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CLINICAL ORACLE:

MACHINE LEARNING IN MEDICINE

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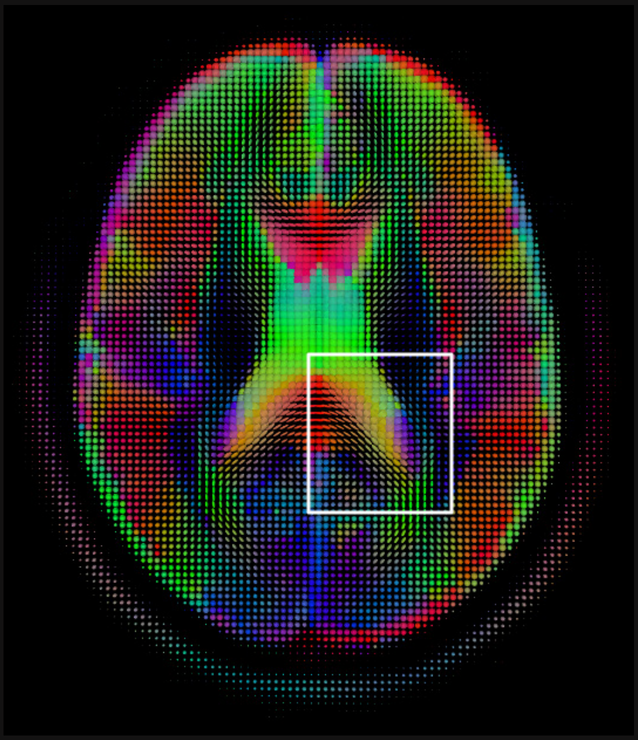

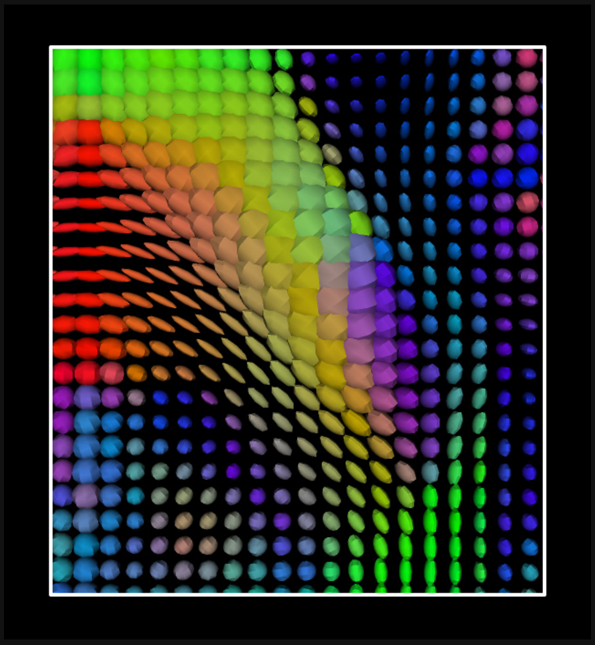

Radiology is the glue that holds every hospital together. Without X-rays, CT scans, and MRIs, it would be very difficult to glean much more than a surface-level understanding of a patient case. We put our faith in radiologists to correctly interpret our medical images so that we know what is wrong with our bodies, and we expect them to be right.

Contrary to what one would hope, radiologist errors are all too common, an estimated day-to-day rate of 3-5%.[1] And these mistakes can be very costly. Of course, misdiagnosis is most damaging to patients—late identification of a disease like cancer can be fatal. However, misdiagnosis can also cost radiologists and their hospitals through malpractice claims. In fact, radiologists are involved in a disproportionately large number of malpractice suits. Despite being the eighth-largest group of American physicians, they are the fourth highest in terms of cases closed against them.[2] Moreover, the most common cause of these suits is misdiagnosis, especially of breast cancer.[3] It's clear that misdiagnosis hurts all parties involved: the hospital, the physician, and most importantly, the patient. But what can be done?

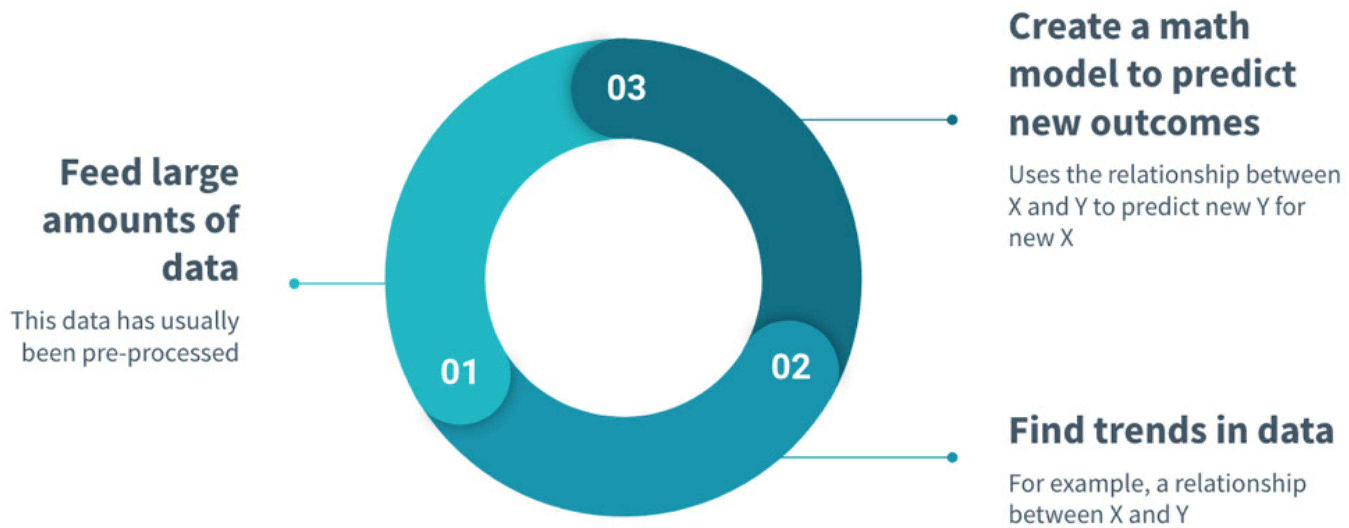

Figure 1: A general pipeline for creating an ML model. *This involves three steps: (1) pre-processed training data is fed into the ML algorithm with input features (e.g. medical images) and their associated output classes (e.g. malignant or benign), (2) the ML algorithm finds trends between the inputs and outputs, and (3) a model is created to predict the output classes for new inputs.*[9]

The field of radiology is steadily marching towards improved diagnoses, largely due to automation. In 1957, the automated film-processor substantially increased radiologists' efficacy.[4] By automating the image development process, X-ray technicians were, both literally and figuratively, brought out of the darkroom and into the light. This eliminated a tedious, mechanical task that had previously been a large part of the radiologists' daily lives, which allowed them to commit more time to interpreting scans. Additionally, this success represented the inception of a larger trend towards increased automation and precision in radiology. Modern developments take this trend a step further.

> "Studies show that receiving a second opinion on medical image screening can significantly increase the accuracy of readings."

The cutting edge of research includes applying the computer science field of machine learning (ML) to medical images to make diagnoses. A study in the journal *Radiology* showed that receiving a second opinion on medical image screening can significantly increase the accuracy of readings.[5] In fact, this study highlighted breast cancer as an area where a second reader is particularly helpful, which is important because breast cancer misdiagnosis is the most common cause of malpractice suits against radiologists. ML models use sophisticated pattern-detection to identify irregularities in medical images and then create highly accurate diagnoses. These reports could act as second opinions, supplementary to a primary radiologist. However, in order to evaluate the current state of ML within radiology, it is necessary to first develop a base-level understanding of the discipline.

THE HISTORY OF ML

The term "machine learning" was coined in 1959 by Arthur Samuel.[6] It is the subset of artificial intelligence that seeks to answer the question: "How can computers learn to solve problems without being explicitly programmed to do so?" Samuel pioneered the use of machine learning in programming a computer to play checkers. Not only was his device capable of comparing choices to pick the one that would bring it closest to winning, but, by remembering every position it had encountered before, the computer was able to learn and improve itself over time. Eventually, Samuel's computer was able to put up a good fight against amateur checker players.[7] This was revolutionary. Computers no longer acted simply as mindless calculators that used rules written into their code to perform predictable operations. Rather, these machines were now able to rival humans in matters of intellect through their own form of complex processing.

Today, ML has grown and branched off in a plethora of different directions. Impressively, ML has become ubiquitous in our daily lives.[8] Examples include autocomplete while texting, targeted advertisements on Amazon, and custom Google search results. Each of these instances of ML seeks to predict something about us: what we're going to type, what we want to buy, and what we want to know. This idea of *prediction*, creating actionable insights from large amounts of data, lies at the heart of ML. Though ML has mostly been used to personalize the customer and company relationship, its opportunities for clinical application are similarly abundant.

ML AND MEDICAL IMAGING

ML could define the future of medicine.[10] Since the price of data collection has plummeted in recent years, hospitals and insurance companies have jumped on the opportunity to gather and store huge amounts of patient information. However, much of this information remains unused. Researchers are actively investigating how to harness this information for good, and one of the most notable achievements in this area has been with breast cancer detection.

Computer-aided diagnosis (CAD) from medical images follows a two-step process. First, relevant high-level information is extracted from images; then, the extracted information is run through a previously-made ML model that outputs a prediction of which one of many classes the inputted features belong to.[11]

For example, microcalcifications (MCs) are small calcium deposits that show up brightly on mammograms, and clustered MCs are good predictors of breast cancer.[12] Thus, one possible CAD pipeline for this case would be first identifying the relative locations, sizes, brightness, and shapes of MCs, and then using that information to predict whether cancer is present.

Because ML models are able to find patterns across a vast array of different images and cases, they are much more accurate than their human counterparts. In fact, Enlictis, a startup applying deep learning to medicine, developed a tool to identify malignant lung tumors.[13] When the accuracy of diagnosis was compared to that of three expert radiologists, the company's model outperformed humans by 50%. Additionally, in an NPR interview, UCSF radiologists in training worried that "they could be replaced by machines" because "computers are awfully good at seeing patterns."[14] However, we should view ML as a tool that helps radiologists do their jobs better rather than another machine that is going to take jobs away from hard-working Americans. This is where content-based image retrieval (CBIR) comes into play.[11]

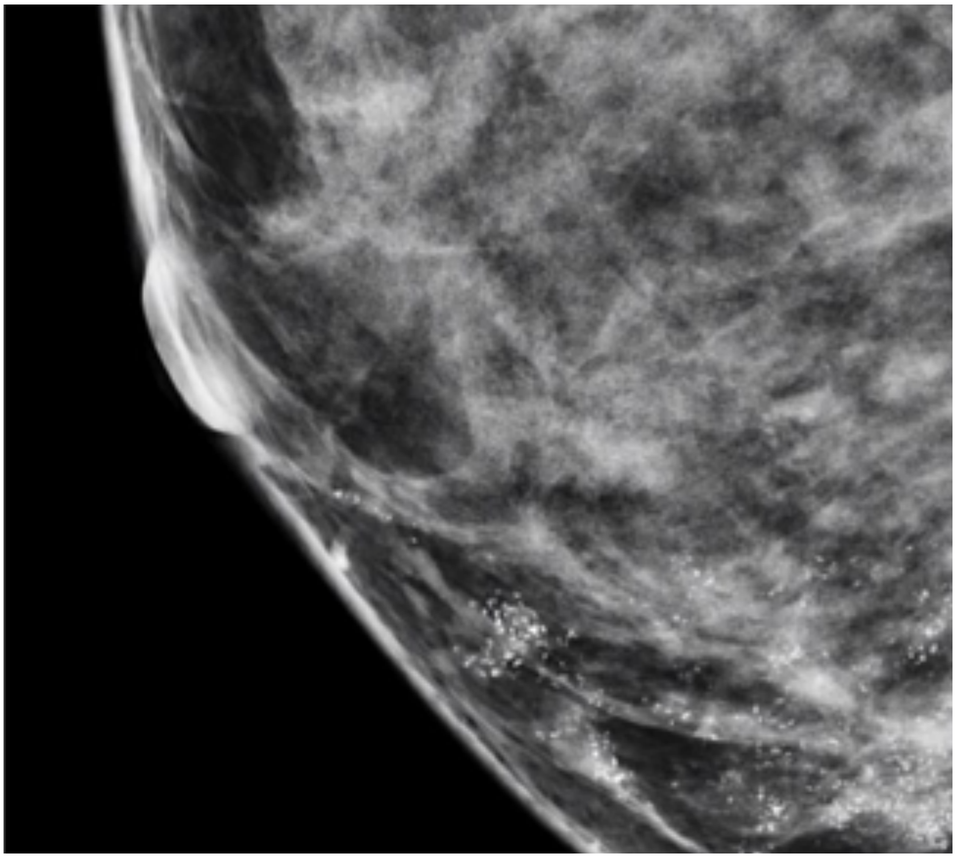

Figure 2: Microcalcifications in a breast scan.[15] *Microcalcifications are seen in this scan as the white dots in the bottom right of the image. They are a reliable early indicator of breast cancer, and radiologists usually decide whether further tests are needed based on their size, density, and distribution.*

Conventionally, ML models don't give explanations for their decisions. These models take in a patient's scans and other relevant information and output a percent likelihood value of malignancy. As a second opinion, these models are only useful if they are able to justify their outputs. CBIR bridges this gap by acting like Google's "search by image" function. [11] In addition to presenting a diagnosis, a system that includes CBIR returns relevant training data most similar to the case being considered. This function greatly improves the model's utility and allows for its use by radiologists in a clinical setting.

Misdiagnosis is a critical issue in radiology. It costs patients tremendous amounts of pain and suffering and costs physicians monetarily in the form of malpractice suits. ML presents a solution to this problem. By gleaning insights from more scans than any one physician could consider in a lifetime, these models are able to be more accurate and powerful than their human counterparts. Because of this potential as well as their novelty, many physicians have been reluctant to adopt them into their daily rou-

> "When the accuracy of ML diagnosis was compared to that of three expert radiologists, the company's model outperformed humans by 50%."

Figure 3: View of Moscow, Russia. *This photograph was edited using Deep Dream Generator (https://deepdreamgenerator.com/)—a computer vision program that allows us to see what a deep neural network is seeing when it is looking at a given image.*

tines. But, if integrated into medical practice, ML does not have to replace jobs. On the contrary, radiologists would be able to increase their relevance by specializing in cases that ML cannot effectively tackle. Thus, the new technology represents a major step in automation and has the potential to revolutionize medicine. By taking advantage of ML as a tool, radiologists can assure that patients receive the best care.

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