Early career Harvard Medical School investigators kick-off the 2019 World Medical Innovation Forum with rapid fire presentations of their high-potential new technologies. Eighteen rising stars from Brigham Health, Massachusetts General Hospital, Massachusetts Eye and Ear Infirmary, McLean Hospital and Spaulding Rehabilitation Hospital will give ten-minute presentations highlighting their discoveries and insights that will disrupt the field of artificial intelligence. This session is designed for investors, leaders, donors, entrepreneurs, investigators and others who share a passion for identifying emerging high-impact technologies.

Two of the top presenters will be awarded the Peter K. Ranney Innovation Award. The prize carries a $10,000 award.
The Peter K. Ranney Innovation Award will be given to honor the top two First Look presenters who embody the innovative, entrepreneurial and visionary spirit that the World Medical Innovation Forum was established to recognize. The two $10,000 awards will be granted based on overall presentation quality, innovativeness, commercial potential, caliber of disruption, and market need.

The Award will be judged throughout the morning session on April 8th with winners announced at the annual Innovator’s Dinner on Wednesday, April 10, 2019.

Note: Speakers and content are subject to change.

BH Brigham and Women’s Hospital | HMS Harvard Medical School
MEE Mass. Eye and Ear | MGH Massachusetts General Hospital
SRN Spaulding Rehabilitation Network

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Leveraging a Deep-Learning Algorithm for the Detection of Acute Intracranial Hemorrhage

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With the rapid progress of machine learning, deep-learning algorithms have the potential to change medicine’s landscape. Specifically, advances in image recognition could increase diagnostic accuracy and speed and enhance physician workflow. However, there are still obstacles hindering the translation of deep-learning systems into clinical environments. This includes the necessary access to large datasets from which to "train" machine-learning, which can be costly and time-consuming to accumulate. An additional obstacle is the inability for users to understand the algorithm’s decision-making process. For example, even if an algorithm correctly identifies a certain diagnosis, how can we understand its justification? In our research, we addressed both challenges by using a small dataset to construct an explainable, deep-learning algorithm for the image detection of acute intracranial hemorrhage (ICH). While using a small, imbalanced dataset of less than 1,000 images, we emphasized the standard of quality. Rather than having general radiologists simply label the presence or absence of ICH in each image, we recruited five specialty neuro-radiologists not only to label the presence of ICH, but also to label its specific subset out of five options. Furthermore, we adjusted the system’s image processing to mimic radiologists’ own workflow. We found that even with a small dataset, enhancing the quality of the data and paralleling the algorithm’s processing to clinical work enabled a system performance similar to that of expert radiologists. Beyond optimizing performance, we made the algorithm explainable, having it create an atlas from the training set which in turn illuminated its decision-making. The “explainability” of an algorithm is essential not only for understanding the system’s predictions, but also for continuing improvement and optimization.

By providing a reliable, accurate second opinion in diagnosing brain hemorrhages, the implementation of this system has the potential to enhance patient care, empower patients and cut costs. The benefits of deep-learning systems extend beyond neuroradiology, and by constructing an explainable deep-learning algorithm from small datasets, our research helps address challenges traditionally hindering their implementation.

Figure 1. A diagram of the explainable deep learning system for ICH detection and classification.

Figure 2. An output summary of the explainable deep learning algorithm. a. Probabilities for the presence of each type of ICH. b. For each positive case, the system generates a color-coded attention map, c. A set of prediction bases that are most relevant to each positive image.
The future of cognitive and behavioral assessment will be digital. New approaches to assessment development are needed to (i) exponentially increase the cycle of innovation and validation, (ii) go beyond print publication models of intellectual property, and (iii) provide continued and long-term commercialization opportunities. Here, we describe the MAIAD approach (Machine-Assisted Iterative Assessment Development), an iterative and high-throughput method to assessment development based on the low-cost collection of large structured datasets and algorithmic optimization of assessment parameters. Rather than providing a specific assessment, algorithm, or technology, MAIAD serves as an engine for the development of novel digital, algorithmic assessments for quantifying cognitive, behavioral, and neuropsychological functions. MAIAD is enabled by two unique capabilities: (1) A structured and participant engagement driven approach to data collection that allows us to capture structured data across massive samples (2.2 million thus far through our digital research platform TestMyBrain.org), and (2) A validated iterative development framework that allows us to rapidly identify tests, items, and item parameters that best capture a particular characteristic, phenotype, or outcome (see Figure 1). New assessments and algorithms can be evaluated in hours or days, rather than the typical months or years. As a proof of concept, we show a straightforward open loop application of MAIAD for capturing visuospatial capability. Using this approach, we were able to develop a measure that uniquely predicts SAT score based on automated identification of item parameters. Cognitive measures developed by this approach are already being incorporated into large scale assessment initiatives, supported by funding across four NIH institutes.

Figure 1. Schematic of Iterative Test Development Procedure Based on Structured A/B Testing and Automated Parameter Selection

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The creation of the Web catalyzed a societal transformation. It enabled discussion forums, instant messaging, smartphones, and wearables. These technologies allow us to communicate better, to interact as a collective, to disseminate knowledge and information, and perhaps most importantly, they act as sensors to measure the pulse of the world and of individuals. While specific areas of healthcare have seen significant advances, our ability to measure, track, treat, and predict treatment outcome of brain-related disorders, and specifically mental health, remains limited. Many existing pharmacological and behavioral therapies remain ineffective. Current approaches rely on intermittent assessments and self or caregiver reports, which are subjective and often unquantifiable. We and our collaborators are changing this by combining modern sensing using brain imaging and smartphones with advances in AI technologies to improve assessments and treatments for mental health and neurological disorders. We have used brain scans to help predict treatment outcome in disorders such as social anxiety and major depression and demonstrated that speech recordings provide viable markers for tracking depression and Parkinson disease. We have developed methods for detecting meningioma tumors and helped advance AI algorithms along the way. In developing these technologies, we now know that more data can help make these methods more robust, but also that we do not really know when and how these models will fail. To address this, we need a fundamental shift away from algorithms that simply learn from more data to algorithmic models that better understand the process. These models will link our targets of interest (e.g., depression level, treatment outcome) to the variations in our sensors (e.g., voice, brain images) and, to the extent possible, to the underlying neurobiology. Over the next decade, we envision using these models in a system that is continuously learning from sensors across individuals, relating information to life and health outcomes, and guiding individuals and caregivers to a more proactive version of care for brain health, and healthcare more broadly.

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The Next Generation of Cognitive and Behavioral Assessment

Assistive Intelligent Technologies for Brain Health
Leveraging Artificial Intelligence for Brain Drug Discovery

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Drug discovery process is incredibly capital-intensive and time-consuming, and it is one of key factors that are driving up the astronomical healthcare costs. This is largely owing to the inefficiency in identifying suitable early leads and optimizing them into drug candidates, which typically involves the synthesis and testing of large numbers of small molecules. Teamed up with Atomwise, Inc, we use AI, i.e. deep convolutional neural networks (DCNN) (Fig. 1) to identify molecules that “fit” through in silico enumeration and evaluation, thereby minimizing the need for expensive chemical synthesis and expansive in vitro/vivo testing. This AI-powered virtual drug screening technology will hopefully shorten the time from initial hit to clinical trial and ultimately reduce the cost of early drug development for unmet medical needs.

With the technology, we can rapidly screen millions of diverse molecules in silico to find ones that bind to a target protein specifically. We can also undertake mechanism of action screens to virtually identify proteins that bind compounds identified as hits in phenotypic screens, and to optimize lead molecules for bioavailability, including in silico prediction of blood-brain barrier (BBB) permeation if needed. This provides researchers with a small set of compounds that not only have a high probability to bind a target protein but also have elevated drug-like properties. Because the initial set of candidate compounds is small, they can often be experimentally validated quickly and inexpensively - using assays that researchers often already have in their lab without the need of developing a new medium or high throughput screening assay. Upon identification of early hits, we can also undertake hit-expansion exercises through in silico enumeration and evaluation, thereby minimizing the need for expensive chemical synthesis and expansive in vitro/vivo testing. This AI-powered virtual drug screening technology will hopefully shorten the time from initial hit to clinical trial and ultimately reduce the cost of early drug development for unmet medical needs.
On Nov 25th, 2018, the United Nations chillingly reported that the most dangerous place for women is inside their own homes. No fewer than 58% of female homicides are committed by current or former intimate partners or family members. Intimate Partner Violence (IPV) is defined as physical, sexual or emotional violence between partners or former partners. One in four women have reported IPV during their lifetime. The CDC estimated the cost of IPV exceeding $5.8 billion dollars ($9.3 billion in 2017 dollars). Despite the high prevalence and fatality of this critical public health issue, IPV continues to be profoundly underdiagnosed due to under-reporting by the victim. The lack of identification of IPV as the primary cause reduces the ability to offer early preventive services and may lead to further violence with each physical injury increasing the likelihood of sustaining a life-threatening injury. Currently an IPV screening questionnaire is a core component of every health care visit but the proportion of identifiable IPV cases to date only represents the tip of the iceberg.

Making the Invisible Visible: Bringing Intimate Partner Violence into Focus

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We believe that rapid advances in imaging, information technology and machine learning present an opportunity to achieve a breakthrough in identifying IPV victims and thereby, activating timely intervention. Our pilot study on “Radiological findings in IPV victims” has allowed us to create an exhaustive list of imaging and clinical findings that are associated with IPV. We are now developing an integrated, multi-dimensional clinical decision support tool that uses patterns derived from expert analysis of historical radiological and clinical data, classification models, statistical evidence and alert system that classifies injuries for their likelihood of being as a result of IPV, and automatically alerts clinicians if a patient’s injuries have a high or low risk probability for IPV. Our goal is to first validate and then implement this alert system locally, nationally, and globally.

Harnessing the Power of Machine Learning to Automate Drug Infusions in the OR and ICU

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Machine learning holds the promise to automate and personalize drug administration in order to achieve optimal health outcome. Administration and titration of medications to a monitored parameter is one of the major sources for medication errors and risk patient safety. We are developing a machine learning automation system to maintain normal maternal blood pressure during cesarean delivery.

Low maternal blood pressure occurs in up to 74.1% of cesarean deliveries. In the US, 900,000 mothers annually experience complications associated with low maternal blood pressure like nausea, lightheadedness, and, infrequently, stroke; resulting in a prolonged recovery. In the baby, low maternal blood pressure can cause acidosis, hypoxia and low Apgar scores, which can lead to neonatal ICU admission and can correlate with poor developmental outcome. All these complications incur more than $100M costs to the healthcare system annually.

Currently, maintaining blood pressure is done by monitoring the vital signs and manually adjusting the rate of drug infusion every minute. We are developing an anesthesia automation system (AAS), which will utilize real-time blood pressure input from the patient, calculate the needs for vasopressor medication using a deep learning algorithm and deliver it directly to the patient via commercially available infusion pump. The software will calculate the amount of drug needed based not only on the current value of the blood pressure, but also on the blood pressure trend for that particular patient, the time course and the pharmacokinetics of the drug. While semi-autonomous, our system is designed to work with the physician present at all times and responsible for the patient care.

Our system would increase the safety and well-being of millions of mothers and babies annually (estimated $600M market for this application alone). As we expand to include medications like propofol and insulin, we envision that AAS will be invaluable also for any complex sedation, general anesthesia or ICU case. In the long run, AAS would augment the workflow of the anesthesiologists, increase patient safety, decrease cost of care and, ultimately, transform the way we perform anesthesia.
AI-Based Care Delivery: A New Paradigm for Curing Cancer

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The global burden of cancer in lives lost and financial costs is expanding exponentially. Every year over two million women are diagnosed with, and over 600,000 women die from, breast cancer worldwide. Current approaches that treat late stage malignant disease are costly and fail to cure. Breast cancer is cured when detected early, yet the vast majority of women do not have access to the benefits of early detection due to 1) lack of accurate risk prediction models to support effective prevention and screening strategies and 2) dearth of specialized radiologists to interpret screening mammograms. The cure for cancer, not only breast cancer but the full diversity of solid tumor cancers, lies in our ability to identify patients at increased risk and to implement effective programs for disease prevention and early detection/treatment.

Our AI-based paradigm delivers high quality, cost effective care by providing two immediate applications for clinical implementation. First, our innovative methods of risk assessment leverage the strength of Artificial Intelligence to identify women at risk for breast cancer. Current breast cancer risk models incorporate only a small fraction of patient data available and have failed to accurately predict future risk in individual women. We have developed a deep-learning (DL) model that operates over a full resolution digital mammogram image with traditional risk factors to predict a patient’s future breast cancer risk. Rather than manually identifying discriminative image patterns, we rely on our machine learning model to discover these patterns directly from the data. Unlike traditional models, our DL model performs equally well across diverse races, ages, and family histories. Second, we have developed a DL model that can provide interpretation of mammograms approximating the level of specialized human readers, transitioning screening mammography from a costly test, highly dependent on subspecialized radiologist expertise, to an inexpensive test that can be read by machines. Our lead scientists from MIT (Dr. Regina Barzilay) and MGH (Dr. Connie Lehman) are uniquely positioned to combine the strength of AI, the wealth of our large curated, modern quality databases, and our expertise in effective clinical implementation to rapidly integrate advanced AI risk models and AI image interpretation into clinical practice.

Figure 1. Deep learning model significantly better at predicting future risk of breast cancer in diverse races than current “best practice” advanced risk model Tyrer-Cuzick version 8.

Figure 2. Deep learning model significantly better at predicting future risk of cancer in diverse races than current “best practice” advanced risk model Tyrer-Cuzick version 8.

Figure 3. Deep learning model detects cancers on modern digital screening mammograms.

Drug overdose deaths have grown exponentially for the past 40 years, with more than 700,000 deaths since the 1990s (Figure 1) and 70,000 in 2017 alone. Astounding increases in opioid-related deaths have lead the US government to declare a national emergency. By 2025, drug overdose deaths will exceed 100,000 each year and nearly half a million people are projected to die from drug overdoses in the next decade. While opioids were involved in nearly 50,000 deaths in 2017, we estimate that there were also nearly a million non-fatal opioid overdoses in 2017. Non-fatal overdoses cause significant financial and medical burdens and greatly increase risk of future overdose. Creative solutions are needed to combat the growth in drug overdose death rates and to slow the opioid epidemic.

Our team is focusing on "digital phenotyping" using personal smartphones and wearables to develop a mobile health ("mHealth") tool for forecasting and detecting drug use, and preventing drug overdose deaths. Personal devices employ numerous internal sensors to make moment-by-moment measurements in a person’s natural environment. These data can be used to decode daily activities, such as walking, sitting, standing, eating, and drinking. Digital phenotyping and machine learning can also be used to detect drug use and prevent overdose deaths (Figure 2). mHealth apps for preventing opioid overdose deaths are available, but they don’t leverage digital phenotyping and machine learning with commonplace personal devices. For example, some apps trigger an emergency response if the drug user does not stop a timer after they are high that they started before overdosing.

We have identified a great need for an evidence-based mHealth tool that provides useful forecasting, feedback, and interventions for preventing overdose deaths that patients will actually use in their natural environment. Our goal is to develop a commercial product based on comprehensive digital phenotyping in patients, application of machine learning and predictive analytics, design and testing in patients, with clinician input, to meet this need.

Figure 1. A) Death rates from unintentional overdoses for Individual drugs from 1999-2016. B) Overdoses from all drugs from 1979-2016 shows drug overdose deaths have been increasing exponentially for the past 40 years. Figure from Jali et al. Science, 2018.

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Using Digital Phenotyping and Machine Learning to Forecast, Detect, and Prevent Drug Overdose Deaths
Mobile Health Technologies for Monitoring Motor Fluctuations in Patients with Parkinson's Disease

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Parkinson’s Disease (PD) is a neurodegenerative condition affecting more than 10 million people worldwide. Typical motor symptoms include tremor, bradykinesia, and rigidity. In the late stage of the disease, patients eventually develop motor complications, such as dyskinesias (i.e., hyperkinetic involuntary movements), and start experimenting fluctuations in symptoms’ severity. Accurate titration of medications is crucial to minimize the impact of motor complications while maintaining effective the management of PD symptoms. Current clinical tools for monitoring motor fluctuations rely on sporadic visits in the clinic and patients’ self-reports, which provide clinicians only with a fragmented and unreliable picture of the subject’s condition. The symbiosis between wearables, mobile devices, wireless technologies, and artificial intelligence, often identified as Mobile Health (mHealth), has the potential to impact the future of healthcare considerably. At the Motion Analysis Lab, we investigate this potential in the context of PD, among others, since almost two decades, collaborating with both academia and industry. For example, we demonstrated that it is possible to use wearables and machine learning to accurately estimate clinical scores for tremor, bradykinesia, and dyskinesia during the performance of standardized tasks and to deploy these models in a web-based platform for remote and longitudinal monitoring of PD subjects in the home setting. Our latest research efforts in this context aim at overcoming the limitations of current approaches, such as the dependency on standardized motor tasks or the unreliable picture of the subject’s condition.

The recent advances in convolutional neural-network machine learning methodologies and the availability of the requisite GPU capability has allowed us to fully leverage the immense value in our institutional image and reporting archive to train an AI-based solution for these workflow and reporting issues. DeepSPINE is an automated and accurate system for lumbar spinal MRI analysis and report generation. Its processing pipeline is comprised of deep-learning algorithm components for automated vertebral segmentation, disc-level labelling, optimized reorienting of image slice angulation, and level-by-level grading of central canal and foraminal stenosis with report text generation. Our efforts have achieved state-of-the-art performance in the machine-learning literature (Proceedings of Machine Learning Research 85:1-16, 2018) but algorithmic performance is only one component of a successful solution. Efficient and elegant integration into pre-existing workflows is essential for both rapid deployment and clinician acceptance and thus has been an equally important focus of our efforts.

As an AI-powered reporting tool, DeepSPINE populates algorithmic outcomes into standardized report templates for more consistent grading terminology. Further development will encompass additional features of spinal degeneration and eventually integrate longitudinal imaging analysis and additional patient data elements from the electronic healthcare record to provide value beyond the traditional radiology report such as workflow prioritization and predictive outcome modelling to aid surgical planning and other therapeutic approaches.

Al-Powered Diagnostic Reporting Tool for Spinal MRI of Degenerative Disease

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Spinal degeneration is a highly prevalent condition with large societal costs, much of which comes from medical imaging. Spinal MRI, the study of choice, is among the most expensive of imaging procedures yet heavily utilized for both initial diagnosis and longitudinal evaluation. Its interpretation is challenging and time-consuming even for those with sub-specialty expertise. Due to this complexity and a lack of universally-accepted grading standards, spinal MRI reporting still exhibits a large degree of inter-reader variability frustrating both referring clinicians and their patients, who increasingly demand direct access to their data documentation.

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$100 billion. National inpatient expenses for spinal fusion surgery increased from $10 billion in to over $50 billion in the last two decades (2% of total national health care expenses). Total hospital charges for these patients are heavily driven by postoperative care: complications can double or triple the cost of spinal fusion surgery. Given a lower bound of 5% complication rate, 450,000 fusion surgeries per year, and surgeries with complications costing twice the amount without complications, the addressable market is at least $1.8 billion in the United States (of the $50+ billion) that can be preoperatively predicted and adequately planned to avoid unnecessary costs and poor patient outcomes. Data science is an emerging area in spine care but existing solutions have failed to adapt to innovations in predictive analytics. Existing tools are based on rough estimations from small studies of less than 100-200 patients. The tools are fragmented, lack peer-reviewed publications and external validation, but are the only options for spinal care providers. To address this tremendous need in spine care, we have developed algorithms by using machine learning, natural language processing and deep learning to prevent adverse events and aid decision making. The most rigorous standards for clinical prediction models have been followed in developing these models. Our algorithms have been published by the leading journals in spine care (The Spine Journal, Neurosurgery). External validation of these algorithms has borne out their utility in diverse populations. The algorithms have been made available for providers as web applications and we have presented our work at the national organizations for spine care. Our usage patterns indicate that these algorithms are accessed daily to guide decision making. The most rigorous standards for clinical prediction models have been followed in developing these models. Our algorithms have been published by the leading journals in spine care (The Spine Journal, Neurosurgery).
Three Computational Techniques and One Tool to Bring the Patient Voice into Care

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Data collected directly from patients has the potential to generate unique insights into the process and outcomes of care. These data are usually collected using structured questionnaires, referred to as patient-reported outcome and experience measures (PROMs and PREMs). Despite their apparent simplicity, both PROMs and PREMs are effective at improving both processes and outcomes of care. Recent notable examples include increased identification of chemotherapy side-effects which translated into significantly improved survival in studies conducted in the US and Europe. Patient experience data can also be used to identify poorer outcomes including unplanned admissions and reoperations. Reliance on static fixed-length questionnaires has led to several issues with the collection and interpretation of patient-reported data. Many PROMs, designed originally to monitor outcomes in clinical trials, are lengthy and do not translate well to clinical practice. In addition to being lengthy, it is often unclear what clinical actions should be taken based on the information collected. Likewise, patient-reported experience measures also suffer from a lack of actionability, as little insight into potential quality improvement mechanisms can be gleaned from a single numeric score. Research conducted within the Brigham and Women’s PROVE Centre has demonstrated that the limitations of patient-reported data tools can be overcome using novel computational tools including computerized adaptive testing and machine learning.

This talk will introduce the current state of the art in the assessment, analysis, and feedback of patient-reported assessments by demonstrating three technologies and one tool to facilitate implementation. Specifically, this talk will introduce three machine learning techniques to individually tailor patient-reported assessments, predict individual outcomes for patients undergoing breast reconstruction, and automatically make sense of open-text feedback about doctor’s performance. Finally, I will introduce Concerto, an open-source platform to facilitate the development and deployment of secure patient-reported assessments which combine cutting-edge AI techniques and flexible user interfaces.


Figure 1. Overview of the Concerto System as it is implemented for patient-reported outcomes and experience assessment.

Figure 2. Individual tailored patient feedback with geo-relevant referral links (see Gibbons et al., 2016)

Figure 3. Machine learning classifications of open-text reports of doctor performance (see Gibbons et al., 2017)

AI-Imaging for Patient-friendly Colon Cancer Screening

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With more than 50,000 annual deaths in the United States, colon cancer is the second leading cause of cancer deaths for men and women in the United States. These deaths could be prevented by early detection and removal of precursor polyps. However, only 62% of adults aged ≥50 years adhere to colorectal screening guidelines today. Laxative (cathartic) bowel preparation, a mandatory pre-exam preparation for optical colonoscopy (OC), has been identified as the single most important barrier to patient adherence to colorectal examinations, especially for the Medicare population, a prime target for colorectal screening, who are fragile to laxative preparation.

Computed tomographic colonography (CTC), also known as virtual colonoscopy, is an alternative complete colon cancer screening method rated as “A” by the US Preventive Services Task Force for the detection of polyps and cancers. Also CTC is usually performed with laxative preparation, whereas we previously developed a computer-assisted laxative-free CTC scheme to eliminate the need for laxatives in colorectal examinations. This could substantially increase the capacity, safety, accuracy, and patient adherence to colorectal examinations. Our multi-center clinical trial showed that laxative-free bowel preparation was easy to tolerate for patients and enabled the detection of large polyps at a sensitivity comparable to that of colonoscopy. However, small polyps were difficult to detect and identify due to a large amount of distracting fecal residue that either hides polyps or mimics their appearance.

We thus employed state-of-the-art deep-learning methods to develop AI colonography, where AI performs virtual bowel cleansing of laxative-free CTC cases by removing the fecal residue from CTC images and then automatically detects and identifies the polyps that would have otherwise disappeared among the abundant distracting fecal residues. Successful deployment of AI colonography is expected to make CTC a patient-friendly yet highly accurate and cost-effective option for large populations, especially for Medicare patients, thereby promoting early diagnosis and ultimately reducing mortality due to colorectal cancer.
Deep Learning for Glaucoma Detection

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Glaucoma is the leading cause of irreversible blindness worldwide, with an estimated global prevalence of 3.5% in persons aged 40 to 80 years, and affecting approximately 64 million people worldwide as of 2013.1 Nearly half of glaucoma cases in the US are undiagnosed with many individuals with significant visual field loss at the time of diagnosis. Glaucoma is an ideal disease to screen for as early treatment of glaucoma, by reduction of intraocular pressure (IOP), has been shown to delay glaucoma progression.2 Current screening strategies rely on clinical examination and physician-interpreted testing and are expensive, time intensive, and lack adequate specificity.3 Successful community screening must be simple and scalable. Automated classification of fundus photographs and optical coherence tomography (OCT) images using deep learning (DL) algorithms has the potential for improving screening accuracy, lowering cost and improving accessibility to eye care.

DL has been used previously for detection of glaucoma using fundus photographs. 4,5 In these prior studies, glaucoma cases have been defined by clinical opinion based on ophthalmoscopically-apparent characteristic changes to the optic nerve head. This method of data labeling is inherently subjective and of poor sensitivity and specificity. As any DL algorithm can only attempt to match its reference standard, for improved screening there is a need to improve this standard. It may be possible to utilize objective measures to identify individuals at high risk for glaucoma. There is significant evidence for genetic risk factors that influence glaucoma susceptibility.6 Additionally, numerous epidemiologic studies have shown that high IOP is a major risk factor for glaucoma.7 We propose to construct a DL model to classify fundus photographs and OCTs in order to identify individuals with high IOP and high genetic risk for glaucoma, and therefore high risk of glaucomatous optic neuropathy. Additionally, we aim to detect fundus photography and macular OCT biomarkers of elevated IOP and high genetic risk for glaucoma that can be used for screening or prognosis purposes. We hypothesize that these algorithms can be harnessed to find new imaging features predictive of glaucomatous optic neuropathy as well as future risk of the disease.

Ultimately we aim to use disease-predicting fundus image features identified in this study to construct multi-modal models using multiple objective modalities such as IOP, genetic risk, and risk derived from fundus images to improve our detection and prediction rates for glaucoma.

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