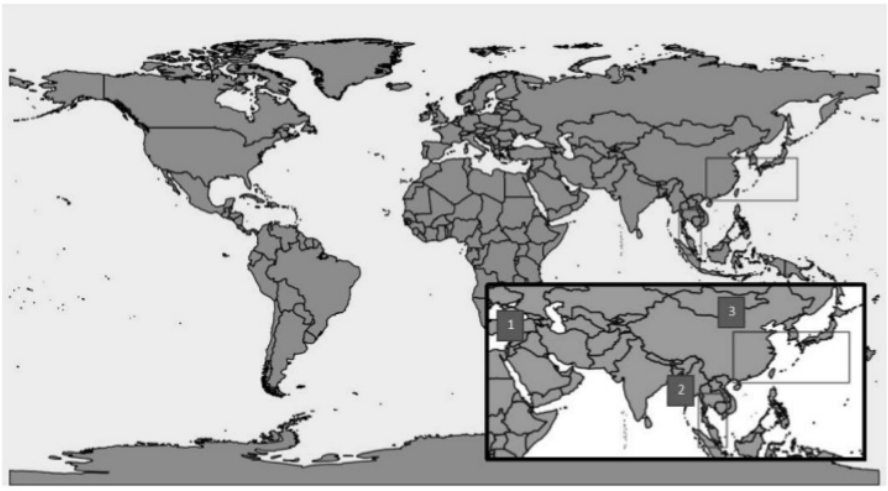


Figure 4.4: Bounding Boxes for Asian Cities

- Box 3: Tokyo, Kyoto, Hong Kong & Taipei

In addition to setting the coordinate boundaries to define the Asian cities, the coordinates of the GSV images have to be the winners for the pairwise comparison to be extracted. In other words, the data have to have coordinate which is (i) in one of the bounding boxes and (ii) a winner in the pairwise comparison in order to be extracted. As a result, the total amount of rows extracted is 108,570.

4.2.2 Undersampling

After extracting the data which focus on Asian cities, statistical analysis was done on the extracted data. As shown in Figure 4.5, the classes are imbalanced since the amount of data in "Lively" class and "Safety" class are exceptionally high.

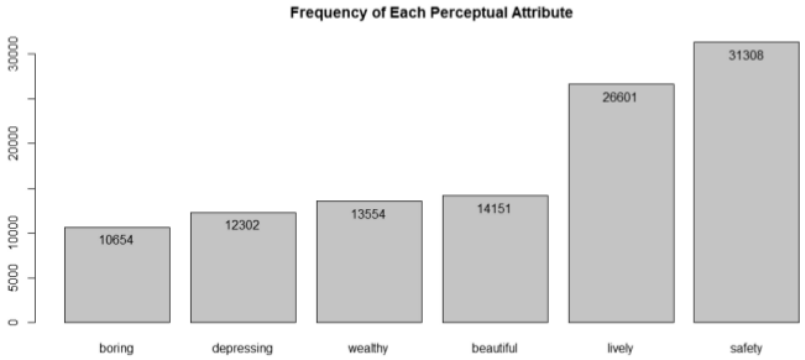


Figure 4.5: Frequency of Each Perceptual Attributes

In the statistical analysis of the extracted data, it was found out that the data are imbalanced with the "Lively" class and the "Safety" class having exceptionally higher amount than the other classes. Hence, random undersampling was used to balance the data. Undersampling was performed on each of the classes to achieve balance. After resampling, each class contains 10,344 records.

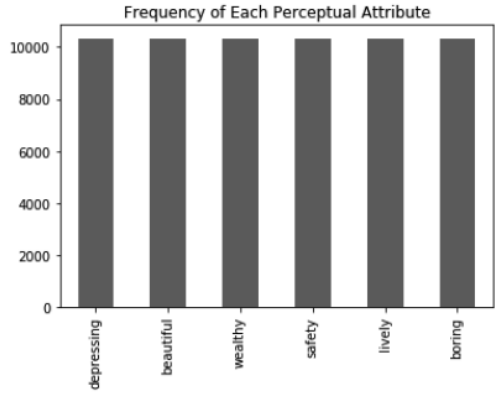


Figure 4.6: Resampled Classes of Perceptual Attributes

4.2.3 Annotation for Training Data

Attributes annotation was done by multilabelling each unique location according to the winner of the pairwise comparison for the targetted perceptual attributes.

Firstly, from the Place Pulse 2.0 dataset, the winners for the pairwise comparisons for one targetted perceptual attribute was extracted out together with the winning perceptual attribute. A list of winners with their own winning perceptual attribute were then created from the extraction. Then, unique winners which are defined by their own unique location and panorama ID (panoID) were extracted from the list of winners.

Each of the panoID of the list of unique winnner was then compared with the panoID of the list of winners. If the panoID from both files match, the winning perceptual attribute from the list of winners were then attached to its own unique location. Figure 4.7 shows an illustration of the whole annotation process.

4.3 Model Building

After the data were gathered and pre-processed, it is ready to be used to train a deep learning model. The task was initially described as a multiclass, single-labelled classification task. However, the training outcome (Section **??**) obtained for this task was not satisfying. Hence another approach was used to tackle the problem statement. The new approach was to do multilabelled classification on a given GSV image. Since the

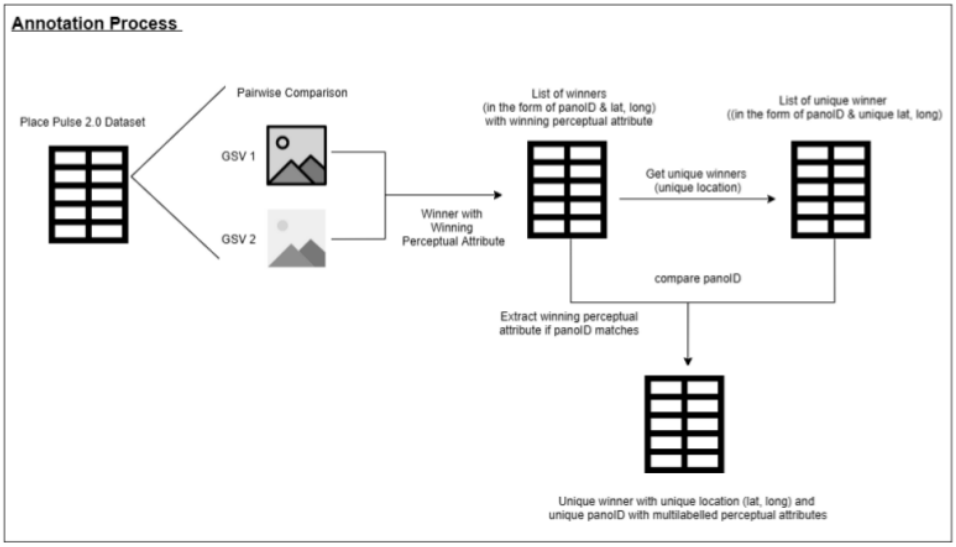


Figure 4.7: Annotation Process

GSV dataset collected was relatively small, transfer learning was opted to be applied.

4.3.1 Model Architecture

The deep transfer learning model used was a model with VGG 16 architecture, pre-trained on Places 365 weight (Zhou, Lapedriza, Khosla, Oliva, & Torralba, 2017). Places365 dataset was used as the pretrained weight because it consists of images that includes indoor scenes, nature scenes, and urban scenes in which nature scenes and urban scenes are particularly similar to the GSV images to be predicted in the multi-labelled classification. After building the feature extraction part of the deep learning model, 6 binary classifiers were added at the fully connected layer to make predictions on the perceptual attributes. The model was compiled using binary cross-entropy loss since the loss computed for each output is not affected by each other.

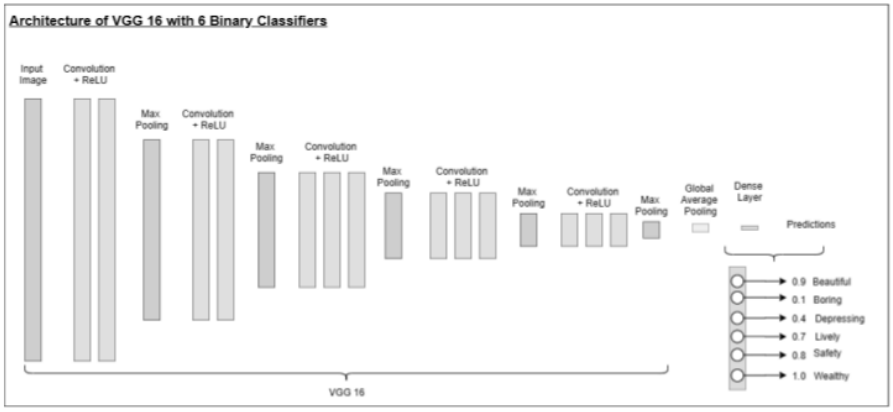


Figure 4.8: Multi-labelled Classifier with 6 Binary Classifiers

Figure 4.8 shows an illustration of the model architecture. At the last layer, we can see that there are 6 binary classifiers which are used to predict 6 different perceptual attributes. The score for each perceptual attribute is not affected by each other.

4.3.2 Fine-Tuning and Data Augmentation

After the whole model was built, the model was fine-tuned on the following parameters: learning rate, batch size and optimiser. Different weight namely ImageNet was also used to try to achieve a better training outcome. Data augmentation was also tried to improve the training outcome. Data augmentation was performed by downloading the GSV images of another angle from the same location. The angle was set to be 90° horizontally rotated.

4.4 Evaluation Metrics of the Model

The dataset of GSV images were split into 90% training data and 10% test data in which training data were further split into 80% training data and 20% validation data.

Since the task was described as a multilabelled classification task, mean average precision (mAP) was used as the evaluation metrics instead of accuracy. The reason of using mAP rather than accuracy is because in multilabel classification, the model's performance is measured by getting the right prediction for each class for each sample instead of getting the whole prediction right for each sample.

The mAP was calculated at the end of each training epoch by averaging the average_precision_score metrics provided by scikit-learn (Pedregosa et al., 2011). In the scikit-learn documentation, it is stated that the formula summarises a precision-recall curve by using the weighted mean of the precisions obtained at a defined threshold, in which the weight is defined as the increase in recall from a previous threshold. The threshold is assumed to be calculated by scikit-learn internally.

$$\mathrm{AP} = \sum_{n} (R_n - R_{n-1}) P_n$$

The equation above is the formula for the average_precision_score by scikit-learn in

which P_n and R_n are the precision and recalll at the n^{th} threshold.

4.5 Data Visualisation

The visualisation of the predicted perceptual attribute score was presented using a map. one of the objectives of the project is to present a city-level visualisation. Kuala Lumpur, Malaysia was chosen as the targeted city since it consists of various kinds of areas with different streetscapes ranging from the very famous Petronas Twin Towers building which intuitively signifies a wealthy area in the human perception to the Kampung Baru area which is a huge contrast to the streetscape of the area where Petronas Twin Towers resides at.

4.5.1 Drawing KL Neighbourhood Map

The whole visualisation is mostly map visualisation, this is because locations are better understood and easier to be visualised using a map. Hence, the first and foremost step would be to draw a KL neighbourhood map for visualisation. The tool to draw KL Neighbourhood map was QGIS, an open sourced geographical information system software. Instead of programically drawing square grids to represent each area of Kuala Lumpur, irregular polygons were drawn to represent each neighbourhood in Kuala Lumpur. The reason for drawing irregular polygons is that it is more intuitive such that the whole neighbourhood can be represented by a certain perceptual score hence it gives a simplified idea on how is the neighbourhood perceived as.

4.5.2 Generating Points and Getting Neighbourhoods Name

After the KL neighbbourhood map was drawn, random points were generated for each neighbourhood so that GSV images of that particular point can be downloaded based on the coordinate of the point. The random points were then snapped to the nearest road by using the Google Maps "Snap to Roads" API so that GSV images for the random points are available to be downloaded.

After the points had been snapped to the nearest road, the points were used to query for its own neighbourhood name. This was done by doing reverse geocoding of the given address using Google Maps "Geocoding" API. The coordinate of the points were used to find out about the neighbourhood where the points belong to.

4.5.3 Choropleth Map

There are several ways in visualising the data. One very direct way is to geospatially labelling the predicted perceptual scores for each perceptual attribute for each neighbourhood. Labelling the scores for each neighbourhood enables us to visualise clearly on which neighbourhood has a higher perceptual score. It also quantifies the answer for questions such as: "How safe is this place?" Hence, a choropleth map for each perceptual attribute was drawn to visualise the perceptual scores.

4.5.4 *Predominance Map*

On top of the choropleth maps, a predominance map was also drawn to visualise the predominant perceptual attribute of the neighbourhoods. A predominance map is useful in showing patterns across different attributes with the same measurement on a map. In this project, since there are 6 perceptual attributes to be looked into, a predominance map was drawn to show the predominant attribute for each neighbourhood.

After the predominant attribute was found out for each neighbourhood, the weight of the predominant attribute among the 6 perceptual attributes was annotated. The weight is calculated as follows:

$$W_p = \frac{PerceptualScore_p}{\sum_{i=1}^{n} PerceptualScore_i}$$

where p represents the predominant attribute. The weight is then used to denote the strength of predominance of the predominant attribute for each neighbourhood.

4.5.5 *Exporting the Maps*

After the maps were drawn, Leaflet, a Javascript library for interactive map was used to visualise the maps onto a web platform. Leaflet was chosen as the visualisation tool because it is light-weighted and it provides built-in interactive features with the maps.

CHAPTER 5

IMPLEMENTATION

The implementation part of the project involves two main parts in order to achieve the objectives of the project, namely to: (1) identify and train a suitable deep learning model to predict the labels of a location given the GSV image of that certain location and (2) present a city-level visualisation on the predicted perceptual attributes.

5.1 Training a Suitable Deep Learning Model

Building a suitable deep learning model was utmost important for the classification task. Before the task was described as a multilabelled task, it was described as a multiclass, single-labelled classification task. However the training outcome was not up to expectation. Thus, the task was then described as a multilabelled classification task.

5.1.1 Evaluation of Model Performance

5.1.1 (a) Training Details and Outcome for Single-Labelled Classification

A few models which include VGG 16, AlexNet and InceptionNet were trained on ImageNet to complete the task. However, the training outcomes were very unsatisfying

in which the highest accuracy reached was only 0.2 and the loss fluctuated between 1.7 and 1.8.

5.1.1 (b) Training Details and Outcome for Multilabelled Classification

Several deep learning models were built according to the architecture of VGG 16 and trained on both ImageNet and Places365 weights. Training outcome for these two were compared and it was found out that models trained on ImageNet could not learn well since it has low variance and high bias on the wrong predictions.

Focus were then put on training models using Places 365 weights. Initially, Adam optimiser was used as the optimiser algorithm. However, the mean average precision (mAP) and the loss fluctuated a lot during the training and could not converge. Hence SGD was used to replace Adam as the optimiser. The training result using SGD as the optimiser indicates that the model learns better.

The learning rate of the model was also fine-tuned to get better result. It is found out that the model learns better with 0.001 learning rate compared to 0.01 learning rate. In a few early model trainings, the number of epochs was set to be 100 but with the implementation with SGD as the optimiser, Keras's Early Stopping was made use of by monitoring the validation loss. The patience of the Early Stopping which denotes the delay of epochs before stopping the training was set to be 100 epochs. In other words, if there is no decrease for the validation loss in 100 epochs, the training would

be stopped.

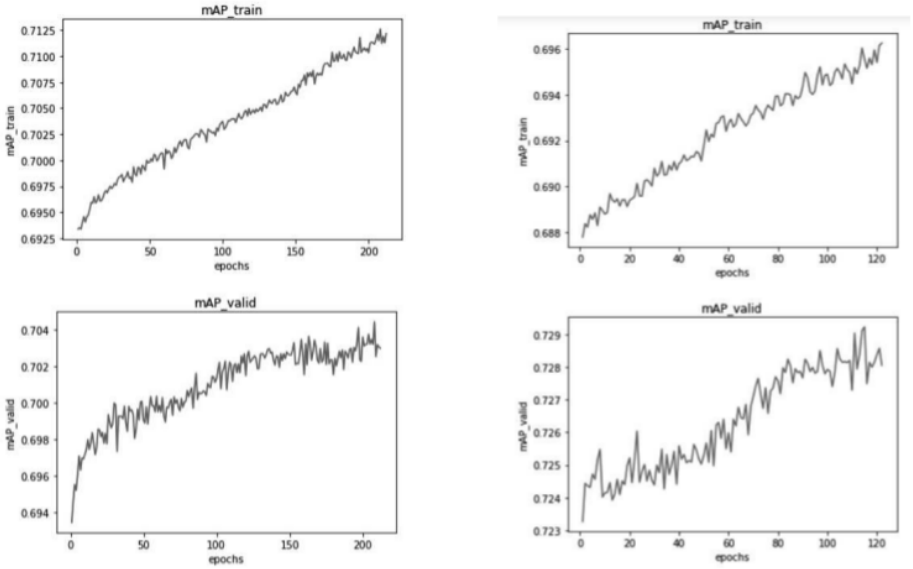
In an effort to increase the model performance, data augmentation was also performed. The newly created GSV images were rotated 90° horizontally on Google Street View. They were downloaded by setting the "heading" parameter for the Google Maps "Static Street View" API to be 90 (i.e., heading=90).

Table 5.1 shows the comparison of training outcomes using different model settings while the architecture and weights used were all respectively VGG16 and Places365. The batch size specified was also constantly 16.

Table 5.1: Comparison of Training Outcomes Using Different Model Settings

Model	Optimiser	Learning Rate	Data Augmentation	Validation Loss	Validation mAP
1	Adam	0.001	No	**0.84**	0.69
2	Adam	0.001	Yes	0.85	0.67
3	SGD	0.01	No	0.85	0.66
4	SGD	0.001	No	0.85	0.70
5	SGD	0.001	Yes	0.86	**0.72**

From Table 5.1, Model 4 and Model 5 both performed similarly well but Model 4 was picked because the training mAP of Model 5 was generally lower than the validation mAP of Model 5. Figure 5.1 shows a comparison of training mAP and validation mAP of Model 4 and Model 5. Model 4 was picked because it behaved more normally.



(a) Training mAP and Validation mAP of Model 4

(b) Training mAP and Validation mAP of Model 5

Figure 5.1: Comparison of Training mAP and Validation mAP of Model 4 & Model 5

5.2 Visualising the Predicted Perceptual Attributes

There are several steps involved in visualising the predicted perceptual attributes. The first step was to draw a KL neighbourhood map since there is no neighbourhood map of Kuala Lumpur currently available online. Next, random points for each neighbourhood are generated. The generated points were used to label the neighbourhood name of each neighbourhood.

After downloading the GSV images for each point, the images were passed to the model created earlier to get predicted perceptual scores for each attribute. The perceptual scores for each neighbourhood were calculated by averaging the perceptual scores

of all the points in a particular neighbourhood. The perceptual score for each attribute for each neighbourhood were then visualised using choropleth maps. A predominant map was also drawn to illustrate the predominant attribute for each neighbourhood. The map visualisation layers were then exported to be an interactive visualisation map using Leaflet, a Javascript library for interactive maps.

5.2.1 KL neighbourhood map

Firstly, a neighbourhood map that covers a part of Kuala Lumpur was drawn using an open-sourced geographical information system software, QGIS. Polygons which cover a certain neighbourhood area would be drawn if GSV is available at that particular area. The process was done by checking if GSV is available while drawing the neighbourhood map manually.

(a) Drawn Kuala Lumpur Neighbourhood Map

(b) Available Google Street View

Figure 5.2: Plotting of Kuala Lumpur Neighbourhood Map by checking if GSV is Available at a Particular Area

Figure 5.2a shows the KL neighbourhood map that was drawn. In Figure 5.2b, the blue lines denote that GSV is available.

5.2.2 Generating New Points for Each Neighbourhood

To generate new points for each neighbourhood, random points were first generated for each neighbourhood by checking if the points fall within the neighbourhood polygon. Then, by making use of the Google Maps "Snap to Roads" API, the generated random points for each neighbourhood were snapped to roads so that GSV images can be downloaded since GSV is mostly available on the road. The process were repeated until there are suffice points to represent the whole neighbourhood.

Figure 5.3 shows the points being plotted on the neighbourhood map. Initially, the number of points were set to be 20 for each neighbourhood, however, due to having fewer roads available for GSV, some areas only have as few as 5 points. Aside from that, most of the areas have 15-20 points.

5.2.3 Getting Neighbourhood Name for Each Neighbourhood

The points are then used to find out the name of the neighbourhood (named as "sublocality" by Google Maps) each of them belongs to. In this part, Google Maps "Geocoding" API were used. The "Geocoding" API is usually used to query for the coordinate of a given location name. Here, a reverse geocoding was done by getting the neighbourhood name given the coordinate of the points.

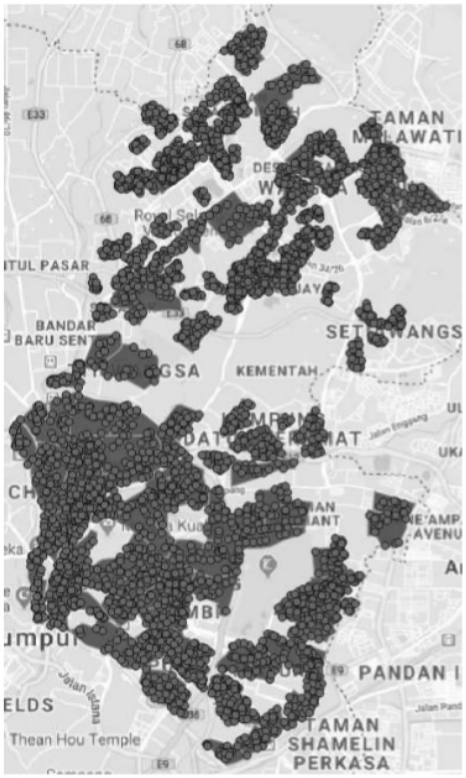


Figure 5.3: Snapped Points on the Neighbourhood Map

Some of the points despite being in the same neighbourhood, the query returned a different neighbourhood name. To solve this problem, The neighbourhood name for the points that appear the most frequent for each neighbourhood were used to be the label as the neighbourhood name for all the points that belong to the particular neighbourhood.

5.2.4 Choropleth Maps to Visualise Each Attribute

The perceptual scores for each neighbourhood were calculated by averaging all the scores of the points for a particular perceptual attribute in a particular neighbourhood. The labelled perceptual scores for each neighbourhood were then used to plot choropleth maps for each perceptual attribute. Figure 5.4 shows the choropleth mas to visualise the perceptual scores in the neighbourhoods. The color encoding of the choropleth map denotes the perceptual score of each area. The perceptual scores for each attribute were divided into 5 ranges.

5.2.5 Predominance Map

In visualising the predominant perceptual attribute for each neighbourhood, a predominance map was drawn.

Figure 5.5 shows the predominance map that was created. The predominant attribute for each neighbourhood was calculated by getting the attribute that has the highest perceptual score across all 6 perceptual attributes. In the map, the transparency encoding of the map represents predominance strength of the predominant attribute among the 6 perceptual attributes. The predominance strength calculated by getting the weight of the predominant attribute. It was divided into 5 levels of transparency.

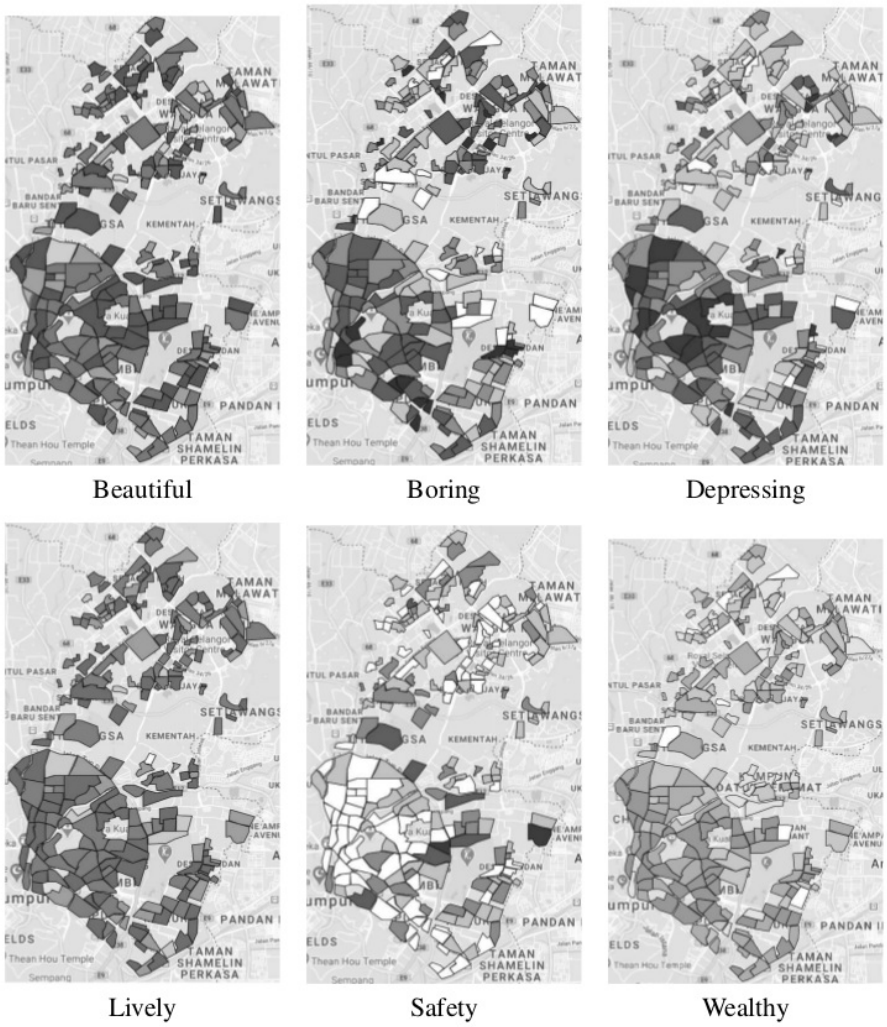


Figure 5.4: Choropleth Maps of the 6 Perceptual Attributes

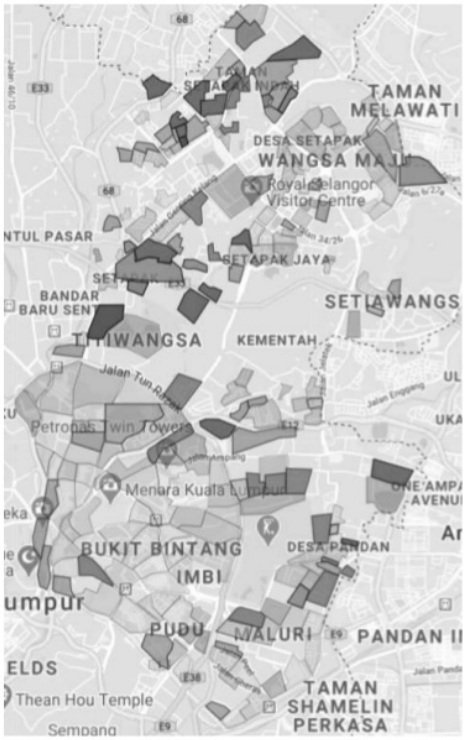


Figure 5.5: Predominance Map for Urban Perception in KL Neighbourhood

5.2.6 Exporting to Web-Based Visualisation

The exporting was done using a plugin, qgis2web on QGIS which exports map layers into Leaflet compatible form.

On the web-based visualisation, Google charts were embedded in each neighbourhood to visualise each perceptual score. Figure 5.6 shows an example of a pop up when mouse is hovered at a particular neighbourhood area.

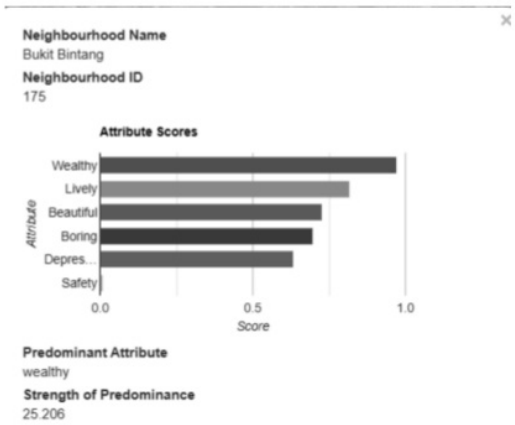


Figure 5.6: Example of a Pop Up from a Neighbourhood

Figure 5.7 shows a screenshot of the exported web-based visualisation. There is search button on the top left to help user locate neighbourhood by its neighbourhood name. The map layers can also be hidden or shown as preferred by the user.

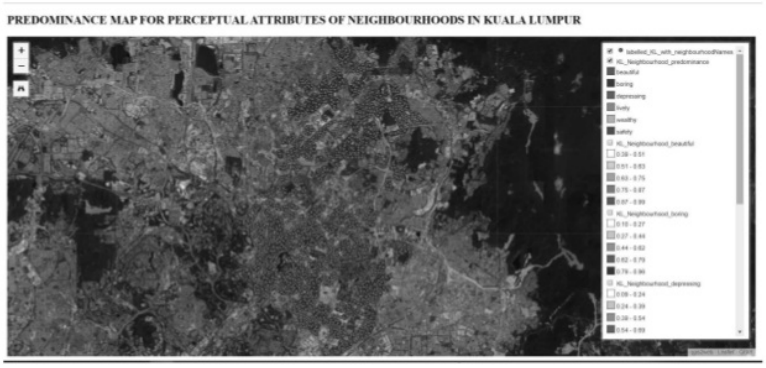


Figure 5.7: Screenshot of exported web-based visualisation

When clicked on the points, pop up such as Figure 5.8 would appear if the user is curious about the GSV images that are used for the prediction of the perceptual scores.

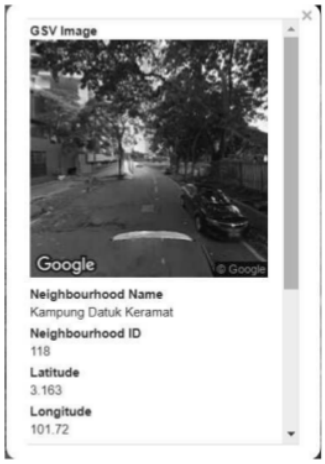


Figure 5.8: Example of a Pop Up from a Point

5.2.7 Analysis of Findings

From the choropleth maps in Figure 5.4, we can see that most of the neighbourhoods in Kuala Lumpur have high beautiful and lively scores. As for the boring, depressing, wealthy attribute, the scores are higher as it goes near the bottom left area where Kuala Lumpur city centre is located at. It is interesting to see how neighbourhoods with high wealthy score also has high boring and depressing scores.

The safety score for all of the areas of in Kuala Lumpur is relatively low compared to all the other perceptual attributes. The highest safety score is only 0.54 whereas all the other attributes achieve at least 0.84 perceptual scores. Moreover, Kuala Lumpur city centre surprisingly have a lower safety score. Furthermore, the depressing score is also

much higher at the Kuala Lumpur city centre. This is probably caused by skyscrapers and towers were perceived as depressing despite being wealthy looking.

CHAPTER 6

CONCLUSION

In this research project, in order to solve the issues of manual social studies on city streetscapes, two research objectives were proposed. As an accomplishment, a suitable deep learning model was identified and trained for the multilabelled classification task to predict the perceptual attributes for a location given a GSV image of that location. Using that model, predictions of perceptual attributes were done for some neighbourhoods in Kuala Lumpur. The predictions were then visualised on a web-based platform which enables user interactions.

For future enhancement, the performance of the deep learning model can still be improved by searching for better suited specifications for the model. If a model with better performance can be identified, the project can be further extended to be a crowdsourced project in which users can expand the neighbourhood map and predictions can be made on the newly expanded map. There is also a need for automating the pipeline of the whole process so that users can get the predictions immediately after drawing the neighbourhood map.

FYP Final Report

ORIGINALITY REPORT

3%	1%	3%	%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	"MultiMedia Modeling", Springer Science and Business Media LLC, 2019 Publication	1%
2	"Intelligent Systems and Applications", Springer Science and Business Media LLC, 2020 Publication	<1%
3	"Computer Vision – ECCV 2016", Springer Nature, 2016 Publication	<1%
4	Jian Gao, Yi-Cheng Zhang, Tao Zhou. "Computational socioeconomics", Physics Reports, 2019 Publication	<1%
5	repository.tudelft.nl Internet Source	<1%
6	Xiaojiang Li, Chuanrong Zhang, Weidong Li. "Does the Visibility of Greenery Increase Perceived Safety in Urban Areas? Evidence from the Place Pulse 1.0 Dataset", ISPRS International Journal of Geo-Information, 2015	<1%

Publication

7	Yao Yao, Zhaotang Liang, Zehao Yuan, Penghua Liu, Yongpan Bie, Jinbao Zhang, Ruoyu Wang, Jiale Wang, Qingfeng Guan. "A human-machine adversarial scoring framework for urban perception assessment using street-view images", International Journal of Geographical Information Science, 2019 Publication	<1%
8	Sohailah Safie, Nik Muhamad Aizuddin Nik Azmi, Rubiyah Yusof, Muhd Ridzuan Muhd Yunus et al. "Chapter 57 Object Localization and Detection for Real-Time Automatic License Plate Detection (ALPR) System Using RetinaNet Algorithm", Springer Science and Business Media LLC, 2020 Publication	<1%
9	scholar.sun.ac.za Internet Source	<1%
10	Eger, E., P. Pinel, S. Dehaene, and A. Kleinschmidt. "Spatially Invariant Coding of Numerical Information in Functionally Defined Subregions of Human Parietal Cortex", Cerebral Cortex, 2013. Publication	<1%
11	Jasper S. Wijnands, Kerry A. Nice, Jason Thompson, Haifeng Zhao, Mark Stevenson.	<1%

"Streetscape augmentation using generative adversarial networks: Insights related to health and wellbeing", Sustainable Cities and Society, 2019
Publication

---

12 "Advances in Computational Intelligence", Springer Science and Business Media LLC, 2019 <1%
Publication

---

13 udspace.udel.edu <1%
Internet Source

---

14 Zhen Shen, Wenzheng Bao, De-Shuang Huang. "Recurrent Neural Network for Predicting Transcription Factor Binding Sites", Scientific Reports, 2018 <1%
Publication

---

15 Hartmann, Oliver, Roland Schweiger, Raimar Wagner, Florian Schule, Michael Gabb, and Klaus Dietmayer. "Night time road curvature estimation based on Convolutional Neural Networks", 2013 IEEE Intelligent Vehicles Symposium (IV), 2013. <1%
Publication

---

16 Tomás Rossetti, Hans Lobel, Víctor Rocco, Ricardo Hurtubia. "Explaining subjective perceptions of public spaces as a function of the built environment: A massive data approach", <1%

Landscape and Urban Planning, 2019
Publication

17 Darshan Santani, Salvador Ruiz-Correa, Daniel Gatica-Perez. "Looking South", ACM Transactions on Social Computing, 2018 <1%
Publication

18 Bao-rui Li, Yi Wang, Guo-hong Dai, Ke-sheng Wang. "Framework and case study of cognitive maintenance in Industry 4.0", Frontiers of Information Technology & Electronic Engineering, 2019 <1%
Publication

Exclude quotes	On	Exclude matches	< 5 words
Exclude bibliography	On		

FYP Final Report

GRADEMARK REPORT

FINAL GRADE

/0

GENERAL COMMENTS

Instructor

PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11

PAGE 12

PAGE 13

PAGE 14

PAGE 15

PAGE 16

PAGE 17

PAGE 18

PAGE 19

PAGE 20

PAGE 21

PAGE 22

PAGE 23

PAGE 24

PAGE 25

PAGE 26

PAGE 27

PAGE 28

PAGE 29

PAGE 30

PAGE 31

PAGE 32

PAGE 33

PAGE 34

PAGE 35

PAGE 36

PAGE 37

PAGE 38

PAGE 39

PAGE 40

PAGE 41

PAGE 42

PAGE 43

PAGE 44

PAGE 45

PAGE 46

PAGE 47

PAGE 48

PAGE 49

PAGE 50

PAGE 51

PAGE 52