Nile Higher Institute for Engineering and Technology
Department of Communications and Electronics

Applying Artificial intelligence for Automatic disease diagnosis

Under the supervision of

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Abstract

Today's era is the one of informatization. With the advancement of tech-neology and scientific theory, traditional medicine with biotechnology as its core, has gradually begun to digitize and to information. And smart healthcare incorporating a new generation of information technology has emerged. Smart healthcare is not just a simple technological advancement, but also an all-round, multi-level change. This change is embodied in the following: medical model changes (from disease-centered to patient-centered care), informatization construction changes (from clinical informatization to regional medical informatization), changes in medical management (from general management to personalized management),and changes in the concept of prevention and treatment (from focusing on disease treatment to focusing on preventive healthcare). These changes focus on meeting the individual needs of people while improving the efficiency of medical care, which greatly enhances the medical and health service experience, and represent the future development direction of modern medicine. The idea was based on medical diagnosis using artificial intelligence using algorithms, as during the past period there was a noticeable increase in the number of patients and pressure on hospitals and doctors, so we had to intervene and build a design that works to treat diseases through medical analyzes and confirm the percentage of doubts among doctors and reassure The patients.

Note :This project is compatible with IEEE Standard for Personal Data Artificial Intelligence (AI) P7006 , You can visit the Appendix for more information about IEEE Standard for Personal Data Artificial Intelligence.

Contents

Acronyms, abbreviations and currencies

AI: Artificial Intelligence

AMA: American Medical Association

API: application programming interface

ATM: automated teller machine(s)

AUROC: area under the ROC curve

BBC: British Broadcasting Corporation

CDC: Centers for Disease Control and Prevention

CDM: common data model

CDS: clinical decision support

CGMP: Current Good Manufacturing Process

CLIA: Clinical Laboratory Improvement Amendments

CMS: Centers for Medicare & Medicaid Services

CONSORT: Consolidated Standards of Reporting Trials

CPIC: Clinical Pharmacogenetics Implementation Consortium

CPU: central processing unit(s)

DARPA: Defense Advanced Research Projects Agency

DHHS: Department of Health and Human Services

DHLC: Digital Health Learning Collaborative

DOJ: Department of Justice

ECA: embodied conversational agents

ECG: electrocardiogram

EFF: Electronic Frontier Foundation

HER: electronic health record(s)

EU: European Union

FAIR: findability, accessibility, interoperability, and reusability

FDA: Food and Drug Administration

FDCA: Federal Food, Drug, and Cosmetic Act

FHIR: Fast Healthcare Interoperability Resource

FRAMIIY: friends and family unpaid caregivers

FTC: Federal Trade Commission

FTCA: Federal Trade Commission Act

GDPR: General Data Protection Regulation

GPS: global positioning system

GPU: graphics processing unit(s)

GWAS: genome-wide association studies

HAZOP: hazard and operability study

HIE: health information exchange

HIPAA: Health Insurance Portability and Accountability Act

HITECH Act: Health Information Technology for Economic and Clinical Health Act

HIV: human immunodeficiency virus

I2B2: Informatics for Integrating Biology & the Bedside

IEEE: Institute of Electrical and Electronics Engineers

IOM: Institute of Medicine

IOT: Internet of Things

IMDRF: International Medical Device Regulators Forum

IP: intellectual property

IT: information technology

IVD: in vitro diagnostic device

IVDMIA: in vitro diagnostic multivariate index assay(s)

JITI: just-in-time adaptive interventions

LDT: laboratory-developed test(s)

LHS: learning health system

LOINC: Logical Observational Identifiers Names and Codes

MIT: Massachusetts Institute of Technology

NAM: National Academy of Medicine

NAS: National Academy of Sciences

NEURIPS: Conference on Neural Information Processing Systems

NHTSA: National Highway Traffic Safety Administration

NIH: National Institutes of Health

NITRC: Neuroimaging Informatics Tools and Resources Clearinghouse

NLP: natural language processing

NNH: number needed to harm

NNT: number needed to treat

NPV: negative predictive value

NRC: National Research Council

NSTC: National Science and Technology Council

OHDSI: Observational Health Data Sciences and Informatics

OHRP: Office for Human Research Protections

OMOP: Observational Medical Outcomes Partnership

ONC: The Office of the National Coordinator for Health Information Technology

PARIHS: Promoting Action on Research Implementation in Health Services

PCORNET: Patient-Centered Clinical Research Network

PDSA: plan-do-study-act

PFS: physician fee schedule

PHI: protected health information

PPV: positive predictive value

PR: precision-recall

Pre-Cert: Digital Health Software Precertification Program

QI: quality improvement

QMS: quality management system

R&D: research and development

ROC: receiver operating characteristic

RWD: real-world data

RWE: real-world evidence

SAMD: software as a medical device

SDOH: social determinants of health

SDLC: software development life-cycle

SMART: Substitutable Medical Apps, Reusable Technology

STARD: Standards for Reporting of Diagnostic Accuracy Studies

TPR: true positive rate

TPU: tensor processing unit(s)

WEIRD: Western, educated, industrialized, rich, and democratic

List of Figures

Chapter 1: Introduction

Recently, many researchers have designed various automated diagnosis models using various supervised learning models. An early diagnosis of disease may control the death rate due to these diseases. In this paper, an efficient automated disease diagnosis model is designed using the machine learning models. In this project, we have selected three critical diseases such as coronavirus, heart disease, and cancer. In the proposed model, the data are entered into an application, the analysis is then performed in a real-time database using a pretrained machine learning model which was trained on the same dataset and deployed in firebase, and finally, the disease detection result is shown in the android app. Logistic regression is used to carry out computation for prediction. Early detection can help in identifying the risk of coronavirus, heart disease, and cancer. Comparative analysis indicates that the proposed model can help doctors to give timely medications for treatment.

Machine learning is used in various areas like education and healthcare. With the advancement of technology, the better computing power and availability of datasets on open-source repositories have further increased the use of machine learning. Machine learning is used in healthcare in vast areas. The healthcare sector produces large amounts of data in terms of images, patient data, and so on that helps to identify patterns and make predictions. Machine learning is used in healthcare to solve various problems heart disease is based on the individual, and the extent of heart disease can vary from person to person. Thus, making a machine learning model, training it on the dataset, and entering individual patient details can help in prediction. The prediction result will be according to the data entered and hence will be specific to that individual. Coronavirus is a disease that has no clearly defined treatment. The coronavirus 2019 (COVID-19) originated from China. There are different treatments that are going on for it but there are no clearly defined steps for treatment. Artificial intelligence (AI) P7006 aims to mimic human cognitive functions. It is bringing a paradigm shift to healthcare, powered by the increasing availability of healthcare data and rapid progress of analytics techniques. many researchers have

Smart healthcare overview

Today's era is the one of informatization. With the advancement of technology and scientific theory, traditional medicine with biotechnology as its core, has gradually begun to digitize and to Informa ionize. And smart healthcare incorporating a new generation of information technology has emerged. Smart healthcare is not just a simple technological advancement, but also an all-round, multi-level change. This change is embodied in the following: medical model changes (from disease-centered to patient-centered care), informatization construction changes (from clinical informatization to regional medical informatization), changes in medical management (from general management to personalized management), and changes in the concept of prevention and treatment (from focusing on disease treatment to focusing on preventive healthcare).These changes focus on meeting the individual needs of people while improving the efficiency of medical care, which greatly enhances the medical and health service experience, and represent the future development direction of modern medicine. This review will start from the concept of smart healthcare, then briefly introduce the key technologies supporting smart healthcare and explain the achievements and challenges of it by reviewing the application status of these technologies in important medical fields, before finally putting forward the future prospects of smart healthcare.

The concept of smart healthcare

Smart healthcare was born out of the concept of “Smart Planet”. Simply put, Smart Planet is an intelligent infrastructure that uses sensors to perceive information, transmits information through the internet of things (IoT), and processes the information using supercomputers and cloud computing. It can coordinate social systems and integrate them to realize the dynamic and refined management of human society. Smart healthcare is a health service system that uses technology such as wearable devices, IoT, and mobile internet to dynamically access information, connect people, materials and institutions related to healthcare, and then actively manages and responds to medical ecosystem needs in an intelligent manner. Smart healthcare can promote interaction between all parties in the healthcare field, ensure that participants get the services they need, help the parties make informed decisions, and facilitate the rational allocation of resources. In short, smart healthcare is a higher stage of information construction in the medical field.

Key technologies of smart healthcare

Smart healthcare consists of multiple participants, such as doctors and patients, hospitals, and research institutions. It is an organic whole that involves multiple dimensions, including disease prevention and monitoring, diagnosis and treatment, hospital management, health decision-making, and medical research. Information technologies, for example, IoT, mobile Internet, cloud computing, big data, 5G, microelectronics, and artificial intelligence, together with modern biotechnology constitute the cornerstone of smart healthcare. These technologies are widely used in all aspects of smart healthcare. From the perspective of patients, they can use wearable devices to monitor their health at all times, seek medical assistance through virtual assistants, and use remote homes to implement remote services; from the perspective of doctors, a variety of intelligent clinical decision support systems are used to assist and improve diagnosis.

Doctors can manage medical information through an integrated information platform that includes Laboratory Information Management System, Picture Archiving and Communication Systems (PACS), Electronic Medical Record, and so on. More precise surgery can be achieved through surgical robots and mixed reality technology.

From the perspective of hospitals, radio-frequency identification (RFID) technology can be used to manage personnel materials and the supply chain, using integrated management platforms to collect information and assist decision-making. The use of mobile medical platforms can enhance patients' experiences, From the perspective of scientific research institutions, it is possible to use techniques such as machine learning instead of manual drug screening and to find suitable subjects using big data. Through the use of these technologies, smart healthcare can effectively reduce the cost and risk of medical procedures, improve the utilization efficiency of medical resources, promote exchanges and cooperation in different regions, push the development of telemedicine and self-service medical care, and ultimately make personalized medical services ubiquitous.

The application status of smart healthcare

The service targets of smart healthcare can be roughly divided into three categories: clinical/scientific research institutions (e.g., hospitals), regional health decision-making institutions, and individual or family users. The application of smart healthcare can be divided as follows, based on different needs:

Assisting diagnosis and treatment

With the application of technologies such as artificial intelligence, surgical robots, and mixed reality, the diagnosis and treatment of diseases has become more intelligent. Using artificial intelligence to build the clinical decision support system, it has achieved certain results, such as the diagnosis of hepatitis, lung cancer, and skin cancer. The accuracy of artificial intelligence diagnosis results exceeds that of human doctors.6, 7, 8 Machine learning-based systems are quite often even more accurate than experienced physicians, especially in pathology and imaging.9 The most outstanding and representative product in the field of clinical decision support systems is IBM's Watson,10 an intelligent cognitive system that provides an optimal solution through in-depth analysis of all clinical data and literature data. The program has a great effect on the diagnosis of diabetes and cancer.11 Through the use of the clinical decision support system, doctors can give expert advice based on algorithms to improve the accuracy of diagnosis, reduce the incidence of missed diagnosis and misdiagnosis, and enable patients to receive timely and appropriate medical treatment.

Based on smart diagnosis, the patient's condition and disease status are more accurately described, which helps to develop a personalized treatment plan, and the program has been affirmed by experts. The treatment process itself will become more precise. For example, in tumor radiotherapy, the patient's radiotherapy process can be monitored dynamically throughout the process with the help of smart radiomics. Doctors can optimize the radiotherapy program, observe disease progress, and avoid the uncertainty of manual operation.13 In terms of surgery, the birth of surgical robots has pushed surgery to a new level.

More famous robot systems include the Da Vinci system (Intuitive Surgical, Sunnyvale, CA, USA), Sensei X robotic catheter system (Hansen Medical, Auris Health, Inc., Redwood City, CA, USA), and Flex Robotic System (Med robotics, Raynham, MA, USA). Compared with traditional endoscopic surgery, patients will have better results and faster recovery, and surgeons will enjoy equipment providing them with greater flexibility and compatibility. The implementation of remote surgery will also be more convenient.14 The application of mixed reality technology makes the development and implementation of the surgical plan easier. Professor Ye Chewie of Wuhan Union Hospital has done a lot of work in this area. His team implemented the world's first mixed reality-guided hip surgery for a 15-year-old patient with a left femoral neck fracture. By modeling the target and projecting it to the real world for exact matching, an interactive information loop is built between the virtual world, the real world, and users. The emergence of this technology will bring subversive changes in medical education, research, communication, and clinical treatment.

Health management

Since the beginning of the 21st century, chronic diseases have gradually occupied the top of the human disease spectrum and become a new epidemic. Chronic diseases have a long course of disease and are incurable and costly; therefore, the health management of the disease is particularly important. However, the traditional hospital- and doctor-centered health management model appears to be incapable of adequately dealing with the increasing number of patients and diseases. The new health management model under smart healthcare pays more attention to patient self-management. It emphasizes real-time self-monitoring of patients, immediate feedback of health data, and timely intervention of medical behavior.

The emergence of implantable/wearable smart devices, smart homes, and smart health information platforms connected by IoT technology provides a solution to this situation. Third-generation wearable/implantable devices can combine advanced sensors, microprocessors, and wireless modules to continuously sense and monitor various physiological indicators of patients in an intelligent manner, while reducing power consumption, improving comfort, and allowing the data to be combined with health information from other channels. This approach involves a leap from scenario monitoring to continuous perception and integrated care.

It further reduces the associated risks caused by the disease while making it easier for medical institutions to monitor the prognosis of the disease. The emergence of smart phones, smart watches, etc., provides a new vehicle for this kind of monitoring. Attempts have been made to integrate biosensors into smartphones. While further improving portability, users can use a high-performance smartphone to monitor the environment and their body more easily.

Smart homes provide home assistance to the elderly and the disabled. Smart homes are special houses or apartments with sensors and actuators integrated into the residential infrastructure that monitor the residents' physical signs and environment. Smart homes also perform operations that improve the living experience. The role of smart homes in healthcare is mainly divided into two aspects: home automation and health monitoring. These technologies can provide some simple services while collecting health data, helping people who need care to reduce their reliance on health care providers and improve their quality of life at home.

Patients can self-manage their condition through apps and a health information platform. For example, the Stress Detection and Alleviation system uses a wearable medical sensor to continuously monitor human body pressure levels and automatically help the body reduce stress. It is also possible to integrate health data from multiple portable devices into a clinical decision support system to create a hierarchical health decision support system that can make full use of the collected data for effective disease diagnosis.

While assisting clinical decision-making, it can predict possible risks for patients and give advice through the cloud calculator and big data in advance. Another idea is to create an open mHealth framework that allows doctors, patients, researchers, and others to engage other doctors, patients, researchers, and others by reducing barriers to entry. It allows patients to easily access telemedicine advice and services, while doctors can dynamically monitor patient status. Clinicians can also be assisted by peer experts and researchers. Mobile architectures such as m-

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The concept of smart healthcare

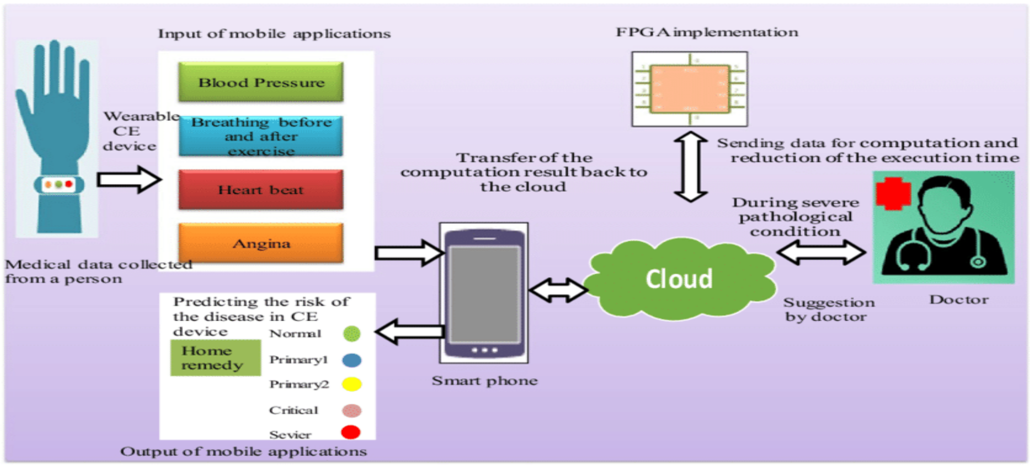

FIGURE 1.1 | Medical analysis by technology

Smart healthcare was born out of the concept of. Simply put, Smart Planet is an intelligent infrastructure that uses sensors to perceive information, transmits information through the internet of things (IoT), and processes the in-formation using supercomputers and cloud computing. It can coordinate social systems and integrate them to realize the dynamic and refined man-agreement of human society. Smart healthcare is a health service system that uses technology such as wearable devices, IoT, and mobile internet to dynamically access information, connect people, materials and institutions related to healthcare, and then actively manages and responds to medical ecosystem needs in an intelligent manner.

Smart healthcare can promote interaction between all parties in the healthcare field, ensure that participants get the services they need, help the parties make informed decisions, and facilitate the rational allocation of resources. In short, smart healthcare is a higher stage of information construction in the medical field the hypothetical, as the popular press often does, and focuses instead on the current and near-future uses and applications of AI.

A formal definition of AI P7006 starts with the Oxford English Dictionary: “The capacity of computers or other machines to exhibit or simulate intelligent behavior; the field of study concerned with this,” or Merriam-Webster online: “1: a branch of computer science dealing with the simulation of intelligent behavior in computers, 2: the capability of a machine to imitate intelligent human behavior.” More nuanced definitions of AI might also consider what type of goal the AI is attempting to achieve and how it is pursuing that goal. In general, AI systems range from those that attempt to accurately model human reasoning to solve a problem, to those that ignore human reasoning and exclusively use large volumes of data to generate a framework to answer the question(s) of interest, to those that attempt to incorporate elements of human reasoning but do not require accurate modeling of human processes. Figure 1-2 includes a hierarchical representation of AI technologies.

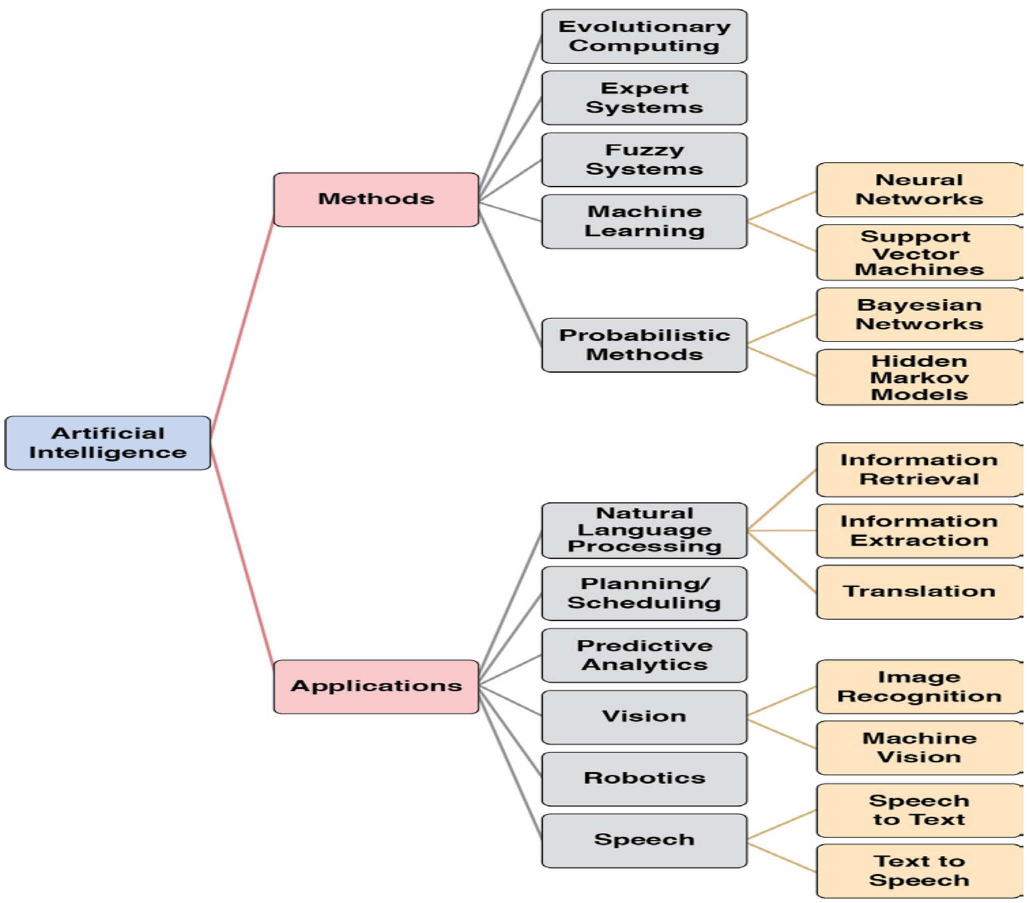

FIGURE 1.2 | A summary of the domains of artificial intelligence

Machine learning is a family of statistical and mathematical modeling techniques that uses a variety of approaches to automatically learn and improve the prediction of a target state, without explicit program- Ming (e.g., Boolean rules). Different methods, such as Bayesian networks, random forests, deep learning, and artificial neural networks, each use different assumptions and mathematical frameworks for how data is ingested, and learning occurs within the algorithm. Regression analyses, such as linear and logistic regression, are also considered machine learning methods, although many users of these algorithms distinguish them from commonly defined machine learning methods (e.g., random forests, Bayesian Networks etc.).

The term “machine learning” is widely used by large businesses, but “AI” is more frequently used for marketing purposes. In most cases, “machine learning” is more appropriate. One way to represent machine learning algorithms is to subcategorize them by how they learn inference from the data.

Natural language processing (NLP) enables computers to understand and organize human languages NLP needs to model human reasoning because it considers the meaning behind written and spoken language in a computable, interpretable, and accurate way. NLP has a higher bar than other AI domains because context, interpretation, and nuance add needed information. NLP incorporates rule-based and data-based learning systems, and many of the internal components of NLP systems are themselves machine learning algorithms with pre-defined inputs and outputs, sometimes operating under additional constraints.

Examples of NLP applications include assessment of cancer disease progression and response to therapy among radiology reports , and identification of post-operative complication from routine EHR documentation. Speech algorithms digitize audio recordings into computable data elements and convert text into human speech. This field is closely connected with NLP, with the added complexity of intonation and syllable emphasis impacting meaning. This complicates both inbound and outbound speech interpretation and generation. For examples of how deep learning neural networks have been applied to this field, see a recent systematic review of this topic.

Expert systems are a set of computer algorithms that seek to emulate the decision-making capacity of human experts. These systems rely largely on a complex set of Boolean and deterministic rules. An expert system is divided into a knowledge base, which encodes the domain logic, and an inference engine, which applies the knowledge base to data presented to the system to provide recommendations or deduce new facts. Examples of this are some of the clinical decision support tools being developed within the Clinical Pharmacogenetics Implementation Consortium, which is promoting the use of knowledge bases such as Pharm to provide personalized recommendations for medication use in patients based on genetic data results.

AI and Human Intelligence

Combining human intelligence and AI into augmented intelligence focuses on a supportive or assistive role for the algorithms, emphasizing that these technologies are designed to enhance human processing, cognition, and work, rather than replace it.

AI systems reliance on data

Data are critical for delivering evidence-based health care and developing any AI algorithm. Without data, the underlying characteristics of the process and outcomes are unknown. This has been a gap in health care for many years, but key trends (such as commodity wearable technologies) in this domain in the last decade have transformed health care into a heterogeneous data-rich environment. It is now common in health and health care for massive amounts of data to be generated about an individual from a variety of sources, such as claims data, genetic information, radiology images, intensive care unit surveillance, electronic health record care documentation, and medical device sensing and surveillance.

Data Aggregation

The accumulation of medical and consumer data has resulted in patients, caregivers, and health care professionals being responsible for aggregating, synthesizing, and interpreting data far beyond human cognitive and decision-making capacities. Predicts the exponential data accumulation

and the limits of human cognition for health care decision making. The growth in data generation and need for data synthesis exceeding human capacity has surpassed prior estimates. This trend most likely underestimates the magnitude of the current data milieu.

AI algorithms require large volumes of training data to achieve performance levels sufficient for “success”, and there are multiple frameworks and standards in place to promote data aggregation for AI use. These include standardized data representations that both manage data at rest1 and data in motion2. For data at rest, mature common data models ,such as Observational Medical Outcomes Partnership, Informatics for Integrating Biology & the Bedside, the Patient-Centered Clinical Research Network, and Sentinel, are increasingly providing a backbone to format, clean, harmonize, and standardize data that can then be used for the training of AI algorithms . Some of these CDMs are also international in focus, which may support compatibility and portability of some AI algorithms across countries.

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In sum, the prospects for smart healthcare are vast. For individual users, smart healthcare can facilitate better health self-management. Timely and appropriate medical services can be accessed when needed, and the content of medical services will be more personalized. For medical institutions, smart healthcare can reduce costs, relieve personnel pressure, achieve unified management of materials and information, and improve the patient’s medical experience.

For research institutions, smart healthcare can reduce the cost of research, reduce research time, and improve the overall efficiency of research. With regard to macro decision-making, smart healthcare can improve the status quo of medical resource inequality, push the process of medical reform, promote the implementation of prevention strategies, and reduce social medical costs. However, there are still some problems in the development process. The solution to these problems depends not only on technological progress, but also on the joint efforts of patients, doc-tors, health institutions, and technology companies.

Problem statement

At the present time, and due to the spread of diseases and epidemics such as the spread of the Corona virus and the increase in doctors’ injuries due to overcrowding in hospitals, we have lost a lot of medical staff and also the presence of human errors that lead to major problems and may lead to the loss of many lives, and because of these problems we have tried to solve them and help the medical field using artificial intelligence And machine learning and data analysis and we collected data on many diseases and then used algorithms in order to enter the analyses of the patient into the device and then show the results and know whether he had this disease or not, and this is what we will know in detail in the coming chapters .

Problem definition

Healthcare system is a dynamic and changing environment so that the healthcare providers continually face new challenges every day such as ; the emergence of epidemics like coronavirus that need to be diagnosed without direct contact between patients and doctors, the emergence of many diseases that need early diagnosis like cancer, doctors' available time is usually limited, and medical errors hinder accurate diagnostic process .

With the rapid development of computer software/hardware and internet of things (IoT) technology, the IoT medical sensors produce large amount of data at an amazing speed. Access to medical data is difficult due to confidentiality of patients' records and the importance of critical individual information. However, the huge amount of hospital and clinical data has a great potential for discovering relations and hidden patterns. Knowledge extraction from the generated data is strongly needed. Using data mining methods reduces time and cost in prognosis and diagnosis of diseases. It also has a special role in the treatment plan and medical.

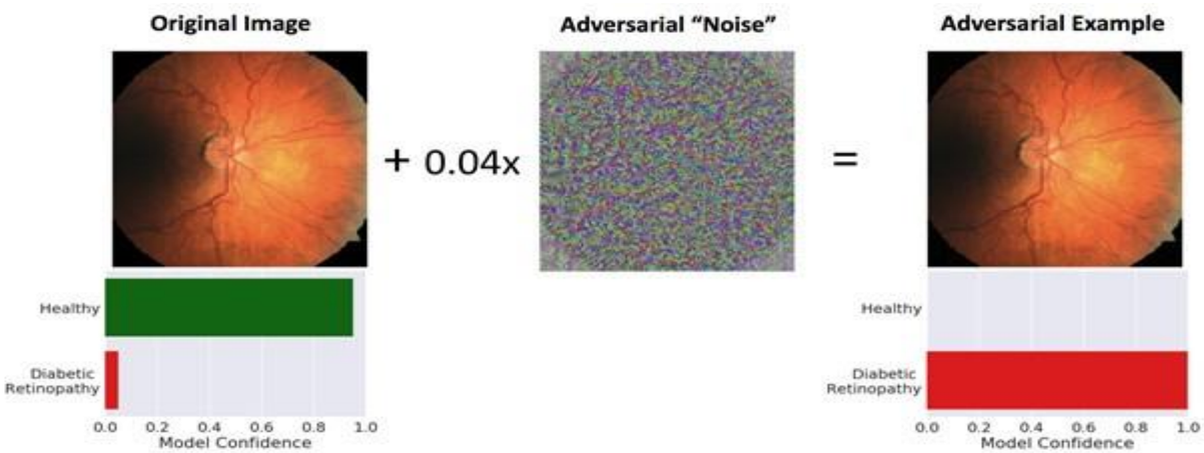

FIGURE 1.3 | Construction of an "adversarial example." Left: An unaltered fundus image of a healthy retina. The AI system (bottom left) correctly identifies it as a healthy eye. Middle: Adversarial "noise"that is constructed with knowledge of the AI system is added to the original image. Right: Resulting adversarial image that superimposes the original image and the adversarial noise. Though the original image is indistinguishable from the adversarial example to human eyes, the AI system has now changed the diagnosis to diabetic retinopathy with essentially 100 percent confidence.

Objective of the graduation project

The device helps the patient to recognize more than one disease, which saves time for the patient as well as the doctor, as with the spread of this device hospitals will be less crowded which improves the patient's psychological condition Applying artificial intelligence to large data sets will help to further customize the way patients are cared for in proportion to each case. The patterns that will emerge will also give us new ideas on how best to build healthier habits and prevent diseases. And also, in the future, if any disease appears or an epidemic such as Coved 19 spreads through artificial intelligence and the device will help in a way to treat.

Proposed solution

The idea of the device and its ability to diagnose diseases.   A device that works using artificial intelligence to medication diseases If these tests match the tests in the device, the device diagnoses this patient and shows the name of the disease. This device also determines the stage of the disease, some diseases have dangerous stages such as cancer and diabetes The device contains many disease data including cancer, diabetes, pressure, heart, heart attack and Covid-19 where it is used in the diagnosis of diseases in accordance with these data with the analysis inside the device

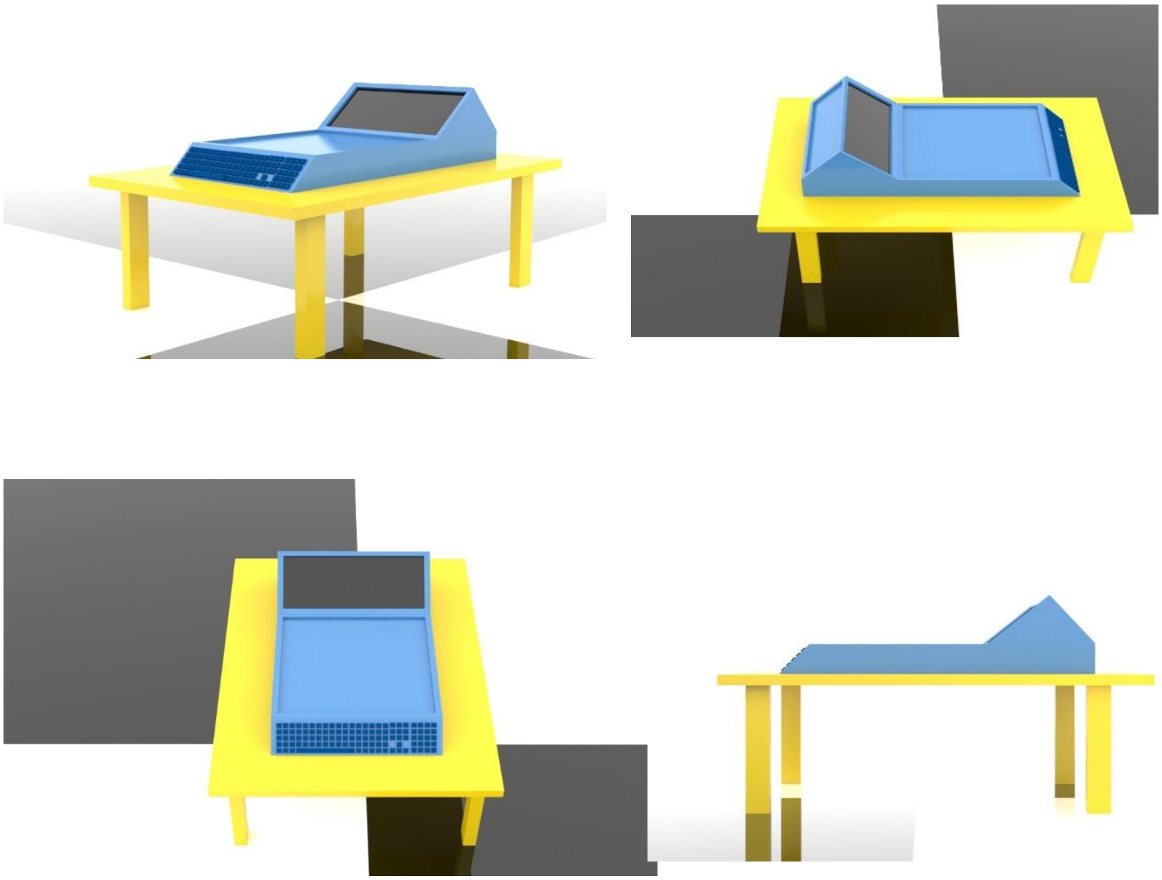

FIGURE 1.4 | Diagnosis Device

Chapter 2: Background and Previous Efforts

What is AI?

The present description of an AI P7006 system is based on the conceptual view of AI detailed in Artificial Intelligence: A Modern Approach (. This view is consistent with a widely used definition of AI as "the study of the computations that make it possible to perceive, reason, and act" and with similar general definitions.

A conceptual view of AI P7006 is first presented as the high-level structure of a generic AI system (also referred to as "intelligent agent. An AI system consists of three main elements: sensors, operational logic and actuators. Sensors collect raw data from the environment, while actuators act to change the state of the environment. The key power of an AI system resides in its operational logic. For a given set of objectives and based on input data from sensors, the operational logic provides output for the actuators. These take the form of recommendations, predictions or decisions that can influence the state of the environment.

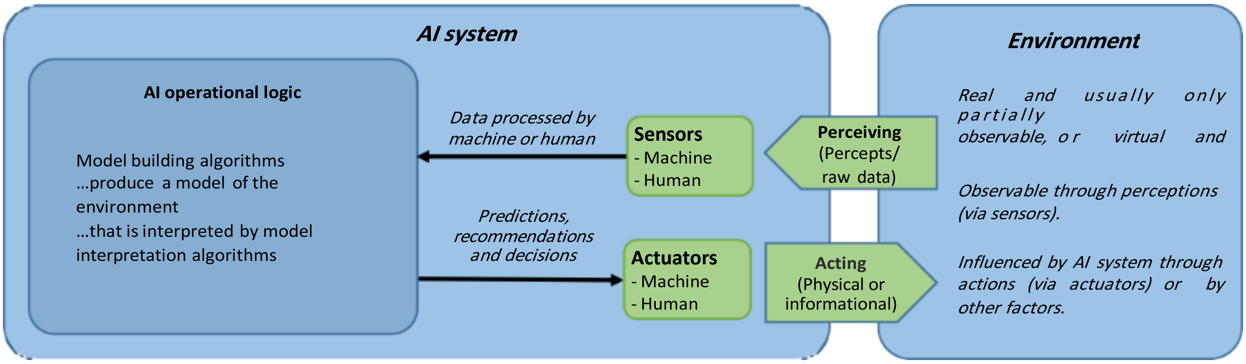

FIGURE 2.1 | A high-level conceptual view of an AI system

A more detailed structure captures the main elements relevant to the policy dimensions of AI systems. To cover different types of AI systems and different scenarios, the diagram separates the model building process (such as ML), from the model itself. Model building is also separate from the model interpretation process, which uses the model to make predictions, recommendations and decisions; actuators use these outputs to influence the environment.

Figure2.2Detailed conceptual view of an AI System

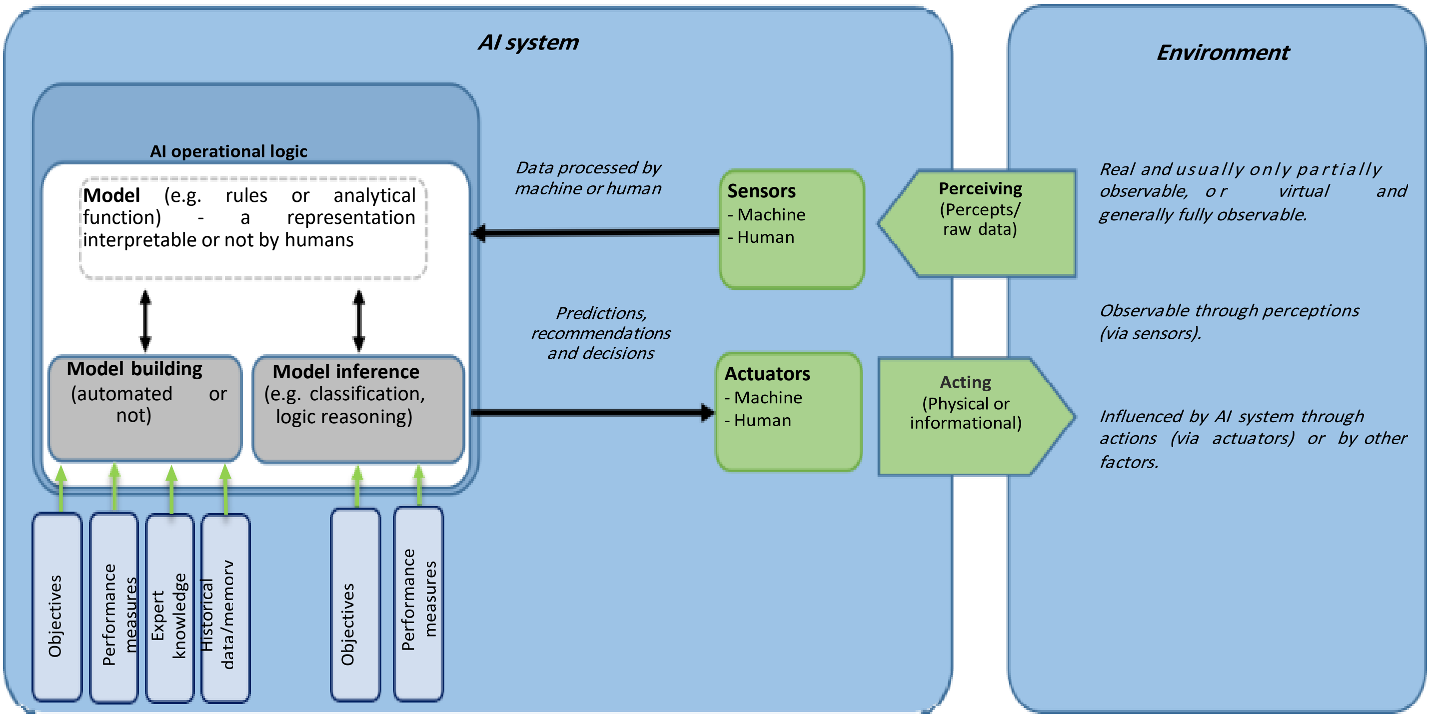

FIGURE 2.2 | **Detailed conceptual view of an AI System**

Environment

An environment in relation to an AI system is a space observable through perceptions (via sensors) and influenced through actions (via actuators). Sensors and actuators are either machines or humans. Environments are either real (e.g. physical, social, mental) and usually only partially observable, or else virtual (e.g. board games) and generally fully observable.

AI system

An AI system is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments. It does so by using machine and/or human-based inputs to: I) perceive real and/or virtual environments; ii) abstract such perceptions into models through analysis in an automated manner (e.g. with ML, or manually); and iii) use model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy.

AI model, model building and model interpretation

The core of an AI system is the AI model, a representation of all or part of the system's external environment that describes the environment's structure and/or dynamics. A model can be based on expert knowledge and/or data, by humans and/or by automated tools (e.g. ML algorithms). Objectives (e.g. output variables) and performance measures (e.g. accuracy, resources for training, representativeness of the dataset) guide the building process. Model inference is the process by which humans and/or automated tools derive an outcome from the model. These take the form of recommendations, predictions or decisions.

Objectives and performance measures guide the execution. In some cases (e.g. deterministic rules), a model can offer a single recommendation. In other cases (e.g. probabilistic models), a model can offer a variety of recommendations. These recommendations are associated with different levels of, for instance, performance measures like level of confidence, robustness or risk. In some cases, during the interpretation process, it is possible to explain why specific recommendations are made. In other cases, explanation is almost impossible.

AI system illustrations

A credit-scoring system illustrates a machine-based system that influences its environment (whether people are granted a loan). It makes recommendations (a credit score) for a given set of objectives (credit-worthiness). It does so by using both machine-based inputs (historical data on people's profiles and on whether they repaid loans) and human-based inputs (a set of rules). With these two sets of inputs, the system perceives real environments (whether people are repaying loans on an ongoing basis). It abstracts such perceptions into models automatically. A credit-scoring algorithm could, for example, use a statistical model. Finally, it uses model inference (the credit-scoring algorithm) to formulate a recommendation (a credit score) of options for outcomes (providing or denying a loan).

Assistant for the visually impaired

An assistant for visually impaired people illustrates how a machine-based system influences its environment. It makes recommendations (e.g. how a visually impaired person can avoid an obstacle or cross the street) for a given set of objectives (travel from one place to another). It does so use machine and/or human-based inputs (large tagged image databases of objects, written words and even human faces) for three ends. First, it perceives images of the environment (a camera captures an image of what is in front of a person and sends it to an application).

Second, it abstracts such perceptions into models automatically (object recognition algorithms that can recognize a traffic light, a car or an obstacle on the sidewalk). Third, it uses model inference to recommend options for outcomes (providing an audio description of the objects detected in the environment) so the person can decide how to act and thereby influence the environment. AlphaGo Zero is an AI system that plays the board game Go better than any professional human Go players. The board game's environment is virtual and fully observable.

Game positions are constrained by the objectives and the rules of the game. AlphaGo Zero is a system that uses both human-based inputs (the rules of Go) and machine-based inputs (learning based on playing iteratively against itself, starting from completely random play). It abstracts the data into a (stochastic) model of actions ("moves" in the game) trained via so-called reinforcement learning. Finally, it uses the model to propose a new move based on the state of play.

Autonomous driving system

Autonomous driving systems illustrate a machine-based system that can influence its environment (whether a car accelerates, decelerates or turns). It makes predictions (whether an object or a sign is an obstacle or an instruction) and/or makes decisions (accelerating, braking, etc.) for a given set of objectives (going from point A to B safely in the least time possible). It does so by using both machine-based inputs (historical driving data) and human-based inputs (a set of driving rules).

These inputs are used to create a model of the car and its environment. In this way, it will allow the system to achieve three goals. First, it can perceive real environments (through sensors such as cameras and sonars). Second, it can abstract such perceptions into models automatically (including object recognition; speed and trajectory detection; and location-based data). Third, it can use model inference. For example, the self-driving algorithm can consist of numerous simulations of possible short-term futures for the vehicle and its environment. In this way, it can recommend options for outcomes (to stop or go).

A short history of artificial intelligence

In 1950, British mathematician Alan Turing published a paper on computing machinery and intelligence (Turing, 1950) posing the question of whether machines can think. He developed a simple heuristic to test his hypothesis: could a computer have a conversation and answer questions in a way that would trick a suspicious human into thinking the computer was actually a human? The resulting "Turing test" is still used today. That same year, Claude Shannon proposed the creation of a machine that could be taught to play chess. The machine could be trained by using brute force or by evaluating a small set of an opponent's strategic moves.

Many consider the Summer as the birthplace of artificial intelligence (AI). At this workshop, the principle of AI was conceptualized by John McCarthy, Alan Newell, Arthur Samuel, Herbert Simon and Marvin Minsky. While AI research has steadily progressed over the past 60 years, the promises of early AI promoters proved to be overly optimistic. This led to an "AI winter" of reduced funding and interest in AI research during the.New funding and interest in AI appeared with advances in computation power that became available in the figure 2.3 .

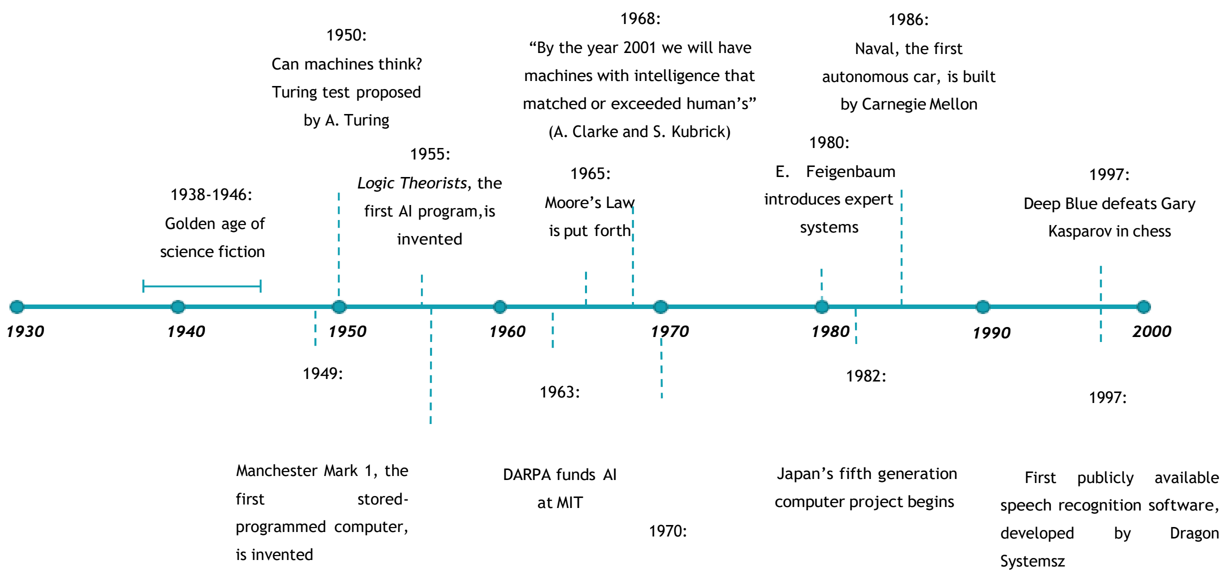

FIGURE 2.3 | **Timeline of early AI developments (1950s to 2000)**

The AI winter ended in the 1990s as computational power and data storage were advancing to the point that complex tasks were becoming feasible. In 1995, AI took a major step forward with Richard Wallace's development of the Artificial Linguistic Internet Computer Entity that could hold basic conversations., IBM developed a computer named Deep Blue that used a brute force approach to play against world chess champion Gary Kasparov. Deep Blue would look ahead six steps or more and could calculate 330 million positions per second in 1996, Deep Blue lost to Kasparov, but won the rematch a year later.

In, Alphabet's DeepMind launched software to play the ancient game of go against the best players in the world. let the program play against itself using trial and error, starting from completely random play with a few simple guiding rules. Entirely from self-play – with no human intervention and using no historical data – AlphaGo Zero surpassed all other versions.

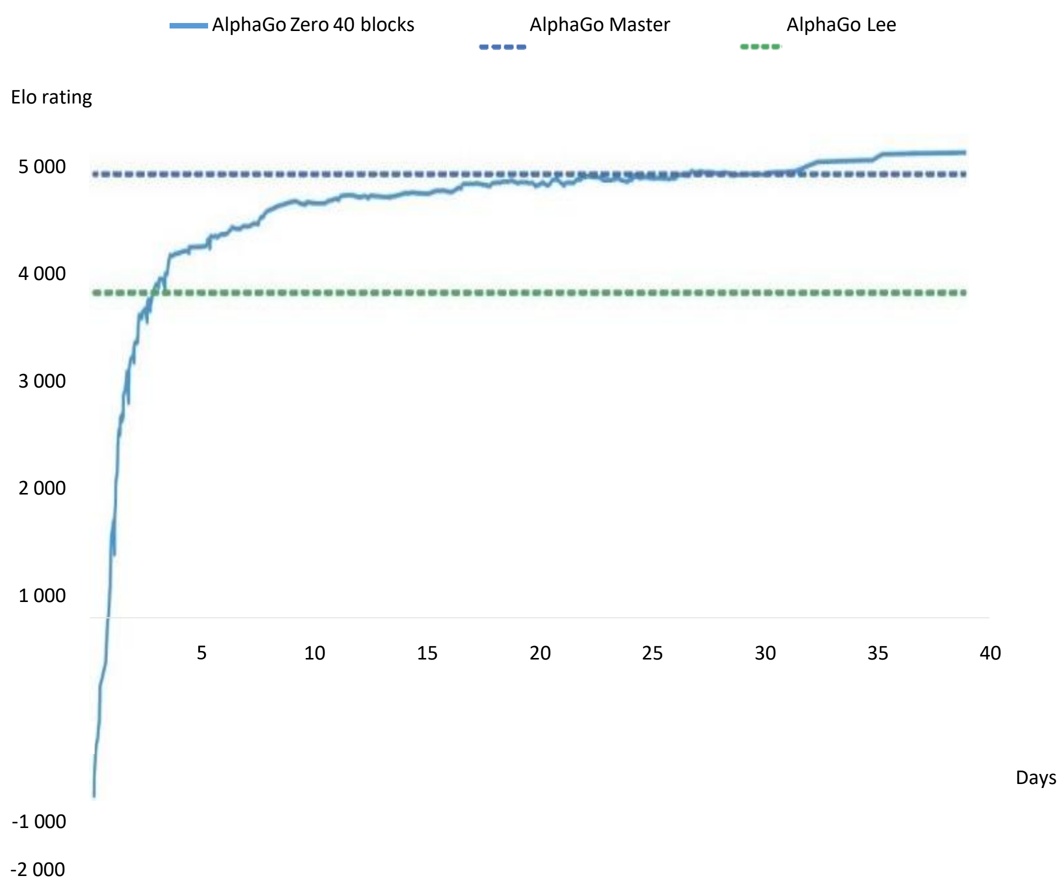

FIGURE 2.4 | AlphaGo's rapid self-learning to become best Go player in the world in 40 days

Where we are today Over the past few years, the availability of big data, cloud computing and the associated computational and storage capacity and breakthroughs in an AI technology called "machine learning" (ML), have dramatically increased the power, availability, growth and impact of AI.

Continuing technological progress is also leading to better and cheaper sensors, which capture more-reliable data for use by AI systems. The amount of data available for AI systems continues to grow as these sensors become smaller and less expensive to deploy. The result is significant progress in many core AI research areas such as:

- natural language processing
- autonomous vehicles and robotics
- computer vision
- language learning.

Artificial narrow intelligence versus artificial general intelligence

Artificial narrow intelligence (ANI) or "applied" AI is designed to accomplish a specific problem-solving or reasoning task. This is the current state-of-the-art. The most advanced AI systems available today, such as Google's AlphaGo, are still "narrow". To some extent, they can generalize pattern recognition such as by transferring knowledge learned in the area of image recognition into speech recognition. However, the human mind is far more versatile.

Applied AI is often contrasted to a (hypothetical) AGI. In AGI, autonomous machines would become capable of general intelligent action. Like humans, they would generalize and abstract learning across different cognitive functions. AGI would have a strong associative memory and be capable of judgment and decision making. It could solve multifaceted problems, learn through reading or experience, create concepts, perceive the world and itself, invent and be creative, react to the unexpected in complex environments and anticipate. With respect to a potential AGI, views vary widely. Experts caution that discussions should be realistic in terms of time scales. They broadly agree that ANI will generate significant new opportunities, risks and challenges. They also agree that the possible advent of an AGI, perhaps sometime during the 21st century, would greatly amplify these consequences.

Some of the most interesting AI developments are outside of computer science in fields such as

health, medicine, biology and finance. In many ways, the AI transition resembles the way computers diffused from a few specialized businesses to the broader economy and society in the 1990s. It also recalls how Internet access expanded beyond multinational firms to a majority of the population in many countries in the 2000s. Economies will increasingly need sector "bilinguals".

These are people specialized in one area such as economics, biology or law, but also skilled at AI techniques such as ML. The present chapter focuses on applications that are in use or foreseeable in the short and medium term rather than possible longer-term developments such as artificial general intelligence.

The AI system lifecycle

by detailing the AI system lifecycle. This lifecycle framework does not represent a new standard for the AI lifecycle or propose prescriptive actions. However, it can help contextualize other international initiatives on AI principles.

An AI system incorporates many phases of traditional software development lifecycles and system development lifecycles more generally. However, the AI system lifecycle typically involves four specific phases. The design, data and models' phase are a context-dependent sequence encompassing planning and design, data collection and processing, as well as model building and interpretation. This is followed by verification and validation, deployment, and operation and monitoring (AI system lifecycle).

These phases often take place in an iterative manner and are not necessarily sequential. The decision to retire an AI system from operation may occur at any point during the operation and monitoring phase.

The AI system lifecycle phases can be described as follows:

1. **Design, data and modelling** includes several activities, whose order may vary for different AI systems:

- **Planning and design** of the AI system involves articulating the system's concept and objectives, underlying assumptions, context and requirements, and potentially building a prototype.

- **Data collection and processing** includes gathering and cleaning data, performing checks for completeness and quality, and documenting the metadata and characteristics of the dataset. Dataset metadata include information on how a dataset was created, its composition, its intended uses and how it has been maintained over time.

- **Model building and interpretation** involves the creation or selection of models or algorithms, their calibration and/or training and interpretation.

2. **Verification and validation** involve executing and tuning models, with tests to assess performance across various dimensions and considerations.
3. **Deployment** into live production involves piloting, checking compatibility with legacy systems, ensuring regulatory compliance, managing organizational change and evaluating user experience.
4. **Operation and monitoring** of an AI system involves operating the AI system and continuously assessing its recommendations and impacts (both intended and unintended) in light of objectives and ethical considerations. This phase identifies problems and adjusts by reverting to other phases or, if necessary, retiring an AI system from production.

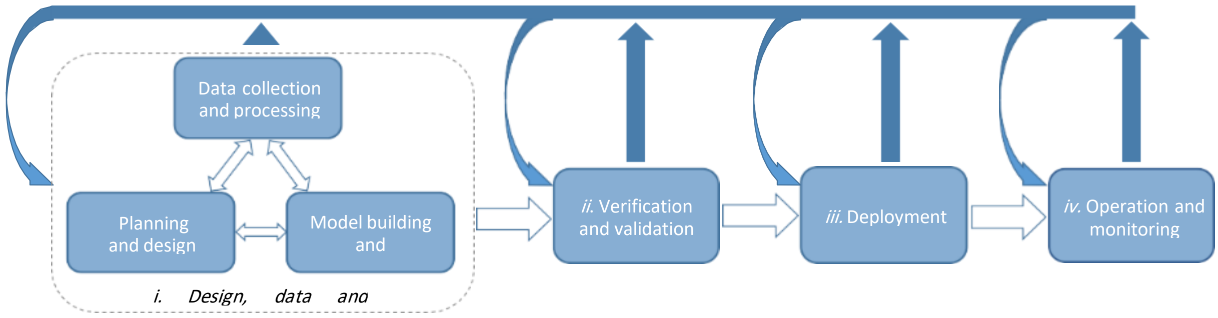

FIGURE 2.5 | **AI system lifecycle** The centrality of data and of models that rely on data for their training and evaluation distinguishes the lifecycle of many AI systems from that of more general system development. Some AI systems based on ML can iterate and evolve over time.

AI research

This section reviews some technical developments with regard to AI research in academia and the private sector that are enabling the AI transition. AI, and particularly its subset called ML, is an active research area in computer science today. A broader range of academic disciplines is leveraging AI techniques for a wide variety of applications.

There is no agreed-upon classification scheme for breaking AI into research streams that is comparable, for example, to the 20 major economics research categories in the Journal of Economic Literature's classification system. This section aims to develop an AI research taxonomy for policy makers to understand some recent AI trends and identify policy issues. Research has historically distinguished symbolic AI from statistical AI.

Symbolic AI uses logical representations to deduce a conclusion from a set of constraints. It requires that researchers build detailed and human-understandable decision structures to translate real- world complexity and help machines arrive at human-like decisions. Symbolic AI is still in widespread use, e.g. for optimization and planning tools. Statistical AI, whereby machines induce a trend from a set of patterns, has seen increasing uptake recently. A number of applications combine symbolic and statistical approaches. For example, natural language processing (NLP) algorithms often combine statistical approaches (that build on large amounts of data) and symbolic approaches (that consider issues such as grammar rules). Combining models built on both data and human expertise is viewed as promising to help address the limitations of both approaches.

AI systems increasingly use ML. This is a set of techniques to allow machines to learn in an automated manner through patterns and inferences rather than through explicit instructions from a human. ML approaches often teach machines to reach an outcome by showing them many examples of correct outcomes. However, they can also define a set of rules and let the machine learn by trial and error. ML is usually used in building or adjusting a model, but can also be used to interpret a model's results .ML contains numerous techniques that have been used by economists, researchers and technologists for decades. These range from linear and logistic regressions, decision trees and principle component analysis to deep neural networks.

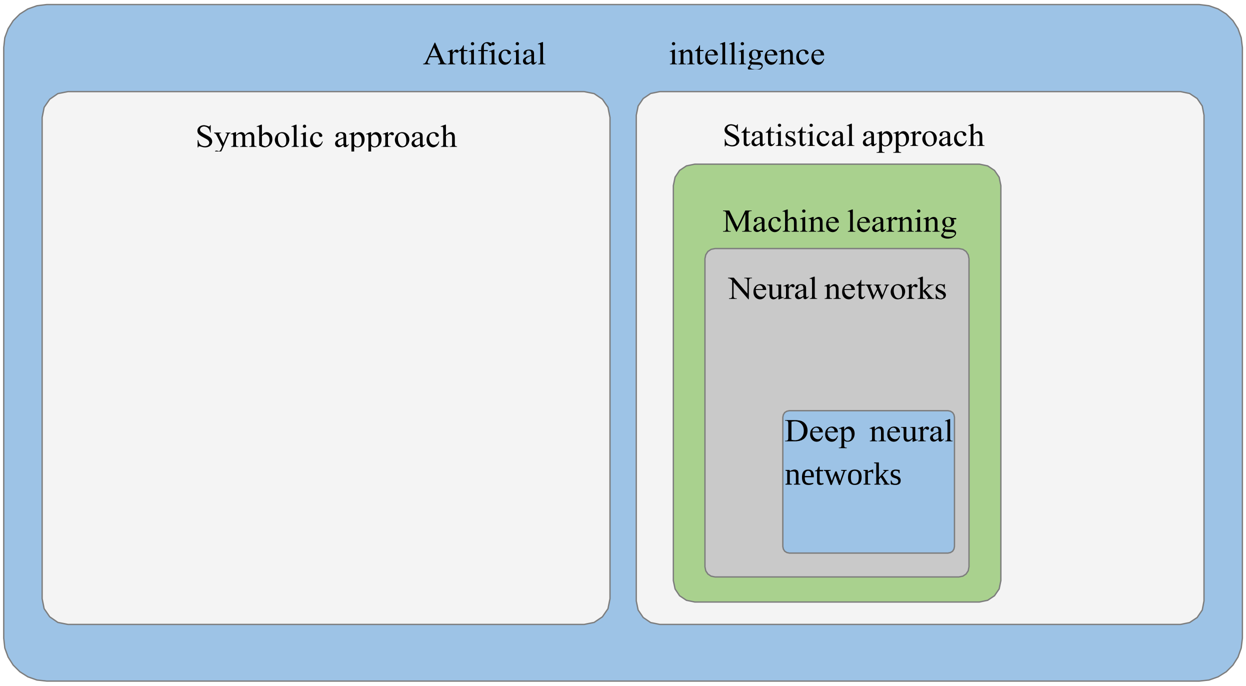

FIGURE 2.6 | The relationship between AI and ML

sets can range from tens of thousands to hundreds of millions of observations. At this scale, researchers rely on more sophisticated and less-understood techniques such as neural networks to make predictions. Interestingly, one core research area of ML is trying to reintroduce the type of explain ability used by economists in these large-scale models.

The real technology behind the current wave of ML applications is a sophisticated statistical modelling technique called "neural networks". This technique is accompanied by growing computational power and the availability of massive datasets ("big data"). Neural networks involve repeatedly interconnecting thousands or millions of simple transformations into a larger statistical machine that can learn sophisticated relationships between inputs and outputs. In other words, neural networks modify their own code to find and optimize links between inputs and outputs. Finally, deep learning is a phrase that refers to particularly large neural networks; there is no defined threshold as to when a neural net becomes "deep".

This evolving dynamic in AI research is paired with continual advances in computational abilities, data availability and neural network design. Together, they mean the statistical approach to AI will likely continue as an important part of AI research in the short term. As a result, policy makers should focus their attention on AI developments that will likely have the largest impact over the coming years and represent some of the most difficult policy challenges. These challenges include unpacking the machines' decisions and making the decision-making process more transparent. Policy makers should also keep in mind that most dynamic AI approaches – statistical AI, specifically "neural networks" – are not relevant for all types of problems. Other AI approaches, and coupling symbolic and statistical methods, remain important.

There is no widely agreed-upon taxonomy for AI research or for the subset of ML. The taxonomy proposed in the next subsection represents 25 AI research streams. They are organized into four broad categories and nine sub-categories, mainly focused on ML. In traditional economic research traditions, researchers may focus on a narrow research area. AI researchers commonly work across multiple clusters simultaneously to solve open research problems.

Cluster 1: ML applications

The first broad research category applies ML methods to solve various practical challenges in the economy and society. Examples of applied ML are emerging in much the same way as Internet connectivity transformed certain industries first and then swept across the entire economy. Chapter 3 provides a range of examples of AI applications emerging across OECD countries. The research streams represent the largest areas of research linked to real-world application development.

Core applied research areas that use ML include natural language processing, computer vision and robotic navigation. Each of these three research areas represents a rich and expanding research field. Research challenges can be confined to just one area or can span multiple streams. For example, researchers in the United States are combining NLP of free text mammogram and pathology notes with computer vision of mammograms to aid with breast cancer screening.

Two research lines focus on ways to contextualize ML. Algorithmic game theory lies at the intersection of economics, game theory and computer science. It uses algorithms to analyze and optimize multi-period games. Collaborative systems are an approach to large challenges where multiple ML systems combine to tackle different parts of complex problems.

Cluster 1: Policy relevance

Several relevant policy issues are linked to AI applications. These include the future of work, the potential impact of AI, and human capital and skills development. They also include understanding in which situations AI applications may or may not be appropriate in sensitive contexts. Other relevant issues include AI's impact on industry players and dynamics, government open data policies, regulations for robotic navigation and privacy policies that govern the collection and use of data.

Cluster 2:ML techniques

The second broad category of research focuses on the techniques and paradigms used in ML. Similar to quantitative methods research in the social sciences, this line of research builds and supplies the technical tools and approaches used in machine-learning applications.

The category is dominated by neural networks (of which "deep learning" is a subcategory) and forms the basis for most ML today. ML techniques also include various paradigms for helping the system learn. Reinforcement learning trains the system in a way that mimics the way humans learn via trial and error. The algorithms are not provided explicit tasks, but rather learn by trying different options in rapid succession. Based on rewards or punishments as outcomes, they adapt accordingly. This has been referred to as relentless experimentation.

Generative models, including generative adversarial networks, train a system to produce new data similar to an existing dataset. They are an exciting area of AI research because they pit two or more unsupervised neural networks against each other in a zero-sum game. In game theory terms, they function and learn as a set of rapidly repeated games. By setting
the systems against each other at computationally high speeds, the systems can learn profitable strategies. This is particularly the case in structured environments with clear rules, such as the game of Go with AlphaGo Zero.

Cluster 2: Policy relevance

Several public policy issues are relevant to the development and deployment of ML technologies. These issues include supporting better training data sets; funding for academic research and basic science; policies to create “bilinguals” who can combine AI skills with other competencies; and computing education. For example, research funding from the Canadian government supported breakthroughs that led to the extraordinary success of modern neural networks.

Cluster 3: Ways of improving ML/optimizations

The third broad category of research focuses on ways to improve and optimize ML tools. It breaks down research streams based on the time horizon for results (current, emerging and future. Short-term research is focusing on speeding up the deep-learning process. It does this either via better data collection or by using distributed computer systems to train the algorithm.

Researchers are also focused on enabling ML on low-power devices such as mobile phones and other connected devices. Significant progress has been made on this front. Projects such as Google’s Teachable Machine now offer open-source ML tools light enough to run in a browser. Teachable Machine is just one example of emerging AI development tools meant to expand the reach and efficiency of ML. There are also significant advances in the development of dedicated AI chips for mobile devices.

ML research with a longer time horizon includes studying the mechanisms that allow neural networks to learn so effectively. Although neural networks have proven to be a powerful ML technique, understanding of how they operate is still limited. Understanding these processes would make it possible to engineer neural networks on a deeper level. Longer- term research is also looking at ways to train neural networks using much smaller sets of training data, sometimes referred to as “one-shot learning”. It is also generally trying to make the training process more efficient. Large models can take weeks or months to train and require hundreds of millions of training examples.

Teachable Machine is a Google experiment that allows people to train a machine to detect different scenarios using a camera built into a phone or computer. The user takes a series of pictures for three different scenarios to train the teachable machine. The machine then analyses the photos in the training data set and can use them to detect different scenarios. For example, the machine can play a sound every time the person smiles in a camera range. Teachable Machine stands out as an ML project because the neural network runs exclusively in the user’s browser without any need for outside computation or data storage.

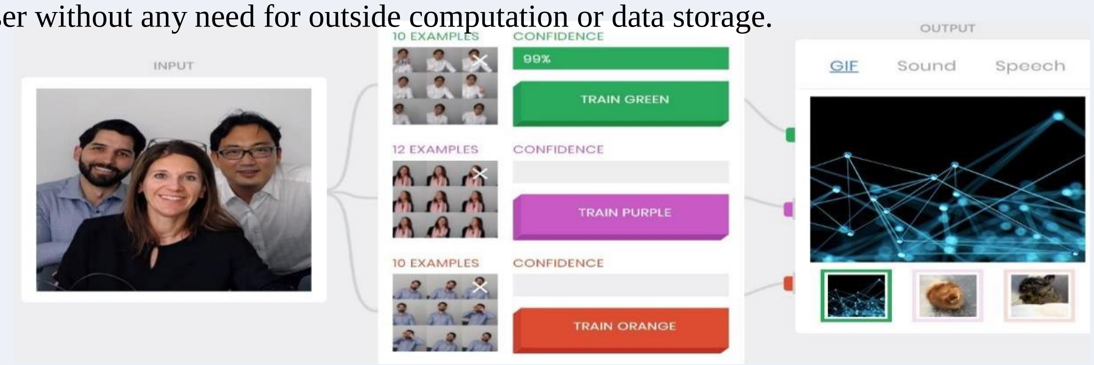

FIGURE 2.7 | Training a machine using a computer’s camera

Cluster 3: Policy relevance

The policy relevance of the third cluster includes the implications of running ML on stand- alone devices and thus of not necessarily sharing data on the cloud. It also includes the potential to reduce energy use, and the need to develop better AI tools to expand its beneficial uses.

Cluster 4: Considering the societal context

The fourth broad research category examines the context for ML from technical, legal and social perspectives. ML systems increasingly rely on algorithms to make important decisions. Therefore, it is important to understand how bias can be introduced, how bias can propagate and how to eliminate bias from outcomes. One of the most active research areas in ML is concerned with transparency and accountability of AI systems. Statistical approaches to AI have led to less human-comprehensible computation in algorithmic decisions.

These can have significant impacts on the lives of individuals – from bank loans to parole decision. Another category of contextual ML research involves steps to ensure the safety and integrity of these systems. Researchers' understanding of how neural networks arrive at decisions is still at an early stage. Neural networks can often be tricked using simple methods such as changing a few pixels in a picture . Research in these streams seeks to defend systems against inadvertent introduction of unintended information and adversarial attacks. It also aims to verify the integrity of ML systems.

Cluster 4: Policy relevance`

Several relevant policy issues are linked to the context surrounding ML. These include requirements for algorithmic accountability, combating bias, the impact of ML systems, product safety, liability and security.

AI in health

Background

AI applications in healthcare and pharmaceuticals can help detect health conditions early, deliver preventative services, optimize clinical decision making, and discover new treatments and medications. They can facilitate personalized healthcare and precision medicine, while powering self-monitoring tools, applications and trackers. AI in healthcare offers potential benefits for quality and cost of care. Nevertheless, it also raises policy questions, in particular concerning access to (health) data (Section “AI in Health”) and privacy. This section focuses on AI’s specific implications for healthcare.

In some ways, the health sector is an ideal platform for AI systems and a perfect illustration of its potential impacts. A knowledge-intensive industry, it depends on data and analytics to improve therapies and practices. There has been tremendous growth in the range of information collected, including clinical, genetic, behavioral and environmental data. Every day, healthcare professionals, biomedical researchers and patients produce vast amounts of data from an array of devices. These include electronic health records (EHRs), genome sequencing machines, high-resolution medical imaging, smartphone applications and ubiquitous sensing, as well as Internet of Things (IoT) devices that monitor patient health.

Beneficial impact of AI on healthcare

If put to use, AI data generated could be of great value to healthcare and research. Indeed, health sectors across countries are undergoing a profound transformation as they capitalize on opportunities provided by information and communication technologies. Key objectives shaping this transformation process include improved efficiency, productivity and quality of care.

Specific illustrations

Improving patient care: Secondary use of health data can improve the quality and effectiveness of patient care, in both clinical and homecare settings. For example, AI systems can alert administrators and front-line clinicians when measures related to quality and patient safety fall outside a normal range. They can also highlight factors that may be contributing to the deviations. A specific aspect of improving patient care concerns precision medicine.

This is based on rapid processing of a variety of complex datasets such as a patient's health records, physiological reactions and genomic data. Another aspect concerns mobile health: mobile technologies provide helpful real-time feedback along the care continuum – from prevention to diagnosis, treatment and monitoring. Linked with other personal information such as location and preferences, AI-enhanced technologies can identify risky behaviors' or encourage beneficial ones. Thus, they can produce tailored interventions to promote healthier behavior (e.g. taking the stairs instead of the lift, drinking water or walking more) and achieve better health outcomes. These technologies, as well as sensor-based monitoring systems, offer continuous and direct monitoring and personalized intervention. As such, they can be particularly useful to improve the quality of elderly care and the care of people with disabilities.

Managing health systems: Health data can inform decisions regarding programmers, policy and funding. In this way, they can help manage and improve the effectiveness and efficiency of the health system. For example, AI systems can reduce costs by identifying ineffective interventions, missed opportunities and duplicated services. Access to care can be increased and wait times reduced through four key ways. First, AI systems understand patient journeys across the continuum of care. Second, they ensure that patients receive the services most appropriate for their needs. Third, they accurately project future healthcare needs of the population. Fourth, they optimize allocation of resources across the system.

With increasing monitoring of therapies and events related to pharmaceuticals and medical devices, countries can use AI to advance identification of patterns, such as systemic failures and successes. More generally, data-driven innovation fosters a vision for a “learning health system”. Such a system can continuously incorporate data from researchers, providers and patients. This allows it to improve comprehensive clinical algorithms, reflecting preferred care at a series of decision nodes for clinical decision support.

Understanding and managing population and public health: In addition to timelier public health surveillance of influenza and other viral outbreaks, data can be used to identify unanticipated side effects and contraindications of new drugs (Canadian Institute for Health Information. AI technologies may allow for early identification of outbreaks and surveillance of disease spreading. Social media, for example, can both detect and disseminate information on public health. AI uses NLP tools to process posts on social media to extract potential side effects.

Facilitating health research: Health data can support clinical research and accelerate discovery of new therapies. Big data analytics offers new and more powerful opportunities to measure disease progression and health for improved diagnosis and care delivery, as well as translational and clinical research, for example, the pharmaceutical company Atom wise collaborated with researchers at the University of Toronto and IBM to use AI technology in performing Ebola treatment research.7 The use of AI is also increasingly tested in medical diagnosis, with a landmark approval by the United States Food and Drug Administration.

The ruling allowed marketing of the first medical device to use AI to “detect greater than a mild level of the eye disease diabetic retinopathy in adults who have diabetes”. Similarly, ML techniques can be used to train models to classify images of the eye, potentially embedding cataract detectors in smartphones and bringing them to remote areas (Lee, Baughman and Lee. In a recent study, a deep-learning algorithm was fed more than 100 000 images of malignant melanomas and benign moles. It eventually outperformed a group of 58 international dermatologists in the detection of skin cancer·

Enabling AI in healthcare – success and risk factors

Sufficient infrastructure and risk mitigation should be in place to take full advantage of AI capabilities in the health sector. Countries are increasingly establishing EHR systems and adopting mobile health (m-health), allowing mobile services to support the practice of medicine and public health Robust evidence demonstrates how EHRs can help reduce medication errors and better co-ordinate care.

On the other hand, the same study showed that only a few countries have achieved high-level integration and capitalized on the possibility of extracting data from EHRs for research, statistics and other secondary uses. Healthcare systems still tend to capture data in silos and analyze them separately. Standards and interoperability are key challenges that must be addressed to realize the full potential of EHRs

Another critical factor for the use of AI in the health sector concerns minimizing the risks to data subjects' privacy. The risks in increased collection and processing of personal data are described in detail in Subsection "Personal data protection" of. This subsection addresses the high sensitivity of health-related information. Bias in the operation of an algorithm recommending specific treatment could create real health risks to certain groups. Other privacy risks are particular to the health sector. For example, questions from the use of data extracted from implantable healthcare devices, such as pacemakers, could be evidenced in court.

Additionally, as these devices become more sophisticated, they raise increasing safety risks, such as a malicious takeover that would administer a harmful operation. Another example is the use of biological samples for ML, which raises complex questions of consent and ownership As a result of these concerns, many countries report legislative barriers to the use of personal health data. These barriers include disabling data linkages and hindering the development of databases from EHRs. The Recommendation of the Council on Health Data Governance is an important step towards a more coherent approach in health data management and use It aims primarily to promote the establishment and implementation of a national health data governance framework.

Such a framework would encourage the availability and use of personal health data to serve health-related public interests. At the same time, it would promote protection of privacy, personal health data and data security. Adopting a coherent approach to data management could help remove the trade-off between data use and security. Involving all relevant stakeholders is an important means of garnering trust and public support in the use of AI and data collection for health purposes.

Similarly, governments could develop appropriate trainings for future health data scientists, or pair data scientists with healthcare practitioners. In this way, they could provide better understanding of the opportunities and risks in this emerging field Involving clinicians in the design and development of AI healthcare systems could prove essential for getting patients and providers to trust AI-based healthcare products and service

Chapter 3: General Overview of disease diagnosis

It was a remarkable situation that surrounded the world during the Corona pandemic, which made us make sure that health is the basis of human work, which made us look for the most diseases that can be done through artificial intelligence, working on data analysis and sharing those results to patients and helping doctors make the right decision towards The initial diagnosis that results from blood analysis, fractal rays, or electrocardiogram, which is the thing that helps artificial intelligence technology in making a decision as a result of training that machine on the many results available from the World Health Organization.

Hence, we decided to work on the following diseases:

1- Heart attack
2- COVID-19
3- Breast cancer
4- Parkinson
5- Malaria

Heart attack

Definition:

A heart attack happens when part of the heart muscle is cut off from oxygen. If the oxygen isn't restored soon, a heart attack occurs. The blood in your coronary arteries carries oxygen to the heart muscle. Most heart attacks occur when a blockage slows or stops blood flow. Heart attack is sometimes called myocardial infarction or acute coronary syndrome. Heart attacks are often treatable when diagnosed quickly. However, they can be fatal.

Symptoms:

One of the most common symptoms Chest pain or discomfort. Most heart attacks involve discomfort in the center or left side of the chest. The discomfort usually lasts for more than a few minutes or goes away and comes back. It can feel like pressure, squeezing, fullness, or pain. It also can feel like heartburn or indigestion. Upper body discomfort. You may feel pain or discomfort in one or both arms, the back, shoulders, neck, jaw, or upper part of the stomach (above the belly button). Shortness of breath. This may be your only symptom, or it may occur before or along with chest pain or discomfort. It can occur when you are resting or doing a little bit of physical activity. Light-headedness or sudden dizziness.

Analyzing:

Risk of Heart Attack by Age and Gender The average age of heart attack risk is 45 for men and 55 for women. Based on the graph, men have a high risk of heart attack more than women. Between 40–59 ages is too risky years; also, men's risk ratio is higher than women. If we look at the 60–79 age range, women's heart attack risk is over men.

COVID-19

Definition:

Coronavirus is highly threatening for both animal and human life. Many types of coronavirus can transfer from animals to the human population. Humans have not previously identified COVID-19 because it is a new species that appeared in 2019. COVID-19 is a global epidemic problem that can spread rapidly among people. COVID-19 has been identified by the World Health Organization (WHO) and the Chinese government as a global pandemic. COVID-19 has typical symptoms that involve shortness of breath, fever, headache, cough, fatigue, sore throat, and muscle pain.

Physical contact is the main reason of the spread of COVID-19 disease among people. The infections are transferred from the infected COVID-19 person to the healthy person through hand contact, mucous contact, or breathe contact. Because of the rapid spread of COVID-19 around the world, it causes a destructive impact on issues like public health, the global economy, and daily activities. Moreover, COVID-19 infection takes less than 4 weeks to quash the medical system once it begins to spread. To this end, early detection of COVID-19 especially with the lacking of specific cures or vaccines, is an essential process for treating and controlling the disease from spreading. Reaction is the most preferable test that is currently used for detecting COVID-19 patients. Although RT-PCR tests are sensitive, fairly quick, and reliable, these tests suffer from the risk of eliciting false-negative and false-positive results.

Consequently, the spread of COVID-19 infection has been increased because RT-PCR tests cannot immediately distinguish the infected people. Chest radiological imaging such as Computed Tomography (CT) images and X-rays play an important role in the early detection and treatment of COVID-19 patients. Despite the advantages of CT images for detecting COVID-19 patients, misclassification may occur between the imaging features of COVID-19 and other.

Symbols:

Generally, the diagnosing of COVID-19 can be achieved using three different methodologies as depicted in These three methodologies are Real-Time reverse transcriptase- chest CT imaging scan, and numerical laboratory tests. RT-PCR tests are fairly quick, sensitive, and reliable. The sample is collected from a person's throat or nose; adding some chemicals for removing any proteins, fats, and other molecules, leaving behind only the existing Ribonucleic Acid. The separated although several studies had observed that the sensitivity of Chest CT in the diagnosing of COVID-19 is Radiology (ACR) has issued guidance that CTs and X-raysAre not accurate tools for diagnosing COVID-19? There are three significant reasons for ACR's recommendation, which are both chest CT and X-ray cannot accurately distinguish between COVID-19 and other respiratory infections.

They can only point to signs of an infection, which could be due to other reasons such as seasonal Fu. A huge number of patients infected with COVID-19 have normal chest CTs, which wrongly convince them that they are healthy. Those convince patients can easily spread the virus to others. The usage of the imaging equipment on COVID-19 patients is a critical hazard for doctors and other patients. CT scanners are complex and large machinery pieces they need to be carefully cleaned after each potential patient.

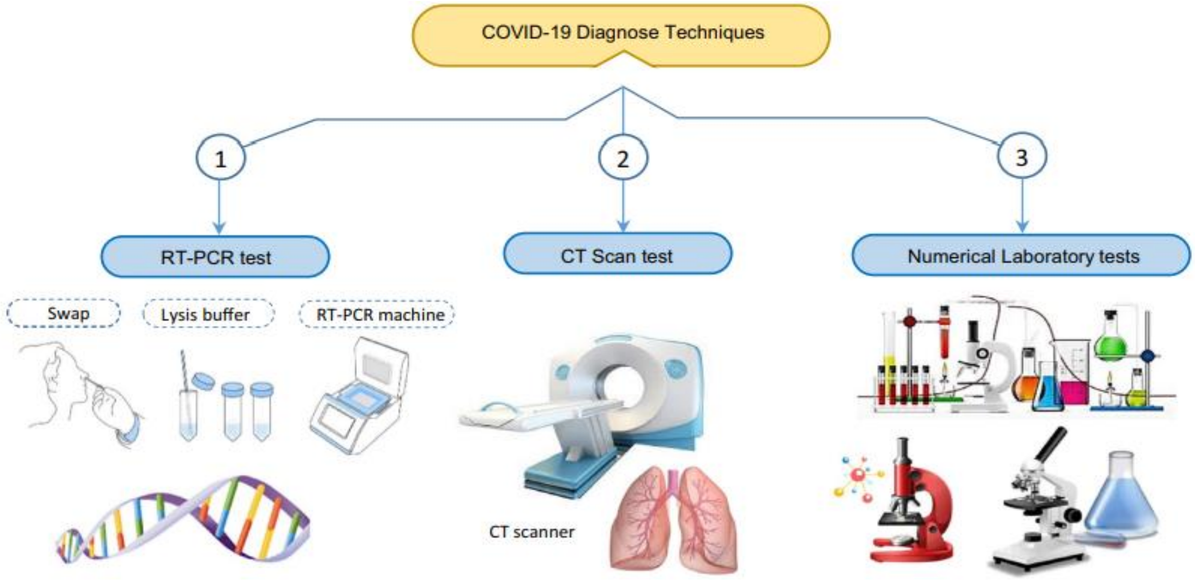

FIGURE 3.1 | COVID-19 Diagnose Techniques.

Treatment:

A-self-care If testing is not available, stay home and away from others for 14 days. While you are in quarantine, do not go to work, school or public places. Ask someone to bring you supplies. Keep at least 1 meter away from others, even your family members. Wear a medical mask to protect others, including if/when you need to seek medical attention. Clean your hands frequently. Stay in a separate room from the rest of the family, and if this is not possible, wear a mask. Keep the room well ventilated. If you share a room, keep the beds at least 1 meter apart. Monitor yourself for any symptoms for 14 days.

medications:

The FDA has authorized certain antiviral medications and monoclonal antibodies to treat mild to moderate COVID-19 in people who are more likely to get very sick Antiviral treatments target specific parts of the virus to stop it from multiplying in the body, helping to prevent severe illness and death. Monoclonal antibodies help the immune system recognize and respond more effectively to the virus.

Breast Cancer

Definition:

Breast cancer is a heterogeneous disease, and by gene expression profiling has been shown to be classifiable into five major biologically distinct intrinsic subtypes: luminal A, luminal B, human epidermal growth factor receptor-2 (HER2) overexpressing, basal-like, and normal-like (1-3).

Symptoms and diagnosis:

Swollen lymph nodes under the arm or around the collarbone. Swelling of all or part of the breast. Skin irritation or dimpling. Breast or nipple pain. Nipple retraction. Redness, scanlines, or thickening of the nipple or breast skin. Nipple discharge. Swelling or thickening of the breast. Dimpling of the breast skin. Nipple crust. Redness or heat of breast skin. New nipple discharge that is not breast milk, including blood. Skin sores. Bumps. Growing veins on the breast. Sunken nipple. Changes in the size or shape of the breast. “Orange peel” skin. Hard lump in the breast.

Treatment:

Surgery is often the first form of treatment for early breast cancer. It can include a mastectomy—a procedure to remove the entire breast—or a lumpectomy to remove only the tumor. The type of treatment given after surgery depends on the characteristics related to the tumor and disease, such as: Tumor size Extent of nodal involvement (i.e., number of lymph nodes involved). Tumor characteristics (Hormone receptor status, HER2 status, and expression of certain other genes, like Ki-67).

Treatment that is given following surgery is called adjuvant therapy. Many patients who receive Verzenio in the early breast cancer setting will have received therapy before surgery (neoadjuvant therapy), such as chemotherapy, because their cancer has certain high-risk characteristics.

Chemotherapy and radiation:

Chemotherapy can be given either before surgery (neoadjuvant) or after surgery (adjuvant). Chemotherapy can help lower the risk of the cancer returning, by killing residual or leftover cancer cells that may be circulating in the body. Chemotherapy is considered a systemic therapy because it travels throughout the body and affects cells beyond the breast. Radiation is generally given after surgery and chemotherapy, and uses targeted beams of intense energy, such as high-energy x-rays, to kill cancer left in or around the breast or nearby lymph nodes.

Parkinson

Definition:

Parkinson's disease is a brain disorder that causes unintended or uncontrollable movements, such as shaking, stiffness, and difficulty with balance and coordination, symptoms usually begin gradually and worsen over time. As the disease progresses, people may have difficulty walking and talking. They may also have mental and behavioral changes, sleep problems, depression, memory difficulties, and fatigue.

Syndrome:

The most prominent signs and symptoms of Parkinson's disease occur when nerve cells in the basal ganglia, an area of the brain that controls movement, become impaired and/or die. Normally, these nerve cells, or neurons, produce an important brain chemical known as dopamine. When the neurons die or become impaired, they produce less dopamine, which causes the movement problems associated with the disease. Scientists still do not know what causes the neurons to die.

Diagnosis:

Because there is no definitive test for the diagnosis of PD, the disease must be diagnosed based on clinical criteria. Rest tremor, bradykinesia, rigidity and loss of postural reflexes are generally considered the cardinal signs of PD. The presence and specific presentation of these features are used to differentiate PD from related parkinsonian disorders. Other clinical features include secondary motor symptoms (e.g., hypomimia, dysarthria, dysphagia, sialorrhea, micrographic, shuffling gait, festination, freezing, dystonia, glabellar reflexes), non-motor symptoms (e.g., autonomic dysfunction, cognitive/neurobehavioral abnormalities, sleep disorders and sensory abnormalities such as anosmia, paresthesia and pain). Absence of rest tremor, early occurrence of gait difficulty, postural instability, dementia, hallucinations, and the presence of dysautonomia, ophthalmoparesis, ataxia and other atypical features, coupled with poor or no response to levodopa, suggest.

five different stages

Stage 1: Mild symptoms that do not typically interfere with daily life, including tremors and movement issues on only one side of the body.

Stage 2: Symptoms continue to become worse with both tremors and rigidity now affecting both sides of the body. Daily tasks become challenging.

Stage 3: Loss of balance and movements with falls becoming frequent and common. The patient is still capable of (typically) living independently.

Stage 4: Symptoms become severe and constraining. The patient is unable to live alone and requires help to perform daily activities.

Stage 5: Likely impossible to walk or stand. The patient is most likely wheelchair bound and may even experience hallucinations.

Malaria

Definition:

Malaria is an acute febrile disease caused by parasites of the family Plasmodium that are transmitted to humans by the bites of infected female Anopheles mosquitoes. There are 5 types of Plasmodium that cause malaria in humans, and there are two types of them that pose the greatest threat: Plasmodium falciparum and Plasmodium vivax. Plasmodium falciparum is the most deadly and prevalent malaria parasite on the African continent. Plasmodium vivax is the dominant malaria parasite species in most countries outside of sub-Saharan Africa.

Symptoms:

The first symptoms of the disease – fever, headache and chills – usually appear within 10-15 days after being bitten by an infected mosquito, and these first symptoms may be mild and difficult to attribute to malaria. Plasmodium falciparum, if left untreated, can develop severe illness and cause death within 24 hours. Malaria signs and symptoms include:Fever, Chills General, feeling of discomfort, Headache, Nausea and vomiting, Diarrhea, Tummy ache, Joint or muscle pain, Fatigue, Breathing rate, Fast heart rate and Cough.

Treatment:

The use of medicines, either alone or in combination, to prevent malaria and its consequences. These include chemoprevention, intermittent preventive therapy for infants and pregnant women, seasonal malaria chemoprevention Device use in treatment: Building in deep learning model to recognize cell images as Infected/Uninfected, Binary classification task. As a deep learning model, I used convolution neural network as they perform great in fetching important information from images.

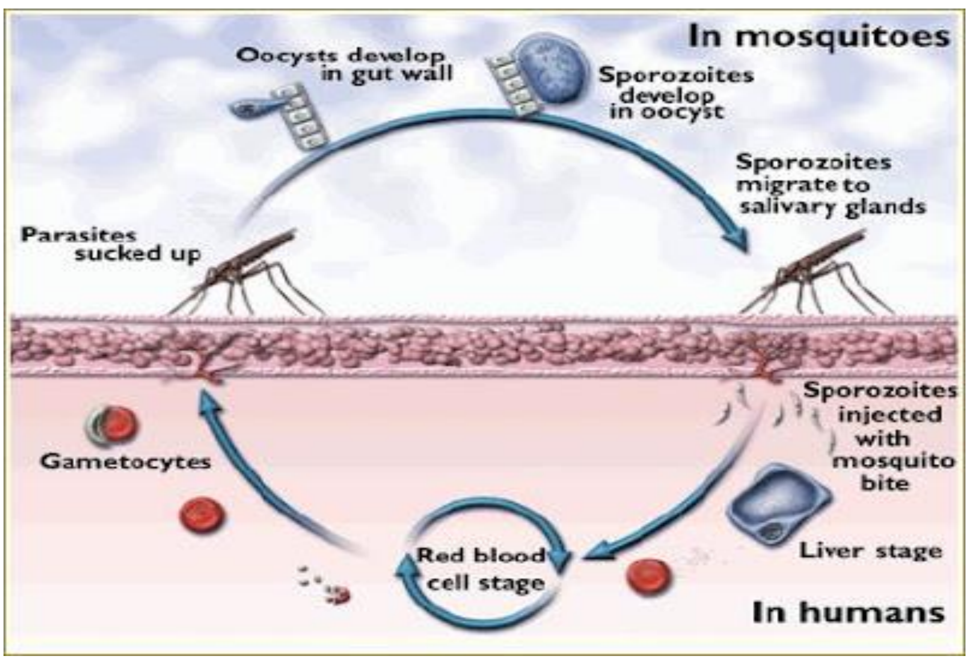

FIGURE 3.2 |: Malaria spreading course

Chapter 4: The proposed project

Software

Web programing languages play important role in our project we use for Front-end some technologies like html CSS JavaScript for backend and server side we use php and framework Laravel for database MySQL

Project submitted web page

Html

The Hypertext Markup Language or HTML is the standard markup language for documents designed to be displayed in a web browser. It can be assisted by technologies such as Cascading Style Sheets (CSS) and scripting languages such as JavaScript. Web browsers receive HTML documents from a web server or from local storage and render the documents into multimedia web pages. HTML describes the structure of a web page semantically and originally included cues for the appearance of the document.

HTML elements are the building blocks of HTML pages. With HTML constructs, images and other objects such as interactive forms may be embedded into the rendered page. HTML provides a means to create structured documents by denoting structural semantics for text such as headings, paragraphs, lists, links, quotes and other items. HTML elements are delineated by tags, written using angle brackets. Tags such as <image /> and <input /> directly introduce content into the page. Other tags such as <p> surround and provide information about document text and may include other tags as sub-elements. Browsers do not display the HTML tags but use them to interpret the content of the page.

HTML can embed programs written in a scripting language such as JavaScript, which affects the behavior and content of web pages. Inclusion of CSS defines the look and layout of content. The World Wide Web Consortium (W3C), former maintainer of the HTML and current maintainer of the CSS standards, has encouraged the use of CSS over explicit presentational HTML since 1997. A form of HTML, known as HTML5, is used to display video and audio, primarily using the <canvas> element, in collaboration with JavaScript.

CSS

Cascading Style Sheets (CSS) is a style sheet language used for describing the presentation of a document written in a markup language such as HTML. CSS is a cornerstone technology of the World Wide Web, alongside HTML and JavaScript.CSS is designed to enable the separation of presentation and content, including layout, colors, and fonts. This separation can improve content accessibility; provide more flexibility and control in the specification of presentation characteristics; enable multiple web pages to share formatting by specifying the relevant CSS in a separate .CSS file, which reduces complexity and repetition in the structural content; and enable the .CSS file to be cached to improve the page load speed between the pages that share the file and its formatting.

Separation of formatting and content also makes it feasible to present the same markup page in different styles for different rendering methods, such as on-screen, in print, by voice (via speech-based browser or screen reader), and on Braille-based tactile devices. CSS also has rules for alternate formatting if the content is accessed on a mobile device. The name cascading comes from the specified priority scheme to determine which style rule applies if more than one rule matches a particular element. This cascading priority scheme is predictable. The CSS specifications are maintained by the World Wide Web Consortium (W3C). Internet media type (MIME type) text/CSS is registered for use with CSS by RFC 2318 (March 1998). The W3C operates a free CSS validation service for CSS documents. In addition to HTML, other markup languages support the use of CSS including XHTML, plain XML, SVG, and XUL.

JavaScript

JavaScript often abbreviated JS, is a programming language that is one of the core technologies of the World Wide Web, alongside HTML and CSS. Over 97% of websites use JavaScript on the client side for web page behavior, often incorporating third-party libraries. All major web browsers have a dedicated JavaScript engine to execute the code on users' devices. JavaScript is a high-level, often just-in-time compiled language that conforms to the ECMAScript standard. It has dynamic typing, prototype-based object-orientation, and first-class functions. It is multi-paradigm, supporting event-driven, functional, and imperative programming styles. It has application programming interfaces (APIs) for working with text, dates, regular expressions, standard data structures, and the Document Object Model (DOM).

The ECMAScript standard does not include any input/output (I/O), such as networking, storage, or graphics facilities. In practice, the web browser or other runtime system provides JavaScript APIs for I/O.
JavaScript engines were originally used only in web browsers, but are now core components of some servers and a variety of applications. The most popular runtime system for this usage is Node.js.Although Java and JavaScript are similar in name, syntax, and respective standard libraries, the two languages are distinct and differ greatly in design.

PHP

PHP is a general-purpose scripting language geared toward web development. It was originally created by Danish-Canadian programmer Rasmus Leadoff in 1994. The PHP reference implementation is now produced by The PHP Group. PHP originally stood for Personal Home Page, but it now stands for the recursive initialism PHP: Hypertext Preprocessor code is usually processed on a web server by a PHP interpreter implemented as a module, a daemon or as a Common Gateway Interface (CGI) executable. On a web server, the result of the interpreted and executed PHP code – which may be any type of data, such as generated HTML or binary image data – would form the whole or part of an HTTP response. Various web template systems, web content management systems, and web frameworks exist which can be employed to orchestrate or facilitate the generation of that response.

Additionally, PHP can be used for many programming tasks outside the web context, such as standalone graphical applications and robotic drone control. PHP code can also be directly executed from the command line.

The standard PHP interpreter, powered by the Zend Engine, is free software released under the PHP License. PHP has been widely ported and can be deployed on most web servers on a variety of operating systems and platforms. The PHP language evolved without a written formal specification or standard until 2014, with the original implementation acting as the de facto standard which other implementations aimed to follow. Since 2014, work has gone on to create a formal PHP specification.

W3 Techs reports that, as of January 2022, "PHP is used by 78.1% of all the websites whose server-side programming language we know. PHP version 7.4 is the most used version. Support for version 7.3 was dropped on 6 December 2021.

Laravel

Taylor Orwell created Laravel as an attempt to provide a more advanced alternative to the CodeIgniter framework, which did not provide certain features such as built-in support for user authentication and authorization. Laravel's first beta release was made available on June 9, 2011, followed by the Laravel 1 release later in the same month. Laravel 1 included built-in support for authentication, localization, models, views, sessions, routing and other mechanisms, but lacked support for controllers that prevented it from being a true MVC framework.

Laravel 2 was released in September 2011, bringing various improvements from the author and community. Major new features included the support for controllers, which made Laravel 2 a fully MVC-compliant framework, built-in support for the inversion of control (IOC) principle, and a templating system called Blade. As a downside, support for third-party packages was removed in Laravel 2.
Laravel 3 was released in February 2012 with a set of new features including the command-line interface (CLI) named Artisan, built-in support for more database management systems, database migrations as a form of version control for database layouts, support for handling events, and a packaging system called Bundles. An increase of Laravel's userbase and popularity lined up with the release of Laravel.

Laravel 4, codenamed Illuminate, was released in May 2013. It was made as a complete rewrite of the Laravel framework, migrating its layout int.o a set of separate packages distributed through Composer, which serves as an application-level package manager. Such a layout improved the extensibility of Laravel 4, which was paired with its official regular release schedule spanning six months between minor point releases. Other new features in the Laravel 4 release include database seeding for the initial population of databases, support for message queues, built-in support for sending different types of email, and support for delayed deletion of database records called soft deletion.

Laravel 5 was released in February 2015 as a result of internal changes that ended up in renumbering the then-future Laravel 4.3 release. New features in the Laravel 5 release include support for scheduling periodically executed tasks through a package called Scheduler, an abstraction layer called Fly system that allows remote storage to be used in the same way as local file systems, improved handling of package assets through Elixir, and simplified externally handled authentication through the optional Socialite package. Laravel 5 also introduced a new internal directory tree structure for developed applications.
Laravel 5.1, released in June 2015, was the first release of Laravel to receive long-term support (LTS). New LTS versions were planned for one every two years.

Laravel 5.3 was released on August 23, 2016. The new features in 5.3 are focused on improving developer speed by adding additional out of the box improvements for common tasks.Laravel 5.4 was released on January 24, 2017, with many new features like Laravel Dusk, Laravel Mix, Blade Components and Slots, Markdown Emails, Automatic Facades, Route Improvements, Higher Order Messaging for Collections, and many others.

Laravel 6 was released on September 3, 2019, shift blueprint code generation, introducing semantic versioning, compatibility with Laravel Vapor, improved authorization responses, improved job middleware, lazy collections, and sub-query improvements. The frontend scaffolding was removed from the main package and moved into the Laravel package.

Laravel 7 was released on March 3, 2020, with new features like Laravel Sanctum, Custom Eloquent Casts, Blade Component Tags, Fluent String Operations and Route Model Binding Improvements.
Laravel 8 was released on September 8, 2020, with new features like Laravel Jetstream, model factory

classes, migration squashing, Tailwind CSS for pagination views and other usability improvements. The latest Laravel version is version 9, which was released on February.

FIGURE 4.1 | Screenshot from web page

Model Development

Establishing Utility

One of the most critical components of developing AI for health care is to define and characterize the problem to be addressed and then evaluate whether it can be solved (or is worth solving) using AI and machine learning. Doing so requires an assessment of utility, feasibility given available data, implementation costs, deployment challenges, clinical uptake, and maintenance over time. This chapter focuses on the process necessary to develop and validate a model,

.

It is useful to think in terms of how one would act given a model's output, when considering the utility of AI in health care. Factors affecting the clinical utility of a predictive model may include lead time offered by the prediction, the existence of a mitigating action, the cost and ease of intervening, the logistics of the intervention, and incentives While model evaluation typically focuses on metrics such as positive predictive value, sensitivity (or recall), specificity, and calibration, constraints on the action triggered by the model's output (e.g., continuous rhythm monitoring might be constrained by availability of Holter monitors) often can have a much larger influence in determining model utility.

For example, if Vera was suspected of having atrial fibrillation based on a personalized risk estimate the execution of follow-up action (such as rhythm monitoring for 24 hours) depends on availability of the right equipment. In the absence of the ability to follow up, having a personalized estimate of having undiagnosed atrial fibrillation does not improve Vera's car Therefore, a framework for assessing the utility of a prediction-action pair resulting from an AI solution is necessary. During this assessment process, there are several key conceptual questions that must be answered. Quantitative answers to these questions can drive analyses for optimizing the desired outcomes, adjusting components of the expected utility formulation and fixing variables that are difficult to modify (e.g., the cost of an action) to derive the bounds of optimal utility.

For effective development and validation of AI/machine learning applications in health care, one needs to carefully formulate the problem to be solved, taking into consideration the properties of the algorithm (e.g., positive predictive value) and the properties of the resulting action (e.g., effectiveness), as well as the constraints on the action (e.g., costs, capacity), given the clinical and psychosocial environment

If Vera's diagnosis was confirmed and subsequently the CHADS2 risk score indicated a high 1-year risk of ischemic stroke, the utility of treating using anticoagulants has to be determined in the light of the positive predictive value .

Selection of a Learning Approach

The subfield of AI focused on learning from data is known as machine learning. Machine learning can be grouped into three main approaches: (1) supervised, (2) unsupervised, and (3) reinforcement learning. Each approach can address different needs within health care. Supervised learning focuses on learning from a collection of labeled examples. Each example (i.e., patient) is represented by input data (e.g., demographics, vital signs, laboratory results) and a label (such as being diabetic or not). The learning algorithm then seeks to learn a mapping from the inputs to the labels that can generalize to new examples.

There have been many successful applications of super- vised learning to health care. Based on the training data, their system learned which image features were most closely associated with the different diagnoses. Such systems can also be used to train models that predict future events. used supervised learning to learn a mapping from the structured as well as textual contents of the EHR to a patient's risk for mortality, readmission, and diagnosis with specific International Classification of Diseases, Ninth Revision (ICD-9) codes by discharge .This method of training a model is popular in settings with a clear outcome and large amounts of labeled data. However, obtaining labeled data is not always straightforward.

Unambiguous labels may be difficult to obtain for a number of reasons: the outcome or classification may be ambiguous, with little agreement; the labeling process may be labor intensive and costly; or labels may simply be unavailable. In many settings, there may not be a large enough dataset to confidently train a model. In such settings, weakly supervised learning can be leveraged when noisy, weak signals are avail- able. For example, to mitigate the burden of expensive annotations, one study used weak supervision to learn a severity score for acute deterioration.

In another study where it was not possible to acquire gold-standard labels, weak supervision was used to learn a disease progression score for Parkinson's. Various other strategies, including semi-supervised learning and active learning, can be deployed to reduce the amount of labeled data needed.

Unsupervised learning seeks to examine a collection of unlabeled examples and group them by some notion of shared commonality. Clustering is one of the common unsupervised learning tasks. Clustering algorithms are largely used for exploratory purposes and can help identify structure and substructure in ’the data. For example, Williams et al. clustered data pertaining to more than 10,000 pediatric intensive care unit admissions, identifying clinically relevant clusters. Unsupervised learning can also be used to stage or subtype heterogeneous disease Here, the difficulty lies not in obtaining the grouping— although such techniques similarly suffer from small datasets—but in evaluating it.

When given a dataset and a clustering algorithm, we always get a grouping. The challenge, then, is whether the presence of the groups (i.e., clusters) or learning that a new patient is deemed a member of a certain group is action- able in the form of offering different treatment options. Most often, the ability to reproduce the same groups in another dataset is considered a sign that the groups are medically meaningful and perhaps they should be managed differently. If the fact that a new record belongs to a certain group allows an assignment of higher (or lower) risk of specific outcomes, that is considered a sign that the learned groups have meaning. For example, Shah et al. analyzed a group of roughly 450 patients who had heart failure with preserved ejection fraction in order to find three subgroups. In data that were not used to learn the groups, application of the grouping scheme sorted patients into high, medium, and low risk of subsequent mortality.

Reinforcement learning differs from supervised and unsupervised learning, because the algorithm learns through interacting with its environments rather than through observational data alone. Such techniques have had recent successes in game settings. In games, an agent begins in some initial stage and then takes actions affecting the environment (i.e., transitioning to a new state) and receiving a reward. This framework mimics how clinicians may interact with their environment, adjusting medication or therapy based on observed effects. Reinforcement learning is most applicable in settings involving sequential decision making where the reward may be delayed (i.e., not received for several time steps).

Although most applications consider online settings, recent work in health care has applied reinforcement learning in an offline setting using observational data. Reinforcement learning holds promise, although its current applications suffer from issues of confounding and lack of actionability.

Learning A Model

To illustrate the process of learning a model, we focus on a supervised learning task for risk stratification t in health care. Assume we have n patients. Each patient is represented by a d-dimensional feature vector that lies in some feature space X In addition, each patient has some label, y, representing that patient's outcome or condition (such as being diabetic or not). In some settings, we may have only a single label for each patient; in others we may have multiple labels that vary over time. We begin with the simple case of only a single binary label per patient. The task is to learn a mapping from the vector X to y. This mapping is called the model and is performed by a learning algorithm such as stochastic gradient descent.

As discussed earlier, the degree to which the resulting model is causal is the degree to which it is an accurate representation of the true underlying process, denoted by f(x) in. Depending on the data available, the degree of prior knowledge used in constraining the model's structure, and the specific learning algorithm employed, we learn models that support differing degrees of causal interpretation.

Once the model is learned, given a new patient represented by a feature vector, we can then estimate the probability of the outcome. The data used to learn the model are called training data, and the new data used to assess how well a model performs are the test data. Training data are often further split into training and validation subsets. Model selection, which is the selection of one specific model from among the many that are possible given the training data, is performed using the validation data.

Key Definitions in Model Development

- **Training dataset:** A dataset of instances used for learning parameters of a model.
- **Validation dataset:** A dataset of instances used to tune the hyperparameters of a model.
- **Test dataset:** A dataset that is independent of the training dataset but follows the same dis-attribution as the training dataset. If part of the original dataset is set aside and used as a test set, it is also called **holdout dataset.**
- **K-fold cross validation:** A dataset is randomly partitioned into K parts and one part is set for testing, and the model is trained on the remaining K-1 parts, and the, the model is evaluated on holdout part.
- **External cross validation:** Perform cross validation across various settings of model parameters and report the best result.
- **Internal cross validation:** Perform cross-validation on the training data and train a modelon the best set of parameters.
- **Sensitivity:** Proportion of actual positives that are correctly identified in a binary classification. It is also called the **true positive rate (TPR),** the **recall**, or **probability of detection.**
- **Specificity:** Proportion of actual negatives that are correctly identified in a binary classification.It is also called the **true negative rate.**
- **Precision:** Proportion of predicted positives that are true positives. It is also called the positive predictive value.
- **Accuracy:** Proportion of correctly identified instances among all instances examined.
- **Receiver operating characteristic (ROC) curve:** Graphical plot created by plotting **the TPR** against the false positive rate. The **area under the ROC curve (AUROC)** is a measure how well a parameter setting can distinguish between two groups.
- **Precision-recall (PR) curve:** Graphical plot created by plotting the precision against the recall to show the trade-off between precision and recall for different parameter settings. The **area under the PR curve** is a better measure for highly imbalanced classification task.
-

Choosing the Data to Learn From

Bad data will result in bad models, recalling the age-old adage “garbage in, garbage out”. There is a tendency to hype AI as something magical that can learn no matter what the inputs are. In practice, the choice of data always trumps the choice of the specific mathematical formulation of the model.

In choosing the data for any model learning exercise, the outcome of interest (e.g., inpatient mortality) and the process for extracting it (e.g., identified using chart review of the discharge summary note) should be described in a reproducible manner. If the problem involves time-series data, the time at which an outcome is observed and recorded versus the time at which it needs to be predicted have to be defined upfront. The window of data used to learn the model and the amount of lead time needed from the prediction should be included.

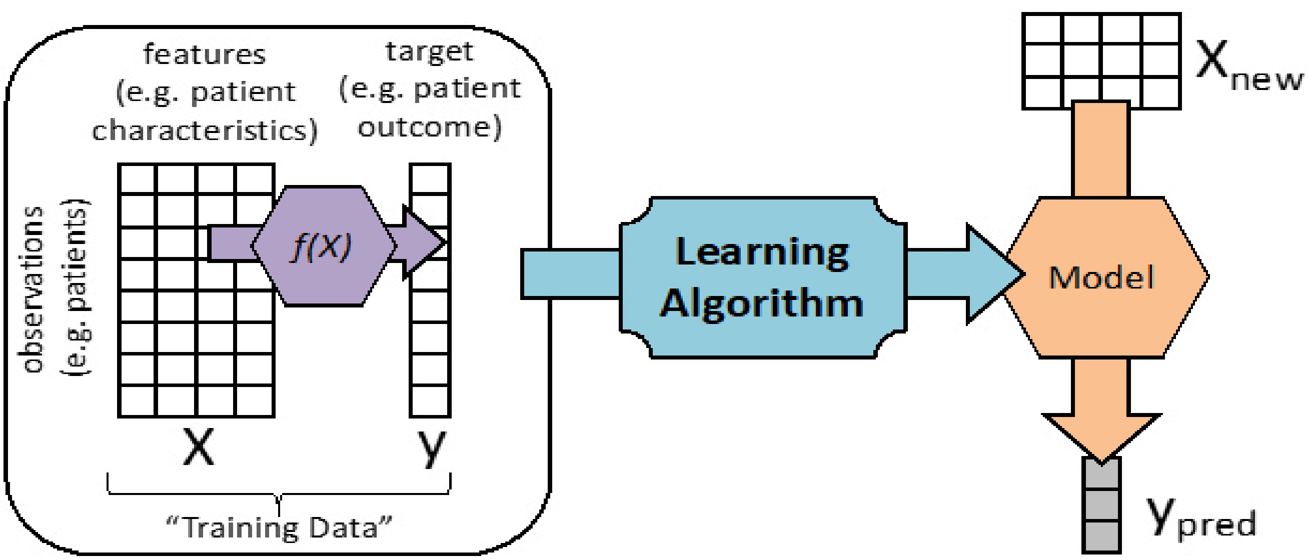

FIGURE 4.2 | Definition the model.

The model: -

A model is a map from inputs *(X)* to an output *(y)*—mathematically, a function. We implicitly assume that there is a real data generating function, *f(x)*, which is unknown and is what we are trying to repre- sent at varying degrees of fidelity.

It is necessary to provide a detailed description of the process of data acquisition, the criteria for sub selecting the training data, and the description and prevalence of attributes that are likely to affect how the model will perform on a new dataset. For example, when building a predictive model, subjects in the training data may not be representative of the target population (i.e., selection bias). Meanwhile, errors in measuring exposure or disease occurrences can be an important source of bias (i.e., measuring bias) especially when using EHR data as a source of measurements. Both selection bias and measurement bias can affect the accuracy as well as generalizability of a predictive model learned from the data.

The degree to which the chosen data affect generalization of a model learned from it depends upon the method used for modeling and the biases inherent in the data during their acquisition. For example, models can be susceptible to provider practice patterns; most models trained using supervised learning assume that practice patterns in the new environment are similar to those in the development environment. The degree of left censoring, right censoring, or missingness can also affect generalization. Finally, the processes by which the data are generated and collected also change over time. This change, known as nonstationary in the data, can have a significant effect on model performance. Using stale data can lead to suboptimal learning by models, which then get labeled as biased or unfair.

The decisions made during the creation and acquisition of datasets will be reflected in downstream models. In addition to knowing the final features representing patient data, any processing steps should be clearly documented and made available with the model. Such data-wrangling steps (e.g., how one dealt with missing values or irregularly sampled data) are often overlooked or not reported. The choices made around data preparation and transformation into the analytical data presentation can contribute significantly to bias that then gets incorporated into the AI algorithm.

Often, the users of the model’s output hold the model itself responsible for such biases, rather than the underlying data and the model developer’s design decisions surrounding the data. In nonmedical fields, there are numerous examples in which model use has reflected biases inherent in the data used to train them. For example, programs

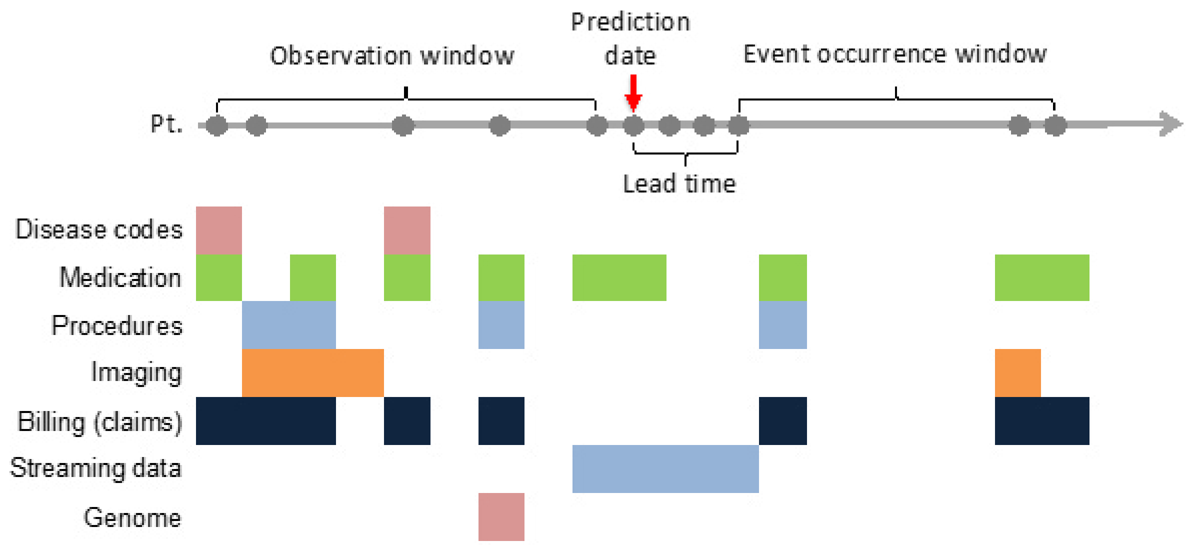

FIGURE 4.3 | Patient timeline and associated data gathering opportunities

Specific events in the time line are denoted by gray circles. The colored portions of the time line below the gray line show the different types of data that may be collected at different encounters and the fact that not everything is collected at the same time. Almost no data source provides a continuous measurement of the patient's health exception data streams of intensive care unit monitors used in short stretches. (Wearables increasingly promise such continuous data but their use in health care is just beginning.) The red arrow shows a chosen point in the time line where a prediction attempt is made.

Only data prior to that are available for model learning for that prediction. Each prediction offers the chance of taking some action before the predicted event happens. The time interval between the pre- diction date and the soonest possible occurrence of the predicted event indicates the lead time avail- able to complete the necessary mitigating action.

designed to aid judges in sentencing by predicting an offender's risk of recidivism have shown racial discrimination. In health care, attempts to use data from the Framingham Heart Study to predict the risk of cardiovascular events in minority populations have led to biased risk estimates. Subtle discrimination inherent in health care delivery may be harder to anticipate; as a result, it may be more difficult to prevent an algorithm from learning and incorporating this type of bias.

Such biases may lead to self-fulfilling prophesies: If clinicians always withdraw care from patients with certain findings (e.g., extreme prematurity or a brain injury), machine learning systems may conclude that such findings are always fatal. (Note that the degree to which such biases may affect actual patient care depends on the degree of causality ascribed to the model and to the process of choosing the downstream action.

Learning Setup

In the machine learning literature, the dataset from which a model is learned is also called the training dataset. Sometimes a portion of this dataset may be set aside for tuning hyperparameters—the weights assigned to different variables and their combinations. This portion of the training data is referred to as the hyperparameter-validation dataset, or often just the validation dataset. The validation dataset confirms whether the choices of the values of the parameters in the model are correct or not. Note that the nomenclature is unfortunate, because these validation data have nothing to do with the notion of clinical validation or external validity.

Given that the model was developed from the training/validation data, it is necessary to evaluate its performance in classifying or making predictions on a "holdout" test set. This test set isheld out in the sense that it was not used to select model parameters or hyperparameters. The test setshould be as close as possible to the data that the model would be applied to in routine use. The choice of metrics used to assess a model's performance is guided by the end goal of the modeling as well as the type of the learning being conducted (e.g., unsupervised versus supervised). Here, we focus on metricsfor supervised binary classifiers (e.g., patient risk stratification tools). The estimation of metrics can beobtained through cross validation where the whole dataset is split randomly into multiple parts with one part set as the test set and the remaining parts used for training a model.

Choosing Metrics of Model Performance

Recall and precision are two of the most debated performance metrics because they exhibit varying importance based on the use case. Sensitivity quantifies a classifier's ability to identify the true positive cases. Typically, a highly sensitive classifier can reliably rule out a disease when its result is negative. Precision quantifies a classifier's ability to correctly identify a true positive case— that is, it estimates the number of times the classifier falsely categorizes a noncash as a case. Specie- fixity quantifies the portion of actual negatives that are correctly identified as such.

There is a trade-off between the recall, precision, and specificity measures, which needs to be resolved based on the clinical question of interest. For situations where we cannot afford to miss a case, high sensitivity is desired. Often, a highly sensitive classifier is followed up with a highly specific test to identify the false positives among those flagged by the sensitive classifier. The trade-off between specificity and sensitivity can be visually explored in the receiver operating characteristic (ROC) curve.

The area under the ROC (AUROC) curve is the most popular index for summarizing the information in the ROC curves. When reporting results on the holdout test set, we recommend going beyond the AUROC curve and instead reporting the entire ROC curve as well as the sensitivity, specificity, positive predictive value, and negative predictive value at a variety of points on the curve that represent reasonable decision-making cutoffs However, the limitations of the ROC curves are well known even though they continue to be widely used. Despite the popularity of AUROC curve and ROC curve for evaluating classifier performance, there are other important considerations.

First, the utility offered by two ROC curves can be wildly different, and it is possible that classifiers with a lower overall AUROC curve have higher utility based on the shape of the ROC curve. Second, in highly imbalanced datasets, where negative and positive labels are not distributed equally, a precision-recall (PR) curve provides a better basis for comparing classifiers. Therefore, in order to enable meaningful comparisons, researchers should report both the AUROC curve and area under the PR curve, along with the actual curves, and error bars around the average classifier performance.

For decision making in the clinic, additional metrics such as calibration, net reclassification, and a utility assessment are necessary While the ROC curves provide information about a classifier's ability to discriminate a true case from a noncash, calibration metrics quantify how well the predicted probabilities, of a true case being a case, agree with observed proportions of cases and no cases. For a well-calibrated classifier, 90 of 100 samples with a predicted probability of 0.9 will be correctly identified true cases.

When evaluating the use of machine learning models, it is also important to develop parallel base- lines, such as a penalized regression model applied on the same data that are supplied to more sophis- ticated models such as deep learning or random forests. Given the non-obvious relationship between a model's positive predictive value, recall, and specificity to its utility, having these parallel models provides another axis of evaluation in terms of cost of implementation, interpretability, and relative performance.

Aside from issues related to quantifying the incremental value of using a model to improve care delivery, there are methodological issues in continuously evaluating or testing a model as the under- lying data change. For example, a model for predicting 24-hour mortality could be retrained every week or every day as new data become available. It is unclear which metrics of the underlying data as well as of the model performance we should monitor to manage such continuously evolving models. It is also unclear how to set the retraining schedule, and what information should guide that decision. The issues of model surveillance and implementation are more deeply addressed in.

Data Quality

A variety of issues affect data integrity in health care. For example, the software for data retrieval, preprocessing, and cleaning is often lost or not maintained, making it impossible to re-create the same dataset. In addition, the data from the source system(s) may have been discarded or may have changed. The problem is further compounded by fast-changing data sources or changes over time in institutional data stores or governance procedures.

Finally, silos of expertise and access around data sources create dependence on individual people or teams. When the collection and provenance of the data that a model is trained on is a black box, researchers must compensate with reliance on trusted individuals or teams, which is suboptimal and not sustainable in the long run. Developing AI based on bad data further amplifies the potential negative impacts of poor-quality data. Consider, for example, that race and ethnicity information is simply not recorded, is missing, or is wrong in more than 30 to 40 percent of the records at most medical centers.

Given the poor quality of these data, arguments about unfairness of predictive models for ethnic groups remain an academic discussion. As a community, we need to address the quality of data that the vast majority of the enterprise is collecting. The quality is highly variable and acknowledging this variability as well as managing it during model building is essential. To effectively use AI, it is essential to follow good data practices in both the creation and curation of retrospective datasets for model training and in the prospective collection of the data. The quality of these data practices affects the development of models and the successful implementation at the point of care.

It is widely accepted that the successful development of an AI system requires high-quality data. However, the assessment of the quality of data that are available and the methodology to create a high- quality dataset are not standardized or often are nonexistent. Methods to assess data validity and repro- educability are often ad hoc. Efforts made by large research networks such as the Observational Health Data Science and Informatics collaborative as well as the Sentinel project have begun to outline quality assurance practices for data used to train AI models. Ideally, data should be cross validated from multiple sources to best determine trustworthiness. Also, multiple subject matter experts should be involved in data validation (for both outcome and explanatory variables). In manually abstracted and annotated datasets, having multiple trained annotators can provide an accurate assessment of the ambiguity and variability inherent in data. For example, when tasked with identifying surgical site infection, there was little ambiguity whether infection was present or not; however, there was little agreement about the severity of the infection.

Insufficiently capturing the provenance and semantics of such outcomes in datasets is at best inefficient. At worst, it can be outright dangerous, because datasets may have unspecified biases or assumptions, leading to models that produce inappropriate results in certain contexts. Ultimately, for the predictions (or classifications) from models to be trusted for clinical use, the semantics and provenance of the data used to derive them must be fully transparent, unambiguously communicated, and available for validation.

An often-missed issue around data is that the data used for training the model must be such that they are actually available in the real-world environment where the AI trained on the data will be used. For example, an AI analyzing electrocardiogram (ECG) waveforms must have a way to access the wave- forms at the point of care. For instance, waveforms captured on a Holter monitor may not be available for clinical interpretation for hours, if not days, due to the difficulty of processing the large amount of data, whereas an irregular heart rhythm presenting on a 12-lead ECG may be interpreted and acted upon within minutes.

Therefore, AI development teams should have information technology (IT) engineers who are knowledgeable about the details of when and where certain data become available and whether the mechanics of data availability and access are compatible with the model being constructed. Another critical point is that the acquisition of the data elements present in the training data must be possible without major effort. Models derived using datasets where data elements are manually abstracted (e.g., Surgical Risk Calculator from the American College of Surgeons) cannot be deployed without significant investment by the deploying site to acquire the necessary data elements for the patient for whom the model needs to be used.

While this issue can be overcome with computational phenotyping methods, such methods struggle with portability due to EHR system variations resulting in different reporting schemes, as well as clinical practice and workflow differences. With the rise of interoperability standards such as FHIR, the magnitude of this problem is likely to decrease in the near future. When computationally defined phenotypes serve as the basis for downstream analytics, it is important that computational phenotypes themselves be well managed and clearly defined and
adequately reflect the target domain.

As a reasonable starting point for minimizing the data quality issues, data should adhere to the FAIR (findability, accessibility, interoperability, and reusability) principles in order to maximize the value of the data Researchers in molecular biology and bioinformatics put forth these principles, and, admittedly, their applicability in health care is not easy or straightforward.

One of the unique challenges (and opportunities) facing impactful design and implementation of AI in health care is the disparate data types that comprise today’s health care data. Today’s EHRs and wear- able devices have greatly increased the volume, variety, and velocity of clinical data. The soon-to-be in-clinic promise of genomic data further complicates the problems of maintaining data provenance, timely availability of data, and knowing what data will be available for which patient at what time.

Always keeping a time-line view of the patient’s medical record is essential as is explicitly knowing the times at which the different data types, across different sources come into existence. It stands to reason that any predictive or classification model operating at a given point in the patient time line can only expect to use data that have come into being prior to the time at which the model is used Such a real-life view of data availability is crucial when building models, because using clean data gives an overly optimistic view of models’ performance and an unrealistic impression of their potential value. Finally, we note that the use of synthetic data, if created to mirror real-life data in its missingness and acquisition delay by data type, can serve as a useful strategy for a model builder to create realistic training and testing environments for novel method.

Education

It is critical that we educate the community regarding data science, AI, medicine, and health care. Progress is contingent on creating a critical mass of experts in data science and AI who understand the mission, culture, workflow, strategic plan, and infrastructure of health care institutions.

As decision makers in health care institutions invest in data, tools, and personnel related to data science and AI, there is enormous pressure for rapid results. Such pressures raise two extremes of issues. On the one hand, the relative ease of implementing newly developed AI solutions rapidly can lead to the implementation of solutions in routine clinical care without an adequate understanding of their validity and potential influence on care, raising the potential for wasted resources and even patient harm On the other hand, holding the AI models to superhuman standards and constantly requiring that evaluations outcompete doctors is also a flawed attitude that could lead to valuable solutions never getting implemented.

Vendors of health care IT have an incentive to over- state the value of data science and AI generally. Limited attention has been given to the significant risk of harm, from wasting resources as well as from relying on evaluation strategies decoupled from the action they influence. or relying evaluation regimes that avoid simple and obvious base- line comparisons.

Key Considerations

The rapid increase in the volume and variety of data in health care has driven the current interest in the use of AI. There is active discussion and interest in addressing the potential ethical issues in using AI, the need for humanizing AI, the potential unintended consequences, and the need to tamper the hype. However, more discovery and work in these areas are needed. The way that AI is developed, evaluated, and utilized in health care needs to change. At present, most of the existing discussion focuses on evaluating the model from a technical standpoint. A critically underassessed area is the net benefit of the integration of AI into clinical practice workflow.

Establishing Utility

When considering the use of AI in health care, it is necessary to know how one would act given a model's output. While model evaluation typically focuses on metrics such as positive predictive value, sensitivity (or recall), specificity, and calibration, constraints on the action triggered by the model's output (e.g., continuous rhythm monitoring constraint based on availability of Holter monitors) often can have a much larger influence in determining model utility. Completing model selection, then doing a net-benefit analysis, and later factoring work constraints are suboptimal. Realizing the benefit of using AI requires defining potential utility upfront. Only by including the characteristics of actions taken on the basis of the model's predictions, and factoring in their imply-cations, can a model's potential usefulness in improving care be properly assessed.

Model Learning

After the potential utility has been established, model developers and model users need to interact closely during model learning because many modeling choices are dependent on the context of use of the model .For example, the need for external validity depends on what one wishes to do with the model, the degree of agency ascribed to the model, and the nature of the action triggered by the model.

It is well known that biased data will result in biased models; thus, the data that are selected to learn from matter far more than the choice of the specific mathematical formulation of the model. Model builders need to pay closer attention to the data they train on and need to think beyond the technical evaluation of models. Even in technical evaluation, it is necessary to look beyond the ROC curves and examine multiple dimensions of performance. For decision making in the clinic, additional metrics such as calibration, net reclassification, and a utility assessment are necessary.

Given the non- obvious relationship between a model's positive predictive value, recall, and specificity to its utility, it is important to examine simple and obvious parallel baselines, such as a penalized regression model applied on the same data that are supplied to more sophisticated models such as deep learning.

The topic of interpretability deserves special discussion because of ongoing debates around inter- pretability, or the lack of it). To the model builder, inter- pretability often means the ability to explain which variables and their combinations, in what manner, led to the output produced by the model. To the clinical user, interpretability could mean one of two things: a sufficient enough understanding of what is going on, so that they can trust the output and/or be able to get liability insurance for its recommendations; or enough causality in the model structure to provide hints as to what mitigating action to take. To avoid wasted effort, it is important to understand what kind of interpretability is needed in a particular application. A black box model may suffice if the output was trusted, and trust can be obtained by prospective assessment of how often the model's predictions are correct and calibrated.

Data Quality

Bad data quality adversely affects patient care and outcomes. A recent system- atic review shows that the AI models could dramatically improve if four particular adjustments were made: use of multicenter datasets, incorporation of time-varying data, assessment of missing data as well as informative censoring, and development of metrics of clinical utility. As

a reasonable starting point for minimizing the data quality issues, data should adhere to the FAIR (find- ability, accessibility, interoperability, and reusability) principles in order to maximize the value of the data. An often-overlooked detail is when and where certain data become avail- able and whether the mechanics of data availability and access are compatible with the model being constructed. In parallel, we need to educate the different stakeholders, and the model builders need to understand the datasets they learn from.

Big data

Big data as an abstract concept currently affects all walks of life, and although its importance has been recognized, its definition varies slightly from field to field. In the field of computer science, big data refers to a dataset that cannot be perceived, acquired, managed, processed, or served within a given time by using traditional IT, software and hardware tools.

Across the medical industry, various types of medical data are generated at high speed. The sources of big data in healthcare are such as; mobile data and wearable devices, academic researches, electronic hospital records, medical claims, pharmacy claims, and government medical claims. Trends indicate that applying big data in the medical field helps to improve the quality of medical care and optimizes medical processes and management strategies.

Data mining

Computer scientists have made outstanding contributions to the application of big data and introduced the concept of data mining to solve difficulties associated with applications. Data mining (also known as knowledge discovery in databases) is the process of analyzing a massive amount of data to identify meaningful patterns and detect relations, which can lead to future trend prediction and appropriate decision making.

Data mining is a step in Knowledge Discovery in Database (KDD) which consists of data selection, data-pre-processing, data transformation, data mining, interpretation or evaluation of the model and using the discovered knowledge.

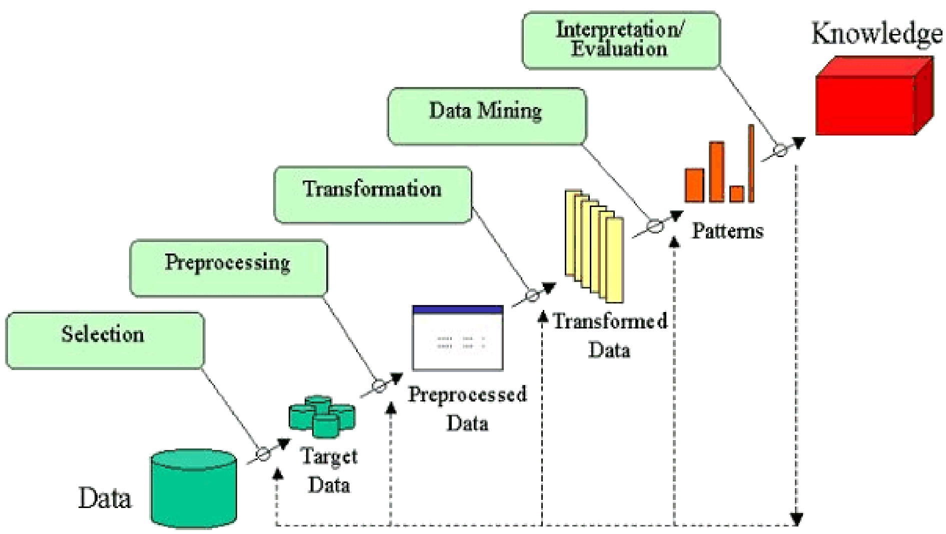

FIGURE 4.4 | Steps of Knowledge discovery in

Data-mining technology does not aim to replace traditional statistical analysis techniques, but it does seek to extend and expand statistical analysis methodologies. Data mining technologies have been applied widely in various fields such as; marketing, telecommunication, disease detection, fraud detection, financial data analysis, intrusion detection, recommender systems, medical systems etc.

Role of data mining in healthcare

Recently, Data Mining is becoming popular and widely used in the healthcare sector because there is a demand for powerful and intelligent analytical methodology that can handle and analyze complex health data to make certain decisions regarding patient health. Data mining provides several benefits such as;

1. Recognize and discover chronic diseases, their symptoms, possible reasons and identify medical treatment methods.
2. Grouping the patients having the same type of health issues or diseases so that healthcare providers can give them effective treatments.
3. It can be used for predicting the duration of the survival of patients in the hospital for medical diagnosis.
4. It can help the healthcare providers to determine effective treatments and best practices as well as to develop guidelines and care protocols.
5. The analysis can be further extended for tracking of high-risk areas which are vulnerable to spread the diseases.
6. It can assist the healthcare researchers for making efficient healthcare policies, designing drug recommendation systems, identifying risk factors, complications, therapies, genetic effects, and environmental effects of diseases.

Data mining tasks

Data mining tasks can be divided into two categories which are descriptive and predictive .Descriptive mining tasks explore the general properties of data so that it can discover the relationship relating the data and results in a few clusters with the same or similar attributes .In contrast, predictive mining tasks perform deduction on the current data in order to make predictions about the variable value of a specific attribute based on the variable values of other attributes.

Hardware

Components:

The hardware part consists of several parts, we will explain that

1- screen: The screen is used to display the application and display the result of diseases.
2- wireless keyboard: To control the application, the keyboard has a touchpad.
3- device: Where there are project components for easy control and display.
4- Wires: It is used in connections between components and the source of electricity.
5- Fan; to cool the device.
6- board: Where there is an app, it is the main control unit in the device The material of the device is aluminum, and the dimensions of the device are about a meter in length by half a meter in width with a height of about 15 cm It was made to be easy to control and easy to transport from one place to another.

FIGURE 4.5 | Implementation of the hard ware in nature

Chapter 5: Conclusions and Future Work

Stakeholder Education and Managing Expectations

The use of AI solutions presents a wide range of legal and ethical challenges, which are still being worked out. For example, when a physician makes decisions assisted by AI, it is not always clear where to place blame in the case of failure. This subtlety is not new to recent technological advancements, and in fact was brought up decades ago. However, most of the legal and ethical issues were never fully addressed in the history of computer-assisted decision support, and a new wave of more powerful AI-driven methods only adds to the complexity of ethical questions.

The model builders need to better understand the datasets they choose to learn from. The decision makers need to look beyond technical evaluations and ask for utility assessments. The media needs to do a better job in articulating both immense potential and the risks of adopting the use of AI in health care. Therefore, it is important to promote a measured approach to adopting AI technology, which would further AI's role as augmenting rather than replacing human actors. This framework could allow the AI community to make progress while managing evaluation challenges as well as ethical challenges that are bound to arise as the technology gets widely adopted.

Feature extraction

In a machine learning-based model or system, feature extraction techniques usually provide a better understanding of the data, a way to improve prediction accuracy, and to reduce computational cost or training time. The aim of feature extraction is to reduce the number of features in a dataset by generating new ones from the existing ones and then discarding the original features. The majority of the information found in the original set of features can then be summarized using this new reduced set of features.

With the increasing rate of data generation in various areas of human life, knowledge extraction from the generated data is strongly needed. In healthcare sector, the huge amount of hospital and clinical data has a great potential for discovering relations and hidden patterns.

Artificial intelligence (AI), particularly, machine learning (ML) have grown rapidly in recent years in the context of data analysis and computing that typically allows the applications to function in an intelligent manner. ML usually provides systems with the ability to learn and enhance from experience automatically without being specifically programmed. Various types of machine learning algorithms such as supervised, unsupervised, semi-supervised, and reinforcement learning exist in the

area. Besides, the deep learning, which is part of a broader family of machine learning methods, can intelligently analyze the data on a large scale. In healthcare field, data mining methods reduce time and cost in detection and diagnosis of diseases. It also has a special role in the treatment plan and medical decisions and helps construct accurate and reliable models Relationship of the project to the environment In light of the state's orientation towards digital transformation and the permanent reference of the President in all conferences on the importance of digital transformation in Egypt 2030.

Our start was to think about a project that serves this transformation and orientation from the state because of its impact on making life easier and faster. Our choice was in the field of health. As we know, the world has been exposed to the Corona pandemic in the past years. So far, it has made the number of doctors required more and more. At the present time, and due to the spread of diseases and epidemics such as the spread of the Corona virus and the increase in doctors' injuries due to overcrowding in hospitals, we have lost a lot of medical staff and also the presence of human errors that lead to major problems and may lead to the loss of many lives, and because of these problems we have tried to solve them and help the medical field using artificial intelligence And machine learning and data analysis and we collected data on many diseases and then used algorithms in order to enter the analyses of the patient into the device and then show the results and know whether he had this disease or not, Also, the state's attempt to use technological developments in everything we used in treating diseases and the emergence of results with high accuracy and this is one of Egypt's 2030 goals .

Future plan

In the future, we expect that this device will be used on a large scale by all doctors in all hospitals, and it will be easy to add any new disease to it and link it to the project site to be easy to update and communicate with users of the device and we will update and improve it by adding a scanner and printer to scan x-rays and print the results. It can also be programmed to read rays directly. A printer can also be added to make the hardware easier to use, we will also change the color, create new hinges, and change the manufacturing material to plastic to be light. We will also connect it to the hospital system to save time and effort and will facilitate our lives as well as the lives of our docto

Appendix

IEEE Standard for Personal Data Artificial Intelligence (AI) P7006

This standard describes the technical elements required to create and grant access to a personalized Artificial Intelligence (AI) thatwill comprise inputs, learning, ethics, rules and values controlled by individuals.

Purpose: With the advent and rise of AI there is a risk that machine-to-machine decisions will be made with black-box inputs determined without input transparency to humans. In order to enable ethics-based AI, individuals will require the means to influence and determine the values, rules and inputs that guide the development of personalized algorithms and Artificial Intelligence. They will need an agent that can negotiate their individual rights and agency in a system of shared social norms, ethics and human rights that also foresee and helps the individual mitigate ethical implications of data processing. This approach will enable individuals to safely organize and share their personal information at a machine-readable level and enable a personalized AI to act as a proxy for machine-to-machine decisions. A key goal for the creation of this standard is to educate government and commercial actors why it is in their best interests to create the mechanisms for individuals to train Personal AI Agents to move beyond asymmetry and harmonize personal data usage for the future. Need for the Project: The most pressing pragmatic reason for Personalized AI comes in the form of The EU General Data Protection Regulation (GDPR). Beginning 25 May 2018 all global organizations need to demonstrate compliance on how they handle EU citizen data and empower the individual in data exchanges or risk facing heavy fines (up to four percent of their gross revenues).

If citizens are empowered through AI that is coordinated with GDPR and other privacy regulations they can direct how their data, devices and location are accessed and used. In conjunction with data reported by organizations in compliance with European Union regulators, these direct insights would accelerate trust-driven business and economic practices around the world while providing metrics that could be utilized in multiple other areas beyond commerce including medicine, insurance, and autonomous and intelligent technologies. While the GDPR provides a core need for this standard to be created, it should be noted that the standards for developing personal AI agents would be designed to be universal in their application for any country or organization to utilize. This standard will articulate a range of ways data, access and permission can be granted to government, commercial, or other actors that allows for technical flexibility, transparency, and informed consensus for individuals. Stakeholders for the Standard: The primary stakeholders for this standard are the individuals whose information is utilized for any data interaction, but also includes the academics, engineers, programmers, marketers or technologists of any kind wishing to utilize said data.

Parkinson code

```
# -*- mode: python ; coding: utf-8 -*-
block_cipher = None
a = Analysis(['application_sc', 'application_sc.spec'],
             pathex=[],
             binaries=[],
             datas=[],
             hiddenimports=[],
             hookspath=[],
             hooksconfig={},
             runtime_hooks=[],
             excludes=[],
             win_no_prefer_redirects=False,
             win_private_assemblies=False,
             cipher=block_cipher,
             noarchive=False)
pyz = PYZ(a.pure, a.zipped_data,
             cipher=block_cipher)
exe = EXE(pyz,
          a.scripts,
          a.binaries,
          a.zipfiles,
          a.datas,
          [],
          name='application_sc',
          debug=False,
          bootloader_ignore_signals=False,
          strip=False,
          upx=True,

          upx_exclude=[],
```

```
runtime_tmpdir=None,
console=True,
disable_windowed_traceback=False,
target_arch=None,
codesign_identity=None,
entitlements_file=None , icon='icon.ico')
```

Breast cancer code

```
# -*- coding: utf-8 -*-
"""
Created on Mon Apr 20 22:33:00 2020

@author: bustami
"""


import numpy as np
import cv2
import tensorflow as tf



from numpy import *
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
from tkinter import *
from PIL import ImageTk, Image
from tkinter import filedialog




def wrt(st,fname):
    file = open(fname,"w+")
    file.write(st)
    file.close()
```

```
def red(fname):
    file = open(fname,"r")
    f=file.read()
    file.close()
    return f


def open_img():
   try:
      x = openfilename()
      wrt(x,"upload");print(x);
      img =Image.open(x)
   except:
      x = 'images/error.png'
      print(x);
      img =Image.open(x)
   img = img.resize((325, 200), Image.ANTIALIAS)
   img = ImageTk.PhotoImage(img)
   panel = Label(root, image = img)
   panel.image = img
   panel.place(x=455, y=100)


from tkinter.filedialog import askopenfilename
def openfilename():
   filename = askopenfilename(title ='UPLOAD IMAGE')
   return filename


def browsefunc():
    filename = askopenfilename(filetypes=(("jpg file", "*.jpg"), ("png file",'*.png'), ("All files", "*.*"),))
```

```
    print("filename",filename)
    return filename



def callback():
  patient="\n IMAGE FILE NOT UPLOADED..."
  try:
    model = load_model('models/breast_cancer_model.h5')

    #test_image=image.load_img(red("upload"),target_size=(128,128,3)) # 128
    #test_image=image.img_to_array(test_image)
    #test_image=expand_dims(test_image,axis=0)
    #result = model.predict(test_image)

    IMAGE_CHANNEL = 1
    IMG_SIZE = 128
    filepath = browsefunc()

    img_array = cv2.imread(filepath, cv2.IMREAD_GRAYSCALE)
    new_array = cv2.resize(img_array, (IMG_SIZE, IMG_SIZE))
    new_array = new_array.reshape(-1, IMG_SIZE, IMG_SIZE, IMAGE_CHANNEL)

    x = tf.keras.Input(shape=(128,128,IMAGE_CHANNEL))

    result = model.predict([new_array])
    print("prediction",result)

    patient= ""
    if int(result[0][0])==1:
            patient = "BENIGN"
    elif int(result[0][1])==1:
```

```
      patient = "MALIGNANT"
    else:
      patient = "NORMAL"

    output.set("\n "+patient+" TISSUE DETECTED !\n");print(patient)
  except Exception as e:
    output.set(patient);print(e)

# [1,0,0] ---> BENIGN
# [0,1,0] ---> MALIGNANT
# [0,0,1] ---> NORMAL

root = Tk()
root.title("BREAST CANCER")
output=StringVar();
#root.attributes('-fullscreen',True)

root.geometry("1250x730")
#root['bg'] = 'black'

background = PhotoImage(file = "images/cover_bc.png")
Label(root,image = background).place(x=0, y=0)

#root.resizable(width = True, height = True)

img =Image.open("images/input.png")
img = img.resize((325, 200), Image.ANTIALIAS)
img = ImageTk.PhotoImage(img)
panel = Label(root, image = img)
panel.image = img
panel.place(x=455, y=100)
```

```
upload = PhotoImage(file = r"images/upload.png")
Button(root, text = "upload",bd=0,highlightthickness=0,image = upload,
       command = open_img).place(x=150, y=150)



Label(root, text="\nOUTPUT\n",
      width=25,
      font=("Bauhaus 93", 20)).place(x=432, y=335)
Label(root, text="",textvariable = output,
           font=("Bauhaus 93", 20)).place(x=432, y=335)



detect = PhotoImage(file = r"images/detect.png")
Button(root, text="detect",bd=0,highlightthickness=0,image = detect,
               command = callback).place(x=150,y=340)
close = PhotoImage(file = r"images/home.png")
Button(root, text = "close",image = close,highlightthickness=0,
               command = root.destroy).place(x=0,y=0)



root.mainloop()
```

Covid Code

```
# -*- coding: utf-8 -*-
"""
Created on Mon Apr 20 22:33:00 2020

@author: bustami
"""


from numpy import *
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
from tkinter import *
from PIL import ImageTk, Image
#from keras.preprocessing import image

import numpy as np
import cv2
import tensorflow as tf




def wrt(st,fname):
    file = open(fname,"w+")
    file.write(st)
    file.close()




def red(fname):
```

```
    file = open(fname,"r")
    f=file.read()
    file.close()
    return f



def open_img():
   try:
      x = openfilename()
      wrt(x,"upload");print(x);
      img =Image.open(x)
   except:
      x = 'images/error.png'
      print(x);
      img =Image.open(x)
   img = img.resize((325, 200), Image.ANTIALIAS)
   img = ImageTk.PhotoImage(img)
   panel = Label(root, image = img)
   panel.image = img
   panel.place(x=455, y=100)



from tkinter.filedialog import askopenfilename

def openfilename():
   filename = askopenfilename(title ='UPLOAD IMAGE')
   return filename



def browsefunc():
    filename = askopenfilename(filetypes=(("jpg file", "*.jpg"), ("png file",'*.png'), ("All files", "*.*"),))
```

```
    print("filename",filename)
    return filename

def callback():
  patient="\n IMAGE FILE NOT UPLOADED..."

  model = load_model('models/covid_model.h5')

  IMAGE_CHANNEL = 3
  IMG_SIZE = 64
  filepath = browsefunc()

  #img_array = cv2.imread(filepath, cv2.IMREAD_GRAYSCALE)
  #new_array = cv2.resize(img_array, (IMG_SIZE, IMG_SIZE))
  #new_array = new_array.reshape(-1, IMG_SIZE, IMG_SIZE, IMAGE_CHANNEL)

  #x = tf.keras.Input(shape=(64,64,IMAGE_CHANNEL))

  #result = model.predict([new_array])
  #print("prediction",result)

  test_image = image.load_img(filepath, target_size = (64, 64))
  test_image = image.img_to_array(test_image)
  test_image = np.expand_dims(test_image, axis = 0)
  result = model.predict(test_image)
  print("result ",result)



  patient="COVID-19" if result[0][0]==1 else "  NORMAL"
  output.set("\n      "+patient+" DETECTED !\n");print(patient)
  #except:
```

```
  #  output.set(patient);print("EXCEPTION")




root = Tk()
root.title("PNEUMONIA")
output=StringVar();
#root.attributes('-fullscreen',True)
root.geometry("1250x730")


background = PhotoImage(file = "images/cover_pn.png")
Label(root,image = background).place(x=0, y=0)




img =Image.open("images/input.png")
img = img.resize((325, 200), Image.ANTIALIAS)
img = ImageTk.PhotoImage(img)
panel = Label(root, image = img)
panel.image = img
panel.place(x=455, y=100)

upload = PhotoImage(file = r"images/upload.png")
Button(root, text = "upload",bd=0,highlightthickness=0,image = upload,
            command = open_img).place(x=150, y=150)


Label(root, text="\nOUTPUT\n",
          width=25,
          font=("Bauhaus 93", 20)).place(x=432, y=335)
```

```
Label(root, text="",textvariable = output,
                  font=("Bauhaus 93", 20)).place(x=432, y=335)



detect = PhotoImage(file = r"images/detect.png")
Button(root, text="detect",bd=0,highlightthickness=0,image = detect,
                         command = callback).place(x=150,y=340)



close = PhotoImage(file = r"images/home.png")
Button(root, text = "close",image = close,highlightthickness=0,
                         command = root.destroy).place(x=0,y=0)



root.mainloop()
```

Malaria Code

```
# -*- coding: utf-8 -*-
"""
Created on Mon Mar  9 00:58:49 2020

@author: R2J
"""


from numpy import *
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
from tkinter import *
from PIL import ImageTk, Image
from tkinter import filedialog




def wrt(st,fname):
    file = open(fname,"w+")
    file.write(st)
    file.close()




def red(fname):
    file = open(fname,"r")
    f=file.read()
    file.close()
    return f
```

```
def open_img():
   try:
      x = openfilename()
      wrt(x,"upload");print(x);
      img =Image.open(x)
   except:
      x = 'images/error.png'
      print(x);
      img =Image.open(x)
   img = img.resize((325, 200), Image.ANTIALIAS)
   img = ImageTk.PhotoImage(img)
   panel = Label(root, image = img)
   panel.image = img
   panel.place(x=455, y=100)



def openfilename():
   filename = filedialog.askopenfilename(title ='UPLOAD IMAGE')
   return filename



def callback():
  cell="\n IMAGE FILE NOT UPLOADED..."
  try:
    model = load_model('models/malaria.h5')
    #model.summary()
    test_image=image.load_img(red("upload"),target_size=(50,50,3))
    #imgplot = plt.imshow(test_image)
```

```
    #plt.show()
    test_image=image.img_to_array(test_image)
    test_image=expand_dims(test_image,axis=0)

    result = model.predict(test_image)

    cell="PARASITIZED" if result[0][1]==1 else "UNINFECTED"
    output.set("\n "+cell+" CELL DETECTED !\n");print(cell)
  except Exception as e:
    output.set(cell);print(e)




root = Tk()
root.title("MALARIA")
output=StringVar();
#root.attributes('-fullscreen',False)

root.geometry("1250x730")
#root['bg'] = 'black'

background = PhotoImage(file = "images/cover_ml.png")
Label(root,image = background).place(x=0, y=0)

root.resizable(width = True, height = True)

img =Image.open("images/input.png")
img = img.resize((325, 200), Image.ANTIALIAS)
img = ImageTk.PhotoImage(img)
panel = Label(root, image = img)
panel.image = img
```

```
panel.place(x=455, y=100)


upload = PhotoImage(file = r"images/upload.png")
Button(root, text = "upload",bd=0,highlightthickness=0,image = upload,
            command = open_img).place(x=150, y=150)



Label(root, text="\nOUTPUT\n",
          width=25,
          font=("Bauhaus 93", 20)).place(x=432, y=335)
Label(root, text="",textvariable = output,
                  font=("Bauhaus 93", 20)).place(x=432, y=335)



detect = PhotoImage(file = r"images/detect.png")
Button(root, text="detect",bd=0,highlightthickness=0,image = detect,
                         command = callback).place(x=150,y=340)

close = PhotoImage(file = r"images/home.png")
Button(root, text = "close",image = close,highlightthickness=0,
                         command = root.destroy).place(x=0,y=0)



root.mainloop()
```

Conclusions

After all of that we could now recognize the function of this device, we wanted to make something to help people and doctors specially in the future as we all know that while Corona virus period, we have lost a lot of doctors because they have exposed to an extra amount of virus and from that we thought in this device by using machine learning as it can support doctors to diagnose diseases as Heart Attack, Malaria, Breast Cancer, Parkinson and Covid- 19 easily and safely for doctors every day. We have developed a model for predicting and diagnosis these diseases by only entering some data set. A public data set related to all of these diseases has been established. We presented the state of the disease and a wide range of risk factors. We Also provided data related to the age of the patient and the gender and their history with the disease. We have also implemented and integrated all these things into a device using AI so that it can be self-diagnosed without the need for human intervention.

References

[1] Aletras, N. et al. (2016), “Predicting judicial decisions of the European Court of Human Rights: A natural language processing perspective”, PeerJ Computer Science, Vol. 2, p. e93, http://dx.doi.org/10.7717/peerj-cs.93.

[2] Angwin, J. et al. (2016), “Machine bias: There’s software used across the country to predict future criminals. And it’s biased against blacks”, ProPublica, https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing.

[3] Ashby, M. (2017), “The value of CCTV surveillance cameras as an investigative tool: An empirical analysis”, European Journal on Criminal Policy and Research, Vol. 23/3, pp. 441- 459, http://dx.doi.org/10.1007/s10610-017-9341-6.

[4] Barocas, S. and A. Selbst (2016), “Big data’s disparate impact”, California Law Review, Vol. 104, pp. 671-729, http://www.californialawreview.org/wp-content/uploads/2016/06/2Barocas-Selbst.pdf.

[5] Bavitz, C. and K. Hessekiel (2018), Algorithms and Justice: Examining the Role of the State in the Development and Deployment of Algorithmic Technologies, Berkman Klein Center for Internet and Society, https://cyber.harvard.edu/story/2018-07/algorithms-and-justice.

[6] Berg, T. et al. (2018), “On the rise of FinTechs – Credit scoring using digital footprints”, Michael J. Brennan Irish Finance Working Paper Series Research Paper, No. 18-12, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3163781.

[7] Bloom, N. et al. (2017), “Are ideas getting harder to find?”, NBER Working Paper, No. 23782, http://dx.doi.org/10.3386/w23782.

[8] Bösch, P. et al. (2018), “Cost-based analysis of autonomous mobility services”, Transport Policy, Vol. 64, pp. 76-91, https://doi.org/10.1016/j.tranpol.2017.09.005

[9] Bose, A. et al. (2016), "The VEICL Act: Safety and security for modern vehicles", Willamette Law Review, Vol. 53, p. 137.

[10] Brayne, S., A. Rosenblat and D. Boyd (2015), "Predictive policing, data & civil rights: A new era of policing and justice", Pennsylvania Law Review, Vol. 163/327, http://www.datacivilrights.org/pubs/2015-1027/Predictive_Policing.pdf.

[11] Brodeur, S. et al. (2017), "HoME: A household multimodal environment", arXiv 1107, https://arxiv.org/abs/1711.11017.

[12] Brodmerkel, S. (2017), "Dynamic pricing: Retailers using artificial intelligence to predict top price you'll pay", ABC News, 27 June, http://www.abc.net.au/news/2017-06-27/dynamic-pricing-retailers-using-artificial-intelligence/8638340.

[13] Brundage, M. et al. (2018), The Malicious Use of Artificial Intelligence: Forecasting, Prevention, and Mitigation, Future of Humanity Institute, University of Oxford, Centre for the Study of Existential Risk, University of Cambridge, Centre for a New American Security, Electronic Frontier Foundation and Open AI, https://arxiv.org/ftp/arxiv/papers/1802/1802.07228.pdf.

[14] Butler, K. et al. (2018), "Machine learning for molecular and materials science", *Nature*, Vol. 559/7715, pp. 547-555, http://dx.doi.org/10.1038/s41586-018-0337-2.

[15] Canadian Institute for Health Information (2013), "Better information for improved health: A vision for health system use of data in Canada", in collaboration with Canada Health Infoway, http://www.cihi.ca/cihi-ext-portal/pdf/internet/hsu_vision_report_en.

[16] Carey, N. and P. Lienert (2018), "Honda to invest $2.75 billion in GM's self-driving car unit", *Reuters*, 3 October, https://www.reuters.com/article/us-gm-autonomous/honda-buys-in-to- gm-cruise-self-driving-unit-idUSKCN1MD1GW.

[17] CFPB (2017), "CFPB explores impact of alternative data on credit access for consumers who are credit invisible", Consumer Financial Protection Bureau, https://www.consumerfinance.gov/about-us/newsroom/cfpb-explores-impact-alternative-data- credit-access-consumers-who-are-credit-invisible/.

[18] Cheng, E. (2017), "Just 10% of trading is regular stock picking, JPMorgan estimates", *CNBC*, 13 June, https://www.cnbc.com/2017/06/13/death-of-the-human-investor-just-10-percent-of- trading-is-regular-stock-picking-jpmorgan-estimates.html.

[19] Chintamani, P. (26 June 2017), *How banks can use AI to reduce regulatory compliance burdens*, digitally. Cognizant blog, https://digitally.cognizant.com/how-banks-can-use-ai-to- reduce-regulatory-compliance-burdens-codex2710/.

[18] Chow, M. (2017), "AI and machine learning get us one step closer to relevance at scale", *Google*, https://www.thinkwithgoogle.com/marketing-resources/ai-personalized-marketing/.

[19] Christin, A., A. Rosenblatt and D. Boyd (2015), *Courts and Predictive Algorithms*, presentation at the "Data & Civil Rights, A New Era of Policing and Justice" conference, Washington, 27October, http://www.law.nyu.edu/sites/default/files/upload_documents/Angele%20Christin.pdf.

[20] Ciardi, C. (2017), *Video Surveillance and Artificial Intelligence: Can A.I. Fill the Growing Gap Between Video Surveillance Usage and Human Resources Availability?*, Balzano Informatik, http://dx.doi.org/10.13140/RG.2.2.13330.66248.

[21] CMU (2015), "Uber, Carnegie Mellon announce strategic partnership and creation of advanced technologies center in Pittsburgh", *Carnegie Mellon University News*, 2 February, https://www.cmu.edu/news/stories/archives/2015/february/uber-partnership.html.

[22] Comfort, S. et al. (2018), "Sorting through the safety data haystack: Using machine learning to identify individual case safety reports in social-digital media", *Drug Safety*, Vol. 41/6, pp. 579-590, https://www.ncbi.nlm.nih.gov/pubmed/29446035.

[23] Cooke, A. (2017), *Digital Earth Australia*, presentation at the "AI: Intelligent Machines, Smart Policies" conference, Paris, 26-27 October, http://www.oecd.org/going-digital/ai-intelligent-machines-smart-policies/conference-agenda/ai-intelligent-machines-smart-policies-cooke.pdf.

[24] De Jesus, A. (2018), "Augmented reality shopping and artificial intelligence – Near-term applications", *Emerj*, 18 December, https://www.techemergence.com/augmented-reality-shopping-and-artificial-intelligence/.

[25] Fagnant, D. and K. Kockelman (2015), “Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations”, *Transportation Research A: Policy andPractice*, Vol. 77, pp. 167-181, https://www.sciencedirect.com/science/article/pii/S0.

[26]FAO (2017), “Can artificial intelligence help improve agricultural productivity?”, *e-agriculture*, 19 December, http://www.fao.org/e-agriculture/news/can-artificial-intelligence-help-improve-agricultural-productivity.

[27] FAO (2009), *How to Feed the World in 2050*, Food and Agriculture Organization of the United Nations, Rome, http://www.fao.org/fileadmin/templates/wsfs/docs/expert_paper/How_to_Feed_the_World_in_2050.pdf.

[28] FDA (2018), *FDA permits marketing of artificial intelligence-based device to detect certain diabetes-related eye problems*, Food and Drug Administration, News Release, 11 April, https://www.fda.gov/NewsEvents/Newsroom/PressAnnouncements/ucm604357.htm.

[29]Ferguson, A. (2014), “Big Data and Predictive Reasonable Suspicion”, *SSRN Electronic Journal*, http://dx.doi.org/10.2139/ssrn.2394683.

[30] Flores, A., K. Bechtel and C. Lowenkamp (2016), *False positives, false negatives, and false analyses: A rejoinder to “Machine bias: There's software used across the country to predictfuture criminals. And it's biased against blacks“*, Federal probation, 80.

[31]Fridman, L. (8 October 2018), “Tesla autopilot miles”, MIT Human-Centered AI blog, https://hcai.mit.edu/tesla-autopilot-miles/.

[32]Fridman, L. et al. (2018), “MIT autonomous vehicle technology study: Large-scale deep learning based analysis of driver behavior and interaction with automation”, *arXiv*, Vol. 30/September, https://arxiv.org/pdf/1711.06976.pdf.

[33]FSB (2017), *Artificial Intelligence and Machine Learning in Financial Services: Market Developments and Financial Stability Implications*, Financial Stability Board, Basel.

[34]FT (2018), "US and China back AI bug-detecting projects", *Financial Times, Cyber Security and Artificial Intelligence*, 28 September, https://www.ft.com/content/64fef986-89d0-11e8-affd-da9960227309.

[35]Gartner (2017), "Gartner's worldwide security spending forecast", Gartner, Press Release, 7 December, https://www.gartner.com/newsroom/id/3836563.

[36]Gordon, M. and V. Stewart (2017), "CFPB insights on alternative data use on credit scoring", *Law 360*, 3 May, https://www.law360.com/articles/919094/cfpb-insights-on-alternative-data- use-in-credit-scoring.

[37]Günger, C. and K. Zengin (2017), *A Survey on Augmented Reality Applications using Deep Learning*, https://www.researchgate.net/publication/322332639_A_Survey_On_Augmented_Reality_Applications_Using_Deep_Learning.

[38] Hall, N. (2017), "8 ways AI makes virtual & augmented reality even more real,", *Topbots,* 13 May, https://www.topbots.com/8-ways-ai-enables-realistic-virtual-augmented-reality-vr-ar/.

[39] Higgins, T. and C. Dawson (2018), "Waymo orders up to 20,000 Jaguar SUVs for driverless fleet", *The Wall Street Journal*, 27 March, https://www.wsj.com/articles/waymo-orders-up-to-20-000-jaguar-suvs-for-driverless-fleet-1522159944.

[40]Hinds, R. (2018), *How Natural Language Processing is shaping the Future of Communication*, MarTechSeries, Marketing Technology Insights, 5 February, https://martechseries.com/mts-insights/guest-authors/how-natural-language-processing-is-shaping-the-future-of- communication/.