The use of artificial intelligence in three-dimensional imaging modalities and diabetic foot disease: A systematic review

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ABSTRACT

Background: Diabetic foot disease (DFD) is serious complication of diabetes with a multifactorial etiology and carries a significant risk of lower limb amputations. The prevalence of DFD continues to grow globally. Artificial intelligence has been proposed in aiding early detection and risk stratification for ulceration and other major complications, including sepsis, minor or major lower limb amputation, and death. We systematically reviewed the literature available on the use of artificial intelligence in three-dimensional imaging modalities in DFD.

Methods: A literature review was conducted in accordance with PRISMA guidelines. Embase and Medline (via the Ovid interface), CINAHL (via Ebsco Host), Web of Science, and Scopus databases were searched. The gray literature was also reviewed on ClinicalTrials.gov and the National Institute for Health Research journals library. The medical subject headings terms "diabetes" AND "diabetic foot disease" AND "artificial intelligence" and various permutations of three-dimensional imaging modalities, including "computed tomography," "magnetic resonance imaging" and "positron emission tomography" were used in the primary search string. The articles were independently screened and reviewed by two reviewers.

Results: We identified 4865 studies and removed 102 duplicates. We excluded 4721 during title and abstract screening. Overall, 42 articles underwent full text review and 1 article was included in the final review, which used computed tomography scanning in patients with DFD to create a risk prediction model.

Conclusions: The use of machine learning and deep learning models is still being explored and evaluated in this context. Current methodologies focus on wound imaging classification, plantar thermography and plantar pressures. Specialized models that evaluate three-dimensional imaging are currently primitive and limited in their use; however, they have potential for the generation of suprahuman insights into existing imaging, extraction of novel metadata features, and prediction using integration of multidimensional patient characteristics. (JVS-Vascular Insights 2024;2:100057.)

Keywords: Artificial intelligence; Computed tomography; Deep learning; Diabetic foot; Lower limb; Magnetic resonance imaging

The prevalence of diabetes continues to increase exponentially worldwide owing to a number of factors, including diet, sedentary lifestyles, and obesity. It is estimated that >537 million people are affected by diabetes globally.[1] At present, there are approximately 4.8 million people living with diabetes in the UK. It is estimated that another 1 million people are undiagnosed diabetics and 13.6 million are at an increased risk of developing type 2 diabetes in the UK in 2024.[2] The United States has a diabetic population of 37 million with another 96 million people over the age of 18 classified as prediabetic.[3] These figures have prompted the World Health Organization to establish the first set of global coverage targets for diabetes in May 2022 including diagnosis,

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glycemic control, blood pressure management, use of statins, and self-monitoring.[1]

Diabetic foot ulceration (DFU) and diabetic foot disease (DFD) are serious complications and are attributed to multifactorial underlying mechanisms including, diabetic neuropathy, altered foot biomechanics, and altered peripheral microvasculature and macrovasculature.[4,5] DFU and DFD can often lead to infection and minor or major amputation, making it extremely costly for health services to provide care, including multiple hospital admissions, social care, and rehabilitation services. Patients with diabetes are 20 times more likely to have an amputation.[6] Of all amputations performed in the UK on a weekly basis, 80% are a direct result of ulceration in the preceding weeks or months, which are often preventable.[7,8]

Diabetes and its complications also financially burden the National Health Service (NHS), costing approximately £1 billion pounds, which may be the single biggest cost to the NHS.[6–8] It is estimated that decreasing the prevalence of DFUs by 33% would save the NHS ≤£262 million annually.[6,7] The James Lind Alliance diabetic foot priority setting exercise in 2021 involving patients and health care professionals established the top 10 questions or priorities in DFD. This work included establishing effective ways to prevent DFU and amputations as the top two priorities.[9] The growing prevalence and high-cost burden of DFD has incentivized strategies for identification of predictive metrics to facilitate early diagnosis and risk stratification of patients who are risk of developing such complications.[5–7,9]

The Oxford English dictionary defines artificial intelligence (AI) as the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages.[10] AI is further stratified into machine learning (ML) and deep learning models (Figure 1).

ML is a subset of AI that uses statistical analyses to execute certain tasks without overt programming. This process includes supervised learning models, unsupervised learning models, and reinforcement learning models. Supervised learning uses labelled data to create classification and learning models, that is, the presence or absence of certain malignant lesions. Supervised learning can be a classification task, where the output is qualitative, or a regression task, where the output is quantitative. Examples of these include linear regression, decision trees, K-nearest neighbor, and support vector machines. Unsupervised learning models is where the ML models use unlabeled datasets to find similarities and cluster the datapoints together.[11,12] This work requires human input to nominate the desired number of distinct clusters and ultimately to verify whether the groupings are logical. Reinforcement learning models use a reward or penalty mechanism to encourage positive decision-making based on critical feedback.[13] This process is often used in game theory, which explores how people make decisions in certain competitive environments, and control theory, which uses feedback to influence a system to achieve a certain goal.[13]

ARTICLE HIGHLIGHTS

- **Type of Research:** Systematic review
- **Key Findings:** There is minimal use of artificial intelligence and deep learning models in vascular surgery at present. There is scope for imaging-related deep learning models in vascular surgery and, in particular, diabetic foot disease.
- **Take Home Message:** Artificial intelligence and deep learning models can be applied to various aspects of diabetic foot disease.

Deep learning is a subset of both AI and ML. This technique is an attempt to recreate the architecture of our own central nervous system. These artificial neural networks contain structures similar to the network of individual neurons in our brains. The individual decision unit (neuron) is called a "perceptron." A dense architecture of thousands of perceptrons allows information to be filtered through multiple computational layers to extract complex information and formulate decisions. Multiple different layer conformations exist including convolutional, recurrent, and recursive neural networks depending on the nature of the task at hand.[13]

Convolutional neural networks are the most relevant architecture when considering decision-making related to medical imaging. The convolutional architecture scans over the pixels of an image, first detecting simple edges, then via deep layers, combining edges into sequentially more complex shape features. Through iterating through multiple dense layers, complex features such as faces, text, or even more abstract elements such as gray matter granularity can be identified. It is a feed-forward network that depends on a fixed input and output size, only moving sequentially forward to build complex features from simple ones. Recurrent neural networks build on sequential models and have a memory of sorts which allows them to incorporate what it learns.[12,13]

Increasingly, AI and its various subsets are gradually being incorporated into every aspect of medicine. The hope is to improve early diagnostics, data augmentation, data analysis, risk prediction, and the current move toward developing personalized treatment. The market for AI use in health care is expected to grow by from its last valued $US4.9 billion industry in 2020 to a $US45.2 billion industry in 2026, with the expectation that patient data and risk analysis will capture the largest share of AI in the arena of AI-related health care.[14] Vascular surgery is suited to the use of ML owing the mainstream use of endovascular and minimally invasive treatment options, well-defined thresholds for intervention, the highly

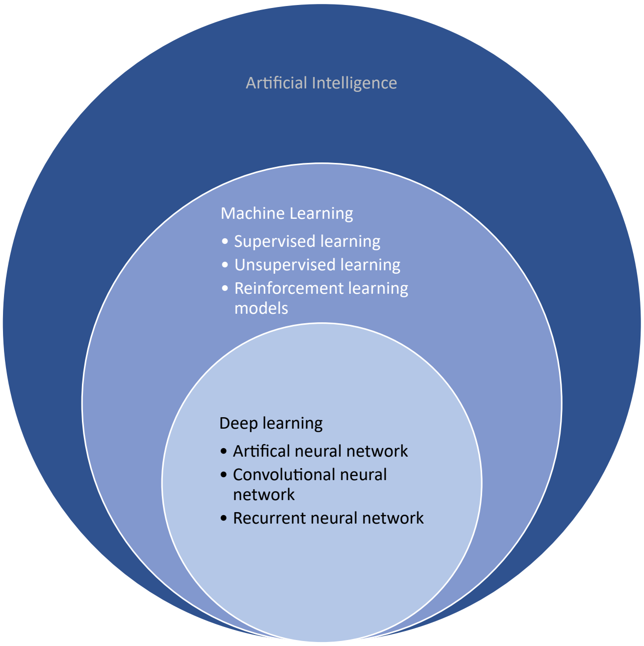

Fig 1. Subsets of artificial intelligence (AI).

evidence-based nature of the specialty, which drives its current treatment modalities, and the ongoing need for risk prediction and analysis owing to the complexity of multimorbid patient cohorts in the specialty. The use of ML has been attempted and applied in abdominal aortic aneurysm growth prediction, carotid stenoses, severity of peripheral arterial disease, prediction in venous reflux, venous ulcer development and healing, and DFD.[15]

The aim of this review was to identify studies involving the use of ML/deep learning models and their application to three-dimensional imaging modalities in DFU and DFD detection, stratification or the use of imaging-based markers to predict the likelihood of DFD and DFU development. The objectives evaluated included the AI methods used and the accuracy in diagnosis and/or prediction.

METHODS

The systematic review was performed and reported in accordance with the PRISMA statement.[16] The literature was searched using Embase and Medline (via Ovid interface), CINAHL (via Ebsco Host), Web of Science, and Scopus databases. The gray literature was also reviewed on ClinicalTrials.gov and the National Institute for Health Research journals library. The medical subject headings terms "diabetes" AND "diabetic foot disease" AND "artificial intelligence" and various permutations of three-dimensional imaging, including "CT," "MRI," and "PET," were used in the primary search string. The complete list of search terms and search strategy syntax is included in Supplementary Tables I and II, online only. The population comprised of patients with a diagnosis of type 1 or type 2 diabetes mellitus or who had or were at risk of DFD or ulceration. Computed tomography (CT) scans, magnetic resonance imaging (MRI), and positron emission tomography were the imaging modalities included.

There was no time limitation placed on the reviews and articles up to December 2022 were included. The inclusion criteria comprised articles including reviews, randomized control trials, cohort, cross-sectional or case-control studies, human studies, and studies in all languages. The exclusion criteria were composed of articles reporting animal studies, posters, abstracts, commentaries, book chapters, case reports, editorials and expert opinions, and studies on the use of AI models using wound or ulcer pictures, plantar thermography, or plantar pressures, because these have modalities been the subjects of multiple prior systematic reviews and meta-analyses and were not the focus of our review (Table I).

The results were reviewed on Covidence software by two independent reviewers where the initial abstract screening and full article reviews were conducted. Any discrepancies regarding article inclusion or exclusion were discussed by the two reviewers and any disagreements by discussing with a third reviewer to reach a final consensus.

The data for the systematic reviews was collected on a Microsoft Excel spreadsheet, which is included in the results section as Table I. The information included the author, journal, year, the patient demographic, duration of diabetes, imaging modalities used, any statistical analysis regarding the sensitivity and specificity and receiver operator curve characteristics. The data collected included the study, the year of the study, number of patients, the type of AI used, the data collected, and any statistical analysis undertaken. Risk of bias was assessed using the Prediction model Risk Of Bias Assessment Tool (PROBAST) tool.[17] It is worth noting that the PROBAST-AI tool has been proposed for AI-based prediction model studies and is in development.[18]

RESULTS

We identified 4865 studies from the database and registers, including Medline (n = 444), Embase (n = 3446), CINAHL (n = 8), and Web of Science (n = 967). No relevant results were found on Scopus, clinicaltrials.gov, the Cochrane library, the or National Institute for Health Research library. We removed 102 duplicates and excluded 4721 articles in the title and abstract screening. Overall, 42 articles underwent full text review. Of these, 29 had the incorrect method or outcomes. These included two-dimensional imaging modalities such as wound photo classification, thermography imaging classification, or Doppler waveform analysis using ML models. The incorrect outcomes consisted of classifying images into categories or use of the incorrect imaging techniques. Five were pertaining to the use of AI and plantar pressures, 4 reviews were not relevant to our topic, and 2

Table I. Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
No time limitation articles	AI models using diabetic foot wound/ulcer pictures
All languages	Artificial intelligence models using plantar thermography
Systematic reviews	AI models using plantar thermography
Randomized control trials	Animal studies
Cohort studies	Posters
Cross sectional or	Abstracts
Case -control studies,	Commentaries
Human studies	Book chapters
	Case reports
	Editorials
	Expert opinions

AI, Artificial intelligence.

were excluded for miscellaneous reasons, including imaging of other vasculature (ie carotids) and an abstract. No ongoing studies or papers were found in the gray literature. One article was included in the final review. Our results are summarized in the PRISMA flow diagram (Figure 2). Owing to a lack of sufficient number of studies, a meta-analysis could not be performed.

One study was included in the final review which used CT angiography results (ie, the level of disease and the severity of stenosis) in patients with DFU using and artificial neural network in predicting DFU and determining the prognosis of DFU[19] (Table II). However, this study started with >20,000 patients, of which 203 are included in the study; all patients had DFUs. The prognosis end point is not entirely clarified in the paper (ie, resolution of ulceration or amputation). It does, however, demonstrate an accuracy of 91.6% in the training set and 88.9% in the validation set. The receiver operator characteristics area under the curve is 0.955, which is excellent, but does not state if this is calculated using the training or the validation set. It is superior to preestablished logistic regression methods when compared in this study. The study is novel, but does not use direct detection or measurement from the imaging, but rather the findings of the imaging are used for the creation of a predictive model. It remains at high risk of bias (Table III) owing to the small number of patients included, the only patient cohort being those with preexisting ulceration and no comparative cohort.[17] The focus of the study is on the prognostic correlation with other factors including age, body mass index, gender, duration of symptoms, and so on, and is an important step in using the correlation between these factors in predicting the risk and considers the binary information on the basis of CT imaging. However, this is the first step toward using three-dimensional imaging modalities in predictive models in the realm of DFD.

DISCUSSION

The concept of radiomics—the conversion of digital medical images into mineable high-quality data—is gradually but surely establishing itself.[20] The exponential increase in this technology has been accelerated by the availability of vast quantities of electronically available medical records providing multidimensional data points, including patient demographics and medical conditions; biochemical, pictorial, and radiological data; and outcomes and decisions in real time, which has allowed us to map these and aid the development of ML models.[20] This modality is currently being tested and applied in various areas of vascular surgery, including the aortic aneurysm growth prediction and outcomes, carotid disease, venous ulceration, and image classification.[15] ML models can be simple and modified to the task required, using readily available open-source platforms such as GitHub, which allow the use of preexisting coding. These models can also be tested in low resource software applications such as SPSS, R, or MATLAB, depending on the type of data and imaging available. This process is now gradually being superseded by no-code or low-code platforms that remove the onerous tasks for clinicians to code and allows greater accessibility to clinicians. However, depending on the complexity of the images, the information sought, and the number of tasks involved, the complexity of code required can change. The overall development and ongoing evolution of radiomics is also helped by collaborative efforts across radiology, vascular surgeons, and data analysts to provide useful and accurate ML models that can be validated and applied in the world of health care.

AI models can be developed on smaller datasets; however, they are less likely to be accurate and the quantity of data provided is reciprocal in its accuracy and specificity. The availability of large, high-quality datasets requiring curation, labelling, and segmentation is a labor-intensive and time-consuming task, but important in supervised learning models, although it can be bypassed in unsupervised learning models to an extent. The risk with unsupervised learning models is the potential lower accuracy and specificity rates that still require human verification. The rationale for this is an ML model requires the data to be split into training, test, and validation sets in an 80:10:10 split, the result of which is determined by the overall numbers available. Although the ML may perform very well on the modelled or training data, when introduced to new and previously unseen datapoints with increasing complexity, it tends devolve into a less accurate model, thus requiring a validation and test set.[21] Although there is no set number of images required to deploy and test the ML models, the overall accuracy of the ML and deep learning model increases

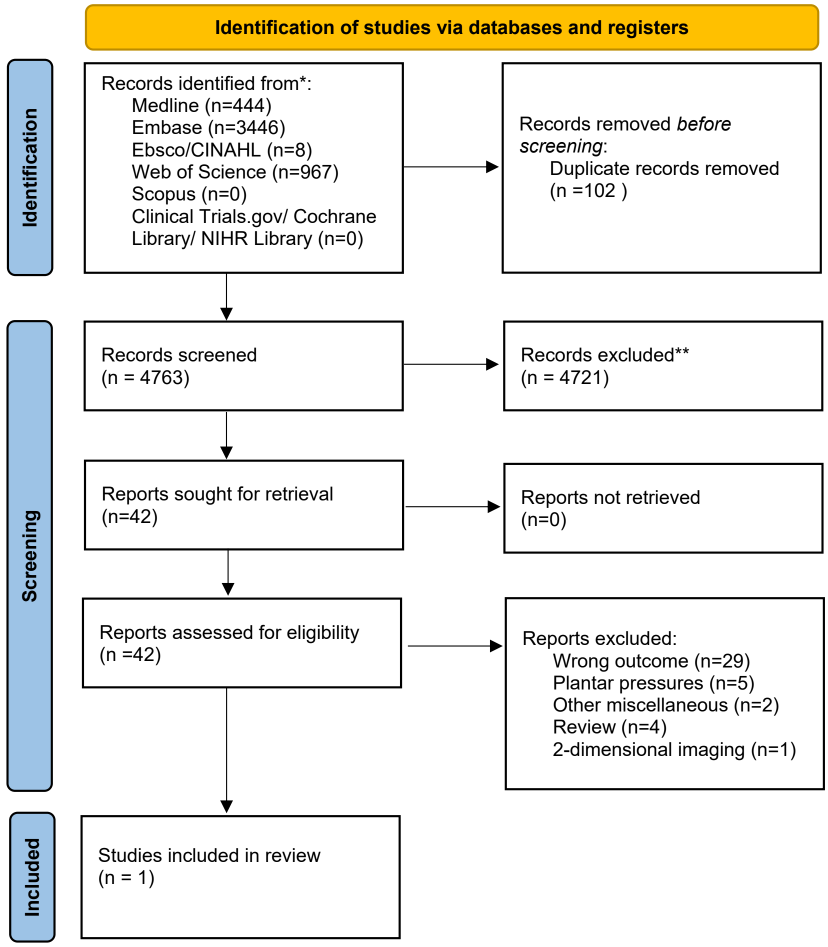

Fig 2. PRISMA flow diagram.

with the amount of data available. This requirement can be difficult in rare diseases or uncommon conditions, where limited data are available and data augmentation may be required to increase the test set.

The use of AI in vascular surgery is not entirely new, but continues to evolve with improved imaging modalities, lower costs, and improved data storage and processing capabilities, as well as greater data availability. Three-dimensional imaging has been used in vascular surgery in the surveillance, grading, and prognostication of aortic, peripheral arterial, and venous pathologies.[15] For example, current models are able to predict ambulation potential and surgical site infections after lower limb revascularization, and automatically segment lower limb muscles in venous disease and calf-pump failure cohorts.[22] In diabetes and DFD, the use of ML models has been evaluated in blood glucose management, predicting adverse glycemic events and diabetic complications, patient risk stratification, and decision support systems for lifestyle changes.[23–27] AI has also been used in measuring plantar pressures using wearable sensors, which plays an important role in ulcer development as the biomechanics of the foot changes in patients with diabetes.[28–31] The use of artificial neural networks has been applied in the classification of peak plantar pressures in high-risk regions of the foot to classify walking intensity over varying durations and speeds and how it may have an impact on the overall plantar soft tissues.[30] Chen et al,[30] for example, reported a faster walking pace yielded a more prominent plantar image when compared with individuals who walked slower over a longer period of time.

Plantar image analysis using deep learning models have also been evaluated as a potential method of foot progression angle analysis to detect gait pathologies.[28,31] The implication of these studies could potentially allow early gait changes indicative of DFD to be detected using AI at an earlier stage.

The number of studies incorporating deep learning models and DFD has seen an exponential rise in the preceding decade. These are primarily focused on two-dimensional imaging modalities, such as ulcer detection and, more recently, classifying the wounds based on the extent of granulation tissue.[15,19,27] There are also multiple studies using deep learning models and segmentation of plantar thermography images.[15,25,29] Other studies have

Table II. Summary of included study

Study	Year	No. of patients	Imaging Modality	AI	Software	Input layer	Output layer	Data split	Aim	Findings
Zhang	2022	203 (all with DFU)	CT angiography	ANN	SPSS	Age, gender, body mass index, duration of diabetes mellitus, duration of a DFU, limb symptoms, degree of lower-extremity arterial stenosis, segment of lower-limb arterial stenosis, severity of arterial calcification, comorbidities	Wagner score	3:1:1	Prediction and prognosis of DFU	Accuracy, sensitivity, specificity, positive predictive value, negative predictive value, and area under the curve of the overall ANN model were 91.6%, 92.3%, 93.5%, 87.0%, 94.2%, and 0.955. Evaluated with the holdout sample, the accuracy, sensitivity, specificity, positive predictive value and negative predictive value were 88.9%, 90.0%, 88.5%, 75.0%, and 95.8%,

AI, Artificial intelligence; *ANN*, artificial neural network; *CT*, computed tomography; *DFU*, diabetic foot ulcer.

also used two-dimensional imaging such as arterial duplex scans and artificial bee colony technology, an optimization algorithm technique based on the real-world, nature-based foraging techniques of bees to seek quality food and mimics swarm intelligence. This stochastic technique of searching has been used to improve the quality of arterial ultrasound imaging in patients with DFD.[32] This technique poses two problems. The current use of AI and ML is being applied to well-established, existing disease, when individuals demonstrate external manifestations of the disease, including ulceration and infection, which are often quite late in the overall spectrum of the disease trajectory.

Prediction models based on risk factors to predict amputation and mortality in patients with DFD are also being evaluated.[15,33,34] They have also been used to identify other risk factors which may contribute to the severity of DFD.[35] Other uses have included using AI in multispectral autofluorescence imaging to identify the gram type of bacteria in DFU.[36] However, the use of AI in three-dimensional imaging modalities in DFU and DFD remains elusive. Although this process can be complex owing to the multiaxial nature of its imaging, it is not impossible and is currently being done in other specialties, such as dynamic cardiac MRI, neurosurgery, and other areas of vascular surgery.[37–40]

CURRENT LIMITATIONS AND FUTURE PROSPECTS

The current limitations to further development include a lack of large, deidentified, high-quality datasets of DFD imaging to allow the use and validation of the methods being developed and reported, which often lack transparency and remain vague in reporting, thus giving rise to several ethical challenges. This is not the case in other specialties and wider industry where large datasets and imaging repositories are available to the public for use on software development platforms and repository hosting

Table III. Summary of Prediction model Risk Of Bias Assessment Tool (PROBAST) risk of bias assessment

Study	Year	Type of prediction model	Patient selection	Predictors	Outcomes	Analysis
Zhang	2022	Development only	High	Low	High	High

service such as GitHub. Furthermore, large data repositories allow access to multiple users for research, including the open functional MRI, the National Institutes of Health pediatric MRI data repository, King's College London healthy adult human brain imaging dataset, AccuRetina Dataset, chronic obstructive pulmonary disease ML datasets, Stanford university center for AI in medicine, and imaging shared datasets, to name a few.

Where studies are conducted, the source coding is not clarified or provided, which hinders external validation, replication of the findings, and transposition of methodologies. In the last several years, the emergence of no-code and low-code platforms have also allowed clinicians to use ML models in studies. No-coding platforms bypass the learning curve needed for computer programming through visual modelling and graphical user interface and can be used by software developers and health care professionals with minimal to no experience to expedite software building and productivity. Although this strategy is being used in other areas, including business, marketing, and social app development, its use in health care is being accepted with caveats—primarily owing to security and copyright- and ownership-related reasons and with the advent of General Data Protection Regulation-related fines. However, the rate of software development and cybersecurity buttressing continues to evolve at a rapid pace, and it is perhaps just a matter of time before no-coding and low-coding platforms are created to cater to health professionals and health care systems solely. However, this objective is not stated in the vast majority of studies, and this concern has been reflected and addressed in the 2020 consensus statement on "Guidelines for clinical trial protocols for interventions involving AI: the SPIRIT-AI extension," which asks for clarification in the context of the intended use in the clinical pathway, including the purpose and intended users, the procedure for acquiring and selection of data, the output from AI use, the point at which there is expected human-AI, identifying performance errors, access to the code, or restrictions to access or reuse.[41]

The next frontier is to explore the role of AI in three-dimensional imaging in the early detection and prognostication of DFU. High-resolution, three-dimensional imaging models may allow for very granular and holistic insights into DFD, including changes in the osteology, vasculature, musculature, and gross mechanics of the foot. This process is now becoming more accessible to health care professionals owing to the ongoing commercialization and user-friendly applications, a plethora of resources to allow health care professionals to use and evaluate current ML models and their applicability including Amazon Web Services, Meta's new segmentation tool, and Google Cloud's Auto ML model. Many of these tools are evolving and, with time, it is hoped that the use of these will be easily accessible and available to improve diagnostics and prevention.

CONCLUSIONS

Current ML models are primarily being used in two-dimensional imaging modalities in patients with DFD. Scope exists for evaluating this in three-dimensional imaging and incorporating existing risk prediction models. Specialized models which evaluate three-dimensional imaging are currently primitive and limited in their use; however, they have the potential for generation of suprahuman insights into existing imaging, extraction of novel metadata features, and prediction using integration of multidimensional patient characteristics.

AUTHOR CONTRIBUTIONS

Conception and design: MA, JS, AD
Analysis and interpretation: MA, MT, HB
Data collection: MA, MT
Writing the article: MA
Critical revision of the article: MA, MT, HB, JS, AD
Final approval of the article: MA, MT, HB, JS, AD
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Overall responsibility: MA

DISCLOSURES

None.

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Supplementary Table I (online only). Search strategy: Medline

#	Query
1	Diabetic Foot/ or DFU.mp. or Wound Healing/
2	Diabetic foot ulcer.mp. or exp Skin Ulcer/
3	Diabet*.mp.
4	diabetic foot disease.mp.
5	DFU dataset.mp.
6	artificial intelligence/ or machine learning/ or deep learning/ or supervised machine learning/ or unsupervised machine learning/ or neural networks, computer/ or "sensitivity and specificity"/
7	exp Image Interpretation, Computer-Assisted/ or exp Image Processing, Computer-Assisted/ or exp Neural Networks, Computer/ or exp Algorithms/ or exp Signal Processing, Computer-Assisted/ or exp Pattern Recognition, Automated/
8	convolutional neural network.mp.
9	deep Convolutional neural network.mp.
10	artificial neural network.mp.
11	natural language processing.mp. or exp Natural Language Processing/
12	self organizing map.mp.
13	computational intelligence.mp.
14	intelligent measurement.mp.
15	transfer learning.mp.
16	exp Diagnosis, Computer-Assisted/ or exp Fuzzy Logic/
17	boolean logic.mp.
18	exp Support Vector Machine/
19	random forest.mp.
20	naive bayes.mp.
21	k-nearest neighbour.mp.
22	radiomics.mp.
23	exp Image Interpretation, Computer-Assisted/ or medical image analysis.mp.
24	semantic segmentation.mp.
25	object detection.mp.
26	Pattern Recognition, Automated/
27	exp Data Mining/mt, st, sn, td [Methods, Standards, Statistics & Numerical Data, Trends]
28	lower extremity/ or ankle/ or foot/ or leg/
29	1 or 2 or 3 or 4 or 5
30	28 and 29
31	6 or 7 or 8 or 9 or 10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24 or 25 or 26 or 27
32	30 and 31
33	limit 32 to humans

Supplementary Table II (online only). Search strategy: Embase

#	Query
1	exp diabetes mellitus/
2	diabet*.mp.
3	exp diabetic foot/ or exp diabetic complication/ or exp foot disease/ or exp skin ulcer/
4	diabetic foot ulcer.mp. or exp diabetic foot/
5	DFU.mp.
6	DFU dataset.mp.
7	1 or 2 or 3 or 4 or 5 or 6
8	leg/ or exp lower limb/ or exp ankle/ or exp foot/ or exp leg blood vessel/ or exp leg muscle/
9	7 and 8
10	exp artificial intelligence/
11	deep learning/
12	exp supervised machine learning/
13	exp machine learning/ or exp artificial neural network/ or exp automated pattern recognition/ or exp automatic speech recognition/ or exp back propagation/ or exp bayesian learning/ or exp classification algorithm/ or exp classifier/ or exp computer heuristics/ or exp cross validation/ or exp data mining/ or exp feature detection/ or exp feature extraction/ or exp "feature learning (machine learning)"/ or exp feature ranking/ or exp feature selection/ or exp fuzzy system/ or exp k nearest neighbor/ or exp kernel method/ or exp knowledge discovery/ or exp markov state model/ or exp multicriteria decision analysis/ or exp multifactor dimensionality reduction/ or exp network learning/ or exp online analytical processing/ or exp outlier detection/ or exp perceptron/ or exp radial basis function/ or exp random forest/ or exp recursive feature elimination/ or exp recursive partitioning/ or exp relevance vector machine/ or exp rough set/ or exp semi supervised machine learning/ or exp supervised machine learning/ or exp support vector machine/ or exp unsupervised machine learning/
14	exp artificial neural network/ or exp automated pattern recognition/ or exp convolutional neural network/ or exp computer assisted diagnosis/
15	exp information processing/ or exp computer analysis/ or exp natural language processing/ or exp information retrieval/
16	self organizing map.mp.
17	computational intelligence.mp.
18	intelligent measurement.mp.
19	transfer learning.mp.
20	image interpretation.mp.
21	exp segmentation algorithm/ or exp image segmentation/
22	"imaging and display"/ or diagnostic imaging/ or image display/ or image enhancement/ or image processing/ or image retrieval/ or image segmentation/ or image subtraction/ or imaging/ or imaging algorithm/ or three-dimensional imaging/
23	exp data mining/
24	pattern recognition/ or exp feature detection/ or exp feature extraction/ or exp feature selection/
25	MRI.mp. or exp nuclear magnetic resonance imaging/
26	exp x-ray computed tomography/ or exp computer assisted tomography/ or CT.mp.
27	PET.mp. or exp positron emission tomography/
28	10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24
29	25 or 26 or 27
30	28 and 29
31	9 and 30
32	limit 31 to human
33	limit 32 to "remove medline records"