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The Advent of Artificial Intelligence in Diabetes Diagnosis: Current Practices and Building Blocks for Future Prospects

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THE ADVENT OF ARTIFICIAL INTELLIGENCE IN DIABETES DIAGNOSIS: CURRENT PRACTICES AND BUILDING BLOCKS FOR FUTURE PROSPECTS

Abstract: India has the highest proportion of diabetes patients, and it is estimated that there will be 134 Million diabetics in India by 2045 as per IDF. Also, the disease burden is increasing to the young population between ages 25-40 as more of them are diagnosed positive according to JAMA recently. Moreover, there are only 4.8 Doctors per 10,000 population, and in villages, the ratio is the lowest possible in this country, according to the Indian Journal of Public Health. Therefore, screening & predicting Diabetes at an early stage remains a priority for clinicians. It reduces the risk of major complications and improves patients' quality of life with diabetes, and builds resilience and well-being amongst other citizens. With the advancement of Computer Science & Artificial Intelligence, it is now possible to predict diabetes and other such diseases through applying deep learning algorithms in high-quality data sets. This helps in a more accurate and faster diagnosis of Pre-diabetes, Diabetes & diabetes-related progressive eye diseases. In this study, a systematic review of the Pubmed repository for current practices to diagnose Diabetes based on AI intervention in the Indian context is carried out. Also, a critical analysis was done on various pioneered companies currently offering AI-based Diabetes diagnostic services in India. The study represents different concepts of AI tools used to predict the diseases currently available in India. Although most of the studies were carried out on Diabetic Retinopathy screening, future opportunities can be in several other areas such as Clinical Decision Support, Predictive Population Risk Stratification and Patient Self-Management Tools.

Keywords: Diabetes diagnosis, AI-based Diabetes Diagnosis, AI intervention in Diabetes Diagnosis and Management

Introduction

India is one of seven countries in the SEA Region of the IDF. 463 million people globally have diabetes, and 88 million people in the SEA zone have diabetes, which will grow to 153 million by 2045. (IDF.Org, 2021).

- Complete population for adults: 859,956,100
- Diabetes incidence in adults: 8.9 percent
- Total cases of adult diabetes: 77,005,6005. (IDF.Org, 2021).

The risk of type 2 diabetes (T2DM) among younger Indians has been increased by sedentary lifestyles and elevated visceral adiposity.

For middle-aged Indians with T2DM, there is a greater risk of biological aging. Among middle-aged Indians, the production of T2DM is more general. T2DM can accelerate the aging process and can subsequently predispose Indians at a very early age to different age-related complications (Banerjee et al., 2020).

In comparison to the belief of having 7 doctors per 10,000 persons, there were just 4.8 practicing doctors per 10,000 populations available in India in 2014. The majority of the licensed physicians have either retired from the country or have emigrated to practice abroad. It is projected that only by 2030 will the nation be able to reach a ratio of around 6.9 practicing doctors per 10,000 individuals.

Given these results of the current accessibility of physicians per 10,000 individuals and their growth prospects over the next 15 years, achieving even a modest doctor population ratio of 1:1000 by 2030 seems to be an unlikely task (Potnuru, 2017).

Early diabetes screening and prediction is often a priority for physicians since it decreases the likelihood of significant complications and increases the quality of life of diabetes patients, and builds resilience and well-being among other people (Trikkalinou, 2017).

Table 1: Common AI Approaches used in Diabetes Care

Common AI Approaches used in Diabetes Care			
Sl No	Method	How it works	Applications
1	Multilayer perceptron	Neurons in each layer are connected to all neurons in the next layer, consisting of neurons in the input layer, output layer, and several hidden layers, making each layer completely connected to the next. Learn by the form of 'backpropagation.'	Prediction models, patient self-management tools
2	Convolutional neural network (CNN)	Composed of several neuron layers with neurons in the convolution layer that look at small patches of the input image at a time, like a filter, and are transformed across the entire input image, and parameters are shared throughout the image. Learn by the form of 'backpropagation' The presence of unique features across space is detected by each CNN layer, detecting more high-level features as they move forward.	Retinal Screening
3	Random forest	Creates an assembly of trees of judgment. A random collection of features for evaluating root nodes and splits are considered in each tree.	Retinal Screening, decision support, prediction models, patient self-management tools
4	Fuzzy logic/ fuzzy system	Provide a probability value between 0 and 1 for membership of a certain class rather than a deterministic decision (0 or 1).	Retinal screening, decision support, sensors, and artificial pancreas
5	Support vector machine (SVM)	Method of classification for binary results (not often used for multiclass problems, but techniques for multiclass SVM exist). Works by adding information to a high-dimensional space and finds a hyperplane separating the best two groups (that maximizes the distance between the plane and nearby data points, or margin)	Retinal Screening, decision support, prediction models, patient self-management tools

6	Logistic regression	Method for binary outcome classification. Predicts the possibility of an outcome (0 or 1) depending on the characteristics. Learn the model coefficients by the calculation of maximum probability. Searches for a line or hyperplane that best represents the points of data.	Prediction models
7	Natural language processing	Computational tools and techniques for human language processing, interpretation, and inference efficiency.	Prediction models
8	K-nearest neighbors algorithm	Categorizes input data using its k nearest neighbors into several groups.	Retinal Screening, decision support, prediction models, patient self-management tools

This helps in a more accurate and faster diagnosis of Pre-diabetes, Diabetes & diabetes-related progressive eye diseases. AI's ability to rapidly interpret and process enormous amounts of data into simple, actionable guidance. AI has significant potential to improve the screening, diagnosis, and management of patients with diabetes (Lo´pez B. *et al.*, 2018).

Background

In the 2019 IDF South-East Asia (SEA) area, 88 million adults (20-79) live with diabetes. By 2045, this number is expected to grow to 153 million. More than half (57 percent) of people with diabetes in the IDF SEA Area are undiagnosed. In 2019, diabetes accounted for 1.2 million deaths in the IDF SEA area. Hyperglycaemia in pregnancy affects 1 in 4 live births in the IDF SEA Area. In 2019, USD 8.1 billion was spent on health care for people with diabetes, the second-lowest expense among all IDF regions in 2019. (IDF Diabetes Atlas 9th Edition 2019).

Table 2 : Countries with maximum number of people with Diabetes (20-79 years)

Top 5 Countries for Number of People with Diabetes (20-79 Years, 2019)	
	Millions
India	77.0
Bangladesh	8.4
Sri Lanka	1.2
Nepal	0.7
Mauritius	0.2

The rapid urbanization, sedentary lifestyle, high-calorie diet, visceral adiposity, and high genetic predisposition have been established as the key factors that increase the risk of type 2 diabetes mellitus (T2DM) among Indians at a much younger age and a lower body mass index (BMI) than the western population (R. Pradeepa *et al.*, 2011). Various population-based studies have shown that in age groups below 50 years of age, the average onset of T2DM among Indians is steadily growing (R. Pradeepa *et al.,* 2011, Kumar *et al.*, 2018). Chronic hyperglycemia, dyslipidemia, and increased insulin resistance are the key pathological features of T2DM, contributing to a plethora of metabolic and molecular alterations, eventually leading to the development of diabetes-associated vascular complications (Donath, 2014)

One of the most significant causes of the backwardness of Indian health status is the relative inaccessibility of primary health care and undernourishment among children in India. The total number of licensed physicians rose from approximately 75,594 in 1960, to 393,424 in 1990, 566,102 in 2000, 824,673 in 2010, and to 943,529 by 2014. (MCI, 2019). The rapid growth of medical doctors through the recent expansion of private medical education has not dramatically changed the population's basic health outcomes. The key factors are: one, the recent rise in the number of medical practitioners is not sufficient to balance the risk's very rapid increase in overall health care needs, rising population; two, the higher capabilities and expectations of the medical practitioners, especially specialist doctors, do not match with the primary health care requirements and affordability of the majority of people in rural areas; and three, increase in the number of registered doctors (stock) do not reflect the actual availability of doctors in the country, i.e., the stock is wrongly viewed as the availability of doctors in the country is unaware of attrition due to retirement, emigration, change of occupation, etc. The Government of India has 7 doctors per 10,000 communities, according to the WHO and the Ministry of Health and Family Welfare (WHO, 2019). This ratio, however, is derived from the registration stock of doctors accumulated in India, including those doctors who were trained and registered since the beginning of the 20th century (MCI, 2019). This has not been updated to strength due to retirement, discontinuation of practice, emigration, and death of doctors.

The key purpose of early diagnosis and treatment of diabetes is the quality of life (QoL). As symptoms begin to arise or comorbidities coexist, diabetic QoL gets worse. Coronary arterial disease accompanied by renal failure, blindness, and the combination of micro-and macrovascular complications and in some studies of sexual dysfunction was prevalent among the complications in health-related quality of life (HRQoL) reduction, but not related to risk factors (genetic, birth weight, or others). In fact, many are the comorbidities that further deteriorate the effect of diabetes in a patient's life. Obesity, hypertension, dyslipidemia, depression, and arthritis are among them. Among them, obesity, hypertension, dyslipidemia, depression, and arthritis are the most common.

The lack of real-time, key health knowledge required to make informed decisions associated with intensive treatment and strict management of diabetes also hampers optimal care for people with diabetes (PWDs). While advances in technology provide many people in many fields with unparalleled and inexpensive access to critical information, their effect on the treatment of patients with diabetes seems somewhat limited. The rapid extension of medical expertise compounds the complexities of real-time information on diabetes treatment. Rapid developments in artificial intelligence (AI) offer the promise of making accessible for the treatment of PWDs both real-time structured and unstructured health data.

The Turing Archive defines AI for the History of Computing as " the science of making computers do things that require intelligence when done by humans." AI covers a wide range of approaches to simulating human intelligence and performing different tasks of reasoning, such as visual perception, recognition of speech, analytics, decision-making, and language translation. The scope of AI methods is used by cognitive systems to expand and scale human awareness and expertise by allowing humans to easily exploit large sources of knowledge to solve problems. Today, in order to meet customer demand in every sector, including health care, AI uses vast quantities of vital information.

A 2017 study found that 68 percent of developers and publishers of mobile health apps agree that diabetes continues to be the single most significant area of health care with the greatest business potential for digital health solutions in the near future and that 61 percent see AI as the most disruptive technology shaping the digital health sector. This paper aims to better understand what important AI developments can be applicable to PWDs, their primary care clinicians today.

Method

The study team conducted a predefined, online PubMed search of publicly available sources of information using the search terms ‘‘diabetes’’ and ‘‘artificial intelligence (AI).’’ To identify articles with clinically relevant, high-impact diabetes AI applications, the team excluded manuscripts with publication dates before 2010 and those whose purpose was primarily technical in nature (e.g., focused solely on AI algorithm development). The first-pass search identified a total of 20 clinically relevant abstracts. The additional review excluded 9 as duplicative or primarily technical. The second-pass review yielded a total of 11 unique, clinically relevant articles researching the direct application of AI in diabetes prevention, diagnosis, and treatment. The information was then collated and classified. The research was conducted between Dec 2020 and Feb of 2021.

Results

A total of 11 clinically important and high-impact articles published related to the field of applied AI in diabetes care were obtained from the PubMed search. The goal of the AI applications was to enhance a wide range of diabetes care, from diabetes screening and diagnosis to monitoring and treatment, including applications, devices, and systems to support patients, clinicians, and health systems. The published papers included in this search were of high clinical impact in that they aimed to establish and evaluate AI approaches that could have a major impact on diabetes treatment in the areas of access, precision, quality, affordability, speed, and patient, clinician, and caregiver satisfaction. An analysis of the high-impact papers indicates that AI applications seek to turn diabetes treatment into four main areas: automated retinal screening, support for clinical decision-making, stratification of predictive population risk, and tools for patient self-management, as outlined in Table 1. In these studies, a diverse and complex collection of AI methods and cognitive computing systems were employed. The more popular AI approaches mentioned in the research are specified in Table 2, and their clinical applications in diabetes care are listed.

In this study, a systematic review of the PubMed repository for current practices to diagnose Diabetes based on AI intervention in the Indian context is carried out. As seen in table 3 here:

Table 3: Current practices to diagnose Diabetes based on AI intervention in India

Details of the journal/ Book / Book chapter/ website link	**Year of Publication**	**Indexing of journal (Scopus/ SCI index etc.)**	**Main findings or conclusion relevant to proposed research work**
Mohan Rema, Sundaram Premkumar, Balaji Anitha, Raj Deepa, Rajendra Pradeepa, and Viswanathan Mohan; Prevalence of Diabetic Retinopathy in Urban India: The Chennai Urban Rural Epidemiology Study (CURES) Eye Study, I; Investigative Ophthalmology & Visual Science, July 2005, Vol. 46, No. 7 Invest Ophthalmol Vis Sci. 2005;46:2328–2333) DOI:10.1167/iovs.05-0019	Jul-05	iovs.arvojournals.org	This research shows that diabetic retinopathy prevalence in urban South Indians is lower than in other ethnic groups. However, DR is likely to pose a public health burden in India due to a large number of diabetic subjects; regular retinal examination is therefore mandatory for early-stage DR detection.

Shankaracharya, Devang Odedra, Subir Samanta and Ambarish S. Vidyarthi, Computational Intelligence-Based Diagnosis Tool for the Detection of Prediabetes and Type 2 Diabetes in India, The Review of Diabetic Studies; Vol 9, No 1, 2012 DOI 10.1900/RDS.2011.9.55	May-12	www.The-RDS.org	This study describes a highly accurate machine learning prediction method for high-accuracy detection of prediabetic, diabetic, and non-diabetic individuals. In hospitals or diabetes prevention services, the instrument could be used for large-scale screening.
Kim Ramasamy & Rajiv Raman & Manish Tandon, Current State of Care for Diabetic Retinopathy in India; Curr Diab Rep (2013) 13:460–468 DOI 10.1007/s11892-013-0388-6	May-13	Springer Science+Business Media New York 2013	Given the country's diverse geographic characteristics and the shortage of ophthalmologists, telescreening seems to be a very promising method in India. An approach to detecting at least sight-threatening retinopathy rather than any retinopathy is believed to be more useful until India has a sufficient number of trained vitreoretinal specialists or all ophthalmologists become aware of diabetic retinopathy for medical management. There is an important need to raise awareness of diabetes and its associated complications while strengthening primary diabetes treatment. It is important that health care providers connect with each other in the management of patients to ensure that high-risk individuals are screened early. The best treatment available today for diagnosed cases with diabetic retinopathy is on par with that available in developed countries worldwide. However, this treatment is still not available to many people, especially those in rural areas. Patients may have greater access to adequate screening and treatment by technical advancements and thereby reduce unnecessary blindness.
Gadkari *et al.,* Prevalence of diabetic retinopathy in India: The All India Ophthalmological Society Diabetic Retinopathy Eye Screening Study 2014 Indian J Ophthalmol. 2016 Jan; 64(1): 38–44. doi: 10.4103/0301-4738.178144	Jan-16	Indian Journal of Ophthalmology	In 2014, the All India Ophthalmological Society (AIOS) took an initiative to detect the prevalence of DR in eye clinics across the length and breadth of the country among people with diabetes. The exercise marked the first pan-India effort to take the first steps against the DR blindness issue outside the nation. While the study aimed to determine the prevalence and explore risk factors among known diabetics for the development of DR, it also sought to identify weaknesses in the current case detection process to strengthen future screening programs.
Automated diabetic retinopathy detection in smartphone-based fundus photography using artificial intelligence Ramachandran Rajalakshmi, Radhakrishnan	Mar-18	Springer Nature	In this review, fundus photography evaluates the role of artificial intelligence (AI)-based automated software for diabetic retinopathy (DR) and sight-threatening DR (STDR) detection using a smartphone-based interface

Subashini, Ranjit Mohan Anjana, Viswanathan Mohan Eye (2018) 32:1138–1144 https://doi.org/10.1038/s41433-018-0064-9			and validates it against grading by an ophthalmologist. Grading by the automated ophthalmologist. FOP mobile retinal imaging automated AI analysis has a very high sensitivity for DR and STDR detection. It can therefore be an initial method for mass retinal screening in people with diabetes.

Table 4: Different Pioneered companies currently offering AI-based Diabetes diagnostic services in India

Details of the journal/ Book / Book chapter/ website link	**Year of Publication**	**Indexing of journal (Scopus/ SCI index etc.)**	**Main findings or conclusion relevant to proposed research work**
Gulshan *et al.,* JAMA Ophthalmol. 2019;137(9):987-993. doi:10.1001/jamaophthalmol.2019.2004 Published online June 13, 2019.	Jun-19	Google Research, Mountain View, California (jamaophthalmology.com)	This study shows that in a prospective setting, the automated DR system generalizes to this population of Indian patients and demonstrates the feasibility of extending screening services using an automated DR grading system.
Natarajan *et al.,* JAMA Ophthalmol. 2019;137(10):1182-1188. doi:10.1001/jamaophthalmol.2019.2923 Published online August 8, 2019.	Aug-19	jamaophthalmology.com	In community screening for referable diabetic retinopathy with a smartphone-based fundus camera, these pilot study results show promise in the use of an offline AI device. In remote areas where ophthalmology services are not available, the use of AI will allow screening for referable diabetic retinopathy. This research was performed on patients with diabetes attending a clinic that provides the community with curative services at the primary level. However, to expand the findings to general population screening, a study with a larger sample size may be required.
Ramachandran Rajalakshmi, The impact of artificial intelligence in screening for diabetic retinopathy in India Eye (2020) 34:420–421 https://doi.org/10.1038/s41433-019-0626-5	Dec-19	Springer Nature	As per this study, it appears that real-time deployment of AI in screening for DR is feasible. It fits in with the current trend of telemedicine for screening, and automated retinal image analysis extends opportunities to screening in more remote areas. AI-assisted DR algorithms could potentially expedite early detection of DR at the primary care level and would be helpful in screening large numbers of people with diabetes in low and middle-income countries like

			India.
Sosale B, Aravind SR, Murthy H, et al. Simple, Mobile-based Artificial Intelligence Algorithm in the detection of Diabetic Retinopathy (SMART) study. BMJ Open Diab Res Care 2020;8:e000892. doi:10.1136/bmjdrc-2019-000892	Jan-20	BMJ Open Diabetes Research & Care	In the diagnosis of diabetic retinopathy (DR) using non-mydriatic (NM) retinal photos, this study evaluated the efficiency of the offline smartphone-based Medios artificial intelligence (AI) algorithm. In the detection of RDR using NM retinal images, the Medios AI has high sensitivity and specificity.
Bardhan *et al.*, CONNECTING SYSTEMS, DATA, AND PEOPLE: A MULTIDISCIPLINARY RESEARCH ROADMAP FOR CHRONIC DISEASE MANAGEMENT	Mar-20	MIS Quarterly	It Showcases research that focuses and contributes to the role of AI and analytics in the management and prevention of chronic diseases. We give a summary below of emerging trends from previous studies on the use of analytics in the management of chronic diseases. Since research on health information systems has been reviewed in prior work, the emphasis is mainly on prior research on analytics; although the focus is on prior research on analytics The treatment of chronic diseases is not limited to these past reviews. Furthermore, this paper leverages a "connecting systems, data, and people" structure to provide a roadmap for future research in this space.
Gunasekeran *et al.*, Artificial intelligence for diabetic retinopathy screening, prediction and management; Curr Opin Ophthalmol. 2020 Sep;31(5):357-365. doi:10.1097/ICU.0000000000000693	Sep-20	Pubmed	This paper summarizes developments in artificial intelligence and teleophthalmology for diabetic retinopathy screening, including real-world artificial intelligence implementations and cost-effectiveness studies. In addition, initial research on the use of artificial intelligence models for risk stratification and management of DME for diabetic retinopathy is outlined alongside possible future guidance. Finally, in answer to COVID 19, the need for artificial intelligence adoption within ophthalmology is addressed.

A critical analysis done on various pioneered companies currently offering AI-based Diabetes diagnostic services in India. As seen in table 5 here:

Table 5: A Critical Analysis of various pioneered companies currently offering AI-based Diabetes diagnostic services in India

Details of the journal/ Book / Book chapter/ website link	**Main findings or conclusion relevant to proposed research work**
Map my Genome https://mapmygenome.in/	The Genomepatri test gives individuals insight into their genomes to help them make proactive decisions about their health. Mapmygenome is a molecular diagnostic company. The company offers personalized health solutions that help people get to know about themselves based on genetic tests. Mapmygenome provides actionable steps for individuals and their physicians towards a healthier life by combining genetic health profile & health history with genetic counselling. With proprietary AI/ML-based data analysis algorithms, they provide genomic assessment for more than 200 conditions.
Microsoft India (https://news.microsoft.com/en-in/tag/launch-microsoft-intelligent-network-for-eyecare-mine-government-health-it-conference-and-exihibition/)	Microsoft India partnered with L V Prasad Eye Institute and collaborated with global experts to launch an AI platform for Microsoft Intelligent Network for Eyecare (MINE) to provide healthcare by screening for eye problems and preventing 'avoidable blindness' for children with eye problems.
Google (https://www.healthcareitnews.com/news/google-verify-using-ai-screen-diabetic-retinopathy-india)	Google has trained its image recognition algorithms in conjunction with Aravind Eye Care Systems to detect signs of diabetic-related eye problems and a human doctor, leading to timely intervention and preventing blindness. Physicians will be able to grade diabetic retinopathy to a certain level of identification, mainly for screening, with AI and Google's machine learning algorithm.
DRISHTI from SigTuple.com	Drishti is a SaaS platform for diabetic retinopathy (DR) screening (as per ICO2017 standards) and has the ability to use fundus images to flag age-related macular degeneration (AMD) and glaucoma. Drishti DR is a registered SaMD product, a cloud-based artificial intelligence (AI) system capable of automated image analysis captured from the Fundus Diabetic Retinopathy screening camera (DR). To offer end-to-end reporting, the software can be integrated with a Fundus camera.
Orbuculum	Orbuculum utilizes artificial intelligence through genomic data to predict diseases such as cancer, diabetes, neurological disorders, and cardiovascular diseases. It serves as a fast, accurate, highly cost-effective process for diagnosing and predicting diseases. We are a reliable solution that can meet the needs of the poor and save their lives by diagnosis at a very early stage, reducing the time taken for diagnosis of diseases and at the same time predicting the onset of diseases in the future. With an increasing amount of genomic data being generated globally, our tool is essential for extracting meaningful information from this data and putting it into

	practice.
Arya-ai (arya.ai)	In drug discovery, diagnostics, and personalized medicine, Arya ai utilizes deep learning technology.
Inayo (www.inayo.in)	Inayo is a personal assistant to patients suffering from diabetes. Artificial Intelligence and Machine Learning are at the core of Inayo. In consultation with senior diabetologists, nutritionists, diabetes educators, podiatrists, ophthalmologists, and endocrinologists, more than half a million combinations of unique diabetes profiles have been developed, and algorithms developed. The core components of the diabetes management program are as follows: diabetes education and advice, self-care and lifestyle management, home comfort medication and diagnostic tests, and expert monitoring.
Details of the journal/ Book / Book chapter/ website link	Main findings or conclusion relevant to proposed research work
DRISTi from Artelus (Artificial Learning Systems India Pvt. Ltd) https://artelus.com/products.php#dristi	Diabetic Retinopathy Screening (DRISTi) (CE Class 1) is an AI product designed to instantly detect the early presence of Diabetic Retinopathy (DR) in patients during eye testing. AI on a Chip Artelus has taken DR screening to the most remote areas of India by cutting the cord and creating the first of its kind. This offline solution does not rely on the internet or the cloud and brings the forgotten billions who need this service to the Point of Care diagnostics.
ChironX (www.chironx.ai)	ChironX works in the area of medical diagnostics powered by AI. It offers diagnostic software from medical images to diagnose complex diseases. An image processing technique is currently used to diagnose diabetic retinopathy, hypertensive retinopathy, and other retinal disorders. To examine retinal fundus images in seconds, it uses deep learning and AI in its apps. It allows doctors and even non-specialists to have a more rapid diagnosis with far more detail by annotating lesions and anomalies. It has more than 95 percent clinical sensitivity, and the findings are confirmed scientifically and statistically. Age-related macular dege is one of the other diseases it can detect. Some of the other diseases it can detect are age-related macular degeneration, diabetic macular edema, and more.

BeatO (www.beatoapp.com)	Since 2015, this AI-based software has been supporting diabetic patients. It has been downloaded over 100,000 times on the Play Store, having supported more than 50,000 customers in over 1500 cities since last year. The app is built around the needs of an average diabetes-positive Indian middle-class customer. In addition to controlling diets by recommending diabetic-friendly foods and cereals, it uses AI and data analytics to provide appropriate nutrition resources to help users recognise safe foods, the amount of food, and identify the patient's glycemic index. The software comes with a glucometer, which can be plugged for reading into a smartphone. The reading is then saved in the app and can be used for managing diet by suggesting diabetic-friendly food and cereals. The app comes with a glucometer which can be plugged into a smartphone to take the reading. The reading is then saved in the app and can be used for further guidance and intervention in case of an emergency. The app can be synced to various fitness trackers such as Fitbit and others.
HealthifyMe (www.healthifyme.com)	This start-up focused on AI works on diseases of the lifestyle such as obesity, hypertension, and diabetes. It features AI-enabled nutrition coach Ria who talks to people to assist them very effectively with diabetes-related queries. Ria is an AI-enabled conversational nutritionist who blends the power of technology to have measurable effects with real human services. Ria uses key lessons learned from 150 million monitored meals from HealthifyMe and more than 10 million message exchanges between coaches and customers to develop over time. It indicates that the consumer of the food plan for diabetes helps them keep the condition under control.
LiveHealth (www.livehealth.in)	This start-up focused on AI provides clients with diagnostics through automation. As soon as they are available, this company provides reports to patients or organisations online. It also makes online payments, tracks all patient operations in real-time, and allows doctors to access patient details at any time. With only one click, doctors can also sign their patient reports. In providing medical diagnostics, their priority is full digitization and automation, due to which report entry errors are entirely eliminated.
Neurosynaptic Communications Pvt Ltd (www.neurosynaptic.com)	They aim to make health care available through their start-up to all the masses. It offers high-quality Online Healthcare Delivery Solutions from ReMeDi. It remotely gathers knowledge about different physiological aspects of patients and provides them with a diagnosis. They make the entire process of diagnosis affordable by doing this. They currently operate in four cities with a primary emphasis on the delivery of healthcare. So far, the bulk of their work has been in schools, and they also have an app-based tool for parents to prepare their children's healthy meals.

OnliDoc	OnliDoc utilizes AI and ML for end-to-end medical diagnosis. It has a phone app used to locate physicians, book appointments, and shop prescriptions and medical records. It has an artificial intelligence and symptom checker for deep learning and offers reports online. It utilizes AI and deep learning to assist in the choice of care and advises the first steps to be taken. Their software is available for iOS and the Play Store.
Aadar	Healthcare begins with preventive care, which simply means taking reasonable measures to nip illnesses in the bud and keeping a check on different health conditions. AADAR is one such venture operating in the preventive healthcare space "inspired by Ayurveda." AADAR provides herb-based products such as protein shortages, blood sugar, indigestion, cholesterol, and obesity to curb lifestyle ailments.

Future Prospects

Although majority of the studies are carried out on Diabetic Retinopathy screening, future opportunities can be in several other areas such as Clinical Decision Support, Predictive Population Risk Stratification and Patient Self-Management Tools. As seen in figures 1, 2, 3 & 4 here.

Predictive Modeling and Risk Stratification						
Author, date	**Title**	**Learning model**	**Training data/ validation data/ features**	**Testing data/ features**	**Study outcomes**	**Model performance application**
Han L., 2015	Rule Extraction from support Vector Machine Using Ensemble Learning Approach: An Application for Diagnosis of Diabetes	Ensemble learning using SVM and RF rule extraction	Data set: China Health and Nutrition Survey data (n=7913, 646 diabetic). Training data: 90% of dataset Validation: 10-fold cross-validation for model parameter selection. 15 features selected using univariate LR, chi-square tests, information gain-based method and RF	Test data: remaining 10% of data	For positive cases: Precision: 89.6% Recall: 44.3% F-score: 0.593 For all cases: Weighted average precision: 94.2% Weighted average recall: 93.9%	The proposed hybrid system can provide a tool for the diagnosis of diabetes from population-based nutritional surveys, and it supports a second opinion for lay users
Shankaracharya, 2012	Computational Intelligence-based Diagnosis Tool for the Detection of Prediabetes and Type 2 Diabetes in India	Mixture of expert system based on MLP	Data set: 1415 subjects (947 diabetic) Training data: 1104/1415	Test data: 311/1415	Best result achieved Sensitivity: 99.5% Specificity: 99.07% Accuracy: 99.36%	The proposed tool for identifying individuals with prediabetes, diabetes and nondiabetes is highly accurate and may be used for large-scale diabetic screening
Wei WQ, 2010	A High Throughput Semantic Concept Frequency Based Approach for Patient Identification: A Case Study Using Type 2 Diabetes Mellitus Clinical Notes	NLP, SVM and semantic knowledge	Data set: 57,707 electronic notes from 1600 DM patients and 1600 control patients in Mayo Clinic. Validation: 10-fold cross-validation for model selection. Features: Semantic concept units extracted from notes and classified into semantic type groups	No separate test data were specified	F-score for cases: 0.956 F-score for controls: 0.957 Precision for cases: 0.968. Semantic knowledge: varying degrees of F-score, precision, and recall values reported	The proposed approach is accurate and responsive to the urgent need to develop a general automatic approach for diabetic patient case-finding and characterization
Corey KE, 2016	Development and Validation of an Algorithm to Identify Nonalcoholic Fatty Liver Disease (NAFLD) in the Electronic Medical Record	LR with adaptive LASSO	Data set: electronic medical records from 620 patient randomly selected from the high-risk patients in Partners Healthcare	Test data: randomly selected 611 high-risk patients identified by classification algorithm. Additional validation: independent test set of 314,292 patients. Ground truth: 100 random positive case record review	Specificity: 91% Sensitivity: 51% PPV: 89% NPV: 56% AUC: 0.85 (compared to 0.75 using ICD-9 billing codes only, p<0.0001)	The NAFLD classification algorithm is superior to ICD-9 billing data alone. This approach is simple to develop, deploy and can be applied across different institutions to create EMR-based cohorts of individuals with NAFLD.
Neves J., 2015	A Soft Computing Approach to Kidney Diabetes Evaluation	Logic Programming, ANN	Data set: data from 558 total patients (175 diagnosed with CKD) Training data: 2/3 of data set Clinical information about CKD as rewritten into Logic Programming algorithms, and its terms as training and test sets of ANN	Test data: remaining 1/3 of data	ANN performance in test data set Sensitivity: 93.19% Specificity: 91.9% PPV: 84.4% NPV: 96.6%	The proposed model showed good performance in predicting the likelihood of a CKD diagnosis
Rau HH., 2016	Development of a Web-based Liver Cancer Prediction Model for Type II Diabetes Patients by Using an Artificial Neural Network	ANN, LR	Data set: data from 2060 diabetic patients in the National Health Insurance Research Database (NHIRD) of Taiwan Training data: 1442/2060	Test data: 618/2060	ANN performance was superior to that of LR for predicting diabetes who will be diagnosed with liver cancer in the next 6 years. Sensitivity: 0.757 Specificity: 0.755 AUC: 0.873	Data mining systems enable clinicians to predict those diabetics at greater risk for the development of liver cancer
Vyas R., 2016	Building and Analysis of Protein-Protein Interactions Related to Diabetes Mellitus Using Support Vector Machine, Biomedical Text Mining and Network Analysis	SVM	Training data: positive and negative proteins from PDB and UniProt databases (n=2653)	Test data: 129 proteins extracted via text mining from literature	Accuracy: 78.20% Precision: 68.26% AUC: 0.788	This integrated approach has a potential to identify disease-related proteins, functional annotation, and other proteomics studies
Lopez B., 2018	Single Nucleotide Polymorphism (SNP) Relevance Learning with Random Forests for Type 2 Diabetes Risk Prediction	Random forest, k-NN	Data set: data from 677 subjects (248 diabetic), each containing 96 SNPs regarding type 2 diabetes Features: SNP data, clinical information, SNP value relevance	Test data: 10-fold cross validation used. No separate test data were specified	For risk prediction AUC: 0.89 RF outperformed SVM and LR in terms of prediction accuracy and stability of the estimated relevance	RF is a useful method for learning predictive models to help physicians to identify the relevant SNPs associated with and predictive of type 2 diabetes

Figure 1: Predictive Modeling & Risk Stratification

Author, date	Title	Learning model	Training data/ validation data/ features	Testing data/ features	Study outcomes	Model performance application
Clinical Decision Support						
Lo-Ciganic WH., 2015	Using Machine Learning to Examine Medication Adherence Thresholds and Risk of Hospitalization	Random survival forests, survival trees models	Data set: 33,130 non-dual-eligible Medicated enrollees with type 2 diabetes. Training data: 90% of data set Features: sociodemographics, measures of service use, health status, diabetes treatment intensity	Test data: remaining 10% data	The adherence thresholds most discriminating for risk of all-cause hospitalization varied from 46% to 94% - the widely used 80% adherence threshold is not optimal for predicting risk of hospitalization	Machine learning approaches hold promise as an inituitive and powerful approach for customizing interventions in medication adherence in diabetics and optimizing health outcomes
Shu T., 2017	An Extensive Analysis of Various Texture Feature Extractors to Detect Diabetes Mellitus Using Facial Specific Regions	k-NN, SVM with 8 image extractor methods	Data set: 284 diabetes mellitus and 231 healthy samples	Test data: 10-fold cross validation used. No separate test data were specified	The best texture feature extractor, Image Gray-scale Histogram (bin n= 256),	Compared with traditional diagnostic methods that rely on blood samples, the Image Gray-scale Histogram is a highly accurate, non-invasive way to diagnose diabetes using facial and tongue features.
Katigari KM., 2017	Fuzzy Expert System for Diagnosing Diabetic Neuropathy	Fuzzy expert system	Data set: diagnostic parameters and their importance developed by specialists used to develop fuzzy expert system	Test data: 213 medical records of patients diagnosed with diabetic neuropathy	For diagnosis and severity of diabetic neuropathy Sensitivity: 89% Specificity: 98% Accuracy: 93%	The fuzzy expert system can help diagnose and determine the severity of diabetic neuropathy
Wang L., 2017	Area Determination of Diabetic Foot Ulcer Images Using a Cascaded Two-Stage SVM-Based Classification	Two-stage SVM with simple linear iterative clustering and conditional random fields	Data set: 100 foot ulcer images from 15 patients	Test data: cross-validation used. No separate test data were specified	Sensitivity: 73.3% Specificity = 94.6%	Computer-based systems provide high performance rates for measuring diabetic wounds and monitoring wound healing status and are sufficiently efficient for smartphone-based image analysis

Figure 2: Clinical Decision Support

Author, date	Title	Learning model	Training data/ validation data/ features	Testing data/ features	Study outcomes	Model performance application
Glucose Sensors and Artificial Pancreas						
Mauseth R., 2015	Testing of an Artificial Pancreas System With Pizza and Exercise Leads to Improvements in the System's Fuzzy Logic Controller	Fuzzy Logic Controller systems (FLC)	N/A	Total 17 meal, 13 exercise studies in 10 subjects with type 1 diabetes (TID) FLC v2.0 test: 9 meal and 4 exercise studies with FLC v2.0, followed by interim analysis. FLC v2.1 test: remaining 8 meal and 9 exercise studies using updated FLC	FLC v2.1 showed improvements in mean blood glucose after pizza consumption, after exercise testing, in reducing hyperglycemia, and percentage time spent in euglycemic range	Stress testing the AP system followed by adjustments to the dosing matrix significantly improved FLC performance when retested for mean blood glucose, high blood glucose and normal blood glucose
Ling SH., 2012	Natural Occurrence of Nocturnal Hypoglycemia Detection Using Hybrid Particle Swarm Optimized Fuzzy Reasoning Model	Fuzzy reasoning model with hybrid particle swarm optimization with wavelet mutation	Data set: 16 type 1 diabetic patients Training data: 320 data points from 8/16 patients	Test data: remaining 269 data points from 8/16 patients	Advanced noctural hypoglycemic episode detection Sensitivity: 85.7% Specificity: 79.8% Hypoglycemic episodes detection Sensitivity: 80.0% Specificity: 55.1%	The proposed system offers a noninvasive means to detect hypoglycemic episodes in type 1 diabetic patients
Herrero P., 2015	Advanced Insulin Bolus Advisor Based on Run-To-Run Control and Case-Based Reasoning	Combination of R2R and CBR	N/A	In silico testing using commercial type 1 diabetes simulator generated 1-month data for 10 adolescents scenarios	Using CBR(R2R), mean blood glucose improved in both adult and adolescent populations and hypoglycemia was completely eliminated (R2R alone was not able to do it in the adolescent population)	The proposed smartphone system keeps the simplicity of a standard bolus calculator while enhancing its performance by providing more adaptibility and flexibility
DeJoumett L., 2016	In Silico Testing of an Artificial-Intelligence-Based Artificial Pancreas Designed for Use in the Intensive Care Unit Setting	Knowledge-based system	N/A	In silico analysis: 126 000 unique 5-day simulations resulting in 107 million glucose values	On average, time in control range was 94.2%, time in range 70-140 mg/dl was 97.8%, time in hyperglycemic range was 0.09% Average coefficient of variation: 11.1%	An AI-based closed-loop glucose controller may be able to improve on results achieved by currently existing ICU-based PID/ MPC controllers

Figure 3: Glucose Sensors and Artificial Pancreas

Author, date	Title	Learning model	Training data/ validation data/ features	Testing data/ features	Study outcomes	Model performance application
Patient Diabetes Self-Management Tools						
Zhang W., 2015	"Snap-n-Eat": Food Recognition and Nutrition Estimation on a Smartphone	SVM	Data set: 2000 food images comprising 15 predefined categories Ground truth: manual annotation	Test data: 5-fold cross validation	Accuracy: 85%	The proposed smartphone mobile system can recognize food items present on a plate and estimates their calorific and nutrition content, automatically helping diabetic patients make more informed food choice decisions.
Cvetkovic B. 2016	Activity Recognition for Diabetic Patients Using a Smartphone	Ensemble of models (SVM, J48, random forest, Jrip, AdaBoost and Bagging algorithms), symbolic rules	Data set: average 11 hours of phone and 7.5 hours of ECG recordings per day for 2 weeks from 9 healthy volunteers. Training data: first week of recordings Features (if present): sound, location, acceleration, heart-rate, respiration-rate	Test data: second week of recordings	Best result achieved by Multi-Classifier Adaptive Training (MCAT) method. Accuracy: 83.4% F-score: 0.82	Smartphone sensors using machine learning and symbolic reasoning can recognize and quantify high-level lifestyle activities of diabetic patients and help them make more informed activity choices.
Wang L., 2015	Smartphone-based Wound Assessment System for Patients with Diabetes	Image boundary detection: mean-shift segmentation algorithm Color segmentation: K-means clustering	N/A	30 simulated wound images, 34 actual patient wound images	Visual evaluation for simulated images Mathews Correlation Coefficient: 0.736	The proposed smartphone camera system enables diabetic patients and their caregivers to take a more active role in daily wound care
Rigla M., 2018	Gestational Diabetes Management (GDM) Using Smart Mobile Telemedicine	Mobile telemedicine system	NA	20 patients diagnosed with GDM (Parallel observational prospectively captured clinical data for historical control)	Metabolic and perinatal outcomes were similar except for BP, which was lower in patients using the telemedicine system	Artificial-intelligence-augmented telemedicine has been proposed as a helpful tool to facilitate an efficient widespread medical assistance to GDM

Figure 4: Patient Diabetes Self-Management Tools

References

International Diabetes Federation, IDF Diabetes Atlas eighth ed Brussels, *Belgium International Diabetes Federation,* 2017, July 2019, http://www.diabetesatlas.org.

R. M. Anjana, on behalf of the ICMR–INDIAB Collaborative Study Group, R. Pradeepa, et al., "Prevalence of diabetes and prediabetes (impaired fasting glucose and/or impaired glucose tolerance) in urban and rural India: phase I results of the Indian Council of Medical Research–INdia DIABetes (ICMR–INDIAB) study," *Diabetologia*, vol. 54, no. 12, pp. 3022–3027, 2011.

K. N. Kumar, S. Katkuri, and I. Ramyacharitha, "A study to assess prevalence of diabetes mellitus and its associated risk factors among adult residents of rural Khammam," *International Journal Of Community Medicine And Public Health*, vol. 5, no. 4, pp. 1360–1365, 2018.

M. Y. Donath, "Targeting inflammation in the treatment of type 2 diabetes: time to start," *Nature Reviews Drug Discovery*, vol. 13, no. 6, pp. 465–476, 2014.

Medical Council of India. New Delhi. Available from: http://www. mciindia.org/home.aspx. [Last accessed on 2019 Nov 10].

World Health Organization. World Health Statistics 2019. Part II: Global Health Indicators. Geneva: World Health Organization; 2019

Trikkalinou A, Papazafiropoulou AK, Melidonis A. Type 2 diabetes and quality of life. *World J Diabetes* 2017; 8(4): 120-129 Available from: URL: http://www.wjgnet.com/1948-9358/full/ v8/i4/120.htm DOI: http://dx.doi.org/10.4239/wjd.v8.i4.120

Liu J, Wang R, Ganz ML, Paprocki Y, Schneider D, Weatherall J. The burden of severe hypoglycemia in type 2 diabetes. *Curr Med Res Opin* 2018; 34:179–186.

Centers for Disease Control and Prevention. Estimates of diabetes and its burden in the United States. Washington, DC: *US Department of Health and Human Services*, 2017: 1–20.

The Diabetes Control and Complication Trial Research Group. The effect of intensive treatment of diabetes on the development and progression of long-term complications in insulin-dependent diabetes mellitus. *N Engl J Med* 1993; 329:977–986.

Latts L. ADA/IBM Watson Health Study (N>300,000) finds that nearly 60% of people with T2D discontinue therapy after one year. Presented at: *American Diabetes Association 78th Scientific Session*, June 22–26, 2018, Orlando, FL.

National Center for Biotechnology Information; *US National Library ofMedicine. PubMed*. https://www.ncbi.nlm.nih.gov/ pubmed/ Accessed July 18, 2018.

Lewis K. Humans and systems: *creating natural interfaces to augment human ability*. https://www.ibm.com/blogs/internetof- things/creating-natural-interfaces/ Accessed July 18, 2018.

Aggarwal M, Madhukar M. IBM's Watson analytics for health care: a miracle made true. Hershey, *PA: IGI Global*, 2016:117–134.

Turing Archive for the History of Computing. www.alanturing.net/turing_archive/archive/index/archiveindex.html Accessed July 18, 2018.

Research 2 Guidance. Top 3 therapy fields with the best market potential for digital health apps. https://research2guidance.com/top-3-therapy-fields-with-the-best-marketpotential-for-digital-health-apps/ Accessed July 18, 2018.

Yeung S, Downing NL, Fei-Fei L, Milstein A. Bedside computer vision—moving artificial intelligence from driver assistance to patient safety. *N Engl J Med* 2018; 378:1271–1273.

Young K. Newly approved software uses AI to improve diabetic retinopathy. https://www.jwatch.org/fw114063/2018/04/12/newly-approved-software-uses-ai-detect-diabetic Accessed July 18, 2018.

Pfaffl MW. A new mathematical model for relative quantification in real-time RT-PCR. *Nucleic Acids Res* 2001; 29:45e.

Lo´pez B, Martin C, Vin˜as PH. Special section on artificial intelligence for diabetes. *Artif Intell Med* 2018; 85:27–28.

Raghupathi W, Raghupathi V. Big data analytics in healthcare: promise and potential. *Health Inf Sci Syst* 2014; 2:3.

Hoyt RE, Snider D, Thompson C, Mantravadi S. IBM Watson analytics: automating visualization, descriptive, and predictive statistics. *JMIR Public Heal Surveill* 2016; 2:e157.

Vijan S, Hofer TP, Hayward RA. Cost-utility analysis of screening intervals for diabetic retinopathy in patients with type 2 diabetes mellitus. *JAMA* 2000; 283:889–896.

Gulshan V, Peng L, Coram M, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA* 2016; 316:2402–2410.

Tariq A, Akram MU, Shaukat A, Khan SA. Automated detection and grading of diabetic maculopathy in digital retinal images. *J Digit Imaging* 2013; 26:803–812.

Rahim SS, Palade V, Shuttleworth J, Jayne C. Automatic screening and classification of diabetic retinopathy fundus images. In: Mladenov V, Jayne C, Iliadis L, eds. Engineering applications of neural networks. *Communications in computer and information science*. Vol 459. Basel, Switzerland: Springer Nature Switzerland AG, 2014:113–122.

Lam C, Yu C, Huang L, Rubin D. Retinal lesion detection with deep learning using image patches. *Invest Ophthalmol Vis Sci* 2018; 59:590–596.

US Food and Drug Administration. *FDA permits marketing of artificial intelligence-based device to detectcertain diabetes-related eye problems*. https://www.fda.gov/ NewsEvents/Newsroom/PressAnnouncements/ucm604357.htm Accessed July 18, 2018.

Keel S, Lee PY, Scheetz J, et al. Feasibility and patient acceptability of a novel artificial intelligence-based screening model for diabetic retinopathy at endocrinology outpatient services: a pilot study. *Sci Rep* 2018; 8:4330.

Matimba A, Woodward R, Tambo E, Ramsay M, Gwanzura L, Guramatunhu S. Tele-ophthalmology: opportunities for improving diabetes eye care in resource- and specialist limited Sub-Saharan African countries. *J Telemed Telecare* 2016; 22:311–316.

Han L, Luo S, Yu J, Pan L, Chen S. Rule extraction from support vector machines using ensemble learning approach: an application for diagnosis of diabetes. *IEEE J Biomed Health Inform* 2015; 19:728–734.

Shankaracharya, Odedra D, Samanta S, Vidyarthi AS. Computational intelligence-based diagnosis tool for the detection of prediabetes and type 2 diabetes in India. *Rev Diabet Stud* 2012; 9:55–62.

Wei W-Q, Tao C, Jiang G, Chute CG. A high throughput semantic concept frequency-based approach for patient identification: a case study using type 2 diabetes mellitus clinical notes. *AMIA Annu Symp Proc* 2010; 2010:857–861. TRANSFORMING DIABETES CARE THROUGH AI 241

Corey KE, Kartoun U, Zheng H, Shaw SY. Development and validation of an algorithm to identify nonalcoholic fatty liver disease in the electronic medical record. *Dig Dis Sci* 2016; 61:913–919.

Neves J, Martins MR, Vilhena J, et al. A soft computing approach to kidney diseases evaluation. *J Med Syst* 2015; 39:131.

Rau H-H, Hsu C-Y, Lin Y-A, et al. Development of a web-based liver cancer prediction model for type II diabetes patients by using an artificial neural network. *Comput Methods Programs Biomed* 2016; 125:58- 65.

Weber C, Neeser K. Using individualized predictive disease modeling to identify patients with the potential to benefit from a disease management program for diabetes mellitus. *Dis Manag* 2006; 9:242–256.

Vyas R, Bapat S, Jain E, Karthikeyan M, Tambe S, Kulkarni BD. Building and analysis of protein-protein interactions related to diabetes mellitus using support vector machine, biomedical text mining, and network analysis. *Comput Biol Chem* 2016; 65:37–44.

Lo´pez B, Torrent-Fontbona F, Vin˜as R, Ferna´ndez-Real JM. Single nucleotide polymorphism relevance learning with random forests for type 2 diabetes risk prediction. *Artif Intell Med* 2018; 85:43–49.

Lo-Ciganic WH, Donohue JM, Thorpe JM, et al. Using machine learning to examine medication adherence thresholds and risk of hospitalization. *Med Care* 2015; 53:720–728.

Shu T, Zhang B, Yan Tang Y. An extensive analysis of various texture feature extractors to detect diabetes mellitus using facial specific regions. *Comput Biol Med* 2017; 83: 69–83.

Katigari MR, Ayatollahi H, Malek M, Haghighi MK. Fuzzy expert system for diagnosing diabetic neuropathy. *World J Diabetes* 2017; 8:80–88.

Wang L, Pedersen PC, Agu E, Strong DiM, Tulu B. Area determination of diabetic foot ulcer images using a cascaded two-wtage SVM-based classification. *IEEE Trans Biomed Eng* 2017; 64:2098–2109.

Mauseth R, Lord SM, Hirsch IB, Kircher RC, Matheson DP, Greenbaum CJ. Stress testing of an artificial pancreas system with pizza and exercise leads to improvements in the system's fuzzy logic controller. *J Diabetes Sci Technol* 2015; 9:1253–1259.

Ling SH, Nguyen HT. Natural occurrence of nocturnal hypoglycemia detection using hybrid particle swarm optimized fuzzy reasoning model. *Artif Intell Med* 2012; 55: 177–184.

Herrero P, Pesl P, Reddy M, Oliver N, Georgiou P, Toumazou C. Advanced insulin bolus advisor based on run-torun control and case-based reasoning. *IEEE J Biomed Health Inform* 2015; 19:1087–1096.

DeJournett L, DeJournett J. In silico testing of an artificialintelligence-based artificial pancreas designed for use in the intensive care unit setting. *J Diabetes Sci Technol* 2016; 10:1360–1371.

Thabit H, Tauschmann M, Allen JM, et al. Home use of an artificial beta cell in type 1 diabetes. *N Engl J Med* 2015; 373:2129–2140.

Trevitt S, Simpson S, Wood A. Artificial pancreas device systems for the closed-loop control of type 1 diabetes: what systems are in development? *J Diabetes Sci Technol* 2016; 10:714–723.

Zhang W, Yu Q, Siddiquie B, Divakaran A, Sawhney H.''Snap-n-Eat'': food recognition and nutrition estimation on a smartphone. *J Diabetes Sci Technol* 2015; 9:525–533.

Cvetkovic´ B, Janko V, Romero AE, Kafalı O¨ , Stathis K, Lusˇtrek M. Activity recognition for diabetic patients using a smartphone. *J Med Syst* 2016; 40:256.

Wang L, Pedersen PC, Strong DM, Tulu B, Agu E, Ignotz R. Smartphone-based wound assessment system for patients with diabetes. *IEEE Trans Biomed Eng* 2015; 62:477–488.

Rigla M, Martı´nez-Sarriegui I, Garcı´a-Sa´ez G, Pons B, Hernando ME. Gestational diabetes management using smart mobile telemedicine. *J Diabetes Sci Technol* 2018; 12:260–264.

ClinicalTrails.gov. Adult accuracy study of the Elite 3 Glucose Censor (E3). https://www.clinicaltrials.gov/ct2/show/study/NCT02246582?term=NCT02246582&rank=1&sect=X0123456 Accessed July 18, 2018.

Neemuchwala H. Sugar.IQ improves time-in-range by 36 mins/day, time >180 by 30 mins/day, time <70 by 6mins/day. Presented at: *American Diabetes Association 78th Scientific Session*, June 22–26, 2018, Orlando, FL.

Benson T. Principles of health interoperability HL7 and SNOMED, 2nd edition. London: *Springer Verlag*, 2012.

Adler-Milstein J, DesRoches CM, Kralovec P, et al. Electronic health record adoption in us hospitals: Progress continues, but challenges persist. *Health Aff* (Millwood) 2015;34:2174–2180.

Hutson TM. Missing data hinder replication of artificial intelligence studies. www.sciencemag.org/news/2018/02/missing-data-hinder-replication-artificial-intelligence-studies? Accessed July 18, 2018.