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Coursework Part One

Applying geographically representative photographs to estimate land use in London

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Background

Land use and land cover (LULC) contains rich geospatial information, which is of great significance to urban planning, government management and sustainable development (Zhang et al., 2018 and Dewangkoro & Arymurthy, 2021). The rapid development of global economy and cities has resulted in the diversification of urban land use patterns and complex urban functional areas. However, urban land use pattern is not only affected by government policies, but also by the continuous change of urban development processes. Since land use data gathered in geospatial databases might become outdated quickly, there is a requirement for automatic update processes (Yang, Rottensteiner & Heipke, 2018). Therefore, effective identification of urban land use patterns is of great significance for the formulation of effective urban planning policies.

With the development of machine learning technologies, abilities of deep learning techniques in processing unstructured data, such as image data, are identified, applying multilayer learning algorithm to achieve nonlinear mapping and discover hidden structure of input data (Zhu et al., 2019). Convolutional neural network (CNN), as a popular deep learning model with strong fault tolerance and robustness, is characterized by network simplification, pooling operations and weight sharing (Zhou, Jin & Dong, 2017). Since 2018, many studies have confirmed that CNN could be effectively applied in the land use classification tasks. However, most of them only focused on the aerial images and satellite images, ignoring the potential features which could be extracted from street view images other than roof structures. Therefore, this essay will test and compare abilities of CNN models on identifying land use in London using online geographically representative photographs, in order to provide some insights for urban planning field.

Literature review

Land use scenes classification based on high-resolution remote sensing images with high quality and accuracy is critical for related scientific research and land management applications (Weng et al., 2018). Research on the CNN models for satellite images have tried to optimize the models via different methods and explore the practical applications. For example, separate transfer models based on AlexNet, GoogLeNet, and VGGNet were compared (Cao, Dragićević & Li, 2019), automatic iteration times were investigated (Zhang et al., 2019), and parameters, such as convolutional kernels, convolutional layers, pooling methods, were optimized (Li et al., 2020). In addition, according to Xu et al. (2020), multi-structure joint decision-making approach can significantly improve the land use classification accuracy of indistinguishable categories by applying different CNN models separately and making final decision jointly.

However, research on the ability of ground-level street view images in land use classification have not attracted enough attention in the field. As emphasized by Cao et al. (2018), although aerial images alone could possibly achieve relatively high accuracy, the ground-level images with unique information could still improve the results, especially when the images have lower resolutions. This opinion was also supported by Kang et al. (2018) who have applied the integration of remote sensing images and street view images on the building functionality classification in Canadian and American cities. Therefore, this paper will optimize the CNN models on land use classification based on ground-level images, in order to support the future research on the integration of aerial images, satellite images and ground-level images to estimate land use.

Data collection

GEOFABRIK website (for collecting OpenStreetMap data) and the geography website for Great Britain and Ireland are the two main data sources utilized in the analysis. From GEOFABRIK (2021), it is able to obtain the recent land use information for London, representing the geospatial location and shape of different functional areas. As shown in Figure 1, the land use categories with relatively higher proportions have been selected and visualized. Generally, residential areas account for most of the proportion, commercial areas are concentrated in City of London and its neighbourhood regions, while retail stores are located along the streets. Besides, agricultural and industrial regions are distributed in the suburbs, and parks are scattered everywhere.

Images dataset was obtained from the geography website for Great Britain and Ireland by python crawler program. Based on comma-separated value file provided by Seresinhe, Preis and Moat (2017), it is possibly to retrieve those publicly available image data from the geography website. Through the process, the images are downloaded in separate file folders for commercial, farmland, industrial, park, residential and retail, classified based on land use information in OpenStreetMap. Those images can probably achieve the representativeness of geographical coverage of London (see Figure 1). Examples for the land use classification with identifiable characteristics have been represented in Figure 2. Besides, in order to better perform the research, latitude and longitude were combined to form the name of each image.

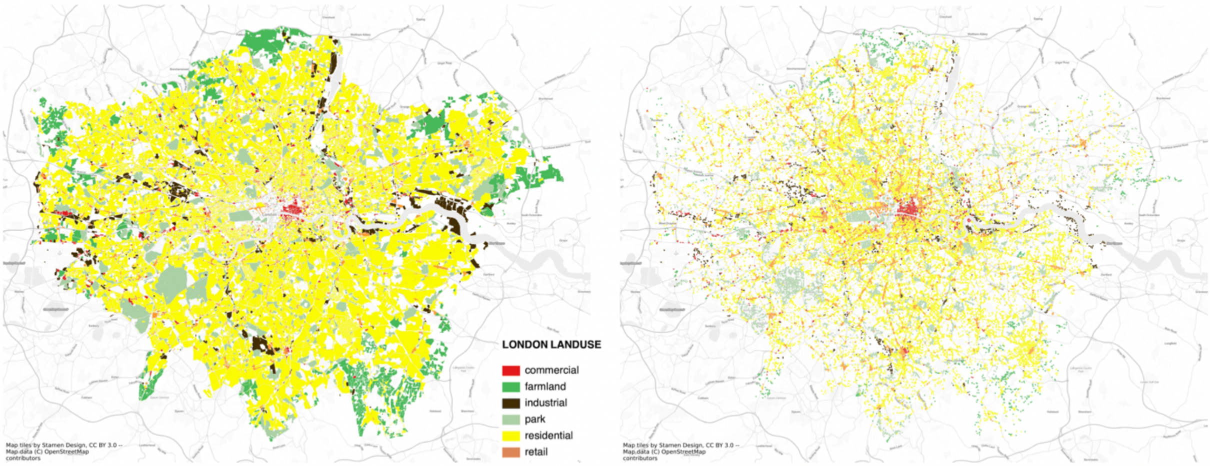

Figure 1: Datasets for the land use classification research (Source: Author's own)

Figure 2: Examples of land-use classification (Source: Author's own)

Methodology

In order to make the models achieve better performance, the research keeps a balanced dataset, randomly selecting a thousand images for each category. As mentioned by Piri, Delen & Liu (2018), imbalanced dataset might probably deteriorate the performance of classification models. Considering the CNN models, most relevant hyperparameters are tested first with 10 epochs. According to Bhosle & Musande (2019) and Li et al. (2020), the optimization of convolutional layers, convolutional kernels, optimizer, activation function, pooling methods, filter size, learning rate and batch size of CNN models can facilitate the improvement of model accuracy. Therefore, following the CNN architecture with 3x3 filters applied in VGG (Simonyan and Zisserman, 2014), simple 2x2 max pooling method and 0.01 learning rate, the model has tested other parameters to achieve better performance.

In order to visualize the results and correctly estimate the accuracy variation trends with the increase of epochs and avoid overfitting problem, Tensorboard website is applied to facilitate the model optimization processes. On the local website, it is able to compare the trends of accuracy and loss of both train and test datasets for each model. The models with larger fluctuation and lower accuracy are screened out. After finally selecting the CNN model with the best performance, this certain model is conducted again with 30 epochs, in order to achieve further improvements through iterative optimization.

Results

Overall, models with relu activation function achieve better ground-level imagery classification performance. In contrast, models with another activation function, ‘sigmoid’, indicate a decrease between 20 and 30% accuracy compared with ‘relu’ models, which might because the slight transformation close to the saturation and the derivatives approaching zero may cause information loss. Apart from that, other parameters have been tuned and Table 1 has displayed the best 3 models with their evaluation results (see detailed trend in Appendix A). In general, the classification accuracy of all these 3 models ranges from 42% to 45%, while the best-performed one applies 3 convolutional layers, 128 convolutional kernels and 32 batch size.

Table 1: Top 3 models with better performance (Source: Author's own)

CNN models	Train loss	Train accuracy	Validation loss	Validation accuracy
3-conv-128-kernels -32-batch size	1.3993	0.4344	1.3658	0.4500
2-conv-64-kernels -64-batch size	1.3863	0.4415	1.4226	0.4217
3-conv-64-kernels -32-batch size	1.4029	0.4363	1.4039	0.4217

After confirming the best performance of '3-conv-128-kernels-32-batch size' CNN model, it is conducted again with 30 epochs. As represented in Figure 3, the model accuracy experiences an increasing trend with a decrease in model loss before 15 epochs, where around 45% accuracy can be achieved for both train (0.8xtotal dataset) and validation (0.2xtotal dataset) datasets. After that point, the accuracy and loss values begin to level off, fluctuated between 0.40 and 0.45, and 1.4 and 1.5 respectively, with a potential risk of overfitting.

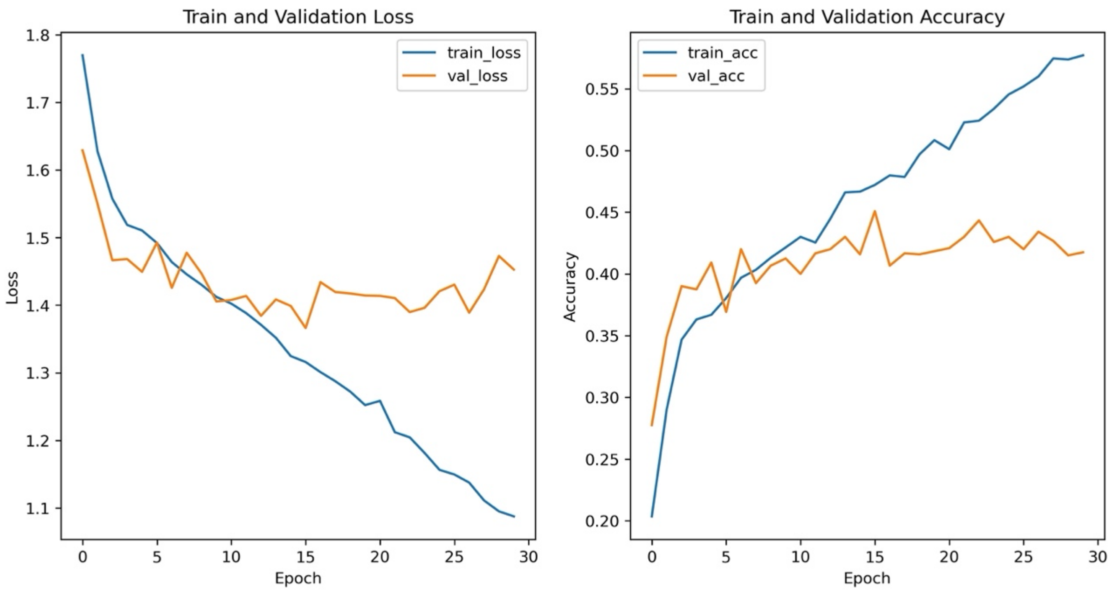

Figure 3: Accuracy and loss for train and validation datasets (Source: Author's own)

To discover the reason of misclassification, confusion matrix in Figure 4 has represents the correlation between classification of different categories following the 15-epoch model. Among 200 samples in each category, most samples in 'farmland' and 'retail' categories could be predicted correctly. In contrast, four fifth of 'residential' images would be misclassified. In addition, there is great possibility that 'commercial', 'industrial' and 'residential' samples would be predicted as 'retail', which might because retail outlets are always located on the ground floor of buildings with various facades along the streets. Besides, classification of 'farmland' and 'park' with several similar characteristics might also affect each other.

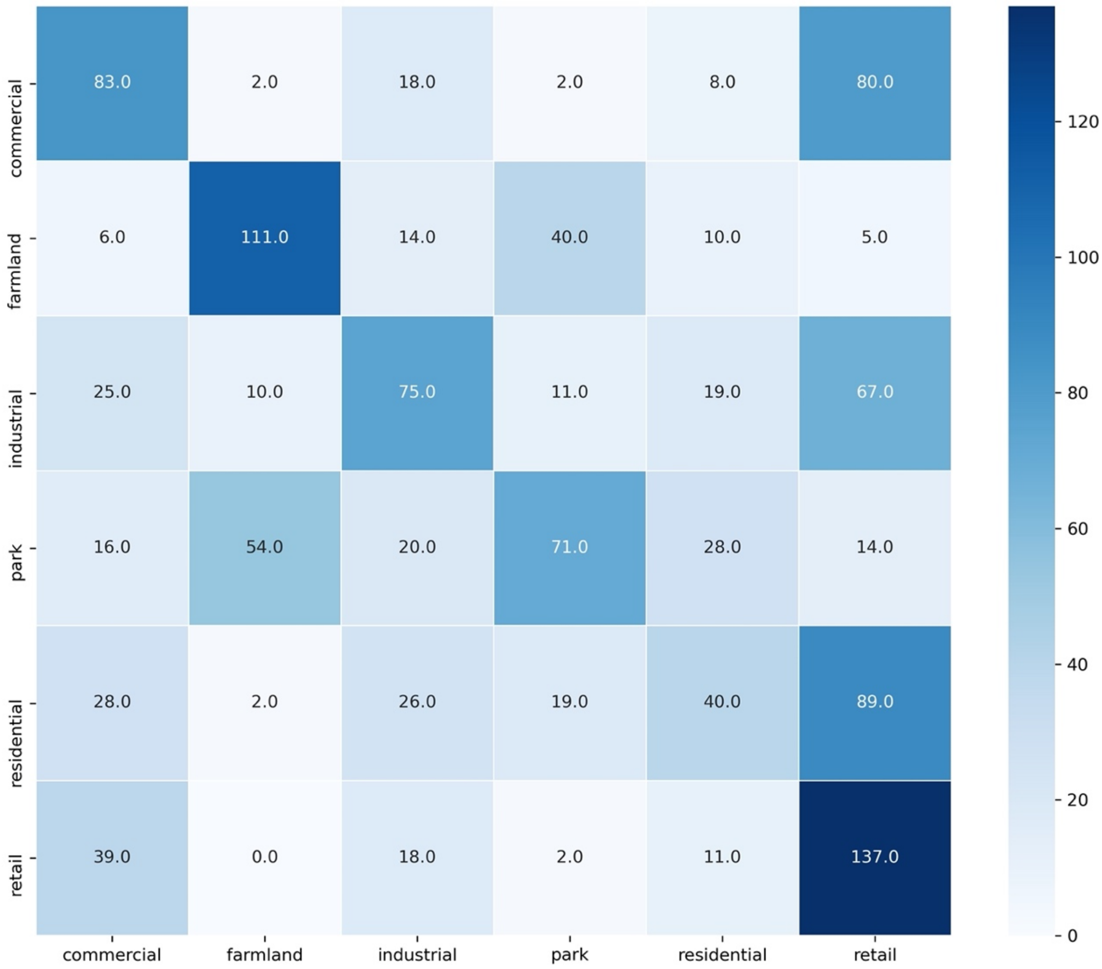

Figure 4: Confusion matrix for the category classification performance
(Source: Author's own)

Apart from that, Figure 5 has visualized the actual and predicted classification results of the test dataset, displaying the special variation of land use in London. Although there are over half samples being misclassified, the similar distribution patterns of those functionality areas can still be identified. Besides, the discovery described above is also reflected in the spatial visualization.

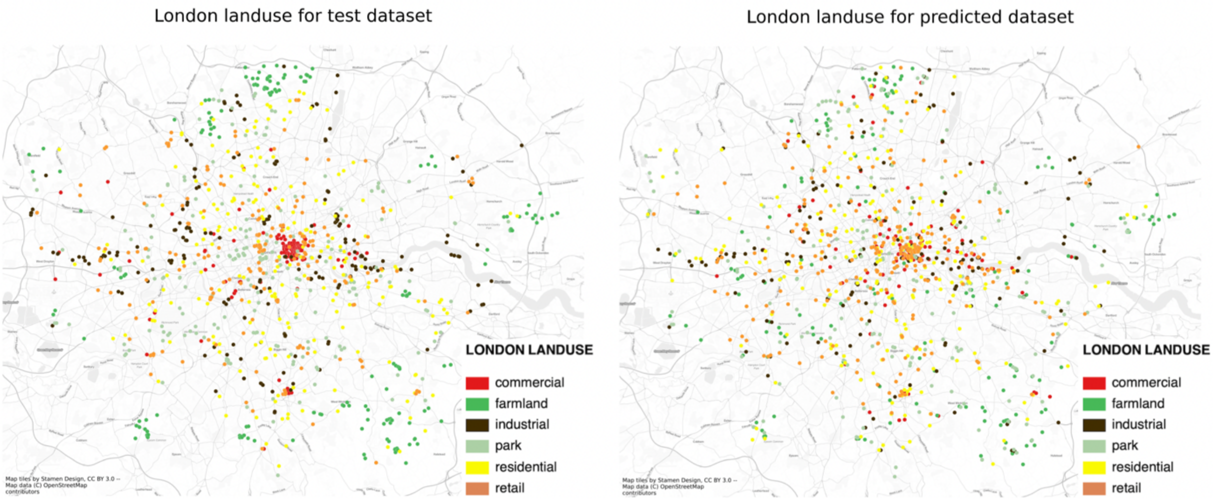

Figure 5: Spatial visualization of land use classification for actual and predicted values of test dataset (see original imagery in Appendix B; Source: Author's own)

The research has also conducted the similar experimental steps for 4 categories, including commercial, industrial, park and residential, avoiding the identified negative influence of retail and farmland. According to Hoffmann et al. (2019), the highly compact classification strategy with commercial, industrial, public, and residential categories has essential value to urban geography, since they are closely associated with socio-demographic variables, such as income and population density. As shown in Table 2, the models' performance for these 4 categories is much better than that for original classification scheme, with accuracy ranging from 49% to 54% for 10-epoch models (see detailed trend in Appendix C).

Table 2: Top 3 models with better performance (Source: Author's own)

CNN models	Train loss	Train accuracy	Validation loss	Validation accuracy
3-conv-64-kernels -64-batch size	1.1608	0.5015	1.0967	0.5312
4-conv-128-kernels -32-batch size	1.1323	0.5170	1.1275	0.5188
4-conv-64-kernels -32-batch size	1.1665	0.4900	1.1329	0.5225

Following the ‘3-conv-63-kernels-64-batch size’ model with the best performance, Figure 6 has represented its accuracy and loss of the model conducted again with 30 epochs. During the process, the model accuracy for both train and validation datasets continuously increases reaching 0.55, while the loss gradually decreases reaching 1.1 with slight fluctuations. Therefore, compared with previous land use classification scheme, actual and fitted values for these 4 classes have higher fitting precision without overfitting issues.

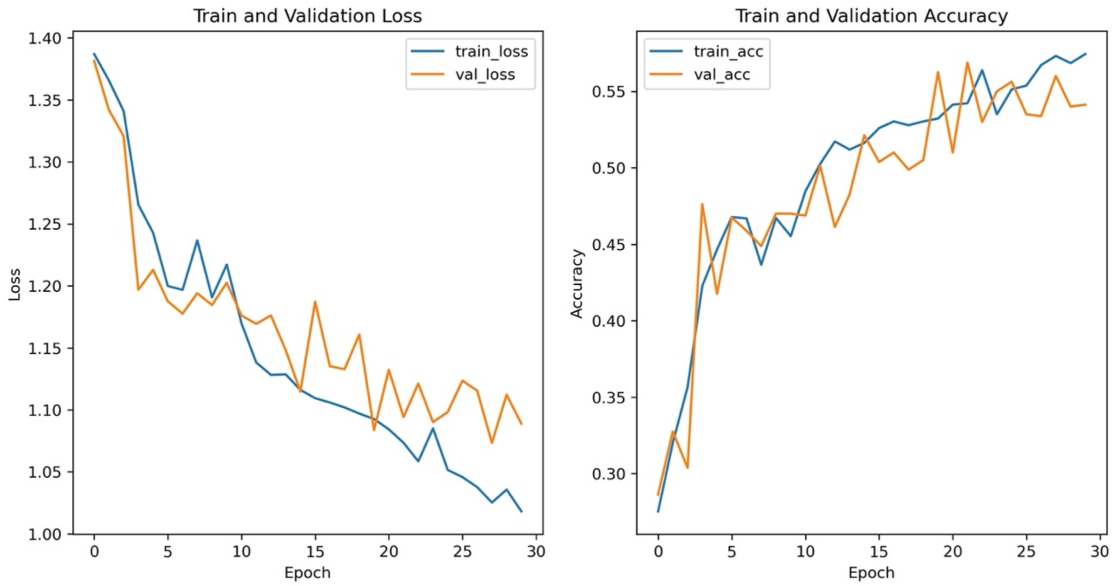

Figure 6: Accuracy and loss for train and validation datasets (Source: Author’s own)

Confusion matrix analysis for the category classification performance and spatial visualization of land use classification for actual and predicted values of test dataset have also been conducted (see Figure 7 and Figure 8). It is apparent that although confusion between buildings with different functionalities still exist, the probability of correct classification has been greatly improved. In particular, over half samples for ‘commercial’, ‘park’ and ‘residential’ classes can be correctly identified. Because of the limited number of samples, it is difficult to recognize the overall land use pattern in London. In addition, as represented in Figure 8, photographs collected by geography website tend to be more concentrated in central urban areas (as test dataset acquisition also follows random selection approach), which also affect the representativeness of the dataset.

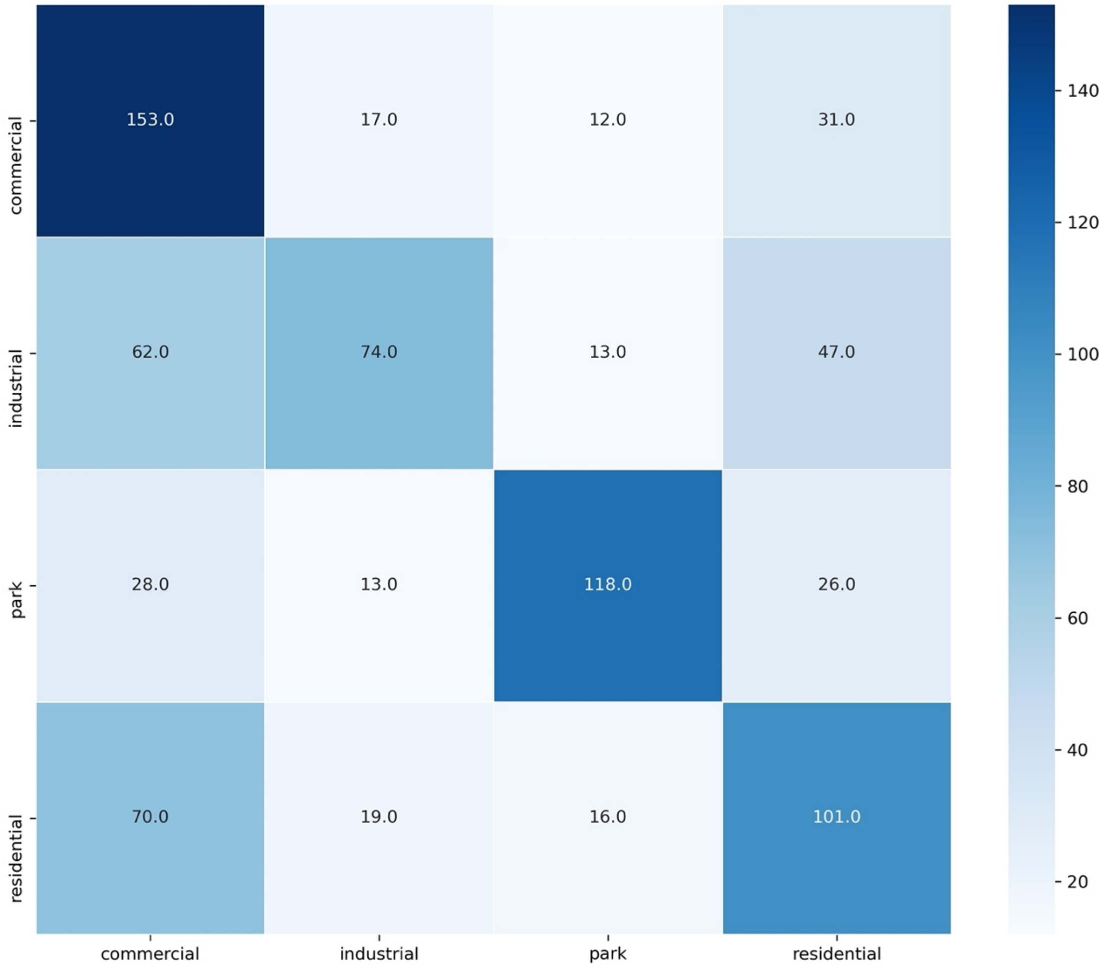

Figure 7: Confusion matrix for the category classification performance (Source: Author's own)

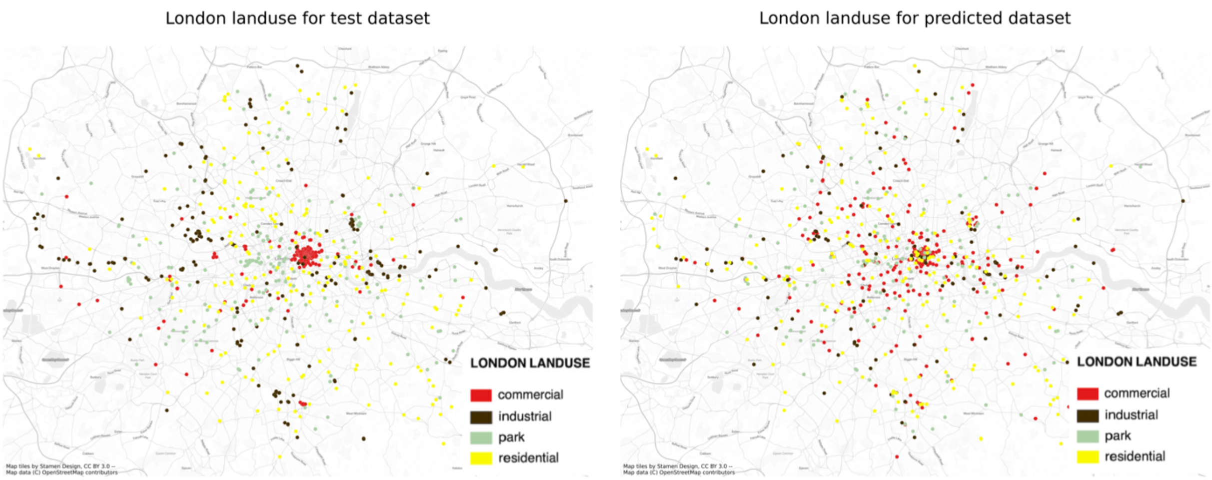

Figure 8: Spatial visualization of land use classification for actual and predicted values of test dataset (see original imagery in Appendix D; Source: Author's own)

Conclusion

In conclusion, the research has proved the ability of street view imagery as a basis for land use classification. During the process, various CNN models have been tuned and compared, in order to achieve better performance. Among them, models with ‘relu’ activation function and more convolutional kernels seem to be more accurate. Considering the prediction ability, retail buildings are the most difficult ones to be identified, influencing classification for other categories and affecting the overall model fit, which requires further investigation on more accurate machine learning techniques. Besides, as explained above, the online human-generated dataset on geography website inevitably has representativeness bias. However, the optimization of related CNN models and visualization of the results still have laid the foundation for the combination of CNN models based on aerial imagery, satellite imagery and ground-level imagery to estimate land use. Hopefully, the complementary advantages between different models can probably increase land use prediction accuracy in the future.

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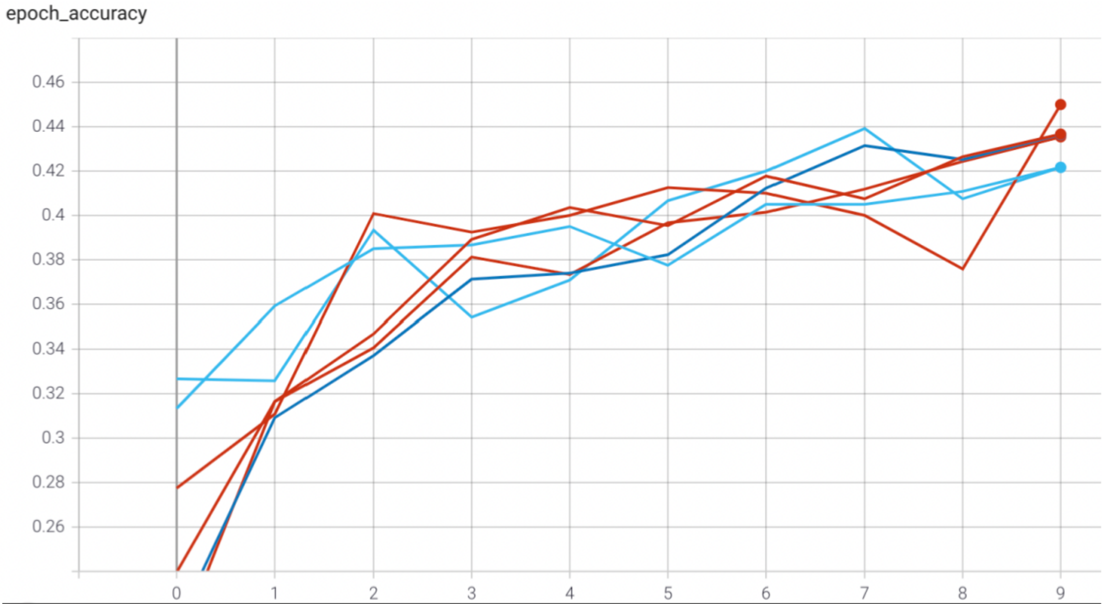
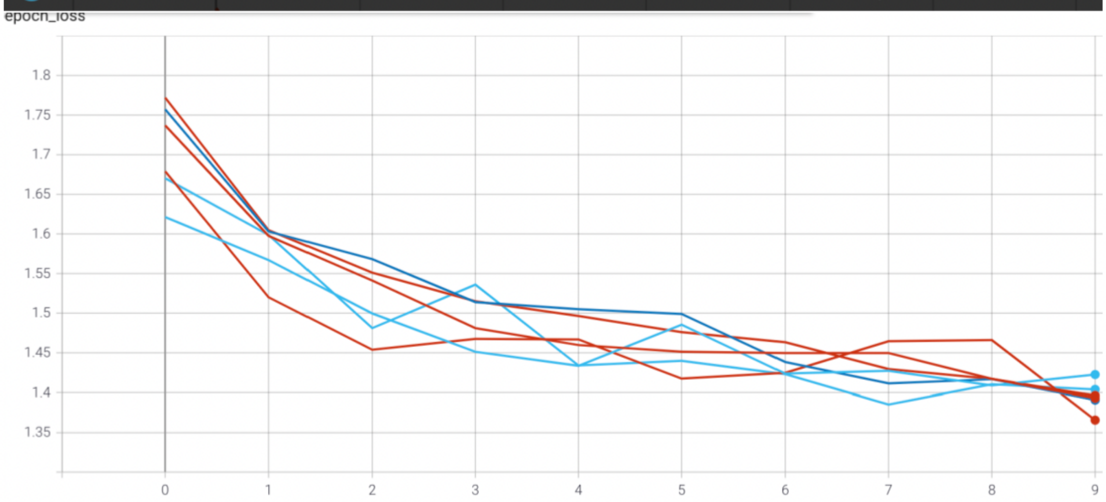
Appendices

Appendix A: Detailed trends for model accuracy and loss displayed on Tensorboard website for 6-class models



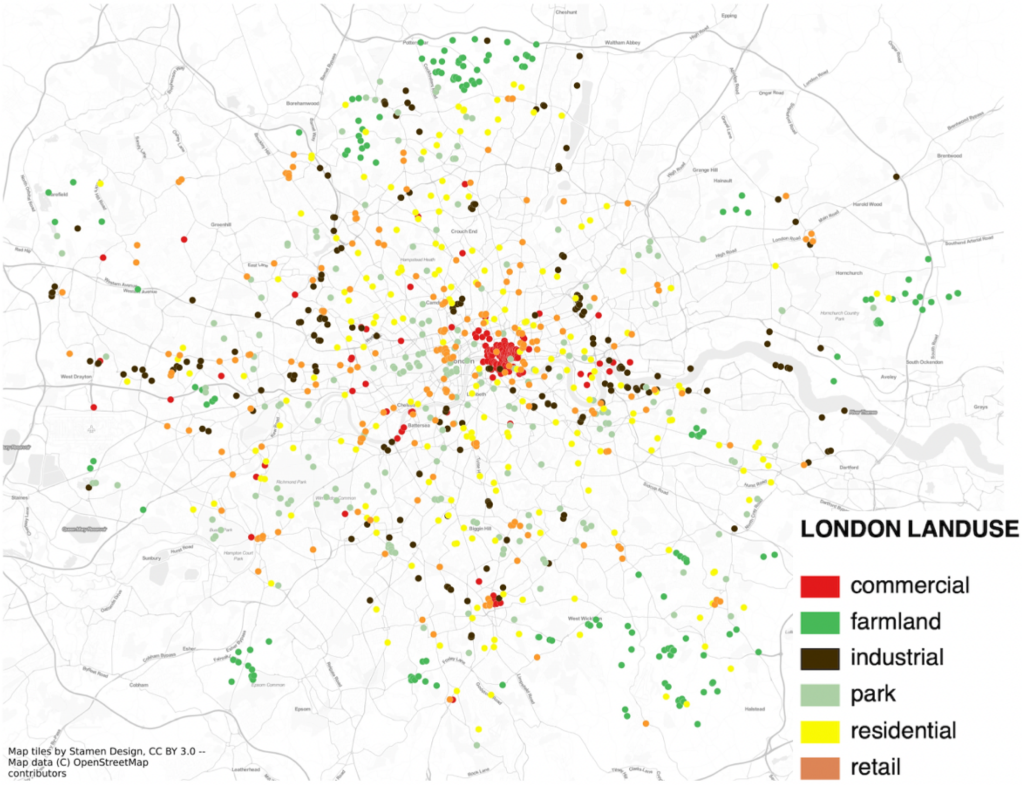
Name	Smoothed	Value	Step	Time	Relative
2-conv-64-nodes-relu-0.01-lr-64-batch/train	0.4367	0.4367	9	Sat May 1, 00:02:52	1m 49s
2-conv-64-nodes-relu-0.01-lr-64-batch/validation	0.4217	0.4217	9	Sat May 1, 00:02:52	1m 49s
3-conv-128-nodes-relu-0.01-lr-32-batch/train	0.4365	0.4365	9	Sat May 1, 01:40:50	4m 49s
3-conv-128-nodes-relu-0.01-lr-32-batch/validation	0.45	0.45	9	Sat May 1, 01:40:50	4m 49s
3-conv-64-nodes-relu-0.01-lr-32-batch/train	0.4354	0.4354	9	Sat May 1, 00:18:47	2m 11s
3-conv-64-nodes-relu-0.01-lr-32-batch/validation	0.4217	0.4217	9	Sat May 1, 00:18:47	2m 11s



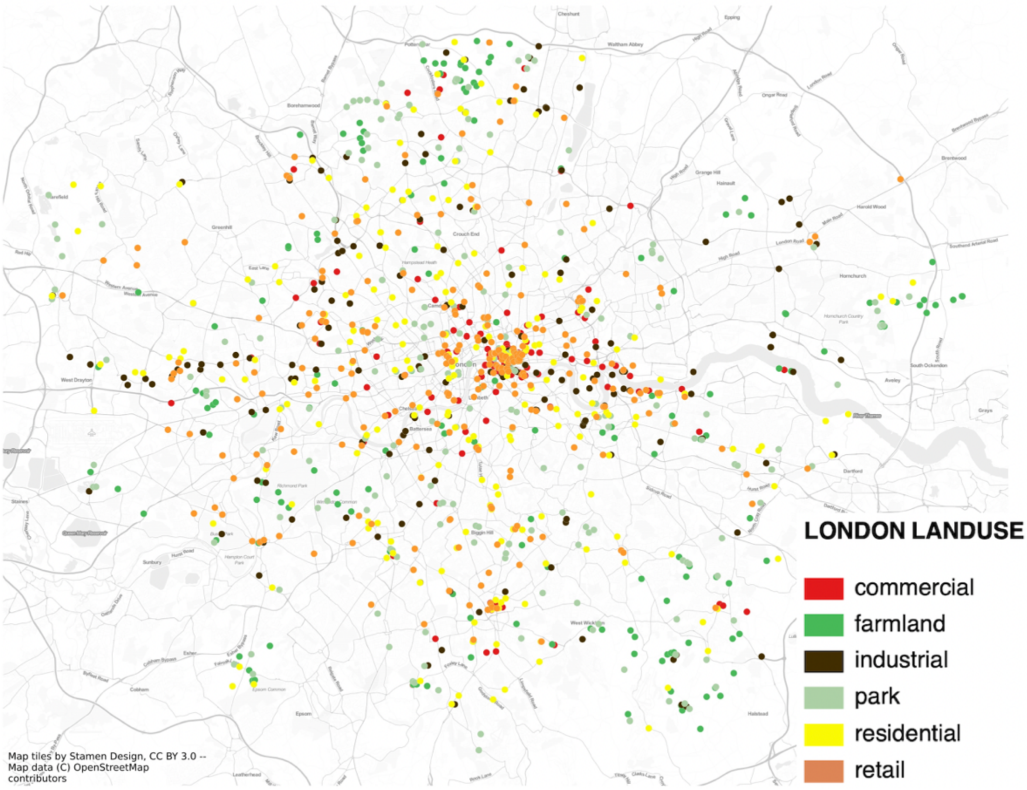
Name	Smoothed	Value	Step	Time	Relative
2-conv-64-nodes-relu-0.01-lr-64-batch/train	1.393	1.393	9	Sat May 1, 00:02:52	1m 49s
2-conv-64-nodes-relu-0.01-lr-64-batch/validation	1.423	1.423	9	Sat May 1, 00:02:52	1m 49s
3-conv-128-nodes-relu-0.01-lr-32-batch/train	1.391	1.391	9	Sat May 1, 01:40:50	4m 49s
3-conv-128-nodes-relu-0.01-lr-32-batch/validation	1.366	1.366	9	Sat May 1, 01:40:50	4m 49s
3-conv-64-nodes-relu-0.01-lr-32-batch/train	1.396	1.396	9	Sat May 1, 00:18:47	2m 11s
3-conv-64-nodes-relu-0.01-lr-32-batch/validation	1.404	1.404	9	Sat May 1, 00:18:47	2m 11s

Appendix B: Spatial visualization of land use classification for actual and predicted values of test dataset (6-class classification scheme)

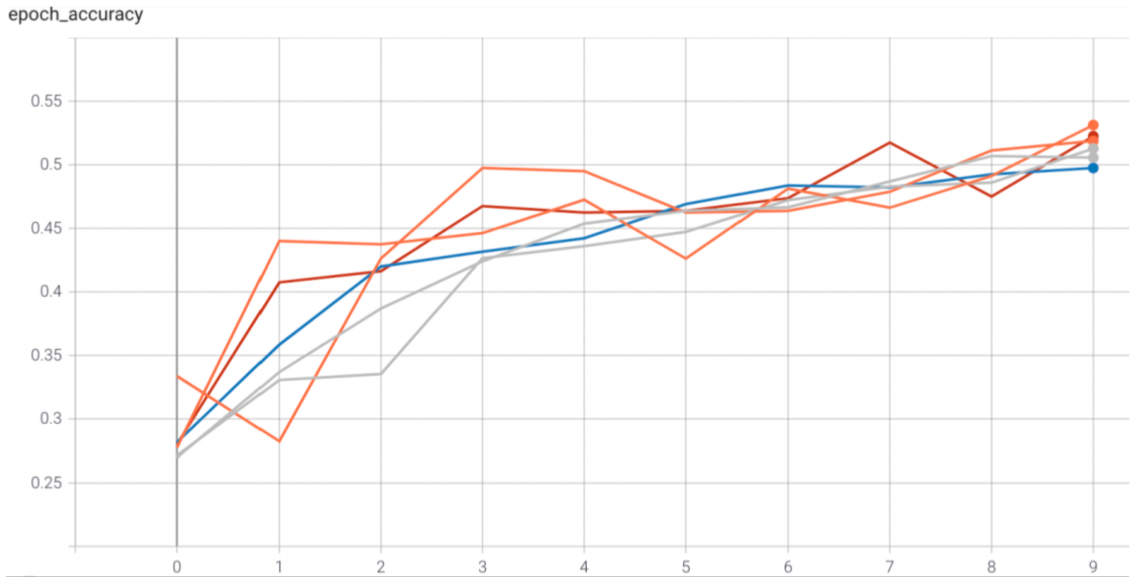
London landuse for test dataset



London landuse for predicted dataset



Appendix C: Detailed trends for model accuracy and loss displayed on Tensorboard website for 4-class models



Name	Smoothed	Value	Step	Time	Relative
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4-conv-128-nodes-32-batch/train	0.5128	0.5128	9	Sat May 1, 12:35:57	3m 35s
4-conv-128-nodes-32-batch/validation	0.5188	0.5188	9	Sat May 1, 12:35:57	3m 35s
4-conv-64-nodes-32-batch/train	0.4975	0.4975	9	Sat May 1, 12:15:35	1m 39s
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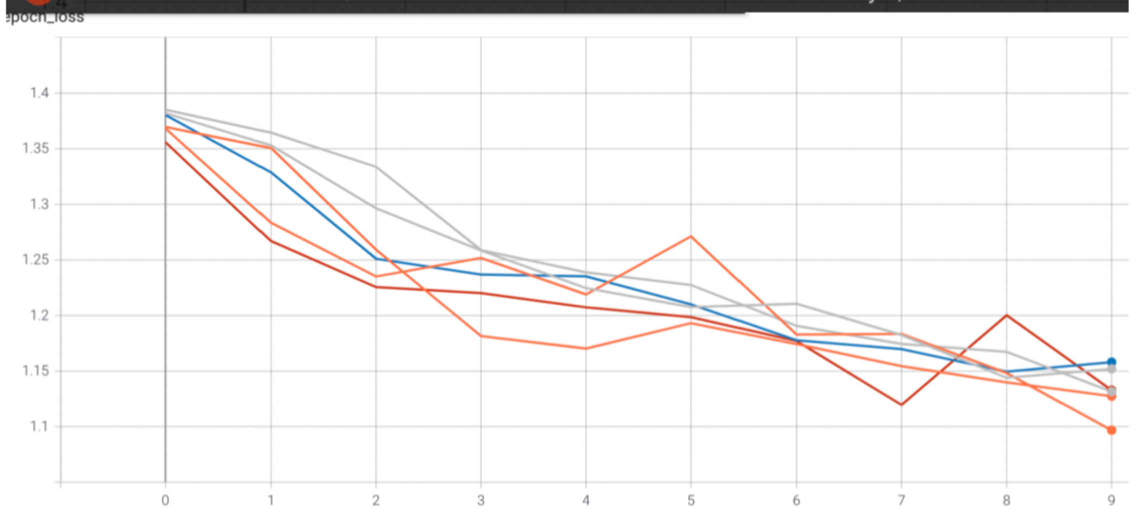

Name	Smoothed	Value	Step	Time	Relative
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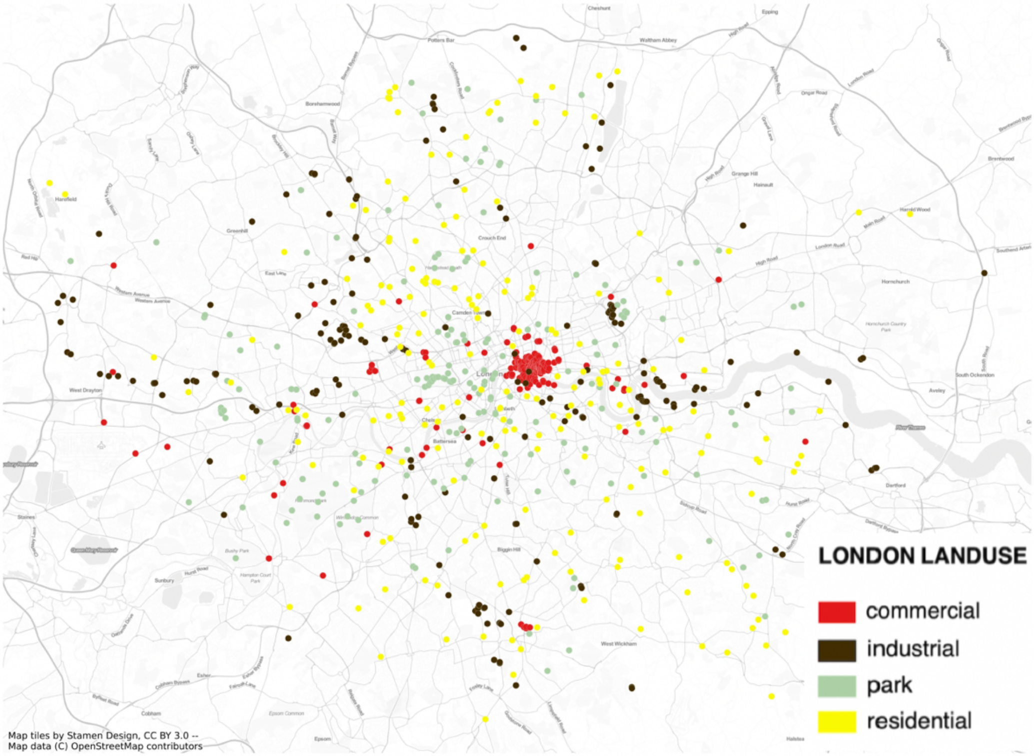
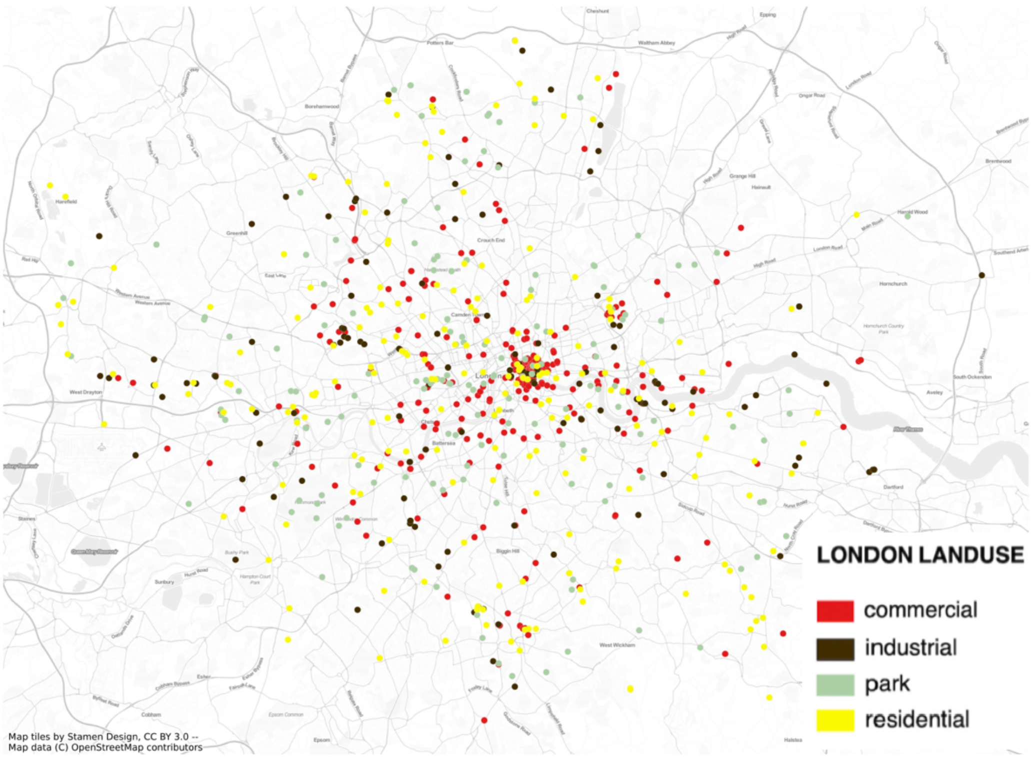
3-conv-64-nodes-64-batch/validation	1.097	1.097	9	Sat May 1, 12:13:44	1m 29s
4-conv-128-nodes-32-batch/train	1.132	1.132	9	Sat May 1, 12:35:57	3m 35s
4-conv-128-nodes-32-batch/validation	1.128	1.128	9	Sat May 1, 12:35:57	3m 35s
4-conv-64-nodes-32-batch/train	1.158	1.158	9	Sat May 1, 12:15:35	1m 39s
4-conv-64-nodes-32-batch/validation	1.133	1.133	9	Sat May 1, 12:15:35	1m 39s

Appendix D: Spatial visualization of land use classification for actual and predicted values of test dataset (4-class classification scheme)

London landuse for test dataset



London landuse for predicted dataset



Coursework Part Two

Web map for analysis on distribution of fast-food outlets

Online website: http://178.79.152.249/zczlah6/

Background

With the improvement of living standards, people are more and more concerned about health and nutrition. Obesity has become one of the major public health problems with over 30% adult obesity prevalence globally (Ng et al., 2014). Health survey for England has also indicated that the proportion of excess weight people, including the obese and overweight, has reach 46.3% in London (London Datastore, 2013). Besides, considering the age groups, obesity symptoms begin to become more common in working age (ibid.). Therefore, the investigation on obesity reasons for the working age group can probably contribution to the existing relevant research and be applied as foundation for government to perform necessary intervention.

Food type availability could largely influence the obesity disparities across metropolitan regions. According to Michimi & Wimberly (2015), adults living in cities with more supermarkets and catering services are likely to be healthy, while those living in cities with more convenient stores and fast-food restaurants are more likely to be obese. Therefore, the distribution of fast-food outlets in London might affect the obesity epidemic among workers. Besides, their diet and preference for fast-food (for saving time or not) also affect the obesity. Mentioned by Mihrete (2012), it has become a common phenomenon among office workers to consume fast food, which is associated with malnutrition and obesity, further causing low performance and absenteeism.

It is possible for government to curb the obesity by improving healthy food accessibility, abating obesogenic environment and implementing reasonable land use policies (Fraser et al., 2010 and Wu et al., 2021). However, the deployment of necessary urban features should be carefully assessed. Therefore, this report will examine the current distribution of fast-food outlets and integrate with employment condition in different-level administrative areas in London to discover potential relations, in order to benefit future workplace health intervention.

Data preparation

The research mainly applied three datasets from GEOFABRIK (2021) and London Datastore (2021). The point dataset for fast-food outlets in London is extracted from the whole point features dataset for England, accounting for 2686 objects. Besides, by merging shapefile and Comma-Separated Values file and calculating the employment rate, corresponding interactive choropleth maps could be visualized on the website.

Web map creation

Creating interactive web maps are the geographical data visualization approach for this research. In order to allow audience to acquire more information, there are three base maps (two simplified base maps for overall analysis, as shown in Figure 2; OpenStreetMap layer for local analysis, as shown in Figure 1) and separate three switchable main layers being provided. Among them, the layer for fast-food outlets distribution is displayed in point map format. Apart from that, the other two layers for the employment rate for London Middle Layer Super Output Area (MSOA) and Lower Layer Super Output Areas (LSOA) are all represented in the choropleth map format. Categories for the choropleth maps are based on quintile to clearly represent the relative rating (quintiles for the MSOA-level and LSOA-level are the same). At the first sight, the point map for fast-food outlets and choropleth map for London MSOA-level can be seen, as they are added directly to the map. By switching the layers, the relationships between fast-food outlets and employment condition at different administrative levels can be apparently discovered by changing overlay choices.

Details of the maps have also been emphasized. To increase the interactivity and convenience, the functionality of these interactive maps is carefully designed, including navigation function to pan and zoom, as well as the interactive pop-up windows with corresponding information of specific areas (see Figure 1 and Figure 3). Considering the colour scheme, strategies such as intuition, gradient and contrast are applied. For the choropleth maps, greenish colours are chosen, since green is the stereotypical colour for ‘good’ (Datawrapper, 2021). Besides, the gradient colour palette can make readers identify specific categories quickly (ibid.). In addition, fast-food outlets are plotted by ‘black’ points, able to be identified even tog on the choropleth map layers.

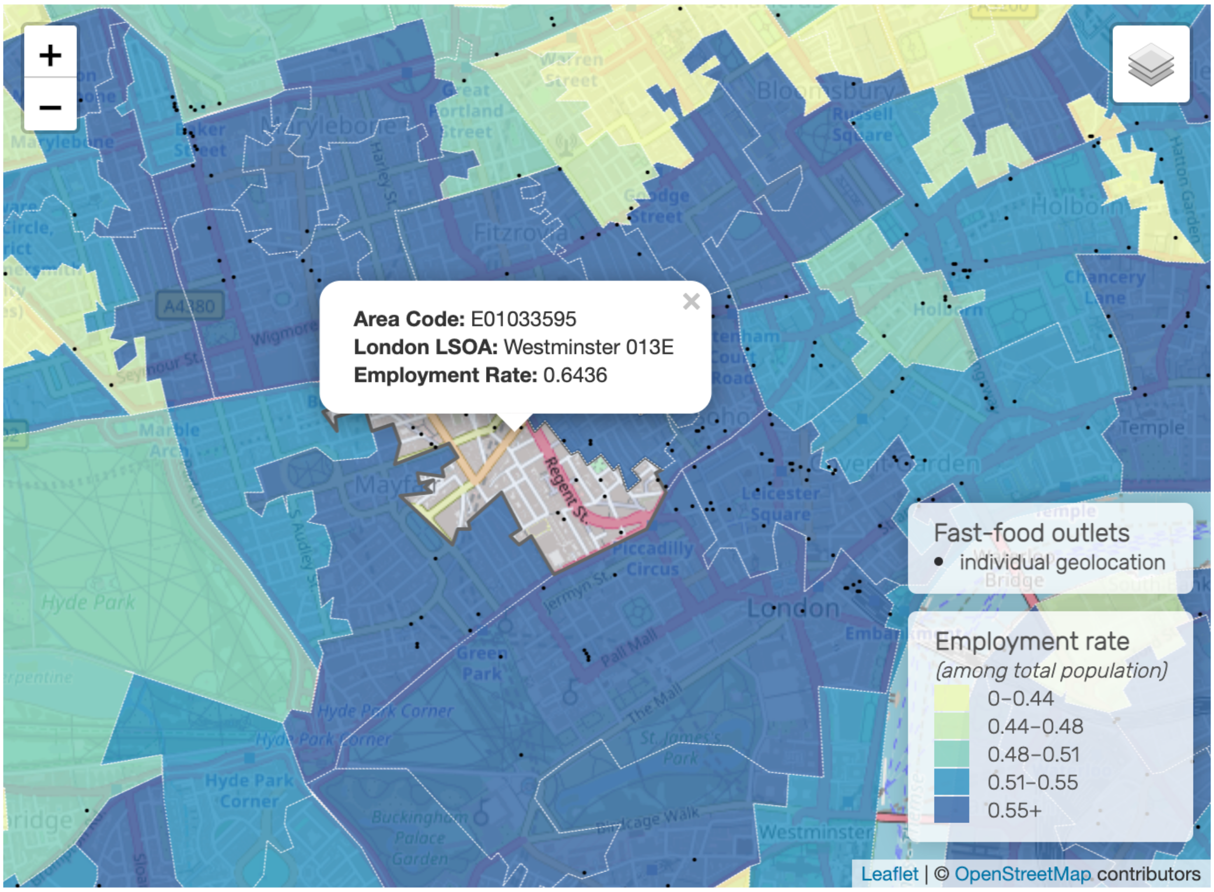


Figure 1: Integrate main layers with OpenStreetMap base map
(Source: Author’s own)

Discussion

To simply interpret the interactive maps, Figure 2 and Figure 3 have displayed two overlay choices, intending to provide some insights of this inequality. It is apparent that Southwest London and central London areas with higher fast-food density also have higher employment rate. Overall, this phenomenon reflects the location selection strategy of the fast-food restaurants to a certain extent and indicates the unhealthy environment exposure for workers. In that case, local planning regulations should be taken as a weapon to benefit them (Fraser et al., 2010).

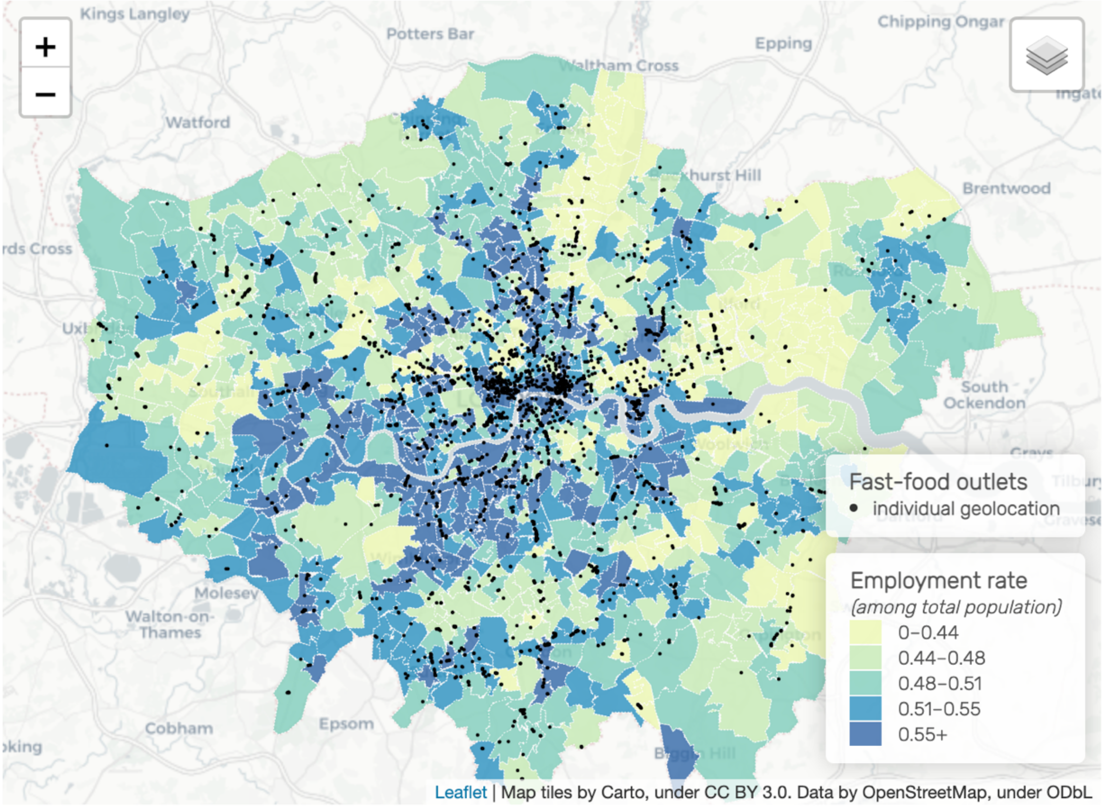


Figure 2: Overlay layers of fast-food outlets' locations and employment rates for London MSOAs (Source: Author's own)

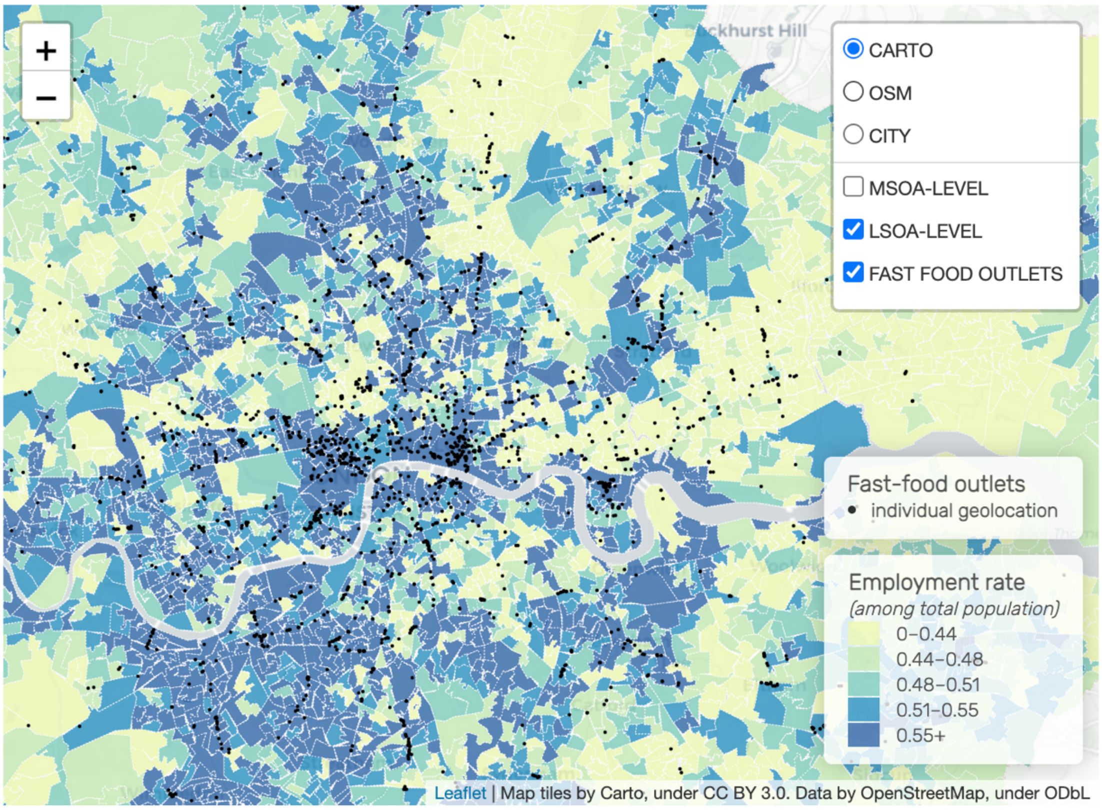


Figure 3: Overlay layers of fast-food outlets' locations and employment rates for London LSOAs (Source: Author's own)

Self-reflection

Considering the web maps' performance, they could nicely represent the relationship between fast-food outlets distribution and employment condition in London by overlaying different layers. Therefore, the interactive maps can be seen as a guidance for potential interventions and positive social change. However, considering the technological aspect, the interface design can be improved further. For example, allowing audience to select colour scheme for the interactive maps might be a better choice, although that scheme has been chosen based on previous related theories. Besides, although the legend for different layers do not need to be turned off considering the aim of the maps, there is still a potential inconsistency issue. In addition, it would be user-friendly if there is a search function for audience to choose their interested areas.

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