LUISS

Department of Business and Management
Bachelor's Degree in management & Computer Science
Course of Artificial Intelligence and Machine Learning

Academic Year 2022/2023

"Utilising Machine Learning in the Battle against COVID-19: A Focus on Healthcare Resource Allocation"

Supervisor: Prof. Giuseppe Italiano

Candidate: Emanuele Veneziani (m. 256481)

A mio nonno Giorgio, con cui avrei tanto voluto condividere questo traguardo e al quale vorrei stringermi in un ultimo e infinito abbraccio.

Hai visto, nonno?

INDEX

1. Introduction

1.1 Background and Context

The 21st century has witnessed unprecedented progress in many sectors and demonstrated it in many forms, and that progress is exactly what drives this thesis. During this journey we will focus, in particular, on the research and scientific progress in Artificial Intelligence (to which we will refer as AI) and Machine Learning (ML). Important advancements and discoveries in this field have brought solutions to problems transforming various environments: in particular, healthcare stands to benefit from this revolution. As time goes by, AI and ML are increasingly being embraced as tools to enhance care streamline hospital administration, and improve clinical decision making.

In the year 2020 and beyond the global healthcare sector faced a challenge in the form of COVID-19, this crisis not only pushed healthcare systems to their limits but also exposed weaknesses in resource allocation strategies within hospitals. Making decisions regarding resource allocation – including managing staff, Intensive Care Units (ICUs) Personal Protective Equipment (PPE), and vaccine distribution – directly impacted outcomes and the overall ability of healthcare systems to effectively respond to the pandemic.
Given this situation, there is a growing interest in exploring how AI and ML can optimize resource allocation, in healthcare settings beyond their roles of disease prediction and treatment. What makes these technologies potentially highly effective is their ability to process amounts of data quickly, a key element in assisting with resource allocation during a pandemic. For instance, machine learning models can help predict the spread of the virus forecast patient outcomes, optimize staff schedules, and manage the supply chain for equipment and medications. However, it is important to note that despite their benefits there has been limited research on implementing these technologies in healthcare resource allocation during rapidly evolving situations like COVID-19. This study aims to explore how machine learning can be effectively used to optimize resource allocation

within healthcare settings during COVID-19. The objective is to provide insights that can guide crisis responses while also critically evaluating these approaches.

Throughout this research, it is crucial to recognize that AI and machine learning alone are not solutions. Considering their far-reaching aims, these should be seen as tools that can improve and overturn decision-making processes. Additionally, it is essential to consider factors such as data privacy and potential biases within AI/ML models when utilizing these technologies, for resource management during a pandemic.

1.2 Problem Statement

The COVID-19 pandemic has put a strain, on healthcare systems worldwide. One of the challenges is effectively managing resources such as medical supplies, hospital beds, and the time of healthcare workers given the constantly changing nature of the pandemic. Ensuring patient outcomes in this environment is of utmost importance.
Traditionally resource allocation during health crises like pandemics has heavily relied on decision making. However, this approach comes with its set of complexities. Subjective biases, information overload, and the rapid pace of changes make decision-making a task. In scenarios, there is potential to integrate Artificial Intelligence (AI) into healthcare systems to support and assist decision-makers.
There is a growing interest in leveraging AI within healthcare to optimize resource allocation. Various models have been developed for this purpose, including Adjutorium and COXREG. Additionally, companies like Cerner HealtheIntent, Google's DeepMind, and IBMs Watson Health have also contributed their models to address these challenges. However, it remains vital to comprehend how these models function and their respective strengths and weaknesses. Moreover evaluating their effectiveness compared to one another is essential, in tackling the challenges posed by the COVID-19 pandemic.
The main objective of this thesis is to fill the gap, in knowledge by analyzing and evaluating established AI models used for distributing healthcare resources during COVID-19. Of starting from scratch our approach involves assessing and comparing the performance of these existing models. Our research will mainly focus on understanding

the characteristics of these models identifying any limitations they may have and evaluating how effective they are when dealing with the challenges posed by a pandemic. Through this study, we aim to contribute to the existing body of knowledge about AI's role in healthcare and provide insights that can lead to improvements, in models guide future AI development efforts and ultimately enhance healthcare outcomes during pandemics.

1.3 Research Objectives

The primary aim of this research is to understand and evaluate the role and potential of machine learning in optimizing healthcare resource allocation, especially during the COVID-19 pandemic. Based on the scope and depth suitable for a bachelor's thesis, this investigation is structured around the following specific objectives:

1. To critically review the existing literature on the application of machine learning in healthcare resource allocation, particularly during pandemics, to comprehend the current state of knowledge in this field.

2. To gain insights into the functioning and implementation of selected machine learning models, specifically Adjutorium and COXREG, in resource allocation during the COVID-19 pandemic.

3. To analyze the potential benefits and challenges of using machine learning for resource allocation during pandemics, based on case studies and real-life scenarios identified in the literature.

4. To explore the considerations linked to the utilization of AI and machine learning, in allocating resources during pandemics. Examine how these concerns are being addressed.

5. To suggest recommendations for research in the field of healthcare resource allocation during pandemics using machine learning based on the insights obtained from a review of existing literature

1.4 Significance of the Study

The COVID-19 pandemic has presented challenges to healthcare systems worldwide necessitating the allocation of resources within overwhelmed systems. However, there is still a knowledge gap regarding the utilization of technologies like intelligence and machine learning in resource allocation during healthcare crises.
This study holds importance as it aims to address this knowledge gap on levels:

1. Contribution to Existing Knowledge: The study seeks to contribute to the body of research on leveraging AI and machine learning in healthcare resource allocation during pandemics. By analyzing existing models and their application during the pandemic this research expands our understanding of how machine learning can be employed in situations.

2. Real-world Implications and Beneficiaries: Healthcare professionals and administrators responsible, for making resource allocation decisions during pandemics will directly benefit from this study.

By offering insights, into the strengths and limitations of using AI and machine learning this research can significantly improve decision-making processes.

Research Guidance

This study identifies areas that need improvement and unexplored research directions when it comes to applying AI and machine learning to resource allocation. As a result, it can be a reference for studies in this field. Ultimately this will contribute to advancing and refining these technologies within the healthcare sector leading to progress in care and hospital management.

Machine learning shows promise in the healthcare industry given its relevance that has been highlighted during the pandemic. By exploring its potential in resource allocation this research does not only contribute academically but also has practical implications for real-world healthcare administration and patient care during crises. The insights gained from this study can serve as a foundation for research endeavors as well as the development of improved models and strategies for resource allocation, in healthcare settings.

1.5 Thesis Structure

This thesis is structured to provide an understanding of how machine learning is utilized in allocating healthcare resources during the COVID-19 pandemic. After this chapter, the thesis is divided into seven chapters as outlined below:

Chapter 2: Review of Existing Literature: In this chapter, we delve into a comprehensive examination of literature concerning the COVID-19 pandemic and how it impacts healthcare systems. We explore strategies and challenges related to allocating resources, in hospitals during pandemics as the significant role that AI and Machine Learning play in addressing this health crisis. Additionally, we analyze existing studies on the application of Machine Learning in resource allocation.

Chapter 3: Framework: This chapter provides an overview of Machine Learning and its relevance to our study. We introduce machine learning models called Adjutorium and COXREG which have been identified as suitable for our analysis purposes. Furthermore, we discuss the considerations surrounding the use of AI and machine learning in healthcare.

Chapter 4: Methodology: In this chapter, we focus on highlighting the advantages of using machine learning for resource allocation during pandemics. We also identify any limitations or challenges that may arise during its implementation.

Chapter 5: Discussion: This chapter offers an interpretation of our research findings. Discusses their implications for hospital operations and patient care during pandemics. Additionally, we compare our findings with existing studies, on this topic.

Chapter 6: Conclusions and Future Recommendations: The final chapter serves as a summary of our research outlining its contributions and acknowledging any limitations encountered along the way.
Moreover, it offers suggestions, for exploration and implementation in pandemics to aid in addressing difficulties and optimizing advantages in the allocation of healthcare resources.

By adopting this framework, the thesis strives to cover the principles of machine learning, the real-world implementation of these technologies, in healthcare resource distribution, and the potential opportunities and obstacles linked to this implementation amidst the COVID-19 pandemic.

2. Literature Review

Embarking on an exploration of the existing body of literature, in our study we aim to bring together significant discoveries and theories that will serve as the foundation of our investigation. Our focus will be to understand the ranging effects of the COVID-19 pandemic on global healthcare systems and comprehend the subsequent need for innovative strategies in resource allocation as healthcare facilities were overwhelmed by a surge in patients.

Our objective goes beyond the summarization of these works and recent studies. Instead, we intend to evaluate their conclusions thereby informing our investigation into how AI and Machine Learning could have revolutionized healthcare delivery during the pandemic.

Aligned with our research goals we initiate our exploration by delving into a range of literature that documents the challenges faced by healthcare systems worldwide due to the COVID-19 pandemic. This exploration will aid us in assessing how the sudden increase in numbers strained resources and facilities necessitating approaches to resource allocation. Which is the focal point of our research question.

2.1 The COVID-19 Pandemic and Its Impact on Healthcare Systems

2.1.1 The Effect of COVID-19, on Mortality Rates: A Study Conducted by Woolf et al. (2020)

Introduction and Relevance to Research

The global impact of COVID-19, on mortality rates has been significant. A notable study in this field is the research article titled "Excess Deaths from COVID-19 and Other Causes, March July 2020" by Woolf et al. (2020) which was published in the Journal of the American Medical Association (JAMA). This article provides an understanding of how the pandemic has affected mortality in the United States not by considering deaths directly attributed to COVID-19 but also by examining excess deaths from other causes giving us a broader perspective on its overall health impact.

Insights, on Methodology and Key Discoveries

In their study, Woolf et al. (2020) utilize a Poisson regression model to predict expected deaths based on patterns. This quantitative approach enables an analysis of deaths revealing a 20% increase in mortality between March and August 2020 with 67% of these additional deaths linked to COVID-19. However, it is important to note that this study does have some limitations. It relies on data. Recognizes potential inaccuracies in death certificates highlighting areas, for further research that may involve more definitive data sources or international comparisons (Woolf et al., 2020). The research aligns, with the discussion that supports the need for a thorough understanding of how pandemics affect public health. However, it differs by including deaths from causes like heart disease and Alzheimer's, which also experienced mortality rates during the pandemic (Woolf et al., 2020). This approach addresses a gap, in the existing literature, which often focuses on the causes of deaths during pandemics. However, it would have been beneficial if the article had discussed how resource allocation is affected during pandemics, an area that has been explored in works.

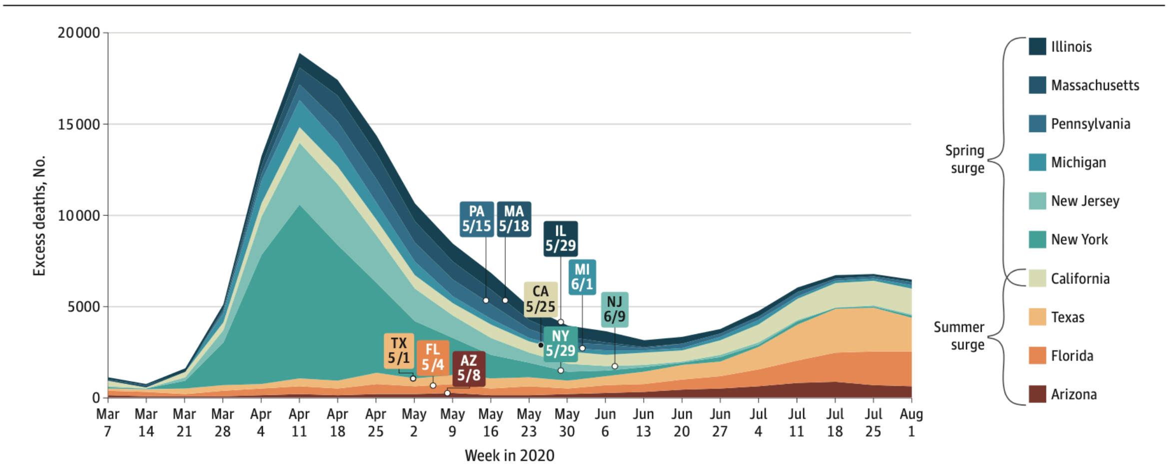


Figure 1: Excess Deaths from March to July 2020 in some Selected States (Woolf et al. 2020)

Implications for Future Research

This article lays the groundwork for researchers who are studying the health impacts of COVID-19. Its robust methodology and comprehensive scope provide insights for my research especially if it's decided to examine excess deaths among different demographic groups or in various geographic locations. Incorporating the findings and methodologies of Woolf et al. (2020) into this literature review section not only contributes to discussions on COVID-19's impact on mortality but most of all provides a solid framework for future research endeavors.

2.1.2 Global Impact and Vulnerability Assessment: Study by Shrestha (2020)

Introduction and Relevance to Research

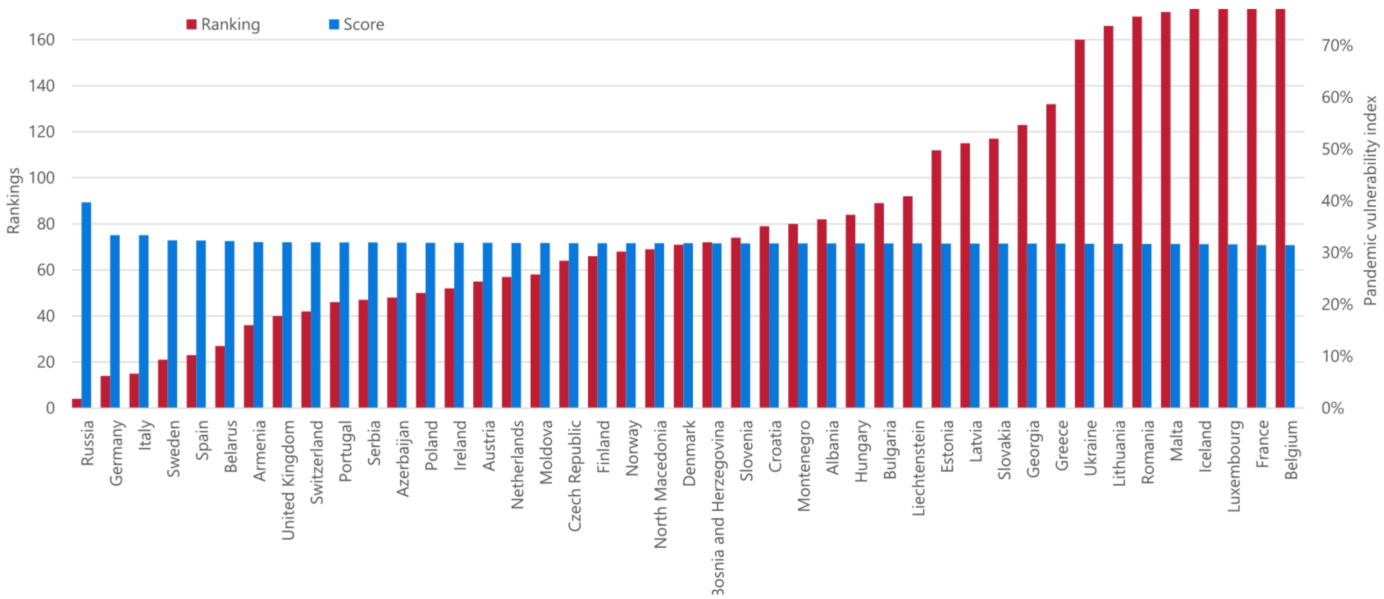
In exploring the socio consequences of pandemics, the article "The impact of COVID-19 on globalization", by Nistha Shrestha et al. (2020) serves as a very valuable resource. Published in the journal One Health this paper aims to quantify the multifaceted impacts of the pandemic on interconnectedness regarding mobility, economy, and healthcare systems.

This comprehensive framework serves as a reference point either confirming or challenging the assumptions underlying my research.

Insights, on Methodology and Key Discoveries

Shrestha et al. (2020) adopt a mixed-method approach that incorporates quantitative data. They utilize the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to calculate a Pandemic Vulnerability Index (PVI). This unique methodology allows them to identify countries at risk of being affected by the pandemic, including South Africa, Egypt, Russia, Germany, Italy, and the United States. These significant findings contribute to our existing knowledge and provide a deeper understanding of how the pandemic has profoundly impacted global economies and healthcare systems. While this article aligns with studying the consequences of pandemics it stands out by introducing a measure called PVI for evaluating vulnerability. This deviation is both its strength and limitation. Although PVI offers a perspective on vulnerability it is still a new concept that may require further validation for broader applicability.

Figure 2: PVI Ranking and Scores per State in Europe (Shrestha et al. 2020)



Implications for Research and Integration of Insights

The study's findings emphasize the necessity for country strategies, in mitigating the impacts of pandemics an area that could enrich my research. Moreover, the concept of PVI introduced by Shrestha et al. (2020) resonates with other scholarly works that discuss the economic and healthcare impacts of pandemics, thereby offering a valuable tool for my research methodology. In the specifics, we can state that the article by Shrestha et al. (2020) provides a view of the impact of COVID-19 on various sectors, making it a seminal work in the field of pandemic research, most of all because of its innovative methodology and key findings challenge the whole research community to delve deeper into the complexities of global pandemics.

The findings derived from the study add a complementary layer of understanding to the conclusions drawn by Woolf et al., revealing the intricate dynamics between the healthcare system, the disease itself, and the much broader socioeconomic landscape. Shrestha's work underscores the complex socioeconomic effects and long-term strain on global healthcare capacities due to the pandemic. It emphasizes, moreover, the global interconnectedness of healthcare systems and studies how the domino effect of a pandemic can cause ripple effects across the world. Taken together, these studies present a clear picture of the significant impacts of the COVID-19 pandemic on healthcare systems worldwide. They emphasize the way the sudden surge in patient numbers has overwhelmed facilities and strained resources, necessitating innovative and efficient resource allocation strategies. The overwhelming scale of the crisis has spurred interest in new tools and technologies to manage resources effectively, leading us to the next part of our review. We will investigate these novel strategies in more depth, specifically focusing on the increasingly pivotal role of AI and Machine Learning in resource allocation during such health crises.

2.2. Challenges, in Allocating Resources in Hospitals during Pandemics

The management of resources during a pandemic brings about significant ethical and practical challenges for healthcare systems worldwide. Gaining an understanding of the strategies and associated challenges involved in resource allocation can provide insights into decision-making processes during a crisis. In this section, we will examine the existing literature on resource allocation in hospitals during pandemics with a focus on the circumstances presented by the COVID-19 pandemic.

2.2.1 "Resource Allocation at the Forefront of Public Health Preparedness and Response"

Introduction and Relevance to Research

The complexities of allocating resources in public health emergencies go beyond logistics: they are deeply intertwined with legal considerations. The groundbreaking work by Barnett et al. In 2009 it acted as a cornerstone within this landscape. Through their summit, the authors aimed to address the lack of principles guiding resource allocation during health crises thereby filling an important gap, in existing research. Their study holds relevance to the research question of this thesis, which aims to explore the ethical and legal frameworks that underpin resource allocation during public health emergencies.

Barnett et al. adopting an approach utilized an exercise to simulate a scenario involving a public health emergency. This approach resulted in the creation of ten principles, which are divided into responsibilities, towards the community finding a balance between freedom and community well-being and promoting preparedness practices. These principles serve as a guide for public health experts and policymakers. They offer a framework that combines considerations with legal obligations (Barnett et al., 2009).

While the article's contributions are significant, it falls short of addressing the challenges of implementing these principles in contexts. Additionally, the summit from which these principles originated may not fully represent all perspectives within the field. These limitations not only open avenues for research but also shape the methodology and scope of this thesis. The principles outlined by Barnett et al. (2009) can serve as a framework for analyzing real-world case studies thereby enhancing the depth of this research.

Final Thoughts

The work of Barnett et al. (2009) is a reference in discussions about legal considerations related to public health resource allocation. It does not offer an approach, to a complex issue but also encourages academic and professional communities to engage in deeper more nuanced conversations.

Therefore, it functions as both a base and a driving force, for this thesis directing its methodology and influencing the questions it seeks to answer.

2.2.2 "Fair Allocation of Scarce Medical Resources in the Time of Covid-19" by Ezekiel J. Emanuel

Introduction and Relevance

In the article titled "Fair Allocation of Scarce Medical Resources, in the Time of Covid 19" authored by Ezekiel J. Emanuel, Govind Persad, Ross Upshur, and others published in 2020 in the New England Journal of Medicine an exploration is conducted on the considerations surrounding resource allocation during the COVID 19. The central research question addressed is how to distribute resources when healthcare infrastructure becomes overwhelmed due to a pandemic (Emanuel et al., 2020). This article holds relevance to my research which focuses on healthcare ethics and policy during pandemics. It offers a framework for making decisions that can play a crucial role in shaping effective and morally sound policies. Moreover, it challenges the belief that medical resources should solely be allocated based on urgency by introducing often overlooked ethical considerations.

The article puts forth a framework for resource allocation that emphasizes four core values: maximizing benefits ensuring equal treatment for all individuals promoting and rewarding instrumental value and giving priority to those who are worst off. The methodology employed is qualitative, in nature relying on analysis as well as existing literature.

The authors argue that determining resource allocation requires an approach that considers values rather than relying solely on one value (Emanuel et al., 2020).

Critical Analysis

This article aligns with the trend, in ethics advocating for a comprehensive decision-making process that goes beyond clinical or economic factors alone. It differs from approaches by incorporating various ethical values thereby enriching the discourse within the field.

Ethical Values and Guiding Principles	Application to COVID-19 Pandemic
Maximize benefits	
Save the most lives	Receives the highest priority
Save the most life-years — maximize prognosis	Receives the highest priority
Treat people equally	
First-come, first-served	Should not be used
Random selection	Used for selecting among patients with similar prognosis
Promote and reward instrumental value (benefit to others)	
Retrospective — priority to those who have made relevant contributions	Gives priority to research participants and health care workers when other factors such as maximizing benefits are equal
Prospective — priority to those who are likely to make relevant contributions	Gives priority to health care workers
Give priority to the worst off	
Sickest first	Used when it aligns with maximizing benefits

Figure 3: Ethical Values to Guide Rationing of Absolutely Scarce Health Care Resources in a Covid-19 Pandemic (Emmanuel et al., 2020)

Although this article presents a framework it does not delve into implementation challenges such as cultural variations in ethical perceptions or the influence of political decision making, on resource allocation. Additionally, since it is based on analysis it may not fully capture the complexities of real-world scenarios.

Implications

This article complements sources in my review that focus on healthcare policy and ethics. It explicitly introduces a perspective. Offers actionable recommendations. The multi-value ethical framework can be adapted to healthcare settings thereby informing my research methodology. Emanuel et al. (2020) article provides a nuanced framework to guide the allocation of medical resources during pandemics.

This research addresses an aspect that has been missing in the existing literature. It focuses on the considerations related to a relevant issue and proposes a framework that will be crucial, for my research. This framework aims to shape healthcare policies during pandemics ensuring they are both ethically sound and effective.

Synthesis and Future Directions

Regarding resource allocation during pandemics, the complexities involved are well demonstrated in the studies conducted by Barnett et al. (2020). Emanuel et al. (2020). Both articles highlight the balance between obligations and practical utility although they approach the matter from slightly different perspectives. Barnett et al. (2020) emphasize the significance of engagement and transparency in decision-making making giving weight to societal values and individual rights. On the other hand, Emanuel et al. (2020) put forward a prescriptive ethical framework that centers around maximizing benefits treating individuals equally, and prioritizing those who are most disadvantaged.

While these two studies provide insights, they also shed light on gaps and limitations present in current approaches. Barnett's work rightly emphasizes the need for discourse. Falls short of providing a structured ethical framework to guide such discussions effectively. In contrast, Emanuel et al. (2020) contribution lies in offering a valuable ethical framework; however, it overlooks practical challenges associated with implementation such, as political influences or cultural factors.

Furthermore, both studies fail to address the changing nature of pandemics, where resource requirements and ethical considerations can rapidly shift. This underscores the importance of frameworks that can adapt in time guided by continuous data collection and public input.

In conclusion, while determining resource allocation during pandemics is complex, due to dilemmas and practical limitations these studies provide insights that pave the way for more nuanced and fair strategies. They highlight the need for standards, active public participation, and the ability to adjust policies effectively. The lessons we have learned from the COVID-19 pandemic serve as an invaluable compass, for navigating the ethical challenges of future public health crises.

2.3 The Role of AI and Machine Learning, in Healthcare Amidst the COVID-19 Pandemic

The utilization of Machine Learning and Artificial Intelligence has played a role in addressing the challenges posed by the COVID-19 pandemic. These technologies have proven valuable not only in modeling but also in enhancing patient care. Let's explore their applications considering both their advantages and disadvantages as discussed in the research.

2.3.1 AI-Powered Search Tools (by Kricka et al., 2020)

In this era of the COVID-19 the scientific community has been faced with numerous challenges ranging from swift disease detection to effectively managing extensive datasets. A noteworthy study conducted by Kricka et al. (2020) sheds light on how Artificial Intelligence (AI) has transformed our ability to tackle these challenges head-on. This review aims to evaluate the contributions, limitations, and broader implications of their article within the realm of AI in healthcare.

According to the authors' perspective, AI has emerged as a game changer on a scale when it comes to responding to COVID-19. They highlight three areas where AI has shown promise: curating datasets like CORD 19 introducing AI driven search tools such, as WellAI and SciSight, and incorporating mobile technology for digital contact tracing. This comprehensive approach supports the idea that AI can serve as a tool, in healthcare during times of crisis. For example, SciSight, an AI-driven visualization tool allows for the exploration of connections between concepts found in the CORD 19 Dataset. This efficiently maps the network of literature associated with COVID-19 (Kricka et al., 2020). The article takes an approach by providing a narrative review of AI initiatives during the pandemic. While this gives an overview it lacks validation. The absence of data or controlled studies limits the article's ability to definitively confirm the effectiveness of AI tools. This methodological gap does not highlight a limitation. Also suggests areas for future empirical research.

What is known about transmission, incubation, and environmental stability?
What do we know about COVID-19 risk factors?
What do we know about virus genetics, origin, and evolution?
What do we know about vaccines and therapeutics?
What has been published about medical care?
What do we know about non-pharmaceutical interventions?
What do we know about diagnostics and surveillance?
What has been published about ethical and social science considerations?
What has been published about information sharing and inter-sectoral collaboration?

Figure 4: Covid-19 Open Research Dataset Challenge (CORD 19) tasks (Kricka et al. 2020)

Digital contact tracing has emerged as a solution to an age problem. Prominent tech companies like Apple and Google have collaborated to develop tracking technology that works on both Android smartphones (Kricka et al., 2020). However, concerns regarding privacy ethics have become obstacles to the adoption of these technologies (Kricka et al. 2020). The article notably overlooks this aspect creating a gap, in the existing literature.

The article's emphasis, on research aligns with scholarly works that advocate for a multi-disciplinary approach to addressing healthcare challenges. It also highlights the importance of understanding how AI can be effectively and ethically utilized in healthcare settings. For researchers studying the role of AI in healthcare, Kricka et al.'s (2020) work provides a framework for assessing the capabilities and limitations of AI-powered tools.

Final Thoughts

This article serves as a resource for comprehending the role of AI during COVID-19. While it makes contributions to the field it also presents opportunities for exploration particularly in terms of empirically validating AI tools and considering ethical implications. Therefore, it is not. Also motivates the research community to delve deeper into the complexities surrounding the implementation of AI, in healthcare.

2.3.2 Progress Using COVID-19 Patient Data to Train Machine Learning Models for Healthcare

One of the significant trends in contemporary medical research is the application of machine learning models to predict and manage healthcare needs, particularly in the context of emergent health crises like the COVID-19 pandemic. Van der Schaar's study from Cambridge University is instrumental in revealing the advancements made in this domain.

Van der Schaar and her team aimed to demonstrate the utility of machine learning in predicting the healthcare demands of COVID-19, from the requirements at individual patient levels to larger hospital resources like ICU beds. Their principal tool in this endeavor was "Adjutorium," a system that could effectively make predictions based on the data it was trained with.

Leveraging data from Public Health England, the researchers obtained information from nearly 1,700 patients. This data, albeit depersonalized, was comprehensive, providing details on laboratory results, hospitalizations, risk factors, and outcomes. Noteworthy is their use of "AutoPrognosis", an automated machine learning framework initially developed for cardiovascular issues but found application in various other areas (Van der Schaar et al. 2020).

Key Findings, Significance, and Implications

Adjutorium, once trained, outperformed traditional methods of prediction such as Cox regression or the Charlson comorbidity index. For instance, its accuracy in predicting mortality was measured at 0.871 ± 0.002, significantly higher than the Cox regression accuracy of 0.773 ± 0.003 (Van der Schaar et al. 2020). This highlights a pivotal shift in the medical field, suggesting that machine learning techniques might offer more accurate predictions than some traditional methods, especially in unprecedented situations like a pandemic. Especially in times of unpredictable health crises, Machine Learning has more importance and calls for effective implementation strategies for the scientific community. It also highlights the necessity of comprehensive and quality data for training these models. As Van der Schaar notes, while Adjutorium achieved significant results, the system's performance could be further enhanced with access to a more substantial portion of global COVID-19 data. (Van der Schaar et al. 2020)

Event	Adjutorium accuracy	Cox regression accuracy	Charlson index accuracy
Mortality	0.871 ± 0.002	0.773 ± 0.003	0.596 ± 0.002
ICU admission	0.835 ± 0.001	0.771 ± 0.002	0.556 ± 0.013
Ventilation	0.771 ± 0.002	0.690 ± 0.002	0.618 ± 0.002

Future Directions and Conclusions

Not only does the research conducted have a groundbreaking effect, but what it does most of all is highlight the importance of data collection and validation: in fact, there's a specific need to gather data that provides an understanding of patient progress during their hospital stay. Obtaining data, on the usage and impact of ventilators would surely enable accurate predictions regarding patient outcomes. One notable aspect is the collaboration between Public Health England and the NHS, which we know suggests the significance of integrating these tools into mainstream healthcare systems. They must be user-friendly and easily interpretable by healthcare professionals. The study conducted by Van der Schaar et al. provides valuable insights into machine learning in healthcare within the context of the COVID-19 pandemic. On the practical side, It showcases applications and underscores the necessity for continued collaboration, data collection, and validation with the long-term aim of exploiting the potential of these technologies in improving healthcare outcomes.

It's important to acknowledge that this literature review primarily focuses on applying machine learning techniques to predict and manage healthcare requirements during COVID-19. The broader implications of these studies along with works in this field emphasize how healthcare research continually evolves and how integrating modern technologies plays a critical role, in enhancing patient care outcomes.

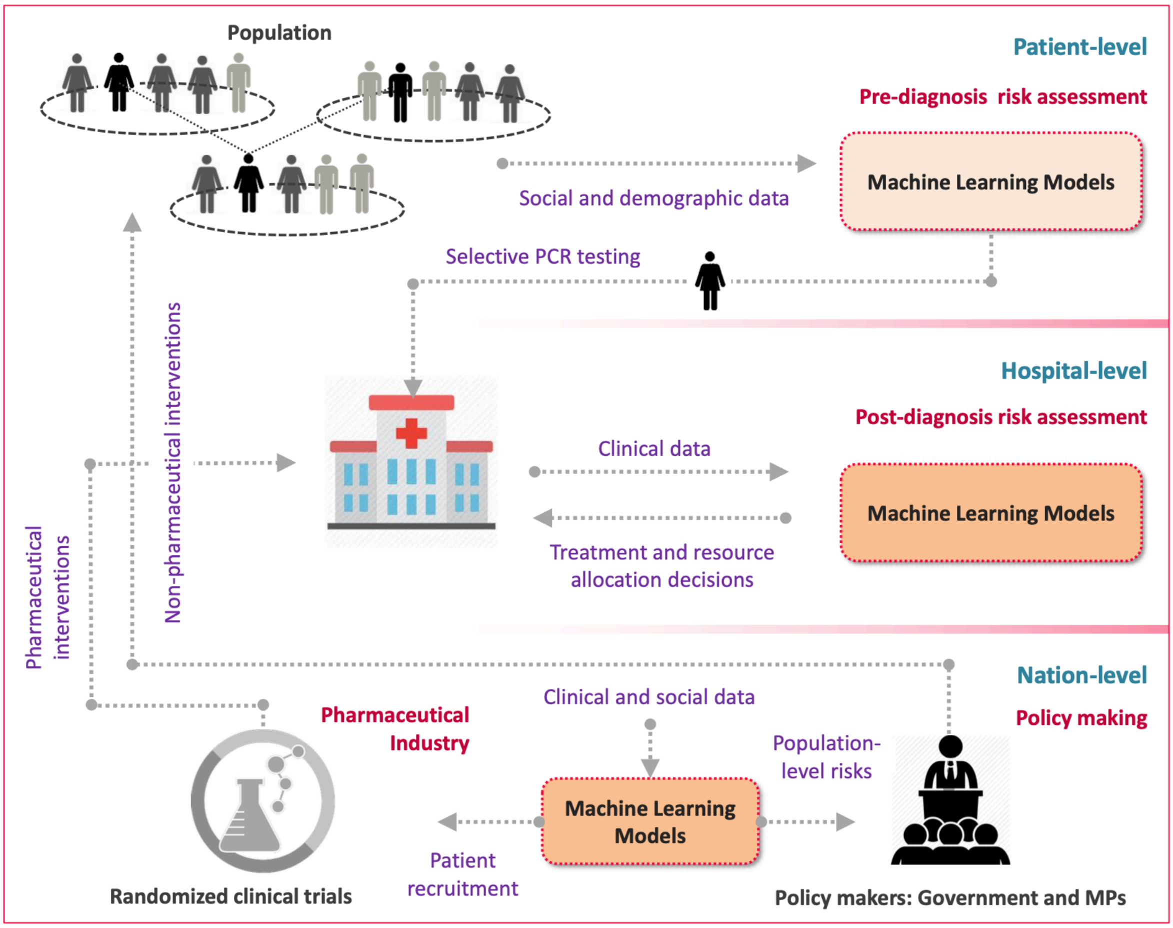


Figure 5: High-Level Illustration of how ML and AI solutions could help healthcare respond to Covid-19 (Van der Schaar, 2020)

3 Theoretical Background

3.1 Introduction to Machine Learning

Understanding Machine Learning

With the words "Machine learning" (ML), we depict a subset of artificial intelligence (AI), which practically has been instrumental in transforming a myriad of sectors, including healthcare. Rooted in statistical theory and computational learning, ML algorithms have the capacity to learn from data and subsequently make informed decisions or predictions. In this study machine learning is essential for two reasons. Firstly it powers the optimization algorithms used for healthcare resource allocation. Secondly, it provides a framework to comprehend the often nonlinear relationships between healthcare variables. Thus machine learning does not only aid in aspects but also offers insights into complex healthcare dynamics.

Different Types of Machine Learning

Supervised Learning

Supervised learning is considered one of the forms of machine learning. Is often taught as the initial algorithmic approach, in ML courses. In learning algorithms learn from labeled datasets. Use input data to make predictions or decisions.

This kind of learning is similar, to a situation where a teacher oversees the learning process. The teacher knows the correct answer and the algorithm makes predictions and gets corrected by the teacher allowing the model to learn gradually. In healthcare, supervised learning algorithms can be used for analysis like predicting readmissions or determining the success rate of a specific treatment based on historical data.

Unsupervised

On the other hand, unsupervised learning involves modeling with datasets that don't have labeled responses. The system tries to understand patterns and structures from the data without any guidance. This type of learning can help group patients into risk categories based on features when there's no clear indication of what outcome variable should be used. For instance, unsupervised learning algorithms can identify clusters of patients with symptoms which could aid in resource allocation, in healthcare settings.

Reinforcement

Reinforcement learning, instead, is inspired by psychology where agents take actions in an environment to achieve a goal. To achieve a goal the agent learns by finding the way, known as the policy that will guide them to the desired end state while maximizing a measure of reward. In healthcare reinforcement learning algorithms can be utilized to determine the treatment plans, in dynamic situations thereby assisting in the efficient allocation of resources.

Essential Concepts in Machine Learning

Regression

Regression analysis explores, as a modeling technique, the relationship between one (or more in case of multiple regression) variables and a dependent variable. This is particularly valuable in healthcare for predicting outcomes (such as age) based on one or more predictor variables. The foundations of regression can be traced back to statistics. Have been adapted and expanded within the field of machine learning. For example, regression models can be utilized to predict the occupancy rate of hospital beds at a given time aiding in resource allocation.

Classification

Classification is another concept, in machine learning that involves categorizing data into classes. It builds upon the principles of regression. Focuses on predicting outcomes instead of continuous ones. For instance, in the field of healthcare, a classification model can be employed to determine whether a patient should be classified as 'high risk' or 'low risk' based on their records. This information is vital for healthcare providers to optimize resource allocation and enhance efficiency.

Clustering

On the other hand, clustering is a learning technique used in statistical data analysis. Unlike classification, clustering algorithms divide a dataset into subsets based on the characteristics of the data. The main objective is to group individuals, with traits and assign them to clusters. In healthcare, clustering can be utilized to identify patterns, within data, which can then inform targeted treatment plans or efficient allocation of resources. For example, clustering algorithms can help identify groups of patients who are likely to respond to a specific treatment enabling healthcare providers to offer more personalized solutions.

Core Algorithms in Ensemble Models

Random Forest

Random Forest is an ensemble learning method that operates by constructing multiple decision trees during the training phase. The more trees in the 'forest,' the more robust the model. Mathematically, the output for classification problems is the mode of the classes output by individual trees, and for regression, it's the mean prediction of the individual trees. The algorithm uses bagging and feature randomness when building each tree to try to create an uncorrelated forest of trees whose prediction is more accurate than that of any individual tree.

$$\text{Random Forest Prediction} = \frac{1}{n}\sum_{i=1}^{n} Prediction\ of\ Tree_i$$

In healthcare, Random Forest is often used for its ability to handle a large number of features and its ease of interpretation, making it a popular choice for diagnostic and prognostic studies.

Neural Networks

Neural Networks are inspired by the structure and function of the biological neural network. They consist of interconnected layers of nodes or "neurons," with each layer transforming its input into a slightly more abstract representation. Mathematically, the transformation is often a linear transformation followed by a non-linear activation function.

$$f(x) = \sigma(Wx + b)$$

Where σ is the activation function, W is the weight matrix, and b is the bias vector. Neural Networks are particularly useful in image recognition tasks, such as MRI or X-ray interpretation, and have been instrumental in advancing the field of personalized medicine.

Gradient Boosting

Gradient Boosting is an ensemble learning technique that aims to minimize a loss function by adding weak learners, usually decision trees. The algorithm builds trees one at a time, where each new tree helps to correct errors made by the previously trained tree. Mathematically, each tree fits the residual errors of the ensemble of existing trees.

$$F_m(x) = F_{m-1}(x) + \alpha \sum_{j=1}^{J} \gamma_{jm} I(x \in R_{jm})$$

Here, $Fm(x)$ is the boosted ensemble after m iterations, α is the learning rate, γ is the parameters of the individual trees, and R indicates the regions partitioned by the individual trees. In healthcare, Gradient Boosting has been effective in predicting disease outbreaks and patient readmissions.

AdaBoost (Adaptive Boosting)

AdaBoost is a boosting algorithm used primarily for classification problems. It works by weighting instances in the dataset by how easy or difficult they are to classify, allowing the algorithm to pay more or less attention to them in the construction of subsequent models. The final prediction is a weighted sum of the predictions from all learners.

$$H(x) = sign(\sum_{t=1}^{T} \alpha_t h_t(x))$$

Where $H(x)$ is the final prediction, α_t is the weight of the t^{th} weak learner, and $h_t(x)$ is the prediction of the t^{th} weak learner. AdaBoost is particularly useful in scenarios where the cost of false negatives and false positives are significantly different, such as in cancer diagnosis.

3.2 Relevant Machine Learning Models for Resource Allocation: Adjutorium and COXREG

3.2.1 Adjutorium: A Comprehensive Exploration

Overview and objectives

Adjutorium is a machine learning tool that was initially created to predict prognosis and treatment benefits for breast cancer. It has been employing a huge amount of data from large-scale cohorts, consisting of 1 million women profiles in the United Kingdom and the United States. Compared to existing tools like PREDICT v2.1 Adjutorium has demonstrated significantly improved accuracy. Moreover, it has been adapted to predict resource requirements during the COVID-19 pandemic, such as ventilators and ICU beds at both the patient and hospital levels (Van der Schaar, 2020).

The nature of the exploration we are going to conduct of Adjutorium, directly aligns with the problem statement of this thesis, which emphasizes the role of AI in optimizing healthcare resource allocation during the COVID-19 pandemic. It also gives a response to the research objective by providing an in-depth understanding of how Adjutorium functions in resource allocation, during pandemics.

Theoretic aspect

The underlying machine learning model used by Adjutorium is a model that consists of four basic machine learning algorithms: random forest, neural network, gradient boosting,

and AdaBoost. The predictions made by Adjutorium are derived from a combination of these four algorithms predictions.
This approach of using AI emphasizes the effectiveness of methods in improving prediction accuracy along with the theoretical concepts we've discussed in the core course about "Neural Networks" and "CART Trees and Random Forests.”. In Adjutorium the ensemble model is built using the AutoPrognosis framework, consequently automating ML models' application in clinical prognostic modeling. AutoPrognosis optimizes a combination of machine-learning models by tuning their parameters through advanced Bayesian optimization techniques. Each algorithm within the ensemble contributes differently to the prediction and these contributions are determined by assigned weights (Alaa et al., 2020). Adjutorium is designed to handle missing data. It can generate predictions even when some prognostic factors are not available. The model utilizes imputation algorithms to manage missing data. Adjutorium, concluding, does not rely on assumptions about risks being linear or hazards being proportional over time, and this allows it to identify, of course in a data-driven manner, interactions and nonlinear associations (Alaa et al., 2020).

Considering its capabilities Adjutorium can be categorized as a model that can handle both classification and regression tasks. This aligns, with the concepts we've covered regarding "Classification" and "Regression" throughout this course.

Adjutorium's effectiveness is evaluated using metrics such as the area under the curve (AUC ROC) over time Harrell's concordance index (C index) and Uno's C index (Alaa et al. 2020). These metrics are the main reference in the field of machine learning and so are accepted to provide a measure of how accurately the model predicts outcomes.

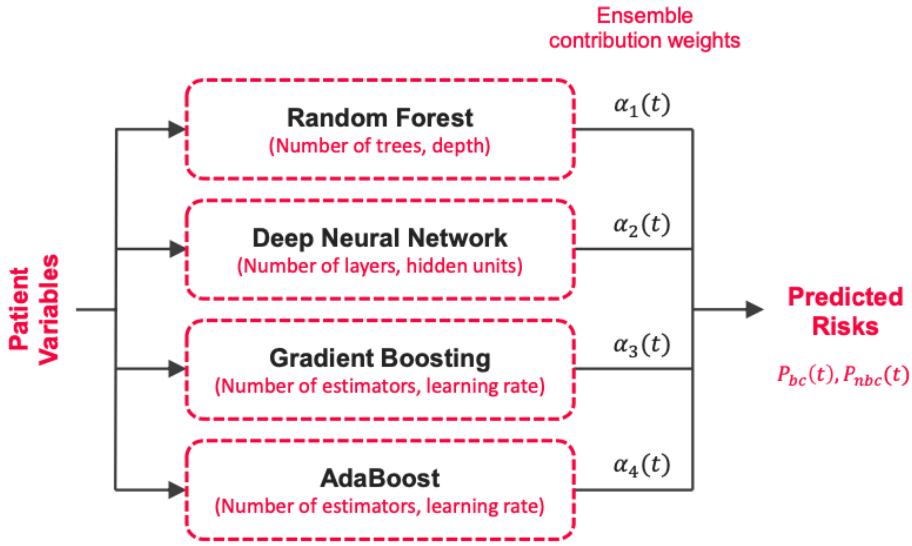


Figure 6: The Ensemble Method Learned by the AutoPrognosis Software (Alaa et al. 2020)

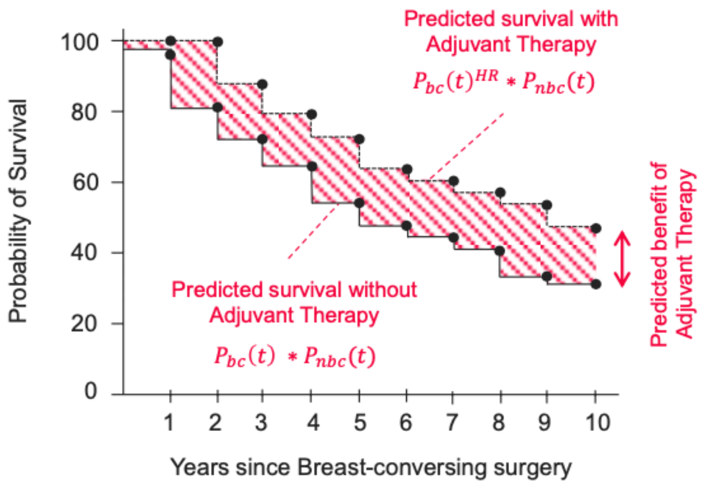


Figure 7: The predicted survival curve for an exemplary patient (with and without adjuvant therapy) (Alaa et al. 2020)

Historical Development and Challenges

Adjutorium was powered and made possible by AutoPrognosis, an open-source software appositely designed to automate machine learning deployment in clinical prognostic modeling. Initially created for breast cancer prognosis it was later adapted for resource allocation during COVID-19). Although Adjutorium has shown results it remains crucial to continuously validate the model using new and high-quality data. The model's performance can be influenced by data quality during training. There is a need for longitudinal data to gain a deeper understanding of patient progression (Van der Schaar, 2020).

Conclusion

Adjutorium has proven itself as a reliable machine learning tool not only for breast cancer prognosis but also for effectively allocating resources, during pandemics.
Its combination of methods enables it to handle incomplete data and thorough validation makes it a promising tool, for future healthcare purposes.

3.2.2 Understanding COXREG: A Detailed Analysis

Overview and Objectives.

Let’s get to know the Cox Regression Mode: it’s also called the “Cox Proportional Hazards model" and it’s a statistical method mainly used as a tool for survival analysis. This algorithm basically must examine how various factors impact the time it takes for a specific event to occur. In the healthcare field, this "event" often refers to patient mortality, but it can also include incidents like heart attacks or strokes that are of interest (McKnight, 2017).
The Cox Regression model’s presence in this thesis is relevant to address the complexities and challenges that decision-making imposes during health crises adopting a more traditional approach towards it, the main one. By studying COXREG, this research aims to achieve its second objective of gaining insights into how machine learning models can be utilized for resource allocation during pandemics.

Theoretical Foundations and Functionality.

The Cox Regression model is essentially a type of regression model discussed in the Artificial Intelligence and Machine Learning course's section on "Regression. It has to be specified that COXREG also differs from traditional regression models by specifically handling data related to time-to-event occurrences, meaning it does not merely focus on whether an event happened or not, but also it takes into account when it occurred.

Because it doesn't assume anything about the baseline hazard function, the model is classifiable as a semi-parametric one, allowing for non-parametric estimation of it (McKnight, 2017).

The Cox Regression model is usually written in terms of the hazard function. The hazard function $\lambda(t)$ is expressed as:

$$\lambda(t)=\lambda 0(t)\times e\beta 1x1+\beta 2x2+\ldots+\beta kxk$$

$\lambda 0(t)$ is here the baseline hazard, and $\beta 1$, $\beta 2$, …, βk are the coefficients for $x1$, $x2$,…, xk, our predictor variables.

Here the model estimates the risk or hazard of an event occurring based on certain predictor variables, among different types (they can be categorical, like gender or treatment group, or continuous, like age). The model calculates a hazard ratio for each predictor, to effectively show how the hazard changes following a one-unit change in the predictor variable. Supposing the hazard ratio for a particular treatment is 2, it means that there is twice the risk of experiencing the event for patients receiving that treatment compared to those who don't receive it (McKnight, 2017). To ensure good performance of the model the right variables for Cox Regression must be chosen it's fundamental that overfitting or underfittings avoided, even if multiple predictor variables can be included in the model. Overfitting occurs when too many variables are included and makes the model overly complex and less generalizable. On the other hand, underfitting happens when too few variables are included and fail to capture underlying relationships effectively (McKnight, 2017).

hazard ratios remain constant throughout according to this model's assumptions of proportional hazards over time (McKnight, 2017).

Although the standard Cox Regression model is widely used, there are variations and extensions available to address specific limitations. One example is the Stratified Cox model, which allows for different baseline hazards across different strata or groups).

Historical Context

Setting a historical context, Sir David Cox developed the Cox Regression model in 1972 and it has since become a fundamental tool in survival analysis. Its applications span various fields but it's in healthcare that it finds its critical role in analyzing patient survival times and evaluating treatment effectiveness (McKnight, 2017).

3.2.3 Overview of Other Algorithms in Healthcare Resource Allocation

Support Vector Machines (SVM)

Moving on to other algorithms in healthcare resource allocation, we have Support Vector Machines (SVM). SVM is a supervised learning algorithm primarily employed for classification and regression tasks. It excels in handling high dimensional data thanks to its kernel trick that efficiently deals with nonlinear data. Within healthcare, SVM finds applications in disease prediction and medical imaging among other domains. (M. Sailaja et al. 2021).

Cerner's HealthIntent

Cerner Corporation's HealthIntent is a platform that serves as a data analysis and insights tool. What it does is gather and standardize data from different types of sources, including, as an example, both clinical and non-clinical sources, to generate valuable insights that can be used functionally. It is through the use of these intelligent models that the platform effectively analyzes the data and detects any anomalies, allowing healthcare providers to prioritize patient care. Health Intent was specifically designed to address the challenges associated with collecting comprehensive data across different formats and proprietary barriers (Sullivan, Tom. "Why EHR Data Interoperability Is Such a Mess in 3 Charts." Healthcare IT News 2018).

Google DeepMind

DeepMind Technologies Limited is another relevant example for our algorithm-excursus, being it is a subsidiary of Google dedicated to applying AI and machine learning techniques especially to enhance healthcare systems. One notable project involved collaborating with the Royal Free London NHS Foundation Trust to manage acute kidney injury cases. However, this project encountered obstacles related to privacy concerns and power dynamics. The ultimate goal of DeepMind is to utilize AI technology to provide crucial alerts and actionable analytics within the healthcare sector (Julia Powles & Hal Hodson, 2017).

3.3 Ethical and Legal Considerations in AI and Machine Learning

The incorporation of Artificial Intelligence (AI) and Machine Learning (ML) into healthcare systems is not just a technological advancement, but it has some complex ethical and legal discussions lying behind it. As highlighted by Naik et al. (2022) in their article titled "Legal and Ethical Consideration in Artificial Intelligence in Healthcare: Who Takes Responsibility?", the absence of well-defined regulations and governance frameworks raises crucial questions about accountability, particularly when it comes to healthcare-related decisions. Challenges presented by AI implementation cannot be ignored just because of its evident powers.

One of the most significant concerns revolves around the "black box" phenomenon, where the internal workings of AI algorithms remain opaque, even to healthcare professionals (Naik et al., 2022) and we know that this can bring some lack of accountability (which is fundamental as a value in medicine!). In a field where the least error can have life-altering consequences, the inability to comprehend or question how an AI system makes decisions can't help being a huge ethical issue, and it's for this purpose that Naik et al.'s paper delves into the notion of "algorithmic fairness and biases" (Naik et al., 2022).

In the field of healthcare, personalized treatment has a crucial role. It is important to recognize, though, that algorithmic biases exist and can occur, whether based on race, social/economic, or gender factors. These biases can have as a consequence unequal and unjust healthcare outcomes and the issue of significant ethical concerns that require policymakers' and the public's attention. Data privacy is another crucial aspect to consider: With the increased use of electronic health records and digital data, there is a higher risk of data breaches and unauthorized access to sensitive information and so there occurs a conflict between the ethical obligation to protect patient confidentiality and the data-intensive (and sometimes invasive!) nature of AI algorithms.

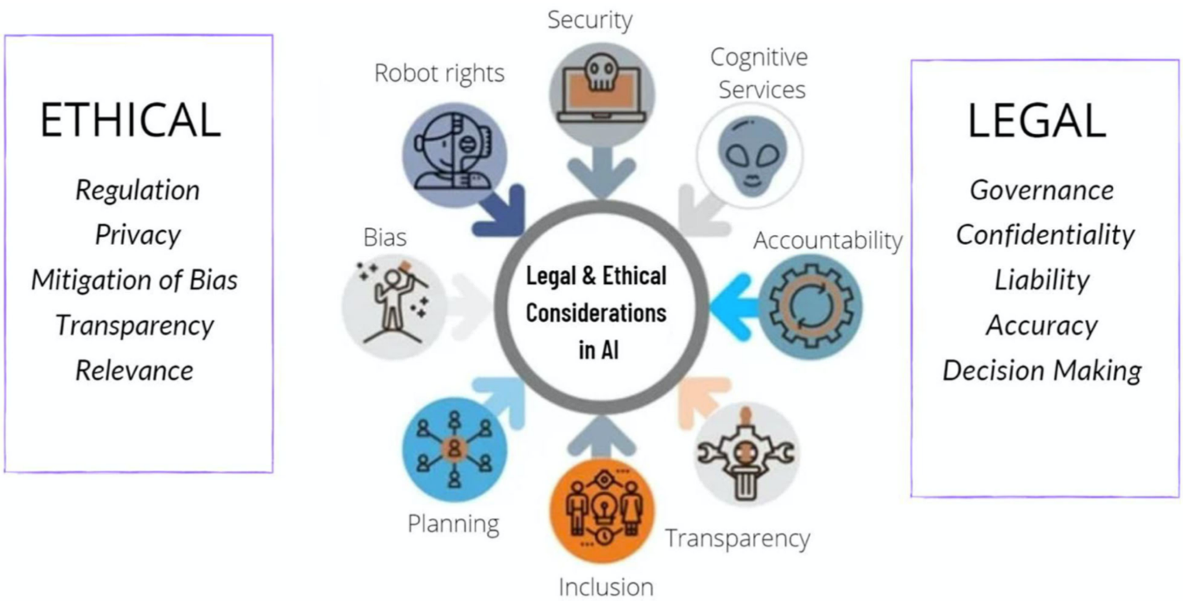


Figure 8. Various ethical and legal conundrums involved with the usage of Artificial Intelligence in Healthcare (Naik et al. 2022)

Let's summarize at this point: while AI and ML bring out exceptional opportunities for enhancing healthcare, they also highlight numerous ethical and legal challenges that demand proactive solutions. Without a solid governance structure in place, not only is the ethical integrity of healthcare jeopardized, but patient safety and confidentiality are also. As we embrace the digital age, it becomes increasingly important to handle these ethical and legal concerns completely and ethically.

4. Analysis

4.1 Potential Benefits of Machine Learning in Allocating Resources during Pandemics

When it comes to resource allocation, the COVID-19 pandemic has exposed weaknesses (other than highlighted new possibilities) in healthcare systems. There is a pressing need for intelligent decision-making based on data, given that hospitals were facing a demand for intensive care units (ICUs) ventilators, and medical staff. In this section, we will describe and evaluate the advantages of using machine learning algorithms to allocate resources during pandemics (with the main example of COVID-19, focusing specifically on the Adjutorium tool and the Cox Regression.

4.1.1 Adjutorium, A Real-Life Example

Introduction to Adjutorium

Adjutorium is a tool based on machine learning that was created to forecast treatment benefits and prognostic outcomes for breast cancer patients. Developed by Mihaela Van Der Schaar and her team at the Cambridge Centre for AI in Medicine, this tool exploits a combo of ML algorithms to come up with an in-depth understanding of patient needs and resource requirements in healthcare settings. This algorithm's applications have expanded far beyond the original breast cancer prognosis, with the scope to include resource allocation during pandemics demonstrating its ability to adapt and remain reliable.

The unexpected and urgent need for resource allocation presented itself during the COVID-19 pandemic as a challenge that Adjutorium was surprisingly well prepared to tackle.

While the focus of Adjutorium was, as already said, initially on predicting breast cancer outcomes, the tools underlying machine learning algorithms have proven to be highly adaptable for applications in healthcare. During the pandemic (as soon as it began to scare Europe) Adjutorium was trained using data provided by Public Health England. The goal was to try and forecast resource needs (such as ventilators, ICU beds, …) both at a patient level and within hospitals to better evaluate and study the impact of COVID-19. This adaptability proves Adjutorium’s versatility in facing other types of healthcare-related challenges beyond its original purpose.

Data Training and Performance

In terms of data training and performance, Adjutorium required a (not so huge as one would expect) dataset to effectively function during the pandemic. 1,700 patient records containing essential information on their profiles (lab results, hospitalization details, risk factors, and outcomes) were utilized for this task. The tool was initially developed using a machine learning framework known as AutoPrognosis, which allowed for model training and validation enabling healthcare providers and coordinators to make real-time accurate data-driven decisions. The model was trained on subsets of this dataset to predict mortality rates, ICU admissions, and ventilation requirements. Afterward, Its accuracy was tested using subsets from the same dataset. The quality and comprehensiveness of the data played an almost crucial role, in ensuring the model's predictive precision.

During that period, Adjutorium exhibited impressive performance metrics that are truly stunning and praiseworthy.

The tool demonstrated, after having been trained, very high accuracy in making predictions, even surpassing established and well-known analysis techniques like Cox regression and indexes such as the Charlson comorbidity index. When it came to predicting mortality Adjutorium achieved an accuracy of 0.871 ± 0.002, outperforming Cox regression’s 0.773 ± 0.003. Charlson index’s 0.596 ± 0.002. These metrics do not universally confirm the effectiveness of this tool, but it is sure that they establish a new standard for predictive healthcare.

Future Implications and Work: Beyond the Pandemic

The success of Adjutorium during the COVID-19 pandemic serves as proof and an ulterior signal that machine learning can be broadly applied in a healthcare setting with our immediate focus being the validation of the developed models so that healthcare professionals can securely rely on this system for their needs and researches. Mihaela Van Der Schaar’s team aimed to gather data to gain deeper insights into how patients progress during hospitalization since in those difficult months there was limited knowledge about

COVID-19. This data will provide information and enable decision makers to effectively analyze and interpret the generated insights from this system thus making it a trusted tool in the hands of healthcare professionals.

This comprehensive analysis of Adjutorium's role in allocating resources during a pandemic underlines its adaptability, resilience, and potential, for future applications and studies a real-life example of how ML algorithms can be integrated into healthcare during times of crisis (such as Covid-19) when efficient allocation of resources can mean the difference between life and death.

4.1.2 Traditional Approach: Cox Regression

Introduction to Cox Regression in Healthcare

Cox Regression also known as the Cox Proportional Hazards Model has been widely used in survival analysis for a time. While newer predictive healthcare methods like Adjutorium based on machine learning are emerging traditional statistical approaches like Cox Regression still hold their value in survival analysis. This section of the analysis will explore how effective and useful Cox Regression is in addressing the challenges posed by the COVID-19 pandemic with a focus on its applications in patient management.

A Study in Survival Analysis

The COVID-19 pandemic has required strategies, for managing healthcare especially when it comes to survival analysis. Research conducted by Mostafa Atlam et al. (2021) introduced two systems named Cox_COVID_19 and Deep_Cox_COVID_19 that utilize Cox Regression for analyzing the survival rates of COVID-19 patients. These systems were developed to assist hospitals in the hostile task of identifying patients with chances of survival and predicting key symptoms that impact their probability of surviving. This is tied hand in glove with the decision to be made concerning resource allocation, depending later on the patient's conditions.

The research utilized a dataset from clinical cases involving 1,085 patients diagnosed with COVID-19. It discovered that different key factors (age, muscle pain, pneumonia, and throat pain had) an impact on mortality rates.

Predictive Power and Practical Implications

In terms of implications and predictive accuracy, the Cox_COVID_19 system proved to be highly valuable. It effectively predicted the likelihood of survival. Successfully distinguished severe cases from fatal ones by identifying important symptoms. Furthermore, the study revealed that the Deep_Cox_COVID_19 system, which combines learning with Cox Regression techniques outperformed the Cox_COVID_19 system in terms of agreement levels (concordance) accuracy and precision. Specifically speaking to testing performance, the Deep_Cox_COVID_19 system achieved a concordance rate of 0.999 compared to 0.896 for the Cox_COVID_19 system. These metrics highlight how Cox Regression remains relevant and adaptable in light of emerging machine learning algorithms.

Applying Cox Regression within the context of the COVID-19 pandemic is not merely an exercise but rather an invaluable practical tool that has lifesaving potential. By pinpointing factors influencing mortality rates healthcare providers can allocate resources more effectively and implement interventions accordingly essential considerations given the limited availability of healthcare resources during these challenging times. This predictive model has the primary goal of empowering clinicians to make informed decisions, about treatment plans which can potentially contribute to reducing mortality rates.

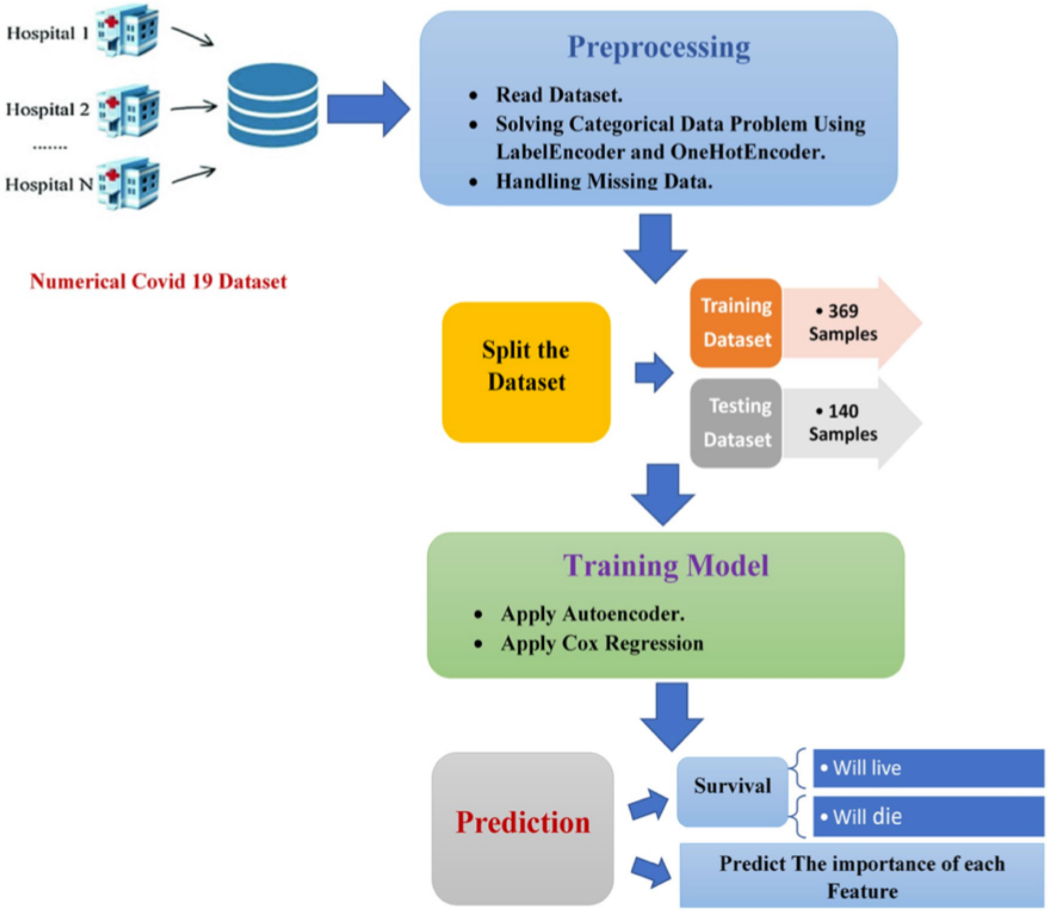


Figure 9: Proposed survival analysis system architecture (Atlam et al. 2021)

Future Directions and Challenges

Looking ahead and considering the challenges it's important to acknowledge that while Cox Regression has been proven effective in combating COVID 19 it does have its limitations. To utilize this model successfully a strong grasp of the underlying assumptions is necessary, and the quality and completeness of the data can impact its performance. Moving forward it would be beneficial to explore combining Cox Regression with machine learning algorithms to develop models that leverage the strengths of both approaches. The reliability and robustness of Cox Regression in survival analysis during COVID-19 cannot be understated. Its ability to predict survival probabilities and identify factors influencing mortality make it an invaluable tool in managing the healthcare crisis brought on by this pandemic. While new frontiers like Adjutorium predictive healthcare solutions through machine learning algorithms, traditional methods such, as Cox Regression continue to provide valuable insights that remain pertinent in today's ever-evolving landscape of healthcare analytics.

4.1.3 Comparative Analysis: Adjutorium and Cox Regression

Bridging the Gap Between the Two Approaches

Both kinds of models (a traditional statistical one such ass Cox Regression and modern ML algorithms like Adjutorium) have found their important roles to play in healthcare. While they serve purposes and offer distinct advantages their ultimate objective remains the same: to provide valuable insights that can assist healthcare professionals in making well-informed decisions particularly when it comes to allocating limited resources during pandemics. This section aims to provide a comparison between these two approaches highlighting their strengths, limitations, and suitability for various healthcare challenges. Adjutorium simply offers a much more comprehensive data-driven methodology, in facts by integrating algorithms it does present a holistic perspective on healthcare scenarios. Its ability to handle missing data effectively and generate accurate predictions makes it an adaptable tool, especially when dealing with unknown variables in new pandemics like COVID-19. On the other hand, Cox Regression specializes in survival analysis by offering detailed insights into time-to-event data and assessing the impact of different predictors, on event occurrence risk.

The enduring relevance of its application in the healthcare industry is evident from its ability to adapt and be effective during COVID-19. It has been utilized to forecast survival probabilities and identify factors that impact mortality.

Exploring the Balance between Accuracy and Interpretability

One notable distinction between Adjutorium and Cox Regression lies in how they approach the tradeoff between model interpretability and accuracy. Adjutorium, powered by machine learning often operates as a " box " making it challenging to comprehend its decision-making process. However, it compensates for this with predictive accuracy. For instance, when predicting mortality during the COVID-19 19 Adjutorium achieved an accuracy of 0.871 ± 0.002 surpassing Cox Regressions of 0.773 ± 0.003.

In contrast, Cox Regression provides a transparent model that allows for a clearer understanding of how different variables contribute to outcomes. This transparency is crucial in healthcare since understanding the reasoning behind a prediction can be as important as the prediction itself. Nonetheless, it may come at the expense of lower predictive accuracy as observed in the aforementioned example.

Future Prospects: Integration and Hybrid Models

As healthcare analytics continues to advance, there is excitement around integrating statistical models, with machine learning algorithms for future research.

Hybrid models that combine the interpretability of Cox Regression with the power of machine learning algorithms like Adjutorium have the potential to provide the best of both worlds. We can conclude that both algorithms (Adjutorium and Cox Regression) offer valuable approaches to healthcare analytics and resource allocation, particularly in the context of pandemics. Adjutorium excels in accuracy and can adapt to various healthcare scenarios although it may be less interpretable due to its complexity. On the other hand Cox Regression while possibly less accurate in certain cases offers the advantage of interpretability and long-established reliability in survival analysis.

4.2 Limitations and Challenges in Implementing Machine Learning for Resource Allocation in Pandemics

Introduction: The Complexities of Machine Learning in Healthcare

The rise of machine learning algorithms like Adjutorium in addition to more traditional models such as Cox Regression has brought out new opportunities for allocating healthcare resources during pandemics. It’s impossible to implement these technologies seamlessly, without their natural complexities that extend far beyond challenges.

These challenges concern aspects such as the quality of data interpretability of different algorithms, ethical considerations, and logistical constraints. This section’s goal is to come up with an analysis of these complexities and shed light on the multiple issues that hospital professionals, policymakers, and data scientists must bear with to fully exploit the potential of machine learning in healthcare.

Beyond Numbers and Algorithms

Data quality may seem straightforward at a glance but in the realm of healthcare, it becomes a complex matter. The data used for machine learning models is typically collected from health records, clinical trials, and other healthcare databases. However, these sources can be prone to inconsistencies missing values, and even biases that exist within the system. For example, data from underserved communities may not be adequately represented in these datasets resulting in models that are less effective for those specific populations. Moreover, it happens that the healthcare sector faces challenges with "data silos," where valuable information is stored in databases that lack interoperability, making it useless. This aspect significantly limits the comprehensiveness and reliability of ML models and therefore the challenge lies not only in gathering high-quality data but also in ensuring its representativeness, and comprehensiveness while being free, from systemic biases.

Understanding the "Black Box": Implications of Interpreting Machine Learning Algorithms

When we talk about the "box" in machine learning we're referring to algorithms that make decisions or predictions without clear explanations that humans can easily understand. While these algorithms, like neural networks, often offer impressive predictive capabilities their lack of transparency raises ethical and practical concerns. In healthcare settings, where the stakes are high, and a wrong prediction or recommendation could be a matter of life and death clinicians are understandably cautious about using algorithms they can't interpret. Additionally, this lack of transparency can create challenges as well. If an algorithmic decision leads to an error determining accountability becomes a complex issue. So, it's not about improving transparency: it also involves establishing an ethical and legal framework for accountability.

Ethical Worries and Implementation Obstacles

The consequences of implementing machine learning in healthcare are extensive and intricate and are worth reflecting on. One (or maybe “the”) major concern is bias, which can take various forms such, as racial, socioeconomic, or gender biases. These aren't mere reflections of existing societal inequalities, but they can even make them worse.

For instance, if an algorithm is trained using data from well-off communities its recommendations may not be suitable or advantageous for patients who come from socio-economic backgrounds with lower means. This raises fair concerns about equal access to healthcare resources and the potential of machine learning to effectively and seamlessly alleviate existing disparities. Furthermore, the utilization of data raises privacy and consent issues: patients legally need the assurance that their data will be handled properly in respect of the existing regulations (depending on the territory) and that they keep control over its usage, which adds another layer of complexity. The practical challenges of implementing machine learning models in healthcare are often underestimated. These models are not solutions: they must be integrated into already complex and unwieldy healthcare systems. This integration demands not only technical expertise but also substantial financial investment. Additionally, healthcare professionals must receive training on utilizing these new tools, a time-consuming process that necessitates ongoing support as well. Regulatory obstacles, those related to patient data privacy and compliance with healthcare standards contribute further complexity. For example, different countries have varying regulations concerning data privacy so a machine learning model deployed across countries must adhere to all these regulations thus making the implementation process even more demanding.

In conclusion: The Imperative for a Holistic Approach

As seen, the implementation of machine learning in the healthcare field presents a range of interconnected challenges. These challenges ethical, legal, and operational aspects requiring a holistic approach to effectively resolve them. Healthcare systems increasingly rely, as time goes by, on machine learning solutions during crises such as pandemics. Given this, it becomes crucial to have a nuanced understanding of these challenges to be able to comprehensively face these problems and get to know the (so far still) unexplored potential of machine learning algorithms in healthcare. In other words, advanced algorithms would serve as tools for a fair, efficient, and equal allocation of healthcare resources.

4.3 The Future of Machine Learning, in Allocating Resources During Pandemics

Utilizing Data-Driven Approaches for Healthcare Decision-Making

It becomes every day clearer that machine learning algorithms offer more than simple "solutions" when it comes to having to bear with the complex dynamics of resource allocation in healthcare during pandemics. They seriously open up possibilities for huge advancements in the field: these algorithms' ductility and accuracy make them suitable for future research commitments. It is essential, though, to state that even the most promising technologies have their limitations and challenges. This section precisely discusses this: in light of the results we have observed, in which directions machine learning could further integrate into healthcare systems, particularly during times of crisis?

An important study conducted by Arash Heidari et al. (2022) titled "Machine Learning in Healthcare: A Comprehensive Review " points out at an analysis of the state and prospective of machine learning applications in healthcare. The study mostly focuses on the important role played by datasets in achieving reliable and so high-quality outcomes through machine learning methods. Nowadays healthcare systems are (comprehensibly) always heading towards the embracing of digitalization, and thus we can expect a growth, in the two main features of data: quality and large-scale availability.

This would be the best antidote for one of the limitations of ensuring quality training data. Whether machine learning models have the potential to enhance their accuracy and their applicability, highly depends on the availability and the of data, across healthcare environments and patient populations. This stands of course for algorithms like Adjutorium, which benefit from extensive datasets and utilizing ensemble methods.

Regulatory Landscape and Implementation

As these models grow more sophisticated, more regulatory challenges are being posed by the implementation of machine learning algorithms, and they're likely to become more intricate. One significant concern is the " box" nature of algorithms as mentioned earlier. It is fundamental to address this issue by either developing algorithms or creating frameworks that enable healthcare providers to comprehend and make them keen to trust the decisions made by these algorithms. Heidari et al.'s study (2022) also points out the aspect of safety in addition to flexibility and accuracy. Going forward is vital to adopt an approach that considers both ethical and technical dimensions, in machine learning. Unfortunately, the practical limitations that come with the implementation of machine learning algorithms in healthcare settings cannot be overstated. Future commitments and objectives should be orientated at the creation of user interfaces and the ideation of protocols for the ease of these algorithms' integration into existing healthcare systems. Furthermore, according to the research, by Heidari et al. (2022) it is important for future studies to also examine the safety implications of these algorithms making sure they do not unintentionally cause harm to patients or healthcare providers.

Conclusion: The Confluence of Technology and Healthcare

The convergence of technology and healthcare brings both promise and challenges when it comes to the study of these ML solutions for better resource allocation or accurate forecasting. As we progress in this field it is crucial to approach it with a sense of optimism. While machine learning provides opportunities for enhancing healthcare it also presents challenges that require proactive and considerate solutions. The key to unlocking its potential lies in the following: addressing these challenges by making it clear that algorithms are not only technically robust but also ethically responsible and practical in implementation.

It's only by adopting an approach considering the ethical and practical aspects of machine learning that we can hope and aspire towards a future where resource allocation in healthcare remains efficient, fair, and just even during the most demanding times.

5. Discussion

5.1 Interpretation of Findings

Analyzing the Results: A Fresh Perspective on Allocating Resources

The results obtained from the examination of the Adjutorium, and Cox Regression models offer an overview of how resources are allocated (using AI models) in healthcare during stress-test periods. Although both models proved useful in predicting outcomes and resource requirements the ensemble approach of Adjutorium displayed an advantage in terms of predictive accuracy over Cox Regression. This is an achievement going beyond significance it represents an advancement in our ability to be able to predict healthcare needs in particular in crisis scenarios.

A proper paradigm shift in healthcare management is represented by the superiority of Adjutorium, across metrics like mortality prediction and allocation of ICU beds, suggesting that if machine learning algorithms are finetuned and rigorously validated, they lowkey have the potential to outperform methods, and this discovery inevitably carries implications for the future of healthcare: it symbolizes the passage from a reactive to proactive management. In a world where pandemics and healthcare crises are becoming increasingly prevalent, accurately predicting outcomes and resource requirements is not just advantageous but becomes crucial.

Furthermore, the findings also unveiled some patterns. For instance, it was observed that Adjutorium's performance improved with extensive datasets implying that machine learning algorithms could potentially become even more accurate as they encounter greater diversity, in data.

This has the potential to create an impact, during health crises as there is plenty of data available but its effective utilization is not always happening.

Connecting Theory and Application: A Mutually Beneficial Relationship

The practical discoveries from the analysis strongly resonate with the frameworks discussed in Chapter 3 regarding ensemble methods in machine learning. The theory behind using a combination of algorithms like what was seen in Adjutorium was confirmed by its performance in real-world situations. This does not reinforce the theories

about ensemble methods but also showcases their practical applicability in complex real-life systems such as healthcare.
However, it is important to note that while the data supports the effectiveness of machine learning for allocating healthcare resources it also raises concerns about the limitations of these technologies that were discussed theoretically. For instance, some machine learning algorithms have a " box" nature – a concern mentioned in Chapter 3 – which was evident when they were practically applied. While Adjutorium proved to be effective, its intricate ensemble approach made it less interpretable compared to the Cox Regression model:
Doing some resulting considerations, these findings serve as validation, for the explored concepts while also highlighting the complexities that unavoidably arise when putting theory into practice.

The interconnectedness, between theory and practice extends beyond discourse: it is a real-life dynamic that directly affects healthcare results. This interplay enhances our comprehension of the subject matter. Offers a nuanced perspective that is both academically robust and practically applicable.

5.2 Implications for Hospital Operations and Patient Care during Pandemics

The Advantages of Machine Learning in Hospital Operations

Machine learning algorithms such as Adjutorium and Cox Regression have the potential to bring about a transformation in hospital operations particularly when dealing with the challenges of a pandemic. The ability to accurately predict the utilization of ICU beds for example is not a matter of convenience but plays a crucial role in effectively managing healthcare resources. During a pandemic where resources are often scarce, and errors can have severe consequences the predictive accuracy offered by these algorithms can be truly lifesaving.

Consider a scenario where a hospital is reaching its capacity limit, for ICU beds. Traditional methods would involve time-consuming analysis of multiple variables to forecast future needs. However, with machine learning algorithms this prediction process can be accelerated while ensuring accuracy levels. This empowers hospitals to make decisions promptly—whether it is reallocating staff procuring additional supplies or collaborating with other healthcare facilities to streamline patient flow. This kind of excellence aims to establish a resistant healthcare system that is agile and capable of smoothly adapting to continuously changing conditions, so it goes beyond the efficiency parameter.

These implications extend beyond aspects: they shape the very essence of healthcare management. The use of algorithms brings about an understanding of patients' needs allowing for a shift from a one-size-fits-all approach to a more personalized care strategy. For example, hospitals can proactively allocate resources to those patients who are more likely to require ICU admission based on predictions made by the algorithms. This optimization ensures patient outcomes and resource management.

Patient-centered Care, Going Beyond Numbers

While the operational advantages of machine learning algorithms are significant their impact on care is even more remarkable. These algorithms go beyond generating numbers: they provide insights that directly influence patient outcomes. For instance, advanced prediction models, like Adjutorium can contribute to diagnoses resulting in effective treatment plans.

In today's healthcare landscape, where medicine takes precedence the ability to accurately predict patient needs is incredibly valuable. It empowers healthcare providers to tailor their interventions based on each patient's requirements of relying on generalized treatment protocols. This becomes especially crucial during times like the pandemic when healthcare resources are limited, and the consequences of diagnoses can have severe implications.

Furthermore, these algorithms offer an approach towards care. By analyzing factors such as history, lab results, and socioeconomic conditions these algorithms provide a more

comprehensive understanding of patient health. This enables healthcare providers to consider a multitude of elements when making treatment decisions resulting in quality of care and potentially reducing disparities in healthcare.
Machine learning algorithms have already today an impact on hospital operations and patient care. At nowadays' progress speed, it is easily predictable that they will reach the power to reshape an entire healthcare system that's no longer enough efficient and to transform it into a fairer and centered around patients.
By bridging the gap, between meeting needs and achieving desired patient outcomes these algorithms have the potential to bring about a transformation in healthcare delivery in challenging situations such as a pandemic.

5.3 Ethical Considerations, in the Adoption of AI in Healthcare

The integration of AI technologies like Adjutorium and Cox Regression into healthcare systems raises concerns that cannot be ignored. According to Pennestrì and Banfi (2022), the ethical landscape surrounding AI in healthcare requires a balance between improving patient care and potential challenges to patient autonomy and trust. Patient autonomy, which allows individuals to make decisions about their health can be both. Questioned by AI technologies. While AI can offer predictions and personalized treatment plans it also raises concerns regarding informed consent and data privacy.
Furthermore, the concept of trust in healthcare takes on dimensions in the era of AI. Traditionally trust has been an idea deeply rooted in the relationship between healthcare providers and patients. However, with the introduction of AI technologies, this trust becomes more complex. Can we rely on machines for healthcare decisions? This question is not just theoretical. Carries implications for patient adherence to treatment plans and their overall confidence, in the healthcare system.
The ethical principle of beneficence, which obligates healthcare providers to act in the interest of patients is also influenced by the emergence of AI: while AI technologies have the potential to greatly enhance the accuracy of diagnoses and effectiveness of treatments it is important to recognize that they can also unintentionally introduce biases or errors which may impact the quality of healthcare. This dual nature requires us to have oversight and continuously evaluate AI technologies ensuring that they adhere to the fundamental

principles of healthcare ethics such, as respecting autonomy promoting well-being avoiding harm, and upholding justice.

In summary, the ethical considerations surrounding AI in healthcare are complex and interconnected with the advantages these technologies provide. As we progress towards an integrated healthcare system, with AI it is crucial that we navigate these challenges thoughtfully and ensure that technological advancements do not compromise the fundamental principles guiding patient care.

Practical Implications: Fairness and Bias

The practical implications of machine learning, in healthcare are undeniable. It offers solutions for diagnosis, treatment planning, and resource allocation. However, with this technological advancement comes complexities related to fairness and bias. While machine learning algorithms are increasingly integrated into healthcare systems the ethical aspect of fairness is often overlooked. This oversight has consequences for marginalized communities who may be disproportionately affected by biased algorithms.

Recent studies highlight that fairness in machine learning for healthcare is often treated as an afterthought rather than a part of algorithm development (Gichoya et al. 2021). This is not an oversight but a significant ethical concern that can worsen existing healthcare disparities. As we approach implementation of these technologies in settings it is crucial to prioritize fairness as a foundational principle. This goes beyond mentions in research papers or guidelines: it requires involving the public, particularly those from marginalized communities in establishing acceptable standards, for fairness.

Moreover, it is important to have definitions of what constitutes 'fairness and a commitment to continuously monitor the real-world effects of these algorithms (Gichoya et al. 2021).

In essence incorporating fairness into the foundation of machine learning, in healthcare is not only a matter of ethics but also a practical necessity. Ensuring that the transformative benefits of machine learning are evenly distributed is crucial for fostering trust and inclusivity within healthcare systems. Therefore, as we move forward fairness should no longer be seen as a feature but rather as an element in the development and implementation of machine learning tools, in healthcare.

6. Conclusion

Addressing the research question

At the end of this journey, to build our canvas to draw conclusions, let's recall the main goal of this thesis, which was to examine in depth and evaluate the effectiveness of existing AI models (with the main focus being posed on a few of them), not before having explained how these algorithms work, concentrating on the problem of allocating healthcare resources and decision making during the COVID-19 pandemic. This study was not driven by mere curiosity, but largely by a fascination I have with the healthcare sector and mission, and by the urgent necessity arising from the tremendous strain on global healthcare systems. The research has already demonstrated that a new pro level of sophistication can be achieved and implemented through new technologies, going, as we have seen in the specifics, beyond more traditional solutions in performance areas. There's more: the research has made it also crystal clear that the direction steered by AI-oriented strategies and tool integration is the one of progress, which in medical terms is translated into saving lives and, why not, making them longer.

When it comes to resource allocation during health crises, this finding could (and should) serve as brilliant guidance not only for healthcare administrators or policymakers at a high administration level but also for clinicians who face everyday hospital challenges. In situations where livers are at stake and variables constantly change due to the nature of pandemics having agile and adaptable AI models like Adjutorium could make a significant difference. It could be the factor, between a healthcare system that simply survives and one that thrives.

AI's role consists also of aiming to enhance human decision-making intelligently and ethically, other than optimizing numbers or maximizing efficiency. The AI models studied here have the potential to address some of the biases and subjectivities in traditional resource allocation processes. It is a heavy contribution towards the

achievement of a fair distribution of healthcare resources, which is particularly crucial during pandemics where decision-makers have to be quick and effective to limit damages, decisions with far-reaching consequences need to be made while ensuring healthcare equity, for all patients.
Indeed, the purpose of the thesis, contextualized in the so-called 'bigger picture', goes far beyond the academic contribution or technical notions covered, it is more about gathering useful information and insights for the healthcare sector for the intelligent direction in which it is heading, aligning itself with the rest of the sectors in the most industrialized countries, and to observe how the various hospital systems responded to a stressful situation such as the unexpected covid outbreak in 2020. This thesis serves as an investigation and a practical roadmap in the optic of AI's integration into healthcare through an accurate study and contribution of existing knowledge and the recommendation of steering visions and strategies for real-world implementation.

Insights on Methodology, Limitations, and Future Directions

During the design and writing of the thesis, as in the study phase, a combination of qualitative and quantitative analysis was used, to have a complete idea and a multifaceted understanding of the artificial intelligence models and the dynamics covered. Although the approach was robust it was not without limitations. One significant constraint was the quality and extent of the data used as highlighted by Arash Heidari et al.s study (2022). research emphasis is placed on the role of data quality at the disposal of algorithms for training, especially in an area such as public health where data reliability is a tool for decisions on life and death issues.
Furthermore, although this thesis briefly addressed aspects of AI in healthcare it did not extensively explore them.

However, it is important to address concerns surrounding algorithmic bias, data privacy, and the "black box" phenomenon. These ethical issues do not have immediate implications for patient care but also raise long-term questions about accountability, transparency, and social justice within healthcare systems. For example, the lack of transparency in decision-making can undermine medical ethics principles such as autonomy and beneficence since healthcare professionals may struggle to explain AI-driven decisions to patients. Moreover, the potential for biases based on race, gender, or socioeconomic factors can worsen existing healthcare disparities and give rise to ethical dilemmas that require immediate attention.

These research-induced difficulties must necessarily be considered as a starting point for future research. Working on the unreliability of data, their operability (see data silos), and the barriers that complicate the implementation of algorithms must be crucial in terms of research, as well as policymaking.

Also, a clear insight is the need for research delving in very depth eviscerating the implications of AI in Healthcare. Such research should explore how these technologies align with or challenge existing frameworks and healthcare regulations to provide policymakers with a broader and clearer understanding of all relevant aspects involved.

Practitioners and policymakers should look at the findings and the insights gathered throughout the projecting and writing of this bachelor thesis as a (very) first step towards developing healthcare systems that are more efficient, ethical, and fair. This research provides a theoretical basis, as well as quantitative insights gained from real-life cases, which can turn out to be useful for future studies to explore the complex relationship between methodology, ethics, and practical considerations when it comes to the implementation of AI models which are going to be deciding for more than someone's life.

Contributions to the Field and Final Thoughts

By evaluating and observing how different models work, this research paper aims primarily to effectively explore the theoretical foundations of algorithms and aims to give them practical meaning through data and insights from real-life cases, which can pave the way (or at least begin to do so) to a new level of policymaking and health care practices. Upon reflection, this thesis sheds light on both the potential and limitations of using AI models for allocating healthcare resources in challenging situations. While our journey has been enlightening it is by no means the end. Hopefully, the issues raised, and knowledge acquired serve as a foundation, for future research, contributing to the shaping of a new, resilient, and intelligent healthcare system.

7. BIBLIOGRAPHY

1. Introduction

2. Literature Review

Woolf, S. H., Chapman, D. A., Sabo, R. T., Weinberger, D. M., Hill, L., & Taylor, D. D. H. (2020). Excess Deaths From COVID-19 and Other Causes, March-July 2020. Journal of the American Medical Association (JAMA).

Shrestha, N., Shad, M. Y., Ulvi, O., Khan, M. H., Karim, M. A., Alam, A. S., ... & Ahmed, H. U. (2020). The impact of COVID-19 on globalization. One Health.

Barnett, D. J., Taylor, H. A., Hodge, J. G., & Links, J. M. (2009). Resource Allocation on the Frontlines of Public Health Preparedness and Response: Report of a Summit on Legal and Ethical Issues. Public Health Reports.

Emanuel, E. J., Persad, G., Upshur, R., Thome, B., Parker, M., Glickman, A., ... & Phillips, J. P. (2020). Fair Allocation of Scarce Medical Resources in the Time of Covid-19. New England Journal of Medicine.

Kricka, L. J., Polevikov, S., Park, J. Y., Fortina, P., Bernardini, S., & Satchkov, D. (2020). Artificial Intelligence-powered Search Tools and Resources in the Fight Against COVID-19. Journal of Medical Internet Research.

Van der Schaar, M., Alaa, A. M., Floto, A., & Gimson, A. (2020). How Artificial Intelligence and Machine Learning Can Help Healthcare Systems Respond to COVID-19. Journal of Healthcare Informatics Research.

3. Theoretical Background

Alaa, A.M., Gurdasani, D., Harris, A.L. et al. Machine learning to guide the use of adjuvant therapies for breast cancer. Nat Mach Intell 3, 716–726 (2021)
Van der Schaar, M. (2020). Progress using COVID-19 patient data to train machine learning models for healthcare. Cambridge University website.

Barbara McKnight, Ph.D. Professor Department of Biostatistics University of Washington. Module 12: Introduction to Survival Analysis Summer Institute in Statistics for Clinical Research University of Washington, July, 2017.

M. Sailaja et al. 2021 J. Phys.: Conf. Ser. 2089 012082

Sullivan, Tom. "Why EHR Data Interoperability Is Such a Mess in 3 Charts." Healthcare IT News, Oct. 11, 2018.

Julia Powles & Hal Hodson. "Google DeepMind and healthcare in an age of algorithms." Health Technol. (2017).

Naik et al., 2022. "Legal and Ethical Consideration in Artificial Intelligence in Healthcare: Who Takes Responsibility?"

4. Analysis

Van der Schaar, M. (2020). Progress using COVID-19 patient data to train machine learning models for healthcare. Cambridge University website.

Atlam, M., Torkey, H., El-Fishawy, N., & Salem, H. (2021). Coronavirus disease 2019 (COVID-19): survival analysis using deep learning and Cox regression model. Pattern Analysis and Applications.

Heidari, A., et al. (2022). Machine learning applications for COVID-19 outbreak management. Neural Computing and Applications.

5. Discussion

Pennestrì, F., & Banfi, P. (2022). Ethical considerations in the adoption of AI in healthcare. Journal of Medical Ethics.

Wawira Gichoya, J., McCoy, L. G., Celi, L. A., et al. (2021). Equity in essence: a call for operationalising fairness in machine learning for healthcare. BMJ Health Care Inform.

6. Conclusion

Heidari, A., et al. (2022). Machine learning applications for COVID-19 outbreak management. Neural Computing and Applications.

A conclusione di questo elaborato, mi è doveroso ringraziare quelle poche persone senza le quali questo lavoro di tesi non esisterebbe nemmeno:

Ringrazio la mia mamma e il mio papà per il sostegno incondizionato che mi hanno dato e per avermi motivato senza sosta durante tutto il percorso di Laurea Triennale;

Ringrazio mia sorella Mariapaola per essere, anche da lontano, la mia spalla e la mia migliore amica;

Infine, ringrazio i miei colleghi studenti Walter e Jacopo, per essermi stati a fianco durante questo percorso intenso e, adesso, per gioire con me dei traguardi raggiunti.