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From Machine Learning to Artificial Intelligence Applications in Cardiac Care

Real-World Examples in Improving Imaging and Patient Access

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ABSTRACT: Artificial intelligence offers the potential for transformational advancement in cardiovascular care delivery, yet practical applications of this technology have yet to be embedded in clinical workflows and systems. Recent advances in machine learning algorithms and accessibility to big data sources have created the ability for software to solve highly specialized problems outside of health care, such as autonomous driving, speech recognition, and game playing (chess and Go), at superhuman efficiency previously not thought possible. To date, high-order cognitive problems in cardiovascular research such as differential diagnosis, treatment options, and clinical risk stratification have been difficult to address at scale with artificial intelligence. The practical application of artificial intelligence in the underlying operational processes in the delivery of cardiac care may be more amenable where adoption has great potential to fundamentally transform care delivery while maintaining the core quality and service that our patients demand. In this article, we provide an overview on how these artificial intelligence platforms can be implemented to improve the operational delivery of care for patients with cardiovascular disease.

Andrew Ng, Stanford Professor and a founding contributor in deep learning technology, states "Artificial Intelligence is the new electricity."[1] Artificial intelligence (AI) has the promise to power multiple industries and become embedded in our way of life. Statistical methodologies of machine learning and deep learning models have thus far been used in imaging, clinical-risk stratification, and precision medicine, aimed at automating cognitive insights toward scalable interpretation of the vast medical data sets in health care. Prior reviews have presented the statistical methodologies and overviews of machine learning model types and how they are applied in medicine.[2,3] Here we present a review and examples of the operational application of machine learning in cardiac clinical care, and highlight the benefits and challenges of using AI-powered applications in the practical delivery of health care.

FROM MACHINE LEARNING TO AI APPLICATIONS IN HEALTH CARE

The field of AI has existed in research for nearly 70 years since the term was first coined in 1955,[4] but only recently, in the past decade, has it begun to flourish in industry applications because of the advent of ubiquitous computing power

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and data access. Widespread adoption and interest in machine learning methodologies has reinvigorated the field of data science and engineering, becoming a driving engine at many enterprises toward AI-powered applications and products. The focus of industry has shifted from the creation of algorithms solely to a focus on incorporation of such algorithms into AI-powered platforms and solutions.

Machine learning is the algorithmic basis for AI, where the leveraging of statistical models and methods to derive insight from large sets of data drives the basis of AI software. As reviewed in prior articles, the machine learning toolset has grown large and includes a multitude of mathematical models such as decision trees, neural networks, support vector machines, Bayesian classifiers, clustering algorithms, and component analysis.[2,5] Moreover, recent interest has focused on the performance capabilities of deep learning, a subclass of machine learning that uses multilayered neural networks.[6] These algorithms have shown ability to outperform humans in a multitude of tasks such as image and speech recognition,[7] or complex games such as chess or Go.[8] Initially, domains in medicine that contain large accessible amounts of raw data (imaging, physiology, etc) were amenable initial targets of this technology, whereas traditional clinical care operations were out of reach because of disjointed legacy systems and fragmented information technology infrastructure. Because interoperability standards and data integration capabilities have flourished at most enterprises, AI-based solutions have now begun to focus on operative and clinical pathways. Moreover, the landscape for health care has increased focus on value-based care and providing less costly care at equal or higher quality, necessitating many healthcare enterprises to embrace AI applications to enact automation beyond traditional information technology and electronic medical record use cases.

AI IN HEALTH CARE: CHALLENGES IN IMPLEMENTATION

To date, AI applications in health care have not attained widespread adoption in everyday clinical care, despite significant advances within both the research community and in industry. Several reviews and opinions in this Journal and others have highlighted the limitations of machine learning[2] and inflated expectations of its ease of implementation in medicine.[9] For example, highly predictive algorithms of disease states have been created, yet algorithms alone offer no real solution toward reducing risk without identification of modifiable factors. Moreover, the black-box nature of machine learning algorithms is problematic in medical care where insight and understanding are necessary for intervention. And, although these challenges are common to the application of machine learning in general, in the authors' opinion, the slow adoption of AI applications in health care specifically is attributable in large part to 2 issues: first, an initial focus in the field on higher-order clinical cognitive tasks in clinical decision support, and second, insufficient integration of machine learning into everyday clinical operations to create a human-in-the-loop training paradigm.

The focus on machine learning and its utility in clinical decision support is rooted in the history of cardiovascular and clinical research efforts in risk stratification and computer-aided diagnosis. Risk stratification has been a fundamental concept in cardiac care: the Framingham Risk, TIMI, CHA_2DS_2-Vasc, HAS-BLED, and other scores have been crucial advances in standard cardiac care and gauging the utility of emerging therapies.[10–13] It is a natural extension, then, that machine learning models that are inherently predictive in nature would lend themselves to this area of research. In parallel, computer-aided diagnosis, in particular, in the field of radiological imaging, has been pursued since the first digitization of clinical films in the 1960s[14] and continues to be a large focus of machine learning efforts today given the enormous volume of imaging data.

In the field of medicine, the early successes for AI therefore have been in diagnostic problems in imaging. A Google team recently showed that neural networks were able to predict the severity of diabetic retinopathy from fundoscopic images with specificity and sensitivity comparable to board-certified ophthalmologists.[15] A similar study on dermatologic malignancy was able to assess skin cancer classification with performance again at expert levels.[16] In contrast to the progress achieved in diagnostic imaging, efforts in coordinating care operations and delivery have not yet achieved as much success. This is primarily because of the paucity of clean data from a traditional fragmented information technology infrastructure that is readily digestible by machine learning. An important relevant concept in this context is Big Data hubris, a concept introduced by researchers analyzing the failure of the Google Flu prediction system[17]; although having large data sets as in health care is of potential value, such data sets are not a substitute for traditional experimental rigor that goes to great lengths to ensure that data collection and analysis are valid and reliable. More simply put, electronic medical records and information technology ancillary systems in health care were never created or intended for machine learning,[18] and thus it is much more difficult to convert these types of data into scientifically rigorous signals for actionable analysis. To move beyond image classification use cases in health care, significant work in standardization, integration, and validation of data sources is a prerequisite for any successful machine learning effort.

Applied AI in Cardiovascular Care

Although there are current hurdles to the application of AI for cardiac risk stratification and image analysis, practical application of machine learning has immediate applications in qualitatively increasing the efficiency and access to cardiovascular care. At NewYork-Presbyterian, we are undertaking several implementation initiatives in AI to streamline clinical operations underlying the delivery of cardiac care. In general, we outline a strategy that increases access to cardiovascular care by reducing the bottlenecks in care delivery that occur in both the inpatient and outpatient setting. In particular, we advocate for redefining care operations and processes in implementation of AI technologies, where data-driven strategy and automation of cognitive insight can be leveraged to optimize resource delivery.

Improving Access to Cardiac Diagnostic Imaging

An important focus for cardiovascular care delivery is the efficiency and availability with which we provide diagnostic studies to our relevant patients. Traditionally, the cost and barriers of diagnostic imaging studies and performance thereof have been significant enough that access to appropriate screening studies can be limited, in particular, for underserved populations. However, the ability of AI and machine learning technologies to automate acquisition and interpretation of studies shows promise toward reducing the total cost of delivery of these studies and removing limitations of trained resources that often gate access.

Recent machine learning studies in cardiac imaging have made significant progress in autointerpretation and autoquantification in echocardiography,[19,20] single photon emission computed tomography,[21,22] and cardiac MRI.[23–25] Of these modalities, cardiac MRI has the unique capability to provide highly quantifiable information on cardiac function, valvular disease, blood flow, perfusion, and vascular anatomy.[26] However, cardiac MRI and, in particular, 4-dimensional (4D) flow MRI, is a relatively limited resource in comparison with echocardiography and single photon emission computed tomography; the level of expertise and experience required to perform the postprocessing 3-dimensional segmentation, visualization, and 4D analysis is reserved to a handful of cardiology and radiology experts. Yet the diagnostic utility is substantial. Four-dimensional flow cardiac MRI captures 3-dimensional cardiac data in a time-resolved, ECG-gated manner producing 3-dimensional velocity vectors, comprehensive analysis of flow volumes and patterns, regional wall motion analysis, pressure gradient quantification, and vascular hemodynamics in a single study. Expertise is not the only limitation to access; because cardiac MRI requires manual review to segment and measure a significant amount of 2-dimensional and 3-dimensional data (up to 20 minutes for segmentation of 1 ventricular chamber), study interpretation is a time-consuming process with interoperator variability.[27]

At our institution, we have deployed a Food and Drug Administration–approved cloud-based deep learning platform that runs on a scalable distributed graphics processing unit architecture (Arterys) to accelerate the clinical workflows in cardiac MRI. For cardiac MRI, we are focusing our efforts on augmenting the postprocessing quantification to reduce time to diagnosis. Through automated anatomic segmentation, flow quantification, and visualization, cardiac 4D flow studies can be assessed within minutes to quantify valvular lesions, hemodynamic flow, and function (Figure, A). This framework establishes an operational model for continuous improvement; by aggregation of cardiac MRI studies in a common cloud platform, the deep learning models used are able to retrain with every study, learning from the labeling by each human expert. Thus, as the studies performed within the system increase, consequent gains in efficiency can be leveraged in future cases. Four-dimensional flow combined with newer acquisition methods in parallel imaging and compressed sensing techniques now offer fast (<10 minute) acquisition times.[28,29] Combined with postprocessing machine learning, cardiac MRI operations can thus be streamlined such that increased access and availability to a larger cardiac patient population is practically possible; it is reasonable to anticipate that at least a 10-fold increase in capacity for cardiac MRI 4D flow studies can be achieved given an ≈90% reduction in postprocessing time. Although we present an example of how AI aids in postprocessing of 4D flow cardiac MRI, we believe that similar approaches can aid any diagnostic modality where significant processing such as segmentation, transformation, and interpretation is required.

Leveraging AI to automate acquisition of cardiac diagnostic studies is also a practical strategy toward increasing access to cardiac care. In contrast to cardiac MRI, echocardiography is a lower-cost, more widely used technology that is unconstrained from the physical MRI infrastructure. Cardiac ultrasound as a diagnostic tool is a mainstay in cardiology, unparalleled in affordability and portability in comparison with other modalities. Echocardiography is a candidate imaging modality for point-of-care evaluation at the bedside at the present time, with the potential for rapid assessment of cardiac function, structure, and hemodynamics. Recent advances in miniaturization of ultrasound technology, in particular, in Micro-Electro-Mechanical Systems chip–based ultrasound acquisition, now makes handheld ultrasound devices a reality, with several devices commercially available on the market (GE VScan,

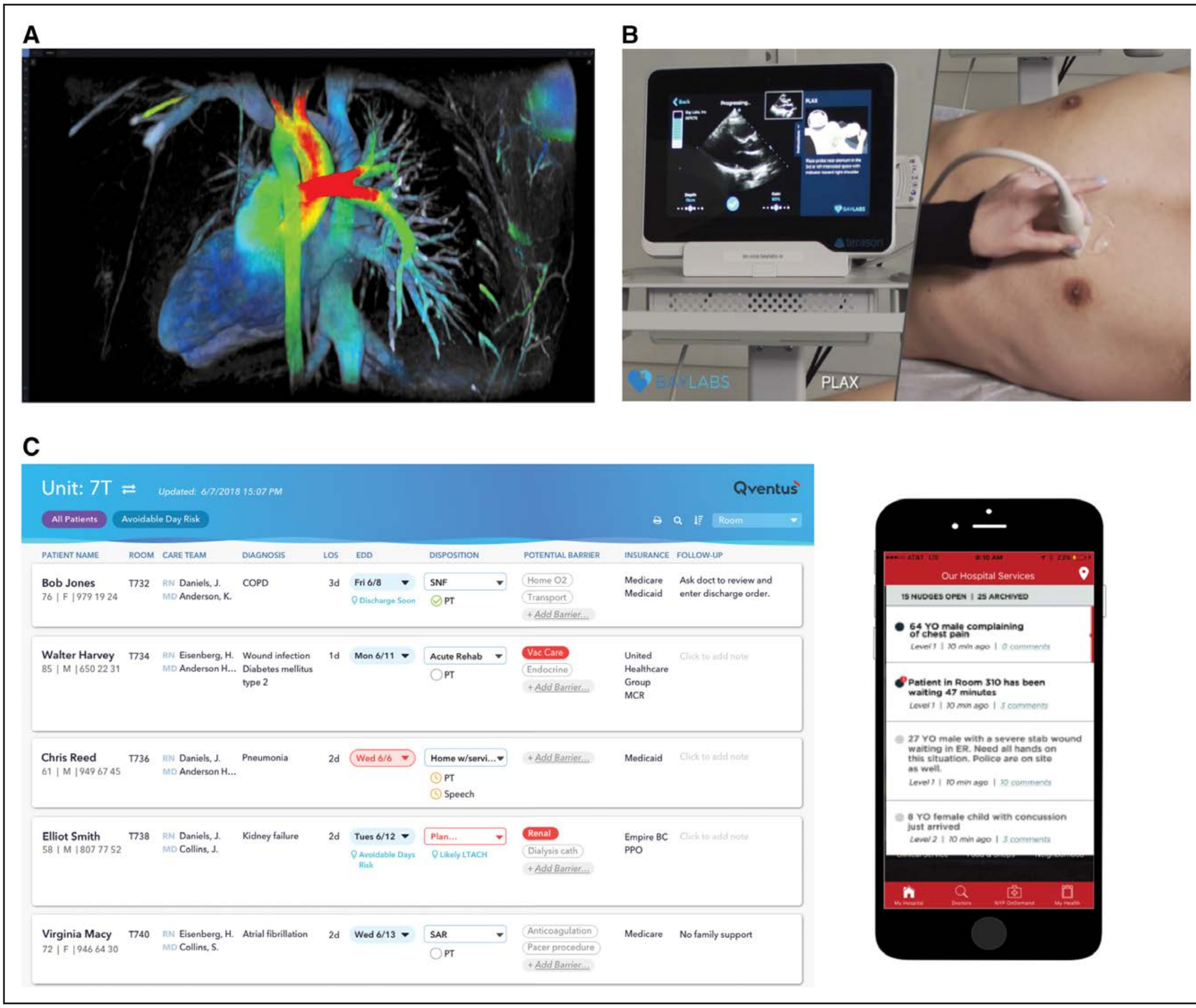

Figure. Applied artificial intelligence in cardiac care.
(**A**) Machine learning for improved postprocessing of cardiac MRI. Image shown here is a 4-dimensional (4D) flow cardiac MRI illustrating blood flow through the heart and pulmonary arteries. Deep learning can be used to automate postprocessing of 4D flow cardiac MRI studies, normally performed manually at dedicated 3-dimensional laboratories. 4D flow cardiac MRI image courtesy of Arterys, Inc. (**B**) Machine learning for automated acquisition of focused cardiac ultrasound. Image shown here depicts automatic acquisition of parasternal long-axis transthoracic echocardiography view. Deep learning networks can guide untrained providers to automate acquisition and diagnosis of standard echocardiographic views in focused cardiac ultrasound. EchoGPS image courtesy of Bay Labs, Inc. (**C**) Machine learning for inpatient cardiac care delivery. Sample views of real-time patient status electronic board and mobile nudge care alerts. Real-time machine learning predictions around length of stay, severity of illness, discharge readiness, and care delays are used for automation/coordination of hospital operations and care pathways. Clinical team feedback to real-time alerts are used as labels to further train machine learning algorithms for improved performance. Images courtesy of Qventus, Inc.

Philips Lumify, Butterfly Inc, Butterfly IQ). The American Society of Echocardiography has published guidelines on "Focused Cardiac Ultrasound" that provide a framework for utilization of point-of-care usage within the scope of practice, and recommend formal training pathways for providers.[30] Recent studies indicate the utility of bedside focused sonography to aid in the rapid assessment and triage of patients both in the outpatient and inpatient setting.[31,32]

The potential for focused cardiac ultrasound at the bedside is however limited by the number of providers and technicians that can be trained in ultrasound acquisition. Utilization of cardiac sonographers who are trained to perform comprehensive examinations is inefficient and time delayed, because trained sonographers are not always immediately available and near the bedside. Proficient training in accurately obtaining proper cardiac windows is, at minimum, a 3- to 6-month process, and requires regular practice and skill maintenance. These barriers create a bottleneck that limits widespread adoption of focused cardiac ultrasound.

For focused cardiac ultrasound at the bedside to become widely adopted, the acquisition of cardiac ultrasound needs to be automated, removing the training and skill maintenance requirements. This challenge can be addressed through novel deep learning technology that automates the acquisition of focused cardiac ultrasound (Baylabs). Using deep learning technology, any untrained person can acquire accurate cardiac ultrasound views at the bedside; the operator optimizes an accuracy signal that indicates to the user how close the desired echocardiographic window is (Figure, B). In our preliminary tests of this methodology, we have observed parasternal long-axis window acquisition times by an untrained user within 30 seconds from start to acquisition. Clinical pilots in the outpatient, emergency department, intensive care unit, and perioperative settings are being pursued to assess the clinical utility of this technology. Clinical case acquisition data will be used to further improve the deep learning platform, adding capabilities of rapid assessment of left ventricular ejection fraction and the presence of valvular disease such as aortic stenosis or mitral regurgitation. At a future state, the possibility of obtaining focused echocardiography with immediate and accurate autointerpretation may allow for point-of-care cardiac screening or triage of patient populations at scale with lower cost.

Improving Delivery Efficiency of Inpatient Cardiac Care

A significant proportion of cardiac care delivery is hospital based with a wide range of services offered in the catheterization laboratories, diagnostic imaging suites, operating facilities, and inpatient units. Although cardiology as a field has been at the forefront of incorporating leading technology into its diagnostic and treatment options, the basic operations of delivering that care through scheduling, transport, resource optimization, and care coordination are woefully lacking by comparison. Indeed, other than protocolization and standardization for a few specific cardiac care pathways (for example, acute coronary syndrome), there is little expectation of service levels (for example, <90 minutes door-to-balloon for ST-segment–elevation myocardial infarction, <48 hours angiography/percutaneous coronary intervention for non–ST-segment–elevation myocardial infarction) associated with the majority of instances of care delivery. A significant challenge contributing to this is the heterogeneity of cardiac diagnosis along with associated comorbidities and concurrent disease states (diabetes mellitus, chronic obstructive pulmonary disease, peripheral vascular disease, etc) that add great complexity to a hospital admission. Moreover, with an aging population that typically marks a busy cardiac service line, demand for hospital-based cardiac services frequently outstrips resource supply (transthoracic echocardiograms, catheterization laboratory, etc) at any given time.

How do we deliver cardiac services efficiently in this environment? It is the opinion of the authors that a real-time and predictive data-driven strategy driving clinical operations is foundational. Cardiac service resources of limited supply can only be effectively managed if there are systems to identify the patients with the highest need. From a clinical perspective, we have these systems in place: the STAT order or the critical escalation pathways create urgency and reprioritization of hospital resources to those that are in critical condition. Yet, for the noncritical patient population that makes up the majority of inpatients at any given moment, we have few systems that help coordinate care delivery and prioritize care to maximize efficiency in utilization.

At NewYork-Presbyterian, we have addressed this issue through a cross-departmental operations initiative that leverages a real-time machine learning platform (Figure, C; Qventus) to optimize our inpatient length of stay for cardiac patients. Through a machine learning data platform, the status of every patient on our cardiac units is tracked in real time, including prediction of barriers that may potentially delay care. By using a series of machine learning algorithms, prediction signals around estimated length of stay, clinical care delays (physical therapy, transthoracic echocardiography, procedures, computed tomography/MRI), severity of illness, and discharge barriers (insurance barriers, postacute placement) are generated early in the inpatient stay to indicate and prioritize resource needs. Operationally, automated predictions are generated through daily scanning of all inpatient charts that are then surfaced to an interdisciplinary care team with physicians, nurses, social workers, and care managers who are tasked to reprioritize resources as needed. Furthermore, decisions made by the clinical care teams are used to further improve training of the predictive algorithms as a human-in-the-loop paradigm; for instance, the appropriateness of a predicted delay in ancillary services (MRI, computed tomography, physical therapy, etc) is recorded and fed back into the training models for further improvement of the machine learning. In our initial deployment in 2 academic hospitals, we have observed year over year decreases in length of stay from this operational effort, without sacrificing quality of care or readmission rates. As we continue to train these machine learning models in our clinical operations, we plan to continue building automated care delivery pathways that are customized and specific to each unique patient.

Machine Learning for Healthcare Delivery

As the healthcare landscape shifts from a fee-for-service to value-based models, the need for technology platforms to streamline the basic operations of healthcare delivery is enhanced. Although continued development in diagnostic and clinical support is warranted, much of the near-term application successes of AI will be in the automation and operationalization of existing bottlenecks in care delivery. As described earlier, we outline a strategy for utilization of machine learning algorithms to augment existing clinical care processes, thereby increasing access, efficiency, and availability of cardiac services. Although we mention specific technologies that we use at NewYork-Presbyterian, these are simply illustrative of our approach and focus on operational and access issues within a cardiac care service line.

Recent advances in machine learning capabilities suggest that significant change to the healthcare industry is on the horizon. Neural networks are currently able to outperform human performance with both computer vision in image classification,[33] natural language processing in reading comprehension,[34] and audio modeling in speech recognition.[35] The implications of these technology breakthroughs suggest that significant use of voice technologies and medical record analysis will transform healthcare delivery. Unstructured medical record notes will transform into interpretable data streams that will power clinical decision support and monitor adherence to standardized treatment pathways. Documentation, coding, and billing will be significantly streamlined through voice technology and natural language processing, resulting in higher accuracy of the medical record, and reduced time in manual note creation, as well. It is likely that conversational AI systems combined with voice recognition technologies will supplant healthcare call centers and reception desks as improved alternatives with higher service and availability.

In this brave new world of AI-powered technologies, we envision a healthcare system that returns to its roots of patient-centered care. With mainstream media predictions of robot doctors and automatons, the opposite is more likely to occur, with the patient-doctor relationship strengthened through these new technologies. With AI and automation, data retrieval can be more instant and seamless, diagnostic uncertainties less frequent, and documentation/coding less burdensome. The consequences of these technologies should be increased time with patients, more focus on diagnostic dilemmas, and an increased capability to practice the art of medicine. Healthcare systems that embrace and invest in AI technologies will therefore be best positioned to bend the cost structures and time constraints that plague our delivery of care today, and ultimately provide the highest quality and efficient patient-centered care for all.

ARTICLE INFORMATION

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Disclosures

None.

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