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An Intelligent ABM-based Framework for Developing Pandemic-Resilient Urban Spaces in Post-COVID Smart Cities

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Abstract

As of August 2022, the COVID-19 pandemic has accounted for over six million deaths globally. The urban population has been severely affected by this viral pandemic and the ensuing lockdowns, resulting in increased poverty and inequality, slowed economic growth, and a general decline in quality of life. This paper proposes a framework to evaluate the effects of the pandemic by combining agent-based simulations—based on Susceptible-Infectious-Recovered (SIR) model—with a hybrid neural network. A baseline agent-based model (ABM) incorporating various epidemiological parameters of a viral pandemic was developed, followed by an additional functional layer that integrates factors like agent mobility restrictions and isolation. It is inferred from the results that low population densities of agents and high restrictions on agent mobility could inhibit the rapid spread of the pandemic. This framework also envisages a hybrid neural network that combines the layers of convolutional neural network (CNN) and long-short-term memory (LSTM) architecture for predicting the spatiotemporal probability of infection spread using real-world pandemic data for future pandemics. This framework could aid designers, regulators, urban planners, and policymakers develop resilient, healthy, and sustainable urban spaces in post-COVID smart cities.

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1. Introduction

Smart city generally refers to utilising information and communication technology (ICT) and allied infrastructure to sense and control the city processes and use the resources optimally in a city [1]. Sensing and control systems, smart buildings, and smart urban spaces are essential components of smart cities which have seen a surge in interest post-pandemic [2-4].

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The definition of a smart city can be viewed from four perspectives: a) technical infrastructure, focussing on connecting ICT, physical, business and social infrastructures of a city; b) domain application, involving various dimensions to assess smart cities like people, economy, governance, environment, mobility, and buildings; c) system integration, which considers a smart city as an organic integration of various city-systems; and d) data processing which involves the collection of live real-world data, and processing of data for insights generation and decision-making [5]. The Covid-19 pandemic has affected the functioning and processes of smart cities. It has altered the priorities of smart cities by focusing more on smart medical services than on other activities like tourism or social gathering, and so on [6].

The World Health Organisation (WHO) classified the novel Coronavirus disease as a pandemic on 11th March 2020. Individuals over 65 years of age and people with an underlying medical condition were at an increased risk of severe illness upon exposure [7]. The disease can spread from person to person through droplets generated from the nose or mouth of the infected person while coughing, sneezing, and speaking [8,9]. It can also spread by touching eyes, nose, or mouth after physical contact with any contaminated surface [10]. The COVID outbreak has led governments worldwide to impose stringent urban policy measures like nationwide lockdowns and permanent closure of institutions to control the spread of the pandemic. Such measures have had a significant adverse impact on both social life and the economies of the countries, as has the rise in new infections across many countries.

In countries like Italy, the virus had spread from certain regions like Lombardy, which acted as the initial epicentre zones. Infected people with active social life contributed to the increasing cases of infections in the initial phase of the pandemic. Moreover, large public gatherings for religious purposes and the like led to a sharp increase in the infected cases in countries like India, the United States and others [11–13]. It is not only the existing culture or cultural habits of a country but also the planning and design of cities that influence how people behave and interact. For example, spaces like theatres, stadiums, malls, and parks are not merely recreational zones for people but act as vibrant socio-cultural spaces. Even the unbuilt spaces (like the spaces between built forms) and the interface of the built structures (like balconies or shop fronts) become potential spaces of human interaction daily.

This paper introduces a framework for analysing the spread of a viral pandemic and assessing mobility-based interventions in a region. In the present study, Agent-based Modelling is used for simulating the virus transmission in an area. Multiple scenarios were analysed for the impact of mobility interventions on the spread of disease, and the infectivity rates were compared to the baseline simulations. The paper also describes the integration of ABM simulations and Hybrid Neural Networks to predict the infection progression in an urban space. There is also a discussion on how the major sub-systems are integrated into the framework. The remainder of the paper is organised as follows: Section 2 describes the works relevant to this study, followed by section 3, which details the methodology for developing the framework. Post this, sections 4 and 5 present the results and conclusions of the study.

2. Related works

Analytical models such as the SIR model proposed by Kermack and McKendrick [14] can be used to estimate the progression of the pandemic in a closed population. These models successfully predicted the outbreaks of previously recorded epidemics [15]. Based on the first-order differential equations, this model was modified multiple times to account for the complexities in the system, such as differences in demography, geography, and so on. In their work, one such application of analytical modelling was demonstrated by Singh et al.; an age-structured SIR model was used for estimating the progression of COVID-19 in India [16]. The analytical models characterise a population as a homogeneous unit, the differences in the populations can be accounted for by creating multiple population groups in the model. The model is then used to compute the results for each group, and all interactions are captured as group interactions. To capture the interactions between individuals at a much granular level, the agent-based modelling (ABM) approach is utilised. The epidemiological modelling using an ABM captures the system dynamics through defined rules that govern the agents in the simulated world [17]. These agents represent the human population that could be programmed to mimic the behaviour of interest. Hunter et al. have proposed a taxonomy of ABM methodologies for modelling the disease progression in a population. ABMs can also be used to design better policies and mitigation strategies in a pandemic situation by simulating multiple scenarios through the model. For example, Dimka et al. and Kai et al. aimed to test the efficacy of non-pharmaceutical control measures on the progression of the pandemic through simulations [18,19]. Machine learning-based approaches like Convolutional Neural networks (CNN), Recurrent Neural Networks (RNN), and Multi-layer Perceptrons (MLP) are also employed in ascertaining the pandemic's impact [20, 21]. Forecasting models based on the CNN-LSTM hybrid architectures are one such class of models that utilises the time-series data for predicting the course of the infection [22, 23].

3. Methodology

The proposed framework facilitates the analysis of the pandemic's spread in a region and evaluates various policy measures to mitigate it. The framework's development followed two steps; first, a representative (baseline) ABM was developed that simulates the phenomena of the spread of the virus. After simulating multiple scenarios by varying the model's parameters, this baseline ABM was extended to accommodate the space subdivisions (i.e., an abstraction for mobility restrictions) with the agent interactions among these spaces. The simulation results were presented for the different scenarios, highlighting the impact of agent mobility and special subdivisions on the progression of the pandemic in the simulated space. Following the description of the overall framework, the integration of ABMs to hybrid neural networks (HNN) having CNN and LSTM layers is described for its applicability in a real-world scenario. This HNN needs to be tested with real-time data for future pandemics.

3.1 Baseline ABM

3.1.1 Overview

An abstract ABM was created to simulate disease transmission in a virtual space, represented by a digital space spanning100 pixels in length and width. The Cartesian coordinate system, with its origin in the bottom-left corner of the space, is used to calculate the distances and directions of the agents. Every agent in the model is defined by the property variables that primarily contain information related to the infection and its location in space. These variables, along with their descriptions, are listed in table 1.

Table 1. Agent property variables

Variable Name	Value Range	Description
Who	System generated number	Unique identifier of an agent.
Heading	Integer b/w 0-360	The angle with respect to the horizontal in degrees is used for measuring an agent's movement direction.
Xcor	Integer b/w 0-100	X coordinate of an agent in the space.
Ycor	Integer b/w 0-100	Y coordinate of an agent in the space.
Infected	Binary (True/ False)	This state variable reports the infectivity of an agent.
Infection_duration	Positive Integer	A variable to measure the infectivity duration of an agent.
Recovery_time	Positive real number	The fixed duration post which an agent is expected to recover from the infection.
Recovered	Binary (True/ False)	State variable to indicate an agent's recovery
Region_id	Integer	Stores the colour value of the patch under an agent.

In addition to the agent's properties, some global variables are defined in the model that represents key parameters of an infectious disease. These variables could be adjusted to describe the dynamics of the spread of a viral infection. By altering these values at the beginning of the simulations, multiple scenarios could be simulated with the same model. Table2 describes these variables, along with their corresponding ranges and units.

Table 2. Global variables in ABM

Variable Name	Value Range	Description
Population	Integer between 100-1000	The number of agents in the space
Initial_carrier	Between 1-10%	Percentage of infected agents at the beginning of the simulation.
Infection_chance	Between 0-99.99%	Probability of infection upon coming in contact with an infected agent
Recovery_chance	Between 0-100%	Probability of recovery after the recovery period.
Avg_recovery_time	Between 0.5-20 weeks	Average time after which the agents may recover from the infection.

3.1.2 Model Architecture

The ABM is constructed in NetLogo (software for creating ABM) with five major functions. These procedures are ‘move’, ‘infect’, ‘recover’, ‘setup’ and ‘go’, which are described as follows:

1. Setup: This procedure sets up the initial values of all the state variables of the agents—highlighted in table 1—as well as the global variables, as shown in Table 2.

2. Move: it instructs the agents to move forward one unit of the pixel on the simulation space per time step, followed by updating their ‘heading’, which refers to the direction of the agent’s movement at that instant. The heading is incremented by 10 degrees to the left or the right based on a condition that compares a random number generated at the instance to a fixed value.

3. Infect: This procedure identifies non-infected agents in the neighbourhood of an infected agent and then infects them based on a condition that compares a randomly generated number against the variable ‘infection_chance’. Before changing the infected state of an agent, this function also checks for the previous infection of the agent. An agent is prone to infection if it is not infected previously and the variable ‘infected’ takes the value ‘true’ in case of a confirmed infection.

4. Recover: After a fixed duration, an infected agent either recovers from the infection or is removed from the space, signifying the agent’s death. Agents are either recovered or removed from the space based on a condition that compares a random integer to the variable ‘recovery_chance’. Upon recovery, the agents attain immunity and could not get infected further (Values being ‘infected’= false and ‘recovered’ = true).

5. Go: this procedure is called after the setup and executes iteratively until all agents in the space are recovered. In each iteration, this function calls other procedures, ‘move’, ‘infect’, ’recover’ and computes the percentage of the population getting infected over time.

The model parameters were systematically changed in sequence to construct multiple situations for simulating the spread of the pandemic. Table 3 indicates the values for each variable. The combinations from these values produced 125 possible cases, which were run 100 times each.

3.2 Integrating mobility restrictions in the model

3.2.1 Overview

In this variation of the baseline model, the simulation space is divided into a specific number of regions adjacent to each other based on the Voronoi principle. In this partitioning, regions are created about a specific point (or nucleus) to encompass any point in the space closer to its nucleus than any other nuclei.

Table 3. Variable values for simulation

Variable Name	Values				
Population (No. of agents)	100	300	500	700	900
Initial_carrier (% of total agent population)	1	2	3	4	5
Infection_chance (%)	10	25	40	75	90

Hence, a Voronoi region S_k related to a nucleus N_k is a set of possible points in X whose distance to N_k is lesser than their distance to any other nucleus N_j (where $j \neq k$). If d(x, N) represents the distance between points x and N, then the Voronoi region S_k can be described in equation (1):

$$S_k = \{x \in X \mid d(x, N_k) \leq d(x, N_j) \text{ for all } j \neq k\} \quad (1)$$

Voronoi diagrams have been utilised in solving various spatial problems, especially in forestry, agriculture, geology, geography and so on [24]. Voronoi diagrams preserve features of real-world data like hierarchical relations and spatial structures, making them suitable for analysing urban areas which exhibit problems of natural and anthropogenic origins [24]. The total number of such regions in the model can be controlled from the interface. The interaction amongst the agents of different regions, which influences the infection spread, is programmed using the 'check_collison' function. The model is simulated by varying the number of such regions across different populations to observe the effect of the increment in the Voronoi regions and the subsequent mobility restrictions of the agents on the spread of infection.

3.2.2 Additional parameters and procedures

In addition to the parameters in the baseline model (refer to tables 1 and 2), this model has two additional global variables, namely, 'region_numbers' and 'mobility_restriction'. The former specifies the number of Voronoi regions that are created in the simulation space at the beginning of each run, and the latter provides the degree of the interaction of the agents at the region boundaries; it is programmed at four levels: 'no restriction', 'low', 'medium', and 'high'. This model has two essential procedures, 'setup-region' and 'check-collision', in addition to those present in the baseline case, which are described as follows:

a. Setup-region: this function generates Voronoi regions over the simulation space based on the total number of regions provided by the variable 'region_numbers'. The nuclei for the regions are distributed normally on the space, with both parameters, i.e., mean and standard deviation, taken as 50 units. This was done to ensure adequate partitioning. The pixels enclosed in a Voronoi region are assigned a colour, which is then stored as an integer in the patch variable 'region_id'.

b. Check-collision: This function controls the interaction of an agent with other agents at the boundary of a region. The distance between agents is controlled by tracking the patch's colour located at a certain (defined) distance ahead. This is done through the 'mobility_restriction' variable. Also, the agents stay within their assigned regions by constantly checking the patch colour ahead.

The simulation of this model was performed for 320 combinations of the initial conditions (an instance is shown in fig 1), which were obtained by systematically varying the values of the variables mentioned above. For each set of values, the simulation was run 50 times totalling 16,000 runs. For this study, the variables 'Infection_chance' and 'Initial_carrier' were fixed at 75% and 1%, respectively. Table 4 provides the complete details of these values. The results of these simulations are presented in section 4, along with the framework discussion.

Table 4. Variable values for simulation for the second model

Variable Name	Values				
Population (No. of agents)	100	300	500	700	900
Region_Numbers	1	2	3	4	5
	10	15	20	30	40
	50	75	100	150	250
	500	-	-	-	-
Mobility_restriction	No-restriction	Low	Medium	High	-

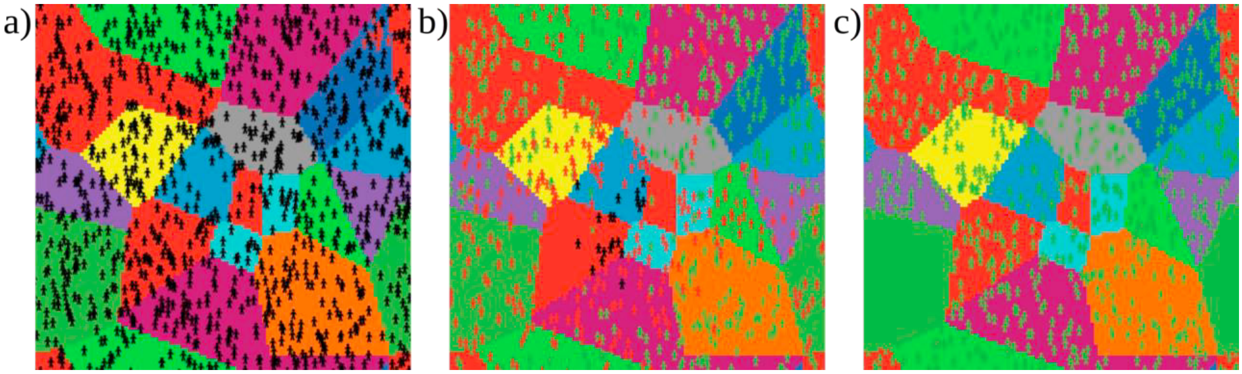

Fig. 1. Progression of the virus in the model having 20 sub-divisions with distinct colours. The images indicate the infection state at different time instants: a) at t =0, b) t =100, c)t =161.

4. Results and Discussions

4.1 Simulation Results

The simulation for each initial condition was run 100 times for the first model and 50 times for the second one. The visualisations of the mean value of all runs were plotted as a graph between the fraction of the population infected and the number of Voronoi regions. For the baseline model, it has been observed that with the increase in the infection chance (gradually from 10% to 90% in the simulations), the maximum value of the infected population fraction increases while saturating at the higher values of infection chance (i.e., at 75% and 90%). The initial infection percentage did not affect the maximum value of the infected population; however, the time to attain maxima is reduced. Additionally, the impact of agent movement in a region was compared by parameterising it through another variable called the mobility factor (MF). MF ranges from 0-1, corresponding to the degree of agent's movement from minimal (single cell in the space) to maximum (greater than two cells). The data showed that the proportion of the infected population was higher with high agent mobility (fig. 2).

In the refined model for all the cases of the agent population (100, 300, 500, 700, and 900), the maximum fraction of the infected population for a Voronoi partitioning decreased sharply with the increase in the number of the Voronoi regions. The only exception to this trend is observed when there is no movement restriction on the agents across the Voronoi cells. Additionally, the rate of decrease of the maximum value of the infected population varies with the degree of mobility restrictions, as revealed in fig 3.

4.2 Real-world application

The simulation results of the later model—in which the simulation space is divided into different Voronoi regions—revealed an overall decline in the 'percentage population infected at the peak of the pandemic outbreak' with the increase in the number of the Voronoi regions for a specific agent population. Such observations could provide vital insights into the planning and design of pandemic–resilient urban spaces comprising residential, recreational, commercial, and institutional zones. For instance, the cellular Voronoi boundary, as illustrated in the simulation, could be regarded as analogous to the precincts of a residential community on an urban scale. These residential communities comprise many dwelling units or apartments situated in proximity forming a cluster. The agent movements in and around the Voronoi cell represent human movements within and around a residential cluster for socialisation, occupation, availing services, etc. In the event of a pandemic, the cells in the ABM could represent different zones in the city/area. The policies on the movement restrictions can then be evaluated (using ABM) for optimum results.

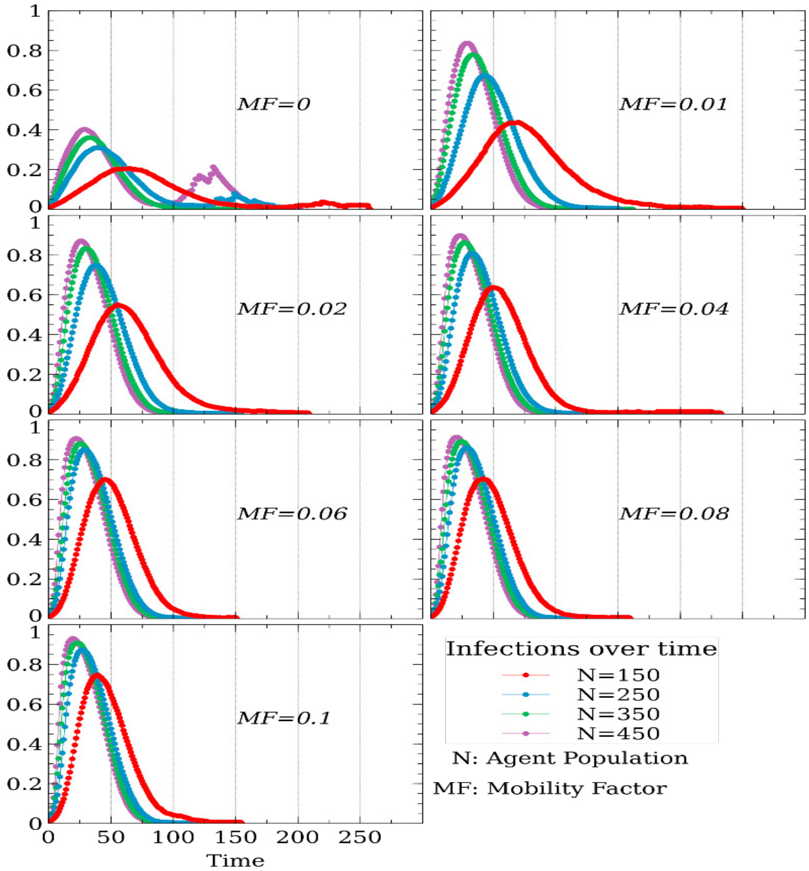

Fig. 2. Progression of the infection in the agent population over time. The vertical axis represents the fraction of the population from 0-1, and the horizontal axis represents the simulation time.

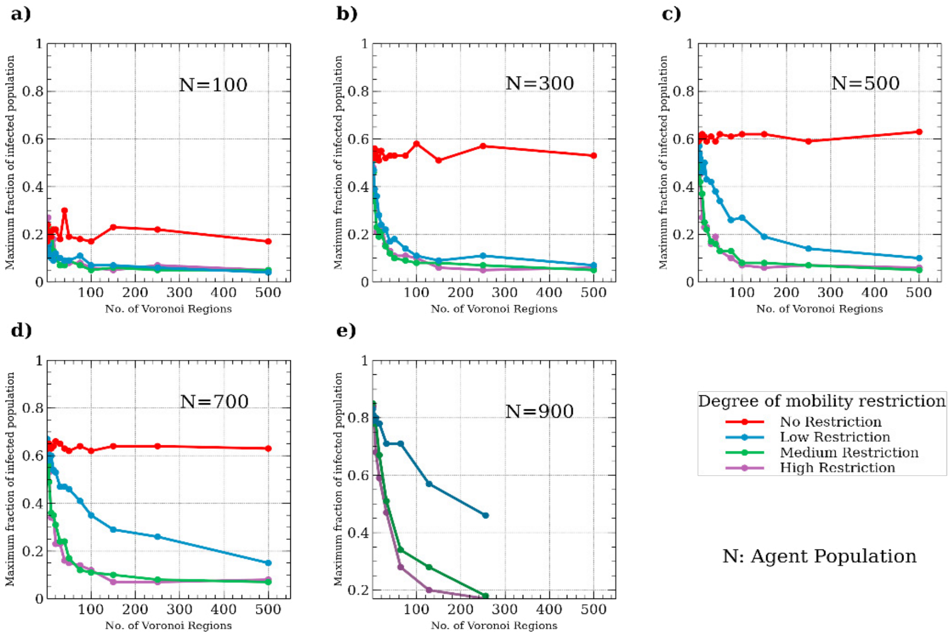

Fig. 3. Variation of the maximum value of the infected population with respect to the number of Voronoi regions for various degrees of mobility restrictions for the agent populations of a)100, b)300, c) 500, d) 700, and e) 900, respectively.

4.3 Framework development

The data generated—locally and globally in the current or past pandemic scenarios—could be of great importance in formulating an effective policy for such situations. It can be used to train Machine Learning (ML) models like Regression or Neural Networks to access the current situation. Alternatively, an ML model could also be trained on the data generated by an agent-based model with all possible combinations of input parameters to predict the likely pandemic progression. As suggested in previous works, the ABM and ML can interface through the observations from the former being used as a training dataset for the latter, and also the results from the ML influencing the dynamics of the agents [20, 21].

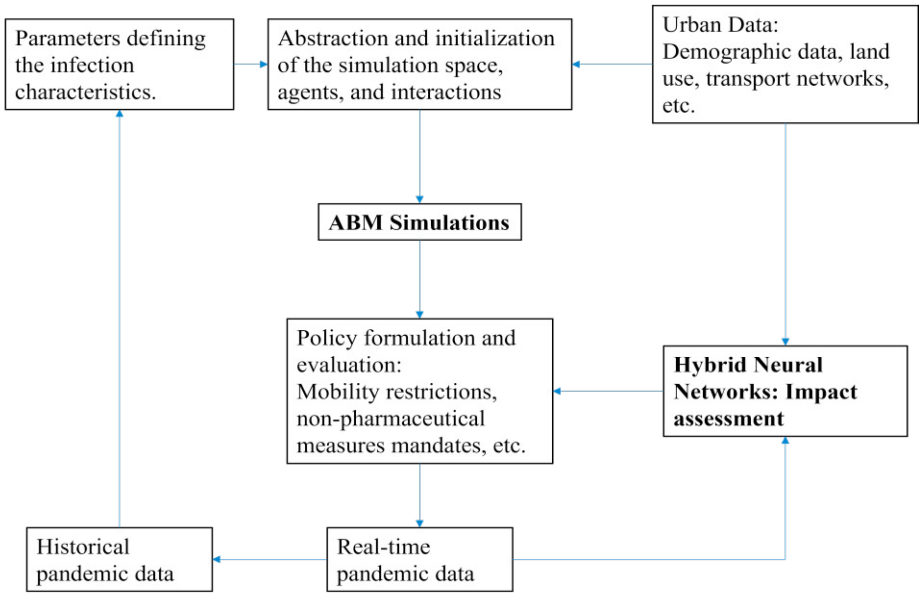

Fig. 4. The Proposed Framework

The framework proposed in this study is summarised in figure 4, which uses pandemic data (both historical and current) along with ABM and Hybrid Neural Network (HNN) as tools to estimate the impact and evaluate policy interventions. Here, an ABM is created based on two data streams: a) urban data such as population, demographics, mobility networks, and so on; b) historic pandemic data that can be used as a starting point for determining the transmission dynamics, and other epidemiological parameters (R_0 and likewise). This model will then simulate multiple likely scenarios based on which policies could be formulated and evaluated. The results obtained from the ABM simulations consist of the trend of the pandemic progression in a simulated urban space. This data describes the infectivity characteristics such as virus growth rate, time to peak, maximum infected population fraction, and so on. The output dataset for all simulated scenarios is spatiotemporal, i.e., it describes the progression of the infection for different spatial parameters in a region (i.e., the number of isolated regions, population mobility, and so on).

In a real-world scenario, the ABM can be utilised to simulate the spread of the infection in a simulated space representing the area in focus (such as a city or a district). The dynamics for such a case would follow the algorithmic structure like the one presented in section 3, post which several likely scenarios could be simulated using the model. This time-series data can then be used to train a hybrid model that utilises the feature-rich data and its time-series characteristics. The CNN-LSTM hybrid model could be one such candidate, the CNN layer in this network would be used to process the data matrix, which would then be converted into a vector for the input to the LSTM layer. The LSTM layer is especially beneficial here as it facilitates the storage and transmission of information from the past; this combined with a fully connected layer having ReLU activation, would provide the required output, as shown in fig. 5.

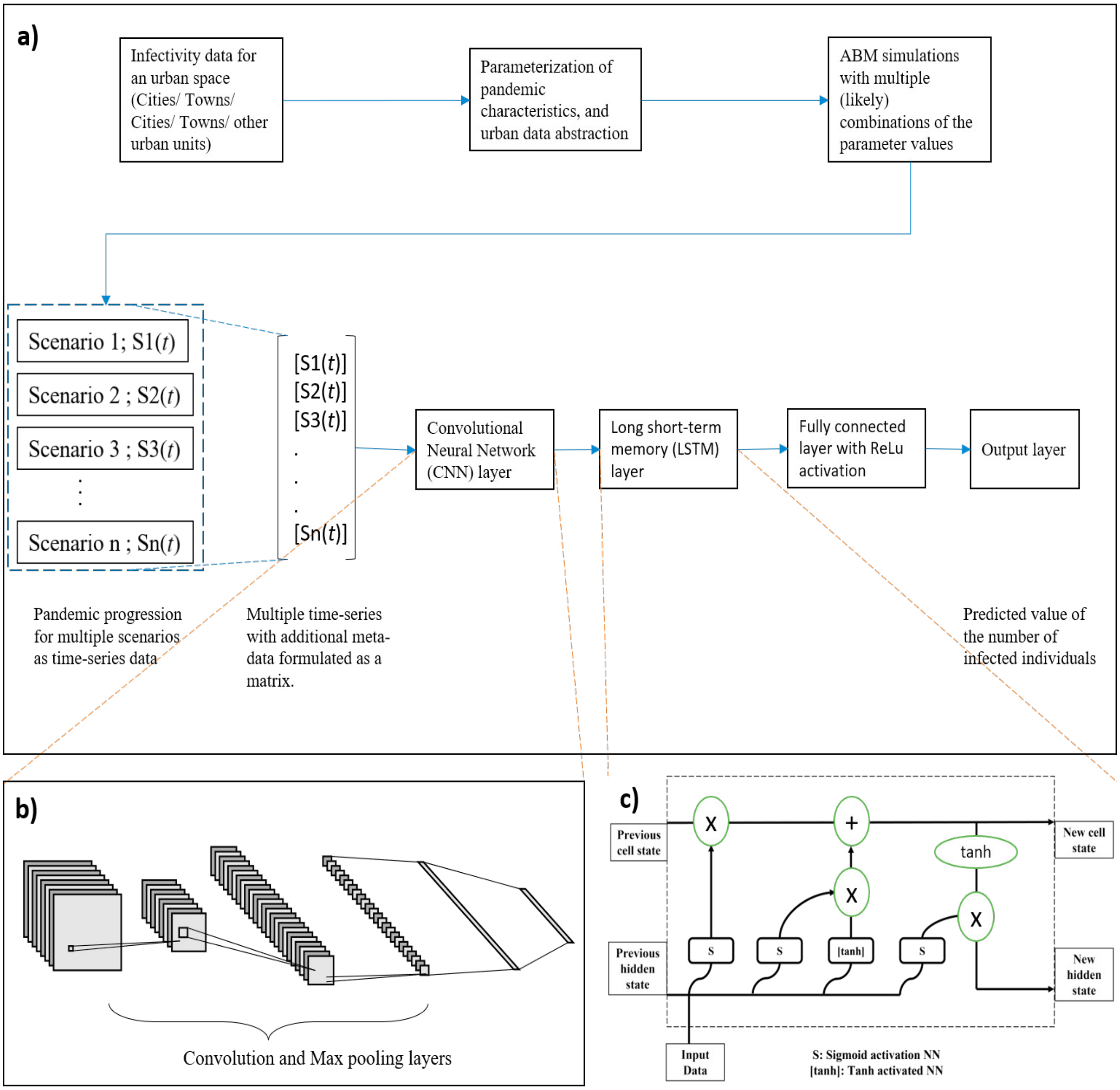

Fig. 5 a) Integration of ABM simulations and Hybrid CNN-LSTM NN, b) Convolution and max pooling layers in CNN, c) LSTM layer schematic.

5. Conclusion

This paper proposes a framework consisting of Agent-Based Modelling and a hybrid neural network for simulating the progression of a viral pandemic like COVID-19 in any given region. The ABM utilises the SIR model for simulating the spread of the infection. The baseline model was developed with several key parameters, which describe the epidemiological characteristics of the viral pandemic and the mobility of individuals in a region. The model also incorporates region segmentation and agent mobility restrictions using the concept of Voronoi partitions. Similar to Dimka et al. [18] and Kai et al. [19], this study utilises ABM to examine the dynamics of the pandemic and the impact of non-pharmaceutical interventions on the spread of infection. The result from the proposed model concludes that the agent's mobility in a closed population impacts the maximum number of infected individuals. Also, high mobility restrictions of agents coupled with multiple isolated regions could reduce the peak of the infected population in an urban area. This ABM framework integrated with HNN would eventually forecast the spatiotemporal probability of pandemic spread with the help of real-time data and geospatial location mapping. In the post-COVID era, this framework would further assist in developing pandemic-resilient urban spaces for smart, healthy, and sustainable cities by supporting the decision-making process of smart-city designers, urban planners, and policymakers.

References

[1] "What is a smart city? – definition and examples." https://www.twi-global.com/technical-knowledge/faqs/what-is-a-smart-city
[2] Kumar, Tarun, and Monto Mani. (2017) "An energy-neutrality based evaluation into the effectiveness of occupancy sensors in buildings: An integrated life-cycle study." Vol. II, PLEA Conference Proceedings: Design to Thrive. Edinburgh: PLEA.
[3] Kumar, Tarun, and Monto Mani. (2017) "Life cycle assessment (LCA) to assess energy neutrality in occupancy sensors." International Conference on Research into Design. Springer, Singapore. https://doi.org/10.1007/978-981-10-3521-0_9
[4] Kumar, Tarun, Ravi Srinivasan, and Monto Mani. (2022) "An Emergy-based Approach to Evaluate the Effectiveness of Integrating IoT-based Sensing Systems into Smart Buildings." Sustainable Energy Technologies and Assessments **52**: 102225. https://doi.org/10.1016/j.seta.2022.102225
[5] Yin, ChuanTao, Zhang Xiong, Hui Chen, JingYuan Wang, Daven Cooper, and Bertrand David. (2015) "A literature survey on smart cities." *Science China Information Sciences* **58(10)**: 1–18.
[6] Gade, Dipak S., and P. S. Aithal. (2021) "Smart Cities Development During and Post COVID-19 Pandemic–A Predictive Analysis." *International Journal of Management, Technology, and Social Sciences (IJMTS)* **6(1)**: 189–202.
[7] CDC. (2020) "People Who Are at Increased Risk for Severe Illness." Centers Dis. Control Prev. https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/people-at-increased-risk.html.
[8] CDC. (2019) "How to Protect Yourself & Others." Coronavirus Dis. 2019. para. 4. https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/prevention.html.
[9] WHO. (2020) "Novel Coronavirus." World Heal. Organ. 1–7. https://www.who.int/indonesia/news/novel-coronavirus/qa-for-public.
[10] WHO. (2020) "Q&A: How is COVID-19 transmitted?" Dep. Commun. WHO Glob. https://www.who.int/news-room/q-a-detail/q-a-how-is-covid-19-transmitted.
[11] Aschwanden, Christie. (2020) "How 'Superspreading' Events Drive Most COVID-19 Spread." Sci. Am. https://www.scientificamerican.com/article/how-superspreading-events-drive-most-covid-19-spread1/.
[12] BBC. (2020) "Coronavirus: Outbreak spreads in Europe from Italy." https://www.bbc.com/news/world-europe-51638095.
[13] Srinivasan, Chandrashekar. (2020) "30 Per Cent Of Coronavirus Cases Linked To Delhi Mosque Event: Government." www.ndtv.com//india-news/coronavirus-tablighi-jamaat-30-per-cent-of-coronavirus-cases-linked-to-delhi-mosque-event-government-2206163.
[14] Kermack, William Ogilvy, and Anderson G. McKendrick. (1927) "A contribution to the mathematical theory of epidemics." Proc. R. Soc. London 115: 700–721.
[15] Keeling, Matt J., and Pejman Rohani. (2011) "Modeling infectious diseases in humans and animals." Princeton University Press. https://doi.org/10.1016/s1473-3099(08)70147-6.
[16] Singh, Rajesh, and Ronojoy Adhikari. (2020) "Age-structured impact of social distancing on the COVID-19 epidemic in India." ArXiv Prepr. ArXiv2003.12055.
[17] Roche, Benjamin, John M. Drake, and Pejman Rohani. (2011) "An Agent-Based Model to study the epidemiological and evolutionary dynamics of Influenza viruses." BMC Bioinformatics **12**: 87.
[18] Dimka, Jessica, Carolyn Orbann, and Lisa Sattenspiel. (2014) "Applications of Agent-Based Modelling Techniques to Studies of Historical Epidemics: The 1918 Flu in Newfoundland and Labrador." J. Can. Hist. Assoc. La Société Hist. Du Canada **25**: 265–296.
[19] Kai, De, Guy-Philippe Goldstein, Alexey Morgunov, Vishal Nangalia, and Anna Rotkirch. (2020) "Universal masking is urgent in the covid-19 pandemic: Seir and agent based models, empirical validation, policy recommendations." ArXiv Prepr. ArXiv2004.13553.
[20] W. Rand. (2006) "Machine Learning Meets Agent-Based Modeling: When Not to Go to a Bar." Northwestern University, Evanston, IL, Mach. Learn.
[21] Johannes, Dahlke, and Bernd Ebersberger Kristina Bogner, Matthias Mueller, Thomas Berger, Andreas Pyka. (2015) "Is the Juice Worth the Squeeze?" Machine Learning in and for Agent-Based Modelling: 13–21.
[22] Zain, Zuhaira M, and Nazik M. Alturki (2021) "COvID-19 Pandemic Forecasting Using CNN-LSTM: A Hybrid Approach." Journal of Control Science and Engineering. https://doi.org/10.1155/2021/8785636
[23] Ketu, Shwet, and Pramod Kumar Mishra (2021) "India perspective: CNN-LSTM hybrid deep learning model-based COVID-19 prediction and current statues of medical resource availability." Soft Computing **26**: 645-664
[24] Figurska, Marta, Agnieszka Dawidowicz, and Elżbieta Zysk. (2022) "Voronoi Diagrams for Senior-Friendly Cities*." International Journal of Environmental Research and Public Health* **19(12)**: 7447.