ISSN: 0974-5823 Vol. 7 No. 1 January, 2022

International Journal of Mechanical Engineering

A Review on Mathematical Models for COVID-19 Identification and Prediction

Padma Bhushan Borah, Department of Mathematics, Gauhati University, Guwahati, Assam, India

Dr. Hemanta Kr. Sarmah, Professor, Department of Mathematics, Gauhati University, Guwahati, Assam, India

Abstract: In the current era, the whole community is in a panic about a pandemic as the new variants of COVID-19 are coming, which will put the world economy down and also pose a life-threatening situation. Therefore, there is a need for some computation methods for the identification and prediction of the outbreak of the disease so that prior preventive measures can be taken. Mathematical modeling is critical in estimating and managing the latest COVID-19 epidemic. In this pandemic, most nations implement significant intervention strategies to slow the spreading of COVID-19, although improved modeling techniques might help. The best answer depends on empirical evidence, which is heavily reliant on building best models. Among the most critical matters during this emergency is if we can construct realistic epidemic models to foresee the virus's progress and assess the success of various intervention efforts and their economic consequences. In this article, we provided some critical assessments of mathematical models produced since then for COVID-19 outbreak forecasting. The mathematical models used various parameters like CFR, SIR, SEIR, BRN and Asymptomatic ones which are important for the analysis of the models. Apart from it intelligent approaches have the ability to enhance the effectiveness of the models which are generally used for the COVID-19 and thus the analysis of various approaches based on it has been done in this paper. The integration of the intelligent approaches along with the mathematical modeling has the tendency to predict the outbreak efficiently with the right time.

Keywords: *COVID-19, CFR, SIR, SEIR, SVM, CNN, Asymptomatic, Accuracy, Sensitivity, Outbreak*

1. Introduction:

COVID-19 also termed as SARS-CoV-related infectious illness [1]. It is expected to cause the world's worst health disaster of the twenty-first century in 2020, and numerous new viral variations, such as omicron, are on the way. Chronic cough, temperature, and breathing problems are frequent signs in patients [2]. The most important problem with COVID-19 is its rapid global spread. As a result, the World Health Organization (WHO) proclaimed it a worldwide pandemic on March 11, 2020, after the first case being recorded in Wuhan, China [3]. The epidemic of a new corona virus known as COVID-19 in China has stimulated the interest of many scientists, particularly mathematicians who engage in mathematical modeling. At the moment, the COVID-19 epidemic has expanded globally as a pandemic. Many researchers are working around the clock to find ways to limit its impacts through vaccine, but aside from that, forecasting the epidemic and identifying it may be highly useful, reducing the harm to a large extent. Under various conditions, epidemiologic statistical methods have the capacity to forecast the epidemic crest of COVID-19. Shutdown is one of most successful mitigation techniques used throughout the world for mitigating COVID-19 infections. In practice, an epidemic works in a similar manner, this can be quantitatively predicted. Originally, the number of active patients climbed steadily, as is typical of exponential behavior. When it reaches the top, it rolls over and eventually diminishes. Eventually, the outbreak declines to zero, indicating the ending of the pandemic.

Models may be used for a variety of purposes, such as analyzing the key drivers of patterns or organizing trials. Models are, by definition, abstractions of the primary mechanisms that underlie COVID-19 transmission, and they are not intended to reflect the entire complexities of human relationships. As the number of cases declines, coincidence plays a key role in deciding the outbreak's future trend. Because of the variability of infectiousness, this is especially true for COVID-19. About 20% of sick persons generate approximately 80% of illnesses in generally. This actually makes sense; how an outbreak would spread from such a single sick individual is determined by their traits and behavior. Anyone who stays alone but works from home are less capable of spreading disease than somebody who operates in a high-risk environment or resides in a congested environment.

Mathematical models are idealized realizations that allow different situations to be examined without having to experience them firsthand. Under many conditions, they have the ability to detect and forecast the epidemic. To comprehend the spread pattern of a pandemic, many mathematical models have been presented [4–7]. Among all these methods, Susceptible (S)-Infected (I)-Recovered (R), has already been widely utilized earlier to forecast the impact of HIV virus [8-9], plague [10], and so on. The SIR technique has recently been used to forecast the COVID-19 progression. Such investigations, however, were conducted at a very initial point of the epidemic. Additionally, most research have already been largely focused on the COVID-19 spread monitoring under normal settings, hence the prognosis for epidemic peak seems to be less reliable.

During previous and current pandemics situations, mathematical models have been widely employed to get a better understanding of disease propagation mechanisms and to forecast when and at what cost the illness will be suppressed. Mathematical modeling can be a key tool in combating COVID-19, and it is critical to combine available research in this field and identify obstacles and open issues. AI has primarily been utilized in medical picture separation and identification to determine whether an individual has COVID-19 or the seriousness of the illness. These paintings' pictures have been mostly generated from X-ray radiography or Computed Tomography (CT). CT scans are used to identify anomalies in the body, such as malignancies and hemorrhages. It can also identify amniotic fluid, and respiratory infections. This certifies it for the identification of COVID-19, an illness that causes the lungs and respiratory. Using AI techniques in conjunction with mathematical modeling will allow for the efficient prediction and identification of COVID-19 and its variations. As a result, there is a need to understand the process underlying the models used for COVID-19 identification and prediction so that, in the future, if someone wants to construct a new one model, they have the necessary conditions.

The main contributions of this paper are:

1. It explains the mathematical models that have already been constructed thus far, as well as the parameters used to evaluate the COVID-19.
2. It provides the detailed literature work that has been done pertaining to the mathematical models for COVID-19 identification and prediction, along with the intelligent approaches used for the classification of COVID-19 cases.
3. Through comparative analysis, it also highlights the major factors for evaluating mathematical models as well as intelligent modeling techniques.

The manuscript is classified into following sections. The details about the mathematical models for COVID-19 and the main issues associated with them are defined in 1st section. The main factors for the model working are highlighted in section 2nd. The work done by others in the field of COVID-19 modeling has been mentioned in section 3rd. Comparative analysis of various models and intelligent modeling approaches has been executed in section 4th which is followed by the conclusion as the 5th section.

2. Mathematical Models and Factors for Analysis

Among the most critical matters during the outbreak is if one can construct mathematical techniques to anticipate the progress of the epidemic and assess the efficiency of different intervention methods as well as their economic consequences. The techniques have a significant impact on policy and analytical decision-making. Empirical models, incorporating Machine Learning (ML), statistical, and dynamic approaches, are the most common types of models used in epidemiology. There are various factors that are being considered while evaluating the models which are defined below.

Case Fatality Ratio (CFR): One of most worrying aspects of a pandemic is its intensity. The mortality ratio is a good metric for describing the intensity of a communicable illness. It is difficult to forecast the mortality rate since it evolves over time and may be monitored in a range of ways throughout an epidemic. The CFR is a common statistic that represents the ratio of disease-related mortality to the reported cases diagnosed [11].

Susceptible-Infected-Removed (SIR): The goal of preventive measures is to develop a prediction approach in terms of understanding the elements that drive COVID-19 spread. The SIR is a key that depicts the behaviors of an infectious epidemic in the presence of a large community which has already been exposed, contaminated, and cured [12]. Considering that the virus is spread only once, an affected individual usually dies or cures. As the infection spreads, those who are vulnerable are more likely to become infected, and those who are afflicted are more likely to be dropped. This indicates that individual either die or heal. It is considered that the overall population is constant and also that the overall sick population ultimately falls into the deleted group. The transmission of an infectious virus is influenced by variables other than illness. These include societal, cultural, sociological, economical, and geographical factors.

Basic Reproduction Number (BRN): The BRN, abbreviated R0, is a significant aspect in epidemiology for determining that whether infectious illness may spread to become a pandemic. According to the SIR model, R0 is the mean number of additional cases spread by a one sick person in a total population [13]. In particular, if R0 is bigger than one, the pandemic spreads quickly. In contrast, if R0 is smaller than value one, epidemic spreads slowly and eventually dies before all become infected.

Asymptomatic transmission: People contaminated with COVID-19 may exhibit a various symptoms during the epidemic. But, it is also likely that a large percentage of persons have no indications, referred to as asymptomatic cases, owing to illness ignorance or testing capability limitations. If an infected person exhibits no signs, it is difficult to detect an epidemic since they may be transmitting the virus without really realizing it [14]. As a result, asymptomatic spreading is perhaps the most difficult aspect of addressing the current COVID-19 outbreak. The SEIR is a modification to the standard SIR that takes asymptomatic infection into account. The SEIR model introduces a new class called "Exposed" (E), which contains the incubating population.

Herd Immunity (HI): It is a core notion in pandemic theory that refers to the population-level impact of personal immunity in preventing pathogen spread. HI for a disease occurs when a sufficiently enough percentage of the population is naturally immune, minimizing the chance of active contact among sick and sensitive persons [15]. HI is impacted by a variety of factors, including viral dynamics and transmission mechanisms, as well as the people in the herd who develop immunity. To avoid an infectious virus epidemic, a significant number of persons must be resistant to guarantee that the susceptible proportion is minimal sufficient, indicates that now the average infective quantity is less than one. It is being developed in two ways. One is the natural immunity and other one is developed through the vaccination after a period of time.

Intervention measures: When a vaccination is not accessible, preventative efforts aimed at lowering transmission speed in the community and therefore minimizing viral infection are crucial for an infectious epidemic [16]. Precautionary and containment approaches can be classified into two parts: pharmacological initiatives, which include antiviral and immunizations, and non-pharmaceutical intervention strategies (NPIs), which include case separation, domestic quarantine, store, college, or place of work closing, travel bans, and so on. These actions are also known as "community mitigation techniques." NPIs [17] are categorized into four categories: (a) correspondence for behavior influence, (b) individual safety precautions (such as hand washing and surgical masks), (c) environmental initiatives (such as changing moisture and rising airflow), (d) social distancing initiatives, and (d) transportation initiatives.

Many major predictions in projecting the destiny of the COVID-19 pandemic have been relied on insufficient evidence. Models can efficiently capture features of epidemics while failing to accommodate for other characteristics like clinical diagnostic reliability, whether immunity would fade fast, age structure, and risk factors such as smoke and air pollutants. Models can be valuable tools, but they should not be overly construed, especially for long-term forecasts such as the precise date of an infection peak.

3. Literature Work

In this section the work that has been done the field of modeling done for the COVID-19 identification and prediction on the basis of various models and factors that have discussed above by various researchers is expressed. We have outline the work based on various themes as mentioned below. First of all work related to models defined has been highlighted and then the work based on factors usage as defined in the above section has been described. Also the models and techniques that make use of AI in COVID-19 has also been outlined.

3.1 Mathematical Models Related Work

According to the authors of [18], SEIR and SIR methods are the most extensively used for forecasting, while deep learning approaches based on Convolution Neural Network (CNN) seem to be the most frequently used approach for categorization of X-ray and CT relevant to COVID-19 treatment. In [19] provides a detailed analysis of several deterministic and stochastic modeling methodologies, stressing the assumptions required in developing the models. The researchers published a similar analysis utilizing simple SIR and SEIR to examine epidemiological aspects and intervention options in [20] and [21]. The authors of [22] emphasize the relevance of mathematical modeling while also pointing out that estimating even basic epidemiological parameters raises significant technical challenges. The SIR model, which is based on nations such as Italy, Germany, Spain, and the United Kingdom, is explored in [23]. This SIR model's model variable evaluation and control options are also discussed. Similarly, the author [24] emphasizes the applicability, potentials, and limits of mathematical model-based investigations. Fixed transmission speeds and modeling that is confined to human-to-human, avoiding a drop in communication owing to the rise in conformance, are highlighted as shortcomings in [24].

3.2 Factors Based Models Related Work

In [25] authors used a SIR with a time-dependent rate of infection to predict and anticipate the peak dates for COVID-19 infections in eight countries. In [26] examined the progression of the COVID-19 epidemic in Italy, France, and China using a modified SIR with a "dead" D segment. The authors of [27] applied the SIR model to new networks in order to analyze COVID-19. They investigated the distance travelled between hotspots and the number of instances. The authors of [28] used an age based SIR to assess the results of social-distancing estimations to stop the spread of the epidemic in India. The authors used survey data and Bayesian interpolation to calculate the basic reproduction ratios. They believe the amount of asymptomatic cases was zero due to a lack of existing evidence. Another author [29] used a Bayesian hierarchical system to build the eSIR model. A very few individuals of the diseased and eliminated persons are constructed using state-space frameworks in this case. The authors calculated the features of the eSIR and forecasted the number of sick and deleted persons at a future time point utilizing Monte Carlo simulation.

The impact of a containment approach and symptomatic assessment on a simulated COVID-19 distribution scenario at the position in India is simulated using SEIR in [30]. The authors of [31] investigated how differences in population mixing influenced the evolution of the new corona virus epidemic in Wuhan by using contact patterns particular to simulated areas in Wuhan whereas the lockdown restrictions were in place. The SEIR is used in [32] to examine the mechanisms of COVID-19 dissemination and prevention. Probability in case observation is also taken into account in this model, for different asymptomatic COVID-19 events. The authors [33] suggest a modified SEIR model. They looked at six different scientific methods of states. The authors of [34] adjusted the SEIR to incorporate the rate of state change based on the current position as well as the history, due to the fact that the COVID viruses are contagious during the incubation phase. Their forecasts are mostly limited to the Chinese city of Wuhan. The authors [35] compared logistic growth approaches, traditional SEIR structure, and expanded SEIR structure to forecast the spread of COVID-19 illness. The findings revealed that the length and duration of the first quarantine are critical variables in controlling the epidemic magnitude. Furthermore, authors [36] used the segmented Poisson model, which also is focused on power function and exponential curve, to predict the COVID-19. The authors of [37] proposed a mathematical model to predict the probability of spread of the highly contagious COVID-19 illness. They have employ mobility parameters to determine the likelihood of disease transmission.

3.3 Other Related Models Work

The authors [38] analyze data in Brazil using a Susceptible-Infectious-Quarantined-Recovered (SIQR) framework. It is assumed that the quantity of quarantined people increased dramatically and then stabilized. Later, the SEIQR paradigm with timing differences for delay and an asymptomatic period is created by a variation of this approach with one more element, "exposed" [39]. Recently, the Bats-Hosts-Reservoir-People transmission system [40] is utilized to predict the possible transmission between bats to people. Another technique is being established to measure age-specific propagation using the age-specific Susceptible, Exposed, Symptomatic, Asymptomatic, Recovered, Seafood Market (SEIARW) prototype based on these two suspicious transmission paths [41]. The researchers noted that COVID-19 communicability is greater in the aged than in the children. The impact of measures and self-protection mechanisms on COVID-19 mode of transmission is modeled using the Markov Chain Monte Carlo (MCMC) technique in [42]. The SPSS modeler is also utilized to look at the relationship between daily average heat and COVID-19 growth rates in affected countries [43]. It has been demonstrated that pandemic percentages are greater in case studies with lower average temperatures.

3.4 Intelligence Techniques in Modeling Related Work

The authors of [44] combined CNN for the dataset of chest x-ray radiographic pictures of patients to try to offer doctors with a clearer understanding of the essential elements impacting COVID-19 instances. Three CNN-based algorithms are presented in [45] for identifying COVID-19 in pneumonia individuals using chest X-ray radiography pictures. They employed ROC assessments and confusion matrix to compare performance and discovered that the ResNet50 model has performed as best classifier. The identification of COVID-19 is accomplished using CNN in [46]. They identified COVID patients based on visual characteristics retrieved from volumetric chest CT scans. They observed that the approach is not only capable of detecting COVID-19 cases, but also of distinguishing them from other infections associated bronchitis and non-pneumonic lung disorders. The authors of [47] constructed seven alternative CNN architectures with the goal of supporting radiologists in the automated diagnosis of COVID-19. The authors of [48] revealed an early identification of COVID-19 using Support Vector Machines (SVM). They have used this technique for abdominal CT scans.

To determine COVID-19 disease in X-ray pictures, in [49] authors use a mix of deep feature extractor and SVM. The suggested model has a 95.38 percent accuracy rating. SVM is used to characteristics collected from chest X-ray radiography pictures in [50] to detect COVID-19 patients early. The characteristics of the photos are extracted using a multi-level threshold. Logistic Regression (LR) is used in [51] to find clinical and CT properties that reflect COVID-19 intensity. In [52] extracts feature representations from COVID-19 sufferer chest X-ray pictures using the SMOTE approach, which is utilised to equalize datasets from COVID-19 and typical patients. Furthermore, Machine Learning (ML) methods such as Random Forest (RF) and XGBoost have been used to categories the data based on the characteristics. The authors of [53] used traditional statistical study with ML to extract characteristics from CT images. A mixed classifier system that is based on Naive Bayes (NB) is then used to classify the retrieved features. LDA is employed in [54] to investigate the features and rules of hematological alterations in COVID-19 patients. The individuals clinical and laboratory test data are analyzed, and several hematological characteristics are fitted using LDA.

4. Model Analysis and Interpretations

There are various mathematical models which are formulated pertaining to COVID-19 identification and prediction. There are many factors that are involved in the analysis of this pandemic, but still, there are some inferences that have been drawn from the work that has been highlighted in the above sections so that insights about the major challenges and research areas which are still uncovered can be addressed to the researchers who are willing to start their work in the same direction using modeling techniques.

In table 1 below, the comparison of various mathematical models for the COVID-19 identification or prediction is analyzed based on the factors that are important for the implementation and evaluation of the same. The major parameters that are considered are SIR, SEIR, CFR, intelligence and data set usage. They are regarded as important parameters for model analysis because the vast majority of mathematical models must adhere to the aforementioned parameters during execution.

Table 1: Comparative analysis of mathematical models for COVIS-19 based on parameters

Reference Model	SIR Based	SEIR Based	CFR Based	Intelligent Based	Data Set Usage
[18]	✓	✓	×	✓	✓
[19]	✓	✓	×	×	×
[20]	✓	✓	✓	×	×
[21]	×	✓	✓	×	×
[22]	×	✓	✓	×	×
[23]	✓	×	×	×	×
[24]	×	×	×	×	×
[38]	×	✓	×	×	×
[40]	×	×	×	✓	✓
[42]	×	✓	×	×	✓

It is inferred from table 1 that the majority of models are SEIR-based in addition to SIR. It is also inferred that CFR is being used in most of the models that are SEIR based. Intelligence-based models are not very common, and if the SEIR can be added with intelligent approaches, then it will make an efficient model for the predication of COVID-19. Also, data sets are used only in those models that have used AI-based approaches for their execution.

Table 2 depicts the models that have used the AI-based approaches and methods for the COVID-19 identification along with the factors that they have considered during the performance evaluation of the same. Here, the techniques that are used like CNN, SVM, LR, etc. are also mentioned along with the category of dataset on which the model is being analyzed. The data sets are either public or private, where permission is required before their usage. The factors that are considered are accuracy, sensitivity, and positive prediction estimation (PPE). The majority of the techniques use the concept of a confusion matrix for calculating the effectiveness of the intended approach.

Table 2: Comparative analysis of mathematical models for COVIS-19 based on parameters using AI approaches

Model Reference	Technique Used	Dataset Usage	Accuracy	Sensitivity	Positive Prediction Estimation
[44]	CNN	Public	✓	✓	✓
[45]	CNN	Public	✓	×	×
[46]	CNN	Private	×	✓	×
[47]	CNN	Private	✓	×	×
[48]	SVM	Private	✓	×	×
[49]	SVM	Public	✓	✓	×
[50]	SVM	Public	✓	✓	✓
[51]	LR	Private	✓	✓	✓
[52]	LR	Public	✓	✓	✓
[53]	NB	Public	✓	×	×
[54]	LDA	Public	✓	✓	✓

It is being inferred from table 2 that CNN and SVM are the two approaches of AI that have been widely used for the identification and prediction of COVID-19 and the majority of the work has been done using the public datasets available. Most of the models have considered the accuracy and also have a good sensitivity value, which means that they are able to perform the task efficiently. However, only a few of them take PPE into account, which is also one of the major concerns that represent the effectiveness of the right prediction by a specific approach.

5. **Conclusion and Future Work**

The COVID-19 cases are rising at an exponential manner, and the trails of the new vaccinations are also going in parallel. Another challenge is that the virus is creating new strains owing to mutations. Mathematical modeling proves an effective way of identifying and predicting the pandemic, but the main concern is that they must have followed the parameters for its effective implementation. In this paper, the various mathematical models for COVID-19 have been analyzed under parameters like SIR, SEIR, BRN, CFR, herd immunity and intervention measures. The mathematical modeling of an ongoing pandemic situation is a cumbersome task to be executed as different symptoms are observed for each new variant of COVID-19. It is being inferred that most of the models are SEIR-based in addition to SIR. It is also inferred that CFR is being used in most of the models that are SEIR based. Most of the models have used CNN and SVM in their work for image classification. Most of the models have considered the accuracy and also have a good sensitivity value, which means that they are able to perform the task in an efficient manner. Future research on preventive actions with a cost constraint could be initiated. Moreover, work is required on the latest datasets that contain more features related to the infections caused by COVID-19. Last but not least, efficient mathematical models are required to design hybrid approaches in the near future.

References:

1. Li, R., Pei, S., Chen, B., Song, Y., Zhang, T., Yang, W., & Shaman, J. (2020). Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV-2). *Science*, *368*(6490), 489-493..
2. World Health Organization, 2. (2020). WHO Director-General's remarks at the media briefing on 2019-nCoV on 11 February 2020.
3. Li, Q., Guan, X., Wu, P., Wang, X., Zhou, L., Tong, Y., ... & Feng, Z. (2020). Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia. *New England journal of medicine*.
4. Calafiore, G. C., Novara, C., & Possieri, C. (2020, December). A modified SIR model for the COVID-19 contagion in Italy. In *2020 59th IEEE Conference on Decision and Control (CDC)* (pp. 3889-3894). IEEE.
5. Dhanwant, J. N., & Ramanathan, V. (2020). Forecasting covid 19 growth in india using susceptible-infected-recovered (sir) model. *arXiv preprint arXiv:2004.00696*.
6. Dhillon, P., Kundu, S., Shekhar, C., Ram, U., Dwivedi, L. K., Yadav, S., & Unisa, S. (2020). Case-fatality ratio and recovery rate of COVID-19: scenario of most affected countries and Indian states. *IIPS Analytical Series on Covid*, *19*.
7. Poonia, N., & Azad, S. (2020). Short-term forecasts of COVID-19 spread across Indian states until 1 May 2020. *arXiv preprint arXiv:2004.13538*.
8. Anderson, R. M. (1988). The role of mathematical models in the study of HIV transmission and the epidemiology of AIDS. *Journal of Acquired Immune Deficiency Syndromes*, *1*(3), 241-256.
9. Didelot, X., Whittles, L. K., & Hall, I. (2017). Model-based analysis of an outbreak of bubonic plague in Cairo in 1801. *Journal of The Royal Society Interface*, *14*(131), 20170160.
10. cai Cai, Q., wu Jiang, Q., feng Xu, Q., Cheng, X., Guo, Q., wen Sun, Q., & ming Zhao, G. (2005). To develop a model on severe acute respiratory syndrome epidemics to quantitatively evaluate the effectiveness of intervention measures. *Zhonghua liu xing bing xue za zhi= Zhonghua liuxingbingxue zazhi*, *26*(3).
11. Böttcher, L., Xia, M., & Chou, T. (2020). Why case fatality ratios can be misleading: individual-and population-based mortality estimates and factors influencing them. *Physical biology*, *17*(6), 065003.
12. Hethcote, H. W. (1989). Three basic epidemiological models. In *Applied mathematical ecology* (pp. 119-144). Springer, Berlin, Heidelberg.
13. Sahoo, B. (2016). Disease control through provision of alternative food to predator: a model based study. *International Journal of Dynamics and Control*, *4*(3), 239-253.
14. Ferretti, L., Wymant, C., Kendall, M., Zhao, L., Nurtay, A., Abeler-Dörner, L., ... & Fraser, C. (2020). Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. *Science*, *368*(6491).
15. Fine, P., Eames, K., & Heymann, D. L. (2011). "Herd immunity": a rough guide. *Clinical infectious diseases*, *52*(7), 911-916.
16. Ferguson, N., Cummings, D., Fraser, C., Cajka, J., Cooley, P., & Burke, D. (2006). Estimating disease burden of a potential 602 A (H7N9) pandemic influenza outbreak in the United States. *Nature*, *442*(7101), 448-52.
17. Liu, Y., Morgenstern, C., Kelly, J., Lowe, R., & Jit, M. (2021). The impact of non-pharmaceutical interventions on SARS-CoV-2 transmission across 130 countries and territories. *BMC medicine*, *19*(1), 1-12.
18. Mohamadou, Y., Halidou, A., & Kapen, P. T. (2020). A review of mathematical modeling, artificial intelligence and datasets used in the study, prediction and management of COVID-19. *Applied Intelligence*, *50*(11), 3913-3925.
19. Tang, L., Zhou, Y., Wang, L., Purkayastha, S., Zhang, L., He, J., ... & Song, P. X. K. (2020). A review of multi-compartment infectious disease models. *International Statistical Review*, *88*(2), 462-513.
20. Wang, N., Fu, Y., Zhang, H., & Shi, H. (2020). An evaluation of mathematical models for the outbreak of COVID-19. *Precision Clinical Medicine*, *3*(2), 85-93.
21. Lin, Y. F., Duan, Q., Zhou, Y., Yuan, T., Li, P., Fitzpatrick, T., ... & Zou, H. (2020). Spread and impact of COVID-19 in China: a systematic review and synthesis of predictions from transmission-dynamic models. *frontiers in Medicine*, *7*, 321.

22. Meehan, M. T., Rojas, D. P., Adekunle, A. I., Adegboye, O. A., Caldwell, J. M., Turek, E., ... & McBryde, E. S. (2020). Modelling insights into the COVID-19 pandemic. *Paediatric respiratory reviews*, *35*, 64-69.
23. Bärwolff, G. (2020). Mathematical modeling and simulation of the COVID-19 pandemic. *Systems*, *8*(3), 24.
24. Wang, J. (2020). Mathematical models for COVID-19: applications, limitations, and potentials. *Journal of public health and emergency*, *4*.
25. Barmparis, G. D., & Tsironis, G. P. (2020). Estimating the infection horizon of COVID-19 in eight countries with a data-driven approach. *Chaos, Solitons & Fractals*, *135*, 109842.
26. Fanelli, D., & Piazza, F. (2020). Analysis and forecast of COVID-19 spreading in China, Italy and France. *Chaos, Solitons & Fractals*, *134*, 109761.
27. Biswas, K., Khaleque, A., & Sen, P. (2020). Covid-19 spread: Reproduction of data and prediction using a SIR model on Euclidean network. *arXiv preprint arXiv:2003.07063*.
28. Singh, R., & Adhikari, R. (2020). Age-structured impact of social distancing on the COVID-19 epidemic in India. *arXiv preprint arXiv:2003.12055*.
29. Ray, D., Salvatore, M., Bhattacharyya, R., Wang, L., Du, J., Mohammed, S., ... & Mukherjee, B. (2020). Predictions, role of interventions and effects of a historic national lockdown in India's response to the COVID-19 pandemic: data science call to arms. *Harvard data science review*, *2020*(Suppl 1).
30. Mandal, S., Bhatnagar, T., Arinaminpathy, N., Agarwal, A., Chowdhury, A., Murhekar, M., ... & Sarkar, S. (2020). Prudent public health intervention strategies to control the coronavirus disease 2019 transmission in India: A mathematical model-based approach. *The Indian journal of medical research*, *151*(2-3), 190.
31. Prem, K., Liu, Y., Russell, T. W., Kucharski, A. J., Eggo, R. M., Davies, N., ... & Klepac, P. (2020). The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: a modelling study. *The Lancet Public Health*, *5*(5), e261-e270.
32. Kucharski, A. J., Russell, T. W., Diamond, C., Liu, Y., Edmunds, J., Funk, S., ... & Flasche, S. (2020). Early dynamics of transmission and control of COVID-19: a mathematical modelling study. *The lancet infectious diseases*, *20*(5), 553-558.
33. Cao, J., Jiang, X., & Zhao, B. (2020). Mathematical modeling and epidemic prediction of COVID-19 and its significance to epidemic prevention and control measures. *Journal of Biomedical Research & Innovation*, *1*(1), 1-19.
34. Tang, Z., Li, X., & Li, H. (2020). Prediction of new coronavirus infection based on a modified SEIR model. *medRxiv*.
35. Zhou, X., Ma, X., Hong, N., Su, L., Ma, Y., He, J., ... & Long, Y. (2020). Forecasting the worldwide spread of COVID-19 based on logistic model and SEIR model. *MedRxiv*.
36. Zhang, X., Ma, R., & Wang, L. (2020). Predicting turning point, duration and attack rate of COVID-19 outbreaks in major Western countries. *Chaos, Solitons & Fractals*, *135*, 109829.
37. Islam, M. M., Islam, M. M., Hossain, M. J., & Ahmed, F. (2020). Modeling risk of infectious diseases: a case of Coronavirus outbreak in four countries. *MedRxiv*.
38. Crokidakis, N. (2020). Modeling the early evolution of the COVID-19 in Brazil: Results from a Susceptible–Infectious–Quarantined–Recovered (SIQR) model. *International Journal of Modern Physics C, 31*(10), 2050135.
39. Vyasarayani, C. P., & Chatterjee, A. (2020). New approximations, and policy implications, from a delayed dynamic model of a fast pandemic. *Physica D: Nonlinear Phenomena*, *414*, 132701.
40. Chen, T. M., Rui, J., Wang, Q. P., Zhao, Z. Y., Cui, J. A., & Yin, L. (2020). A mathematical model for simulating the phase-based transmissibility of a novel coronavirus. *Infectious diseases of poverty*, *9*(1), 1-8.
41. Zhao, Z., Zhu, Y. Z., Xu, J. W., Hu, Q. Q., Lei, Z., Rui, J., ... & Chen, T. (2020). A mathematical model for estimating the age-specific transmissibility of a novel coronavirus. *Medrxiv*.
42. Wan, H., Cui, J. A., & Yang, G. J. (2020). Risk estimation and prediction by modeling the transmission of the novel coronavirus (COVID-19) in mainland China excluding Hubei province. *medRxiv*.
43. Pirouz, B., Golmohammadi, A., Masouleh, H. S., Delazzari, C., Violini, G., & Pirouz, B. (2020). Relationship between average daily temperature and average cumulative daily rate of confirmed cases of COVID-19. *MedRxiv*.
44. Wang, L., Lin, Z. Q., & Wong, A. (2020). Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. *Scientific Reports*, *10*(1), 1-12.
45. Narin, A., Kaya, C., & Pamuk, Z. (2021). Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. *Pattern Analysis and Applications*, 1-14.
46. Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., ... & Xia, J. (2020). Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT. *Radiology*.
47. Hemdan, E. E. D., Shouman, M. A., & Karar, M. E. (2020). Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images. *arXiv preprint arXiv:2003.11055*.
48. Barstugan, M., Ozkaya, U., & Ozturk, S. (2020). Coronavirus (covid-19) classification using ct images by machine learning methods. *arXiv preprint arXiv:2003.09424*.
49. Sethy, P. K., & Behera, S. K. (2020). Detection of coronavirus disease (covid-19) based on deep features.
50. Mahdy, L. N., Ezzat, K. A., Elmousalami, H. H., Ella, H. A., & Hassanien, A. E. (2020). Automatic x-ray covid-19 lung image classification system based on multi-level thresholding and support vector machine. *MedRxiv*.
51. Li, K., Wu, J., Wu, F., Guo, D., Chen, L., Fang, Z., & Li, C. (2020). The clinical and chest CT features associated with severe and critical COVID-19 pneumonia. *Investigative radiology*.

52. Kumar, R., Arora, R., Bansal, V., Sahayasheela, V. J., Buckchash, H., Imran, J., ... & Raman, B. (2020). Accurate prediction of COVID-19 using chest X-Ray images through deep feature learning model with SMOTE and machine learning classifiers. *MedRxiv*.
53. Farid, A. A., Selim, G. I., & Khater, H. A. A. (2020). A novel approach of CT images feature analysis and prediction to screen for corona virus disease (COVID-19).
54. Wang, C., Deng, R., Gou, L., Fu, Z., Zhang, X., Shao, F., ... & Li, C. (2020). Preliminary study to identify severe from moderate cases of COVID-19 using combined hematology parameters. *Annals of translational medicine*, *8*(9).