Machine Learning for Healthcare:
History and Unique Challenges

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In healthcare, we see the use of many technologies, from simple oximeters to complex MRI machines, that allow easy monitoring of patients' well-being. These instruments are also helpful in gathering patients' data, which allows us to study the statistics of many medical conditions. This data gathering and statistical analysis sparked interest in developing predictive models for healthcare applications. There have been many developments in the history of healthcare to develop simple models that allow patients to understand their health without a visit to a doctor. We will understand the history of such model development, the challenges present in those models, modern modeling techniques using machine learning, and why we still don't see much use of these technologies.

Historic algorithms in healthcare:

Earlier healthcare model development primarily used two types of techniques to predict health. First, there were human-designed algorithms that required certain inputs from users to generate a health status report. Examples include the Body Mass Index (**BMI**), which uses simple measures to assess body fat level. The **TNM** (Tumor-Node-Metastasis) staging system predicts cancer stages based on the size of the tumor, the presence of cancer cells in lymph nodes, and the spread of cancer to another body part. The **PHQ-9** (Patient Health Questionnaire) assesses the mental health of a person using nine questions related to the symptoms of depression. The second type were systems consisting of a feedback system or some interconnected networks that assess individual health. These systems are also called AI-based because they work somewhat like modern neural networking methods. These algorithms are the **MYCIN** expert system (1970s), designed for identifying severe bacterial infections; the **CASNET** (causal-associational network) consultation system (1970s) for diagnosing glaucoma; and the **INTERNIST-1** expert system (1980s), providing diagnostic support in internal medicine. These models used sophisticated approaches, combining computational power and medical knowledge, to enhance diagnostic precision in healthcare.

Historic challenges:

The methods used above to create prediction models were good and provided valuable results, but there were problems associated with their development. Some of these problems were:

- *Data and Labeling:* Making good prediction models requires large amounts of electronic data. In the 20th century, computers were not common, so there was a lack of electronic records from hospitals, and data gathering and labeling required lots of manual work.
- *Standardization:* Different hospitals used different archiving standards, making it difficult for others to work with their data. This lack of common standards made it tough for different systems to share and understand information.
- *Computation limits:* Even processing small amounts of data was tough because getting powerful computers was very difficult. This meant the development of models only using simple rule-based algorithms, limiting the complexity of the model.

Modern developments:

The healthcare industry recognizes the challenges present in developing a good and accurate model and has worked on improving things. Following are the improvements made

- *Open datasets:* Numerous hospitals and organizations have made their extensive datasets available for public and private entities to develop machine learning and artificial intelligence models. Examples include MIMIC-PhysioNet, TCGA (the Cancer Genome Atlas Program), Temple University Hospital Data, etc. These datasets include information on thousands of healthy and sick individuals, providing good features and labeled data to develop robust models.

- *Multiple data sources*: The expansion and wide spread use of semiconductors in modern technology have allowed for cheaper electronic devices in industries. This means that data collection is possible even on a small or individual scale. For example, mobile phones and smart watches have various apps that collect data. Also, on a large scale, hospitals have shifted medical testing to computers. This allows easy storage and access to data.

- *Standardization*: The medical industry has established numerous national and international standards for the storage and labeling of data in specific formats. This allows the development and utilization of machine learning models with various types of data of a similar nature. For example, if hospitals use the Unified Medical Language System (UMLS), they can use models trained on UMLS standards without any changes because both follow the same standards.

- *Computational advances*: In recent years, many organizations have started using computers, and even government organizations are increasingly adopting them. This means that most of the patient information is recorded electronically, which makes accessing health data easier. Additionally, there is a rise in the use of powerful computers, making it faster to train models. This allows training models on large datasets, which leads to better predictions by ML models.

- *Algorithmic advances*: All the data standardization, collection, and storage improvements will be of no use if they cannot be used for model development. Earlier development methods like INTERNIST-1 required manual effort to form networks. But advances in machine learning and artificial intelligence techniques have made capturing relevant features easier with neural networks. This subject is still actively researched, with many scientists working on creating faster and more powerful algorithms. Additionally, there are various high-quality open-source softwares, such as scikit-learn, PyTorch, Tensorflow, etc., that simplify machine learning tasks. Furthermore, many researchers have made their work public, enabling small organizations to use high-quality pre-trained models like VGG and Inception.

- *Improved investments*: Since the beginning of the 21st century, there has been a steady rise of technological giants like Meta, Apple, Microsoft, Google, etc. These companies are trying to capitalize and expand in various fields, including healthcare. The adoption of modern technologies in medicine has created opportunities for increased investment in this field. Tech giants are collaborating with various medical industries to create state-of-the art software, contributing to advancements in the health sector. This has allowed research institutions to secure substantial funding to advance the development of modern models and algorithms..

Modern Challenges:
Even after much improvement in the design and implementation of machine learning models, their application in healthcare is very limited, and there are not many success stories. We need to understand the unique challenges faced by machine learning in healthcare.

- *Life and death decision*: In healthcare, decisions made by ML algorithms can have life-altering consequences. These decisions should be made by a robust system to consistently give accurate results. Even highly accurate and precise results may not be of much use in machine learning, as systems cannot be held accountable for bad decisions. Additionally, there is a need for the development of checks and balances like fail-safe mechanisms and the ability to override automated decisions in critical situations. There are many rules and challenges that these computer programs must follow, making it tough to meet all the requirements.

- *Unsupervised learning*: In medicine, we keep on discovering different subtypes of diseases. Lack of labeled information in such cases requires unsupervised learning to learn patterns or similarities in data. But assessing such models will be quite difficult without evaluation metrics.

- *Small number of samples*: One of the key challenges is the lack of a large dataset, especially for rare diseases, which makes it hard to generalize the model function. The prediction models in such cases are prone to overfitting and failing on new unseen data.

- *Missing information and censoring data*: Proper data handling and storage is key for training new prediction models, but traditionally, data storage has been an issue in the health industry. One way or another, data is not properly organized or filed, leading to missing information. Also, a lot of patient information is private, which leads to the censorship of information. This sensor information, like height, weight, age, etc., might be important features unavailable for use. Missing or censored labels can result in inaccurate models, limiting their application in real-world circumstances.

- *Difficulty of De-identifying Data*: Removing the personal information of patients from their file is a legal requirement that, although possible, is a long and time-consuming process. Any mistakes can lead to serious consequences, which makes the task more difficult.

- *Difficulty of deploying ML*: The existing commercial electronic health record software is difficult to modify, making it difficult to integrate new algorithms into it. Moreover, these algorithms require rigorous testing on existing algorithms before any modifications are made.

- *Non technical issues*: Medicine is a highly regulated field, and meeting regulatory requirements for medical applications can slow down the deployment of machine learning models. Also, many nurses and healthcare workers do not fully understand how machine learning works. Training them to work with ML is difficult because people are usually reluctant to change. This makes it hard to introduce and educate them about machine learning. Additionally, the healthcare industry still lacks use of cloud computing and data sharing services. This limits collaborative research and development between various organizations.

Healthcare AI deployment experiences:

In recent years, healthcare has witnessed various experiences with the deployment of ML and AI models. Learning about a few of them will help us understand the challenges faced in integrating them for real-world applications. In 2016, Google introduced a deep learning model for diabetic retinopathy grading, which was later deployed in 11 Thai hospitals from 2018 to 2019. While the model sped up the process when accurate, it faced issues with different lighting conditions, and unnecessary referrals to specialists caused delays. Another deep learning model for skin cancer detection performed well in the lab, but when validated by independent researchers, its performance dropped significantly. Similarly, Epic's sepsis model developed to monitor and send alerts for sepsis risk performed poorly, identifying only 33% of sepsis cases accurately and raising lots of false alarms. IBM's Watson Health was launched about 10 years ago to revolutionize medical AI and raised a $5 billion investment. Later, IBM sold off Watson Health for about 1 billion dollars in 2022, indicating a substantial financial loss. Medtronic and Watson Health combined their expertise to develop the Sugar.IQ diabetes assistant, which performed reasonably well, but operating at a loss does not work for the healthcare industry.

In summary, using machine learning in healthcare has improved, but challenges remain. Medical decisions are crucial, some diseases lack enough data, and there are problems with data quality and integrating AI into healthcare systems. These difficulties show that bringing AI into healthcare is not easy.