ARTIFICIAL INTELLIGENCE FRAMEWORK FOR THREAT ASSESSMENT AND CONTAINMENT FOR COVID-19 AND FUTURE EPIDEMICS WHILE MITIGATING THE SOCIOECONOMIC IMPACT TO WOMEN CHILDREN AND UNDERPRIVILEGED GROUPS

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RESEARCH ARTICLE

Artificial intelligence framework for threat assessment and containment for covid-19 and future epidemics while mitigating the socioeconomic impact to women, children, and underprivileged groups

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Abstract: With the emergency situation that arises with COVID-19, the intense containment strategies adopted by many countries had little or no consideration towards socio-economic ramifications or the impact on women, children, socio-economically underprivileged groups. The existence of many adverse impacts raises questions on the approaches taken and demands proper analysis, scrutiny and review of the policies. Therefore, a framework was developed using the artificial intelligence (AI) techniques to detect, model, and predict the behaviour of the COVID-19 pandemic containment strategies, understanding the socio-economic impact of these strategies on identified diverse vulnerable groups, and the development of AI-based solutions, to predict and manage a future spread of COVID or similar infectious disease outbreaks while mitigating the social and economic toil. Based on generated behaviour and movements, AI tools were developed to conduct contact tracing and socio-economic impact mitigation actions in a more informed, socially conscious and responsible manner in the case of the next wave of COVID-19 infections or a different future infectious disease.

Keywords: Artificial intelligence, COVID-19, socio-economic impacts.

INTRODUCTION

The novel coronavirus named Severe Acute Respiratory Syndrome-Coronavirus-2 (SARS-CoV-2), was first recognized in an outbreak in Wuhan, China in December 2019 and has since then swept the modern world into unprecedented turmoil. The World Health Organization (WHO) was compelled to declare the coronavirus disease-2019 (COVID-19) a pandemic on March 11, 2020, when the total number of cases amounted to more than 118,000 with the disease spread in over 110 countries worldwide.

COVID-19 essentially pushed human civilization to a standstill. This global crisis tested the human response as communities, localities, countries, regions and the entire world (WHO, 2020). Almost all the affected countries initiated social distancing protocols with movement restrictions and eventually went into some form of a "lock-down". However, different countries adopted different measures to contain the spread of the virus. In Sri Lanka, the first patient with COVID-19 was reported on January 27, 2020, a Chinese female visiting the country. When the first local patient was reported on March 11, Sri Lanka initiated rigorous measures to reduce the spread of the disease. The government suspended all arriving international flights and ships while imposing a nationwide curfew on March 20. In selected districts and some designated areas in some districts, curfew was continued till June 6, whereas in other districts curfew was relaxed periodically. Curfew

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was relaxed systematically and from June 28th, curfew was lifted countrywide.

There are numerous claims where individuals and groups were subjected to excessive pressure, stress, discomfort or discrimination due to some of the measures adopted for the sake of combatting the propagation of COVID-19 (ILO, 2020; FAO, 2020; UN WTO, 2020). In other words, the impact of the COVID-19 pandemic, as well as the adopted containment strategies, had a disproportionate and inhomogeneous impact over various demographic and socio-economic groups of classification in the society. Such notable identifiable groups include women (who hold around 70% of the jobs in the health and social care sectors and around 54% in the tourism sector), informal service sector workers, labour-intensive manufacturing and construction sector workers, informal economy workers, casual and temporary workers, informal workers in the agriculture and food supply sector, younger and elderly workers, refugees and migrant workers, micro-entrepreneurs, and the self-employed.

Especially, the impact of containment measures taken by policymakers was severe on women, children, and the above-mentioned socio-economically underprivileged groups (called 'identified diverse groups' hereafter) (UN WTO, 2020; UNICEF, 2020). The mere existence of such issues raises questions on the approaches taken and demands proper analysis, scrutiny, and review of the policies. This would be beneficial in formulating the response towards addressing not only the future progress of COVID-19 but also any other future similar crisis of global scale.

Typically, even in the data-driven systematic analysis of a problem, the concerns of women, children, and socio-economically underprivileged are under-represented and/or simply lost in the process of averaging out. Therefore, the special and unique concerns of these groups remain invisible or unrecognized. Through a 3000-household survey (*https://covid.eng.pdn.ac.lk/household.php*) conducted to understand the broader impacts of COVID-19 outbreak and to identify those segments of the population that are disproportionately affected by the pandemic, it was found that the overall policy frameworks fail to address the issues and concerns of 'identified diverse groups.'

Considering the impact of emergency containment measures (such as open, social-distancing, restricted, lock-down, and shut-down) taken by the governments worldwide to combat COVID 19 on a diverse group of people based on occupation (such as daily wage labourers, mass factory workers, domestic workers, ad-hoc workers, and self-employed personal) and occupancy (such as urban slums, urban multi-storey flats, and metropolitan setups), it is vital to investigate the socio-economic impact on the 'identified diverse groups.' Having understood such impacts, this paper discusses, the development and use of artificial intelligence (AI) techniques to detect, model, and predict the behaviour of 'identified diverse groups' under COVID-19 pandemic containment strategies; understanding the impact of these strategies initiated in Sri Lanka; and the development of AI-based solutions, to predict and manage a future spread of COVID or similar infectious disease outbreaks. Socio-economic impact due to COVID-19 has been studied with respect to several isolated factors such as economic activities, health and poverty. For example, a study has been conducted in Nigeria (Obi *et al*., 2020) comprising of 300 respondents to collect information on the impact on economic activities only whereas, in our proposed work, a larger population of respondents is involved in the survey. In another case study conducted in San Francisco Bay area (Martin *et al*., 2020), the impact on households and poverty has been analysed under different containment policies through mathematical modelling using past data. However, this does not reflect the real scenario during the pandemic as there was an abrupt change in employment and economic activities. Consequently, we address the gap of current information by collecting data on employment covering periods before and during the pandemic. In addition, the impact on health programs in India has been analysed in (Gopalan & Misra, 2020). This has been done using historical census data and COVID-19 reports rather than reaching out to the public to collect information on their concerns. In the proposed work, we dedicate a section to collecting data on selected health programs to analyse the impact of COVID-19 on essential sections of the health sector. Moreover, these studies use statistical analysis (Ozili, 2020; Das *et al*., 2022) to make interpretations and develop passive measures instead of using them to provide proactive measures. In the proposed research, the data collection will facilitate an AI to model, forecast, and emulate different strategies to lessen the adverse effects of COVID-19 on socioeconomics.

METHODOLOGY

This project has a number of stages namely, data collection, data analysis, simulator design, analysing the disease spread using the simulator, and generating outputs such as impact of different containment measures. Initially, the data such as census data, visual data (satellite image data), and infectious data from publicly available databases for

Sri Lanka and many other countries as available were collected. Then, according to the current status, a deep learning-based forecasting tool was developed to predict the number of cases and deaths fourteen days ahead which is robust under fluctuating testing conditions and limited infection data. An impact analysis was conducted to better understand the interplay between a region's demographics and its possible susceptibility to being impacted by a pandemic. In addition, a correlation study has been carried out using background data and case data of different nationalities to find a relationship between demography and cases. Further, the satellite images were used to find a correlation between aerial visuals and socio-economic data to map to covid threats as this would facilitate an alternate means for region-based containment strategies to be devised based on visual information.

An island-wide survey of 3000 households (about 12000 individuals) was conducted representing a diverse population based on gender, ethnicity, economy, etc. The household survey was carried out by using Face-to-face CAPI (Computer Aided Personal Interviews) (Lavrakas, 2008) using a structured questionnaire (Scott & Usher, 2004; Lavrakas, 2008). The questionnaire was designed to cover questions related to demographic characteristics of the household (age, gender, occupation, etc of each household member), geographical location, broader effects of COVID-19 on household (whether or not any household member experienced any effect on health, livelihoods, income, etc.). The questionnaire was translated into local languages, ethical clearance was obtained from the ethical committee of the Faculty of Arts of the University of Peradeniya and was piloted (Sinhala/Tamil) before conducting face-to-face Computer-Assisted Personal Interviewing (CAPI). The second phase of the task, which is ongoing, will commence holding focus group discussions. For this, approximately 216 individuals are invited to participate from the people who partook in the island-wide survey. The discussions are conducted to collect more detailed information on the socio-economic impact due to the pandemic, which was not covered in the national survey. Further, roughly 242 individuals are selected from the survey data to represent various employment/occupational categories. The interviews are used to collect data on mobility and behaviour patterns of the participants before, during and after the pandemic. The interviews happen in parallel with the focus group discussions. In the meantime, 150 interviewees are involved to collect data on present movement patterns using a positioning app installed on mobile phones.

As future work, all data collected will be organized to use with artificial intelligence techniques. Before applying the AI techniques, the focus will be placed on reconstructing missing and partial data, enhancing the resolution of data and pre-processing of data if/when required from the data collection tasks. For example, smoothing and reconstruction techniques will be applied to estimate missing time series data for case data to mitigate the impact of fluctuating or non-uniform testing patterns. Then, hyperspectral satellite data will be used to generate high-resolution information maps to better link it to the collected socio-demographic information and heatmaps will be generated from case data to better display covid severity visually.

After data collection and organization, AI tools will be used for collision estimation, clustering, threat assessment, and generalized representations. Specifically, the emulation engine that is being developed will assess the disease propagation from and to different occupational sectors, locations, and social groups based on movement, behaviour and interaction modelling at the population level. Furthermore, case forecasting or pandemic threat assessment algorithms will be upgraded to include socio-economical, ecological, and geographical factors for a more generalized representation. At the same time, satellite imagery is being used for unsupervised clustering to identify high-risk areas based on the correlation between the image data and socio-economic data. In addition, the impact analysis will enable the development of better linkages between demographics and covid threat severity. This will enable policymakers to identify the more vulnerable portions of society. Thereafter once the optimal link between demographics and the covid threat is established the identified demographic metrics can be used to generate tools for assessment of current pandemic threat level from infection data features. The information extracted from the detailed interviews and the survey data will be used to tune the emulation engine to better emulate real-world conditions under various containment strategies and thereby estimate the socio-economic impact and effectiveness of containment measures more accurately. Then the preceding tasks will be aggregated to generate helpful information and insights related to the pandemic and socio-economic impact.

The intermediate outcomes of the AI models will be matched and validated in the field using experimental studies. Twenty individuals will be randomly selected for each study group to represent various age groups, socio-economic backgrounds, educational levels, etc. A control group and an experimental group will be constructed from the selected individuals, and the outcomes of the AI models will be applied to the experimental group.

Finally, the outcomes of the AI models will be mapped to actionable policies. Moreover, workshops will be conducted as the final task to effectively develop accessible outcomes for the policymakers and medical professionals.

Figure 1 shows data collection, processing and output approach based on the methodological approach described above.

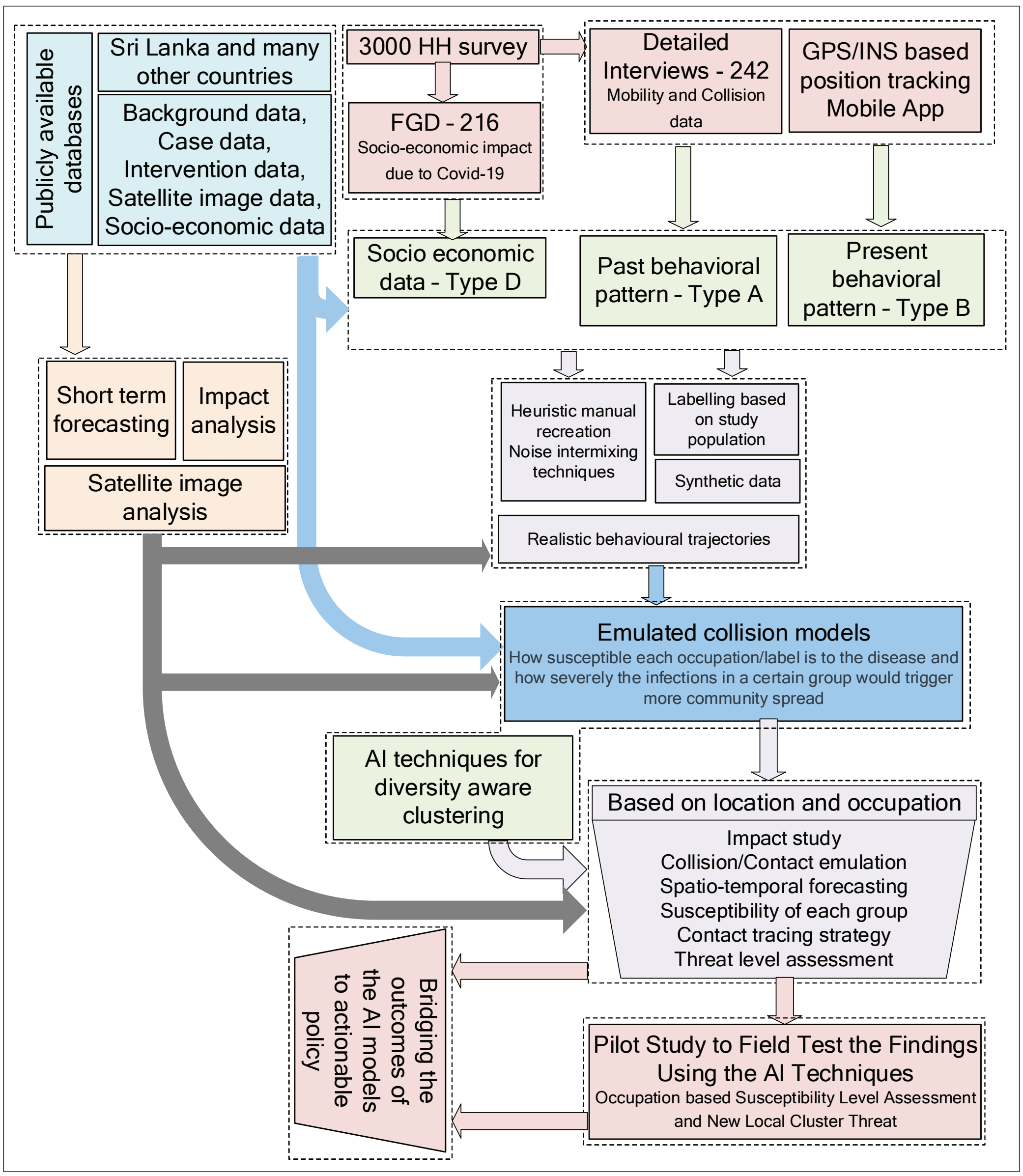

Figure 1: Methodological approach of this project

RESULTS AND DISCUSSION

Household survey

The massive socio-economic impact of COVID-19 has caused measurable and non-measurable changes to human lives. These impacts are diverse among different groups of people depending on their gender, income, ethnicity, culture and other social and economical aspects. In support of analysing these impacts and finding the best possible solutions to mitigate the adverse impacts, a large household survey was conducted in Sri Lanka. This survey was completed by the mid of December 2021 covering 3020 households and 12153 individuals. Data collection was conducted all around the country including 20 districts, 89 divisional secretariat divisions and 201 Grama-Niladhari divisions. These areas were selected purposively using reports by the Department of Census and Statistics, Epidemiology Unit, Ministry of Health, news bulletins, press releases and expertise knowledge. The high-risk areas were considered according to the risk maps by the Department of Census and Statistics. Further, major economic zones such as agricultural, fishing, estate and industrial were specifically selected using the past statistics of various issues of Central Bank and census reports. A total number of 15 households from each Grama-Niladhari division were sampled with the help of village-level administrative officers. Enumerators were well trained for interviews and all enumerators were undergraduates who were pursuing degrees related to social sciences at the time of data collection.

Preliminary qualitative results of the survey

Impacts on employment, education, health, income, food intake, mobility, cultural activities and socio-political aspects due to the COVID-19 pandemic were gathered from this survey. The basic demographic data and qualitative findings, especially the impacts of employment and education, are presented in this study. According to the descriptive statistics, the whole data set has a proper gender balance (female 57.3% and male 42.7%) and age distribution. The sample consists of diversified ethnicities including Sinhalese, Muslim, Tamil and mixed ethnicities. The education level of individuals ranged from no education to postgraduate level qualifications in the selected sample.

According to the qualitative results of the survey, most of the families were severely affected due to the pandemic either economically, socially, spiritually or culturally. Among them, the impact on income sources was severe. Containment strategies like travel restrictions, lockdowns and social distancing limited most of the employment, especially own businesses:

"I am a tourist driver. I lost my employment completely due to the pandemic and the restrictions imposed" (Male, aged 50, Kandy)

"I had a retail shop, and it is my household's main income source. Due to the pandemic I had to close the shop because public transportation was completely stopped" (Female, aged 48, Alawwa)

The education system was changed drastically due to the pandemic creating both positive and negative outcomes. According to the results, students' preference towards modes of education was diverse among different age groups and educational levels. Some students are still waiting for their usual classroom education while some of them highly prefer online education due to many reasons. Additionally, most of the students prefer a hybrid system of education which consist of both face-to-face and online classes:

"I prefer online education because it saves my time for transportation. Also, I can access classes from many teachers if needed. Therefore, online learning is far better than face-to-face education" (Female student, aged 17, Kaluthara)

"I missed being with my friend because of online education" (Male student, aged 15, Negambo)

"I prefer a hybrid system. I have household chores as a mother. Therefore, it will facilitate me to choose among the mode of education" (Female postgraduate student, aged 28, Gampaha)

Future work using the household data

This large survey data will facilitate the selection of specific groups of people such as students, informal and formal sector workers, elderly people, ethnic minors and village level administrative officers for Focus Group Discussions (FGDs). This task will collect data on the socio-economic impact of individually selected groups and create a broader picture of the impact of the pandemic. Furthermore, these data collected from the household survey and FGDs demonstrate the socio-economic impact of the pandemic on severely impacted groups in Sri Lanka at a high-resolution level. These data will be used to analyse further socio-economic impacts of the COVID-19 pandemic on identified diverse groups using social science research methods and to feed the emulation engine to produce outputs using AI-informed strategies.

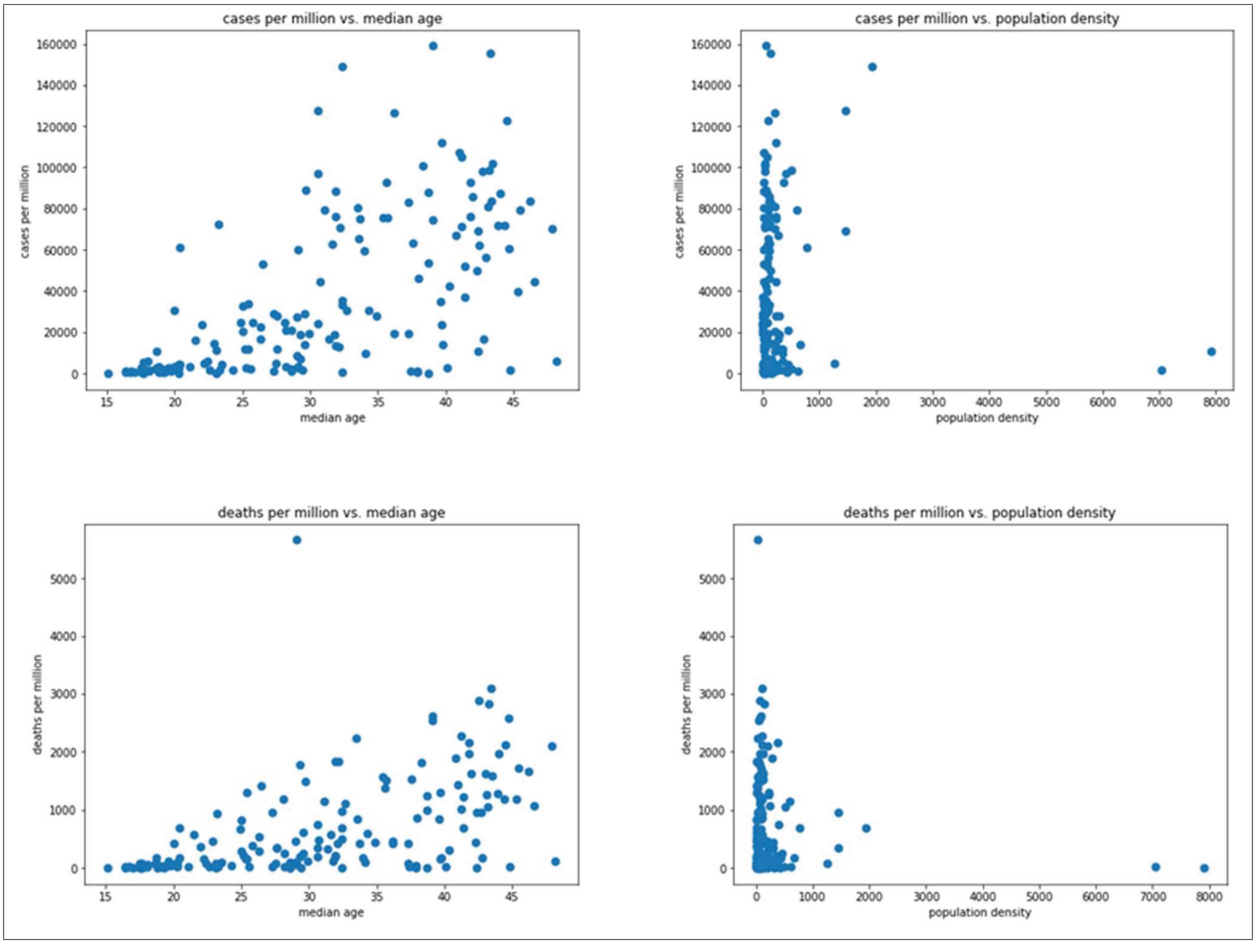

Figure 2: Correlation of the cumulative cases and deaths per million with median age and population density

Impact analysis

The demographic profile of a country is at play when it comes to the progression of COVID-19 as it spreads through contacts. The demographic profile (or population pyramid) provides cues about the general socio-economic status of the population of a country (Heenan, 1965; Peters *et al*., 2010). To study the effect of the demography on the cumulative cases and deaths of a country, prominent demographic parameters, median age and population density, were considered as the independent variables. The strength of the relationship between the independent and dependent variables was defined using the correlation coefficient between the variables. The correlation results are depicted in Figure 2 for cumulative cases and deaths under median age and population density.

According to the correlation study, it was observed that the median age was better correlated with the cumulative cases and deaths than population density as the independent variable. In particular, median age recorded a correlation coefficient of 0.6311 and 0.5876 with cases and deaths per million respectively. A correlation of this magnitude indicates that the variables are moderately correlated. On the other hand, population density had a correlation coefficient of -0.0107 and -0.1274 with cases and deaths per million respectively, which concludes that the variables are weakly correlated. This instigates that the severity in terms of normalized cases and deaths is better related to the age demographics of a country rather than the residency demographics.

However, median age only represents a cross-section of the age demographics of a country as the median age does not change with symmetric alterations to the population pyramid around the median age. Therefore, it is important to consider the entire population profile when assessing the relationship between the age demographics and cumulative normalized cases and deaths of the country for severity. For simplicity, the Bloomberg resilience index (Bloomberg, 2021), a numerical quantification of COVID-19 severity, was used to study the connection between the population pyramid to Covid severity.

For that, the population pyramid was clustered using the UMAP algorithm and the results are depicted in Table 1. The embedding algorithm maps countries with similar population pyramids to nearby locations and vice versa. According to the classification results, it was observed that, in general, countries with similar demographic profiles had similar resilience rankings which suggest that the total age demographics is a suitable candidate to study the Covid severity of a country. These impact studies enable a better understanding of the relationship between population demographics to pandemic threat for policymakers. These enable us to identify vulnerabilities in our population demographic spread. The next step would be to link infection time series data features to better assess current threat levels of the pandemic. This will help policymakers respond in proportion to the actual threat present.

Table 1: Clusters of countries according to demographic profile and respective resilience scores

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Japan -14	Czech Republic-31	Norway-7	Israel-4	Sri Lanka-47	UAE-12
Italy-30	UK-11	Singapore-2	Argentina-53	Iran-48	Nigeria-37
Portugal-20	Canada-18	Russia-26	Brazil-51	Indonesia-42	Iraq-44
Greece-33	Poland-39	US-13	Vietnam-23	Malaysia-35	Pakistan-46
Germany-28	South Korea-5	New Zealand-1	Turkey-41	India-50	
Spain-17	Belgium-25	Australia-3	Colombia-52	Saudi Arabia-19	
	Romania-38	Tahiland-27	Peru-49		
	Denmark-8	Ireland-22			
	France-24	China-9			
	Switzerland-16	Chile-36			
	Netherlands-29				
	Hong Kong-10				
	Bangladesh-40				
	Austria-21				

Satellite image-based threat assessment

The basic idea in this task is to find a correlation, between data retrieved from satellite image clustering and demographic parameters. In particular, this task intended to identify low income dense urban-dwelling areas using spectral clustering techniques. This will help in assessing how much of a risk it is for a particular area to be a Covid hotspot. Satellite images of the city area of Kandy and Colombo were obtained in the resolution of 4318×3904 for this purpose. The satellite image area of Kandy is shown in Figure 3. Satellite images were clustered using spectral clustering and k-means clustering to see the best method that can be used for grouping data from satellite images. Figure 4 shows a result of clustering a small segment of the satellite image.

As the Grama-Niladhari division is the smallest division in Sri Lanka, this resolution was selected for demographic data collection. Land use, ethnicity, and industry sector data were collected from data available in the Department of Census and Statistics, Sri Lanka. According to the collected data, the relevant Grama-Niladhari division was clustered into groups. As the next step, we will be developing a correlation between the clusters from the satellite image processing and demographics data clustering. These enable us to develop visual identification tools for threat assessment and containment. It also helps the policymakers to prioritise response levels based on regional clusters to focus more energy on the more vulnerable zones.

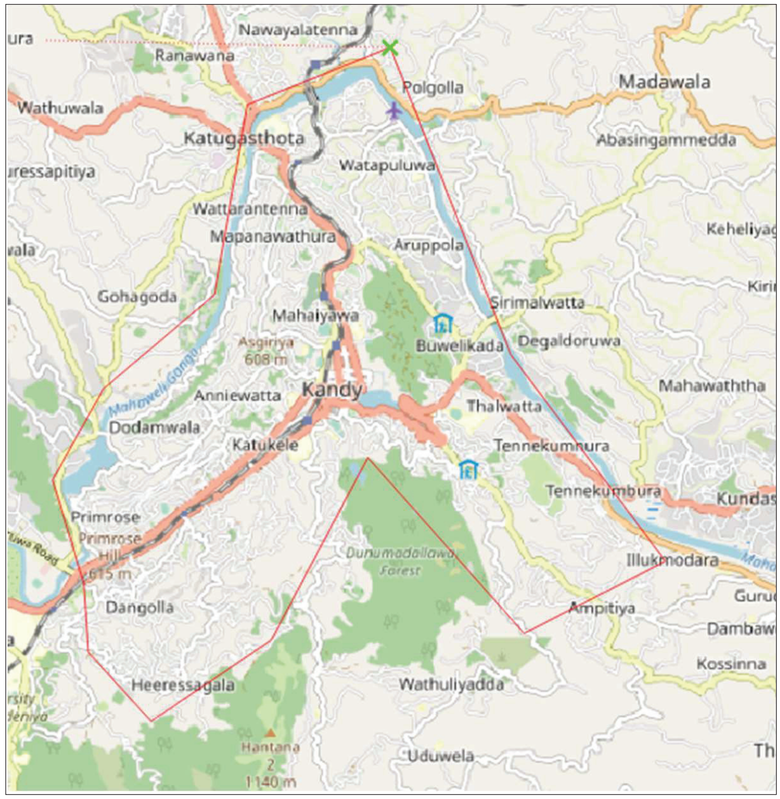

Figure 3: Study area of Kandy from the received satellite image

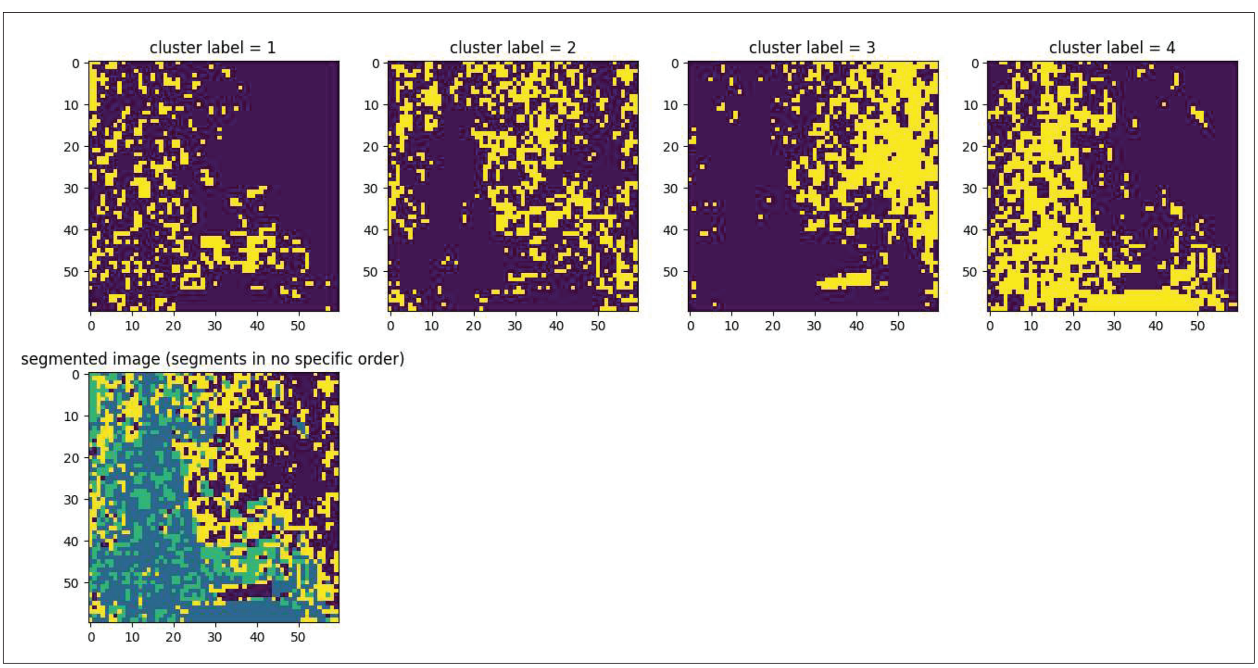

Figure 4: Individual clusters and the segmented image from satellite data of the city area of Kandy

COVID-19 forecasting

There are several compartment modelling methods like SIR, SIER models to analyse the spread of diseases. They construct mathematical relationships between each compartment using the number of people in each compartment and the rate of change of the people. The infection epi-curve of the model is fitted to real-world data by fine-tuning the parameters of these mathematical relationships to forecast future cases. However, these compartment models give the overall picture of the spread of the disease, and it does not identify the impact on each individual or group of people. Also, these compartment models forecast the number of cases for a long period and the number of cases in the immediate future (two weeks in advance) is not accurate. The objective of developing a forecasting model is to have accurate short-term predictions that would be useful in implementing containment measures at a country level or a regional level. This could help avoid or mitigate the adverse impacts on vulnerable groups due to actions taken using long term predictions.

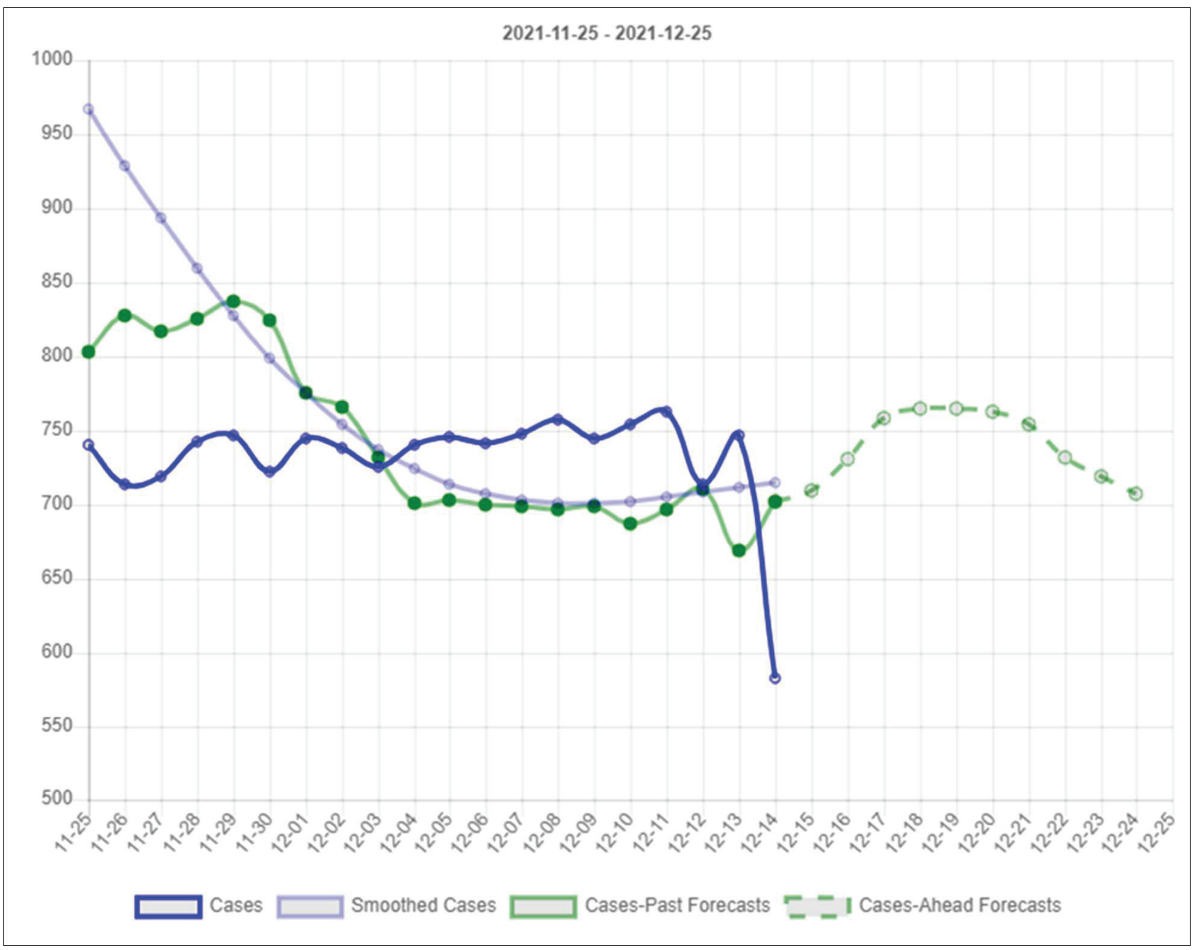

Figure 5: Two-week prediction of new COVID-19 cases in Sri Lanka

The data collected from many countries have a significant noise on each epi-curve of new COVID-19 cases because most of the countries have a varying number of tests each day. Also, some of the test results were released with a delay that makes the daily new cases higher than actual cases. To mitigate these issues a novel smoothing technique is presented which is adaptive to each epi-curve. The collected regional data from different countries were first smoothed using adaptive low pass cut-off frequency in the Fourier domain. Then these data were normalized and split into training and testing samples. These data were then trained using a Long-Short Term Memory (LSTM) neural network to predict the future new number of cases up to two weeks using 50 reported daily new cases. Since there is a lack of COVID-19 data for training, district-wise data and county-wise data from a diverse set of countries were used to train the data. The two-week prediction of Sri Lankan COVID-19 cases and the previous predictions were illustrated in Figure 5.

COVID-19 simulation

The simulator developed using an agent-based model uses data collected from the survey to simulate groups of people classified by their occupation to move around a virtual environment. The demographics of the simulated population of 300 is shown in Figure 6. These movements are adjusted in such a way that reflects real-life movements. The environment is modelled by implementing each location (Homes, Parks, Hospitals, Schools, Offices, etc) in a tree-like structure which gives hierarchical features to these locations. A simple example of the tree structure is shown in Figure 7.

The mobility of the agents is ingrained into the simulator using the probability of visiting a particular location during a given time of the day. Using this probability of visiting a location, assume that the simulator decides the daily routine of a particular agent is going to the park from home and then later coming back home after visiting a shop in the commercial zone. The movement can be simulated in the simulator as shown in Figure 7, where the agent first moves from the house to the park through the housing scheme. Then, the agent should move from the residential zone to the commercial zone to visit the shop. In the figure, the locations visited by an agent during the day are marked as A, B, and C. The path that the agent takes to traverse the tree is shown by a black line. Thus, using a hierarchical tree structure to model the environment is useful when simulating such complex movement patterns. Also, there are different transportation methods implemented in the simulator. For example, the agents will use public transport systems when travelling from residential zones to commercial zones. Also, when the agents are inside a building or a park, they will walk or ride using a bicycle.

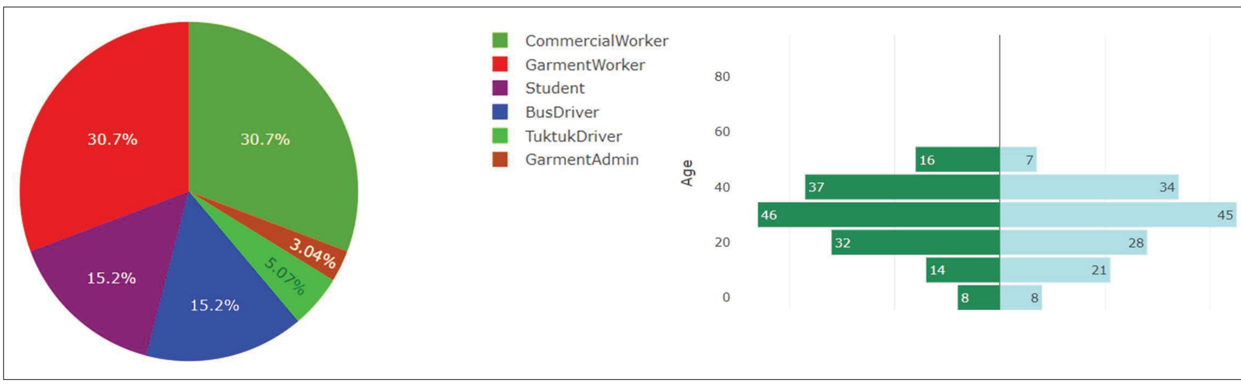

Figure 6: Occupation distribution and Population pyramid of the simulated population

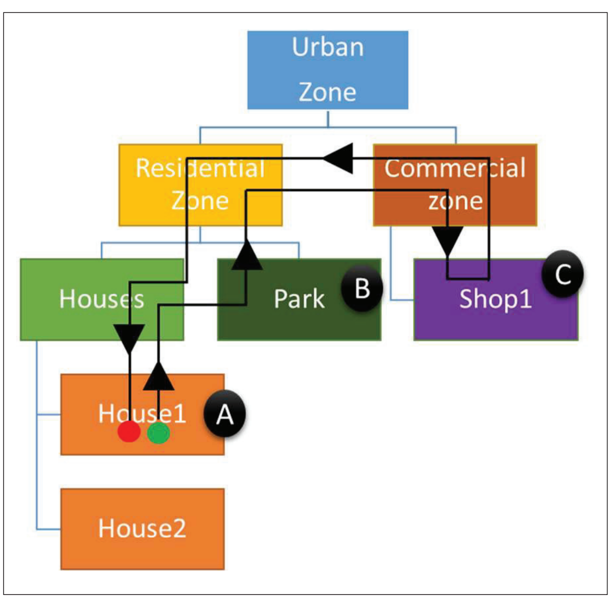

Figure 7: Hierarchical structure of a simple environment modelled in the simulator

The different states of each agent are logged to identify the spread of the disease. Also, when an agent is infected by another agent, the source of the infection, location of the infection is recorded to analyse the critical locations that spread the disease. Further, the people who are in contact with each other are also recorded to find the groups of people who are actively engaged with other people. Different states (Infected, Susceptible, Recovered, and Dead) of the population and other features like vaccination and testing information are illustrated in Figure 8.

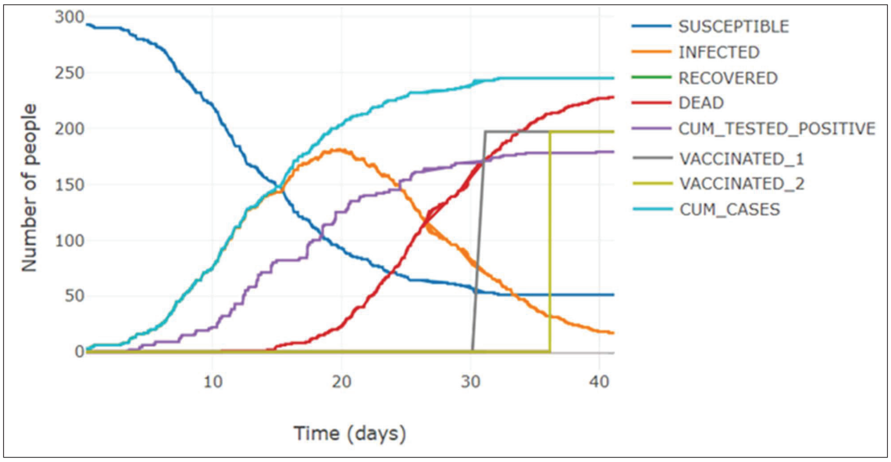

Figure 8: Variation of population states with time

Figure 8 reflects the normal compartment model distribution of states with time. But the ABM simulator is capable of identifying different vulnerable groups in detail and uses contact tracing to track the spread of the disease as well. Also, different testing and containment strategies can be employed to analyse the effect of those policies using the simulator.

CONCLUSION

COVID-19 caught the world off-guard. The world was unprepared for a pandemic of this magnitude and proportion, as was evident by the hasty response and reaction offered by nations and stakeholder organizations. Though many of the measures adopted were generally in "good faith" while considering the "best data and information available at the time", and with the sole intention of reducing the spread of the disease (i.e. "flattening the curve"), they instigated numerous adverse socio-economic consequences.

In the face of the sudden rise in the number of cases and deaths due to COVID-19 as well as the high case-fatality rate and the high infectivity rates reported early on, prompted many countries to take various containment strategies ranging from open (no containment), social-distancing, restricted, lock-down, to complete shut-down. Especially, the intense containment strategies adopted by many countries had little or no consideration towards socio-economic ramifications of the said response or the impact on women, children, socio-economically underprivileged groups. The existence of many adverse impacts raises questions on the approaches taken and demands proper analysis, scrutiny, and rigorous review of the policies. Equipped with the wealth of data, lived experience, and diverse scenarios collected over the COVID-19 pandemic thus far, AI poses a viable paradigm for such scrutiny. In this study impact of these diverse containment measures was investigated using a survey while considering identified diverse groups such as women, children, and the socio-economically underprivileged groups. The survey data were collected from 12153 individuals, and they are now being processed to be fed into AI tools that are under development. The data will also be analysed quantitatively and qualitatively to draw immediate impact metrics for under-identified diverse groups.

Considering fact that the optimal containment is not only country/region-specific but also situation-specific, a proper understanding of region-specific demographics and how they link to covid threat levels is essential. Therefore, satellite imaging and the population pyramid will be linked to pandemic threats. In addition, accurate estimation of current covid threat level and predictions of threat for the near future is required for timely yet rapid response decisions making.

The core of the AI engine is under development to identify different vulnerable groups in detail and uses contact tracing to track the spread of the disease. This engine can be used to identify the origin of the disease spreader events, analyse the effect of different containment and testing strategies, track the groups of people who are frequently in contact and predict the severity of the outbreaks using the data from the real world.

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