

An AI-based Analysis of the effect of COVID-19 Stringency Index on Infection rates: A case of India

Krishna Prasad K.¹, P. S. Aithal ², Vinayachandra³, & Geetha Poornima K.⁴

¹Associate Professor & Post-Doctoral Research Fellow, College of Computer & Information Sciences, Srinivas University, Mangalore, Karnataka, India

Orcid ID: 0000-0001-5282-9038; E-mail: krishnaprasadkcci@srinivasuniversity.edu.in

²Vice Chancellor, Srinivas University, Mangalore – 575001, India.

Orcid ID: 0000-0002-4691-8736; E-mail: psaithal@gmail.com

³Research Scholar, College of Computer & Information Sciences, Srinivas University, Mangalore, Karnataka, India and Assistant Professor, Dept of Computer Science, St Philomena College, Puttur, Karnataka, India

Orcid ID: 0000-0002-9374-4871; E-mail: veeciashu@gmail.com

⁴Research Scholar, College of Computer & Information Sciences, Srinivas University, Mangalore, Karnataka, India and Assistant Professor, Dept of Computer Science, St Philomena College, Puttur, Karnataka, India

Orcid ID: 0000-0001-9095-0349; E-mail: poornima.sanjay@gmail.com

Area/Section: Health Sciences.

Type of the Paper: Analytical Research.

Type of Review: Peer Reviewed as per [C|O|P|E](#) guidance.

Indexed in: OpenAIRE.

DOI: <http://doi.org/10.5281/zenodo.4732767>

Google Scholar Citation: [IJHSP](#)

How to Cite this Paper:

Krishna Prasad, K., Aithal, P. S., Geetha Poornima, K., & Vinayachandra, (2021). An AI-based Analysis of the effect of COVID-19 Stringency Index on Infection rates: A case of India. *International Journal of Health Sciences and Pharmacy (IJHSP)*, 5(1), 87-102. DOI: <http://doi.org/10.5281/zenodo.4732767>.

International Journal of Health Sciences and Pharmacy (IJHSP)

A Refereed International Journal of Srinivas University, India.

Crossref DOI : <https://doi.org/10.47992/IJHSP.2581.6411.0063>

© With Author.



This work is licensed under a [Creative Commons Attribution-Non-Commercial 4.0 International License](#) subject to proper citation to the publication source of the work.

Disclaimer: The scholarly papers as reviewed and published by the Srinivas Publications (S.P.), India are the views and opinions of their respective authors and are not the views or opinions of the SP. The SP disclaims of any harm or loss caused due to the published content to any party.

An AI-based Analysis of the effect of COVID-19 Stringency Index on Infection rates: A case of India

Krishna Prasad K.¹, P. S. Aithal ², Vinayachandra³, & Geetha Poornima K.⁴

¹Associate Professor & Post-Doctoral Research Fellow, College of Computer & Information Sciences, Srinivas University, Mangalore, Karnataka, India

Orcid ID: 0000-0001-5282-9038; E-mail: krishnaprasadkcci@srinivasuniversity.edu.in

²Vice Chancellor, Srinivas University, Mangalore – 575001, India.

Orcid ID: 0000-0002-4691-8736; E-mail: psaithal@gmail.com

³Research Scholar, College of Computer & Information Sciences, Srinivas University, Mangalore, Karnataka, India and Assistant Professor, Dept of Computer Science, St Philomena College, Puttur, Karnataka, India

Orcid ID: 0000-0002-9374-4871; E-mail: veeciashu@gmail.com

⁴Research Scholar, College of Computer & Information Sciences, Srinivas University, Mangalore, Karnataka, India and Assistant Professor, Dept of Computer Science, St Philomena College, Puttur, Karnataka, India

Orcid ID: 0000-0001-9095-0349; E-mail: poornima.sanjay@gmail.com

ABSTRACT

Purpose: The impact of the COVID-19 pandemic has already been felt worldwide, disrupting the unremarkable life of individuals. Social consequences and viral transmission are challenges that must be resolved to effectively overcome the problems that occur throughout this pandemic. The COVID-19 infection data about India were represented using different statistical models. In this paper, the authors focus on the data collected between 1st January 2020 and 12th April 2021, try analyzing the different indexes related to India, and predict the number of infected people in the near future. Based on the infection rate, it is possible to classify a country as “fixed,” “evolving” and “exponential.” Based on the prediction, some recommendations are proposed to contain the outbreak of the disease. This will also help the government and policymakers to identify and analyze various risks associated with 'opening up' and 'shutting down' in response to the outbreak of the disease. With the help of these models, it is possible to predict the number of cases in the near future.

Methodology: COVID-19 Stringency Index, Government Response Index, and Containment Health Index calculated, published, and updated real-time by a research group from Oxford University (<https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker>) on 21 mitigation and suppression measures employed by different countries were analyzed using a few mathematical models to find the relationship between Stringency Index and infection rates and forecast trends. A new model was proposed after analyzing a few mathematical models proposed by the researchers. Data analytics was also conducted using AI-based data analytics tools available online. The dataset was kept updated until the date April 20, 2021, was downloaded for this purpose. The appropriate values were extracted from the original dataset and used to construct a sub-dataset, which was then used for the analytics. An AI-based online Data Analytics tool provided by datapine was used to forecast trends.

Findings/Result: It was observed that in India, as in other countries, there is a close association between Stringency Level and COVID-19 cases. The higher the degree of stringency, the lower the cases, and vice versa. The same can be said about the government's role and degree of containment & health.

Originality: In this paper, we analyzed various mathematical models for predicting the total number of COVID-19 cases and deaths due to COVID-19 in India. We also examined the relationship between total cases and the Government's Response Index, Containment & Health Index, and

Stringency Index indicators. The model we proposed to predict COVID-19 cases on a day-by-day basis had a 98 percent accuracy rate and a 2% error rate.

Paper Type: Analytical. With prerecorded datasets obtained from online resources, and data analysis was conducted using mathematical models and AI-based analytical tools.

Keywords: COVID-19, Stringency Index, Infection Rate, Prediction, Statistical Model

1. INTRODUCTION :

The COVID-19 is caused by 'Novel Coronavirus'. The first case of COVID-19 was reported at the end of December 2019 in China. More than 200 countries affected by the disease and as a result, the World Health Organization has declared it a pandemic. During the COVID-19 disease outbreak, many countries, including India, are struggling difficult to combat the adversities that came with it. Every country is exploring out ways to deal with the disease's numerous challenges. Humanity's struggles and challenges stimulated the creation of new theories, strategies, and processes. The entire planet is undergoing massive transformations right now. Infections and deaths have been a major impediment to humanity's progress. Overall, the pandemic has brought a new era, especially in the case of developing countries [1].

The COVID-19 has caused panic worldwide due to the high rate of disease transmission and lack of adequate therapeutic interventions. The successful implementation of containment and mitigation methods necessarily requires the effective usage of technology. There is a tremendous need for technological inventions as the number of infected individuals grows exponentially each day. Since up-to-date data related to the infected people, government policies, etc. are readily available, advanced analytics will greatly speed up the decision-making process. To learn more about the infected and disease probable emerging technologies and statistical analysis can be of great help [2].

Different countries implement different levels of restrictions to reduce the infections and death rates caused by the COVID-19. The OxCGRT follows a systematic technique to measure the responses followed by different governments to flatten the curve. The OxCGRT collects data on policies implemented by various countries, such as school closures, travel bans, and so on. The OxCGRT efficiently assembles all the information data across 187 countries on 21 key indicators. The analysis of these data enables the countries to determine the various threats associated with 'opening up' and 'shutting down' as a response to the coronavirus emergency. A dataset that holds numerous key indicators identified by various governments is constantly updated by a group of 100 Oxford Community Members. The key indicators identified contribute to the implementation of containment policies. Data from 21 key indicators were compiled into various indices. These indices have a magnitude ranging from 0 to 100. The level of government action in each field is represented by this ranking [3].

The overtly available data can be used to analyze and predict future outcomes using Artificial Intelligence (AI), Machine Learning (ML) with the help of some statistical models. Based on the data the disease outbreak in the near future can be predicted accurately. This will enable the authorities to take preventive measures to contain the spread [4].

In this paper, the authors focus on the data collected between 1st January 2020 and 12th April 2021, try analyzing the different indexes related to India, and predict the number of infected people in the near future. This will also help the government and policymakers to identify and analyze various risks associated with 'opening up' and 'shutting down' in response to the outbreak of the disease.

2. RELATED WORK :

Different papers that performed an analysis of real-time data using AI and ML between 2018 and 2021 are referred to during the analysis. Blood lactate concentration is one of the crucial factors that are used to determine the fitness of athletes. The authors developed a model to measure the blood lactate level using ML algorithms the model is tested by real-time data [5]. To maximize the performance and minimize the risk of injuries among the athletes' AI and ML algorithms are used [6]. The authors developed a generalized methodology to classify the data related to different diseases. The essential features required for classification are ranked and ML algorithms are applied to classify the dataset [7]. With the help of the AI technique, the authors analyzed the openly accessible data related to COVID-19 patients to predict the severity of the disease and concluded that boosting will help to enhance the accuracy of predictions [8]. To ensure the optimum utilization of healthcare resources and extreme safety of patients a model is developed. The authors concluded that there is a hidden relationship among various safety parameters and found ML as an effective technique

to identify them [9]. The challenging task of classification of clinical data is done using ML algorithms. They used the SIRD model to predict the outbreak of COVID-19. The analysis is carried out based on the reproduction rate of the virus that causes COVID-19[10]. They analyzed different game-specific parameters that are used to measure the performance of athletes AI and ML are used [11]. The authors applied different matrices to analyze the effect of COVID-19 on the number of publications during the outbreak of the pandemic [12]. Researchers explored different ML algorithms and devised a model that predicts the possibility of cardiac arrest among the patients who are in intensive care units of hospitals. Different features that contribute to the expected events are extracted, the model developed is trained using the openly available data, and found that classifier has maximum accuracy when compared to other ML techniques [13]. To analyze various pandemics such as Ebola ML techniques are extensively being used. The authors developed different models using ML to predict the vulnerability of people to the disease based on different risk factors [14]. The summary of findings is given in Table 1.

Table 1: Analysis conducted by researchers on a similar set of datasets using mathematical models

S. No	Authors	Finding
1	Etxegarai et al. (2018) [5]	Designed a model that helps the estimation of lactate threshold which is a crucial parameter in determining the fitness of athletes.
2	Naglah et al. (2018) [6]	Accurate prediction of injuries is done using AI and ML models and the models are tested based on the injury data of different athletes and found to be of expected accuracy.
3	Alam et al. (2019) [7]	Developed a generalized model to classify the clinical information related to different diseases and trained the model using different ML algorithms. Attribute selection for classification is carried out based on the rank of the attribute.
4	Iwendi et al. (2020) [8]	Developed a model that uses data related to COVID-19 patients to predict the severity of the disease and the time taken to recover. Explored different AI techniques and found out the accuracy of a technique is increases with boosting.
5	Qazi et al. (2020) [9]	Used tree-based ML algorithms to evaluate the safety of patients. The analysis revealed a hidden relationship among different parameters that enable the safety culture of patients.
6	Anastassopoulou et al. (2020) [10]	Proposed a technique to calculate different parameters associated with the outbreak of COVID-19 pandemic based on the openly available data. Used SIRD model and basic reproduction rate to predict the outbreak of the disease.
7	Oytun et al. (2020) [11]	To identify the non-linear relationship among different parameters of athletes and to increase the chance of winning ML models are developed.
8	Homolak et al. (2020) [12]	Performed analysis of COVID-19 data using different tools and matrices to evaluate the response of researchers during the outbreak of COVID-19 when the SI was at its maximum.
9	Krishna Prasad et al. (2021) [13]	Performed analysis and prediction of cardiac arrests occur among the patients who are under emergency care using different ML algorithms. The analysis is carried out using publicly available datasets.
10	Agrawal & Gupta (2021) [14]	Performed analysis of COVID-19 data related to different countries using ML techniques to predict the vulnerability of people to the pandemic.

3. OBJECTIVES :

1. To represent COVID-19 India's cases using appropriate statistical models
2. To perform future prediction of COVID-19 infection using a suitable statistical model
3. To examine the interconnections between Government Response Index (GRI), Containment & Health Index (CHI) and Stringency Index (SI) of the total number of COVID-19 cases in India
4. To forecast COVID-19 cases and related deaths in India for next three months

4. METHODOLOGY :

COVID-19 Stringency Index, Government Response Index, and Containment Health Index calculated, published, and updated real-time by a research group from Oxford University (<https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker>) on 21 mitigation and suppression measures employed by different countries were analyzed using a few mathematical models to find the relationship between Stringency Index and infection rates and forecast trends. A new model was proposed after analyzing a few mathematical models proposed by the researchers. Data Analytics was also conducted using AI-based Data Analytics tools available online. The dataset was kept updated until the date April 20, 2021, was downloaded for this purpose. The appropriate values were extracted from the original dataset and used to construct a sub-dataset, which was then used for the analytics. An AI-based online Data Analytics tool provided by datapine (<https://secure.datapine.com/#onboarding>) was used to forecast trends.

5. ABOUT DATASET :

The OxCGRT collects data from different sources that are publicly available. These sources include news articles, press notes, government information portals, etc. Data were collected by 100 well-trained Oxford Community Members, including University students, staff, and trusted collaborators. Data are periodically being updated by the authorized members and are publicly made available for analysis. When storing the data in the database utmost care is taken to ensure that it originates from a trusted source. After the data entry, it is being reviewed and certified by another person to ensure truthfulness.

The publicly available information about 21 key indicators of government responses to COVID-19 is recorded in the database. The key indicator is a measure on a scale of 0–10, a specific monetary value, or a free response that is preferably text-type data. If the indicators are ‘targeted’ then they are applied only to a specific region, if they are generic, they are applied throughout the country. Data collection occurs periodically, the database is updated and reviewed to provide precise up-to-date information. Figure 1 gives the list of key indicators identified by the OxCGRT. The key indicators are categorized as Containment and Closure, and Economic Response, and Health System, and Miscellaneous. The category Containment and Closure have eight indicators, which are coded C1-C8. They are C1-School Closing, C2-Workplace Closing, C3-Cancel Public Events, C4-Restrictions on Gathering Size, C5-Close Public Transportation, C6-Stay at Home Requirements, C7-Restrictions on Internal Movement, and C8-Restrictions on International Travel. The Economic Response category has four indicators, which are coded E1-E4. They are E1-Income Support, E2-Debt/Contract Relief for Households, E3-Fiscal Measures, and E4- Giving International Support. The Health System category has eight indicators, which are coded H1-H6. They are H1-Public Information Campaign, H2-Testing Policy, H3-Contact Tracing, H4-Emergency Investment in Healthcare, H5-Investment in COVID-19 Vaccine, H6-Facial Coverings, H7-Vaccination Policy, and H8-Protection of Elderly People [15-16]. Only one indicator is placed under the category Miscellaneous, i.e. M1- Other responses. The 21 indicators mentioned under various categories are depicted in Figure 1.



Fig. 1: Key Indicators Identified by the OxCGRT

The different indicators that are used to calculate the Government Response Index (GRI) are shown in Figure 2 below. The values of 8 (C1-C8) Containment and Closure, 2 (E1, E2) Economic Response, and 6 (H1-H3, H6-H8) Health System indicators are put under evaluation to calculate Government Response Index.



Fig. 2: Key Indicators Identified by the OxCGRT to calculate GRI

Fourteen indicators that are used to calculate the Containment and Health Index (CHI) are shown in Figure 3 below. 8 (C1-C8) Containment and Closure, and 6 (H1-H3, H6-H8) Health System indicators are used to calculate Containment and Health Index.



Fig. 3: Key Indicators Identified by the OxCGRT to calculate CHI

Nine indicators that are used to calculate the Stringency Index (SI) are shown in Figure 4 below. 8 (C1-C8) Containment and Closure, and 1 (H1) Health System indicators are used to calculate Stringency Index.



Fig. 4: Key Indicators Identified by the OxCGRT to calculate SI

According to OxCGRT the key indicators used to calculate GRI, CHI and SI are shown in Figure 2, Figure 3, and Figure 4, respectively. SI is calculated based on C1 to C8 and H1. The parameter C1 represents the closing of schools and can take a value between 0 and 3. If the value is 0, it indicates no closure of schools and the value 3 indicates all schools and universities should remain closed. If the value is 1, it is recommended to close the schools and if the value is 2 it must close schools. The key indicator C2 can also take a value

between 0 and 3. The meaning of parameters is the same as that of C1, whereas when the value of C2 is 3 all workplaces except essential services such as hospitals, grocery shops, diagnostic centers, clinics, medical insurance offices, banks, pharmacies, etc. remain closed. C3 expresses the cancelation of public events. The possible values are 0, 1, and 2. The value 2 means all the public events are to be canceled. The key indicator C4 is the counterpart of C3. However, it takes 5 levels from 0 to 4. The value 0 means there is no restriction on private events. 3 means only 11 to 100 people are permitted [17].

6. POLICY INDICES COVID-19 GOVERNMENT RESPONSES :

Different governments have responded differently to contain the outbreak of COVID-19. A comparison of responses related to each country is a tedious job. There are different indices to measure responses related to each country. They depend upon various key indicators. Different indices identified include

Different indices identified include

- Government Response Index (GRI), which indicates how the response of the governments has changed the overall indicators. Governments are taking various policies during the COVID-19 outbreak. If the value of this index is more, it indicates the response of the government is stronger during the disease outbreak.
- Containment and Health Index (CHI): combines many key indicators such as the closure of schools and workplaces, travel restrictions, measures taken for contact tracing, emergency measures to be taken in the healthcare sector such as the purchase of testing equipment, ventilators, vaccine policies, etc.
- Economic Support Index (ESI): is used to measure the economic status of the country. It includes key indicators such as lockdown policies, tax policies, various credit policies, business support schemes adopted by the governments during the outbreak of COVID-19
- Stringency Index (SI): provides a clear picture of measures taken by the country to contain the outbreak of COVID-19. The key indicators include the closure of schools and workplaces, travel bans, a ban on public gatherings, the cancelation of public events such as rallies, processions, cancelation of public transports, international travel restrictions, etc. SI is an important consideration when determining a country's response to the COVID-19 outbreak. It gives a clear understanding of the various restrictions that a government introduced. The greater the level of stringency, the higher will be the value of SI [3][18].

7. INDIA SCENARIO :

The COVID-19 pandemic has affected billions of people across 187 nations around the world. Since the disease had no particular medication or vaccine it had created waves of panic especially in thickly populated countries like India. The healthcare resources and infrastructure were put into test during the outbreak of the pandemic.

The first case of COVID-19 was reported in India on the 30th of January, 2020, on the 14th of March 100th case was reported. The count of infected continued increasing exponentially and on the 13th of April, 2020 1000th case was reported. On the 18th of May, 2020, the total number of infected people reached 1 Lakhs. The count was doubled on the 12th of June, 2020. The count crossed 1 million on 16th July 2020 and became more than 5 million on 15th September 2020.

It crossed 1 crore on 18th December 2020. As of 22nd April 2021, 1,50,061805 people reported positive for COVID-19. The first COVID-19 fatality was reported on the 11th of March 2020, the 10th was reported on the 23rd March 2020 and the 100th death was reported on 6th April 2021. It crossed 10,000 on 16th June 2020 and 1 Lack on 2nd October 2020. As of 22nd April, 2021 total number of deaths reported in India is 1,78,768. India responded appropriately and took every possible measure to contain the spread of the disease. Thermal screening of overseas passengers, isolation of COVID-19 infected people, quarantine of COVID-19 probable, observing social distancing, shutting down of schools and colleges, increasing the healthcare facilities, etc. were some of the measures taken. The Indian government took proactive measures and stringent actions to detect, treat and reduce the spread of the virus. To restraint the growing fright it distributed authentic information on the virus, preventive measures, guidelines, and accelerated the steps to develop a vaccine for the virus. The stringent actions taken by the government can be observed from the SI of India calculated by the OxCGRT. It delivers a clear representation of measures taken by the country to contain the spread of the disease.

In January 2020 the SI of India was 5.56. When COVID-19 cases were detected in some countries, preventive

measures were taken and SI was 10.19 at the end of Jan 2020. On the 15th March 2020, it was 26.85 and it reached 50 on the 18th of March 2020. Between 25th March 2020 and 19th, April 2020 SI of India was at its threshold value that is 100. During this period the government of India imposed strict lockdown. When compared to the SI of the United States, the United Kingdom, France, Germany, and Italy the government response was more in India. It is observed that when SI is more, the spread of the disease is less.

Table 2 shows different parameters that are affected by the SI from the data recorded by the OxCGRT. As indicated in the table when the SI was more, the number of COVID-19 positive cases was less. When there are travel restrictions, restrictions on public gatherings, shut down of schools and colleges, etc. the value of SI was more.

It is found that the infection rate is growing exponentially during the post-lockdown period when compared to the lockdown period based on the value of SI. The positivity rate is used to measure the spread of infection. From Table 2 it is clear that the positivity rate was less when SI was high this means that when there are restrictions imposed by the government the spread of the disease was less. During the post-lockdown period, the value of positivity got increased as SI was less [17], [19].

Table 2: Impact of SI on positivity rate

Date	Stringency Index	Absolute Change	Relative Change	Total No. of COVID-19 Cases	New COVID-19 Cases Added	Positive Rate	No. of Deaths due to COVID-19	No. of New Deaths due to COVID-19
1/02/2020	10.19	-	-	1	1	-	0	-
1/03/2020	10.19	+0.00	+0%	3	2	-	0	0
1/04/2020	100	+89.81	+881%	1998	1995	0.69	58	58
1/05/2020	96.30	-3.70	-4%	37257	35259	0.035	1223	1165
1/06/2020	75.46	-20.84	-22%	198370	161113	0.066	5608	4385
1/07/2020	74.06	-1.39	-2%	604641	406271	0.089	17834	12226
1/08/2020	79.63	+5.56	+8%	1750723	1146082	0.104	37364	19530
1/09/2020	81.02	+1.39	+2%	3769523	2018800	0.084	66333	28969
1/10/2020	73.61	-7.41	-9%	6394068	2624545	0.07	99773	33440
1/11/2020	61.57	-12.04	-16%	8229313	1835245	0.043	122607	22834
1/12/2020	68.98	+7.41	+12%	9499413	1270100	0.036	138122	15515
1/01/2021	68.98	+0.00	+0%	10286709	787296	0.017	148994	10872
1/02/2021	61.57	-7.41	-11%	10766245	479536	0.019	154486	5492
1/03/2021	63.43	+1.86	+3%	11124527	358282	0.02	157248	2762
1/04/2021	57.87	-5.56	-9%	12303131	1178604	0.063	163396	6148
12/4/2021	69.91	+12.04	+2%	13689453	1386322	0.114	171058	7662

The positivity rate and mortality rate are not solely determined by the SI value. SI simply indicates that the government has implemented a specific policy or measure. It makes no mention of executing or complying with the law. The decrease in the number of promising cases, on the other hand, is indicative of the effectiveness of the measures undertaken. The GRI and CHI are the two indices identified by the OxCGRT which also affect the positivity rate. The GRI depends upon 16 key indicators including vaccination rate. The COVID-19 vaccination provides some sort of protection against the virus. The vaccine is strictly evaluated in different levels of clinical trials. Studies show that fully vaccinated people are less likely to get affected by the COVID-19 virus. Hence, they are potentially less likely to spread the disease. Immunity also reduces the risk of hospitalization and fatality rate. Table 3 lists different indices, positivity rate, count, and the percentage of people who are fully vaccinated in India between 1st March 2021 and 25th March 2021[17].

Table 3: Datasets showing different indices, positive rate, total cases and vaccination details for the month March 2021

Date	Total Cases	Positive Rate	Tests Per Case	People Fully Vaccinated	Vaccination %	Stringency index	Government Response Index	Containment Health Index
------	-------------	---------------	----------------	-------------------------	---------------	------------------	---------------------------	--------------------------

01-03-21	11124527	0.02	49.1	2597799	1.08	63.43	69.64	72.44
02-03-21	11139516	0.02	49.3	2713978	1.13	63.43	69.64	72.44
03-03-21	11156923	0.02	48.8	2876927	1.2	63.43	69.64	72.44
04-03-21	11173761	0.021	48.5	3208668	1.3	63.43	69.64	72.44
05-03-21	11192045	0.021	47.1	3501021	1.41	63.43	69.64	72.44
06-03-21	11210799	0.022	46.1	3754041	1.52	63.43	69.64	72.44
07-03-21	11229398	0.023	44.4	3761107	1.52	63.43	69.64	72.44
08-03-21	11244786	0.023	43.4	4065450	1.67	63.43	69.64	72.44
09-03-21	11262707	0.024	41.4	4363679	1.77	57.87	66.51	68.87
10-03-21	11285561	0.025	39.5	4650530	1.86	57.87	66.51	68.87
11-03-21	11308846	0.027	37.6	4729079	1.9	57.87	66.51	68.87
12-03-21	11333728	0.028	35.7	5142953	2.04	57.87	66.51	68.87
13-03-21	11359048	0.029	34.7	5430774	2.15	57.87	66.51	68.87
14-03-21	11385339	0.03	33.8	5455653	2.17	57.87	66.51	68.87
15-03-21	11409831	0.031	32.3	5867948	2.39	57.87	66.51	68.87
16-03-21	11438734	0.032	31.6	6202499	2.54	57.87	66.51	68.87
17-03-21	11474605	0.033	30.5	6542468	2.69	57.87	66.51	68.87
18-03-21	11514331	0.034	29.5	6913587	2.85	57.87	66.51	68.87
19-03-21	11555284	0.035	28.8	7221362	3.05	57.87	66.51	68.87
20-03-21	11599130	0.036	27.5	7478654	3.23	57.87	66.51	68.87
21-03-21	11646081	0.039	25.8	7491696	3.27	57.87	66.51	68.87
22-03-21	11686796	0.039	25.4	7863441	3.51	57.87	66.51	68.87
23-03-21	11734058	0.041	24.2	8109334	3.68	57.87	66.51	68.87
24-03-21	11787534	0.044	23	8299171	3.85	57.87	66.51	68.87
25-03-21	11846652	0.046	21.6	8502968	4.02	57.87	66.51	68.87
26-03-21	11908910	0.049	20.5	8683155	4.21	57.87	66.51	68.87
27-03-21	11971624	0.051	19.7	8828346	4.37	57.87	66.51	68.87
28-03-21	12039644	0.052	19.1	8870201	4.39	57.87	66.51	68.87

29-03-21	12095855	0.055	18.1	8901956	4.43	57.87	66.51	68.87
30-03-21	12149335	0.057	17.4	9065318	4.57	57.87	66.51	68.87
31-03-21	12221665	0.06	16.7	9334695	4.72	57.87	66.51	68.87

Studies show that when more and more people get vaccinated, their immunity level against the virus will get increased. But there is still a possibility that the vaccinated person may become the carrier of the virus and pass it to someone else. Experts recommend the use of sanitizers, observation of social distance, and wearing of masks is to be continued even after getting vaccinated. When 70% of the total population develops immunity, it is a good sign of progress for any country.

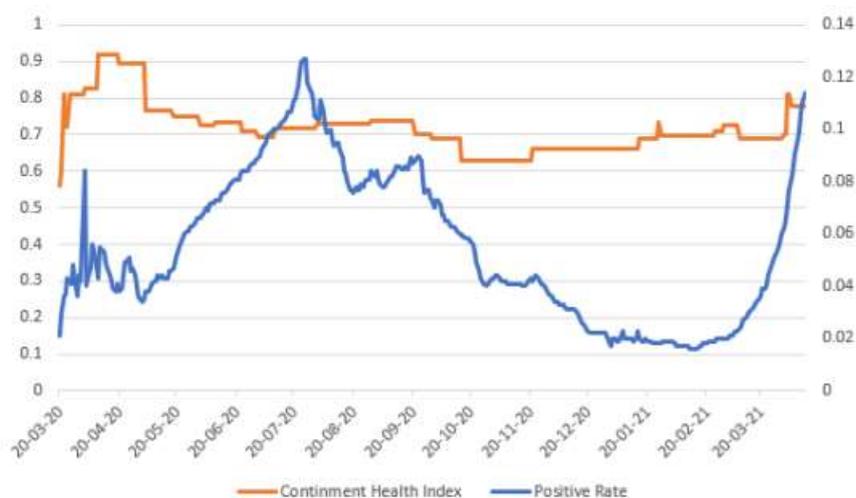


Fig. 5: Stringency Level and COVID-19 Positive cases between 20th March 2020 and 20th March 2021

SI is considered as the key product of the OxCGRT. It depends upon 14 different key indicators and ranges from 0 to 100. Between 25th March 2020 and 19th April 2020, the government imposed a strict lockdown. Hence during that period, the value of SI was 100. As indicated in Figure 5, when the Stringency Index was more the positive rate was less. There were a smaller number of positive cases between 20th June 2020 and 20th March 2021. When the SI value dropped, there is a sudden surge in the number of positive cases. At the end of March 2021, there is a spike in the number of positive cases [20].

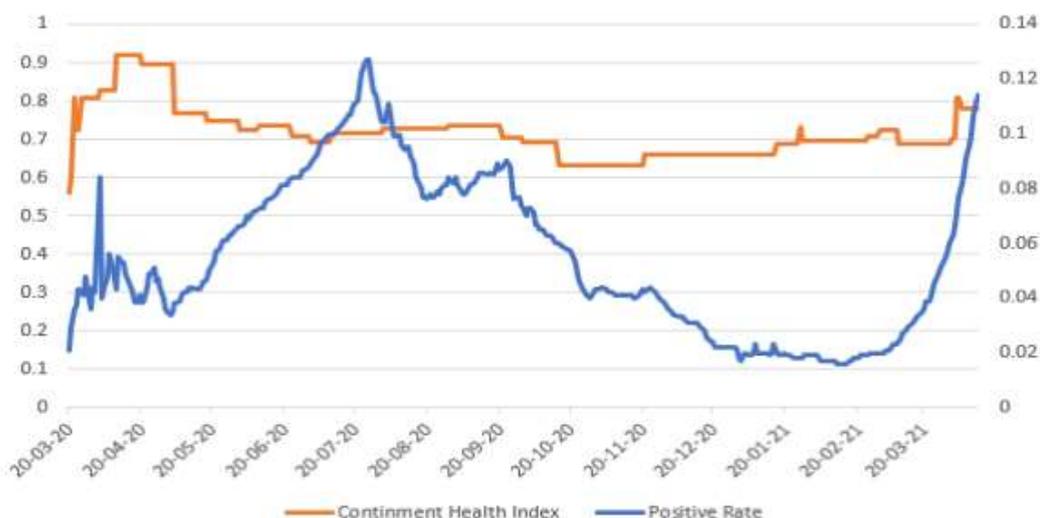


Fig. 6: Government Response Level and COVID-19 Positive cases between 20th March 2020 and 20th March 2021.

Figure 6 indicates the relationship between GRI and COVID-19 positive cases between 20th March 2020 and

20th March 2021. The GRI depends upon 16 different key indicators. When the GRI value was dropped, there is a sudden surge in the number of positive cases. The positive rate was more in July 2020 and it was dropped was the GRI was almost steady between April 2020 and March 2021. At the end of March 2021, there is a surge in the number of positive cases [21].

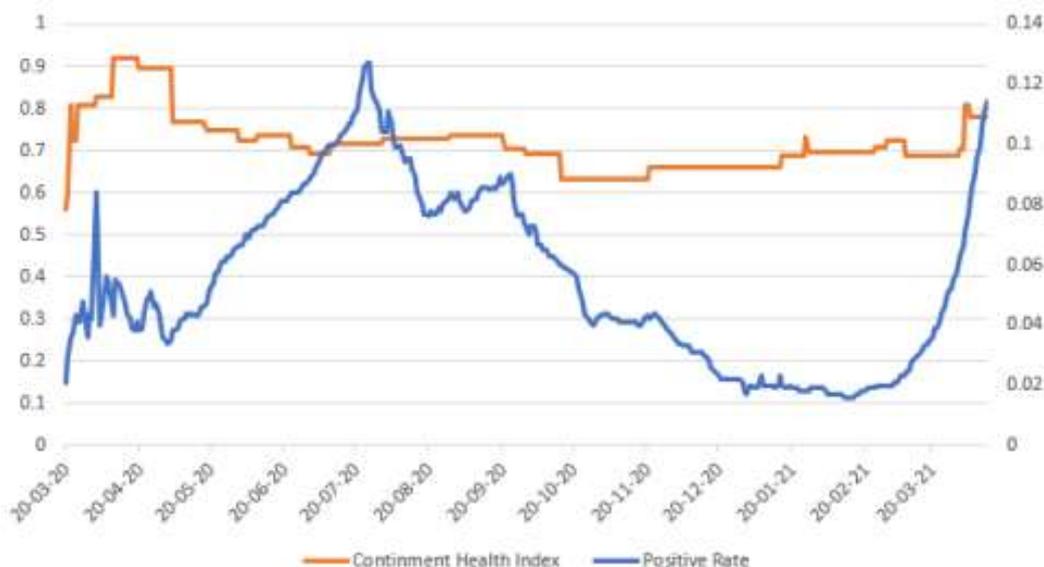


Fig. 7: Containment and Health Level and COVID-19 Positive cases between 20th March 2020 and 20th March 2021.

Containment measures are implemented by a country to stop the spread of the virus. Figure 7 indicates the relationship between CHI and COVID-19 positive cases between 20th March 2020 and 20th March 2021. The CHI depends upon 14 different key indicators. When the CHI value was dropped, there is a sudden surge in the number of positive cases. The positive rate was more in July 2020 and it was dropped was the CHI was almost steady between April 2020 and March 2021. These results indicate that the measures followed by the country are found to be effective in flattening the curve of positive rate. As a result of the decrease in the CHI at the end of March 2021, there is a gush in the number of positive cases [22].

8. COVID-19 INFECTION FORECASTING :

According to Buzrul *et al.* [modell] in some countries, the total number of cases at a given time ‘t’ shows sigmoid behavior. The statistical model is indicated by using the formula

$$y(t) = \frac{a^m \cdot t^m}{b^m + t^n}$$

Equation (1)

In equation (1) y(t) is the total number of cases, a, b, m, and n are parameters whose value can be adjustable. At time t=0 y(t) is also 0 which indicates that to begin with the total number of cases was zero. When the value of m is greater than that of n as $t \rightarrow \infty$, $y(t) \rightarrow \infty$ which means that the total number of cases increases continuously. When m is less than n as $t \rightarrow \infty$, $y(t) \rightarrow 0$ this means that when the value of the adjustable parameter m is less than that of n, the total number of cases decreases as time passes and will reach zero. The formula takes a special value when m is equal to n as

$$y(t) = \frac{a^m \cdot t^m}{b^m + t^m}$$

Equation (2)

Equation (2) shows the same value as that of Equation (1) when t is 0. When $t \rightarrow \infty$, the total number of cases converges at a given value after a certain point of time.

Jayatileke *et al.* [Model2] used the SIRD (susceptible, infected, recovered, dead) model to predict the number of cases in the near future. The model uses a sliding window with equal intervals and the method of least squares to estimate the accuracy of predictions. N represents the total number of populations at a given time t, which is the sum of susceptible, infected, recovered, and dead as mentioned in Equation (3).

$$N = S(t) + I(t) + R(t) + D(t)$$

Equation (3)

If α , β , and γ denote the projected rate of infection, rate of recovery, and death rate respectively then to

calculate the probability of susceptibility the equation (4) can be used.

$$S(t) = S(t-1) - \frac{\alpha}{N} \cdot S(t-1) \cdot I(t-1) \quad \text{Equation (4)}$$

The number of infected at time t is calculated using the equation (5)

$$I(t) = I(t-1) + \frac{\alpha}{N} \cdot S(t-1) \cdot I(t-1) \quad \text{Equation (5)}$$

The total number of recovered cases at time t is calculated using the equation (6)

$$R(t) = R(t-1) + \beta \cdot I(t-1) \quad \text{Equation (6)}$$

The number of deaths can be estimated using the equation (7)

$$D(t) = D(t-1) + \gamma \cdot I(t-1) \quad \text{Equation (7)}$$

This model also requires another parameter R_0 which is the basic reproduction rate. It is calculated using equation (8)

$$R_0 = \frac{\alpha}{\beta + \gamma} \quad \text{Equation (8) [18] [23][24]}$$

9. PROCASE MODEL FOR FORECASTING :

The statistical models mentioned in section 7 do not consider the percentage of vaccination. The rate of infection is found to be dependent on several factors. It is low where protective measures such as social distancing, disinfectant use, and sanitization have properly adhered. Other than the intensity of the virus's replication rate, numerous factors influence fatality, recovery, and rates of infection. It also depends on demographic data, a person's disease risk, co-morbidities, and the availability of services in the emergency care departments, such as oxygen cylinders and ventilators. It is also observed that the severity of the disease is very low if a person is vaccinated.

A new mathematical model, ProCase (Project Case) was developed using the models listed above to forecast COVID-19 cases daily. This is seen as an equation (9) below.

$$C_d = C_{d-1} + C_{d-1} \left(\frac{(vpt)^2}{GCS} \right) \quad \text{Equation (9)}$$

Based on the statistics of the day, this model can be used to forecast COVID-19 cases that will be registered tomorrow. Where C_d is the total cases forecasted, C_{d-1} is the total cases reported today, v is the vaccination percent, p is the positive rate, t is the number of tests performed per case, G is the Government Response Index, C is the Containment and Health Index, and S is the Stringency Index. Using ten pre-recorded data sets, the equation's operation is investigated. The accuracy of the analysis is ≥ 98 percent, with a $\leq 2\%$ error rate and same is produced below as Table 4 [17].

Table 4: Datasets used for the verification of the model and its result

Date	Positive Rate	Tests Per Case	Vaccination %	Stringency index	Government Response Index	Containment Health Index	Projected Cases	Actual Cases of the Day	% of Error
01-04-21	0.063	16	4.98	57.87	66.51	70.3	12222803	12303131	0.65
02-04-21	0.066	15.1	5.29	57.87	66.51	70.3	12304394	12392260	0.70
03-04-21	0.071	14	5.51	74.54	70.89	81.01	12393128	12485509	0.74
04-04-21	0.077	13.1	5.73	74.54	70.89	81.01	12486483	12589067	0.81
05-04-21	0.082	12.1	6.02	69.91	68.28	78.04	12590272	12686049	0.75

06-04-21	0.086	11.6	6.31	69.91	68.28	78.04	12687398	12801785	0.89
07-04-21	0.091	11	6.54	69.91	68.28	78.04	12803257	12928574	0.97
08-04-21	0.096	10.4	6.84	69.91	68.28	78.04	12930193	13060542	1.00
09-04-21	0.1	10	7.11	69.91	68.28	78.04	13062316	13205926	1.09
10-04-21	0.106	9.5	7.36	69.91	68.28	78.04	13207874	13358805	1.12

10. DISCUSSION :

AI-based Predictive Analytics tools may also be used to forecast or predict COVID-19-related statistics. We used Datapine's online Data Analytics tool to forecast COVID-19 incidents, Stringency Index, and deaths for the next three months, i.e., May, June, and July 2021. A different group of data has been used to predict different parameters.

Prediction of Stringency Index: index of date and stringency extracted from the above-mentioned dataset was used to map the Stringency Index from February 1, 2020, to April 12, 2021, and to forecast the same for the next three months. To find the future value, it was asked to measure aggregate data using median values accumulated over time. Set a parameter to use a power line to display the trend. The month has been used to establish data points as the interval of time. All data points were used in the projection, with more recent periods being given higher weights. The 95 percent confidence interval for model quality was chosen.

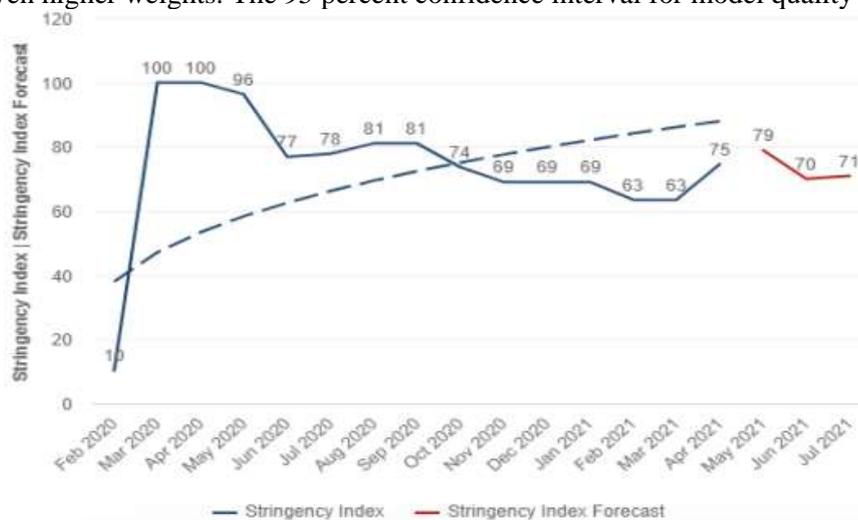


Fig. 8: Predicted Stringency Index for May, June, and July 2021

As seen in the Figure 8 above, the aggregate median stringency index for May, June, and July is expected to be 79, 70, and 71. That means the degree of strictness will be reduced after May, as the establishment may relax a few restrictions.

Prediction of COVID-19 cases: index of date and total cases extracted from the above-mentioned dataset was used to map the COVID-19 cases from April 1, 2021, to April 28, 2021, and to forecast the same for the next three months. To find the future value, it was asked to measure aggregate data using median values accumulated over time. Set a parameter to use a power line to display the trend. The days have been used to establish data points as the interval of time. All data points were used in the projection, with more recent periods being given higher weights. The 95 percent confidence interval for model quality was chosen.

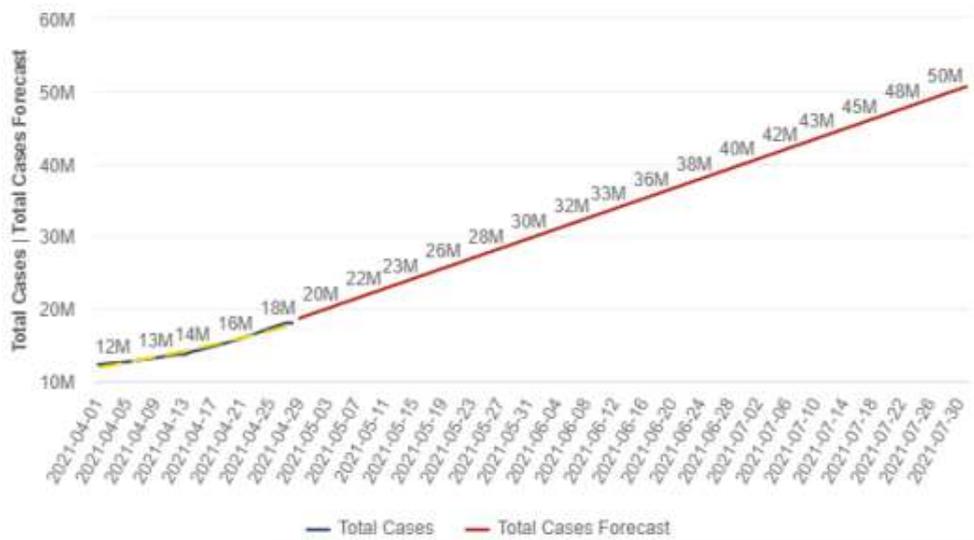


Fig. 9: Predicted COVID-19 cases in India for May, June, and July 2021

As shown in Figure 9 above, by the end of July 2021, the aggregate median cumulative cases are projected to reach 50 million. In April 2021, the total number of cases reported is expected to be about 18 million. It will reach 20 million in the first week of May, 30 million in the second, 40 million in the third week of July, and 50 million in the fourth.

Prediction of Total deaths: index of date and total deaths due to COVID-19 extracted from the above-mentioned dataset was used to map the COVID-19 cases from April 1, 2021, to April 28, 2021, and to forecast the same for the next three months. To find the future value, it was asked to measure aggregate data using median values accumulated over time. Set a parameter to use a power line to display the trend. The days have been used to establish data points as the interval of time. All data points were used in the projection, with more recent periods being given higher weights. The 95 percent confidence interval for model quality was chosen

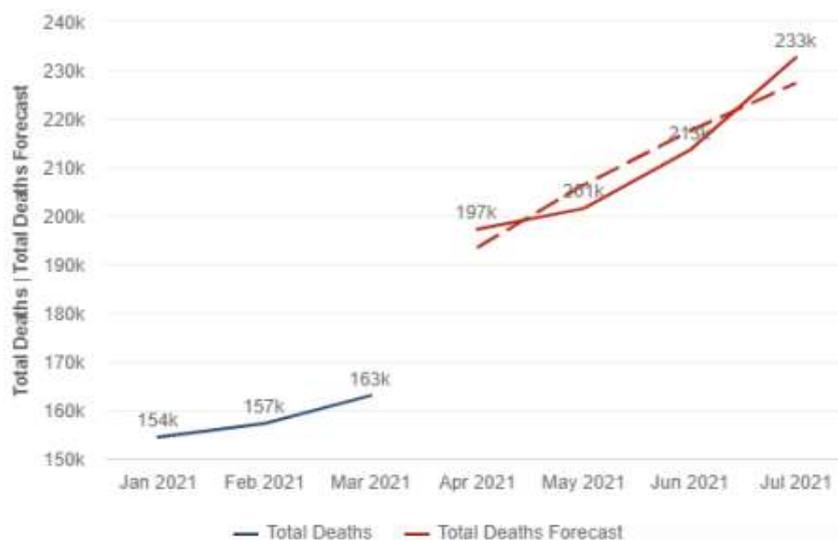


Fig. 10: Predicted deaths due to COVID-19 for May, June, and July 2021

As shown in Figure 10 above, the total number of deaths in India due to COVID-19 is projected to reach 2.33 lakhs by the end of July 2021. It is expected to be around 1.97 lakhs at the end of April 2021, 2.0 lakhs in May, and 2.13 lakhs in June. There is a possibility of the deterioration of the number of COVID-19 infections after July as the vaccination will be made available to more people [24-26].

11. CONCLUSION :

The Oxford COVID-19 Government Response Tracker tracks the level of rigor with which a government implements COVID-19 prevention and suppression measures. These indexes take into account all steps that

governments around the world have adopted and are thus applicable to India as well. It was observed that in India, as in other countries, there is a close association between Stringency Level and COVID-19 cases. The higher the degree of stringency, the lower the cases, and vice versa. The same can be said about the government's role and degree of containment & health. In this paper, we analyzed various mathematical models for predicting the total number of COVID-19 cases and deaths due to COVID-19 in India. We also examined the relationship between total cases and the Government's Response Index, Containment & Health Index, and Stringency Index indicators. The model we proposed to predict COVID-19 cases on a day-by-day basis had a 98 percent accuracy rate and a 2% error rate.

REFERENCES :

- [1] Rajeshwari M. et al. (2020). Web-Oriented Things Systems with 5T Policy to Manage and Contain COVID-19. *International Journal of Applied Engineering and Management Letters (IJAEML)*, 4(2), 138-158.
- [2] Geetha Poornima K. et al. (2020). *Integration of Adaptive Technologies with Healthcare for the Early Identification and Control of COVID-19 Pandemic Disease. International Journal of Health Sciences and Pharmacy (IJHSP)*, 4(2), 5-28.
- [3] COVID-19 Government Response Tracker. (2020). Retrieved from <https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker> on 28-04-2021.
- [4] Naudé, W. (2020). Artificial intelligence vs COVID-19: limitations, constraints and pitfalls. *AI & society*, 35(3), 761-765.
- [5] Etxegarai, U., Portillo, E., Irazusta, J., Arriandiaga, A., & Cabanes, I. (2018). Estimation of lactate threshold with machine learning techniques in recreational runners. *Applied Soft Computing Journal*, 63(1), 181–196.
- [6] Naglah, A., Khalifa, F., Mahmoud, A., Ghazal, M., Jones, P., Murray, T., ... & El-Baz, A. (2018, December). Athlete-customized injury prediction using training load statistical records and machine learning. In *2018 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)* (pp. 459-464). IEEE.
- [7] Iwendi, C., Bashir, A. K., Peshkar, A., Sujatha, R., Chatterjee, J. M., Pasupuleti, S., Mishra, R., Pillai, S., & Jo, O. (2020). COVID-19 patient health prediction using boosted random forest algorithm. *Frontiers in Public Health*, 8(7), 1–9.
- [8] Simsekler, M. C. E., Qazi, A., Alalami, M. A., Ellahham, S., & Ozonoff, A. (2020). Evaluation of patient safety culture using a random forest algorithm. *Reliability Engineering & System Safety*, 204(1), 1-9.
- [9] Anastassopoulou, C., Russo, L., Tsakris, A., & Siettos, C. (2020). Data-based analysis, modelling and forecasting of the COVID-19 outbreak. *PloS one*, 15(3), 1-21.
- [10] Oytun, M., Tinazci, C., Sekeroglu, B., Acikada, C., & Yavuz, H. U. (2020). Performance Prediction and Evaluation in Female Handball Players Using Machine Learning Models. *IEEE Access*, 8, 116321–116335.
- [11] Homolak, J., Kodvanj, I., & Virag, D. (2020). Preliminary analysis of COVID-19 academic information patterns: a call for open science in the times of closed borders. *Scientometrics*, 124(3), 2687-2701.
- [12] Krishna Prasad, K., Aithal, P. S., Bappalige, Navin N., & Soumya, S., (2021). An Integration of Cardiovascular Event Data and Machine Learning Models for Cardiac Arrest Predictions. *International Journal of Health Sciences and Pharmacy (IJHSP)*, 5(1), 55-54.
- [13] Agrawal, R., & Gupta, N. (2021). Analysis of COVID-19 Data Using Machine Learning Techniques. In *Data Analytics and Management* (pp. 595-603). Springer, Singapore.
- [14] Buzrul, S., Food, K., Food, K., & Food, K. (2020). *Journal of Population Therapeutics & Clinical Pharmacology*. 27(10), 76–84.
- [15] Cross, M., Ng, S. K., & Scuffham, P. (2020). Trading Health for Wealth: The Effect of COVID-19 Response Stringency. *International Journal of Environmental Research and Public Health*, 17(23),

8725.

- [16] Prol, J. L., & Sungmin, O. (2020). Impact of COVID-19 measures on short-term electricity consumption in the most affected EU countries and USA states. *iscience*, 23(10), 427-436.
- [17] OxCGRT/covid-policy-tracker. (2020). Retrieved from GitHub website: <https://github.com/OxCGRT/covid-policy-tracker/tree/master/data> on 22-02-2021
- [18] Doti, J. L. (2021). Examining the impact of socioeconomic variables on COVID-19 death rates at the state level. *Journal of Bioeconomics*, 23(1), 15-53.
- [19] Pal, R., & Yadav, U. (2020). COVID-19 pandemic in india: present scenario and a steep climb ahead. *Journal of Primary Care & Community Health*, 11(7),1-4.
- [20] Musić A., Telalović J.H., Đulović D. (2021) The Influence of Stringency Measures and Socio-Economic Data on COVID-19 Outcomes. In: Hasic Telalovic J., Kantardzic M. (eds) Mediterranean Forum – Data Science Conference. MeFDATA 2020. *Communications in Computer and Information Science*, 1343(1), 39-54.
- [21] Kumaresan, J., Bolaji, B., Kingsley, J. P., & Sathiakumar, N. (2020). Is the COVID-19 pandemic an opportunity to advance the global noncommunicable disease agenda?. *International Journal of Noncommunicable Diseases*, 5(2), 43-44.
- [22] Navaretti, G. B., Calzolari, G., Dossena, A., Lanza, A., & Pozzolo, A. F. (2020). In and out lockdowns: Identifying the centrality of economic activities. *Covid Economics*, 17(1), 189-204.
- [23] Gapen, M., Millar, J., Blerina, U., & Sriram, P. (2020). Assessing the effectiveness of alternative measures to slow the spread of COVID-19 in the United States. *Covid Economics*, 40(1), 46-75.
- [24] Data Analytics using AI Tools Retrieved, from <https://secure.datapine.com/#onboarding> on 22-04-2021
- [25] Jiang, X., Coffee, M., Bari, A., Wang, J., & Jiang, X. (2020). Towards an Artificial Intelligence Framework for Data-Driven Prediction of Coronavirus Clinical Severity Towards an Artificial Intelligence Framework for Data-Driven Prediction of Coronavirus Clinical Severity. *Computers, Materials & Continua*, 63(1), 537-551.
- [26] Bansal, A., Padappayil, R. P., Garg, C., Singal, A., Gupta, M., & Klein, A. (2020). Utility of artificial intelligence amidst the COVID 19 pandemic: a review. *Journal of Medical Systems*, 44(9), 1-6.
