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Applications of AI and ML in Covid-19 (SARS-CoV-2): A Survey

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Abstract: Artificial intelligence (AI) has been applied widely in our daily lives in a variety of ways with numerous successful stories. AI has also contributed to dealing with the coronavirus disease (COVID-19) pandemic, which has been happening around the globe. This paper presents a survey of AI methods being used in various applications in the fight against the COVID-19 outbreak and outlines the crucial roles of AI research in this unprecedented battle. We touch on a number of areas where AI plays as an essential component, from medical image processing, data analytics, text mining and natural language processing, the Internet of Things, to computational biology and medicine. Research directions on exploring the potentials of AI and enhancing its capabilities and power in the battle are thoroughly discussed. This paper aims to comprehensively review the role of AI and ML as one significant method in the arena of screening, predicting, forecasting, contact tracing, and drug development for SARS-CoV-2 and its related epidemic.

Keywords: Artificial intelligence; AI; machine learning; coronavirus; COVID-19; SARS CoV-2; pandemic; epidemic; outbreak; survey; review; overview; future research directions.

I. INTRODUCTION

The application of artificial intelligence (AI) to healthcare has increased rapidly [1]. AI involves the development of sophisticated algorithms to execute complex tasks efficiently and effectively. The main objective of applying AI to healthcare is to unfold hidden information from big data and assist healthcare policymakers and clinicians in making effective clinical decisions[2]. However, the application of AI technology to disease detection, cancer patient screening, therapy selection, reducing medication errors, and productivity improvement is now growing [3–6]. Furthermore, AI application to COVID-19 research has increased, especially to the diagnosis, classification, detection, severity, and mortality risk[7–9]. AI technology has already shown its potentiality to track the spread of coronavirus, as well as stratifying high-risk patients. It has also shown great effectiveness in predicting real-time infection rates by adequately analyzing the previous data [10]. This paper focuses on the novel Covid-19 epidemic and how the modern AI and ML technology were recently employed to solve the challenges during the outburst. We present comprehensive reviews of studies on the model and technology applied to tackle the novel Covid-19 pandemic. This paper goes into detail about specific practical challenges faced by healthcare systems, and how AI and machine learning can improve decision-making to ensure the best outcomes possible.

First, AI and machine learning can help us identify people who are at highest risk of being infected by the novel coronavirus. This can be done by integrating electronic health record data with a multitude of “big data” pertaining to human-to-human interactions (from cellular operators, traffic, airlines, social media, etc.). This will make allocation of resources like testing kits more efficient, as well as informing how we, as a society, respond to this crisis over time. AI and machine learning can also help us work out which infected patients are more likely to suffer more severely from COVID-19. We can provide more accurate patient risk scores that will help clinical professionals decide who needs urgent treatment (and resources), and when.

Secondly, COVID-19 symptoms and disease evolution vary widely from patient to patient in terms of severity and characteristics. A one-size-fits-all approach for treatment doesn’t work. We also are a long way off from mass-producing a vaccine. Machine learning techniques can help determine the most efficient course of treatment for each individual patient on the basis of observational data about previous patients, including their characteristics and treatments administered. We can use machine learning to answer key “what-if” questions about each patient, such as “What if we postpone a couple hours before putting them on a ventilator?” or “Would the outcome for this patient be better if we switched them from supportive care to an experimental treatment earlier?”

Third, we have seen a large variety of approaches taken by decision-makers when deciding on policies to respond to COVID-19. This is true from the individual level (i.e. practitioners) all the way up to the government level. For example, differences in triaging protocols used by medical institutions and practitioners could mean that two patients with similar profiles will end up receiving different types of treatment depending on where they happen to live. It is hard to get a clear sense of which decisions result in the best outcomes. In such a stressful situation, it is also hard for

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decision-makers to be aware of the outcomes of decisions being made by their counterparts elsewhere. Once again, data-driven AI and machine learning can provide objective and usable insights that far exceed the capabilities of existing methods. We can gain valuable insight into what the differences between policies are, why policies are different, which policies work better, and how to design and adopt improved policies. This information can be shared between decision-makers at all levels, improving consistency and efficiency across the board. The result is that routine decisions can be made in a more coordinated and timely way, freeing up valuable medical attention to the cases that demand real-time expertise.

Fourth, randomized clinical trials (RCTs) are generally used to judge the relative effectiveness of a new treatment. However, these trials can be slow and costly, and may fail to uncover specific subgroups for which a treatment may be most effective. A specific problem posed by COVID-19 is that subjects selected for RCTs tend not to be elderly, or to have other conditions; as we know, COVID-19 has a particularly severe impact on both those patient groups. Rather than recruiting and assigning subjects at random, machine learning methods can recruit subjects from identifiable subgroups, and assign them to treatment or control groups in a way that speeds up learning. These methods have been shown to significantly reduce error and achieve a prescribed level of confidence in findings, while also requiring fewer subjects. We can also use machine learning to target particular treatments to specific subgroups and to understand what treatments are suitable for the population as a whole.

II. ML AND AI RECENTLY EMPLOYED to TACKLE HEALTH CARE SARS-COV-2 OUTBREAK

AI and ML technology are used to improve the accuracy of prediction for screening both infectious and non-infectious diseases [6]. The relation with health care begins with the evolution of the first expert system called MYCIN developed in 1976[7] . MYCIN was designed to use 450 rules collected from a medical expert to treat bacterial infection by suggesting antibiotics to the patients. Such an expert system serves as clinical decision support for clinicians and medical experts [8] . Recent studies evident on the prospect of ML and AI technology for the various pandemic outbreak, it supports healthcare experts in various communicable diseases (SARS, EBOLA, HIV, COVID_19)[9-17] and non-communicable diseases (Cancer, Diabetic, Heart disease, and Stroke)[18-25] outbreak.

2.1. ML and AI Technology in SARS-CoV-2 Screening and Treatment

Early detection of any disease be it infectious and non-infectious, is critically an important task for early treatment to save more lives [26,27]. Fast diagnosis and screening process helps prevent the spread of pandemic diseases like SARS-CoV-2, cost-effective, and speed up the related diagnosis. The development of an expert system for health care assists in the new order of identification screening and management of SARS-CoV-2 carrier by more cost-effective compared to the traditional method. ML and AI are used to augment the diagnosis and screening process of the identified patient with radio imaging technology akin to Computed Tomography (CT), X-Ray, and Clinical blood sample data. In this regard, Table I shows selective information on diagnosis and screening proposed for the Coronavirus disease. The healthcare expert can use radiology images like X-ray and CT scans as routine tools to augment traditional diagnosis and screening. Unfortunately, the performance of such devices is moderate during the high outburst of the SARS-CoV-2 pandemic. In this regard, studies[28] show the potential of AI and ML tools by suggesting a new model that comes with rapid and valid method SARS-CoV-2 diagnosis using Deep Convolutional Network. The study shows that diagnosis utilizing an expert system employing AI and ML on 1020 CT images of 108 Covid-19 infected patients along with viral pneumonia of 86 patients, the remarkable performance suggests the use of the convolutional neural network (Resnet-101) as an adjuvant tool for radiologist resulting 86.27%, 83.33% of accuracy and specificity respectively.

Recent studies design an auxiliary tool to increase the accuracy of Covid-19 diagnosis with new model Automatic COVID-19 detection based on deep learning algorithm [29]. The developed model uses raw chest X-ray images of 127 infected patients with 500 no findings and pneumonia cases of 500 records. With remarkable performance accuracy, binary class of 98.08%, and multi-class with 87.02%. Multi-classes proved the applicability of the expert system to assist radiology in validating in screening process rapidly and accurately.

Furthermore, researchers have found four important medical features combinations of clinical, laboratory features, and demographic information using GHS, CD3 percentage, total protein, and patient age employing Support Vector Machine as the primary feature classification model [30]. The new model is effective and robust in predicting patients in critical/severe conditions, and the empirical results show that a combination of the four-feature results an AUROC of 0.9996 and 0.9757 in training and testing datasets respectively. The survival and the cox-multivariant regression analysis revealed the model's significance towards and auxiliary tools for the healthcare expert.

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TABLE I ML AND AL TECHNOLOGY IN SARS-COV-2 SCREENING.

Publication	ML/AI method	Types of data	No of patients	Validation method	Sample size	Accuracy
Ardakani, A. A et al ., [28]	Deep Convolutional Neural Network ResNet-101	Clinical, Mamographic	1020, 86	Holdout	1020 CT images of 108 volume of patients with laboratory confirmed Covid-19, 86 CT images of viral and atypical pneumonia patients,	Accuracy: 99.51% Specificity: 99.02%
Ozturk, T. et al ., [29]	Convolutional Neural Network DarkCovidNet Architecture	Clinical, Mamographic	127, 43 f, 82 m 500, 500	Cross-validation	127 X-ray images with 43 female and 82 male positive cases 500 no-findings and pneumonia cases of 500	Accuracy: 98.08% on Binary classes Accuracy: 87.02% on Multi-classes
Sun, L et al ., [30]	Support Vector Machine	Clinical, laboratory features, Demographics	336, 220	Holdout	336 infected patients with PCR kit, 26 severe/critical cases and 310 non-serious cases and with another related disease79 hypertension,29diabetes, 17 coronary disease and 7 having history of tuberculosis	Accuracy: 77.5% Specificity: 78.4% AUROC reaches 0.99 training and 0.98 testing dataset
Wu, J. et al ., [31]	Random forest Algorithm	Clinical, Demographics	253, 169, 49,24	Cross-validation	Total of 253 samples from 169 patients suspected with Covid-19 collected from multiple sources. Clinical blood test of 49 patients derived from commercial clinic center. 24 samples infected patient with Covid-19	Accuracy: 95.95% Specificity: 96.95%
Xiaowei Xu. et al ., [47]	deep learning, computed tomography,convolution neural network, location-attention network	CT samples	618	Cross-validation	A total of 618 CT samples were collected: 219 from 110 patients with COVID-19, 224 CT samples from 224 patients with Influenza-A viral pneumonia, and 175 CT samples from healthy people.	Accuracy: 86.7 %
Shuo Jin. et al ., [48]	A combination of 3D UNet++ and ResNet-50	CT images	1,136	Cross-validation	A total of 1,136 training cases (723 positives for COVID-19) from 5 hospitals	Sensitivity : 0.974 specificity : 0.922

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After evaluating 253 clinical blood amples from Wuhan, researchers found eleven (bilirubin total, creatine kinase isoenzyme, GLU, creatinine, kalium, lactate dehydrogenase, platelet distribution width, calcium, basophil, total protein, and magnesium) key relevant indices which can assist as a discrimination tool of Covid-19 for healthcare expert toward rapid diagnosis [31]. The studies show that 11 relevant indices are extracted after employing the Random Forest algorithm with an overall accuracy of 95.95% and 96.97% specificity respectively.
The above studies give the evidence of an application of the expert system; designing rapid diagnosis was the main objective along with augmentation of accuracy. However, majority of the studied paper employed a single classification algorithm on individual data or more. Therefore it is suggested to come up with a hybrid classification method applying more potential algorithm on multi-database or hybrid-database consisting of clinical, mammographic, and demographic data, as each type of data has a significant factor that could represent the true identity of the infected patients and deployment of the application in the real world.

2.2. ML and AI Technology in SARS-Cov-2 Contact Ttracing

If a person diagnoses and is confirmed with Covid-19, the next important step is contact tracing prevention of the wider spread of the disease. According to WHO, the infection spreads from personto-person primarily through saliva, droplets, or discharges from the nose through contact transmission [32] . To take control on the spread of SARS-Cov-2, contact tracing is an essential public health tool used to break the chain of virus transmission [33]. The process of contact tracing is to identify and manage people who are recently exposed to an infected Covid-19 patient to avoid further spread. Generally, the process identifies the infected person with a follow-up for 14 days since the exposure. If employed thoroughly, this process can break the transmission chain of the current novel coronavirus and suppress the outbreak by giving a higher chance of adequate controls and helping reduce the magnitude of the recent pandemic. In this regard, various infected countries come up with a digital contact tracing process with the mobile application, utilizing different technologies like Bluetooth, Global Positioning System (GPS), Social graph, contact details, network-based API, mobile tracking data, card transaction data, and system physical address. The digital contact tracing process can perform virtually real-time and much faster compared to the non-digital system. All these digital apps are designed to collect individual personal data, which will be analysed by ML and AI tools to trace a person who is vulnerable to the novel virus due to their recent contacted chain.
Concerning contact tracing, studies have proven the use of ML and AI in augmentation of contact tracing process against infectious Chronic Wasting disease [36]. After applying Graph theory on infectious animal disease epidemics data, mainly shipment data between each farm, the resultant graph properties generated by the proposed model can be used to exploit to augment contact tracing more efficiently. Moreover, the generated graphs have a potential prediction impact on the number of infections that can take place. However, there are still limitations in addressing the scenario, privacy, control over the data, and even data security breach. Countries are working to overcome the challenges; some countries like Israel "passed an emergency law to use mobile phone data" to tackle the current pandemic [37]. Among the world contact tracing apps, some countries app violated privacy law and reported unsafe [35] so far they do the job acceptably by supplement the manual tracing process. However, virtually every country has their contact tracing application individually, as the outbreak continues to spread across the world, it becomes a global health emergency. To fight against the Covid-19 as one, one should provide a standard de-facto centralized contact tracing application to trace every human being all around the world.

2.3. ML and AI Technology in SARS-CoV-2 Prediction and Forecasting

Recent studies suggested a novel model using a supervised multi-layered recursive classifier called XGBoost on clinical and mammographic factor datasets. After applying the model, researchers found out those three significant key features (high-sensitivity Creactive protein, lymphocyte and lactic dehydrogenase (LDH)) of the 75 features clinical and blood test samples result to be the highest rank of 90% accuracy in predicting and assessing Covid-19 patient into general, severe and mortality rate [39].
Furthermore, comparatively higher value in single lactic dehydrogenase appears to be a significant factor in classifying most patients in need of intensive medical care, as LDH degree related to various respiratory disorder diseases, namely asthma and bronchitis, and pneumonia. The forecast model employed decision rule to forecast rapidly and predict infected individuals at the highest risk, authorized patients to be manageable for intensive care, and possibly lessen the transience rate.

2.4. ML and AI Technology in SARS-CoV-2 Drugs and Vaccination

Since the coronavirus epidemic fury, researchers and healthcare experts around the globe ubiquitously urged to develop a possible choice to tackle the development of drug and vaccine for the SARS-CoV-2 pandemic, and ML/AI technology constitutes to be an enthralling road. Concerning the possibility of drug choice for infected patient's

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treatment, instant testing on the existing old marketable medicines for novel SARS-CoV-2 carrier in a human being is essential.

Table II ML and AI applications: prediction and forecasting SARS-CoV-2

Publication	ML/AI method	Types of data	No of patients	Validation method	Results
Ribeiro, M. H. D. M., et al ., [37]	Support Vector Regression and stacking-ensemble	Clinical	40.581	Holdout	Accuracy: Error in range of 0.87%-3.51% one, 1 .02%–5.63% three and 0.95% -6.90% six day ahead
Yan, L. et al ., [38]	XGBoost classifier	Clinical, Blood samples of 75 features	485	Cross-validation	Accuracy: 90%
Chimmula, V.K.R., et al ., [39]	Deep Learning using LSTM network	Demographic	John Hopkins University & Canadian Health authority, data containing infected cases upto March 31, 2020	Cross-validation	Ending point of the pandemic outbreak in Canada was predicted on June 2020
Chakraborty, T. and Ghosh, I. [40]	Hybrid Wavelet-autoregressive integrated moving average model and regression tree	Demographic	India: 64 UK: 65 Canada:70 France: 71 South Korea: 76	Cross-validation	Real-time forecast and 10 days ahead, Observed seven key features associated with dead rate.
Chowdhury, M. E.,[49]	Deep convolutional neural networks with Transfer Learning	Demographic	1,341, 1,345, 190	Cross-validation	Accuracy of 98.3%
Maghdid, H. S.,[50]	A new CNN and pre-trained AlexNet with transfer learning	Demographic	170,361	Cross-validation	Accuracy of 98% on X-ray images and 94.1% on CT images

The selected review paper adopted various methodologies and technologies addressing the classical method of classification based on statistics to an advanced modern AI and ML algorithm. The use of computational tools, combined with docking application, was found to be more active in predicting the reusability of an existing old drug on Covid-19 medication and dramatically minimize the level of a risk factor in the development of medicine more cost effective process. During this urgency, the use of ML and AI can augment the drug development process by lessening the time slot on discovering a supplementary treatment and medication for the carrier by drawing a vast probability over security, manageability, and clinical information on the existing drug compound. Issues and challenges found in this area were the limited resource of comprehensive hybrid data and real-life deployment of the application.

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III. CONCLUSION AND DISCUSSION

Since the outbreak of the novel SARS-CoV-2, scientists and medical industries around the globe ubiquitously urged to fight against the pandemic, searching alternative method of rapid screening and prediction process, contact tracing, forecasting, and development of vaccine or in augmenting the researchers in multiple angles, addressing the troubles and challenges while using such algorithm in assisting medical expert in real-world problems. This paper also discusses suggestions conveying researchers on AI/ML based model design, medical experts, and policymakers on few errors encountered in the current situation while tackling the current pandemic. This review shows that the use of modern technology with AI and ML dramatically improves the screening, prediction, contact tracing, forecasting, and drug/vaccine development with extreme reliability. Majority of the paper employed deep learning algorithms and is found to have more potential, robust, and advance among the other learning algorithms. The efficiency and diversity of applications of AI (e.g., machine learning and deep learning) to patient screening, early treatments, and improving patient care are already visible, and the further implementation of AI in real-world clinical practice is expected to increase, which ultimately will help to address any pandemic such as COVID-19.

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