Visualising the relationship between EV charging stations and economic areas with web GIS.

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ABSTRACT

In 21st century, the rapid development of technologies enables crime scene investigators to execute their work more quickly and efficiently. This study aims to expand new method of collecting crime scene evidences using tablets and smartphones. Low cost LiDAR sensor integrated on Apple Ipad Pro 2020 was utilised to map the indoor crime scene. Two calibration types involved using measuring tapes to validate and compare the results generated from the tablet. Then, 3D model of indoor crime room simulation was acquired to be compare with the benchmark data from terrestrial laser scanner. After that, an accuracy assessment was made on physical evidences remarked with number tags. Among eight physical evidences, there were only three objects are recognizable. Lastly, a crime scenario and story development were made using information extracted from 3D model. In conclusion, from the values different obtained from analysis, Apple Ipad Pro showed an acceptable performance for indoor crime mapping.

Keywords: *Economic areas, Electric Vehicle Charging Stations, Geographic information System, Python, Web Map,*

1.0 INTRODUCTION

By 2040, more than 200 businesses and organisations want to reduce their carbon footprints and achieve net-zero emissions. In collaboration with Malaysian Green Technology and Climate Change Centre (MGTC), Ministry of Environment and Water (KASA) is proposing the Low Carbon Mobility Blueprint 2021–2030 that involves vehicle fuel economy and emission improvement, EVs and low emission vehicle adoption, alternative fuel adoption, and GHG emission and energy reduction via mode shifts (Veza et al. 2022). Numerous businesses are setting goals to cut greenhouse gas emissions and satisfy consumer demand as concern over climate change rises. EVs and PHEVs are currently offered in a variety of car classes. Over 50 EV and PHEV vehicles are now available, and more models are anticipated to be produced in the upcoming years.

Small and medium-sized businesses, like some schools, transit systems, delivery fleets, and local governments, profit from vehicle electrification just as much as major firms do. Along with the advancement of EVCS infrastructure and the liberalization of the electricity retail market, the profitable selling price strategy and economical energy management of smart EVCSs could enable EVCS owners to accelerate the investment in EVCS infrastructure, thereby achieving transportation electrification (Lee and Choi 2021) . These pollution reduction goals will spur additional development in the sales of electric vehicles across worldwide for many different vehicle types. This rush of activity gives EV experts

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the chance to provide advice on converting to EVs and developing the charging infrastructure required to make EVs an intelligent business decision. The manufacture of EVs receives the majority of attention, but the infrastructure for charging stations must also keep up with demand.

It is obvious that EV ownership affects the demand for charging infrastructure. More drivers want to be able to charge quickly while on the road, which is driving up demand in particular for fast chargers. Although many early adopters were content to charge at home, there has recently been an upsurge in demand for public charging as more people own electric cars and the global market for electric vehicles grows. EV acceptance depends on the availability of charging stations (CSs), charging time and cost, user facilities, and convenience (Islam, Shareef, and Mohamed n.d.). To keep up with the rise in EV ownership, charging infrastructure must be established. In particular, difficulties with some places' low charging station density and insufficient rapid charging alternatives must be resolved. Concerns have also been raised about how many EV chargers are concentrated in middle- and upper-class areas, which presents an extra challenge for low-income EV users. Convenient public charging infrastructure is essential for overcoming this challenge because those who live in apartment complexes could find it challenging to charge at home.

Regrettably, some places have a concentration of EV charging stations while others have little possibilities. Many governments across the globe are creating subsidies for installing EV chargers to help overcome infrastructure issues. The Malaysian government has been encouraging the production of EVs by their local brands' manufacturers in a future plan bid of breaking both regional and world markets (Adnan et al. 2017). Recently, Malaysia government announced to install 10,000 EV charging stations in Malaysia by 2025 with collaboration with private sector (Anon n.d.). This lead to the problem statement that can the installation of 10000 EV infrastructures go as expected by 2025 and are they placed in the right place or not.

This research proposed to focus on the relationship between electric vehicle charging stations and economic areas using interactive map with data-driven visualization to help monitoring the installation of stations. It has the objectives: to build a more complete database for EV charging stations POIs, using web map to indicate the relationship between EV charging stations and economic areas showing proportional connection and lastly using the visualization to analyse the where the next EV charging stations should be installed.

2.0 LITERATURE REVIEW

According to the research done by (Prah, Kmetec, and Knez 2022), the data collected are the geolocation of 308 public EVCSs in Slovenia with 637 charging ports for electric vehicles are taken count into the methodologies. The data were imported in ArcGIS to be output as different type of figures representing different analyses. To make sure the researches were in analytical ways and not just theories, the researchers used Pearson's correlation coefficient to see if there was a link between EVCSs and specific features of municipalities. They then used polynomial regression to dig deeper into the relationship between population size and EVCSs.

Secondly, researchers calculated the density properties of EVCSs in Slovenia. Then, they generated a continuous density surface based on a basic kernel density estimation. They also determined the geographic distribution of EVCSs by computing the mean centre, central feature, and standard deviational ellipse.

Based on another study by (Liu et al. 2018), different load characters in the EVCS allocation model will cause the site selection and capacity allocation of EVCS to be adjusted. The EVCS allocation model will also be influenced by the economy, transportation, land use, and population. Energy structure, electricity consumption during peak and off-peak hours, incentive policies, scheduling tactics, and other factors will affect

EVCS design from the energy storage standpoint. Additionally, from the standpoint of EVCS site selection, factors including ease of charging, charging habits, price mechanisms, the income level of EV users, and others will affect the distribution of EVCS. Therefore, a comprehensive system that incorporates the EVCS allocation impacting factors is necessary to investigate the essential elements.

Based on the statement by (Cromartie and Bucholtz 2008), The choice of a rural definition as economic areas should be based on the purpose of the activity. Alternating the definition of rural also varies the socioeconomic characteristics of designated areas. In addition to being defined as the area outside urban boundaries determined in different ways depending on the concept, rural includes some set of towns and villages below a chosen population threshold. In general, rural definitions can be based on administrative, landuse, or economic concepts, exhibiting considerable variation in socioeconomic characteristics and well-being of the measured population. The economic approach, which is employed in the majority of rural research applications, acknowledges that cities have an impact on markets for labour, trade, and media that go well beyond highly populated cores to cover larger "commuting areas."

3.0 METHODOLOGY

The research methodology of this study is about undergoing the acquisition of spatial data for all Electric Vehicle Charging Station and parameters that represent economic areas, then visualise both of them in various way to show the relationship between them for further analysis.

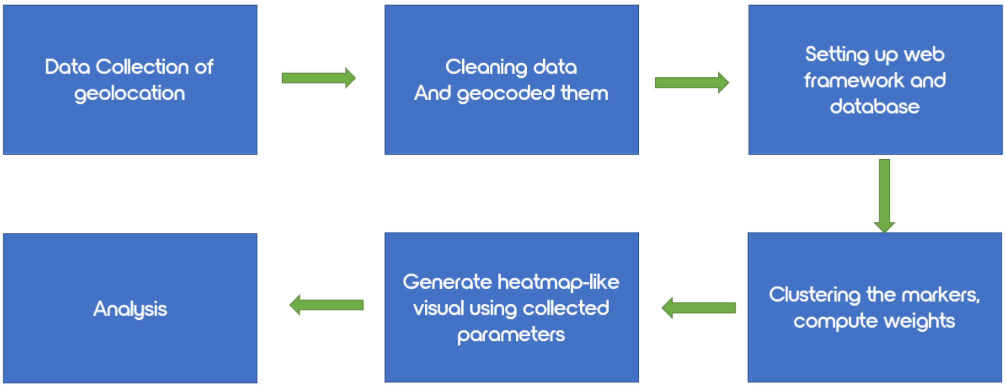


Figure 3.1: Methodology flowchart

3.1 Data Collection and processing

In the early stages, all geolocation data in form of long addresses of desired interests were acquired in order for the competence of this study. In this study, there are 3 factors to be treated as the parameters to represent economic areas which are fast food chain restaurants, government agencies and shopping malls. In this case, all McDonalds locations are chosen as the fast-food chain restaurants, while government agencies geolocation are sourced from the official website, and the shopping malls list is available in Wikipedia.

For the current existing electric vehicle charging stations in Malaysia, there are also some websites available for data collection in this study. The biggest oil and gas company in Malaysia, Petronas also offer a lot of electric vehicle charging stations in Malaysia. It is followed by the Royal Shell oil company and also the other electric vehicle charging stations under car brands and authorities, all of the long addresses data are stored in their official website.

In this study, the Selenium library that built for Python is used to web scraping any data or texts that show on the website, typically in HTML format. Selenium is known for its automation processes that helped save a lot of times in many aspects. In order to achieve this, chrome driver must be first installed in the Python virtual environment to ensure we can collect data with client side not server side. With the source codes available shown in Figure 3.2, it will automatically open the website, scroll the body of website HTML, obtain all the texts commanded by the functions then close the window again. All of the desired data are obtained in the same way using this method. All of the scraped data are then stored in CSV format that can be opened by Microsoft Excel.

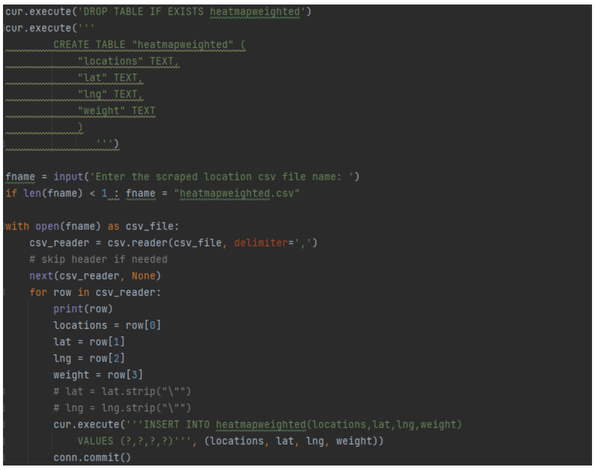
```
from selenium.webdriver.support.wait import WebDriverWait

chromedriver_autoinstaller.install()
# CHROME = Service('./chromedriver')
options = Options()
options.headless = False
# options.add_argument("--headless")

driver = webdriver.Chrome(options=options)
# driver = webdriver.Chrome(service=CHROME, options=options)
# driver = webdriver.Chrome(executable_path=CHROME, options=options)

# ask the driver to navigate to this url
driver.get('https://www.shell.com.my/motorists/shell-recharge/shell-recharge-hpc.html#hpc-locations')
# driver.get('https://www.google.com')


try:
    myElem = WebDriverWait(driver, 10).until(EC.presence_of_element_located((By.ID, 'IdOfMyElement')))
    print ("Page is ready!")
except TimeoutException:
    print ("Loading may not be completed!")
```

Figure 3.2: Example of source code for web scrape goals.

Once the long addresses are collected, we typically performed cleaning up and filtering process either inside Python environment or outside such as open it alone with Microsoft Excel. After all the unwanted data thrown away, the long addresses are all geocoded into data with latitude and longitude using the trial API from Google Geocode API. The processes took a few minutes long.

Figure 3.2: Google Geocoding API in Python

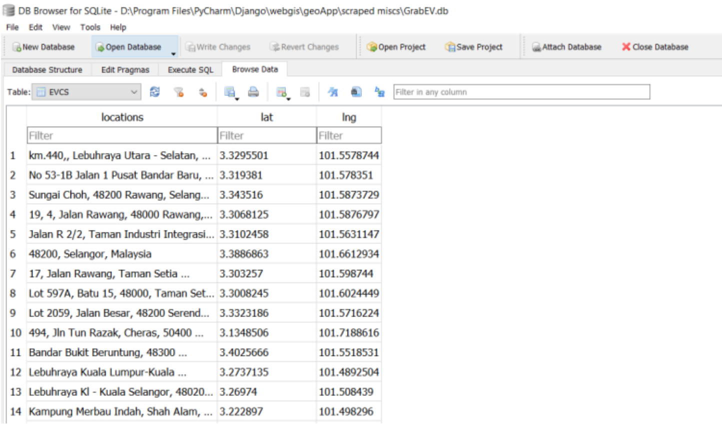
A database is created using the SQLite3 library built in default. As we can see in Figure 3.3, classic SQL commands are performed to create relational database that can store data in rows and columns. From the previous results generated and geocoded by Geocode API, they were directly stored into database since the Python environment is connected to the database using SQLite3 library.



```python
cur.execute('DROP TABLE IF EXISTS heatmapweighted')
cur.execute('''
        CREATE TABLE "heatmapweighted" (
            "locations" TEXT,
            "lat" TEXT,
            "lng" TEXT,
            "weight" TEXT
            )
               ''')

fname = input('Enter the scraped location csv file name: ')
if len(fname) < 1 : fname = "heatmapweighted.csv"

with open(fname) as csv_file:
    csv_reader = csv.reader(csv_file, delimiter=',')
    # skip header if needed
    next(csv_reader, None)
    for row in csv_reader:
        print(row)
        locations = row[0]
        lat = row[1]
        lng = row[2]
        weight = row[3]
        # lat = lat.strip("\"")
        # lng = lng.strip("\"")
        cur.execute('''INSERT INTO heatmapweighted(locations,lat,lng,weight)
            VALUES (?,?,?,?)''', (locations, lat, lng, weight))
        conn.commit()
```

Figure 3.4: Example of source code for web scrape goals.

When everything is imported into the database, *.db file, we can navigate to the database file using any open source software that compatible with it. From Figure 3.5, we can see that all the data was successfully stored inside the file based database which help to accomplish one of the objective of this study, to build a more complete database for electric vehicle charging stations.



	locations	lat	lng
	Filter	Filter	Filter
1	km.440,, Lebuhraya Utara - Selatan, ...	3.3295501	101.5578744
2	No 53-1B Jalan 1 Pusat Bandar Baru, ...	3.319381	101.578351
3	Sungai Choh, 48200 Rawang, Selang...	3.343516	101.5873729
4	19, 4, Jalan Rawang, 48000 Rawang,...	3.3068125	101.5876797
5	Jalan R 2/2, Taman Industri Integrasi...	3.3102458	101.5631147
6	48200, Selangor, Malaysia	3.3886863	101.6612934
7	17, Jalan Rawang, Taman Setia ...	3.303257	101.598744
8	Lot 597A, Batu 15, 48000, Taman Set...	3.3008245	101.6024449
9	Lot 2059, Jalan Besar, 48200 Serend...	3.3323186	101.5716224
10	494, Jln Tun Razak, Cheras, 50400 ...	3.1348506	101.7188616
11	Bandar Bukit Beruntung, 48300 ...	3.4025666	101.5518531
12	Lebuhraya Kuala Lumpur-Kuala ...	3.2737135	101.4892504
13	Lebuhraya Kl - Kuala Selangor, 48020...	3.26974	101.508439
14	Kampung Merbau Indah, Shah Alam, ...	3.222897	101.498296

Figure 3.5: Database for EVCS and misc.

3.2 Web map architecture

Typically, to produce, serve, and use a web map, numerous separate physical machines may be required. These are sometimes shown in diagrams as distinct architectural tiers or levels. A web map might occasionally be created just for internal usage and never appear on the public internet. In this case, the desktop workstation computers may also house client applications. A file server or database that stores all of the GIS data. This machine may have regular backup processes and redundant storage systems to guard against data loss.
This tier would also include a database that could have chosen to use, such as PostgreSQL or MySQL. In this study however, file-based database SQLite3 is used because of the limitation by free online server. A server for geospatial web services with the software and processing power needed to create maps, react to feature-related inquiries, and carry out GIS analysis tasks. Lastly, a web server that serves as the network's online entry point for institutes or company. A proxy server is another name for this. User may also put web application code (such HTML and JavaScript files) there for the web maps as portal to serve users.

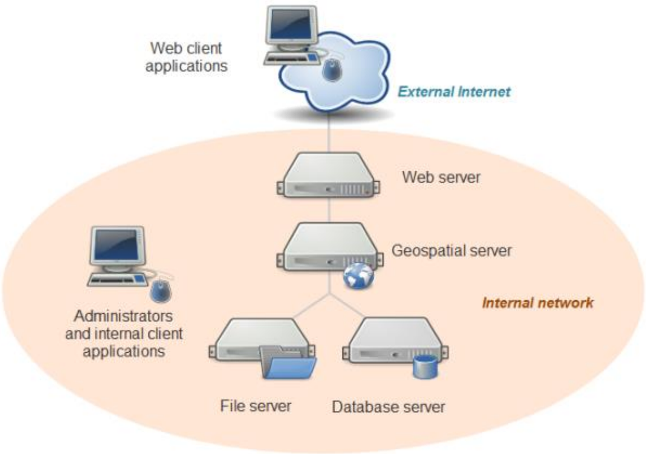


Figure 3.6: Web map architecture sample diagram

In this study, a high-level Python web framework called Django was used to promotes quick development and streamlined, practical design. It was created by seasoned programmers and handles a lot of the hassle associated with web development, freeing users up to concentrate on building their app without having to invent the wheel. It is open source and free. Almost every form of website can be built using Django, from wikis and content management systems to social networks and news websites. It can send material in practically any format and integrate with any client-side framework (including HTML, RSS feeds, JSON, XML, etc).

Python, which works across multiple platforms, in this study is also used to create Django this time. This means that users can run this application on many versions of Linux, Windows, and macOS and that are not restricted to a single server platform. Django is very extensively supported by a wide range of web hosts, who frequently offer specialised infrastructure and documentation for hosting Django sites.

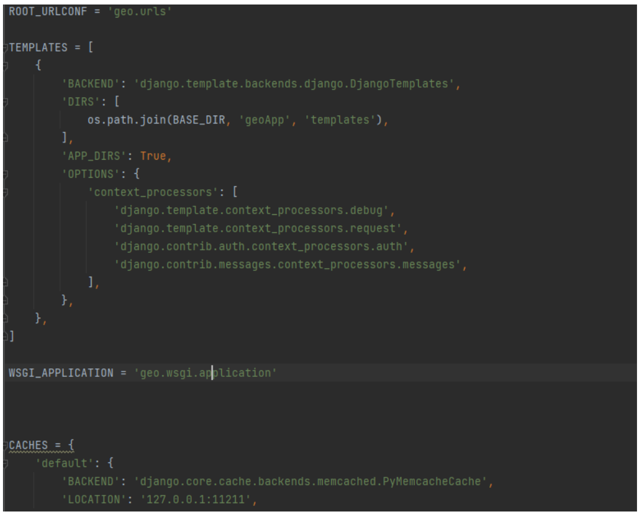

```
ROOT_URLCONF = 'geo.urls'

TEMPLATES = [
    {
        'BACKEND': 'django.template.backends.django.DjangoTemplates',
        'DIRS': [
            os.path.join(BASE_DIR, 'geoApp', 'templates'),
        ],
        'APP_DIRS': True,
        'OPTIONS': {
            'context_processors': [
                'django.template.context_processors.debug',
                'django.template.context_processors.request',
                'django.contrib.auth.context_processors.auth',
                'django.contrib.messages.context_processors.messages',
            ],
        },
    },
]

WSGI_APPLICATION = 'geo.wsgi.application'


CACHES = {
    'default': {
        'BACKEND': 'django.core.cache.backends.memcached.PyMemcacheCache',
        'LOCATION': '127.0.0.1:11211',
```

Figure 3.7: Django sources code automatically generated in Python for easy deployment.

PythonAnywhere is an online integrated development environment and web hosting service based on the Python programming language. It provides in-browser access to server-based Python and Bash command-line interfaces, along with a code editor with syntax highlighting. In this study, the whole Django framework created is directly uploaded on PythonAnywhere website so that this whole project can be deployed and go online worldwide.

3.3 Placing Point of Interests for EVCSs and parameters

In this study, Leaflet maps was made using the potent Python package Folium. Folium automatically generates a map in a separate HTML file. This package is quite helpful for dashboard development because Folium findings are interactive. Inline Jupyter maps can also be produced in Folium. Folium builds on the data manipulation and mapping prowess of the Python ecosystem and the Leaflet.js package. Folium enables Python data manipulation before displaying the results in a Leaflet map.

Folium gives the option of using default tilesets (i.e., map styles) or a specific tileset URL to create a basic map of a given width and height. In this study, OpenStreetMap as base tile is used to avoid copyright issue and also because of its open source characteristics.

To import all the geolocation data as markers and visualise them at once, folium marker functions was used to create simple stock Leaflet markers on the map, with optional popup text or Vincent visualization. The datasets were firstly fetch from the database previously created, then using Python to turn them back into readable data and lastly with the help of folium as shown in Figure 3.8 to visualise them.

```
for i, row in df[["locations","lat", "lng"]].dropna().iterrows():
    icon = "https://encrypted-tbn0.gstatic.com/images?q=tbn:ANd9GcRsMGaR6_5NuBpKQ6FlrxLUUHf-nTrm8UK42w&usqp=CAU"
    icon = folium.CustomIcon(icon, icon_size=(20, 20))
    position = (row["lat"], row["lng"])
    location = row["locations"]
    # iframe = folium.IFrame(
    #     'Address:' + str(location) + '<br>' + 'Name: ' + 'McDonald' + '<br>' + 'Latitude: ' + str(
    #         row["lat"]) + '<br>' + 'Longitude: ' + str(row["lng"]))
    # popup = folium.Popup(iframe, min_width=300, max_width=300)
    folium.Marker(location=(position), popup = f'Address: <br>{str(location)}<br><br>Name: McDonald<br>Latitude & Longitude:'
                                                f'<input type="text" value="{row["lat"]}, {row["lng"]}" id="myInput"><button onclick="myFunction()">Copy location</button><br>',
                                              min_width=300, max_width=300, icon=icon ).add_to(markerClusterMcd)
```

Figure 3.8: Source code of implementing Folium library to visualise markers

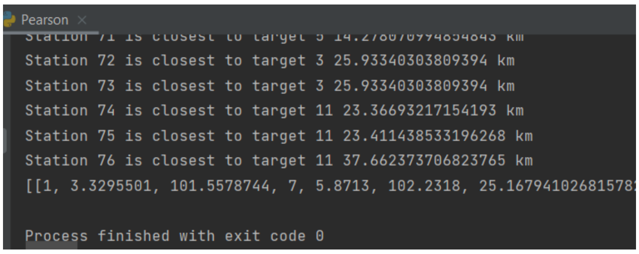
3.4 Calculating weights and generating heatmap

The same methodology is also applied to the heatmap that representing economic areas in this study. In contrast with markers, heatmap was produced using another function built in the Folium library called Heatmap. This heatmap function uses hot and cold analogy. Each point adds to a heatmap adds a certain heat. When they are more points clustered in an area, more heat will generate in that particular area. The weight given to each point is the amount of heat. Even if points have a low weight, they still add heat. A heatmap doesn't make averages, but instead sums the values of overlapping points.

```
dfh = df8.iloc[:, 1:4]
dfh = dfh.astype(float)
print(dfh)

folium.plugins.HeatMap(dfh, name="Economic areas", show=True, blur=25, max_zoom=17, gradient={0.1: 'blue', 0.3: 'lime', 0.5: 'yellow', 0.7: 'orange', 1: 'red'}).add_to(m)
```

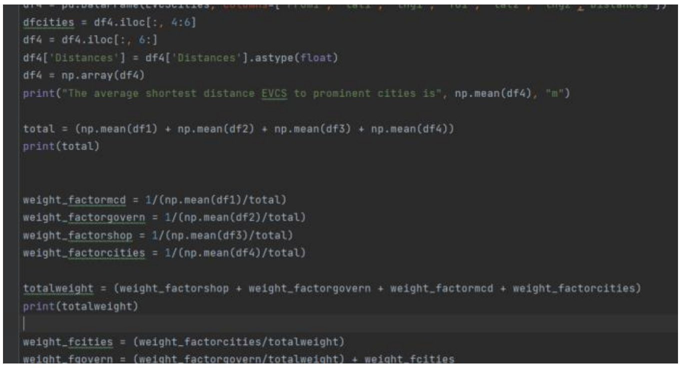
Figure 3.9: Creating heatmap colour ramp with folium heatmap function.

The heatmap function support input of weight factors. In this study, three parameters are used to compute average shortest distance. Distance is used to define the relationship between EVCSs and economic areas, all these parameters are given different weight factors by calculating the shortest distance (geodesy distance) from each EVCS to each parameter respectively. After getting shortest distance from 1 EVCS to 1 mcd, 1 cities etc by looping many rows as shown in Figure 3.10, we obtained 3 arrays of data, for each array of data we computed average shortest distance to get mean. In post calculation, all average shortest distances from 3 arrays are summed up, using each mean to divide the all average mean, and use 1 to divide the resulting values. In this case, we can get the outputs of the further the distance from parameter to EVCSs, the lower the weight value are.



```
Station 72 is closest to target 3 25.93340303809394 km
Station 73 is closest to target 3 25.93340303809394 km
Station 74 is closest to target 11 23.36693217154193 km
Station 75 is closest to target 11 23.411438533196268 km
Station 76 is closest to target 11 37.662373706823765 km
[[1, 3.3295501, 101.5578744, 7, 5.8713, 102.2318, 25.16794102681578

Process finished with exit code 0
```

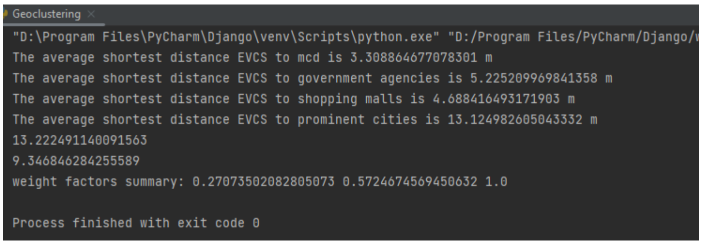
Figure 3.10: Looping the 76 EVCSs to get nearest target for McDonalds, shopping malls and government agencies.



```
dfcities = df4.iloc[:, 4:6]
df4 = df4.iloc[:, 6:]
df4['Distances'] = df4['Distances'].astype(float)
df4 = np.array(df4)
print("The average shortest distance EVCS to prominent cities is", np.mean(df4), "m")

total = (np.mean(df1) + np.mean(df2) + np.mean(df3) + np.mean(df4))
print(total)


weight_factormcd = 1/(np.mean(df1)/total)
weight_factorgovern = 1/(np.mean(df2)/total)
weight_factorshop = 1/(np.mean(df3)/total)
weight_factorcities = 1/(np.mean(df4)/total)

totalweight = (weight_factorshop + weight_factorgovern + weight_factormcd + weight_factorcities)
print(totalweight)

weight_fcities = (weight_factorcities/totalweight)
```

Figure 3.11: Calculation of weight factors distributed to weight factors done in Python.

After the calculation as shown in Figure 3.11 is finished, we obtained weight factor for all parameters displayed in Figure 3.12, which is 0.27 for government agencies, 0.57 for shopping malls and 1.0 for McDonalds restaurant. It is because the average shortest distance for EVCS to government agencies has the largest distance of 5.225km, followed by EVCS to shopping mall has 4.688km, and lastly EVCS to McDonalds has the shortest average distance of 3,309km. In the final stage of this phase, all parameters geolocations are mixed in one table, with weight columns added, then only generate the heatmap using the arranged data. In this case, the heatmap produced consists of weight that computed using shortest distance between EVCSs and parameters. Now the heatmap can represent economic areas in more analytical way, not just assumptions using density based only.



```
Geoclustering
"D:\Program Files\PyCharm\Django\venv\Scripts\python.exe" "D:/Program Files/PyCharm/Django/
The average shortest distance EVCS to mcd is 3.308864677078301 m
The average shortest distance EVCS to government agencies is 5.225209969841358 m
The average shortest distance EVCS to shopping malls is 4.688416493171903 m
The average shortest distance EVCS to prominent cities is 13.124982605043332 m
13.222491140091563
9.346846284255589
weight factors summary: 0.27073502082805073 0.5724674569450632 1.0

Process finished with exit code 0
```

Figure 3.12: Final weight values obtained for heatmap uses.

4.0 RESULT AND ANALYSIS

This chapter will discuss on the results after successfully deploying the web map on live server, including the visualisation results and analysis on it.

4.1 Deployed web map interface

After the whole web framework was successfully deployed on online server, it is now accessible on http://tey.pythonanywhere.com/. From the home page of this website, user can already notice the final visualisation loaded on web page as shown in Figure 4.1. This web map allow user to perform simple interaction such as zoom in and out and control the layers. In addition, user can scroll down to the bottom of page (Figure 4.2) to navigate the databases that applied in the web map.

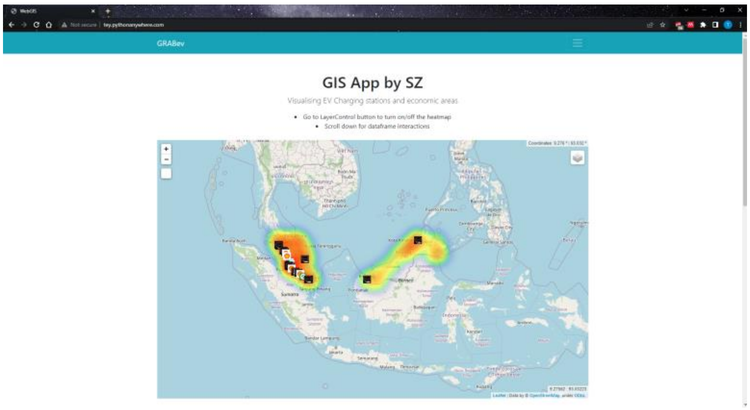


Figure 4.1: The web map interface showing POIs and heatmap.

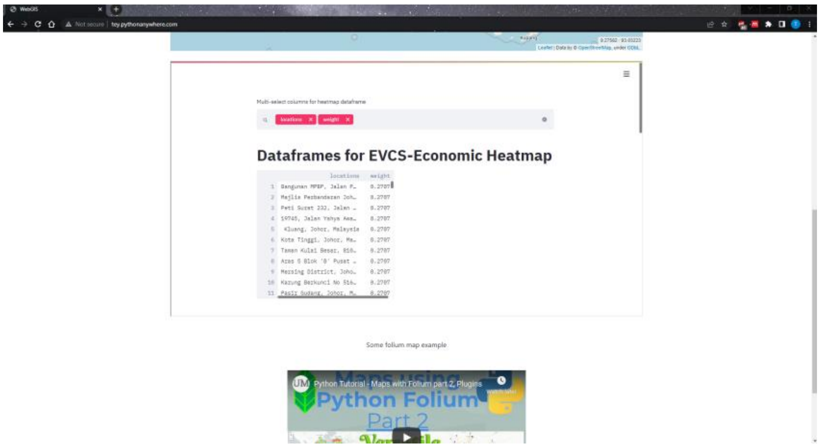


Figure 4.2: Additional functions in the bottom powered by Streamlit.

4.2 Analysis made on the visualisation

Firstly, from the perspective of whole Malaysia in Figure 4.3, we can observe that the East Malaysia which is the Borneo part of Malaysia generally showed a lesser economic activity when compared to West Malaysia, Peninsular Malaysia, showing a blue to lime colour. In contrast, the west coast of Peninsular Malaysia showed a red intensity and high density area while the east coast of Peninsular Malaysia showed a lesser intensity but still better than whole Borneo Malaysia.

For the electric vehicle charging stations POIs, Borneo Malaysia has only around 3 collected electric vehicle charging station geolocation which only located in Kuching, Sarawak and Kota Kinabalu, Sabah. While for west Malaysia, we can observe a pattern and a trend that the EVCSs formed a line following the heatmap most dense and highest intensity area along the west coast of Peninsular Malaysia. Do noted that in the beginning of this study, during the data collection phase, these EVCSs POI and the heatmap parameters data are independent to each other yet. So, from the final results we can made an assumption that the there is a relationship between the EVCSs and economic areas in this web map. The more crowded the economic areas, the higher number of EVCSs can be found in that area.

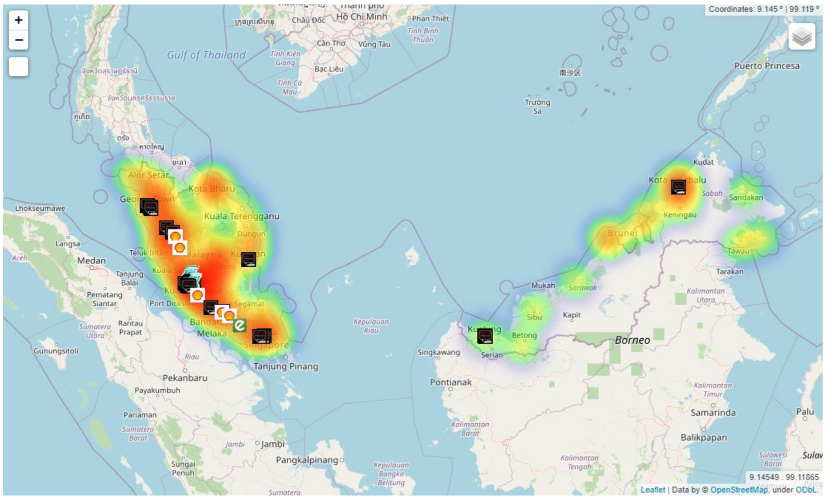


Figure 4.3: Relationship between EVCSs and economic areas for whole Malaysia.

To have a deeper analysis for this visualisation, this study proceeds to narrow down the size of area. Kuala Lumpur as the biggest city and capital city of Malaysia, and second biggest city of Malaysia, Johor Bahru in Johor were chosen to make this analyses.

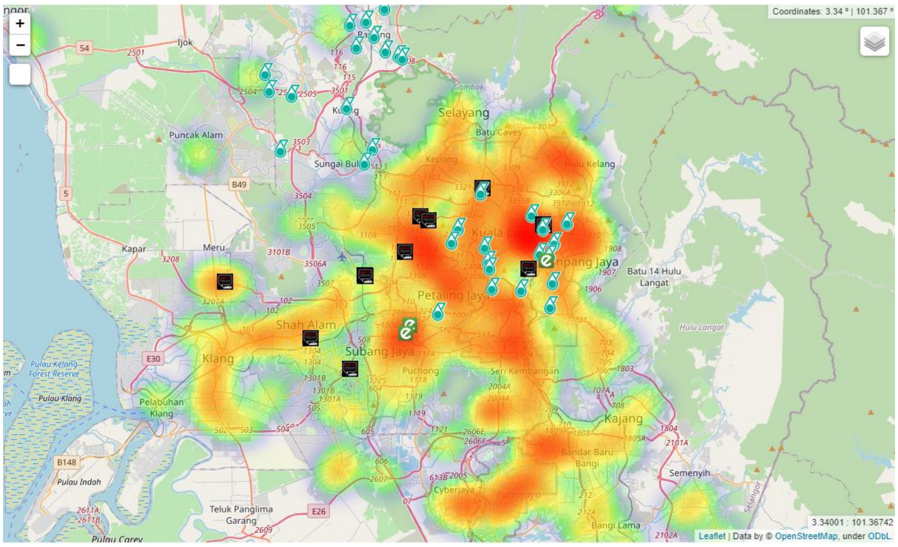


Figure 4.3: Closer look around the Kuala Lumpur city, capital city of Malaysia.

To have a deeper analysis for this visualisation, this study proceeds to narrow down the size of area. Kuala Lumpur as the biggest city and capital city of Malaysia, and second biggest city of Malaysia, Johor Bahru in Johor were chosen to make this analyses.

5.0 CONCLUSION AND RECOMMENDATIONS

The conclusion of this study is made based on the results and analysis carried throughout the study. The conclusion made are also based on the objectives of this study which are to expand the method of scene documentation for development of crime scene analysis, to study the effectiveness and performances of using Apple Ipad Pro 2020 in crime scene analysis and to do evaluation about the accuracy on measurements of evidences on the crime scene by comparing between Ipad output and terrestrial laser scanner output as benchmark.

Firstly, the study began with the literature review on existing among of researches that have been done to obtain more knowledges about this study. From the researches made in the recent decades, it can be found that the best method to produce 3D point cloud model from indoor crime scene is terrestrial laser scanner with LiDAR method. However, terrestrial laser scanner required trained operators, need more budgets for costing, as well as consume a lot of times. Hence, the objectives and problem statement were identified in this study.

To put a close in this study, Apple Ipad Pro have been successfully used in this study to investigate its effectiveness. Throughout this study, it is proven that Apple Ipad Pro can be used as a method to map indoor crime mapping with low cost LiDAR sensor integrated on it. Although the consumer grade handheld laser scanner is not suitable to be used for very large area and also the opposite of it, very small objects, it did give satisfied result more than expected. This study showed that Ipad Pro not only saves a lot of times for crime scene investigators, but also require relatively lesser technical knowledges at the same time obtain acceptable results. The rise of low cost handheld laser scanner can make a new milestone for CSI agents to acquire 3D model of the crime scene instantly, while ensuring access to the earliest evidences.

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