SAS Health Pulse Podcast Transcript
Season 5, Episode 7 – Dr. Greg Goldmacher (EDITED)

Transcript:

ALEX MAIERSPERGER: I'm your host, Alex Maiersperger, and today on the Health Pulse Podcast, we welcome Dr. Greg Goldmacher, Associate Vice President, Clinical Research and Head of Clinical Imaging and Pathology at Merck. Welcome, Greg.

GREG GOLDMACHER: Glad to be here. Thanks, Alex.

So where AI is already making a difference now, a lot of it is in helping-- in radiology, it's mostly in optimizing workflow for radiology, which is basically prioritizing cases and helping organize cases for doctors to read. And the other is in making diagnoses. So for example, screening mammography.

But AI has made tremendous progress, and computer vision has made tremendous progress. And at this point, the use for diagnostics, such as in looking for tumors in a mammogram, is actually a very good use case. And there's over 100 approved-- FDA- approved products for AI in radiology, and most of them are essentially diagnostic cases.

So in the area, in radiology, so the way you basically could apply AI-- so industrialized pattern recognition for images, is number one, there's a potential for AI models to see things in scans that human eyes simply can't. And the other is to automate tasks that are labor intensive, and thus, enable some kinds of analyses to be done at scale in ways that, right now, they could be done, but they're sort of difficult to do economically.

An example of the first type of task-- that is, recognizing things that aren't that are hard for human eyes to see, is the notion of radiomics. So the idea is-- so "-omics" basically refers to rather than looking at one thing, looking at sort of a whole panel. So when you talk about genomics, you're looking at the expression not of one gene, but of, let's say, all the genes.

So similarly in radiomics-- and some people don't like that term because everybody has a genome, but it's a little harder to define what is a radiom, but basically the idea is you've got a scan-- let's say it's a CT scan or an MRI scan, and let's say there's a tumor on the scan. So the way that assessments of whether drugs are working and what's going on with the tumor are done right now it's mostly you just look at how big the tumor is.

But there's a lot of information that's in the scan that is hard to extract visually. It's like textural things, or quantifying the geometry of the margin between the tumor and the normal tissue. How sharp is it? How fuzzy is it? How spiculated is it? And things like that.

So there are features-- so-called features-- basically pixel patterns-- that can be correlated from-- the pattern of pixels on the screen can be correlated with some biological phenomenon, some measure of, let's say in cancer, in the tumor microenvironment. So for example, a measure of inflammation. There's been literature showing that there are pixel patterns that correlate with the degree of inflammation of a tumor.

And that's, of course, really useful because that means that if you were-- you're considering a patient for treatment with some kind of immune therapy, an inflamed tumor is more likely to respond than a non-inflamed tumor. And so that's something where if you have essentially a digital biomarker-- that is, a pattern of pixels that's extracted and that a model can see that the human eye can't see, but that tells you what's going on in the tumor. So that's one application.

The automation of tasks is also a big deal because there are some analyses-- so for example, there's a growing interest right now in a method, again, in oncology for something called tumor growth kinetic analysis, where instead of just measuring the size of tumors and saying, did it grow by a certain percentage or shrink by a certain percentage and declaring a drug to be working or failing based on that, that's pretty far from the biology.

So there is another approach that's being pioneered based on tumor growth kinetic analysis, which involves doing a bit more math, measuring more tumors, and ideally measuring the tumors not just with a diameter, but like in terms of the whole volume, which means drawing a boundary in 3D around the tumor. That is certainly possible to do for humans, but it's expensive because radiologists' time is expensive.

Now all of a sudden, you can scale an analysis where the human, just finds the tumors, and that eventually will get automated, too, but it's a much harder task. And then the AI model basically measuring those tumors across all the scans that have been acquired on a patient during the course of treatment, and from those, extracting these more informative values that tell you more about whether the drug is working or not and let a drug developer make better decisions early in the course of development so that you don't have these expensive late-stage failures.

ALEX MAIERSPERGER: I assume that there's some disparity in who has access to the research or how every patient gets this level of detail or a digital twin and all of the

research that goes into it. How do we scale this across all disease types? And how does every patient that goes in to a doctor know that they're getting the best technology, the best, latest research all pinpointed exactly to their individual cellular level of detail?

GREG GOLDMACHER: So the distinction here is-- so population screening or cohort screening is something like mammography. You're gonna get everybody a mammogram, every woman between whatever ages, you're gonna do a mammogram every year, and that's cohort screening. You're looking for a particular disease.

But what about patients just coming through the emergency department and they get a chest X-ray? If somebody-- a radiologist, when we look at a scan or when we look at a medical imaging study, we are supposed to look at everything, not just at the thing that the ordering doctor asked about. So they may say, you're looking for pneumonia, but of course, you're looking for lung nodules or other kinds of disease. But humans are humans and people are busy and people miss stuff.

And if you have AI tools that are trained to pick up subtle early signs of disease on scans that are being done for other reasons, there's a real opportunity there for earlier diagnosis.

So if you're going to do opportunistic screening, for example, if you want to train AI for that, what you need is you need longitudinal data sets where you can find patients who had the disease, for example, and then go and look for scans that they might have had in the past to use to train the disease-recognizing models.

From a data transparency point of view, though, of course, companies that acquire data as part of their trials are very protective about it. So there's a few things that can be done. I mean, one is that there is a number of consortia. And a lot of the approaches that I was describing earlier, radiomics, growth kinetics, that's coming out of these kind of consortia.

And so essentially, consortia coming up with ways to lower the risks-- of course, trusted third parties, an important factor here-- with proper data-sharing agreements and data use agreements outlined, I think that that's one promising thing.

So there's both the collaborative approaches driven by trusted third parties, and technological approaches, which basically allow data-owners and algorithm developers to

collaborate.

ALEX MAIERSPERGER: Your breadth and depth, already the expertise on display, it sounds like we could ask you questions from a very wide lens. How diverse is your role at Merck and how did you end up in it?

GREG GOLDMACHER: So I trained in diagnostic radiology clinically. My background had been in neuroscience, my PhD was in neuroscience, and I ended up doing as a fellow, research in neuroimaging at Mass General.

I realized that I really enjoyed clinical research and ended up a couple of years later going to one of the imaging CROs, which is an imaging core lab. They collect scans and do independent analysis in the course of trials.

In the big picture, what I think has the great-- the greatest potential, the greatest promise, in order to develop these tools in the most effective way, is what you really need is you need a partnership between clinical development groups, clinicians, data science groups internally within organizations, and external opportunities. So you really need to be able to essentially coordinate.

You need people who really understand the problems. Those are the clinicians and the clinical development teams. They understand the problems that need to be solved. Then you've got the data science and IT groups. They understand the tools, but they often don't know how those tools-- how to apply those tools to the problems or what the important problems actually are.

Everybody sees a different part of the problem, and what you need is you need everybody to be talking in order to bring these tools forward, to develop the right tools for the right problems to solve problems for patients.

ALEX MAIERSPERGER: Out of the millions of records in radiology that you talked about, the billions of data points, the multiple roles and hats that you wear, Dr. Goldmacher, thank you so much for spending some time with us here on the Health Pulse Podcast.

GREG GOLDMACHER: Pleasure to be here. Thank you so much, Alex.