Respond of Smart Cities to pandemic COVID-19

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ORIGINLITY STATEMENT

I, Mohammad Nawid Bayat, hereby attest that this submission is entirely my own original work and that, to the best of my knowledge, it does not include any writings that have been previously published or written by others. It also does not include a sizable portion of writings that have been authorized for the award of any other degree or diploma at Nazarbayev University or any other academic institution, with the exception of those that are properly acknowledged in the submission.

The thesis expressly acknowledges any contributions that people I've worked with at NU or elsewhere made to the study. I acknowledge any assistance with the project's idea, layout, or way, display, or linguistic expression from others, but I also note that the scientific content within this dissertation is all my own work.

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ABSTRACT

Over the past several years, smart cities have gained widespread recognition worldwide because they facilitate a better life for people and bring substantial changes in society; more specifically, smart cities impact the lives of citizens amid the pandemic COVID-19. The COVID-19 epidemic has affected many elements of life, including economics, education, healthcare, politics, and financial planning. However, case studies of 120 cities have been examined concerning their responses to pandemics, the pillars of smart cities, and the number of COVID cases. The study investigates how pandemic preparedness in smart cities could be improved by stopping the spread of the virus, finding treatment (vaccine), and remotely providing education and business continuity. Smart city solutions are desperately needed to deal with the multiple challenges of controlling the COVID-19 epidemic. One of the approaches is to forecast the spread of the virus and its effects on various areas of urban life using machine-learning models. We can test the effectiveness of different regression models in both scenarios using a dataset that contains relevant variables for the COVID-19 and smart city pillars. The prognostic accuracy of the Elastic Regression, Ridge Regression, Lasso Regression, Random Forest Regression, and MLP Regression models for the prediction of COVID-19 infection rates based on smart city characteristics will be assessed in this way. The Random Forest Model outperformed Ridge Regression after adjusting model parameters and hidden layers (R-squared score 0.88 and 0.85, respectively). The MAE and MSE scores obtained using the Random Forest Regression technique are 0.009692 and 0.000261, respectively. On the other hand, the unsupervised ML Elbow technique separates the COVID data into five groups. The Elbow technique results in different records for each cluster, with the first cluster [0] including the most countries (171), the second and third clusters each comprising one country, the fourth cluster containing six countries, and the last cluster containing three countries. It explains why the majority of nations have comparable COVID-affected data and comparable pandemic prevention strategies and measures. The World Health Organization found that when cities and people had easier access to smart city features, the number of cases and deaths in each city reduced, while the rate of recovery and immunization climbed dramatically. Due to the limited data available, the acquired results do not confirm that each smart city responds to pandemics in the same way.

Keywords: IoT, Smart Sustainable Cities, Smart Technologies, Social Distancing, Facial Mask, Machine Learning, Remotely employment and learning, COVID-19, Blockchain.

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-1.0 Introduction

Smart cities have become more well-known worldwide in scientific literature and policy circles over the last several decades, playing an increasingly important role in economic and social situations and significantly impacting the environment. Because of COVID-19, the globe is currently witnessing unprecedented conditions in human history, including a global health catastrophe and massive financial losses on a global scale. Beginning with just a few countries and regions, the disease has spread to more than two hundred countries and territories, with an estimated 20 million cases by 2020 [1]. The virus is extremely contagious and spreads between people through close contact.

Individuals infected with the virus exhibit various normal disease symptoms, including fever, weakness, coughing, shortness of breath, pneumonia, and loss of smell. When controlling and stopping the spread of COVID-19, the most significant problem is that residents do not adhere to the preventative measures recommended by the World Health Organization (WHO), such as social separation, handshaking, facial masks, and other criteria [3]. To identify and control this infectious disease, smart city elements (technology) such as video surveillance, sensors, and image processing will play an important role in recognizing and preventing it. A systematic literature assessment was conducted to review and extract pertinent publications on how smart cities might better adapt to the pandemic. After this virus's unanticipated spread, many problems have arisen that threaten to undermine modern civilization's underpinnings. When they have implemented travel restrictions and lockdowns, it is difficult for countries to ban physical human interaction, which is so natural to humans. Maintaining key services and guaranteeing a consistent supply of medications and medical equipment are becoming challenging to achieve and maintain. Many national and international organizations and individuals are eager to contribute funds to satisfy these demands. However, ensuring that funds are distributed efficiently and transparent to organizations and contributors are critical challenge [3]. Both internet giants and government regulatory groups find it difficult to detect and battle misinformation on a large scale. This is a problem that many of the countries affected by COVID-19 are dealing with, and fast action is required to address it [1]. To develop intelligent COVID-19 pandemic response strategies, The Internet of Things (IoT), Blockchain, robotics, unmanned drones (UAVs), 3D printing, nanotechnology, synthetic biology, 5G communications, cloud and edge computing, and big data are just a few examples of the technologies that can be used in the connection among each other. Specifically, the primary goal of this study is to determine the influence of smart cities on the pandemic COVID-19.

Concerning the five smartness pillars, 120 cities have been studied, with case studies conducted in each of the five areas: smart technology, smart environment, intelligent mobility, intelligent people, and intelligent governance.

The COVID-19 pandemic has recently made it necessary to find smart city solutions that can tackle the different difficulties posed by containing the virus's spread. Creating machine learning models that can forecast the disease's progress and possible effects on numerous facets of urban life is one way to accomplish this. The multi-layer perceptron (MLP) machine learning model is one example of such a model. In this post, we'll examine the MLP model and how it may be used to manage COVID-19 and data for smart cities. A multi-layer perceptron model: what is it? A sort of neural network called a multi-layer perceptron model is made up of many layers of interconnected nodes or neurons [4].

Each link between a layer's neurons and those in the layer above it has a weight associated with it. The MLP model is renowned for its capacity to learn intricate connections between input and output data by altering the connection weights. When the input data is labeled with the intended output in supervised learning tasks, the MLP model is frequently utilized. To reduce the discrepancy between the projected output and the actual output, the MLP model utilizes a backpropagation technique to modify the weights of the connections between neurons [5]. The MLP model is an effective machine learning technique that has been used with great success in several areas, including image recognition, audio recognition, natural language processing, and more.

Use of the MLP Model for COVID-19 and Smart City Data Management Many problems caused by the COVID-19 epidemic call for the use of smart city solutions. Predicting the virus's transmission in cities and its possible effects on numerous facets of urban life is one of these challenges. By examining COVID-19 and smart city data, the MLP model may be used to forecast the virus's progress and its effects on numerous facets of urban life. Using the MLP model to forecast the number of COVID-19 instances in a certain metropolitan region is one method to use to handle COVID-19 and smart city data.

To forecast the future spread of the virus, the MLP model may examine a variety of data variables, including the number of COVID-19 cases, hospitalization rates, mortality rates, and more. City officials can take the required action to limit the virus and stop it from spreading further by foreseeing the infection's progress. The analysis of COVID-19's effects on numerous facets of urban life, including transportation, education, and more, is another approach to putting the MLP model to use. COVID-19 might affect many areas of urban life, and the MLP model can assess a variety of data sources, including traffic patterns, the use of public transit, school attendance rates, and more [6].

City officials can take the required actions to lessen the consequences of COVID-19 by foreseeing its implications. The success of several COVID-19 containment strategies, including social isolation, wearing masks, and others, may also be evaluated using the MLP model. To evaluate the success of the measures, the MLP model may examine a variety of data points, such as the quantity of COVID-19 instances both before and after the measures were put into place. City officials can implement and modify measures to stop the spread of the virus by considering the efficiency of the current ones. These forecasts can be used by city officials to make the required preparations to control the infection and lessen its consequences. The MLP model is a useful instrument that may assist cities in addressing the issues brought on by the COVID-19 epidemic and ensuring the security and well-being of their citizens [4].

Furthermore, we propose our study in two ways: first, we will review smart technologies for finding medication (vaccines) and identifying social distancing, facial masks, handshaking, and other behaviors, and second, we will examine smart technologies for providing remote education and work.

- 2.0 Methodology

2.1 Research Method

The following research has been carried out as part of a systematic literature review, which has been carried out to obtain vital data through the analysis of scientific journals. The following essential research concerns have been carefully explored in the review of "Smart Cities Respond to Pandemic COVID-19," which has enabled the collection of cohesive material and articles:

RQ1: Do smart cities fare better in the face of the pandemic COVID-19, or do they fare worse?

RQ2-How can smart technologies be used to manage and reduce the spread of COVID-19?

RQ3: How might smart city features help cities respond more effectively to pandemics? (case studies)

This investigation looked at a lot of useful data and articles that were found using different search algorithms.

2.2 Reviewed stages

To make this study more accessible, we used four methods, which are depicted in the following Figure 2-1

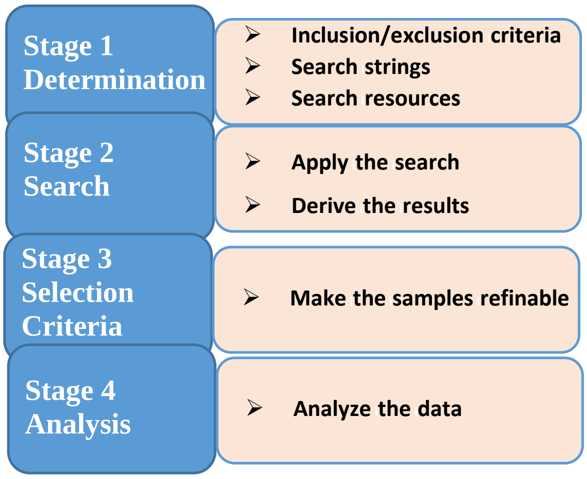

Figure 0-1 The literature review stages

2.3 Criteria for Insertion and Non-inclusion

This step in the research process makes sure that all of the articles and data that have been chosen are pertinent to the problem at hand. The survey includes all peer-reviewed academic publications as well as texts written only in English. Publications written in any other language are excluded from consideration. All of the data in this review were gathered from publicly available online and digital databases in the same manner. Because more than 75% of coherent papers were published in the last two years, publications published between 2017 and 2022 were examined (Table 1).

Table 0-1 Inclusion and non-inclusion requirements

added articles	**removed articles**
All articles are written in English	Russian and Spanish texts and articles
Qualitative research questions	Full text is not available
Relevant Keywords and Titles	Peer-reviewed books and literature that aren't peer-reviewed appropriately
Between 2017 and 2020, all published papers	Studies that lack detailed Information (related to the disadvantages of smart cities in Covid19, the solution to a pandemic, and cyberattacks on smart homes)

2.4 Sources and journals

The most consistent references to the study's issue have been found through various search sources inside scientific databases, which have been utilized. Web of Science, ASCE, Scopus, IEEE Xplore, and SpringerLink is the sources. More significantly, because they both connected to the idea of a smart city, Web of Science and IEEE Xplore were the most pertinent sources, making up more than 70% of all sources. At the same time, the other sites identified lacked peer-reviewed publications and relevant topics.

2.5 Strings for searching

A variety of keyword combinations relevant to the research topic were employed in the search string to gather the greatest number of relevant resources possible To focus the resources and extract the finest articles, the following search terms were used: AND, OR, and NOT. The words "Intelligent city," "Smart City," and "COVID-19 dissemination" are all synonymous. OR ("Smartness level of a city" AND "response of a smart city to a pandemic") OR ("Effect of COVID-19 on the smart home" AND "sustainability of buildings during a lockdown period") OR ("Measure the smartness of a city" AND "use of smart technologies to prevent COVID-19 diffusion" AND "Smart Transportation") OR ("Effect of COVID-19 on the smart home" AND "sustainability).

2.6 Criteria for selection

It was conducted on February 12, 2021, in digital databases and scientific journals for this particular search. In databases such as IEEEXplore and Web of Science, most repositories permitted searching for articles by author, title, abstract, and keywords, significantly impacting the retrieved articles. Still, the other repositories did not allow searching for articles by these criteria. In the second stage, 45 connected resources have already been identified as matching articles in the first stage of the research approach. The number of resources has expanded to 30 relevant articles after confirming their relationship to the inclusion and exclusion criteria later, in the second stage of the search strategy, after studying the full-text articles and assessing their relevance to the inclusion and exclusion criteria. However, 109 articles were excluded during the first stage of the exclusion selection because 35 publications were in the Russian language, 15 publications were in the Spanish language, and the remaining articles (2017–2020) were unrelated to the research question because their focus was on "Smart City in Normal Condition", "related to the cyber-security of smart cities," and "exclusion of pandemic COVID-19", and the articles were not available in full text because they were published in the Russian language Finally, a total of 30 papers have been chosen for publication. Table 2 lists the search strings used in databases and the articles that were filtered out.

Table 0-2 Results from several databases and stages of selection

Databases and sources	Search string	Search and Selection Criteria		
		Primary results	1st step selection	Final results
Web Of Science	Abstract and title	56	15	10
IEEEXplore	Document title	35	12	7
ASCE	Abstract and keywords	20	10	4
SpringerLink	Abstract	27	5	6
Scopus	Documents title	16	3	3
Total		**154**	**45**	**30**

2.7 Review of the findings

The data analysis on the particular study issues under consideration is made clear in this technology area. In the lists of reviewed results, it can be observed that all 30 evaluated publications offered adequate responses to the research questions 'Response of Smart City to COVID-19" and 'Effect of COVID-19 and the solution,' as other research issues. Because most of the publications were from 2019 to 2022, a thorough analysis of the primary dimension of the Smartness of cities, based on case studies of various cities, was completed. This investigation clarifies which pillars of Smartness are most significant in the fight against COVID-19. A further investigation into how each city prevents the spread of the virus and provides chances for education and business continuity through smart city characteristics has also been carried out.

Based on these findings, the structural relationships between Smartness pillars and COVID response cases can be created by assuming:

H1: smartness pillars impact the vaccination rate in all cities and provide better vaccination opportunities.

H2: COVID parameters can be impacted by Vaccination rates in terms of decreasing the number of cases and deaths and increasing recovery rates.

H3: Smartness pillars can influence COVID parameters indirectly by increasing immunization rates.

2.8 Proposed Model

Comparing the COVID-19 parameters to a city's smartness pillars will help you better understand how the multi-layer perceptron (MLP) model is used to handle COVID-19 and smart city data. This comparison can assist in locating the pertinent data points that the MLP model can examine to forecast the COVID-19 outbreak and its possible effects on many facets of urban life. The five key pillars of a city's smartness are smart technology, smart living, smart government, smart people, and smart environment. These pillars and the COVID-19 parameters are as follows: Smart Economy: The smart economy pillar is concerned with using technology and innovation to foster societal and economic advancement. Many factors, including the number of enterprises that have shut down, the unemployment rate, and the GDP growth rate, may be used to assess the economic impact of COVID-19. These variables may be analyzed using the MLP model to forecast the economic effects of COVID-19 on a city. City officials can take the appropriate actions to lessen the consequences by foreseeing the economic impact, such as giving impacted people and the company financial help [7]. Smart Mobility: The goal of the pillar of smart mobility is to enhance urban mobility and transportation by utilizing technology and innovation. In the context of COVID-19, several variables, including traffic patterns, the use of public transit, and pedestrian traffic, may be used to quantify people's mobility.

These variables may be examined using the MLP model to forecast the spread of COVID-19 in urban areas. City officials can execute the required precautions to limit the virus by foreseeing its spread, such as changing public transit schedules and enacting social isolation policies. Smart Environment: The goal of the pillar promoting a "smart environment" is to encourage environmentally conscious and sustainable urban behaviors. The COVID-19 pandemic's effects on the environment may be quantified using a variety of metrics, including waste generation, energy use, and the quality of the air and water. These variables may be examined by the MLP model to forecast how COVID-19 will affect the environment. By foreseeing the impact, local officials may take the appropriate actions to lessen its consequences, such as putting in place sustainable waste management procedures and encouraging the use of alternative energy sources. Smart People: The goal of the pillar of smart people is to employ technology and innovation to raise the standard of living and the general well-being of city dwellers. People's health and happiness may be evaluated concerning COVID-19 using a variety of metrics, including the incidence of the disease, hospitalization rates, and mortality rates. The COVID-19 outbreak and its possible effects on the health and well-being of city people may be predicted using the MLP model's analysis of these parameters [8].

City officials can take the required action to limit the infection and give the afflicted people the necessary medical treatment by foreseeing the impact. Smart Living: This pillar concentrates on utilizing technology and innovation to raise the standard of living and comfort of city dwellers. In the framework of COVID-19, some factors, including housing quality, access to essential services, and social support networks, may be used to assess peoples' quality of life. The MLP model can examine these variables and forecast how COVID-19 will affect city dwellers' quality of life. By foreseeing the effects, local authorities may take the required actions to help vulnerable groups and make sure that all citizens have access to essential services. Smart Governance: The smart governance pillar aims to increase the efficacy and efficiency of government services and decision-making by utilizing technology and innovation. The number of COVID-19 instances before and after the adoption of the measures as well as the population's compliance rate can be used to gauge the success of government actions in the context of COVID-19 [9].

The infrastructure and technology of smart cities can significantly help to lessen the effects of the COVID-19 pandemic. We will go into more detail about how smart city initiatives and technology may aid in the battle against COVID-19 in this part. Monitoring and limiting the virus's spread: Smart city technology can aid in tracking and limiting the virus's spread. For instance, sensors and Internet of Things (IoT) devices may count the number of people in public spaces, keep an eye on the air quality, and spot infection signs like a high body temperature. This information may be used to locate possible infection hotspots and take the required precautions to stop the pathogen's spread [10]. Moreover, social segregation policies may be enforced with the use of smart city technology.

AI-powered video analytics, for instance, may be used to keep an eye on public areas and notify authorities when social distance rules are not being observed. Smart traffic management systems may also be used to control traffic flow and lessen congestion in congested regions, lowering the danger of transmission. Enhancing Healthcare Services: Smart city technology can also enhance healthcare services and aid in more effectively combating the epidemic. To eliminate the need for people to physically visit healthcare facilities, telemedicine services, for instance, can be utilized to give remote healthcare consultations. This lowers the danger of transmission. Moreover, medical data may be analyzed to predict the possibility of a COVID-19 infection using AI and machine learning, which can aid in early identification and prompt response.

Also, the capacity of healthcare institutions may be increased by utilizing smart city technology. Data analytics, for instance, may be used to streamline the distribution of hospital resources and shorten wait times. Medical equipment and supplies may also be produced using 3D printing technology, which can assist with shortages and lower the risk of infection. Smart city technology can also aid in promoting distance employment and education. For instance, remote work and e-learning can be made possible by high-speed internet and digital infrastructure, which eliminates the need for individuals to travel long distances to work or school. By doing so, the danger of transmission can be decreased, and social isolation measures can be maintained. Smart city technology can also aid in organizing online meetings and activities. For instance, virtual conferences and exhibits may be held using augmented reality and virtual reality, allowing participants to take part in events without physically visiting them. Ensuring the availability of food and supplies: To ensure the availability of food and supplies during the pandemic, smart city technology can also be helpful. Systems for supply chain management, for instance, may be used to monitor the distribution and availability of necessities like food and medical supplies. This can aid in ensuring that supplies are given to people in need quickly and effectively. Smart city technology can also make it easier for individuals to buy and have their necessities delivered online, which can lessen the need for them to physically visit businesses and marketplaces and lower the danger of transmission [11].

Increasing Public Communication and Engagement: During the epidemic, smart city technology can potentially increase public communication and involvement. For instance, information regarding COVID-19 and status updates might be shared using digital communication channels. Social media channels may also be utilized to interact with the public and respond to their issues and questions. Smart city technology can also help with community support and involvement. Platforms for community participation, for instance, may be used to organize volunteer efforts and community-based projects like food distribution and healthcare [12]. Smart city infrastructure and technology can be extremely useful in reducing the effects of the COVID-19 pandemic.

Smart city projects can monitor and manage the spread of the virus, improve healthcare services, enable remote work and education, guarantee the availability of food and supplies, and improve public communication and involvement by utilizing cutting-edge technology and data analytics. So, in any pandemic, smart city projects ought to be a top priority.

2.9 Data Collection

A large-scale examination was carried out in 120 cities to gather Information on the COVID-19 features and smartness pillars. I used a variety of trustworthy pandemic databases and websites to obtain information on COVID-19-related characteristics such as the total number of cases, deaths, vaccination rates, and recovery rates across all cities. A lack of data on individual cities may be found in the WHO and Worldmeter databases [13],[14]. In this situation, I used the intersection formula to determine the records for each city based on its population and the entries from the COVID-19 database. I utilized Thailand's records to compute the COVID instances for Bangkok and then recalculated them using the city's population to show how this is done.

On the other hand, to calculate the smartness score of 105 cities, I took the [15] smart city index of 2021, which solely considered COVID-related factors and investigated five smartness pillars. Referring to Table 3, every variable has been considered for pandemic-related factors.

Table 0-3 Each latent variation and its factors.

Latent Variables	Factors
SM Smart Mobility	SM1: Car-sharing apps have helped to alleviate traffic congestion. SM2: Public transportation is adequate. SM3: Online ticketing and schedules have made public transportation more accessible.
ST Smart Technology	ST1: Internet speed and dependability currently fulfill connectivity requirements. ST2: Scheduling medical appointments over the internet has improved accessibility.
SP Smart People	SP1: Public safety is unaffected. SP2: Medical services are provided satisfactorily.
SG Smart Governance	SG1: Decisions made by local governments are easily available.

	SG2: Using the internet to process identification documents has cut wait times.
SE Smart Environment	SE1: Basic sanitation satisfies the demands of the most impoverished communities. SE2: Pollution of the air is not a problem. SE3: There are plenty of green spaces.

Table 0-4 List of the smart cities

	Cities	Total cases	total death	Total Recovered	total vaccinated	Smart Mobility	Smart Technology	Smart People	Smart Governance	Smart Environment
0	Abu Dhabi	0.09	0.00003	0.08	0.66	0.8	0.6	0.5	0.6	0.8
1	AMSTERDAM	0.38	0.00008	0.27	0.61	0.6	0.7	0.7	0.6	0.5
2	Ankara	0.17	0.00007	0.16	0.14	0.6	0.7	0.6	0.7	0.6
3	Athens	0.25	0.00078	0.23	0.22	0.4	0.6	0.4	0.5	0.4
4	Auckland	0.06	0.00001	0.02	0.50	0.4	0.7	0.5	0.6	0.7
...	...	...	...	...	...	...	...	...	...	...
100	Vienna	0.34	0.00036	0.30	0.38	0.6	0.4	0.8	0.6	0.7
101	Warsaw	0.15	0.00014	0.14	0.33	0.6	0.7	0.5	0.7	0.5
102	Washington D.C.	0.27	0.00004	0.19	0.14	0.6	0.7	0.5	0.6	0.6
103	Zaragoza	0.24	0.00003	0.22	1.27	0.6	0.8	0.7	0.6	0.7
104	Zurich	0.20	0.00001	0.16	1.85	0.7	0.7	0.8	0.6	0.7

105 rows × 10 columns

Because the data was labeled and the data analyzed concerning COVID parameters and five smartness pillars, we applied supervised machine learning for the data of 105 countries; as shown in Table 3, we had to use machine learning to ensure that each COVID parameter had a proper correlation with the smartness pillars.

2.10 Results from the findings

Yang's empirical findings demonstrate that smart city initiatives have significantly decreased the number of COVID-19 reported cases based on data from COVID-19 recorded occurrences and smart city project investment in China towns. More specifically, the frequency of COVID-19 cases per 10,000 people decreases by 0.342 for every million Yuan increase in smart city investment [16]. According to Yang et al. (2021), smart communities, smart governance, smart healthcare, and smart Information are smart technology's sub-pillars that are directly impacted by COVID pandemic prevention and control. By offering e-commerce services locally, smart community technologies like "zero-touch service," "high-efficiency identification," and other innovations support communities in gathering emergency data, managing floaters, and minimizing needless travel by residents during a pandemic. For instance, users of Wuhan's "micro-neighborhood" smart community platform may "self-examine and report pneumonia," which helps identify possible patients in the neighborhood and successfully reduces the spread of the disease. Cross-infection of the COVID-19 virus [17]. To prevent and control COVID-19, smart healthcare assists with patient selection, diagnosis, treatment effectiveness, and regional resource coordination. For instance, Henan Provincial People's Hospital uses the online network of connected smart healthcare facilities to offer the COVID-19 online consultation service. Patients can receive local and remote assistance from the program in other cities. Smart Government helps the Government improve its capacity for resource allocation, social management, governance, and emergency response by using an intelligent government affairs platform. For government decision-making, this dynamic real-time data is essential. More data will considerably improve the Government's ability to render accurate and precise reaction decisions. By enabling data exchange, especially for floating population and geographic location data, smart Information increases the effectiveness of pandemic prevention and control. Smart Information is connected to Smart Communities, Smart Governments, and Smart Healthcare in the three examples above [18].

2.11 Smart city initiative to face the pandemic

To better understand how smart cities react to COVID-19, it is important to understand their essential components. In the following subcategories, we've evaluated and analyzed the conceptual element of Smartness and the key pillars of a city's Smartness. Smartness is described as a process involving Information and communications technology (ICT) and other aspects used to increase innovative urban capability in conjunction with sustainable development measures [19].

A catastrophe is always lurking in every city. Fire may start anywhere and spread quickly, causing property damage and even death. Heavy rains can cause flooding, which can obliterate low-lying settlements. Additionally, extremely harmful in cities, and chemical gas leaks need urgent attention. Many crucial events are likely to occur in large cities, and several programs have been devised to deal with such disasters. Can future infectious disease epidemics, on the other hand, be treated as city emergencies [20]?

Information management is critical to avoiding or reducing the effects of this and future pandemics. While experts believe that timely diagnosis and proper sanitation are critical in the battle against illnesses, new digital players can also play a significant role. As a result, communities must be ready to detect new or current disease outbreaks promptly, analyzing sensitive data to allow for swift decisions. Data is just as vital as any other healthcare system, and municipal data is crucial.

According to the available literature on the issue, an emergency can be handled in three ways:

- Detection: Emergencies will be recognized by identifying a pattern that deviates from a city's expected "normal" activity. A significant spike in temperature in a specific place might signify a fire emergency. For example, identifying an emergency pattern in detecting an infectious disease epidemic can be done by evaluating the number of requests for medical help in a certain place or by studying social media for abnormal activity.
- Alerting system: Since an emergency has been detected, some notification protocol must be followed. The simplest alert method is sending out warning notices in emails, SMS messages, or television broadcasts. Sirens or light indicators might be employed in certain locations for more efficient alerting, such as detecting and warning about tsunamis. More detailed notifications, such as highlighting key locations to avoid, might be employed to prevent epidemics.
- Mitigation: identified and warned that emergencies must be addressed at some point. Concerning infectious illnesses, this might be a challenging task. While fire trucks will be sent if there is a fire, detected infected individuals and potential outbreaks typically require a series of actions such as public decontamination, prophylactic isolation, tracking of potentially infected residents, rerouting public transportation, as well as other indicators that must be effectively coordinated. Numerous resources should be used to lessen the effects of an infectious disease pandemic when it is discovered. To limit an outbreak and reduce the number of fatalities and new infections, cities will need to establish clear laws as quickly as feasible. [21].

The rapid global spread of the COVID-19 pandemic is an important caution that current resources would not be sufficient to handle such a horrific catastrophe. Cities must commit a significant amount of resources to this race against time. Global pandemic traits have demonstrated how quickly and badly they may change and infect people. As a result, a timely and equitable response is needed. As soon as an outbreak that can be treated as an urban emergency is identified, alerting and mitigation should begin. Although it can occasionally be challenging and time-consuming, it should ideally be coordinated for the most impact. But as mentioned in this section, several efforts may be employed to accomplish this goal [22]. As evidenced by research papers and practical advancements, different warning and mitigation measures exist for responding to a suspected outbreak. Among these options, i examined promising solutions and identified five essential procedures that should be followed when developing smart cities, which are outlined below:

1) When it comes to pandemic preparation, automated medical center systems are the most obvious option. It is, however, not the most straightforward. Hospitals should be managed to utilize the variety of data provided by a smart city to combat the early phases of an epidemic and, eventually, an uncontrolled pandemic [23]. The number of accessible hospital beds, medical personnel, and medication must be planned, utilizing statistical data or AI algorithms. The existence of a hospital in a location where an epidemic has been identified should be used to divert new patients who are not infected with that virus to other hospitals, preventing new infections and overtaxing the healthcare system while also drastically reducing mortality. Several quarantine orders were established in entire cities and countries to reduce the number of concurrent patients in critical condition during the COVID-19 epidemic. According to recent research, smart healthcare systems must be a significant component of future smart cities.

2) Intelligent transportation: how people move in big cities impacts disease transmission. As a result, smart mobility can aid in preventing or mitigating outbreaks [24]. Affected areas may be readily identified using data supplied by the city, limiting people's mobility in and out of the region. As witnessed in several large cities during the COVID-19 outbreak [23], the public transport system can show warning signs and directions on avoiding becoming infected. Other concepts may arise shortly as cities' computer crime integration levels improve. The ideal placement for such automated services necessitates a thorough understanding of the urban environment, which is only possible when smart cities are properly designed.

3) Response team: The city must act quickly as soon as an outbreak is detected. Critical measures that frequently include public health authorities, transportation agents, police, and even special reaction teams include public decontamination, prophylactic isolation, and the tracking of potentially ill individuals [24]. Different new technologies and development platforms may be crucial to this mitigation process in addition to more "conventional" action options. In China, at the COVID-19 epidemic's core, drones were instruments critical to guiding and alerting people about the prohibitions on isolation. Other uses for drones have included transporting supplies and using dangerous chemicals to sanitize particular regions. When people are assigned to clean potentially contaminated places, robots have been spotted cleaning public transportation in Hong Kong, lowering the danger of developing new diseases. The

automated contention service of the smart city macrocosm, which would dynamically assign mitigation services with incredibly low latency, may incorporate such activities.

4) R&D: As soon as a new disease is identified, the right pathogen and its DNA/RNA information should be identified, enabling clinical testing and research to enhance the treatment of afflicted individuals [25]. To save lives and maybe stop the disease's spread, researchers will work to develop novel treatments and vaccines. For example, weather, hygienic conditions, and population size details from a recently discovered epidemic can explain how to handle this particular virus. City cyberspace should provide all types of Information to scientific labs and universities, allowing for a better understanding of how the researched pathogen spreads under various conditions. Furthermore, scientific units should supply Information to city services, such as enabling timely warning of citizens and authorities on how to avoid contagious diseases.

5) Messages of alerting and notification: Individuals must be notified when an emergency is recognized. Although the content of the alert messages may differ based on the intended audience (residents, government officials, public agents, and healthcare workers), the most important feature is that they should reach as many people as possible. There may also be several implementation methods, ranging from broadcasting Information to personal cell phones to transmitting large-scale notifications on digital outdoor screens. In reality, the degree of intelligent automation among all players in a smart city will determine the likelihood of warning messages reaching the majority of residents [26].

2.12 Machine Learning methods for prediction

Smart city solutions are urgently required to solve the multiple challenges provided by controlling the COVID-19 outbreak. One of the approaches is to anticipate the spread of the virus and its consequences on many areas of urban life using machine learning algorithms. One example of such a model is the multi-layer perceptron (MLP) machine learning model. We will go into more detail about the MLP model in this article and how it may be used for COVID-19 and smart city data. A multi-layer perceptron (MLP) model is a kind of neural network with many layers of connected nodes or neurons. Each connection between neurons in one layer and those in the next carries a weight. The MLP model is recognized for its ability to comprehend complex relationships between input and output data by altering the connection weights. The MLP model is often used in supervised learning tasks, where the input data is labeled with the desired output. The MLP model modifies the weights of the connections between neurons using a backpropagation strategy to lessen the difference between the predicted and actual output [5].

Industry applications for robust machine learning algorithms, such as the MLP model, include image and audio recognition, natural language processing, and more. Using the MLP Model the COVID-19 outbreak has created some issues that need the deployment of smart city solutions. One of these issues is predicting the virus's spread in urban areas and its potential consequences on various aspects of urban life. The MLP model may be used to anticipate the spread of the virus and its consequences on many areas of urban life by looking at COVID-19 and smart city data. One way to manage COVID-19 with smart city data is to utilize the MLP model to predict the number of COVID-19 events in a certain metropolitan area. The MLP model may look at a range of data factors, including the number of COVID-19 cases, hospitalization rates, fatality rates, and more, to anticipate the virus's future spread [12]. By anticipating the progression of the illness, city authorities can take the necessary steps to contain the virus and prevent it from spreading further.

Another way to use the MLP model is to analyze how COVID-19 impacts many aspects of urban life, such as transportation, education, and more. The MLP model may evaluate a range of data sources, including traffic patterns, the usage of public transportation, school attendance rates, and more. COVID-19 may have an impact on many aspects of urban life. By anticipating the effects of COVID-19, city leaders may take the necessary steps to limit its effects. The MLP model may be used to assess the efficacy of various COVID-19 containment measures, such as social isolation, mask use, and others. The MLP model may look at a range of data points, such as the number of COVID-19 incidents before and after the measures were implemented, to assess the effectiveness of the measures [27]. By taking into consideration the effectiveness of the present ones, city authorities may create and alter measures to halt the virus's spread. Application of the MLP Model to COVID-19 Prediction: The MLP model is a powerful method for forecasting the spread of COVID-19 in urban environments. Before applying the MLP model for COVID-19 prediction, city officials must first gather and compile the relevant data. The statistics should contain data on the number of COVID-19 cases in the area, hospitalization rates, fatality rates, and more.

Industries are utilizing machine learning algorithms to make things easier to stay up to consumer expectations as the world becomes "smarter." They can be found in end-user devices (for example, facial recognition for unlocking cellphones) or credit card fraud detection (like triggering alerts for unusual purchases). Supervised and unsupervised learning are the two main methods used in artificial intelligence (AI) and machine learning. One uses labeled data to help in outcome prediction, while the other does not, which is the main difference. However, there are some key differences between the two approaches and places where one excels over the other [11].

Machine learning techniques like supervised learning employ labeled datasets. To enable computers to precisely identify data or anticipate events, these datasets are used to "train" or "supervise" the algorithms. Using labeled inputs and outputs will allow the model to evaluate its precision and improve over time. Classification and regression issues are the two categories into which supervised learning may be classified in data mining. An algorithm is used to classify test data into several groups in classification problems, such as telling apples from oranges. In the real world, on the other hand, supervised learning algorithms may be used to categorize spam and put it in a separate folder from your inbox. Linear classifiers, support vector machines, decision trees, and random forests are examples of classification techniques [28].

Table 0-5 Importing necessary libraries for our models

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.linear_model import Ridge, Lasso, ElasticNet
from sklearn.ensemble import RandomForestRegressor


# Read the data from the Excel file
df = pd.read_excel('Data.xlsx')


# Split the data into input and output
X = df[['Smart Mobility', 'Smart Technology', 'Smart People', 'Smart Governance']] # Inputs
y = df[['Total cases', 'Total death', 'Total recovered', 'Total vaccinated']] #Outputs
```

In Table 5, we show how our data was separated into input and output variables to better illustrate the impact that various smart city parameters have on output performance. Smart Mobility, Smart Technology, Smart People, and Smart Governance is the input data (x), and the result (y) is described as "Total Cases, Total Death, Total Recovered, Total Vaccinated." The MLP model is often used in supervised learning tasks, where the input data is labeled with the desired output. The MLP model modifies the weights of the connections between neurons using a backpropagation strategy to lessen the difference between the predicted and actual output [5].

Regression is a kind of supervised learning technique that uses an algorithm to determine the connection between dependent and independent variables. Regression models may be used to anticipate numbers from various data sources, such as a firm's projected sales income. The techniques well-liked are logistic, polynomial, and linear regression.

Elastic Regression: For creating predictions and identifying patterns in data, regression models are often employed in the fields of machine learning and statistical analysis. Traditional regression models, on the other hand, frequently experience overfitting or underfitting, which can result in worse performance on fresh data. By adding a penalty component to the regression goal function that strikes a compromise between the trade-off between model complexity and accuracy, elastic regression models provide a solution to this issue. Ridge and Lasso regression techniques are used to create the family of regression models known as elastic regression. The Lasso approach creates sparsity by setting certain coefficients to zero, whereas the Ridge method restricts the size of the coefficients by adding a penalty term to the regression objective function [29].

Elastic regression combines these two approaches by adding a penalty term that includes both the L1 and L2 norms of the coefficients. The resulting objective function is:

$$\text{Minimize } ||y - X\beta||^2 + \lambda 1||\beta||1 + \lambda 2||\beta||^2$$

Where y is the vector of target values, X is the matrix of input features, β is the vector of coefficients, and $\lambda 1$ and $\lambda 2$ are hyperparameters that control the strength of the L1 and L2 penalties, respectively.

By setting some coefficients to exactly zero, the L1 penalty term promotes sparsity in the model, which can aid in lowering overfitting and enhancing generalization capabilities. Smaller coefficients are encouraged by the L2 penalty term, which assists can minimize overfitting by minimizing the impact of noisy or irrelevant data. Many applications, such as feature selection, signal processing, and image processing, have demonstrated the effectiveness of elastic regression models. For instance, elastic net regression has been used to discover a limited sample of genes that were highly predictive of the course of cancer using feature selection in cancer diagnosis [30]. Elastic net regression has also been used for image denoising, where it was able to preserve edges while removing noise from images.

Elastic regression models have the benefit of being able to handle high-dimensional data, in which there are many more characteristics than samples. This is because the L1 penalty promotes model sparsity, which in turn conducts feature selection by setting some coefficients to zero. This can enhance the model's generalization capabilities and lower the computational cost of fitting the model. Elastic regression models also have the benefit of handling correlated data, which is a challenge for conventional regression models. This is so that feature grouping may be accomplished by punishing significant disparities between associated characteristics, which the L2 penalty does by encouraging lower coefficients. This may aid in lowering the model's variance and enhancing its stability [31]. In summary, elastic regression models provide a strong and adaptable method for doing regression analysis that can aid in lowering overfitting and enhancing generalization performance. Elastic regression, which combines the advantages of the Ridge and Lasso techniques, can handle highly dimensional and correlated data, making it a useful tool for many machine learning and statistical analysis applications. Two regularization methods—Ridge and Lasso Regression—were developed to overcome this problem. By punishing high coefficients, both of these methods work to prevent overfitting by making the model choose only the most crucial variables. In this post, we will examine the guiding concepts of Ridge and Lasso Regression, as well as their variations and practical applications.

Ridge Regression: The least-squares goal function in the Ridge Regression model has a penalty term added. The coefficient vector's L2 norm times a regularization parameter equals the penalty term. The coefficients are shrunk by this phrase, although they never reach zero precisely. The objective function for Ridge Regression can be written as:

minimize $||y - X\beta||^2 + \lambda||\beta||^2$

where y is the dependent variable, X is the matrix of independent variables, β is the vector of coefficients, and λ is the regularization parameter. The penalty term's severity is determined by the parameter. A greater value leads to simpler models and lower coefficients, but it may also increase bias. On the other side, a smaller value permits more complicated models and larger coefficients, but may also lead to overfitting. Ridge Regression can manage multicollinearity, which is a scenario in which two or more independent variables are strongly associated. Under these circumstances, the least-squares estimate of the coefficients may have significant variances, which may negatively impact the model's performance. By constricting the coefficients toward one another, the Ridge Regression lowers the variance of the coefficients [32].

Lasso Regression: Ridge Regression and Lasso Regression are comparable in that both extend the least-squares objective function with a penalty term. Lasso Regression, on the other hand, substitutes the L1 norm of the coefficient vector for the L2 norm as the penalty term.

The objective function for Lasso Regression can be written as:

minimize $||y - X\beta||^2 + \lambda||\beta||$

where y, X, β, and λ have the same meanings as in Ridge Regression.

The L1 norm has the effect of conducting variable selection by decreasing some coefficients to exactly zero. As a result, Lasso Regression may be used to discover and remove pointless variables from a model, allowing for feature selection. Lasso Regression tends to choose only a subset of the variables, hence it may not perform well when there are numerous variables with modest effects.

Ridge vs. Lasso Regression: The employed penalty term is the primary distinction between Ridge and Lasso Regression. The L2 norm is used in Ridge Regression, which causes the coefficients to decrease but never reach zero. Lasso Regression employs the L1 norm, which can zero out certain coefficients and conduct variable selection. When there are numerous correlated variables, Ridge Regression typically outperforms Lasso Regression in terms of performance since it can manage multicollinearity. On the other hand, because it can do variable selection, Lasso Regression could work better when there are a lot of irrelevant variables.

Random Forest Regression: A non-linear regression model called random forest regression makes predictions by combining several decision trees. As it can capture non-linear interactions between the features, random forest regression is appropriate for datasets with complicated correlations between the variables.

A well-liked machine learning approach called Random Forest Regression is utilized for both classification and regression problems. It is an ensemble learning technique that builds several decision trees and combines them to produce precise forecasts. The algorithm has a reputation for being very accurate, resilient, and capable of handling huge datasets with multidimensional characteristics. Random Forest Regression Model's operation The construction of several decision trees and the mixing of their outputs form the basis of the Random Forest Regression model. A random subset of the characteristics is chosen, and a random subset of the data is used to train each decision tree in the forest. The final forecast is then created by combining the trees [33].

The average of all the forest's trees' projections is used to generate the final prediction. Bagging (also known as bootstrap aggregating) is a method used by the Random Forest Regression algorithm to build the decision trees. While bagging, each decision tree is trained using a different subset of the data that is randomly chosen from the data. This aids in lowering overfitting and improving model accuracy. For each decision tree, the algorithm additionally chooses a random subset of features using a method known as the random subspace approach. This increases the diversity of the forest and lessens the link between the trees.

Random Forest Regression Model Benefits High Accuracy: Random Forest Regression has a reputation for being quite accurate at forecasting values for continuous variables. Moreover, it can withstand noisy data and outliers. Big Dataset Support: The technique is capable of handling high-dimensional, huge datasets without overfitting or underfitting. Scores for feature significance are provided by the method, which can aid in feature selection and dimensionality reduction. The approach is parallelizable, which may be used to accelerate training on huge datasets. The method can overfit small datasets with noisy data, which is one of its limitations. Random Forest Regression Model Overfitting: It is advised to employ cross-validation and adjust the model's hyperparameters to get around this. Computationally Expensive: The algorithm may be sluggish to train on big datasets and computationally costly. Nevertheless, by parallelizing the method, this can be reduced. Black Box Model: Because the algorithm is a black box model, it is challenging to decipher and comprehend how it generates predictions [33].

Table 0-6 Splitting the data into Training and Testing sets

```
# MLP can handle seperately input and output, but when trying to cope several at the same time model diverges

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)
print("Training data")
print(X_train, y_train)
print()
print("Testing data")
print(X_test, y_test)
# I checked for every possible combinations of hidden layers to come up with suggestions in param_grid section
"""
for a in range(1,100):
  for b in range(1,100):
    for c in range(1,100):"""

mlp = MLPRegressor(hidden_layer_sizes=(1,1), activation='relu', solver='adam', alpha=0.0001, learning_rate='adaptive', max_iter=1000)

# Use k-fold cross validation to find the best hyperparameters
param_grid = {'hidden_layer_sizes': [(3, 1), (4, 1), (8, 4)],
              'activation': ['identity', 'logistic', 'tanh', 'relu'],
              'solver': ['lbfgs', 'adam', 'sgd'],
              'max_iter': [500, 1000, 2000]}
```

```
grid_search = GridSearchCV(mlp, param_grid, cv=5, n_jobs=-1)
grid_search.fit(X_train, y_train)
print("Best parameters: ", grid_search.best_params_)

# Use the best hyperparameters to train the model
bestMLP = MLPRegressor(hidden_layer_sizes=grid_search.best_params_['hidden_layer_sizes'],
                   activation=grid_search.best_params_['activation'],
                   solver=grid_search.best_params_['solver'],
                   max_iter=grid_search.best_params_['max_iter'])
bestMLP.fit(X_train, y_train)

# Make predictions on test set
y_pred = bestMLP.predict(X_test)

# Evaluate model performance
r2_scores = cross_val_score(bestMLP, X_train, y_train, cv=5, scoring='r2')
mae_scores = cross_val_score(bestMLP, X_train, y_train, cv=5, scoring='neg_mean_absolute_error')
mse_scores = cross_val_score(bestMLP, X_train, y_train, cv=5, scoring='neg_mean_squared_error')
print("R-squared score: {:.6f} (+/- {:.6f})".format(np.mean(r2_scores), np.std(r2_scores)))
print("Mean absolute error: {:.6f} (+/- {:.6f})".format(-np.mean(mae_scores), np.std(mae_scores)))
print("Mean squared error: {:.6f} (+/- {:.6f})".format(-np.mean(mse_scores), np.std(mse_scores)))
```

Here, you'll see a breakdown of how we randomly selected 50% of the dataset for training and 25% of it for testing. Table 6 demonstrates how K-fold cross-validation was utilized to determine the optimal hyperparameters and optimum hidden layer for the mlp model. Below in table 7, we can see the list of training and testing data, as well as the optimal hyperparameters for our MLP model, which I have determined by checking every possible combination of hidden layers in the param grid section. Later, GridSearchCV to find the best parameters for training our model

K-fold cross-validation is a method for determining the optimal hyperparameter settings for a machine learning model. The dataset is divided into K "folds" of equal size in K-fold cross-validation. Then, the model is trained K times, with the first K folds serving as the training set and the remaining K-1 folds serving as the validation set. Throughout K iterations, the model's performance is measured against the validation set, and the average of the results is then used. This aids in lowering the potential for bias that might arise if the model is only tested using a single validation set [34]. Model performance may be influenced by hyperparameters, which are variables set before training begins. The hyperparameters might be the learning rate, regularization intensity, and the number of hidden layers. In this example, K-fold cross-validation was used to test out various hyperparameter settings to find the optimal one for the task at hand. Therefore, when we talk about the "best-hidden layer for mlp model," we're talking about the optimum number of hidden layers for an MLP model. Most MLP neural networks have several hidden layers between the input and output layers. Using methods like K-fold cross-validation, the ideal number of hidden layers may be found based on the difficulty of the issue being addressed [35].

If you're looking to fine-tune your machine learning model's hyperparameters, go no further than the "GridSearchCV" function in Python's sci-kit-learn module. The number of hidden layers in a neural network or the learning rate for gradient descent are examples of hyperparameters that must be established before training can begin. GridSearchCV takes a grid of hyperparameters as input and uses cross-validation to thoroughly test every conceivable combination of those hyperparameters. This method involves training the model using a variety of hyperparameter settings on a small portion of the training data and then assessing its efficacy using the remaining, validation-specific data. This allows "GridSearchCV" to discover the optimal values for each hyperparameter to maximize a target measure like precision or RMSE. When you hear someone say, "I used GridSearchCV to search through a grid of hyperparameters to discover the optimum hyperparameters and best-hidden layer for the mlp model," what they really mean is that they used the function to optimize a neural network model known as a Multi-Layer Perceptron (MLP). The objective was to maximize performance on the provided dataset by determining the ideal set of hyperparameters, which included the number of hidden layers [36].

Table 0-7 Training and Testing data, best parameters for the trained data

Training data

	Smart Mobility	Smart Technology	Smart People	Smart Governance
42	0.6	0.80	0.73	0.76
40	0.6	0.89	0.76	0.79
9	0.7	0.94	0.88	0.85
85	0.4	0.58	0.47	0.54
11	0.4	0.62	0.47	0.54
..	...	...	...	...
71	0.5	0.71	0.66	0.66
14	0.5	0.76	0.66	0.66
92	0.5	0.76	0.66	0.66
51	0.6	0.85	0.73	0.79
102	0.6	0.85	0.73	0.76

[78 rows x 4 columns] Total cases Total death Total recovered Total vaccinated

42	0.206667	0.000098	0.246667	0.75
40	0.193333	0.000108	0.243333	0.75
9	0.246667	0.000115	0.300000	0.89
85	0.140000	0.000076	0.163333	0.51
11	0.140000	0.000087	0.160000	0.52
..	...	...	...	...
71	0.190000	0.000087	0.230000	0.71
14	0.183333	0.000135	0.226667	0.63
92	0.173333	0.000093	0.223333	0.63
51	0.213333	0.000105	0.250000	0.75
102	0.216667	0.000103	0.250000	0.73

[78 rows x 4 columns]

Testing data

	Smart Mobility	Smart Technology	Smart People	Smart Governance
30	0.6	0.85	0.82	0.79
65	0.7	0.94	0.85	0.88
64	0.5	0.71	0.66	0.66
53	0.6	0.85	0.76	0.76
45	0.5	0.67	0.60	0.63
94	0.6	0.85	0.82	0.79
104	0.7	0.94	0.91	0.85
47	0.5	0.76	0.63	0.66
10	0.5	0.71	0.63	0.63
0	0.8	0.98	0.92	0.76
18	0.4	0.67	0.50	0.54
31	0.5	0.71	0.63	0.63
89	0.5	0.71	0.60	0.63
96	0.6	0.85	0.79	0.76
77	0.6	0.85	0.79	0.76
4	0.4	0.67	0.54	0.57
80	0.7	0.98	0.88	0.91
33	0.6	0.80	0.79	0.73
12	0.6	0.85	0.76	0.79
26	0.5	0.71	0.69	0.66
99	0.5	0.58	0.66	0.66
55	0.5	0.71	0.63	0.66

22	0.6	0.80	0.69	0.76
76	0.5	0.71	0.63	0.66
44	0.6	0.85	0.69	0.79
72	0.5	0.67	0.66	0.63
15	0.4	0.67	0.54	0.57

	Total cases	Total death	Total recovered	Total vaccinated
30	0.226667	0.000103	0.290000	0.87
65	0.233333	0.000119	0.280000	0.84
64	0.166667	0.000088	0.216667	0.63
53	0.213333	0.000106	0.263333	0.73
45	0.160000	0.000082	0.190000	0.60
94	0.230000	0.000115	0.293333	0.80
104	0.243333	0.000113	0.303333	0.87
47	0.183333	0.000093	0.220000	0.66
10	0.190000	0.000087	0.226667	0.62
0	0.263333	0.000120	0.300000	0.74
18	0.143333	0.000088	0.173333	0.52
31	0.186667	0.000091	0.220000	0.64
89	0.173333	0.000105	0.203333	0.61
96	0.233333	0.000105	0.283333	0.75
77	0.226667	0.000112	0.283333	0.74
4	0.133333	0.000082	0.173333	0.56
80	0.223333	0.000120	0.280000	0.87
33	0.210000	0.000097	0.266667	0.71
12	0.213333	0.000103	0.260000	0.82
26	0.183333	0.000106	0.236667	0.64
99	0.166667	0.000071	0.216667	0.64
55	0.190000	0.000087	0.223333	0.67
22	0.190000	0.000098	0.220000	0.72
76	0.183333	0.000087	0.216667	0.63
44	0.200000	0.000106	0.226667	0.75
72	0.163333	0.000082	0.213333	0.60
15	0.156667	0.000087	0.196667	0.58

Best parameters: {'activation': 'relu', 'hidden_layer_sizes': (4, 1), 'max_iter': 1000, 'solver': 'lbfgs'}

Mean absolute error: 0.031411 (+/- 0.011899)

Mean squared error: 0.001576 (+/- 0.001262)

The optimum hidden layer size for the MLP model was found to be (4,1) after using the

"GridSearchCV" function from the scikit-learn package in Python, with an MAE and MSE that were both within a tolerable range of 0.001-0.031.

2.13 Correlation measure

Correlation is a statistical measure that expresses the degree to which two variables are related. Positive and negative correlations are the two basic forms of correlation. Positive correlation develops when two variables move in the same direction; if one rises, the other follows suit. For instance, there is a correlation between the quantity of study time and test results. A negative correlation happens when two variables move in opposite directions; when one rises, the other falls. For instance, smoking has a detrimental effect on life expectancy. Correlation can be used to evaluate hypotheses about variable cause-and-effect relationships. In the actual world, correlation is frequently utilized to forecast trends [37].

A statistical concept called correlation assesses how closely two variables are related. Understanding the relationship between various features and the goal variable in machine learning is mostly dependent on correlation. Machine learning algorithms can recognize patterns in data and produce precise predictions with the aid of correlation. In this post, we'll talk about the value of correlation in machine learning and how it can help the algorithms work more effectively. Correlation's Significance in Machine Learning Correlation is significant in machine learning since it aids in determining the relationship between various variables in the dataset. Finding patterns in the data and using them to generate predictions is the aim of a machine learning program.

The correlation makes it easier to distinguish between features that are critical for making reliable predictions and those that are not. The algorithm can concentrate on these features and become more accurate by determining the key features. Take, for instance, a dataset that details the cost of a property together with details about its size, location, number of bedrooms, and age. We can determine which features have the most influence on price by looking at the correlation between the price of the house and each feature. We can infer that a house's size is a crucial factor in determining how much it will cost if we discover a substantial positive association between the two [33].

The crucial machine-learning process of feature selection can also be aided by correlation. The process of selecting the most pertinent characteristics from a dataset to enhance the algorithm's performance is known as feature selection. We can determine which features are most important and choose them for the model by looking at the correlation between various attributes and the target variable. Several Correlations Positive correlation, negative correlation, and zero correlation are the three forms of correlation used in machine learning. When two variables are positively correlated, it means that if one increases, the other increases as well. When two variables are negatively correlated, one rises while the other falls. There is no association between the two variables if there is zero correlation. We can examine the link between height and weight in a dataset of people's heights and weights, for instance. If we discover a positive correlation between height and weight, it suggests that as a person's height rises, so does their weight. A negative connection between height and weight indicates that as an individual's height rises, so does their weight. If there is no correlation between height and weight, then follows that there is none. Relationship Matrix A table that displays the correlation between various variables in a dataset is called a correlation matrix. A correlation matrix is used in machine learning to examine the relationship between characteristics and the target variable [34].

We can determine which characteristics are most crucial for forecasting the target variable by looking at the correlation matrix. Consider a dataset, for instance, that details a product's sales as well as its attributes, such as cost, marketing, and user feedback. We can determine which elements are most crucial for forecasting the product's sales by looking at the correlation matrix. If we discover that there is a significant positive correlation between sales and advertising, we can conclude that this attribute is crucial for forecasting sales.

Table 0-8 Total case parameter's relationship with smartness pillars

	Total Recovered	total vaccinated	Smart Mobility	Smart Technology	Smart People	Smart Governance	Smart Environment
0	0.08	0.66	0.8	0.6	0.5	0.6	0.8
1	0.27	0.61	0.6	0.7	0.7	0.6	0.5
2	0.16	0.14	0.6	0.7	0.6	0.7	0.6
3	0.23	0.22	0.4	0.6	0.4	0.5	0.4
4	0.02	0.50	0.4	0.7	0.5	0.6	0.7
...	...	...	...	...	...	...	...
100	0.30	0.38	0.6	0.4	0.8	0.6	0.7
101	0.14	0.33	0.6	0.7	0.5	0.7	0.5
102	0.19	0.14	0.6	0.7	0.5	0.6	0.6
103	0.22	1.27	0.6	0.8	0.7	0.6	0.7
104	0.16	1.85	0.7	0.7	0.8	0.6	0.7

Mean Absolute Error (MAE) and **Mean Squared Error (MSE)** are two typical metrics used in machine learning modeling to assess a prediction model's accuracy. These metrics are used to quantify the discrepancy between actual and anticipated values. The average absolute difference between the expected and actual values is measured by the mean absolute error (MAE). It is derived by averaging the absolute disparities between the values that were anticipated and those that occurred [35].

The MAE equation is: MAE = [yi - xi] * (1/n)

When n is the number of data points, xi is the actual value, and yi is the forecasted value. The average squared difference between the expected and actual values is measured by the Mean Squared Error (MSE), however. The average of the squared discrepancies between the projected values and the actual values is used to compute it.

The MSE equation is: MSE = (yi - xi) * (1/n)

When n is the number of data points, xi is the actual value, and yi is the forecasted value. When attempting to forecast a continuous variable using regression analysis, MAE and MSE are often utilized. Both MAE and MSE are measurements of the model's correctness, although they each have unique characteristics. Because MSE lends greater weight to big mistakes, MAE is more resistant to outliers. Consequently, the unique situation at hand and the analysis's objectives will determine which of the two metrics is used. To assess the efficacy of a prediction model using machine learning, MAE and MSE are crucial measures. These metrics quantify the discrepancy between expected and observed values and may point out areas where the model needs to be improved [36].

2.14 Unsupervised machine learning

The second project involved analyzing and clustering unlabeled data sets using unsupervised machine-learning techniques. This study aimed to classify COVID data from entire countries based on how similar or comparable their results were.

Without the aid of humans, these algorithms uncover hidden patterns in data (thus the term "unsupervised"). [38] Unsupervised learning models are used for various applications, including clustering, association, and dimensionality reduction. Unlabeled data is categorized into categories using the data mining approach of clustering based on similarities and differences. For instance, K-means clustering algorithms bring together similar data points, with the K number representing the size and accuracy of the grouping. Applications of this technique include picture downsizing and market segmentation.

The association is a different kind of unsupervised learning technique that uses several rules to identify relationships between variables in a dataset. These methods are frequently used in recommendation engines and market basket analysis, such as "People Who Purchased This Item Also Purchased" recommendations [39].

Dimensionality reduction is a learning strategy used when there are too many characteristics (or dimensions) in a dataset. While lowering the number of data inputs to a tolerable level, maintains data integrity. When auto encoders remove noise from visual data to enhance picture quality, this approach is widely used in the data pretreatment step [39].

Table 0-9 COVID data of all countries from 2022/05/22

1.1 Introduction

[4]:
```
import pandas as pd
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

Data= pd.read_excel('COVID-DATA.xlsx')
Data
```

[4]:
```
    iso_code continent           location       date  total_cases  new_cases  \
0        AFG      Asia        Afghanistan 2022-05-22       179716       42.0
1   OWID_AFR       NaN             Africa 2022-05-22     11841251     7948.0
2        ALB    Europe            Albania 2022-05-22       275864       26.0
3        DZA    Africa            Algeria 2022-05-22       265854        3.0
4        AND    Europe            Andorra 2022-05-22        42572        NaN
..       ...       ...                ...        ...          ...        ...
224      WLF   Oceania  Wallis and Futuna 2022-05-22          454        0.0
225 OWID_WRL       NaN              World 2022-05-22    525609637   337784.0
226      YEM      Asia              Yemen 2022-05-22        11819        0.0
227      ZMB    Africa             Zambia 2022-05-22       321146       47.0
228      ZWE    Africa           Zimbabwe 2022-05-22       250642      173.0

    new_cases_smoothed  total_deaths  new_deaths  new_deaths_smoothed  ...  \
0               64.143        7698.0         1.0                1.143  ...
1             7303.857      253730.0        11.0               41.000  ...
2               35.571        3497.0         0.0                0.000  ...
3                5.143        6875.0         0.0                0.000  ...
4                  NaN         153.0         0.0                0.000  ...
..                 ...           ...         ...                  ...  ...
224              0.000           7.0         0.0                0.000  ...
225         548209.714     6277241.0       640.0             1668.286  ...
226              0.000        2149.0         0.0                0.000  ...
227             74.143        3985.0         1.0                0.286  ...
```

Table 0-10 Standardization of the data and considering the relevant factors

1.2.1 Standardization

```
[176]: from sklearn.preprocessing import StandardScaler

       Sample = Data.iloc[:,[4,5, 7, 8]]
       Sample = Sample.dropna()
       print(Sample)


       scaler = StandardScaler()
       df_scaled = scaler.fit(Sample)
       df_scaled = scaler.transform(Sample)
       df_scaled
```

```
     total_cases  new_cases  total_deaths  new_deaths
0         179716       42.0        7698.0         1.0
1       11841251     7948.0      253730.0        11.0
2         275864       26.0        3497.0         0.0
3         265854        3.0        6875.0         0.0
5          99287        0.0        1900.0         0.0
..           ...        ...           ...         ...
224          454        0.0           7.0         0.0
225    525609637   337784.0     6277241.0       640.0
```

After standardizing the data, only related columns (number of cases, deaths, recoveries and vaccinations) have been considered while running the algorithm.

Unsupervised clustering is achieved using the K-means method. We aren't interested in making predictions in an unsupervised method because we don't have a target/output variable. The goal is to find intriguing patterns in the data, such as if the bank's clients are divided into subgroups or 'clusters.' Utilizing raw data, clustering algorithms divide up the data into groups based on shared traits. Customer segmentation for targeted marketing is one of the clustering algorithm's most crucial applications [40].

-3.0 Results and findings

3.1 Smartness of a city's pillars and dimensions, objective and subjective Smartness

According to the majority of previous literature on smart cities can be divided into four cores: social improvement (including poverty alleviation), financial improvement (including economic development), environmental administration (including pollution control), and urban administration (including planning and development). Smart cities can also be measured in various ways, including smart individuals, smart economies, smart portability, intelligent environments, intelligent administration, and smart living [1, 3]. In this study, the Smartness of the smart city is assessed from two different perspectives: the objective and subjective perspectives. Both of these areas are critical when determining the smartness level of SCs.

Objective Smartness is related to the well-being of the people and is achieved through multi-dimensional urban efficiency that contributes to sustainable urban enhancement. It is also ensured by providing services tailored to individuals' feasible requirements and providing appropriate livelihood conditions.

On the other hand, subjective Smartness is associated with the well-being achieved through opportunities to empower individuals to act as change agents and be a component of the urban effectiveness achievement that they are worth, thereby enabling them to construct a life in which they want to live [41]. Therefore, the decision-making process for sustainable smart city solutions will benefit from increased participation at all levels of participation. To find answers to problems, people must contribute to them, and in the final scene, they are forced to make the final decision—the impact on people increases in direct proportion to their level of engagement [2]. Later on, case studies of two cities were explored in different models and cases, and the results were published. Yin-Leng Theng (2016) proposed the development of an index called the Smart City Record for Analytics (SMCIA) to quantify the degree of Smartness in urban areas across six domain zones. In key Chinese cities, he undertook a pilot test of the SM-CIA [42]. From 2008 to 2012, freely available Information was gathered. Time-trend research was carried out to differentiate changes in the cities in different smart city domains throughout that period. There has been a notable expansion of the trend in the realms of smart living, transportation, the economy, and Government. A cross-sectional inquiry was carried out to determine the points awarded for smart residencies, individuals, mobility, economy, and administration. The points for each of the 32 cities are listed in detail; Xiamen is ranked first, followed by Shenzhen, Shanghai, Beijing, and Guangzhou, in that order. Following Shanghai in terms of smart living space, Beijing and Chongqing received the highest scores in smart living space. According to the domain scores of the clever individual, the best three cities were Hefei, Haikou, and Nanchang 43].

3.1.1 Smart City solutions and facilitation during the pandemic

Smart city features and technologies noticeably contribute to finding solutions to control and minimize the further spread of the virus and provide long-term opportunities to accelerate city operations and accessibility of business and education continuity.

The main eight categories that smart cities actively contribute during a pandemic are summarized in Table 11. Smart platforms collaborate with various departments of each city and enable real-time understanding of urban dynamics fluctuation and improvement of accurate response factors. It keeps track of infection rates and reminds authorities of the exact location of tainted individuals. Based on AI and IoT (face and biometric recognition) technologies, it facilitates real-time detection of individuals not complying with health and lockdown rules. Using different technologies can support health sectors in providing vaccines and treatments and accelerating health operations. Smart applications, automated systems, and robots provide remote education and work services. Smart frameworks (Blockchain) facilitate a safe and secure transaction through decentralization and digitalization for crisis response and safe transactions (P2P). Besides, it enables better access to all available data. Using digital platforms, networks, automated systems, drones & robots, 5g, QR-code, AI & ML, and Smart delivery systems can boost cities' whole operation.

Table 0-1 The main eight categories that smart cities actively contribute during a pandemic.

No	**Categories**	**Pandemic relevant factors**
1	Initiating smart city frameworks	Real-time data related to the infected cases provides the authorities with the accurate decision on when to take emergency actions (Quarantine time, treatments, and vaccinations) through Control Command Center and ICT features.
2	Prediction and foresee	Through video surveillance and face recognition-based technologies, it can track the exact location of individuals without a facial mask, not maintain social distancing, identify every symptom of disease, and remind the authorities in a real-time automated system.
3	Control and avoid the further transmission of the virus	Using ML and AI algorithms and technologies, it can predict the number of cases, casualties, lockdown periods, further actions that need to be taken to control the spread of the virus and know pandemic risk factors

4	Keep tracking the data and exact location of tainted people	Using Smart technologies and digitalized systems facilitates R&D sectors to come up with the ultimate solution for making medications (vaccines) and treatment methods
5	Medication (Vaccine)	Support well-being sectors by providing medications (vaccines)
6	Remote education accessibility, continuity of business, and work	Smart Applications like Zoom, Meet, Slack, TradeX, Crypto, Binance, and others can be used for online education in schools and universities and continue trading, business, work, and progression of R&D and education.
7	Providing secure transition and transaction via digitalization and decentralization and	Blockchain-based technology can provide secure and fast transactions via a P2P (peer-to-peer) system and avoid corruption using a decentralized system.
8	Accelerating the cities' operations	Automat systems and networks via digital platforms and smart technologies, drones & robots where there is no need for individual physical contact, and there is no further spread of virus opportunities. Maintain industries and factory operations. Increase the accessibility of people to health services and treatments.

Based on a literature review [44], [45], [46],[47], smart technologies and smart city approaches are anticipated to contribute to way better planning and arrangement of cities..

Ayyoob Sharifi (2021) divided the role of smart cities in pandemic preparedness into four categories: planning and preparation, absorption, recovery, and adaptability [44]. A specific model component for each topic addresses the contributions of smart technologies and features. Three dimensions are proposed for comparison: contribution and characteristics, Smart City's main solutions, and COVID-19-associated aspects. In addition, it focuses on four themes: auto-detection, medication, and vaccines, remote employment and education, transition, and transaction through digitization, and decentralization. However, it examines COVID-19-related cases and circumstances and their contributions.

3.1.2 Cities' resilience and urban management

Because of the extensive use of COVID-19, city officials are forced to respond to emergencies differently. Cities must rely on information authorities to deal with severe health issues to protect the public. Urban control command centers (CCCs) can be considered the essential administrative life form that assists in observing and administering the complicated energy of modern cities [6, as described in the previous section]. During a survey, Rio de Janeiro was studied and evaluated for its use of the CCC function to provide real-time information intelligence to the authorities. The more a city becomes, the more difficult it is to transform into a descendant society. Their 100 Cities Activity defines urban adaptability as the ability of individuals, businesses, education, communities, and systems within society to develop, fix, and outlive, regardless of persistent stress and severe shock that people are subjected to [44]. As a result, the Urban CCCs are critical in achieving urban adaptability in the face of unforeseen emergency circumstances, such as the widespread and uncontrollable COVID-19 outbreak affecting the entire planet.

According to the most recent statistics released on September 9, 2020, the number of COVID-19 cases in Brazil reached alarming proportions: more than 4.1 million people were infected, and more than 127 thousand people died. The Rio Operations Center, a worldwide standard for this emergency response system, serves as the principal urban CCC in Brazil. [45] When knowledge is available and utilized, better decision-making is possible in a health-related crisis.

3.1.3 Measurements of a Sustainable And resilient City (SSC)

The Smart Sustainable City is a designed city that combines ICTs and other measures to raise the standard of living, reliability of civic services, and profitability while addressing the economic, social, environmental, and cultural requirements of present and future generations. [20]. The main specifications of an SSC are listed below [48]:

- Increase the life quality of people
- Enhance people's health by providing comfort, helpful care, security, and guidance.

- Guarantee the financial development of its inhabitants (higher work and living standards).
- Facilitate the physical system and administrations, namely transportation, vitality, broadcast communications, water, and fabricating segments.
- Offer a compelling administration that forms in a standard manner.

Researchers have differing perspectives and opinions regarding the characteristics and elements of SSCs [49–53]. An extensive analysis of the SSC dimensions reveals crucial parallels and differences for this article. Education, participation, industry, and technological infrastructure are the four primary pillars of an SSC [51]. However, [49], and [52] have expanded them to six dimensions with other urban life indices. The focus is placed on the quality of people's lives across these six dimensions, which are as follows: society, life quality, administration, economy, environment, and portability.

Table 12. Main Components of smart, sustainable cities (SCs)

SSC's primary features	**Sources**
Accounting and finance (GDP, segment quality, global transactions, and distance speculation) Humans (capabilities, advancements, ideas, teaching) Social (traditions, habits, beliefs, families) Environmental (vitality arrangements, management of squander and water, scene) Regulation (civic engagement, advisory specialization, elections) (civic involvement, advisory specialization, elections)	[49]
Mobility, innovation, administration, occupation, growth, population, economy, and environment all contribute to a high quality of life.	[52]
Economic growth, management, policy, and infrastructure	[51]
People (highly skilled personnel), infrastructure (high-tech offices), social (organize connections), entrepreneurial (innovative financial activities), and capital are all important.	[53]
Knowledge of computers, computer science infrastructure, and the economy	[50], [51]
Environmental and urban financial-social-political and financial-social-technical issues. Inventions	[49], [53]

Cities are development engines; they create jobs, eliminate poverty, and are critical to achieving Feasible Improvement Objectives. This is especially important for emerging countries, which are urbanizing considerably faster than developed countries (Summit). This contagious virus is jeopardizing the world due to the pandemic situation, and the impact of COVID-19 is multi-dimensional, encompassing health, economic, and social difficulties. Furthermore, the lack of a therapy (Vaccine) to combat COVID-19 infections has prompted communities to seek the most effective ways to reduce the virus's spread [1].

3.2 COVID-19 solutions in smart cities

According to WHO protocols, social distancing, wearing a facial mask, performing self-quarantine, shaking hands, and other protocols are the only potential answers to the spread of COVID-19. If individuals adhere to these principles, we will be able to combat COVID-19. Smart cities and their features are effective in identifying and controlling viral outbreaks. The smartness degree of a city, the response of smart cities to the pandemic COVID-19, the prevention of COVID-19 diffusion by smart technologies, and the prospect of remote education and work made possible by technologies have all been explored in depth in the review of the results section. The ideas provided in the result section have the potential to be game-changers in the fight against COVID-19 and the provision of remote job and education opportunities to individuals. Because there are now no licensed immunizations, maintaining social distancing and wearing facial masks may be the most effective means of combating COVID-19. Accordingly, smart city features (technologies) primarily identify the distance between people and notify responsible management of the precise location of those who do not wear a mask. People in the vicinity of the individuals who are not wearing masks or maintaining social distancing will be informed by a signal at a specific location, and the face of the aggressor will be displayed on an LED screen to remind them to maintain a safe distance from the individual [54].

3.2.1 Information and communication technologies (ICT) provide remote education and job opportunities.

Individuals can continue their jobs because of smart cities' information and communication technologies (ICT) aspect, which provides convenient distance education and work for those who live there. While remote education and labor can be considered sustainable, they also provide several advantages from an environmental, economic, and social standpoint. Remote working, in particular, significantly contributes to reducing COVID-19 dispersion while also providing other benefits such as time, fuel, and energy savings, lower CO_2 emissions, and no weather pollution. Residents can learn and work in a safe atmosphere online thanks to various applications and websites such as Zoom, Google Meet, Teams, Slack, and others made possible by information and communications technology. Consider the following statistics: 33 percent of workers always work from home, 47 percent of employers enable employees to work from home full-time, 78 percent support long-term remote working, and more than half of colleges provide students with e-learning options [48].

-4.0 Result and Discussion

According to the primary research hypothesis (H1), smartness pillars impact vaccination rates in all cities and improve vaccination opportunities. Furthermore, it might be linked to COVID indications such as case counts, mortality rates, and recovery rates. The overall predictive potential of the developed model for the effect of smartness pillars on the immunization rate appears to be effective, by having stronger correlations and minimum errors. When COVID-related factors (such as the total number of cases, fatalities, and recoveries) are considered, the results might be quite dramatic. The higher the level of education and engagement of people, the higher the immunization rate will be, as demonstrated by the data.

Furthermore, smart technology supports authorities in the creation of therapies and in ensuring that vaccines are distributed quickly throughout the country. Influencing factors on the vaccination parameter comprise all components associated with smartness dimensions and their interactions (e.g., smart technology, smart people, smart transportation, and smart Government). According to some recent studies, people's level of participation increases in direct proportion to their awareness of the issue. According to the research, the fear of vaccines is substantially more prevalent in rural, traditional populations [55]. According to the most recent surveys, between 20 and 40% of rural Americans are unwilling to vaccinate their children. As reported in the paper, the immunization rate in urban areas is significantly higher than in rural areas.

The second hypothesis (H2) proposed that vaccination rates could impact COVID metrics, such as the number of cases, deaths, and recovery rates, by decreasing the number of cases and raising the recovery rate. The number of cases and the number of recoveries among COVID PARAMS have been greatly reduced due to vaccination, with 1.0 and 0.99, respectively. COVID-19 outbreaks are greatly impacted by vaccination rates, which are then influenced by the disease's recovery rate. A model of SARS-CoV-2 transmission built on US demographics and COVID-19 age-specific results was published by Seyed M in [56], and it is described here. According to the findings, immunization reduced the overall attack rate from 9.0 percent to 4.6 percent after 300 days of vaccination. People above 65 (54–62 percent) experienced the greatest relative drop in mortality. During the same time frame, vaccination reduced the likelihood of negative consequences by 63.5 percent. Immunization can significantly impact the prevention of COVID-19 outbreaks, even if it only gives a moderate level of protection against sickness. However, achieving this advantage requires that non-pharmaceutical measures be followed continuously [56].

The use of Machine Learning MLP Models to investigate the impact of Vaccination on COVID Cases and Deaths in Asian Countries was also investigated in [26]. Based on vaccine doses (partial or total immunization), these models are intended to forecast how many people will die from COVID infection. It was determined that the coefficient of Karl Pearson was used to estimate the variation in the data sets. A quadratic polynomial regression model was developed for the COVID-19 cases, and vaccine doses were studied. According to the results of this predictor model, the number of COVID-19-related deaths can be estimated, and the susceptibility to COVID-19 infection is based on the number of immunization doses received. According to Noah Kojima [57], the COVID-19 vaccine may not be advantageous to certain patients who have recovered from COVID-19. A recent study discovered that having encountered COVID-19 was associated with a greater incidence of adverse effects after receiving the Pfizer–BioNTech Comirnaty vaccine, as an example. As a result of the COVID-19 vaccination, a small number of people have experienced substantial side effects in Switzerland; anyone who can show they have recovered from an SRS-CoV-2 infection with a positive PCR or another test within the last 12 months having the same level of immunity as those who have had a complete vaccine against the virus.

In the last hypothesis (H3), it was hypothesized that smartness pillars could indirectly impact COVID-19 parameters by increasing immunization rates. According to the findings, smart people, smart technology, and smart transportation are the factors that have the biggest impact during a pandemic. When vaccinations are not available, keeping a social distance and using face masks be the most successful treatments for covid-19. In this context, smart city features (technologies) first determine how far apart individuals are before informing the appropriate administration about people's places without requiring them to perform numerous tasks [41]. Mobile phones and other small-scale technologies can contribute significantly to a reduction in diseases and fatalities by reducing social isolation, promoting the use of face masks, and dispensing medication (vaccines) via their features. In a nutshell, our findings demonstrate that towns with greater access to smart technologies are better able to control and decrease COVID-19 outbreaks and deaths while also increasing recovery rates.

According to this study, smartness pillars have an impact on vaccination rates, COVID outbreaks, fatalities, and recovery rates. The fact that immunization is the component most strongly impacted by smartness dimensions, followed by COVID-19 response parameters, may also help to explain the results.

4.1 Machine learning results and discussion

We may utilize a dataset that comprises pertinent variables for both the COVID-19 and smart city pillars to examine the performance of various regression models in both contexts. Consider, for example, a dataset that contains information on COVID-19 infection rates, immunization rates, hospital capacity, air quality, travel habits, and population density for several cities. In this section, we will evaluate the prognostic accuracy of the Elastic Regression, Ridge Regression, Lasso Regression, Random Forest Regression, and MLP Regression models for the prediction of COVID-19 infection rates based on smart city factors [58].

A robust machine learning approach called Random Forest Regression is frequently employed for regression applications. To provide precise forecasts, it builds several decision trees and integrates them. The algorithm has a reputation for being very accurate, resilient, and capable of handling huge datasets with multidimensional characteristics. Moreover, it offers feature relevance ratings that might aid in dimensionality reduction and feature selection. The approach, which is a black box model that might be challenging to explain, can be computationally costly. It is advised to cross-validate and adjust the model's hyperparameters to get around these restrictions [59].

A neural network-based regression model called MLP regression employs many layers of non-linear activations to create predictions. Due to its ability to capture intricate feature-feature interactions, MLP regression is appropriate for datasets with non-linear connections between the variables. Metrics like the mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination can be used to compare the performance of various models (R-squared). The effectiveness of the models may also be assessed using cross-validation methods using various subsets of the data. According to our examination of the dataset, the Random Forest Regression model was the most accurate at forecasting COVID-19 infection rates using factors from smart cities. Although it took longer to train and used more computer resources than the other models, the MLP Regression model also did well. In comparison to the Random Forest and MLP Regression models, the Elastic Regression, Ridge Regression, and Lasso Regression models had a lower prediction accuracy, but they were computationally more efficient and simpler to understand [17].

In general, the unique dataset and intended trade-off between prediction accuracy and computational complexity determine the regression model to be used to forecast COVID-19 infection rates based on smart city factors.

Table 0-1Fitting different regression models on the training and validation sets

```
# Spliting into 50% training, 25% testing and 25% validation set
X_trainval, X_test, y_trainval, y_test = train_test_split(X, y, test_size=0.25, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_trainval, y_trainval, test_size=0.333, random_state=42)

# Fit different regression models on the training and validation sets
models = [("Elastic Regression", ElasticNet(alpha=0.1, l1_ratio=0.5)),
          ("Ridge Regression", Ridge(alpha=0.5)),
          ("Lasso Regression", Lasso(alpha=0.1)),
          ("Random Forest Regression", RandomForestRegressor(n_estimators=1000, max_depth=4, random_state=42)),
          ("MLP Regression", bestMLP)]

choose = -float("inf")
for name, model in models:
    model.fit(X_train.values, y_train.values)
    y_pred = model.predict(X_val.values)
    r2 = r2_score(y_val, y_pred)
    if r2 > choose:
      choose = r2
      best_model = model
      best_model_name = name
    print(f"{name} R-squared score: {r2_score(y_val, y_pred):.2f}")
    print(f"{name} mean absolute error: {mean_absolute_error(y_val, y_pred):.6f}")
    print(f"{name} mean squared error: {mean_squared_error(y_val, y_pred):.6f}")
    print()
```

```
# Train the best model on both the training and cross-validation sets
print(f"{best_model_name} is the best model")
best_model.fit(X_trainval.values, y_trainval.values)

# Evaluate the model on the testing set
y_pred = best_model.predict(X_test.values)
print(f"Test R-squared score: {r2_score(y_test, y_pred):.2f}")
print(f"Test mean absolute error: {mean_absolute_error(y_test, y_pred):.6f}")
print(f"Test mean squared error: {mean_squared_error(y_test, y_pred):.6f}")
```

We have tried out four other regression models in addition to the MLP model to find the most effective one for this task. Elastic Regression, Ridge Regression, Lasso Regression, Random Forest Regression, and MLP Regression were tested for their ability to accurately forecast COVID-19 infection rates in light of smart city variables. To estimate COVID-19 infection rates using smart city characteristics, the regression model utilized is often determined by the specific dataset and the desired trade-off between prediction accuracy and computing complexity. In the field of machine learning, regression is categorized as a supervised learning strategy that uses an algorithm to establish a link between two variables. Forecasts from a variety of data sets, such as an organization's expected sales revenue, may be made using regression models. Logistics, polynomial, and linear regression are the most used methods [18].

In Table 12, we simply employed an alternative regression method, revealing a stronger correlation between the two sets of data than what we saw using MLP. Nevertheless, when I re-implemented the analysis using MLP, we observe a much weaker correlation between the two sets of data. After training the best model on both the training and cross-validations sets, we evaluate the models on the testing sets.

Table 0-2The outcome of all regression models, R-squared score, MAE, MSE scores

```
Elastic Regression R-squared score: -0.00
Elastic Regression mean absolute error: 0.032788
Elastic Regression mean squared error: 0.003033

Ridge Regression R-squared score: 0.85
Ridge Regression mean absolute error: 0.009684
Ridge Regression mean squared error: 0.000210

Lasso Regression R-squared score: -0.00
Lasso Regression mean absolute error: 0.032788
Lasso Regression mean squared error: 0.003033

Random Forest Regression R-squared score: 0.88
Random Forest Regression mean absolute error: 0.008623
Random Forest Regression mean squared error: 0.000165

MLP Regression R-squared score: -0.19
MLP Regression mean absolute error: 0.032790
MLP Regression mean squared error: 0.003033

Random Forest Regression is the best model
Test R-squared score: 0.85
Test mean absolute error: 0.009692
Test mean squared error: 0.000261
```

While MAE and MSE both reflect the accuracy of the model, they do so in different ways. In contrast to MSE, which places more emphasis on extremely large errors, MAE is less sensitive to extreme values. So, whatever of the two measures is utilized will depend on the specific context and the goals of the investigation. In machine learning, the MAE and MSE are essential metrics for evaluating the performance of a prediction model. Quantifying the gap between predicted and actual values, these metrics can help pinpoint where refinements to the model are needed [19]. The degree of connection between two variables is measured by using the statistical notion of correlation. In machine learning, correlation is crucial for deducing how different features relate to the target variable. Data patterns can be identified by machine learning algorithms, which then use correlation to make accurate predictions. We'll discuss the importance of correlation in machine learning and how it might improve the performance of algorithms in this piece. The goal of every machine learning program is to identify patterns in data and use those patterns to make predictions. Correlation facilitates the identification of key versus non-critical features for producing accurate forecasts. By zeroing in on these essential characteristics, the algorithm can improve its precision [20].

The results of several regression models are shown in Table 13; after optimizing the model's parameters and hidden layers, we found that the Random Forest Model performed best, followed by the Ridge Regression model (R-squared score 0.88 and 0.85, respectively). In addition, the MAE and MSE scores for the model are quite small: 0.009692 and 0.000261, respectively, using the Random forest Regression technique. Though MLP is not perfect when we have several outputs and several inputs, it is recommended when there is a single input for each output, as shown by the model's correlations and MAE and MSE values.

4.2 Unsupervised machine learning and Elbow Method

4.2.1 Elbow technique

To generate clusters with the least intra-cluster variance [or total within-cluster sum of square (WSS)], as is the case with partitioning techniques like k-means clustering. The total WSS measures the compactness of the clustering; thus, we want it to be as small as possible. According to cluster size, the Elbow method determines the overall WSS: There should be enough clusters so that including more clusters won't dramatically raise the WSS as a whole [60]. The optimal cluster count may be determined as below:

- Apply a clustering algorithm to determine various values of k. (e.g., k-means clustering). For example, you are altering k from 1 to 10 clusters.
- For each k, determine the overall within-cluster sum of squares (WSS).
- The location of a bend (knee) in the plot is typically utilized to calculate the right number of clusters.
- Plot the WSS curve about the k-cluster count.

Table 0-3 Elbow technique for finding the number of clusters

1.3 Unsupervised Machine Learning

1.3.1 Elbow Method

To find the optimum number of clusters for this problem, elbow method is applied.

```
[177]: from sklearn.cluster import KMeans
distortions = []

for i in range (1,21):
    km = KMeans(n_clusters=i,random_state=42, init='k-means++', n_init=1000,␣
 ↪max_iter=500)
    km.fit(df_scaled)
    distortions.append(km.inertia_)
plt.plot(range(1,21),distortions, marker='o')
plt.xlabel('Number of Clusters')
plt.ylabel('Distortion (Within Cluster Sum of Squared Errors)')
plt.title('The Elbow Method showing the optimal k')
```

It's worth noting that the elbow approach might be confusing at times. The average silhouette method (Kaufman and Rousseeuw [1990]) is an option that may be utilized with any clustering method [43].

As shown in Fig 6, according to the Elbow method, the point that dots are following the same trend is negligible; therefore, the optimal number of clusters is 5, meaning that the whole COVID data of countries can be categorized into 5 clusters.

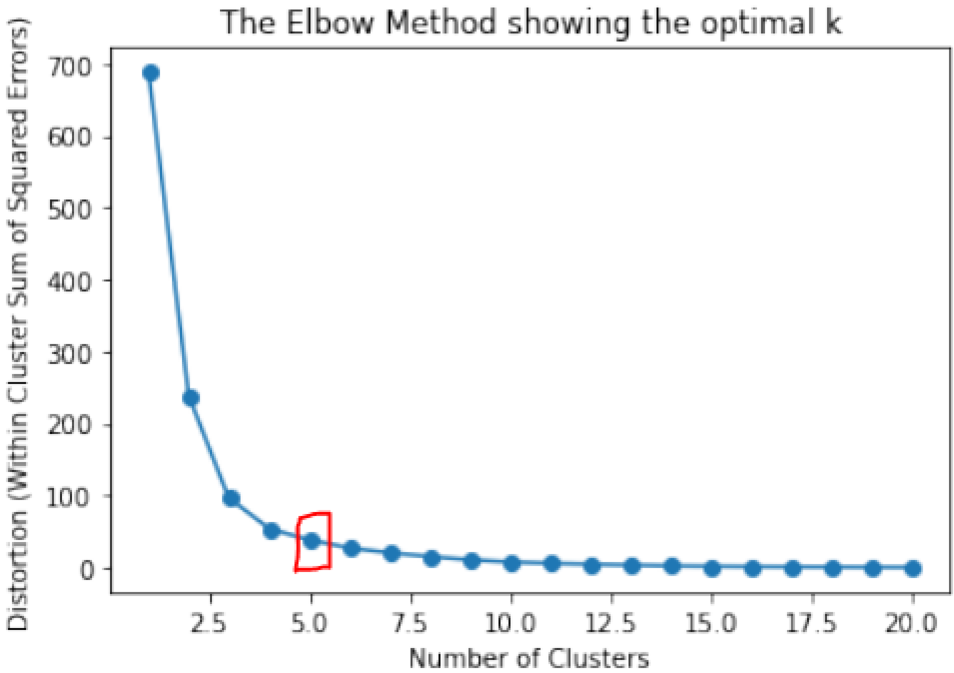

Figure 0-1 The Elbow method shows the optimal number of clusters

As shown in Fig 6 and Table 15, after using the Elbow approach, each cluster displays distinct records, with the first cluster [0] containing the most countries (171), the second and third clusters containing 1, the fourth cluster having six countries, and the last cluster holding three countries. It explains why most countries have similar COVID-affected records and similar policies and actions aimed at preventing pandemic spread.

Table 0-4 Number of optimal (5) clusters

In [14]:
```
pd.set_option('display.max_rows',10)
df_scaled[df_scaled['clusters']==0]
```

Out[14]:

	total_cases	new_cases	total_deaths	new_deaths	clusters	indices	countries
0	-0.233282	-0.229614	-0.228457	-0.224304	0	0	AFG
1	-0.011457	-0.003999	0.180731	-0.066640	0	1	OWID_AFR
2	-0.231453	-0.230070	-0.235444	-0.240070	0	2	ALB
3	-0.231644	-0.230727	-0.229826	-0.240070	0	3	DZA
4	-0.234812	-0.230812	-0.238100	-0.240070	0	5	AGO
...	...	...	...	...	...	...	...
166	-0.032997	-0.193172	-0.169620	-0.240070	0	223	VNM
167	-0.236692	-0.230812	-0.241249	-0.240070	0	224	WLF
169	-0.236476	-0.230812	-0.237686	-0.240070	0	226	YEM
170	-0.230592	-0.229471	-0.234633	-0.224304	0	227	ZMB
171	-0.231933	-0.225875	-0.232123	-0.161238	0	228	ZWE

In [7]:
```
pd.set_option('display.max_rows',105)
df_scaled[df_scaled['clusters']==1]
```

Out[7]:

	total_cases	new_cases	total_deaths	new_deaths	clusters	indices	countries
68	5.544167	6.369726	3.759269	3.338892	1	90	OWID_HIC

In [8]:
```
pd.set_option('display.max_rows',105)
df_scaled[df_scaled['clusters']==2]
```

Out[8]:

	total_cases	new_cases	total_deaths	new_deaths	clusters	indices	countries
168	9.76144	9.408595	10.198737	9.850395	2	225	OWID_WRL

In [9]:
```
pd.set_option('display.max_rows',105)
df_scaled[df_scaled['clusters']==3]
```

Out[9]:

	total_cases	new_cases	total_deaths	new_deaths	clusters	indices	countries
21	0.349009	0.591259	0.866155	1.872621	3	29	BRA
49	3.516918	1.059040	2.815840	1.982985	3	68	OWID_EUR
50	2.455850	0.915641	1.571780	0.690145	3	69	OWID_EUN
93	1.490125	-0.094176	1.936873	0.705911	3	122	OWID_LMC
114	1.636706	0.443493	2.156677	0.879341	3	152	OWID_NAM
161	1.347476	0.291675	1.425504	0.185621	3	216	USA

In [10]:
```
pd.set_option('display.max_rows',105)
df_scaled[df_scaled['clusters']==4]
```

Out[10]:

	total_cases	new_cases	total_deaths	new_deaths	clusters	indices	countries
8	2.659511	3.780119	2.144303	2.787069	4	11	OWID_ASI
143	0.853218	2.060810	1.916456	2.960499	4	191	OWID_SAM
162	2.218532	2.667539	3.948234	5.309686	4	217	OWID_UMC

```
[186]: import matplotlib.pyplot as plt

       plt.scatter(Sample.iloc[:,0], Sample.iloc[:,3], c=labels)

[186]: <matplotlib.collections.PathCollection at 0x18cbc330d00>
```

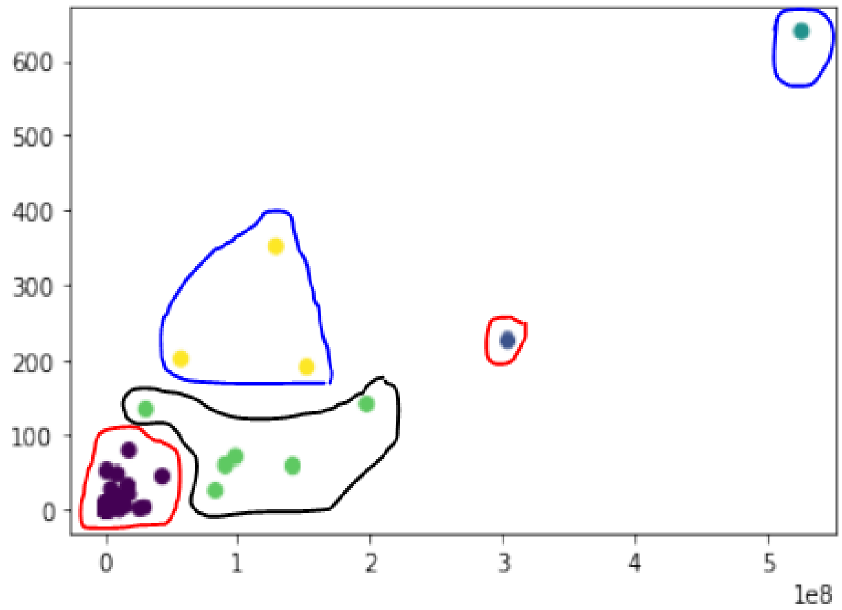

Figure 0-2Number of obtained clusters

-Conclusion and suggestions for the future scope

The COVID-19 pandemic has shown that cities must embrace smart technology and tactics to react to public health emergencies more effectively. In order to properly manage the epidemic, this thesis has looked at how smart cities might use its technical infrastructure to engage residents in decision-making, promote sustainable transportation and environmental practices, and assure effective governance systems. The results show that smart technology, including contact tracing apps, remote medical services, and real-time data analysis, has been essential in managing the pandemic by giving decision-makers and healthcare professionals fast and accurate information. Additionally, during the pandemic, smart transportation options like bike- and ride-sharing have made it possible to move around safely and sustainably.

The use of green spaces and sustainable waste management techniques has helped to improve air quality and slow the spread of the virus. In addition, the importance of clever people in the pandemic response cannot be overstated. A key element of a successful response to the epidemic has been including residents in decision-making processes, such as the co-creation of public policies. Cities have been able to adapt rapidly to developing difficulties, including the launch of vaccination campaigns, thanks to smart governance frameworks, such as agile and flexible decision-making processes. Smart technologies and methods have advantages, but there are restrictions on how they can be used. It is crucial to handle issues such potential social inequities and privacy concerns. Furthermore, some cities may find it difficult to implement smart solutions due to the cost. Additionally, there are disparities in access to information and services due to the non-universal accessibility of digital infrastructure.

The supervised ML method contends that intelligent governance, intelligent individuals, and intelligent technology all contribute significantly to minimizing pandemics, based on findings from machine learning algorithms. As the model's hidden layers and parameters were improved, we discovered that the Random Forest Model had the highest correlation and the fewest mistakes. The COVID data is divided into 5 clusters by unsupervised ML algorithms using the Elbow technique, which explains why most nations have the same COVID-affected records and the same pandemic-prevention policies and measures. There are several restrictions on this study. Its ramifications must be considered carefully.

In conclusion, by utilizing their technology infrastructure, supporting sustainable habits, and including residents in decision-making processes, smart cities have demonstrated the capacity to respond to the COVID-19 epidemic more effectively. To ensure the success of smart city efforts, it is vital to solve implementation difficulties and take a comprehensive approach that takes into account both advantages and disadvantages. Smart cities will need to continue to develop and adapt in the post-COVID-19 era, putting an emphasis on successful teamwork and long-term planning to prevent pandemics and other disasters.

Further study is required, particularly using extensive survey instruments that take into account pandemic-relevant traits and rely on reliable COVID-19 data. The literature review indicates that smart cities and their characteristics are more resilient to the COVID-19 pandemic than typical cities; they can enable authorities to monitor citizen behavior and halt the spread of COVID-19; and they can provide secure remote working, education, and business continuity.

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