Chapter 8
Computational Intelligence Using Big Data for Fight Against Covid-19 Pandemic in Healthcare Environment

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Abstract In world, COVID-19 disease spread over 214 countries and areas which efficiently affects every aspect of our daily lives. In various areas, motivated by recent applications and advances of big data and computational intelligence (CI), this research aims at increasing their significance in COVID-19 response like prevention of severe effects and outbreaks. To improve diagnosis efforts, assess risk factors from blood tests and deliver medical supplies, CI is used during COVID-19. To forecast future COVID-19 cases, CI is used. To check goodness as high accuracy prediction method, the proposed method is checked with real-world data which focus on CI and big data, method which are used in current pandemic. In upcoming days, to enact necessary protection plans, it is very difficult to detect as well as diagnose. For computational methods with help of big data, this research provides prediction and detection of COVID-19. For predicting and detecting cases of COVID-19, performances of proposed models are used as criteria. To improve detection accuracy of COVID-19 cases, proposed method increases combination of big data analytics and CI models with nature-inspired techniques.

Keywords Computational intelligence · COVID-19 · Pandemic · Big data · Diagnosis

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8.1 Computational Intelligence in COVID-19

Medical industry is pursuing new approaches to track and manage dissemination of COVID-19 pandemic [1] in context of this global health crisis. Extreme acute respiratory syndrome coronavirus 2, a beta-coronavirus [2], triggers COVID-19. On 31 December 2019 in Wuhan, Hubei Province of China, first contaminated case of COVID-19 was identified and was swift to spread to almost every country, 215 countries and areas worldwide. There is no evidence of reductions in number of contaminated and dead cases and management of situation.

There are confirmed cases 1,853,265 and dead cases 118,854, with Europe accounted for about 46.2% and 66.7% of cumulative cases, as recorded by European Center for Diseases Prevention and Control [3] (accurate as of April 14 2020). More specifically, as Corona Board 1 study indicates, there are already very high numbers of cases, of +83, 039 and + 6, 295 infected and dead, with a fatality rate of 6.34%.

As in other industries, in field of modern health amount of data generated daily also grows exponentially [4]. In period, many diseases, epidemics, and even pandemics occurred worldwide, according to studies by World Health Organisation (WHO). Figure 8.1 shows most recent ones.

Modern healthcare systems move from volume-based systems to value-based systems that put a growing demand on health data for the optimisation of resources, enhanced care quality, patient happiness, and outcomes of health. The usefulness of health data for value-based health systems management changes from the use of health data to the reporting of facts to the generation of operational knowledge that can be used to design novel treatments, anticipate therapeutical results and deliver healthy lifespan. Advanced methods for health data analysis that enable (a) a) patient/citizen involvement into the medical process, (b) omnipresent domestic

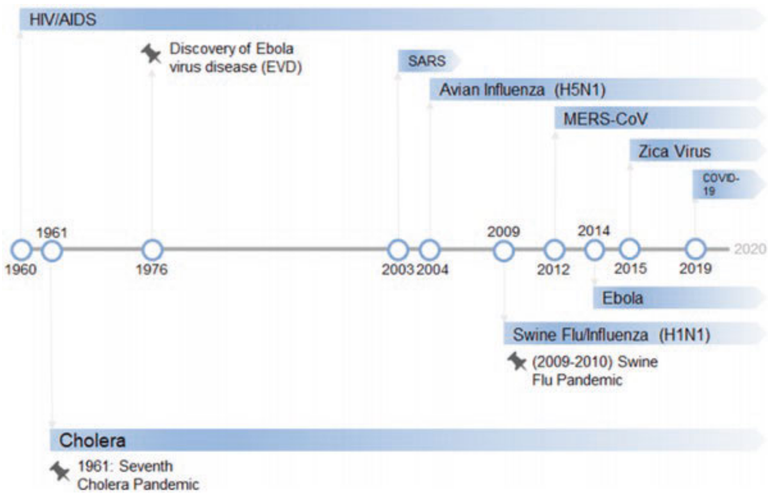


Fig. 8.1 Outbreaks, epidemics and pandemics timeline

healthcare services, extending beyond traditional institutions, (c) improved capturing and integrating heterogeneous healthcare data sources and (d) personalising health data. Health analysis currently comprises sophisticated ways for capturing, integrating and analysing heterogeneous, structured data from clinical and personal health sources in real time to give health care knowledge that is predictive, tailored and patient-centred. A series of intelligent analytical data methods for the data sciences for data management and AI methods for data analytics have been developed by the confluence of Big Data and Artificial Intelligence. Most notably, intelligent methods of health data analysis have the ability to learn, autonomously summarise and understand non-linear connections and causal links inherent in the data. Smart health data analysis (such as: (a) accuracy medicine, (b) forecasting trends and results of disease, (c) healthcare diagnostics for life, (d), support for point of care diagnostics and therapeutic decision making, e) monitoring of ethnographic and (f) optimised use of the healthcare system, are now being used. Machine learning (ML) approaches provide models and associations in data to explore interactions and simulate based on unseen events. ML methods include models. ML methods consist of supervised learning (labeled data learning), unmonitored learning (detection of hidden patterns in data and/or extraction features) and reinforcement education [5]. As ML methods like this can also be classified into techniques for regression, cluster approaches, methods for estimating density and approaches for dimensional reduction. Computational Intelligence (CI) is a subset of ML methods intended to simulate the processing of human knowledge and reasoning processes for the processing of diverse and unknown data sources by algorithms. CI-technologies form a collection of analytical methods and techniques inspired by nature that is created to solve complex real-world information issues that cannot operate as a result of mathematical and conventional modeling: high complexity, unsureness and stochastic nature of systems. The Core CI method trio is produced to solve this growing class of real-world issues, including FL, EA, ANN.

By integrating future healthcare analytics, Big Data changes the health care industry. Doctors can make fast decisions by using Big Data Analytics, on basis of outcome. To provide quality data, big data analytics plays a vital role in handling information that is produced from different resources. Big data plays an important role in healthcare. Big Data has features such as volume, range, velocity and veracity. Big Data not only determines scale but also determines lessons from unstructured, dynamic, heterogeneous, noisy, voluminous data and longitudinal, as information rises dramatically day-by-day [6]. It attempts to compile medical evidence over years into medical libraries, and to digitize the patient histories of payers and providers.

Big data analytics' key problems in the field of health care include the processing, preservation, search, distribution and review of healthcare data. It is also a daunting job to arrange and merge the data after separating them from various layers. In this phase, the medication focused on the reduction of risk must be taken care of in the reduction of mistakes in clinical judgment support and evidence. In compliance with security and safety methods, quality information should be reviewed on – step. Moreover, patients may benefit from lower rates of health care. Real-time

BigData research is the main contribution of the healthcare sector to make predictive decisions. The Big Data chain in public health also needs to be developed because of the need to strengthen successful strategies provided by health sector. Since patients are the final patients in the healthcare sector, they can therefore benefit from money and make informed decisions to protect themselves. These problems should be met as soon as possible by the health sector because they are never standardized [7]. The typical deficiency noted in many exercises of health analysis is (a) the choice of the wrong/suboptimal method of analysis, because of lack of understanding of the relationship between a problem type and the proper analytical options and the method's working; (b) improper data management because data provenance is not understood; and (c) inadequate implementation of a data analysis method.

Rest of this chapter presented Sect. 8.2 is related works, Sect. 8.3 discusses system model, Sect. 8.4 details results and discussion and conclusion in Sect. 8.5.

8.2 State of Art Methods

Ying et al. [8] Use two-dimensional slices, including open cv lung areas. Every 3D chest CT image extracts 15 slices of the entire lungs and each 2D slice inputs Deep Pneumonia, the proposed profound learner-oriented CT diagnostic system (DLD). A pre-trained ResNet-50 will be used to extracted the top K information from each image and applied the Feature Pyramid Network (FPN). The value of each detail is paired with an attentiveness module. Images of Chest CT were taken in 88 COVID-19 cases, in 101 bacterial pneumonia patients and 86 stable patients. Model produces results with an accuracy of 86.0% and 94% accuracy for pneumonia diagnosis.

Zhang et al. [9] ResNet model for X-ray images is available to detect COVID-19. This model contains 2 tasks: one for COVID-19 detection and other for anomaly recognition. The role of abnormalities identification provides an anomaly in the classification score to optimize COVID-19 score. From those two datasets are included X-ray images of 70 patients with COVID-19 and 1008 non-COVID-19 patients with pneumonia. 96.0%, 70.7%, along with an AUC of 0.952 respectively, are sensitivity and specificity.

2D CNN model is indicated to be classified between COVID-19 and standard viral pneumonia in manually delineated area patches in [10]. Chest CT images are being seen in 99 patients (i.e. 44 COVID-19 and 55 common viral pneumonia). Test data sets represents 73.1% accuracy, 67.0% precision and 74.0% sensitivity.

Xu et al. [11] Often utilize candidate infection areas segmented by V-Net model, and region patches, along with the craft features of comparatively distant infection from edges, are sent to ResNet-18 network. Included were CT pictures of 219 patients with COVID-19, 224 patients with Influenza-A, and 175 stable persons. The model's average accuracy is 86.7%.

Shi et al. [12] Using random forest that has shifted. Image is divided into left/right lung, five lung lobes and 18 pulmonary segments during the pre-processing stage, with the aid of a 3D VB-Net [13]. Chest CT images of 2685 patients are included in the results. Results reveal that 90.7% of sensitivity, 83.3% of specificity, and 87.9% of accuracy. Furthermore, results of the test are grouped according to infection sizes which indicate a low sensitivity to patients with small infections.

Five of the most relevant problems in the answer to covid-19 are raised in [14]. In [15], an AI algorithm that utilizes CT images, clinical signs, history of exposure as well as laboratory tests to diagnose covid-19 cases is proposed. Data from 905 patients were obtained from the authors, 419 of whom are laboratory-confirmed positive cases.

In [16], five machine learning algorithms are utilized for processing data of patients and prediction of the mortality risk of patients, namely logistical regression, elastic net, minor partial regression, random forests and versatile bagged discriminant analyses. In [17, 18], the development of a model forecasting the mortality of patients is achieved with different lean-machine methods consists of KNN, SVM and random forest. ML method is utilized for forecasting death and vital incidents in New York in a related attempt [19].

In [20] an algorithm to help make clinical judgment during the pandemic is introduced. In [21] various ML models, including SVM, Decision Tree, KNN, GNB, etc., estimate the age groups in the disease model.

In [22] is used for recognizing patients who may experience extreme coV-19 using a multivariate logistic regression paired with a feature-selection method. In [23] provides a basis for the latest functionality of the Graph Neural Network, which is then used for the classification of nodes using a self-supervised and unattended learning mix. The device is utilized to predict patients' infection and severity. Multivariate logistic regression as well as deep learning method was utilized to determine risk of the developing malignant infection of a patient with mild symptoms [24].

In [25], a data set is used to create a model that forecasts the weak pronostics in covid-19 patients of 13,690 patients in Brazil. Data from a cohort of 1590 patients from 575 health centers were used in [26] to train deep learning method that determines covid-19 patients contracting serious disease based on clinical features. In [27] a feasible approach to identify COVID-19 from chest X-rays differentiates between normal and viral pneumonia affected by DCNN is presented. Three CNN models (EfcientNet B0, VGG16 and Inception V3) pre-entrained in this research were evaluated by means of transmission. The reason for choosing these specified models is their accuracy and efficiency balance with fewer mobile applicable parameters. The dataset utilised for the study is open to the public and compiled from many sources. This study uses profound learning and performance measurement (accuracy, recall, specifcity, precision, and F1 scores). Five modern technologies and their striking applications were disclosed in [28], which may be utilised in mitigating and eliminating COVID-19 difficulties. AI, 3DPT, BDA, HPC and TT. This research examines the application of COVID-19 technologies to promote future research as well as to develop COVID-19 solutions employing AI, 3DPT, BDA, HPC and TT. The research focuses on COVID-19 solutions. In [29] method using a cluster-based routing technique is proposed. In the proposed method, a cluster head (CH) acts as a gateway between the cluster members and the external network, which helps to reduce the network's overhead. In clustering, the cluster's lifetime is a vital parameter for network efficiency. Thus, to optimize the CH's selection process, three evolutionary algorithms are employed, namely, the ant colony optimization (ACO), MOPSO, and CLPSO. Performance of the proposed method is verified by extensive experiments by varying values of different parameters, including the transmission range, node number, node mobility, and grid size. A comprehensive comparative analysis of the three algorithms is conducted by extensive experiments. The results show that, compared with the other methods, the proposed ACO-based method can form clusters more efficiently and increase network lifetime, thus achieving remarkable network and energy efficiency. The proposed ACO-based technique can also be used in other types of ad-hoc networks as well. In [30] it recommended to use a design model to boost the rate of failure detection as the test case selection and prioritying framework. First, we choose test cases for components commonly accessed with observation patterns and second, prioritise test cases for the adoption of certain tactics. An experiment and a comparison with other methodologies validated the proposed framework (previous faults based and random priority). Experimental findings therefore suggest that adjustments have successfully been verified in the proposed framework. The suggested methodology subsequently boosts the rate of failure detection (i.e. more than 90%) over past defects and random priorities (i.e., more than 80% respectively). In order to follow the COVID-19 outbreak and improve health and strategies, the high precision proposed by the AI technique [31, 32] is of great importance. The engagement of huge technology is essential along with the following uses, as scientists, scientists or doctors can be successfully helped in expediting COVID-19 research and development. In [40] the authors showed that they can get 0.901 accuracy, with a positive predictive value of 0.840 and a negative predictive value of 0.982, after training with 499 CT volumes and testing on 131 CT volumes. This study provides a quick way of identifying the patient with COVID-19, which can offer tremendous assistance in timely quarantine and medical treatment. The research in [33] introduces an abnormality quantification procedure based on DL and DL in COVID-19. The entry of uncontrasting chest CT pictures into the suggested learning model while the result is gravity scores such as POO, LSS, POHO and LHOS. In the proposed learning model, the results are good, as Pearson's correlation between ground reality and projected output is 0,97 in POO, 0,98 in POHO, 0,96 in LSS and 0,97 in LHOS, when the data set is trained and tests are 568 CT images and 100 samples.

8.3 System Model

The proposed system model is shown in Fig. 8.2. This system is used to diagnose the COVID-19 pandemics. The COVID dataset is used for data collection process then data is moved from the computational intelligence and big data analytics

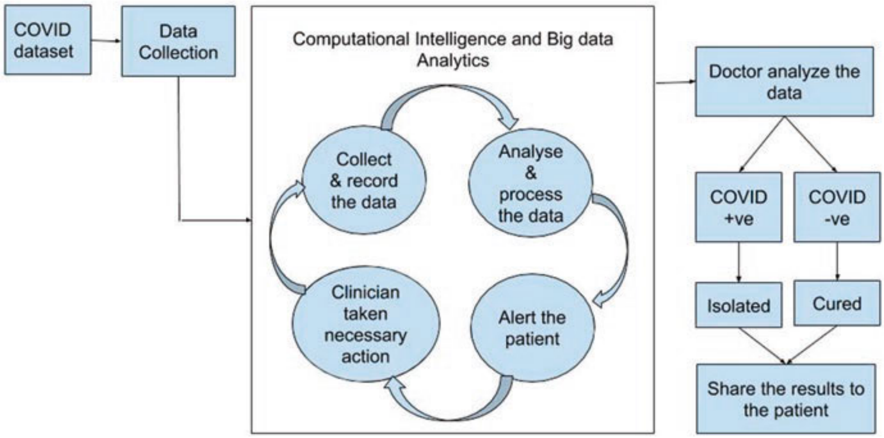


Fig. 8.2 Proposed system model

process. In this section, the data are collected and record that can be analyzed and processed the data, then alert the patient based on analyzing the data finally clinician takes necessary action to the patient. The data can be analyzed by the doctor whether the patients have COVID positive or Negative, if the patient result is positive then the patient is isolated, if the patient result is negative then the patient is cured and finally the results are shared with the patient. Early treatment and forecasting are important as one of the most effective ways for combating the COVID-19 epidemic. The reverse transcription polymerase (RT-PCR) detection technique is currently a standard tool for classifying respiratory viruses. Some work was done to enhance this approach and other alternatives in response to the COVID-19 virus. However, these approaches are frequently time-consuming and costly, have a poor true positive rate, and require particular ingredients. Furthermore, because of restrictions on budgets and technology many countries suffer from a lack of test kits. The usual approach is not therefore adequate for rapid detection and monitoring requirements during the pandemic COVID-19.

8.3.1 COVID Dataset

Illness caused by SARS-CoV-2 virus is COVID-19. A global COVID-19 pandemic was reported in 2020. Reaction to COVID-19 pandemic, COVID-19 has been established by White House and a consortium of leading science groups. CORD-19 is a resource of more than 200,000 scientific articles, including over 100,000 full-text, COVID-19 and SARS-CoV-2. To develop more insights into the current battle against this infectious disease, the globalized scientific community will be provided with this publicly accessible dataset to incorporate the latest advancing natural language and AI technologies. The exponential acceleration of new coronavirus literature is making it impossible for health science communities to keep up with these methods. These approaches are increasingly urgent.

8.3.2 Data Collection

During a pandemic, manner in which data is gathered and quality of the data collected face challenges. Data requirements did not uniform as data are gathered by government employees exposed to illness conditions, creating physical and emotional risks. The details were also not updated promptly. Against context of rapid spread of COVID-19 virus, to determine condition of outbreak and its risks, and to prevent confusion among the population, urgent data updates were necessary.

Owing to a lack of understanding of the danger of the disease at an early stage, the lack of sophisticated data processing means, the huge number of subjects participating in data collection and disclosure and eventual “fragmentation” of large data platforms, however, much of the data has not been revised immediately or optimally. Manual data processing, of course, can result in delays, dissimulation, imprecision and monitoring.

8.3.3 Computational Intelligence and Big Data Analytics

CI is a collection of computational methodologies and methods inspired by nature to solve complex real-world problems that can be useless for mathematical or conventional modeling for a few reasons: the processes may be too complicated for mathematical logic, may involve some uncertainties during the process, or may simply be stochastic. It is crucial to keep people healthy at present and to monitor the situation promptly. But it is still necessary and necessary to analyse how personal data are secure and private. The Zoom video conferencing application scandals its security and privacy issues 4 are a display of this dilemma. During this pandemic, authorities can ask their citizens to supply the personal data necessary to control the issue, to build up to date laws and to take prompt measures, such as the location of GPs and CT tests, diagnostic reporting, travel paths and everyday activities. Data is a necessary to ensure that any AI and Big data platforms are successful; nevertheless, usually, if not officially asked, people will not volunteer their data. There is a compromise: privacy/safety and performance.

8.3.4 Big Data for COVID-19 Fighting

Capacity of big data to tackle infectious diseases such as COVID-19 is proven [34, 35]. Big data may offer some successful options to better counter the epidemic of COVID-19. Big data allows one to consider COVID-19 in terms of outbreak monitoring, the structure of the virus, epidemic treatment and development of vaccines, by CI analyses [36].

For example, large data connected to smart IC tools may produce extensive model simulations with coronavirus data sources for outbreak estimations. This enables health officials to monitor coronavirus transmission and to design better steps to prevent coronavirus transmission [37]. Big-data models also support future COVID-19 forecasting through the way that they can aggregate vast volumes of data for early detection. Also, large-scale COVID-19 experiments will help to establish extensive, highly accurate treatment options from a range of real-world sources, contains infected patients [38, 39]. It will also allow healthcare providers to consider the progression of the virus and a better response to multiple diagnoses and treatments.

Also, AI (and explicit AI [40]) aims at logic and reasoning to construct human intelligence that imitates a learning machine, classifies, and predicts potential outcomes, such as classifications of COVID-19 symptoms. A variety of realistic cases will clarify and address the possible use of each technology in the war against COVID-19. s: A larger dataset provides the basis for the COVID-19 epidemic for AI and big data platforms. Therefore, [1] incentives are needed to invite more people and entities to contribute their own data. For the following reasons, incentives are necessary: 2) the quality of data should be ensured to increase the accuracy and performance in the learning models, and the data should be provided in vast quantities by the persons/entities which the government is unable to request to give their data.

8.4 Results and Discussion

The findings and discussions of this method to assess the polarity of feelings in the sorted texts in the three groups 1 (positive), 0 (neutral) and − 1 (negative).

Figure 8.3 shows the entire dataset sentiment polarity. X and Y-axis show the neutral, positive, negative and values obtained respectively. The neural achieves 58,124, positively achieve 26,375, negative achieves 18,472 in 10^4 respectively.

In comparison, Figs. 8.4 and 8.5 display the approach used to measure probability density for generating data on the relationship between public opinion frequency and time. X and Y axis is time and values obtained respectively. Maroon, Green, Orange is Negative, Positive, Neutral respectively.

In addition, AI has become an interesting technology to facilitate the production of vaccines and drugs. AI employs smart analytical instruments for

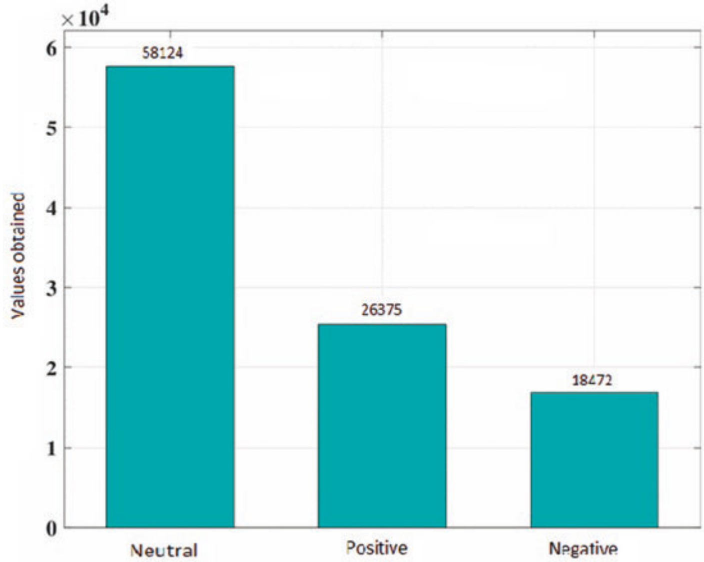
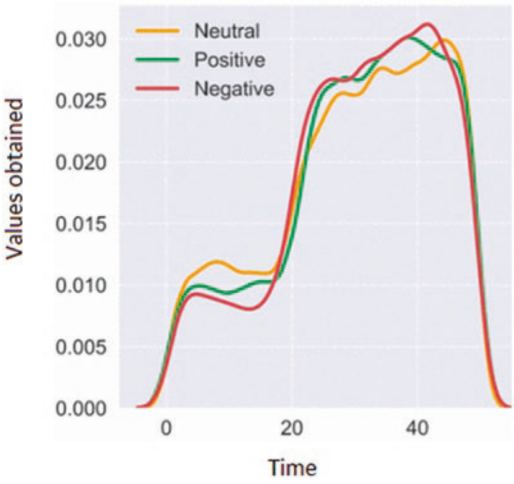


Fig. 8.3 Entire dataset sentiment polarity

Fig. 8.4 Probability density estimation on public opinion



forecasting the effective and safe vaccine/medication against COVID-19 which would be helpful in economic and scientific terms through data sets provided by health organisations, governments, clinical laboratories and patients. AI uses them. Big data, however, have been demonstrated to be able to deal with the COVID-19 epidemic. Big data could offer promising ways to help combat the pandemic of COVID-19. Big data helps us to comprehend COVID-19 in terms of

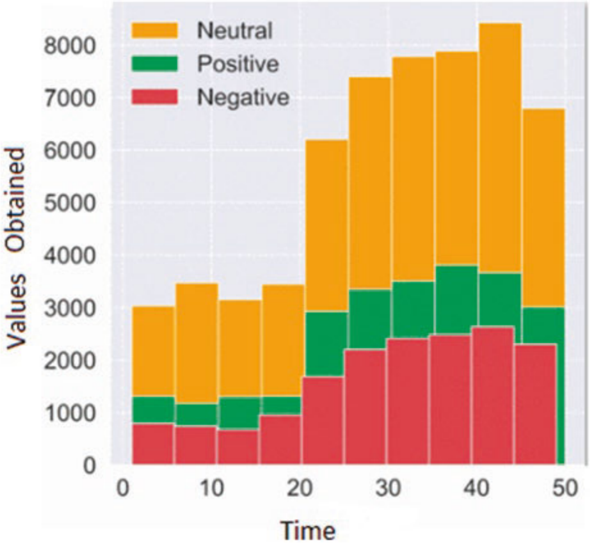


Fig. 8.5 Probability density estimation on time

its virus and illness structure in combination with AI analytics. Big data Big data can aid providers from early diagnosis and disease analysis to treatment result prediction in many medical operations.

8.5 Conclusion

Big data could deliver many promising solutions to help tackle pandemic in COVID-19. Big data allow us to understand Virus structure and disease production in terms of COVID-19, by integrating it with CI analytics. Big data can assist healthcare providers from early diagnosis, condition analysis and estimation of patient outcomes and reliability of data processing for improved COVID-19 diagnosis and treatment in different medical operations. To deliver newly powerful applications to tackle COVID-19, CI and Big Data should be combined with other digital technologies. For future research, further case studies and expert publications on the use of Big Data Analytics and AI in medical setup must be required. This might happen if stakeholders and practitioners in the healthcare system employ these technologies in the real world to further discover the potential of big data analysis and artificial intelligence to improve health quality. Systematic and structured method used in the framework includes both conceptual and technological elements and hence leads research in this area. During the planning of their research activity, others might use the classification scheme and framework.

References

1. Vaishya, R., Javaid, M., Khan, I. H., & Haleem, A. (2020). Artificial intelligence (AI) applications for COVID-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 14*(4), 337–339.
2. Sohrabi, C., Alsafi, Z., O'Neill, N., Khan, M., Kerwan, A., Al-Jabir, A., & Agha, R. (2020). World Health Organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19). *International Journal of Surgery, 76*, 71–76.
3. Situation update worldwide, as of 9 April 2020, 2020. [Online]. Available: https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases
4. Ergüzen, A., & Ünver, M. (2018). Developing a file system structure to solve healthy big data storage and archiving problems using a distributed file system. *Applied Sciences, 8*(6), 913.
5. Iqbal, R., Doctor, F., More, B., Mahmud, S., & Yousuf, U. (2020). Big data analytics: Computational intelligence techniques and application areas. *Technological Forecasting and Social Change, 153*, 119253.
6. Reddy, A. R., & Kumar, P. S. (2016). IEEE 2016 Second International Conference on Computational Intelligence & Communication Technology (CICT) – Ghaziabad, India (2016.2.12-2016.2.13). Second International Conference on Computational Intelligence & Communication Technology (CICT) – Predictive Big Data Analytics in Healthcare (pp. 623–626). https://doi.org/10.1109/CICT.2016.129
7. Emerging Technology series, Big Data analytics in Health, white paper (full report), available on Canada health info way.
8. Song, Y., Zheng, S., Li, L., Zhang, X., Zhang, X., Huang, Z., & Yang, Y. (2021). Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT images. *IEEE/ACM Transactions on Computational Biology and Bioinformatics, 18*, 2775–2780.
9. Zhang, J., Xie, Y., Pang, G., Liao, Z., Verjans, J., Li, W., & Xia, Y. (2020). Viral pneumonia screening on chest X-ray images using confidence-aware anomaly detection. *arXiv preprint arXiv*, 2003.12338.
10. Wang, S., Kang, B., Ma, J., Zeng, X., Xiao, M., Guo, J., ... & Xu, B. (2021). A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19). *European Radiology, 31*(8), 6096–6104.
11. Xu, X., Jiang, X., Ma, C., Du, P., Li, X., Lv, S., & Li, L. (2020). A deep learning system to screen novel coronavirus disease 2019 pneumonia. *Engineering, 6*(10), 1122–1129.
12. Shi, F., Xia, L., Shan, F., Song, B., Wu, D., Wei, Y., & Shen, D. (2021). Large-scale screening to distinguish between COVID-19 and community-acquired pneumonia using infection size-aware classification. *Physics in Medicine & Biology, 66*(6), 065031.
13. Shan, F., Gao, Y., Wang, J., Shi, W., Shi, N., Han, M., & Shi, Y. (2020). Lung infection quantification of COVID-19 in CT images with deep learning. *arXiv preprint arXiv*, 2003.04655.
14. van der Schaar, M., Alaa, A. M., Floto, A., Gimson, A., Scholtes, S., Wood, A., & Ercole, A. (2021). How artificial intelligence and machine learning can help healthcare systems respond to COVID-19. *Machine Learning, 110*(1), 1–14.
15. Mei, X., Lee, H. C., Huang, M., Lin, B., Liu, C., Xie, Z., & Yang, Y. (2020). Artificial intelligence for rapid identification of the coronavirus disease. *medRxiv, 2019*(COVID-19).
16. Chen, X., & Liu, Z. (2020). Early prediction of mortality risk among severe COVID-19 patients using machine learning. *BMJ, 369*, MedRxiv.
17. Thorsen-Meyer, H. C., Nielsen, A. B., Nielsen, A. P., Kaas-Hansen, B. S., Toft, P., Schierbeck, J., & Perner, A. (2020). Dynamic and explainable machine learning prediction of mortality in patients in the intensive care unit: A retrospective study of high-frequency data in electronic patient records. *The Lancet Digital Health, 2*(4), e179–e191.
18. An, C., Lim, H., Kim, D. W., Chang, J. H., Choi, Y. J., & Kim, S. W. (2020). Machine learning prediction for mortality of patients diagnosed with COVID-19: A nationwide Korean cohort study. *Scientific Reports, 10*(1), 1–11.

19. Vaid, A., Somani, S., Russak, A. J., De Freitas, J. K., Chaudhry, F. F., Paranjpe, I., & Glicksberg, B. S. (2020). Machine learning to predict mortality and critical events in COVID-19 positive New York city patients. *medRxiv*.
20. Debnath, S., Barnaby, D. P., Coppa, K., Makhnevich, A., Kim, E. J., Chatterjee, S., & Zanos, T. P. (2020). Machine learning to assist clinical decision-making during the COVID-19 pandemic. *Bioelectronic Medicine, 6*(1), 1–8.
21. Prakash, K. B., Imambi, S. S., Ismail, M., Kumar, T. P., & Pawan, Y. N. (2020). Analysis, prediction and evaluation of COVID-19 datasets using machine learning algorithms. *International Journal, 8*(5), 2199–2204.
22. Yao, Z., Zheng, X., Zheng, Z., Wu, K., & Zheng, J. (2021). Construction and validation of a machine learning-based nomogram: A tool to predict the risk of getting severe coronavirus disease 2019 (COVID-19). *Immunity, Inflammation and Disease, 9*(2), 595–607.
23. Sehanobish, A., Ravindra, N. G., & van Dijk, D. (2020). Gaining insight into SARS-CoV-2 infection and COVID-19 severity using self-supervised edge features and Graph Neural Networks. *arXiv preprint arXiv*, 2006.12971.
24. Tayarani-N, M. H. (2020). Applications of artificial intelligence in battling against COVID-19: A literature review. *Chaos, Solitons & Fractals, 142*, 110338.
25. De Souza, F. S. H., Hojo-Souza, N. S., Dos Santos, E.B., Da Silva, C. M., Guidoni, D. L. (2021). Predicting the disease outcome in COVID-19 positive patients through machine learning: A retrospective cohort study with Brazilian data. *Frontiers in Artificial Intelligence and Applications, 4*, 579931. https://doi.org/10.3389/frai.2021.579931
26. Liang, W., Yao, J., Chen, A., Lv, Q., Zanin, M., Liu, J., & He, J. (2020). Early triage of critically ill COVID-19 patients using deep learning. *Nature Communications, 11*(1), 1–7.
27. Gaur, L., Bhatia, U., Jhanjhi, N. Z., Muhammad, G., & Masud, M. (2021). Medical image-based detection of COVID-19 using deep convolution neural networks. *Multimedia Systems*, 1–10.
28. Brohi, S. N., Jhanjhi, N. Z., Brohi, N. N., Brohi, M. N. (2020). *Key applications of state-of-the-art technologies to mitigate and eliminate COVID-19*. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.12115596.v2
29. Aadil, F., Mehmood, B., Ul Hasan, N., Lim, S., Ejaz, S., & Zaman, N. (2021). Remote health monitoring using IoT-based smart wireless body area network. *CMC-Computers Materials & Continua, 68*(2), 2499–2513.
30. Ali, S., Hafeez, Y., Jhanjhi, N. Z., Humayun, M., Imran, M., Nayyar, A., & Ra, I. H. (2020). Towards pattern-based change verification framework for cloud-enabled healthcare component-based. *IEEE Access, 8*, 148007–148020.
31. Chen, C. M., Jyan, H. W., Chien, S. C., Jen, H. H., Hsu, C. Y., Lee, P. C., & Chan, C. C. (2020). Containing COVID-19 among 627,386 persons in contact with the Diamond Princess cruise ship passengers who disembarked in Taiwan: Big data analytics. *Journal of Medical Internet Research, 22*(5), e19540.
32. Zhang, S., Diao, M., Yu, W., Pei, L., Lin, Z., & Chen, D. (2020). Estimation of the reproductive number of novel coronavirus (COVID-19) and the probable outbreak size on the Diamond Princess cruise ship: A data-driven analysis. *International Journal of Infectious Diseases, 93*, 201–204.
33. Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). *IEEE Access, 6*, 52138–52160.
34. Chae, S., Kwon, S., & Lee, D. (2018). Predicting infectious disease using deep learning and big data. *International Journal of Environmental Research and Public Health, 15*(8), 1596.
35. Bansal, S., Chowell, G., Simonsen, L., Vespignani, A., & Viboud, C. (2018). Big data for infectious disease surveillance and modeling. *The Journal of Infectious Diseases, 214*(suppl_4), S375–S379.
36. Eisenstein, M. (2018). Infection forecasts powered by big data. *Nature, 555*(7697), S2–S2.
37. Buckee, C. (2020). Improving epidemic surveillance and response: Big data is dead, long live big data. *The Lancet Digital Health, 2*(5), e218–e220.

38. Chen, C. M., Jyan, H. W., Chien, S. C., Jen, H. H., Hsu, C. Y., Lee, P. C., & Chan, C. C. (2020). Containing COVID-19 among 627,386 persons in contact with the Diamond Princess cruise ship passengers who disembarked in Taiwan: Big data analytics. *Journal of Medical Internet Research, 22*(5), e19540.
39. Zhang, S., Diao, M., Yu, W., Pei, L., Lin, Z., & Chen, D. (2020). Estimation of the reproductive number of novel coronavirus (COVID-19) and the probable outbreak size on the Diamond Princess cruise ship: A data-driven analysis. *International Journal of Infectious Diseases, 93*, 201–204.
40. Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). *IEEE Access, 6*, 52138–52160.