A Brief Summary on Covid-19 Pandemic and Machine Learning Approaches

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Abstract

Beginning in 2019 the world has been under the effect of a global pandemic caused by SARS-CoV-2 infecting over 134 million people, resulting in approximately three million deaths globally, several shutdowns, a dangerously high burden on the healthcare system, and preventing access to care for those who need it. In this paper we give an overview of the machine learning approaches applied to COVID-19 pandemic-related problems. In this overview we cover the topics of evaluation of COVID-19 pandemic policies, prediction of COVID-19 pandemic progress, contact tracing, infection detection, and bio and pharmaceutical applications of machine learning. In particular, we provide an overview of the machine learning approaches utilized in these pandemic-related problems including convolutional neural networks, reinforcement learning, and graph neural networks. Finally, we discuss the possible adverse effects of utilization of certain machine learning approaches in such a critical setup. We hope that our paper can provide a generalized compact guide to the COVID-19 pandemic and the machine learning perspective for upcoming future research.

1 Introduction

For over a year the world has been subjected to a pandemic caused by SARS-CoV-2 leading to approximately three million deaths and infecting more than 130 million people. Aside from the mortality rate, several studies observed that healed patients suffer from long term effects of COVID-19 infection Nalbandian et al. (2021), Ayoubkhani et al. (2021), Vervoort et al. (2020), Nuzzo et al. (2021). From the beginning of the pandemic governments and international agencies have been alerted to take immediate actions and apply policies to slow the spread of COVID-19 infections, decrease and balance the burden on the healthcare system, search for detection methods to find infected people, and create vaccines to prevent further infections. Many researchers from various fields and disciplines focused on solving these sub-problems introduced by the pandemic. In this paper, we aim to give an overview of the machine learning approaches deployed to solve some of the problems caused by the COVID-19 pandemic and aim to answer the following questions:

- What are the problems caused by SARS-CoV-2 which can be approached via the machine learning perspective?
- What type of machine learning algorithms have been utilized in these problems so far?
- Are there any concerns on deployment of machine learning algorithms in such safety critical tasks?
- What are the possible root causes of the adverse effects of the deployment of machine learning approaches?

For this purpose, we first categorize the application areas into sections, and then we explain what kinds of machine learning methods and datasets have been utilized for the problems under consideration.

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Table 1: Outline of the subareas of the COVID-19-related sub-problems, an overview description of the studies focused on these subareas and the machine learning methods utilized in these sub-problems.

Subareas	Description	Methods
Bio and pharmaceutical	Mostly focusing on drug and protein design related sub-problems	VAE Chenthamarakshan et al. (2020) GAT Sehanobish et al. (2021) RL Skwark et al. (2020)
Pandemic Progress Prediction	Primarily focusing on forecasting methods, contact tracing, and graph modelling using multiple hybrid approaches	Meta Learning Panagopoulos et al. (2021) Transfer Learning Rodriguez et al. (2021) Adversarial Encoder Xiao et al. (2021) DNNs Bengio et al. (2020)
Infection Detection and Prognosis	Majorly focusing on architectures for classification tasks on datasets consisting of X-ray images, CT scans of lungs. Some of the work focusing on creating the datasets	CNN & DNN Ning et al. (2020) GAN Motamed et al. (2020) NN design Ning et al. (2020) DNN Qiu et al. (2021) CNN He et al. (2021)
Pandemic Policy Evaluation	Mostly focused on robustness of the models proposed and critique of the policies applied so far	Bayesian Model Qian et al. (2020) Robustness Sharma et al. (2020)

Finally, to the best of our knowledge, we comment on concerns regarding both robustness and possible sources of bias for some of the machine learning methods used for these sub-problems.

2 Taxonomy

In this section we provide our search methodology for the machine learning studies conducted on COVID-19-related problems, and we categorize these studies in to 4 subsections:

- Bio and pharmaceutical applications including drug and protein design,
- Prediction and control of pandemic progress,
- Detection of infection with SARS-CoV-2 and disease prognosis,
- Evaluation of the policies introduced by the government including nonpharmaceutical interventions (e.g. lockdown policies, business closures, mandatory mask usage, gathering bans).

In our search methodology we consider studies published in Neural Information Processing Systems, International Conference on Machine Learning, International Conference on Learning Representations, Association for the Advancement of Artificial Intelligence, International Joint Conference on Artificial Intelligence, and IEEE Conference on Computer Vision and Pattern Recognition. We searched over these venues with the COVID-19 and SARS-CoV-2 keywords and investigated the papers that matched this description. In each section we provide a brief summary of the problems under consideration, proposed solution methods, and the relationship between respectively similar approaches utilized in these pandemic-related problems. While several studies are conducted for each of these sub-problems, the pandemic progress prediction and the detection of SARS-CoV-2 are the sub-areas that drew significant attention from the machine learning community. We found that while various approaches focused on utilizing graph attention networks (GAT)s, convolutional neural networks (CNN)s, generative adversarial networks (GAN)s, representation learning, transfer learning, deep generative models, and reinforcement learning, some studies instead designed their own architecture for the problem under consideration. After detailed description of the studies conducted on machine learning approaches for COVID-19-related sub-problems we provide a discussion on the possible and probable adverse effects of utilizing machine learning on safety critical tasks.

2.1 Bio and pharmaceutical applications

In bio and pharmaceutical applications we found several works that utilize variational autoencoders (VAE), policy gradient methods from online reinforcement learning, and graph attention networks (GAT)s for protein and drug design-related problems.

Chenthamarakshan et al. (2020) propose an end-to-end framework named CogMol (Controlled Generation of Molecules) for novo drug design. In this work the authors propose to utilize VAE, and apply their proposed framework to three SARS-CoV-2 target proteins. The authors demonstrate that their framework achieves high target specificity and selectivity without requiring target dependent fine tuning.

Skwark et al. (2020) propose to utilize policy gradient algorithms for a protein design framework. In particular, the protein design framework is based on designing a form of the human angiotensin-converting enzyme 2 (ACE2) that binds to SARS-CoV-2 more effectively with the aim of protecting the human cell from SARS-CoV-2 binding.

Sehanobish et al. (2021) focus on investigating the link between SARS-CoV-2 infection and cell transcriptomic (i.e. the set of all RNA transcripts in a given individual cell) patterns. For this purpose the authors propose to utilize GATs and demonstrate their results on single-cell RNA sequencing datasets of infected lung organoids and bronchoalveolar lavage fluid samples.

2.2 Pandemic Progress Prediction and Control

We found that pandemic progress prediction is the second sub-category that drew substantial attention from the machine learning community. While some work in this sub-category focuses on merging machine learning methods with existing models (e.g. learning from graph and compartmental models) Arik et al. (2020), Yang et al. (2020) the majority solely focuses on methods beyond the existing models. Overall in this sub-category we found that representation learning, graph neural networks, adversarial encoders, and transfer learning algorithms have been utilized.

Arik et al. (2020) proposes an end-to-end framework based on learning from a computational graph with integrated time varying covariate encodings embedded into common compartmental models[1]. The authors' aim is to obtain meaningful estimates also for undocumented cases. In particular, the authors use masked supervision from partial observations for the case of learning from limited training data. The authors demonstrate the effectiveness of their forecasting model for the United States, and claim that their forecasting model can be helpful for epidemiologists, policy makers and healthcare institutions.

Panagopoulos et al. (2021) introduces representation learning on graphs to study the effects of mobility on the infection rates of SARS-CoV-2. In particular, the authors build a graph where the nodes represent regions of a given country, and edges represents human mobility from region to region. The authors then utilize graph neural networks for estimating future cases. In addition, the authors in this work employ a model-agnostic meta learning based method to transfer knowledge between countries. Rodriguez et al. (2021) propose a transfer learning based method for forecasting the COVID-19 pandemic. The authors in this work utilize a learning scheme from the historical influenza models and adapt these models automatically to new settings where influenza and SARS-CoV-2 co-exist.

Xiao et al. (2021) propose a framework called C-Watcher to estimate the SARS-COV-19 spread in a new city given the infection rates and spread in a previous epicenter. The proposed framework uses data from Baidu Maps and utilizes adversarial encoders to learn representations from mobility data to enable early detection of the high risk location even without any confirmed cases in the given location.

Bengio et al. (2020) focus on a digital contact tracing based method which aims to resume social and economical activities within society as much as possible while minimizing the spread of the SARS-CoV-2. In this paper the authors utilize feature-based contact tracing by extracting smartphone-

[1] Compartmental models of infectious diseases: Susceptible-Infected-Recovered (SIR) or Susceptible-Exposed-Infectious-Recovered (SEIR). The labels in Susceptible-Infected-Recovered demonstrate the flow patterns.

derived data. By using these features as input, the authors aim to estimate the expected infectiousness[2]. The authors perform distributed inference with deep neural networks and propose a new architecture based on Zaheer et al. (2017) and Lee et al. (2019). The authors evaluate their proposed architecture in the simulation proposed by Gupta et al. (2020).

Yang et al. (2020) try to highlight drawbacks of solely focusing on predictions from macro and micro level models and data. The authors in this paper focus on a hybrid approach both based on macroscopic-learning and microscopic models. In particular, they propose an optimization framework based on conditional stochastic optimization to predict COVID-19 infection rates for a country from the city level infection rates.

Wang et al. (2020) conduct a case study on disease forecasting and compare physics-based models to deep learning based approaches. In this paper, the authors show that their proposed hybrid approach physics-based model performs better than the best deep learning competitor.

2.3 Infection Detection and Prognosis

Most of the infection detection studies we found are conducted on generally three types of datasets consisting of CT scans, X-Ray images, and point of care ultrasound (POCUS) results. Furthermore, the methods utilized are primarily based on using convolutional neural networks to detect the infection.

Ning et al. (2020) utilize a hybrid CNN and DNN based framework for predicting the morbidity or mortality outcomes from chest computed tomography (CT) images. He et al. (2021) focus on a deep learning based solution for the detection of SARS-CoV-2 infection from chest CT scans. The authors in this work build a clean dataset of chest CT scans with the following labels: SARS-CoV-2 pneumonia, common pneumonia, and healthy, consisting of 340190 slices taken from 2698 patients. The authors utilize DenseNet3d121 and ResNet3D34 architectures for their detection problem and achieve 88.63% and 88.14% detection rates respectively. Qiu et al. (2021) provides a neural network design with a lower number of parameters to address the training on CT scans of SARS-CoV-2 patients in a more computationally efficient and practical way.

Motamed et al. (2020) propose to utilize a generative adversarial network (GAN) to differentiate unknown label (e.g. SARS-CoV-2) from the known labels (e.g. normal pneumonia) in X-Ray scans. Roberts & Tsiligkaridis (2020) focus on the robustness of the point of care ultrasound images used in SARS-CoV-2 detection. While several studies are concentrated around optimization of convolutional neural networks to diagnose COVID-19, quite recent work provides a more critical perspective on the proposed methods. In particular, Nanni & Maguolo (2020) provides a critical evaluation of several testing methods used in SARS-CoV-2 detection from X-Ray images.

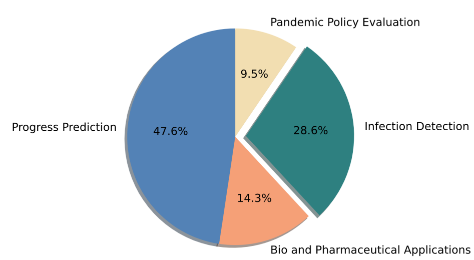

Figure 1: The distribution of sub-categories over the number of published studies in the machine learning conferences under consideration.

In this critique, the authors argue that several methods are not actually learning features relevant to SARS-CoV-2 presence.

2.4 Pandemic Policy Evaluation

In this subsection the studies we found are mostly focused on providing a critical view on the models proposed or the pandemic policies applied so far Sharma et al. (2020).

Qian et al. (2020) propose a Bayesian model to estimate the global effects of the COVID-19 lockdown policies. The authors train their model end-to-end with stochastic variational inference and compare their COVID-19 fatalities with Center for Disease Control (CDC) fatalities to provide analyses on various lockdown policies and their impacts.

[2]The risk of infecting others in past and future.

Sharma et al. (2020) focuses on investigating the stability of infection models for the COVID-19 pandemic to nonpharmaceutical interventions such as: gathering bans, stay-at-home orders and business closures. The authors show that disease transmission models involving noise are more robust and generalizable. Furthermore, the authors mathematically show that nonpharmaceutical interventions (NPIs) are effective even when common assumptions in the NPI effectiveness models do not hold.

3 Concerns on Model Robustness and Biases

The vulnerabilities of deep neural networks Goodfellow et al. (2015), Szegedy et al. (2014), Ilyas et al. (2019), Yin et al. (2019) are still a big concern for the machine learning community. Hence, we think that such a critical application (e.g. medical diagnosis, pandemic control) must be dealt with quite carefully. Robustness problems can have manifold implications, and can be caused by learning biased representations Obermeyer & Mullainathan (2019), Coston et al. (2021), Wiens et al. (2020), by a property of the training dataset used Ilyas et al. (2019), or by intrinsic properties of deep neural networks Goodfellow et al. (2015). Not being limited to classification tasks, these vulnerabilities also arise in deep neural policies either caused by learning non-robust features Korkmaz (2021c), by learning inaccurate representations for sub-optimal policies Korkmaz (2021a), by learning shared adversarial features across MDPs as an intrinsic property of the learning environment Korkmaz (2022), or learning policies that do not generalize under small distributional shifts Korkmaz (2021b). Susceptibilities towards any kind of distributional shift might require significant attention as well as robustness towards particular malicious perturbations.

While the problems described in Coston et al. (2021) can directly effect the proposed methods for the pandemic progress prediction and control sub-problems described in Section 2.2, the issues described in Korkmaz (2021c), Korkmaz (2022) can be a problem for some methods proposed to solve the bio and pharmaceutical sub-problems (e.g. reinforcement learning algorithms) described in Section 2.1. The techniques proposed to address the sub-problems described in the infection detection and prognosis section can also be affected by the issues described in Goodfellow et al. (2015) as a result of utilizing deep neural networks, or by building models based on biased datasets as described in Obermeyer & Mullainathan (2019).

4 Conclusion

In this paper we aimed to provide a summary of the machine learning approaches deployed in COVID-19-related problems. We covered a broad range of problems introduced by the pandemic caused by SARS-CoV-2 such as: epidemic progress prediction, pharmaceutical applications, infection detection, and pandemic policy evaluation. We found for SARS-CoV-2-related problems several different machine learning methods were utilized, ranging from reinforcement learning to graph attention networks, from representation learning to transfer learning, and from convolutional neural networks to variational autoencoders. We observe that while some of the studies focused on deploying existing models for a given setup, some of the work focused on proposing new architectures to solve the problem under consideration. Finally, we emphasize the robustness issues and model biases caused by deploying machine learning algorithms in pandemic-related problems. We hope that our work can provide a useful summary of the machine learning methods deployed in COVID-19-related problems.

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