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Artificial Intelligence and Machine Learning for Healthcare Systems: A Study of COVID-19

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ABSTRACT

The COVID-19 global pandemic is a threat not only to the health of millions of individuals, but also to the stability of infrastructure and economies around the world. The disease will inevitably place an overwhelming burden on healthcare systems that cannot be effectively dealt with by existing facilities or responses based on conventional approaches. We believe that a rigorous clinical and societal response can only be mounted by using intelligence derived from a variety of data sources to better utilize scarce healthcare resources, provide personalized patient management plans, inform policy, and expedite clinical trials. In this work, we introduce five of the most important challenges in responding to COVID-19 and show how each of them can be addressed by recent developments in machine learning (ML) and artificial intelligence (AI). We argue that the integration of these techniques into local, national, and international healthcare systems will save lives, and propose specific methods by which implementation can happen swiftly and efficiently. We offer to extend these resources and knowledge to assist policymakers seeking to implement these techniques.

1. **Introduction:** The international community has seen an unbelievable amount of pressure put on their social and healthcare infrastructure over the past years. This has happened due to the unavailability of resources. In this regard, AI and machine learning can use data to make objective and informed recommendations and can help ensure that scarce resources are allocated as efficiently as possible. Doing so will save lives and can help reduce the burden on healthcare systems and professionals. 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. While the paper is primarily focused on the UK national healthcare system, the challenges and methods highlighted in the paper apply to other countries. First, AI and machine learning can help us identify people who are at highest risk of being infected by the novel coronavirus [1]. 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 the allocation of resources like testing kits more efficient, as well as inform 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. In the meantime, unproven hypotheses about the disease are likely to propagate online, impacting individual behavior and causing systemic risks. This encourages more progress in the area of machine learning and artificial intelligence. Therefore, this study provides all the developments in the area of AI/ML which are used till now for making an efficient health care system [2].

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2. **Practical challenges:** This scarcity of resources is aggravated by the fact that individuals with COVID-19 are known to experience widely different patterns of disease progression and outcomes: while some patients are asymptomatic, others manifest flu-like symptoms of varying severity, and some experience complications such as pneumonia and fatal multi-organ failure (Jiang et al. 2020). Since resources are limited and risk and disease progression so heterogeneous, it is crucial to identify—as early as possible—which individuals are likely to have been infected by the virus, which infected individuals may experience adverse events, which types of medical resources those individuals will require, and when these resources will be required. The scarcity of healthcare resources will be exacerbated by the need to employ those resources to deal with both COVID-19 cases and other patients who require—or will require—medical care. There is thus a clear and urgent need to deploy systems that can provide early warnings for personalized risk and disease progression of individuals, and that can inform medical personnel and healthcare systems about which patients would benefit from what resources and when [3].

2.1 How AI can help: Mature AI-based support systems for a number of chronic diseases already exist, but a pandemic such as COVID-19 presents a problem of a different nature. While chronic diseases jeopardize individual health, pandemics jeopardize public health because they present both individual and systemic risks. Pandemics, by nature, undermine the underlying social structures that connect individuals together. Dealing with these systemic risks requires merging clinical data with a variety of diverse social data. Electronic health records (EHR) hold data that can be used to pinpoint individuals' clinical risk factors (Wang et al. 2020), and which can be linked to the multitude of "big data" pertaining to human-to-human interactions (e.g. data from cellular operators, traffic, airlines, and social media). Machine learning (ML) is especially suited for merging these various sources of data to issue accurate predictions of risk and help uncover the social structures through which systemic risks manifest and spread. In this way, there are many other through which COVID-19 and other infections are treated using the potential of Artificial Intelligence and Machine Learning [4].

3. **Developing personalized patient management and treatment lans:** Vaccines and therapeutics for COVID-19 will take some time to be developed and introduced (Lu 2020). Although a number of antiviral medications are being trialed, none are currently known to be effective. Due to the heterogeneous nature of patient disease trajectories, one-size-fits-all treatment plans (which are developed at the population level, rather than individualized patient level) are very likely to be ineffective in terms of both patient outcomes and use of limited resources. To save lives and effectively use scarce resources, it is therefore essential to develop management and treatment plans that are personalized for each patient, depending on their unique characteristics and needs [5].

3.1 How AI can help:

AI-based models can effectively use current observational data to study the effects of existing medicines on individuals with specific qualities (characteristics) such as pre-existing comorbidities. This can aid in determining the optimal management strategy for each patient based on their characteristics, such as the appropriate policy for using mechanical ventilation and/or experimental treatments [6].

Recent improvements in machine learning models optimized for learning in the observational data scenario can be used to learn customised therapy effects. Gaussian process models (Ahmed et al. 2017), generative adversarial networks (Yoon et al. 2018), as well as deep neural networks (Zhang et al. 2020), are capable of learning individual-level effects. Providing experimental therapies based on observational data (rather than randomized trials), and can potentially be coupled with omics data. We used such strategies can identify patient subgroups for whom Remdesivir, Lopinavir/Ritonavir, and Chloroquine therapies may be effective (Gao et al. 2020). Modeling the evolution of a patient's health condition as they respond to different sequences of therapies and supportive care over time is required for learning individualized management and treatment regimens [7].

4. **Informing policies and enabling effective collaboration:**

Governmental and municipal reactions to the outbreak have been strikingly diverse (Ferguson et al. 2020). Decisions on illness management, prevention, diagnosis, and treatment are decided at the national, regional, institutional, and even individual practitioner levels. Policymakers and healthcare practitioners make different observations, take different measurements, and respond differently based on the evidence in uncertain settings—like those given by COVID-19. For instance, based only on where they happen to be seen, two patients with comparable profles may end up receiving different courses of therapy due to variations in triaging methods between institutions and practitioners. There is wide diversity in resource utilization efficiency and quality because there is little agreement on the policies and practices that are most effective [8].

4.1 How AI can help:

Evidence-based decision-making requires gathering costly observations on the effects of a therapy or resource allocation strategy and then making an informed decision based on the observations accumulated. AI techniques address the following critical and interconnected issues, providing a common language for healthcare practitioners to exchange information and improve policies over time [9].

What are the various diagnostic and therapeutic protocols?
First, we can quantify the decision rules that underpin observed behavior (for example, the norms and protocols that are frequently implicitly inscribed in various institutions). What is learned here is an accessible mapping from information (e.g., patient characteristics and measurements) to actions (i.e., diagnostic tests and treatments) for a concise, standardized description of behaviour a mapping that is immediately indicative of which individual actions are more or less likely to be taken in any given scenario [10]. For example, how badly does a patient have to be doing before a ventilator is used? How does this compare to other hospitals? Transparent policy modeling allows for the identification and comparison of actions taken by various decision-makers [11].

What are the priorities shown by various policies?
Second, we can quantify the preferences and potential biases latent in observed behavior (for example, what treatments are chosen in the absence of other factors, and how time sensitivity and monetary costs influence judgments). What is obtained for a concise, standardized interpretation of various policies is an accessible mapping from behavior to preferences—a mapping that is immediately indicative of which aspects of the decision-making process (e.g., expense, accuracy, time pressure, and patient populations) appear more or less important for a given decision maker. For example, we may anticipate that an institution will diagnose and treat older patients more swiftly than younger patients. But, in fact, do they? And, if so, how much? [12].

What are the greatest ways to improve existing policies?
Third, we can measure the efficacy of both new and old policies in order to determine the optimal policy to apply based on different goals and conditions. While addressing the two preceding questions can help with transparent comparison and comprehension of changes in clinical practice, the ultimate goal here is to prescribe improved diagnosis and treatment strategies. This can be accomplished by combining the answers to the above questions with unique reinforcement learning approaches to inform and guide policy evaluation and policy improvement [13].

What is the degree of trust in learned policies?
Finally, we can measure the uncertainty involved in finding, comprehending, and improving judgments and policies. This is especially important in new situations where predictive expertise is missing, such as when responding to COVID-19. For example, novel diagnostic tests will almost likely contain errors, and the overall efficacy of various therapies is unknown in advance. Quantifying uncertainty allows us to clearly understand which components of our models we can have more confidence in and which we cannot [14].

5. Expediting clinical trials:

In order to compare the efectiveness of a new treatment to an existing one (or to a placebo), randomized clinical trials (RCTs) are considered the gold standard. However, it is a well-known fact that RCTs can be slow and costly, and may fail to uncover specific subpopulations for which treatment would be most effective. Moreover, conclusions drawn from RCTs are typically valid only for the types of patients recruited for that RCT. This is an especially significant problem in the case of COVID-19, as elderly

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patients and patients with comorbidities, who are known to be at higher risk, are typically excluded from RCTs [15].

5.1 How AI can help:

Recent work on enhancing the design of adaptive clinical trials has shown that the use of ML can considerably improve the efficiency and effectiveness of RCTs (Zame et al. 2020). While the majority of RCTs simply assign patients to treatment and control groups, In terms of learning, uniform randomization can be exceedingly suboptimal. Adaptive clinical trials powered by machine learning (Lee et al. 2020; Atan et al. 2019; Zame et al. 2020) can recruit patients in cohorts (rather than all at once), and the consequences on each cohort will be studied [16]. can be noticed prior to enrolling the following batch, and may differ identified patient subgroups (as would be predicted with COVID-19 therapies) Rather than randomly recruiting and assigning participants, ML approaches can recruit from identifiable subgroups and allocate subjects to treatment or control groups in a way that accelerates learning. These strategies have been demonstrated to significantly reduce error and attain a predetermined degree of confidence in findings while using far fewer patients [17].

6. Research Challenges:

Because the COVID-19 pandemic is new, it is being managed with little prior expertise and data. Our understanding of its behavior is highly speculative (Anderson et al., 2020). Furthermore, because the coronavirus may undergo additional natural selection and geographic development as the pandemic proceeds, understanding this evolution and the uncertainties that accompany it will be critical to mitigation**.** To work effectively in this setting, we must measure the degree of uncertainty in our understanding of the condition and then apply this to assess the risks and benefits of therapeutic and social policies used to alleviate it. This is especially critical because unverified theories regarding COVID-19 have already spread quickly online and through numerous media venues, and they are likely to influence individual behavior and thus affect systemic risks. When dealing with the current COVID-19 epidemic, there are three specific sources of uncertainty. For starters, models trained on data from the population tested for SARS-CoV-2 may be biased, because patients who have been tested are not always typical of the broader UK population. Using data from other countries where the outbreak occurred earlier (e.g., China, Italy, Iran, or South Korea) may result in biased models that may not translate well to the UK population. Second, there is a scarcity of information about COVID-19 patients. Given the wide range of patient features and outcomes, broad hypothesis testing about the disease may appear erroneously inconclusive [18].

6.1 How AI can help:

In these three contexts, ML approaches offer a wide range of solutions for modeling uncertainty: Transfer learning methods, which implicitly deal with uncertainty in predictions made for individuals from groups other than those used for training, can address the problem of biased models. International collaboration might result in a big dataset containing data from multiple affected populations, from which a single two-level risk assessment model could be developed and distributed globally. The model must "learn" its uncertainty by making predictions for specific individuals in the UK. Transfer learning models, such as those based on transferable dropout (Chan et al. 2020), achieve this task effectively and have already been demonstrated to operate well for disease prognostication across different countries or healthcare systems.

Not only is transfer learning useful for transferring models across populations, but it is also useful for updating ML models for a single population as the diagnosed cohort evolves over time. Particularly, as diseases and populations vary through time, observable patient distributions—as well as their characteristics and outcomes—may shift. Scalable Bayesian optimization approaches have been developed to update models with fresh information for continuing performance while efficiently exploiting earlier optimizations using successive batches of data as they arrive (Zhang et al. 2019). Importantly, while giving actionable information based on AI-systems, we must understand what we know and what we do not know. New tools have been developed to systematically assess uncertainty in machine learning model predictions (Ahmed 2020; Alaa and van der Schaar 2020). We must require that all predictions made by AI-enabled systems for decision assistance include confidence estimates. Decision-makers will then understand when and for which patients they can rely on the AI system's predictions, and when they cannot have the same level of certainty. Quantifying uncertainty in patient-level outcome projections is critical for guiding hospitalization and treatment decisions. It is also critical that uncertainty measures provide guarantees on their coverage performance, that is, the chance that a confidence interval encompasses the genuine outcome. Recently suggested methods based on infuence functions allow for post-hoc estimation of Jackknife estimations of machine learning outcomes, i.e., it is independent of model architecture or design choices. These approaches have been used on both cross-sectional and longitudinal data models [19].

7. Recommended means of implementing the techniques:

The adoption of the various AI-based models presented can make use of current data infrastructure. Through collaboration between the public and private sectors, information about patients from EHR records can be integrated with data from cellular providers, airlines, traffic applications, and social media. AI models may integrate such collections of static and temporal data streams to enable more tailored forecasts of risk and treatment effects, patient management policies, and better trial design. We'll look at the United Kingdom to see what's possible. Countries with pre-existing viral surveillance systems, such as the United Kingdom, are well positioned to capitalize on accessible data and use the aforementioned AI technologies to improve outcomes. Recent emergency privacy legislation has permitted NHS Digital, the national health and social care data aggregator, to gather, link, and analyze record-level, patient-identifiable data. Furthermore, Public Health England collects all COVID-19 testing data on a national scale, and individuals suspected of being infected are triaged through a national health triage service, with call data made available in real-time [20].

7.1 Individual-level interface

Patients may receive text messages, emails, and phone calls alerting them to undergo testing based on personalised health risk assessments provided by AI models. Installing GPS-enabled mobile applications on people's phones can be used to steer social distancing by alerting people in high-risk areas where a considerable number of COVID-19 cases have been diagnosed or where a significant number of high-risk potential virus carriers are presently present [21].

7.2 Hospital-level interface

In order to support public health risk assessments, risk-modeling tools that show and notify physicians of patients' changing risks within each hospital can be added to the current in-hospital EHR infrastructure. For remote diagnosis and treatment of self-isolating patients with visible symptoms, the NHS's Technology Enabled Care Services (TECS) programme has adopted several telehealth applications. Hospitals can use current hardware infrastructure to connect input data streams from ICUs to software (driven by machine learning models) that shows doctors patient hazards when implementing AI-based models [22].

7.3 Nation-level interface

Centralised applications can be used to support government officials and decision-makers by providing them with up-to-date epidemiological data on COVID-19, hospital occupancy rates for the entire population, and aggregate risk assessments that are stratified geographically. This would interface with the other programmes to gather data on population risk and be immediately connected to the NHS patient registration database [23].

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8. Conclusion:

In this paper, we outline five of the most crucial issues in responding to COVID-19 and illustrate how recent advances in machine learning (ML) and artificial intelligence (AI) can solve each of them. We suggest that incorporating these procedures into local, national, and worldwide healthcare systems will save lives, and we provide specific methods for rapid and efficient implementation. We propose to expand these tools and knowledge to policymakers who want to put these ideas into practise. This publication will assist researchers who are just starting out in this subject to better comprehend it.

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