## AI will be transformative for healthcare

As Roashan believes machine learning has a role to play in the next generation of telemedicine technology, Joel Barthelemy, founder and CEO of GlobalMed, a telemedicine technology vendor, added that artificial intelligence can dramatically improve telehealth.

Currently, the U.S. Food and Drug Administration does not allow a device to diagnose a patient without the input of a physician. But an AI engine could say there’s an 84 percent chance that a patient’s stomach symptoms are related to the flu and that there’s a 4 percent chance they are due to indigestion. A doctor could receive this report and decide whether or not he or she agrees, Barthelemy said.

“An AI engine also is not allowed to prescribe drugs, and that is unlikely to change in the foreseeable future,” he said. “But, based on the experience of many thousands of similar patients with the same symptoms and signs, the AI engine could advise the doctor on which medication to prescribe or which treatment to try. As these learning machines become more and more accurate, doctors will agree with them most of the time unless they know something unique about a patient.”

In that case, they might contact the patient and ask some more questions; but in most cases, patients will no longer have to see primary care doctors in person, he contended.

## New sensors will show up in more places

On another front, sensor technologies built into households and consumer electronics that can trigger consumption of as-needed medical services may be about to change population health forever, said Roy Schoenberg, MD, CEO and co-founder of American Well, a telemedicine technology vendor.

“We see this with Apple’s new heart study with Stanford Medicine, where Apple Watch detects cardiac issues and magically prompts a telehealth doctor to show up on the patient’s phone to initiate a medical intervention within minutes,” he said. “This kind of real-time loop – that combines sensors, analytics and telemedicine – in my mind marks the transition from passive healthcare, which engages with the patient’s ‘chief complaint,’ to proactive healthcare, which dispatches live care as problems are detected.”

The implications will extend not only to how people experience care, but also to the practice of medicine, healthcare cost, healthcare policy, and quite likely how people age and longevity, he added.

<https://www.healthcareitnews.com/news/next-gen-telehealth-ai-chatbots-genomics-and-sensors-advance-population-health>

**EXAMPLES**

Through the [Face2Gene](https://suite.face2gene.com/) app, facial recognition software is being combined with machine learning to help clinicians diagnose rare diseases (in this case, from facial dysmorphic features). Patient photos are analyzed using facial analysis and deep learning to detect phenotypes that correlate with rare genetic diseases.

<https://www.techemergence.com/machine-learning-medical-diagnostics-4-current-applications/>

IBM

Cognitive computers will analyze a patient’s speech or written words to look for tell-tale indicators found in language, including meaning, syntax and intonation. Combining the results of these measurements with those from wearables devices and imaging systems (MRIs and EEGs) can paint a more complete picture of the individual for health professionals to better identify, understand and treat the underlying disease, be it Parkinson’s, Alzheimer’s, Huntington’s disease, PTSD or even neurodevelopmental conditions such as autism and ADHD.

What were once invisible signs will become clear signals of patients’ likelihood of entering a certain mental state or how well their treatment plan is working, complementing regular clinical visits with daily assessments from the comfort of their homes.

<https://www.research.ibm.com/5-in-5/mental-health/>

**THE LOGIC BEHIND**

Medical Diagnosis work in clinical practice generally has four models: [4]

* ***Pattern Recognition***, wherein the doctor recognizes the current patient’s problem based on her past experiences with other patients, e.g., Down’s syndrome.
* ***Hypothetico-deductive***, wherein the doctor performs a certain battery of tests to test a hypothesis, a tentative diagnosis.
* ***the Algorithm Strategy***: the algorithm strategy has been used in Healthcare and has been represented using Medical Logic Modules [5], Arden Syntax for Medical Logic Systems [6] and Clinical Pathways [7] and finally the
* ***Complete History Strategy*** has been defined to be the identification of Diagnosis by possibility. Evidence based medicine is then used to come to a conclusion of the final diagnosis. [8]
* learning,
* reasoning,
* problem-solving,
* perception, and
* language-understanding

<https://imtinnovation.com/2017/10/25/understanding-the-medical-diagnosis-processes-to-build-an-ai-solution/>

**1. AI Applications in Clinical Practice Findings:**

● The process of developing a new technique as an established standard of care uses the robust practice of peer-reviewed R&D, and can provide safeguards against the deceptive or poorly-validated use of AI algorithms. (Section 2.3)

● The use of AI diagnostics as replacements for established steps in medical standards of care will require far more validation than the use of such diagnostics to provide supporting information that aids in decisions. (Section 2.3)

*Recommendations:*

● Support work to prepare AI results for the rigorous approval procedures needed for acceptance for clinical practice. Create testing and validation approaches for AI algorithms to evaluate performance of the algorithms under conditions that differ from the training set. (Section 2.3)

**2. Confluence of AI and Smart Devices for Monitoring Health and Disease Findings:**

● Revolutionary changes in health and health care are already beginning in the use of smart devices to monitor individual health. Many of these developments are taking place outside of traditional diagnostic and clinical settings. (Section 3.1)

● In the future, AI and smart devices will become increasingly interdependent, including in health-related fields. On one hand, AI will be used to power many health-related mobile monitoring devices and apps. On the other hand, mobile devices will create massive datasets that, in theory, could open new possibilities in the development of AI-based health and health care tools. (Section 3.1)

*Recommendations:*

● Support the development of AI applications that can enhance the performance of new mobile monitoring devices and apps. (Section 3.1)

● Develop data infrastructure to capture and integrate data generated from smart devices to support AI applications. (Section 3.1)

● Require that development include approaches to insure privacy and transparency of data use. (Section 3.1)

● Track developments in foreign health care systems, looking for useful technologies and also technology failures. (Section 3.1) 3

**3. Create Comprehensive Training Databases of Health Data for AI Tool Development Findings:**

● The availability of and access to high quality data are critical in the development and ultimate implementation of AI applications in health care. (Section 4)

○ AI algorithms based on high quality training sets have already demonstrated performance for medical image analysis at the level of the medical capability that is captured in their training data. (Section 2.1)

○ AI algorithms cannot be expected to perform at a higher level than their training data, but should deliver the same standard of performance consistently for data within the training space. (Section 2.1)

● Laudable goals for AI tools include accelerating the discovery of novel disease correlations and helping match people to the best treatments based on their specific health, life-experiences, and genetic profile. Definition and integration of the data sets required to develop such AI tools is a major challenge. (Section 4)

● Extreme care is needed in using electronic health records (EHRs) as training sets for AI, where outputs may be useless or misleading if the training sets contain incorrect information or information with unexpected internal correlations. (Section 6.1)

● Techniques for learning from unlabeled data could be helpful in addressing the issues with using data from a diverse set of sources. (Section 4.2)

*Recommendations:*

● Support the development of and access to research databases of labeled and unlabeled health data for the development of AI applications in health. (Section 4)

● Support investigations into how to incentivize the sharing of health data, and new paradigms for data ownership. (Section 4)

● Support the assessment of AI algorithms trained with data labeled at levels that significantly exceed standard assessment, for instance the use of outputs from the next stage of diagnostics (e.g., use of biopsy results to label dermatological images). (Section 2.1)

● Support research to characterize the tradeoffs between data quality, information content (complexity and diversity) and sample size, with the goal of enabling quantitative prediction of the quantity and quality of data needed to support a given AI application. (Section 4)

● Identify and develop strategies to fill important data gaps for health. (Section 4)

● Develop automated curation approaches for broadly based data collections to format them for AI tools, e.g., as with well labeled imagery. (Section 4.2)

**4. Fill in Critical Missing Data Gaps Findings:**

● AI application development requires training data, and will perform poorly when significant data streams are absent. While DNA is the blueprint for life, health outcomes are highly affected by environmental exposures and social behaviors. There is an imbalance in the effort to capture the diverse data needed for application of AI 4 techniques to precision medicine, with information on environmental toxicology and exposure particularly suffering: (Section 5.2.2)

○ Techniques exist to capture individual environmental exposures, e.g., blood toxin screening, diet questionnaires.

○ Techniques exist for environmental pathogen sensing.

○ Technologies exist that can capture environmental exposures geographically and create environment tracking systems.

*Recommendations:*

● Support ambitious and creative collection of environmental exposure data: (Section 5.2.2) ○ Build toxin screening (e.g., dioxin, lead) into routine blood panels, and questions about diet and environmental toxins into health questionnaires.

○ Start urban sensing and tracking programs that align with the geographic areas for the All of Us Research Program and similar projects in the future.

○ Support the development of wearable devices for the sensing of environmental toxins.

○ Support the development of broad-based pathogen sensing for rural and urban environments.

○ Develop protocols and IT capabilities to collect and integrate the diverse data.

**5. Embrace the Crowdsourcing Movement to Support AI development and Data Generation Finding:**

AI competitions have already demonstrated their value in

1) encouraging the creation of large corpuses of data for broad use, and

2) demonstrating the capabilities of AI in health, when provided data that are curated into a well labeled (namely high information content) format. (Section 4.12)

*Recommendations:*

● Support competitions created to advance our understanding of the nature of health and health care data. (Section 4.12)

● Share data in public forums to engage scientists in finding new discoveries that will benefit health. (Section 4.12)

**6. Understand the Limitations of AI Methods in Health and Health care Applications Findings:**

● There is potential for the proliferation of misinformation that could cause harm or impede the adoption of AI applications for health. Websites, Apps, and companies have already emerged that appear questionable based on information available. (Section 3.2)

● Methods to insure transparency in disclosure of large scale computational models and methods in the context of scholarly reproducibility are just beginning to be developed in the scientific community. (Section 6.2)

*Recommendations:*

● Support the development of critical safeguards that are essential to enable the adoption of AI for public health, community health, and health care delivery:

○ Encourage development and adoption of transparent processes and policies to ensure reproducibility for large scale computational models. (Section 6.2)

○ To guard against the proliferation of misinformation in this emerging field, support the engagement of learned bodies to encourage and endorse best practices for deployment of AI applications in health. (Sections 3.2 and 6.2)

<https://www.healthit.gov/sites/default/files/jsr-17-task-002_aiforhealthandhealthcare12122017.pdf>