

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

Ezgi Korkmaz

KTH Royal Institute of Technology,
Stockholm, Sweden
ezgikorkmazk@gmail.com

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. 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 into 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

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 <i>et al.</i> , 2020] GAT [Sehanobish <i>et al.</i> , 2021] RL [Skwark <i>et al.</i> , 2020]
Pandemic Progress Prediction	Primarily focusing on forecasting methods, contact tracing, and graph modelling using multiple hybrid approaches	Meta Learning [Panagopoulos <i>et al.</i> , 2021] Transfer Learning [Rodriguez <i>et al.</i> , 2021] Adversarial Encoder [Xiao <i>et al.</i> , 2021] DNNs [Bengio <i>et al.</i> , 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 <i>et al.</i> , 2020] GAN [Motamed <i>et al.</i> , 2020] NN design [Ning <i>et al.</i> , 2020] DNN [Qiu <i>et al.</i> , 2021] CNN [He <i>et al.</i> , 2021]
Pandemic Policy Evaluation	Mostly focused on robustness of the models proposed and critique of the policies applied so far	Bayesian Model [Qian <i>et al.</i> , 2020] Robustness [Sharma <i>et al.</i> , 2020]

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 subareas 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 models¹. 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

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

can be helpful for epidemiologists, policy makers and health-care 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 represent 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-derived data. By using these features as input, the authors aim to estimate the expected infectiousness². 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 out-

comes 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.

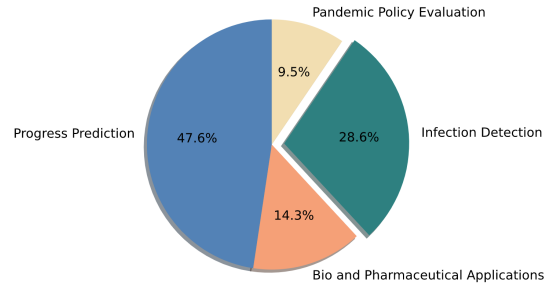


Figure 1: The distribution of sub-categories over the number of published studies in the machine learning conferences under consideration.

[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 and 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 and Maguolo, 2020] provides a critical evaluation of several testing methods used in SARS-CoV-2 detection from X-Ray images. 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.

[Sharma *et al.*, 2020] focuses on investigating the stability of infection models for the COVID-19 pandemic to non-pharmaceutical interventions such as: gathering bans, stay-at-home orders and business closures. The authors show that disease transmission models involving noise are more robust

²The risk of infecting others in past and future.

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 and 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, 2021b], or learning policies that do not generalize under small distributional shifts [Korkmaz, 2021a]. 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] 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 and 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.

References

- [Arik *et al.*, 2020] Sercan Ömer Arik, Chun-Liang Li, Jinsung Yoon, Rajarishi Sinha, Arkady Epshteyn, Long T. Le, Vikas Menon, Shashank Singh, Leyou Zhang, Martin Nikoltchev, Yash Sonthalia, Hootan Nakhost, Elli Kanal, and Tomas Pfister. Interpretable sequence learning for covid-19 forecasting. In Hugo Larochelle, Marc’Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin, editors, *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*, 2020.
- [Ayoubkhani *et al.*, 2021] Daniel Ayoubkhani, Kamlesh Khunti, Vahé Nafilyan, Thomas Maddox, Ben Humberstone, Ian Diamond, and Amitava Banerjee. Post-covid syndrome in individuals admitted to hospital with covid-19: retrospective cohort study. In *bmj*, 2021.
- [Bengio *et al.*, 2020] Yoshua Bengio, Prateek Gupta, Tegan Maharaj, Nasim Rahaman, Martin Weiss, Tristan Deleu, Eilif B. Müller, Meng Qu, Victor Schmidt, Pierre-Luc St-Charles, Hannah Alsdurf, Olexa Bilaniuk, David Buckeridge, Gaétan Marceau Caron, Pierre Luc Carrier, Joumana Ghosn, Satya Ortiz-Gagne, Chris Pal, Irina Rish, Bernhard Schölkopf, Abhinav Sharma, Jian Tang, and Andrew Williams. Predicting infectiousness for proactive contact tracing. *ICLR International Conference on Learning Representations*, 2020.
- [Chenthamarakshan *et al.*, 2020] Vijil Chenthamarakshan, Payel Das, Samuel C. Hoffman, Hendrik Strobelt, Inkit Padhi, Kar Wai Lim, Benjamin Hoover, Matteo Manica, Jannis Born, Teodoro Laino, and Aleksandra Mojsilovic. Cogmol: Target-specific and selective drug design for COVID-19 using deep generative models. In Hugo Larochelle, Marc’Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin, editors, *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*, 2020.
- [Coston *et al.*, 2021] Amanda Coston, Neel Guha, Derek Ouyang, Lisa Lu, Alexandra Chouldechova, and Daniel E. Ho. Leveraging administrative data for bias audits: Assessing disparate coverage with mobility data for COVID-19 policy. In Madeleine Clare Elish, William Isaac, and Richard S. Zemel, editors, *FAccT ’21: 2021 ACM Conference on Fairness, Accountability, and Transparency, Virtual Event / Toronto, Canada, March 3-10, 2021*, pages 173–184. ACM, 2021.
- [Goodfellow *et al.*, 2015] Ian Goodfellow, Jonathan Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. *International Conference on Learning Representations*, 2015.
- [Gupta *et al.*, 2020] Prateek Gupta, Tegan Maharaj, Martin Weiss, Nasim Rahaman, Hannah Alsdurf, Abhinav Sharma, Nanor Minoyan, Soren Harnois-Leblanc, Victor Schmidt, Pierre-Luc St-Charles, Tristan Deleu, Andrew Williams, Akshay Patel, Meng Qu, Olexa Bilaniuk, Gaétan Marceau Caron, Pierre Luc Carrier, Satya

- Ortiz-Gagné, Marc-Andre Rousseau, David Buckeridge, Joumana Ghosn, Yang Zhang, Bernhard Schölkopf, Jian Tang, Irina Rish, Christopher Joseph Pal, Joanna Merckx, Eilif B. Müller, and Yoshua Bengio. Covi-agentsim: an agent-based model for evaluating methods of digital contact tracing. *CoRR*, abs/2010.16004, 2020.
- [He *et al.*, 2021] Xin He, Shihao Wang, Shaohuai Shi, Xiaowen Chu, Jiangping Tang, Xin Liu, Chenggang Yan, Jiyong Zhang, and Guiguang Ding. Benchmarking deep learning models and automated model design for covid-19 detection with chest ct scans. 2021.
- [Ilyas *et al.*, 2019] Andrew Ilyas, Shibani Santurkar, Dimitris Tsipras, Logan Engstrom, Brandon Tran, and Aleksander Madry. Adversarial examples are not bugs, they are features. In Hanna M. Wallach, Hugo Larochelle, Alina Beygelzimer, Florence d’Alché-Buc, Emily B. Fox, and Roman Garnett, editors, *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 125–136, 2019.
- [Korkmaz, 2021a] Ezgi Korkmaz. Adversarial training blocks generalization in neural policies. In *International Conference on Learning Representations (ICLR) Robust Machine Learning Workshop*, 2021.
- [Korkmaz, 2021b] Ezgi Korkmaz. Inaccuracy of state-action value function for non-optimal actions in adversarially trained deep neural policies. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, pages 2323–2327, June 2021.
- [Korkmaz, 2021c] Ezgi Korkmaz. Investigating vulnerabilities of deep neural policies. *Proceedings of the Thirty-Seventh Conference on Uncertainty in Artificial Intelligence (UAI)*, 2021.
- [Lee *et al.*, 2019] Juho Lee, Yoonho Lee, Jungtaek Kim, Adam R. Kosiorek, Seungjin Choi, and Yee Whye Teh. Set transformer: A framework for attention-based permutation-invariant neural networks. In Kamalika Chaudhuri and Ruslan Salakhutdinov, editors, *Proceedings of the 36th International Conference on Machine Learning, ICML 2019, 9-15 June 2019, Long Beach, California, USA*, volume 97 of *Proceedings of Machine Learning Research*, pages 3744–3753. PMLR, 2019.
- [Motamed *et al.*, 2020] Saman Motamed, Patrik Rogalla, and Farzad Khalvati. Randgan: Randomized generative adversarial network for detection of covid-19 in chest x-ray. *NeurIPS Thirty-fourth Annual Conference on Neural Information Processing Systems Medical Imaging Meets NeurIPS Workshop*, 2020.
- [Nalbandian *et al.*, 2021] Ani Nalbandian, Kartik Sehgal, Aakriti Gupta, Mahesh V. Madhavan, Claire McGroder, Jacob S. Stevens, and Joshua R. Cook. Post-acute covid-19 syndrome. In *Nature Medicine*, 2021.
- [Nanni and Maguolo, 2020] Lorris Nanni and Gianluca Maguolo. A critic evaluation of methods for covid-19 automatic detection from x-ray images. *NeurIPS Thirty-fourth Annual Conference on Neural Information Processing Systems Medical Imaging Meets NeurIPS Workshop*, 2020.
- [Ning *et al.*, 2020] Wanshan Ning, Shijun Lei, Jingjing Yang, Yukun Cao, Peiran Jiang, Qianqian Yang, and Jiao Zhang. Open resource of clinical data from patients with pneumonia for the prediction of COVID-19 outcomes via deep learning. *Nature biomedical engineering*, (12):1197–1207, 2020.
- [Nuzzo *et al.*, 2021] Domenico Nuzzo, Gaetano Cambula, Ignazio Bacile, Manfredi Rizzo, Massimo Galia, Paola Mangiapane, Pasquale Picone, Daniela Giacomazza, and Luca Scalisi. Long-term brain disorders in post covid-19 neurological syndrome (pcns) patient. In *Brain Sciences* 11, 2021.
- [Obermeyer and Mullainathan, 2019] Ziad Obermeyer and Sendhil Mullainathan. Dissecting racial bias in an algorithm that guides health decisions for 70 million people. In danah boyd and Jamie H. Morgenstern, editors, *Proceedings of the Conference on Fairness, Accountability, and Transparency, FAT* 2019, Atlanta, GA, USA, January 29-31, 2019*, page 89. ACM, 2019.
- [Panagopoulos *et al.*, 2021] George Panagopoulos, Giannis Nikolentzos, and Michalis Vazirgiannis. United we stand: Transfer graph neural networks for pandemic forecasting. *The Association for the Advancement of Artificial Intelligence (AAAI)*, 2021.
- [Qian *et al.*, 2020] Zhaozhi Qian, Ahmed M. Alaa, and Michaela van der Schaar. When and how to lift the lockdown? global COVID-19 scenario analysis and policy assessment using compartmental gaussian processes. In Hugo Larochelle, Marc’Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin, editors, *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*, 2020.
- [Qiu *et al.*, 2021] Yu Qiu, Yun Liu, and Jing Xu. Miniseg: An extremely minimum network for efficient COVID-19 segmentation. *The Association for the Advancement of Artificial Intelligence (AAAI)*, 2021.
- [Roberts and Tsiligkaridis, 2020] Jay Roberts and Theodoros Tsiligkaridis. Ultrasound diagnosis of covid-19: Robustness and explainability. *NeurIPS Thirty-fourth Annual Conference on Neural Information Processing Systems Medical Imaging Meets NeurIPS Workshop*, 2020.
- [Rodriguez *et al.*, 2021] Alexander Rodriguez, Nikhil Muralidhar, Bijaya Adhikari, Anika Tabassum, Naren Ramakrishnan, and B. Aditya Prakash. Steering a historical disease forecasting model under a pandemic: Case of flu and COVID-19. *The Association for the Advancement of Artificial Intelligence (AAAI)*, 2021.
- [Sehanobish *et al.*, 2021] Arijit Sehanobish, Neal G. Ravindra, and David van Dijk. Gaining insight into sars-cov-

- 2 infection and COVID-19 severity using self-supervised edge features and graph neural networks. *The Association for the Advancement of Artificial Intelligence (AAAI)*, 2021.
- [Sharma *et al.*, 2020] Mrinank Sharma, Sören Mindermann, Jan Markus Brauner, Gavin Leech, Anna B. Stephenson, Tomas Gavenciak, Jan Kulveit, Yee Whye Teh, Leonid Chindelevitch, and Yarin Gal. How robust are the estimated effects of nonpharmaceutical interventions against covid-19? In Hugo Larochelle, Marc’Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin, editors, *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*, 2020.
- [Skwark *et al.*, 2020] Marcin J. Skwark, Nicolás López Carranza, Thomas Pierrot, Joe Phillips, Slim Said, Alexandre Laterre, Amine Kerkeni, Ugur Sahin, and Karim Beguir. Designing a prospective COVID-19 therapeutic with reinforcement learning. *NeurIPS Thirty-fourth Annual Conference on Neural Information Processing Systems COVID-19 Symposium*, 2020.
- [Szegedy *et al.*, 2014] Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dimutru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. In *Proceedings of the International Conference on Learning Representations (ICLR)*, 2014.
- [Vervoort *et al.*, 2020] Dominique Vervoort, Jessica GY Luc, Edward Percy, Sameer Hirji, and Richard Lee. Assessing the collateral damage of the novel coronavirus: A call to action for the post-covid-19 era. In *The Annals of thoracic surgery* 110, 2020.
- [Wang *et al.*, 2020] Rui Wang, Danielle C. Maddix, Christos Faloutsos, Yuyang Wang, and Rose Yu. Bridging physics-based and data-driven modeling for learning dynamical systems. *NeurIPS Thirty-fourth Annual Conference on Neural Information Processing Systems Machine Learning in Public Health Workshop*, 2020.
- [Wiens *et al.*, 2020] Jenna Wiens, Nicholson Price, and Michael Sjoding. Diagnosing bias in data-driven algorithms for healthcare. In *Nature Medicine*, 2020.
- [Xiao *et al.*, 2021] Congxi Xiao, Jingbo Zhou, Jizhou Huang, An Zhuo, Ji Liu, Haoyi Xiong, and Dejing Dou. C-watcher: A framework for early detection of high-risk neighborhoods ahead of COVID-19 outbreak. *The Association for the Advancement of Artificial Intelligence (AAAI)*, 2021.
- [Yang *et al.*, 2020] Yingxiang Yang, Negar Kiyavash, Le Song, and Niao He. The devil is in the detail: A framework for macroscopic prediction via microscopic models. In Hugo Larochelle, Marc’Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin, editors, *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*, 2020.
- [Yin *et al.*, 2019] Dong Yin, Raphael Gontijo Lopes, Jonathon Shlens, Ekin D. Cubuk, and Justin Gilmer. A fourier perspective on model robustness in computer vision. *NeurIPS Thirty-fourth Annual Conference on Neural Information Processing Systems*, 2019.
- [Zaheer *et al.*, 2017] Manzil Zaheer, Satwik Kottur, Siamak Ravanbakhsh, Barnabás Póczos, Ruslan Salakhutdinov, and Alexander J. Smola. Deep sets. *CoRR*, abs/1703.06114, 2017.