Faculty of Engineering and Information Technology

Technical Report

Machine Learning Modeling and Application in Covid-19 Cases, Vaccination Rollout and Transport Restrictions

32933 Research Project – Spring 2021

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Introduction

Since the first outbreak of the novel coronavirus in Wuhan in January 2020, the world has suffered a staggering loss of more than 5 million lives as the highly infectious virus is rapidly spreading globally. Yet 18 months into the pandemic, many countries in the world including Australia are still struggling to keep the positive cases down. Measures and actions taken by the authorities are lagging behind the emergence of the new corona variations. As NSW is going out of the three month of lockdown, mass vaccination seems to be the only ticket for us to go back to normal.

Arguably speaking, vaccine priorities and logistics will be the key and upfront issue for the authorities to address in combating the virus which has evolved into the highly contagious Delta strain. As we are racing against time right now, successful management and organisation on vaccine distribution and logistics will be essential in having people protected especially for those who are the most exposed in this pandemic, and also essential in herding immunity as soon as possible. In this dire situation where the number of cases is still on the increase in some states and lives are lost every day, the capabilities of Artificial Intelligence can be and should be leveraged to provide the authorities with meaningful data that helps order and secure adequate amount of the vaccines from the manufactures by analysing the live data and predicting the numbers in the near future. Additionally, with the restrictions affecting our daily activities including travel and transport selection, the correlation between the spread rate of the virus and the shared transport (public transport and carpooling) is worthwhile to be examined and evaluated. In this research project, a linear regression machine learning model has been developed, using relevant python libraries, in a bid to provide some insights for the authorities when it comes to invoking lockdowns which will significantly affect the traffic volumes and flows. In this project, data is visualised in the form a prototype web application which is rendered by various interactive UIs and makes it easier for the users to analyse and unitise the data.

The aim of this research project is to develop a working prototype that integrates machine learning models to a web application which is capable of providing some meaningful data for the decision makers in the process of vaccine ordering and distribution. In addition, it will also provide services such as predicting the spread rate and case numbers based on the proportion of shared transport mode including public transport, paid transport services such as Uber Drive, and carpooling. Machine learning in traffic restrictions / control and optimisation constitutes an integral part in building a digital smart city.

Objectives of my project include the following.

1. Explore and fulfil the potential capabilities of AI and machine learning through a web application (prototype). The web application would be able to read, analyse and visualise the date uploaded by a user.

2. Process data and develop regression models using python libraries. Integrate the machine models with the front-end UI.

3. Based on the machine learning models, produce the relevant predictive data from the interactive UI.

4. Make insightful findings based on the outcome produced by the prototype application.

Literature review

Purpose Of The Research Topic

While the world has been engulfed in the crisis of Covid-19 and governments from all over the world are scrambling to tackle the challenges to get our lives back to normal, it does also provide the opportunity for us to accelerate the transformation for smart or digital cities. Mobility-as-a-service, traffic flow optimization, the optimization of logistics and autonomous vehicles are some of the key services and applications that transform our cities into smart cities. In addition, the Internet of Things (IoT), Artificial Intelligence (AI), Blockchain and Big Data technology will serve as the core technologies that provide innovative solutions in the process of building smart cities (see studies in [1]-[3]-[4]-[5]-[17]-[18]).

Machine learning can be useful in tracking Covid-19 cases, predicting cases, and generating alerts to maintain social distance and for other possible control mechanisms [2]. However little has been studied in regards to the traffic restrictions / control under due to natural disasters or global pandemic which we are experiencing right now. Potentially, AI and machine learning offer the capabilities that can be integrated into tools and applications and fill in the gaps between what is currently in high demand and the services that are missing. This work represents a continuation of a previous published work around modelling the impact of COVID-19 on the public transport utilisation in the city of Sydney [6], as well as several years of artificial intelligence work that has been applied for modelling people's movement under several restrictions [7]-[8]-[9]-[10]-[11]-[12]-[13]-[14]-[15]-[16]. More advanced techniques are looking at integrating both artificial intelligence methods and simulation modelling together for improving people's movement under several restrictions [19]-[20]-[21]-[22]-[23]-[24]-[25]-[26]-[27].
Another research field that has been explored so far is also the inclusing of detailed modelling for example for malaria cases around the world or for buildign online modelling techniques that can help to understand spread of diseases and the relevant information with relation to these (see [39]-[40]-[41]-[42]-[43]).

Potential Solution And Research Direction

In current circumstances where the development of the Covid-19 crisis is highly volatile and information from different sources is overloading, the decision-making process has been more challenging for the governments and authorities than ever before. AI powered algorithms can be developed to provide autonomous decisions as well as future predictions about different mobility related services and entities [1].

Machine learning models are developed based on historical datasets. Common machine learning models include regression, classification, clustering and deep learning, all of which have been proven relevant and useful in various areas. In the space of Covid-19, machine learning has been applied in diagnosis and prognosis, patient outcome prediction, tracking and predicting cases, medication development, vaccine discovery, false news prediction [3].

Even though AI and machine learning offer some bright and promising capabilities, there are challenges which could hinder the possibilities for us to harness the capabilities of AI. This is the reason why an objective evaluation of AI in terms of its competitiveness and efficiency is required, which should cover disciplines such as engineering, computer science, management, science, or operations research [5]. Despite the challenges and limitations, in my research project I will strive to explore and provide the feasible solutions in regards to how AI / machine learning powered applications can solve the issues arising from the global pandemic. The key aspects that my project will address include vaccine distribution in each LGA in NSW, Covid-19 related decision making and traffic flow control / restrictions.

Systems Requirements

Hardware Requirements

- 1.8 GHz dual-core processor (or better)
- 2 GB of RAM (4 GB recommended)
- 1 GB of free disk space

Operating Systems

- Windows 10 (64-bit)
- Windows 8 (64-bit)
- Windows 7 (64-bit)
- Microsoft Windows Server 2019, since Development Environment 11.6.5
- Microsoft Windows Server 2016

Network Connection

- Minimum speed is 1mbps for downloading and uploading

End User Requirements

Web browser:

- Internet Explorer 11 (latest stable version)
- Edge (latest stable version)
- Firefox (latest stable version)
- Google Chrome (latest stable version)
- Safari (latest stable version)

Mobile:

- Default browser for iOS 7 or higher
- Default browser for Android 4.1 or higher
- Default browser for Windows Phone 8 or higher

System Architecture

Presentation Layer

- Sign-in page
- Home Page
- LGA Profile Page
- Machine Learning Analysis Page
- Admin Page
- Data Upload Page

Logic Layer (Functions)

- Home Page
    - Get data from LGA
- Get data from National_Vaccination_Rates
- LGA Profile Page
- Get the LAG data from LGA, LGA_Traffic_Mode_Profile
    - , Public Transport Movement
    - Calculate dynamic traffic mode proportions
    - Calculate Covid-19 spread rate
- Machine Learning Analysis Page
    - Get the Regression Model parameters from Regression
    - Calculate the predicted case numbers
    - Calculate the predicted vaccine numbers
    - Calculate the predicted Covid-19 spread rate
- Admin Page and data upload
    - Save and update data in LGA
    - Save and update data in National_Vaccination_Rates

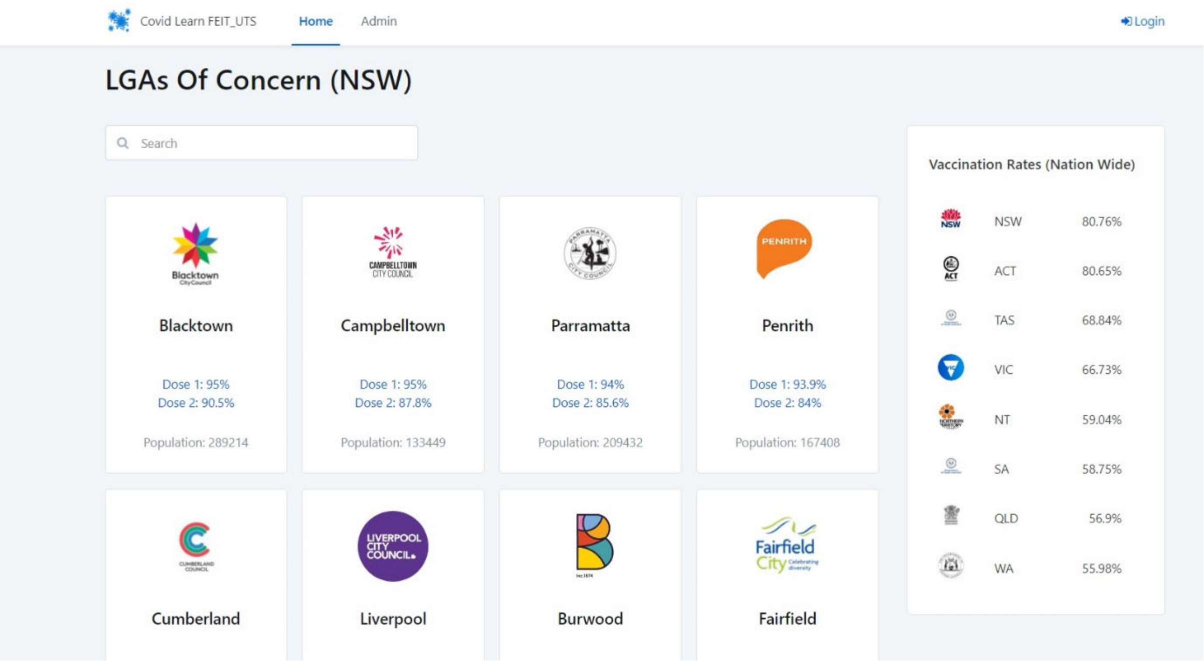
Persistence Layer (Data Entities)

- National_Vaccination_Rates
- LGA (general)
- LGA_Daily_Cases
- Public_Transport_Movement
- LGA_Traffic_Mode_Profile
- TomTom_Road_Traffic_Movements
- Regression_Model

Key Functionalities

Data Visualisation

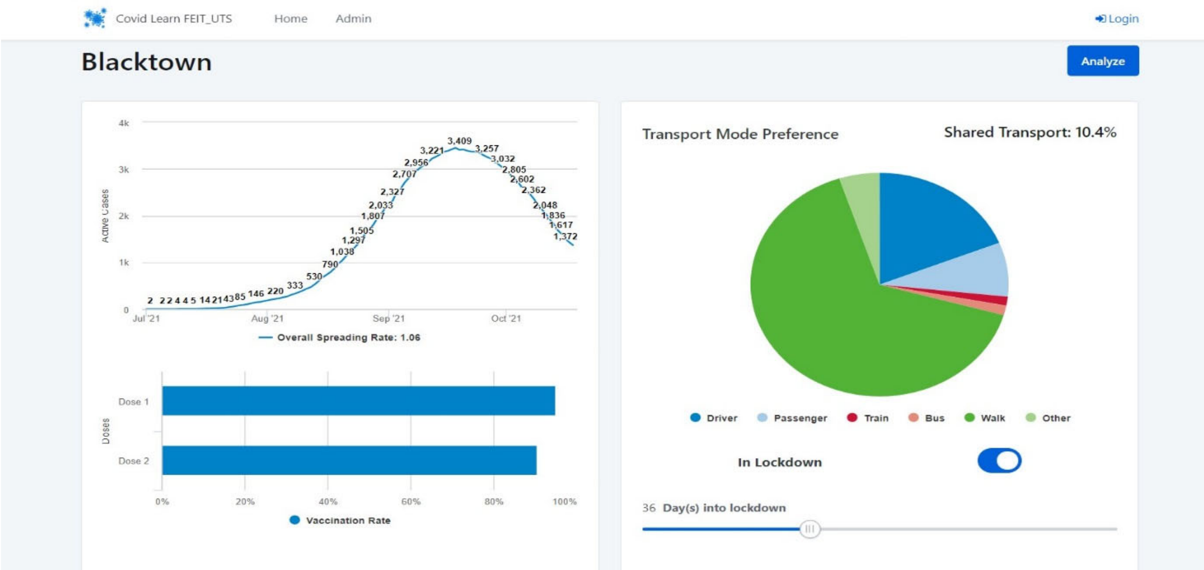
Home Page



(Figure 1)

On the home page, general vaccination information for LGAs of concern and states are displayed in a descending order based on the vaccination rate. A user can click on each card of the LGA and they will be directed to the LGA profile page. On the top menu bar, users can navigate to Admin screen and back to Home page (Figure 1).

LGA Profile screen

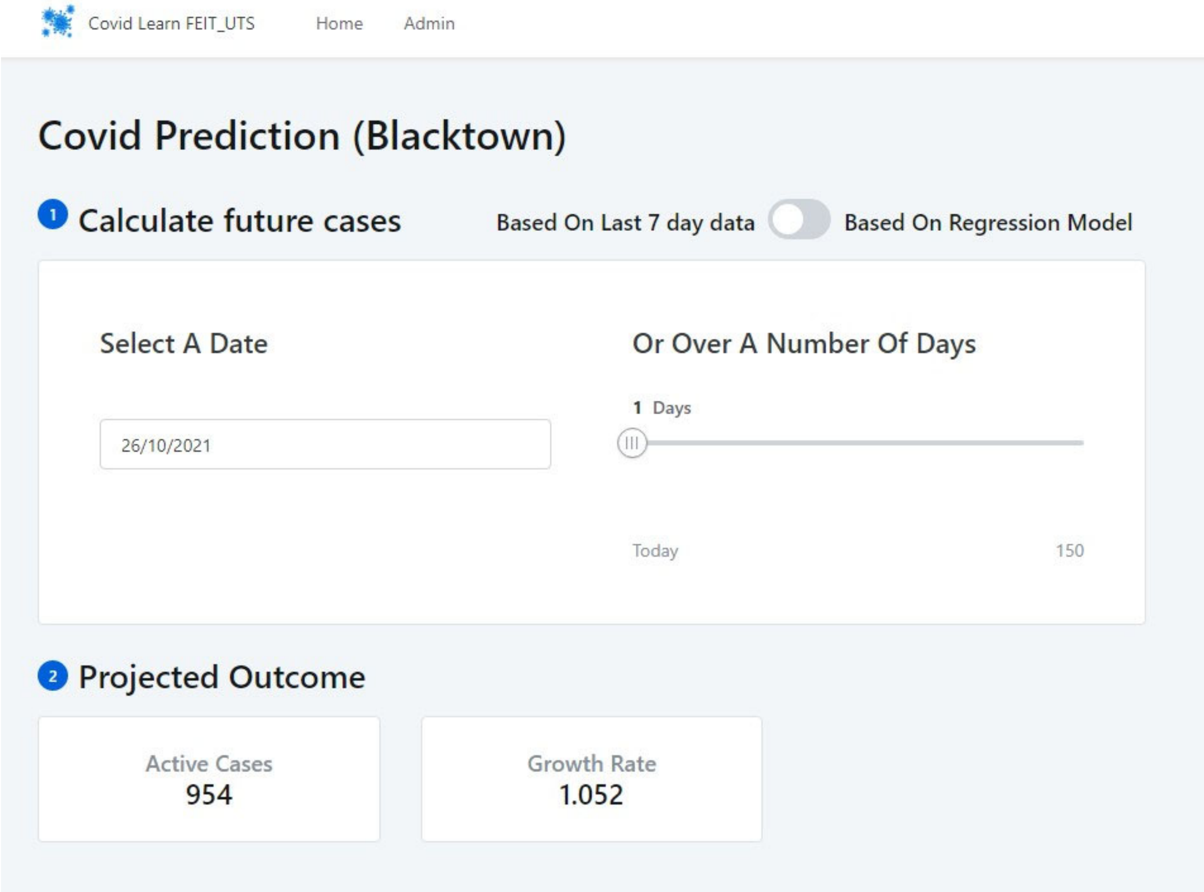


(Figure 2)

On the top left panel, a curve graph illustrates daily cases. When the user hovers on the graph, a tooltip will display the corresponding virus spread rate for a certain date. Below is a bar chart showing the vaccination rates for dose 1 and dose 2. On the right panel, the pie chart dynamically displays the transport mode proportions. Users can use the slider bar to change the days into lockdown (Figure 2).

Machine Learning Analysis Page

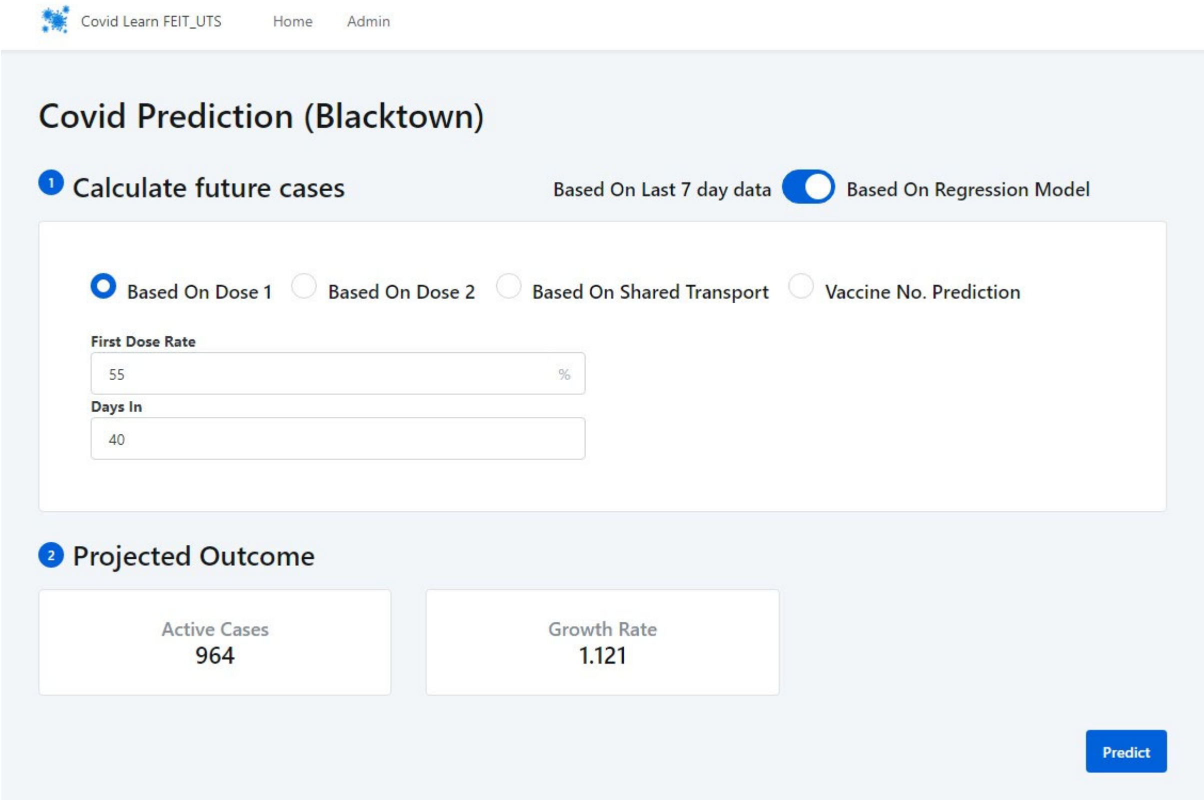
Prediction Based On The Trend Over The Last 7 Days



(Figure 3)

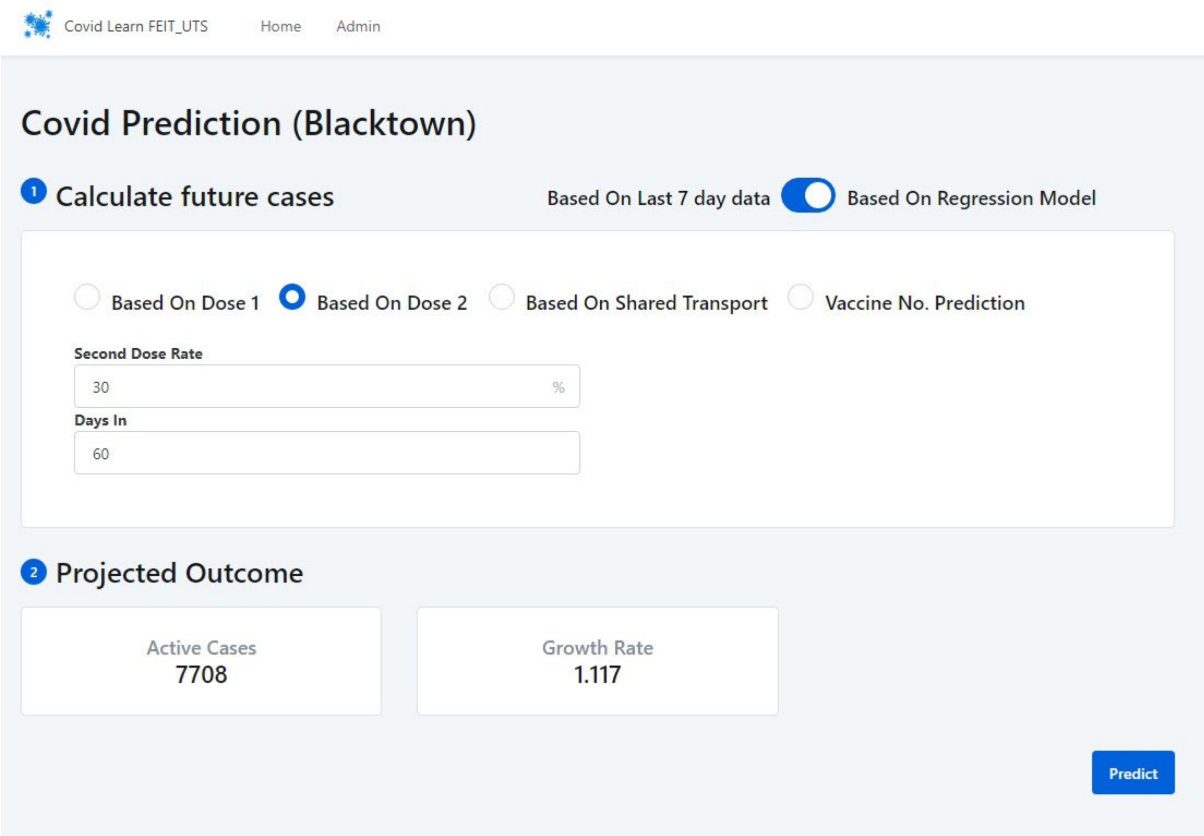
Users can choose a date or choose over a period of time in days. Predicted data will appear in the bottom section (Figure 3).

Prediction Based On Dose 1 And Dose 2



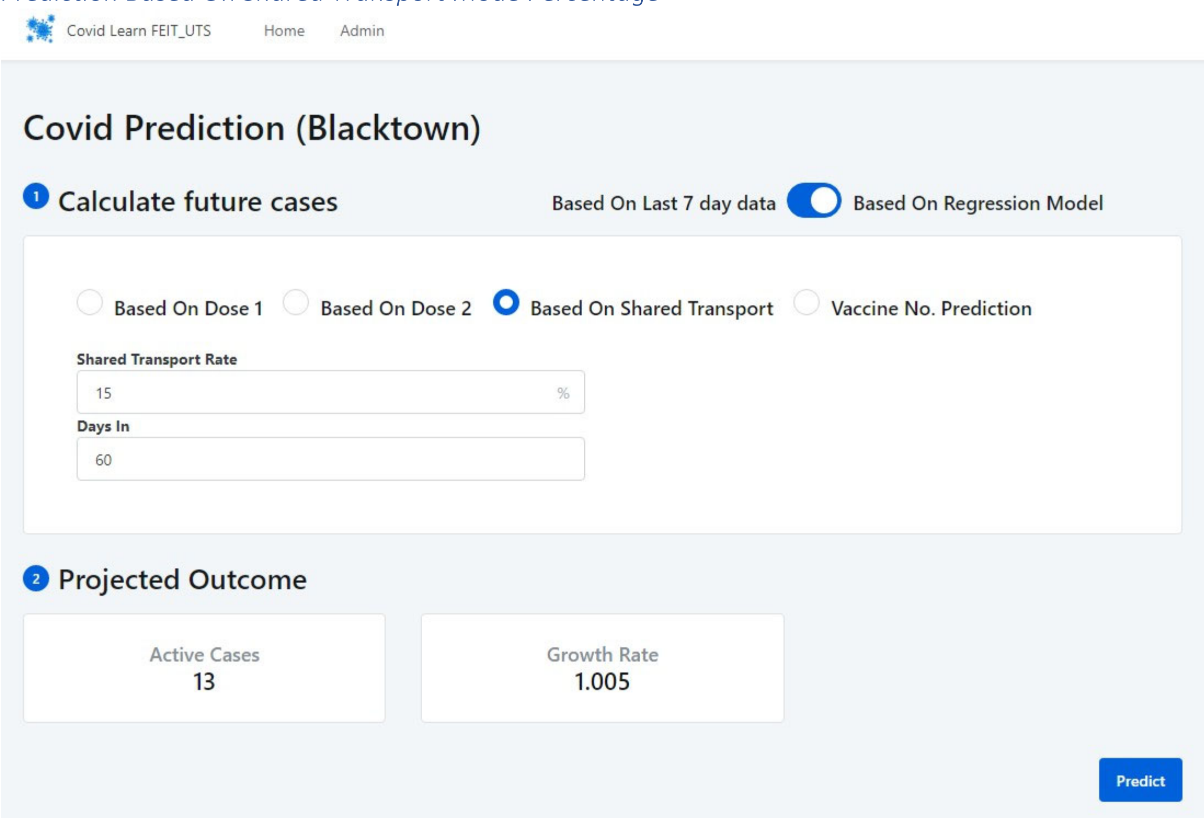
(Figure 4)

A user can change the prediction model to linear regression by using the switch at the top. Then four radio buttons will become visible. The first one is case prediction based on dose 1 percentage where a user can enter the dose 1 rate and the days into the vaccination rollout. The predicted outcome will appear when the predict button is clicked (Figure 4). It is the same logic and flow with prediction based on dose 2 rate (Figure 5).



(Figure 5)

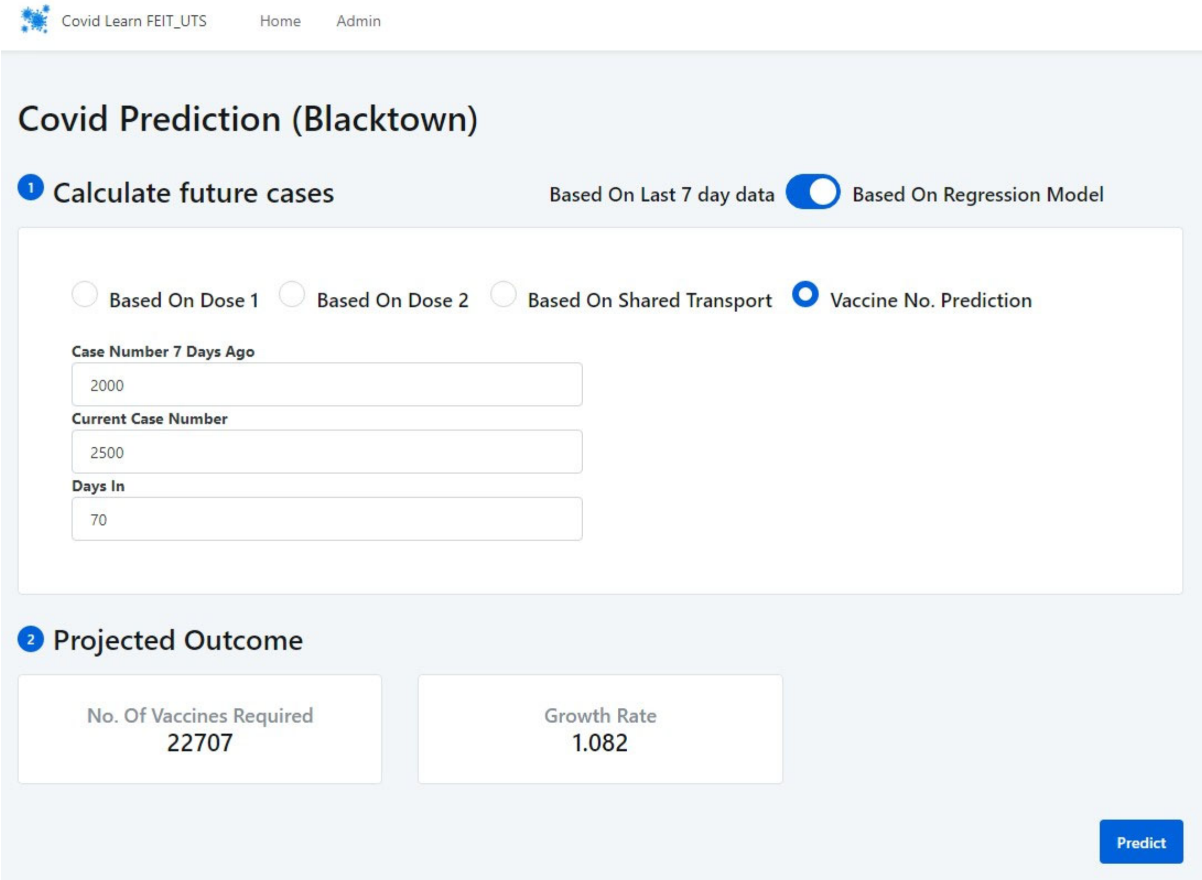
Prediction Based On Shared Transport Mode Percentage



(Figure 6)

Select ‘Shared Transport’, enter the percentage and days into the vaccination rollout / lockdown and click on ‘Predict’. The predicted outcome will appear in the bottom section (Figure 6).

Weekly Administered Vaccine Number Prediction



(Figure 7)

Current case number, case number 7 days before and days into the vaccination rollout / lockdown are required inputs. The outcome will appear in the bottom section (Figure 7). In some LGAs, this function might not be available due to a lower level of Covid-19 case movements.

Machine Learning Model Integration

Data and linear regression models (slope and intercept) were processed and developed using Python. This was achieved by applying Python in VS Code. Then the slope and intercept were entered in the database. The prototype retrieves the slope and the intercept, and

Relevant libraries in Python

```
import pandas
import matplotlib.pyplot as plt
import numpy as np
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
import math
```

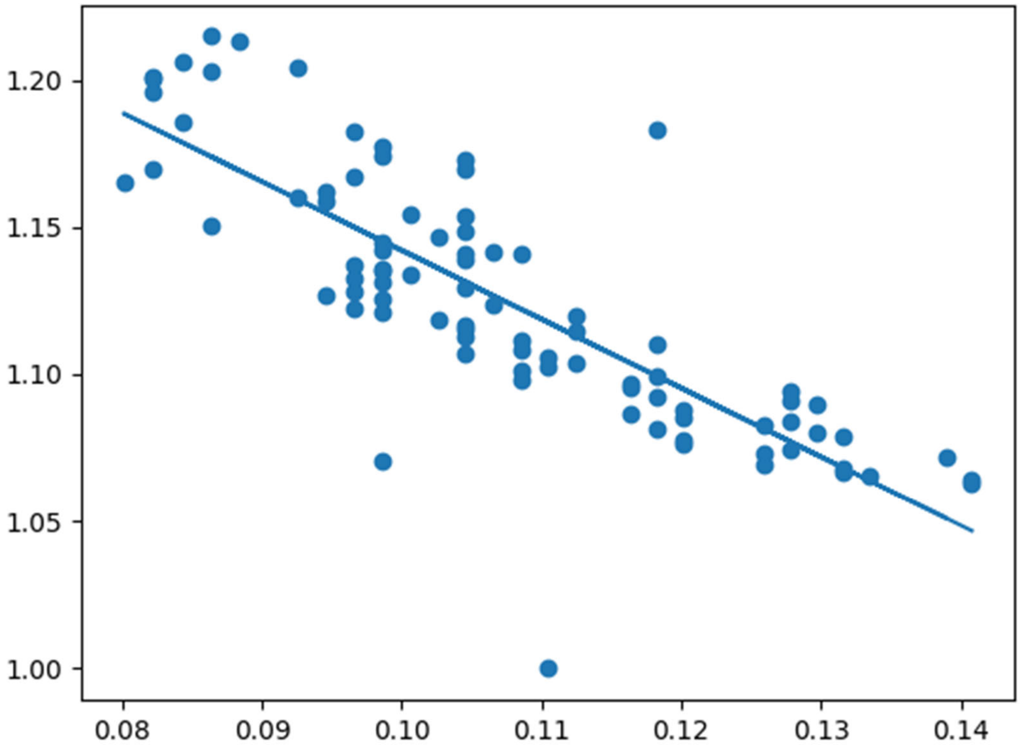
Linear Regression Model

```
slope, intercept, r, p, std_err = stats.linregress(x, y)
```

Data Training And Validation

```
#Separating the dependent and independent data variables into two data frames.
X = df.drop(['Spread_Rate', 'Dose_2', 'Cases',
'Shared_Transport','Days_In'],axis=1)
Y = df['Spread_Rate']

# Splitting the dataset into 80% training data and 20% testing data.
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=.20,
random_state=0)

#Defining MAPE function
def MAPE(Y_actual,Y_Predicted):
    mape = np.mean(np.abs((Y_actual - Y_Predicted)/Y_actual))*100
    return mape


linear_model = LinearRegression().fit(X_train , Y_train)

#Predictions on Testing data
Test_predict = linear_model.predict(X_test)

# Using MAPE error metrics to check for the error rate and accuracy level
MAPE= MAPE(Y_test,Test_predict)

MSE = mean_squared_error(Y_test, Test_predict)

RMSE = math.sqrt(MSE)
```

Line Graph



(Figure 8)

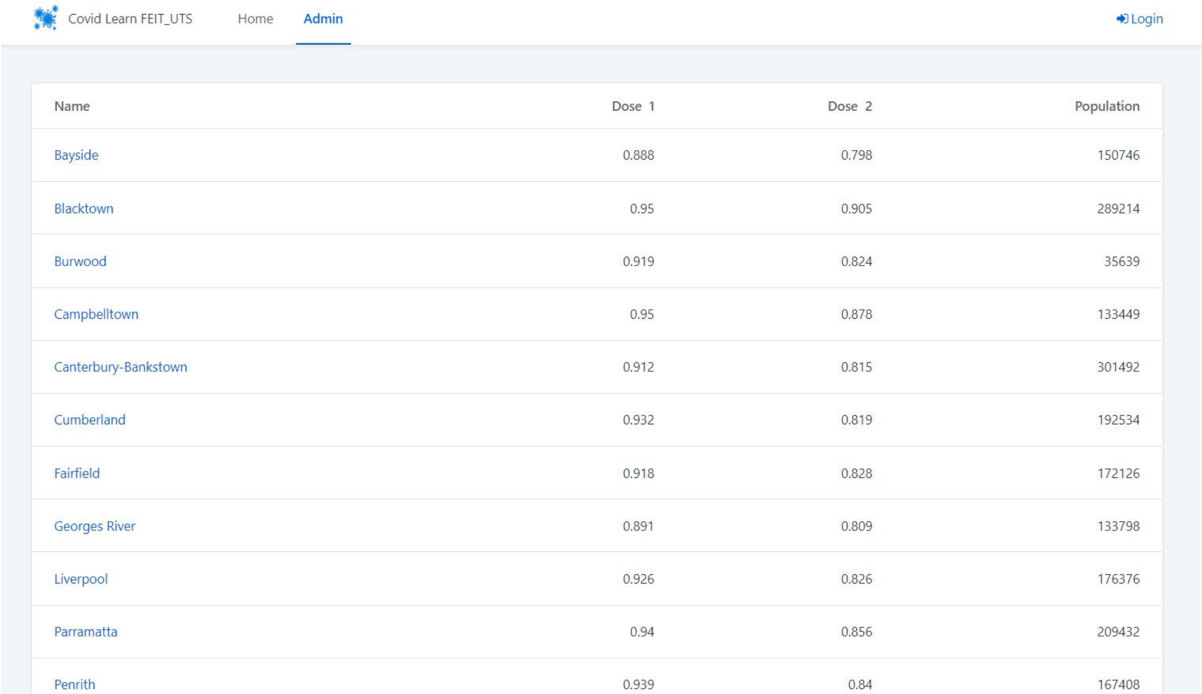
Line graph demonstration for the linear regression model between the shared transport rate and the virus spread rate in Blacktown. The x axis represents the shared transport rate and the y axis represents the spread rate (Figure 8).

Code in Python:

```
def myfunc(x):
  return slope * x + intercept
mymodel = list(map(myfunc, x))
plt.scatter(x, y)
plt.plot(x, mymodel)
plt.savefig('Chart_Feature_Shared_Transport_Blacktown.png')
```

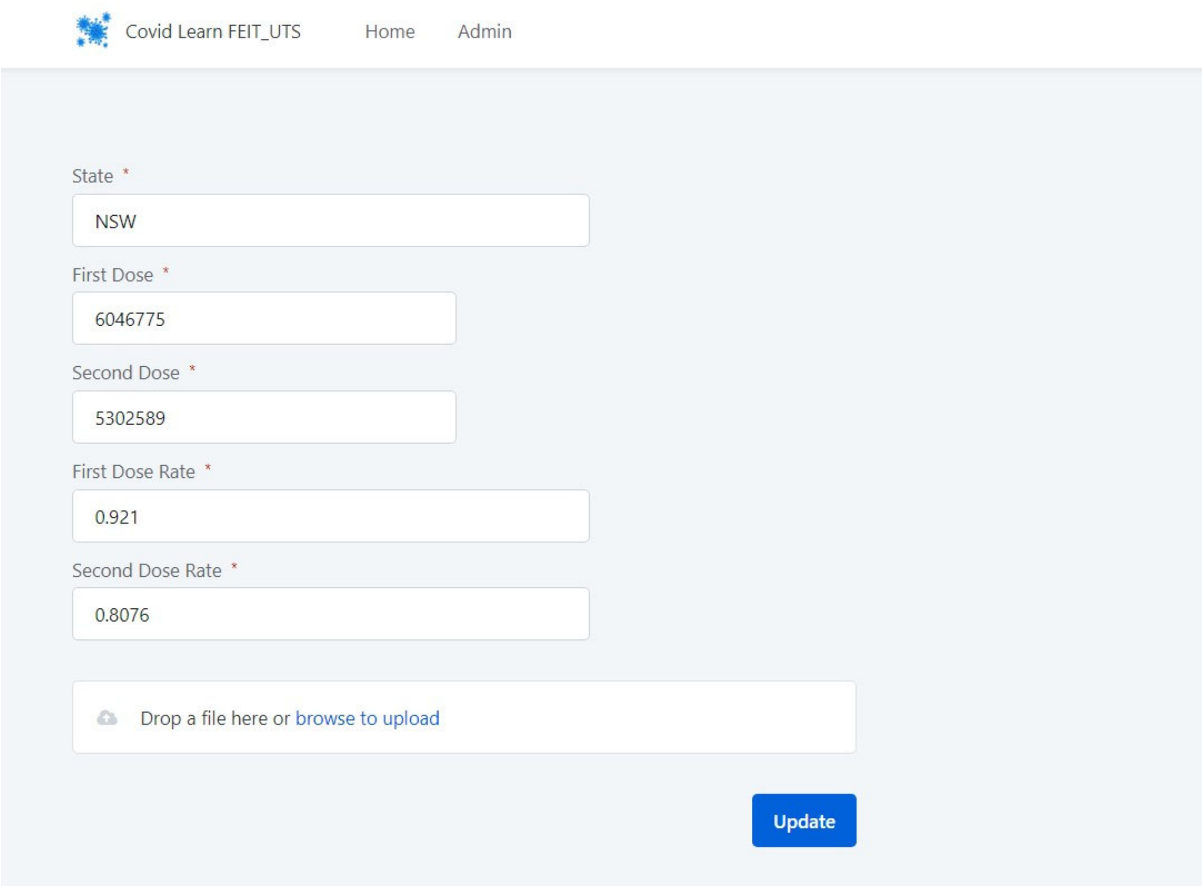
Data Management & Update

Admin Screens



Name	Dose 1	Dose 2	Population
Bayside	0.888	0.798	150746
Blacktown	0.95	0.905	289214
Burwood	0.919	0.824	35639
Campbelltown	0.95	0.878	133449
Canterbury-Bankstown	0.912	0.815	301492
Cumberland	0.932	0.819	192534
Fairfield	0.918	0.828	172126
Georges River	0.891	0.809	133798
Liverpool	0.926	0.826	176376
Parramatta	0.94	0.856	209432
Penrith	0.939	0.84	167408

(Figure 9)



(Figure 10)

In admin, users can update the LGA / state data and change the council / state picture (Figure 9 and 10).

Discussion and Remarks

Due to a tight timeframe and limited access to data, a number of assumptions were made when calculating the dynamic transport mode proportions. Also in some LGAs, the linear regression is only reflective of the early stage the of lockdown / the vaccine rollout period due to relatively low case movements and insufficient data points.

Assumptions made to calculate the dynamic transport mode percentage:

1. 2016 census data was used to get the transport preferences in each LGA and TomTom traffic comparison between 2019 and 2021 was used to adjust the on road traffic reduction. This is based on the assumption that the transport preferences remained the same between 2016 and 2019.

2. A static public transport usage reduction rate (Google Mobility) is applied to each LGA. This is based on the assumption that the public transport usage was relatively steady during the period of the lockdown.

3. When distributing the reduced traffic to 'walk' and 'other' from 'public transport' and 'private transport', the distribution percentage was calculated based on the proportion from 2016 census data. This is based on the assumption that the proportion of the walk mode to that of the other mode remained the same.

Apart from the assumptions above, the time range of the data points in the datasets starts from July 14 around which date the Government started to roll out mass vaccination program in those LGAs of concern, and ends at October 18. Hence the predicted data starts from October 19.

Formula to calculate the virus spread rate:

Spread_Rate = Power (Current_Active_Cases / Initial_Case, 1 / Days)

Formula to calculate the active cases:

Current_Active_Cases = Initial_Case * Power (Spread_Rate, Days)

When predicting the spread rate in the application, after applying the linear regression model, adjustment is made based on the MAPE.

For example:

Spread_rate_before_adjustment = Slope * Shared_transport_percentage + intercept
Spread_rate_after_adjustment = Spread_rate_before_adjustment * (1- MAPE)

Assumption is made that Spread_rate_before_adjustment is always higher than Spread_rate_after_adjustment.

Conclusion and Future Work

In conclusion, based on the linear regression model, there tends to be a negative correlation between the shared transport mode and the Covid-19 spread rate. Not only is it the case in each LGA, but in the comparison between LGAs. This is an interesting finding as intuitively we might think the more we use the shared transport, the faster the virus is going to spread. This can serve as a good indicator that activities where private transport is involved might be a more significant contributing factor in the virus spreading velocity in the communities. This prototype allows a user to predict the spread rate and the case number based on the percentage of the shared transport mode as an input variable. It also allows a user to predict the weekly number of vaccines required to lower the case number to a targeted value. Potentially, the predictive data generated from the prototype can help the officials with vaccine distribution, and decision making over restrictions.

However, due to a relatively short timeframe and limited access to the relevant data, there is still more work to be done to enhance the application and its accuracy.

Future Work

1. More data points. To increase the accuracy of the linear regression model, more data points are needed. Currently, each LGA has approximately 100 data points.

2. Live data for public transport movements. On-road traffic data has been adjusted based on the TomTom traffic comparison. But the public transport data is static data sourced from Google Mobility.

3. More feature variables. There are various factors that might affect the spread rate of the virus. More feature variables can be added and included in the regression model.

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Appendix

Data sources:

https://www.google.com/covid19/mobility/

https://covidlive.com.au/nsw/lga

https://www.tomtom.com/en_gb/traffic-index/sydney-traffic/

https://www.nsw.gov.au/covid-19/stay-safe/data-and-statistics

https://www.abs.gov.au/

https://www.transport.nsw.gov.au/performance-and-analytics/passenger-travel/surveys/household-travel-survey-hts/lga-profiler

https://www.transport.nsw.gov.au/data-and-research/passenger-travel/public-transport-patronage