Potential Use and Limitation of Artificial Intelligence to Screen Diabetes Mellitus in Clinical Practice: A Literature Review

Aqsha Nur[1]*, Defin Yumnanisha[2], Sydney Tjandra[2], Adang Bachtiar[1], Dante Saksono Harbuwono[3]

[1]Faculty of Public Health, Universitas Indonesia, Depok, Indonesia.
[2]Faculty of Medicine Universitas Indonesia, Jakarta, Indonesia.
[3]Division of Endocrinology and Metabolism, Department of Internal Medicine, Faculty of Medicine Universitas Indonesia – Cipto Mangunkusumo Hospital, Jakarta, Indonesia.

***Corresponding Author:**
Aqsha Nur. Faculty of Public Health, Universitas Indonesia, Pondok Cina, Depok 16424, Indonesia. Email: aqsha.nur@lshtm.ac.uk.

ABSTRACT

The burden of undiagnosed diabetes mellitus (DM) is substantial, with approximately 240 million individuals globally unaware of their condition, disproportionately affecting low- and middle-income countries (LMICs), including Indonesia. Without screening, DM and its complications will impose significant pressure on healthcare systems. Current clinical practices for screening and diagnosing DM primarily involve blood or laboratory-based testing which possess limitations on access and cost. To address these challenges, researchers have developed risk-scoring tools to identify high-risk populations. However, considering generalizability, artificial intelligence (AI) technologies offer a promising approach, leveraging diverse data sources for improved accuracy. AI models (i.e., machine learning and deep learning) have yielded prediction performances of up to 98% in various diseases. This article underscores the potential of AI-driven approaches in reducing the burden of DM through accurate prediction of undiagnosed diabetes while highlighting the need for continued innovation and collaboration in healthcare delivery.

Keywords: *diabetes mellitus, artificial intelligence, screening, diagnosis.*

INTRODUCTION

Approximately 240 million people globally are living with undiagnosed diabetes mellitus (DM).[1] Almost 90% of undiagnosed diabetes cases are concentrated in low- and middle-income countries (LMIC), including Indonesia, where 73.7% of cases remain undiagnosed.[2] Undiagnosed DM leads to a higher risk for diabetes complications, including macro- and microvascular complications, as well as deaths. Studies suggest that around 5 years before diagnosis is determined, an individual with an asymptomatic or pre-diabetic condition might have already developed complications.[3 4] At the time of being diagnosed, 35% of people already had macrovascular complications (e.g., ischemic heart disease, stroke, and peripheral arterial disease) or microvascular (e.g., retinopathy, neuropathy, and nephropathy).[5]

In Indonesia, undiagnosed DM has a severe impact on the prevalence of cardiovascular diseases (CVD). In the last 10 years, the prevalence of heart disease and stroke increased from 0.5% to 1.5% and 0.7% to 1.9%, respectively.[6]

Between 2021 and 2022, treatment costs for both diseases increased from IDR 10.9 to 15.3 trillion rupiahs.[7] It is foremost to diagnose DM at an earlier stage. However, developing countries are facing constraints. A study of 28 countries indicated that only 63% of people with DM had undergone tests.[8] This is often the result of poor access and limited resources.[9-11] Therefore, a better tool for screening or diagnosis is needed to allow early treatment and lower the risk of complications and deaths.

Basic Knowledge of Diabetes Mellitus

According to the International Diabetes Foundation (IDF), global DM prevalence is projected to increase from 537 million adults in 2021 to 783 million by 2045.[12] DM is categorised into four types, namely: type 1 diabetes (T1DM), type 2 diabetes (T2DM), gestational diabetes, and diabetes of other forms (e.g., monogenic diabetes syndromes, diseases of the exocrine pancreas, and drug- or chemical-induced diabetes).[13] Approximately 10% of the total cases are attributed to T1DM. IDF also listed the countries with the highest number of DM in 2021, where Indonesia positioned as the fifth.[2] IDF's projection for Indonesia was supported by data from National Basic Health Research surveys. Indonesia's prevalence increased from 6.9% to 10.9% between 2013 and 2018.[6]

Diabetes mellitus is a group of metabolic diseases characterized by hyperglycemia resulting from defects in insulin secretion, insulin action, or both.[14] Classic signs of hyperglycemia are polydipsia, polyuria, and polyphagia. As mentioned earlier, DM has several forms. T1DM is a form of chronic autoimmune disease that is a result of elevated blood glucose levels.[15] Historically, T1DM has been observed as a condition affecting children and adolescents. Nowadays, the age at which symptoms first appear has not been regarded as a constraining factor.[16] T2DM is the most common diabetes category, and it is characterized as hyperglycemia due to insulin resistance in adipose tissue, liver, skeletal muscle, and/ or insufficient insulin production in the body.[13 17] Adiposity, serum biomarkers, an unhealthy dietary pattern, decreased physical activity, high sedentary time, smoking, and some medical conditions (e.g., high systolic blood pressure and metabolic syndrome) are suggested to contribute to T2DM.[18]

Current Clinical Practice for Diabetes Diagnosis

Diagnosis involves identifying diseases based on signs and symptoms, using assessments like patient history, clinical observations, laboratory tests, and imaging studies. In contrast, screening targets individuals at risk of a specific condition, prompting further investigation or preventive action. The primary goal of screening is early disease detection and increased chances of successful treatment, leading to broader coverage.[19] Screening is more dedicated to the population with risk factors, such as overweight/ obesity, physical inactivity, age, diabetes in first-degree relatives, history of gestational diabetes, and ethnicity.[20]

Multiple screening methods are commonly utilized for T2DM, as recommended by clinical practice guidelines from the World Health Organization and the American Diabetes Association. These methods include fasting plasma glucose (FPG), 2-hour glucose during a 75g oral glucose tolerance test (OGTT), HbA1c, and random blood glucose (**Figure 1**; **Table 1).**[21 22]

In Indonesia, the screening and diagnosis of diabetes follow the clinical practice guidelines set by the Indonesian Endocrinologist Association (PERKENI). According to the PERKENI guideline, the diagnosis of T2DM is confirmed through blood glucose and HbA1c examinations. The recommended method for blood glucose examination is enzymatic testing using venous plasma blood samples.[20] Typically, diagnosis is established based on an existing clinical diagnosis, such as individuals presenting with classic symptoms of hyperglycemia (RPG $\geq$ 200 mg/dL). Alternatively, diagnosis may require two abnormal screening test results, measured either simultaneously or at different time points.[25]

Despite established screening procedures, several issues persist regarding the coverage of diabetes screening. Many individuals are reluctant to undergo screening due to various factors, including a lack of awareness about health screens, limited understanding of their preventive purpose, disinterest in the program

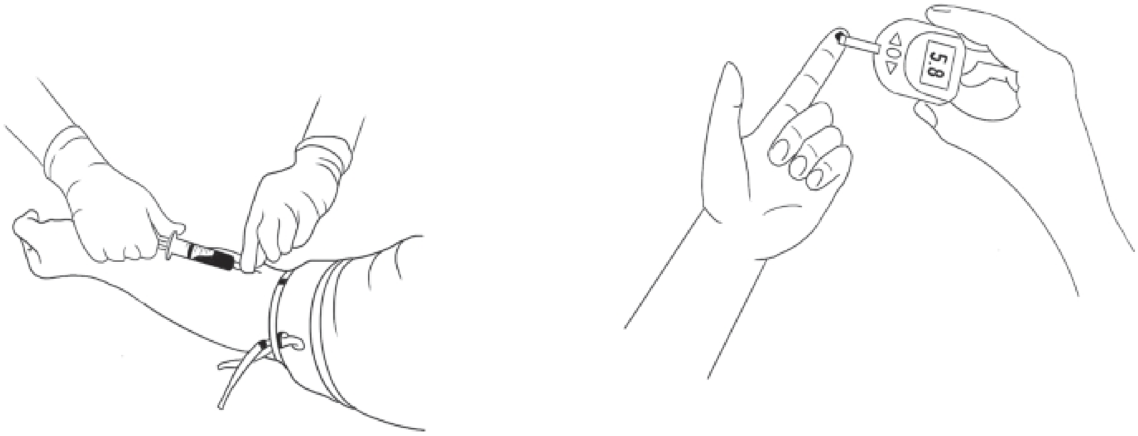

Figure 1. Blood glucose measurement using invasive tests through venous or capillary blood collection.[23]

Table 1. Diabetes tests and cut-off values.[20-22]

Diabetes Tests	World Health Organization	American Diabetes Association	PERKENI
Fasting venous or plasma glucose	≥7.0 mmol/L (126 mg/dL)	≥7.0 mmol/L (126 mg/dL)	≥7.0 mmol/L (126 mg/dL)
2-hour post load venous plasma	≥11.1 mmol/L (200 mg/dL)	≥11.1 mmol/L (200 mg/dL)	≥11.1 mmol/L (200 mg/dL)
2-hour post-load capillary plasma glucose	≥12.2 mmol/L (220 mg/dL)	N/A	N/A
Random plasma glucose	≥11.1 mmol/L (200 mg/dL)	≥11.1 mmol/L (200 mg/dL)	≥11.1 mmol/L (200 mg/dL)
HbA1c	≥ 6.5% (48 mmol/mol)	≥ 6.5% (48 mmol/mol)	≥ 6.5% (48 mmol/mol)

(e.g., influenced by peers, fear of results, lack of motivation), time constraints, difficulties in scheduling appointments, and concerns about the screening environment (e.g., privacy and confidentiality). Therefore, addressing these challenges is crucial to improving screening rates and overall diabetes management.[24]

Limitation of Laboratory-based Diagnosis

Limitations of laboratory-based diagnosis can be divided into two main problems: accuracy and implementation feasibility. Accuracy can be compromised by potential errors in the pre-analytic phase, such as sample contamination and defective blood glucose strips. Factors like ambient conditions, patient medications, and timing of the examination can also influence outcomes, potentially leading to misinterpretation of results. For instance, HbA1c levels may exhibit slight elevations in patients with iron deficiency, affecting diagnostic accuracy. Glucose concentrations may also be falsely low if samples are not promptly processed or stored properly.[25,26] The second problem pertains to the implementation, including the cost and access for the public, especially in low-income countries. Laboratory tests, such as HbA1c, can be expensive, with estimated unit costs for screening reaching USD 14 (IDR 227.000). Additionally, setting up and maintaining the necessary equipment and infrastructure for laboratory testing can require significant financial investment.[27 28]

Risk Scoring as a Tool for Diabetes Screening

Early diagnosis and treatment of type 2 diabetes are among the most relevant actions to prevent complications.[29] According to the ADDITION-Europe Simulation Model Study, an early diagnosis reduces the absolute and relative risk of cardiovascular morbidity and mortality.[30] Responding to this, researchers have developed predictive models, such as the Finnish Diabetes Risk Score (FINDRISC), Indian Diabetes Risk Score (IDRS), and American Diabetes Association Risk Test (ADA Risk Test).[31-33] Risk scores are quantitative instruments that produce a numerical score that represents the level of disease risk for an individual. **Table 2** below presents some popular risk scores, their variables, and performance.

Limitation of Scoring Tools

Although scores are expected to assist in identifying and/or predicting the risk of DM, they are subject to specific debates and limitations. To date, there is a dearth of published research examining the impact of a diabetes risk score on the reduction of incident diabetes. Furthermore, the usefulness of these scores is restricted to comparable populations because they are based on study populations with different sizes and characteristics. The existence of a universally optimal risk score is not feasible, as the effectiveness of any score is contingent not only upon its statistical characteristics but also on its specific application context. Lastly, it is worth noting that although the developers of the majority of diabetes risk scores express a high level of confidence in the positive attributes of their scores, practitioners may hold a different perspective.[35 36]

Artificial Intelligence for Disease Diagnosis or Screening

Artificial intelligence (AI) is a vast field defined as everything a computer algorithm processes automatically, as opposed to conventional computer coding by humans, is increasingly involved in addressing various healthcare aspects.[37 38] Quite notable, however, is the utilization of AI in disease diagnostics. Various studies have investigated its performance in diagnosing diseases of the skin,[39] liver,[40] gastrointestinal system,[41] heart, [42] and hypertension.[43] Furthermore, it has also been able to analyze imaging data. Artificial intelligence is also utilized in respiratory infectious diseases such as COVID-19 by utilizing images of chest X-rays.[44]

Machine learning (ML), a subset of AI, encompasses techniques with advanced algorithms capable of the automated extraction of enhanced features without being programmed explicitly.[45 46] ML can be developed into supervised (regression, classification, and composition), unsupervised (clustering, dimensionality, and association), as well as reinforced learning models. Supervised models entail numerous labelled training cases, allowing the algorithm to learn and produce accurate outputs in a faster manner.[45] Unsupervised models do not receive labelled input and output data; instead, they infer underlying patterns in unlabeled data to identify subclusters within the original dataset.[47] To delve deeper into the workings of artificial intelligence in disease detection, a framework is illustrated in **Figure 2**.

A further subset of machine learning is deep learning (DL), a powerful technique automating complex pattern detection in large datasets through deep structures and numerous processing layers.[45] DL's development for diabetes encompasses prediction, screening, classification, and management. An example is the artificial pancreas, a closed-loop hormone delivery system that automatically regulates blood glucose levels by injecting insulin timely upon abnormal levels detection that are predicted accurately.[48] In diabetes diagnosis, machine learning, as one branch of artificial intelligence, can leverage this sporadic data and discover correlations among these data.[49] Considering the

Table 2. Risk score models for diabetes mellitus.

Risk Scores	Variables	Performance
Finnish Diabetes Risk Score (FINDRISC)[31]	Age, BMI, waist circumference, use of blood pressure medication, history of high blood glucose, physical activity, daily consumption of vegetables, fruits, or berries	Sensitivity: 78% Specificity: 77%
American Diabetes Association Risk Test(ADA)[33]	Age, gender, history of gestational diabetes in women, family history of gestational diabetes, history of hypertension, physical activity, BMI	Sensitivity: 68% Specificity 65%
Bogor Diabetes Risk Prediction (BDRP)[34]	Age, obese, hypertensive, central obesity, physical activity	Sensitivity: 77% Specificity: 50%
Indian Risk Score (IRS)[32]	Age, central obesity, family history of diabetes, physical activity	Sensitivity: 73% Specificity: 60%

BMI, body mass index

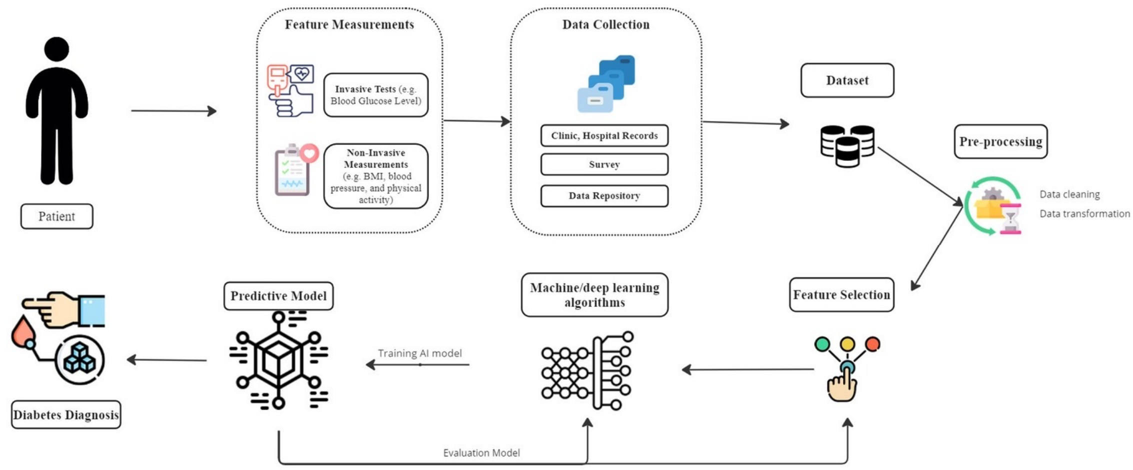

Figure 2. Framework of artificial intelligence for diabetes mellitus diagnosis prediction model.

Table 3. Example of existing machine learning models for disease detection.

Author	Disease	Algorithm	Outcome
Aijaz et al.[39]	Psoriasis	Convolutional neural network (CNN), long short-term memory (LSTM)	Accuracy : 84.2 %; 72.3%
Chuang et al.[40]	Liver	CBR, BPNN, Logistic Regression, Classification	Accuracy : 95 % Sensitivity : 98 % Specificity: 94 %
Plawaik et al.[42]	Arrhytmia	*Deep genetic ensemble of classifiers, ECG signal*	Sensitivity : 94.62 % Accuracy : 99.37 % Specificity: 99.66 %
Owasis et al.[41]	Gastrointestinal disease	Residual network, LSTM	AUC: 97.057%
Luo et al.[44]	Gastrointestinal cancer	GRAIDS, Clopper Pearson Method	Accuracy: 95%

AUC, Area Under the Curve; CBR, Case-Based Reasoning; CNN, Convolutional Neural Network; BPNN, Back Propagation Neural Network; ECG, Electrocardiography; LSTM, Long Short-Term Memory; GRAIDS, Gastrointestinal Artificial Intelligence Diagnostic System

impracticality of conducting HbA1c testing on all at-risk populations, deep learning can address the need for early diabetes onset detection and predict diabetes risk through population screening. Various deep learning models, ranging from LSTM, CNN, SVM, and others, have demonstrated the ability to predict, detect, and classify diabetes cases, even reaching near-perfect models when trained on tidy datasets.[50]

Limitation of AI in Disease Diagnosis or Screening

Although AI has been found to cut healthcare costs, it is stronger in treatment compared to diagnosis,[51] and most assessments have not included the initial investment and operational costs needed for AI implementation.[52] Computing power and data availability are also needed to boost its progress.[45] Although Internet-based clouds provide the possibility to access more data, filtering relevant, non-ambiguous, and meaningful data presents a challenge.[53] These challenges present significant potential for continued improvement and innovation in the field of artificial intelligence.

CONCLUSION

Integrating artificial intelligence (AI) into clinical practice for the screening of diabetes mellitus (DM) offers promising benefits for healthcare providers, including doctors. AI models are tested to be accurate in identifying high-risk individuals and enabling earlier intervention to prevent complications. For clinicians, the adoption of AI tools means a shift towards more proactive and precise management of diabetes. AI can assist in interpreting complex data and predicting patient conditions. This technology can also support large-scale screening programs by identifying individuals who might otherwise remain undiagnosed. However, the successful implementation of AI in clinical settings requires ongoing collaboration between healthcare providers, researchers, and technology developers to address challenges such as data quality, computing systems, and integration with existing healthcare systems. Ultimately, AI has the potential to transform diabetes care by making screening more accessible and diagnosis more accurate. Therefore, continued innovation and collaborative efforts will be essential to maximize the full benefits of AI in clinical practice.

DECLARATION OF INTERESTS

The authors declare that they have no conflict of interest in the production of the study

FUNDING

This study did not receive any specific funding from any sponsors.

REFERENCES

1. Ogurtsova K, Guariguata L, Barengo NC, et al. IDF diabetes Atlas: Global estimates of undiagnosed diabetes in adults for 2021. Diabetes Res Clin Pract 2022;183:109118. doi: 10.1016/j.diabres.2021.109118 [published Online First: 20211206]
2. Magliano DJ, Boyko EJ. The International Diabetes Federation (IDF) Atlas 10th Edition. 10th ed. Brussels: International Diabetes Federation 2021.
3. Heydari I, Radi V, Razmjou S, Amiri A. Chronic complications of diabetes mellitus in newly diagnosed patients. International Journal of Diabetes Mellitus 2010;2(1):61-3. doi: https://doi.org/10.1016/j.ijdm.2009.08.001
4. Gopalan A, Mishra P, Alexeeff SE, et al. Prevalence and predictors of delayed clinical diagnosis of Type 2 diabetes: a longitudinal cohort study. Diabet Med 2018;35(12):1655-62. doi: 10.1111/dme.13808 [published Online First: 20180921]
5. Guariguata L, Whiting D, Weil C, Unwin N. The International Diabetes Federation diabetes atlas methodology for estimating global and national prevalence of diabetes in adults. Diabetes Research and Clinical Practice. 2011;94(3):322-32. doi: https://doi.org/10.1016/j.diabres.2011.10.040
6. National Health Policy Agency. Basic Health Research 2018 [Website]. Jakarta: Ministry of Health Republic of Indonesia,; 2020 [cited 2024 1 May 2024]. Available from: https://layanandata.kemkes.go.id/katalog-data/riskesdas/ketersediaan-data/riskesdas-2018 accessed 1 May 2024 2024.
7. Kementerian Kesehatan. Penyakit berbiaya tertinggi dalam program JKN tahun 2022. Jakarta: Kementerian Kesehatan, 2023.
8. Manne-Goehler J, Geldsetzer P, Agoudavi K, et al. Health system performance for people with diabetes in 28 low- and middle-income countries: A cross-sectional study of nationally representative surveys. PLoS Med. 2019;16(3):e1002751. doi: 10.1371/journal.pmed.1002751 [published Online First: 20190301]
9. Kementerian Kesehatan. Program tematik diabetes melitus tipe-2 tahun 2022. Jakarta: Kementerian Kesehatan, 2023.
10. Siswati T, Kasjono HS, Olfah Y. "Posbindu PTM": The Key of Early Detection and Decreasing Prevalence of Non-Communicable Diseases in Indonesia. Iran J Public Health. 2022;51(7):1683-84. doi: 10.18502/ijph.v51i7.10105
11. Alkaff FF, Illavi F, Salamah S, et al. The impact of the Indonesian chronic disease management program (PROLANIS) on metabolic control and renal function of type 2 diabetes mellitus patients in primary care setting. J Prim Care Community Health. 2021;12:2150132720984409. doi: 10.1177/2150132720984409
12. Cho NH, Shaw JE, Karuranga S, et al. IDF diabetes atlas: Global estimates of diabetes prevalence for 2017 and projections for 2045. Diabetes Res Clin Pract. 2018;138:271-81. doi: 10.1016/j.diabres.2018.02.023 [published Online First: 20180226]
13. Association AD. 2. Classification and diagnosis of diabetes: standards of medical care in diabetes—2021. Diabetes Care. 2021;44(Suppl1):S15-S33.
14. American Diabetes Association. Classification and diagnosis of diabetes: Standards of medical care in diabetes-2020. Diabetes Care. 2020;43(Suppl 1):S14-S31. doi: 10.2337/dc20-S002
15. Gepts W. Pathologic anatomy of the pancreas in juvenile diabetes mellitus. Diabetes. 1965;14(10):619-33. doi: 10.2337/diab.14.10.619
16. Atkinson MA, Eisenbarth GS, Michels AW. Type 1 diabetes. The lancet. 2014;383(9911):69-82.
17. DeFronzo RA. From the triumvirate to the ominous octet: A new paradigm for the treatment of type 2 diabetes mellitus. Diabetes. 2009;58(4):773-95. doi: 10.2337/db09-9028
18. Bellou V, Belbasis L, Tzoulaki I, Evangelou E. Risk factors for type 2 diabetes mellitus: An exposure-wide umbrella review of meta-analyses. PloS One. 2018;13(3):e0194127. doi: 10.1371/journal.pone.0194127 [published Online First: 20180320]
19. Gilbert R, Logan S, Moyer VA, Elliott EJ. Assessing diagnostic and screening tests: Part 1. Concepts. West J Med 2001;174(6):405-9. doi: 10.1136/ewjm.174.6.405
20. Perkumpulan Endokrinologi Indonesia. Pedoman

pengelolaan dan pencegahan DMT2 dewasa di Indonesia. Jakarta: PERKENI, 2021.
21. Committee ADAPP. Introduction and methodology: Standards of care in diabetes—2024. Diabetes Care. 2023;47(Suppl.1):S1-S4. doi: 10.2337/dc24-SINT
22. World Health Organization. Diagnosis and management of type 2 diabetes (HEARTS-D). Geneva: World Health Organization; 2020.
23. Wee BF, Sivakumar S, Lim KH, et al. Diabetes detection based on machine learning and deep learning approaches. Multimedia Tools and Applications. 2024;83(8):24153-85. doi: 10.1007/s11042-023-16407-5
24. AshaRani PV, Devi F, Wang P, et al. Factors influencing uptake of diabetes health screening: a mixed methods study in Asian population. BMC Public Health. 2022;22(1):1511. doi: 10.1186/s12889-022-13914-2 [published Online First: 20220809]
25. Nichols JH. Blood glucose testing in the hospital: error sources and risk management. J Diabetes Sci Technol 2011;5(1):173-7. doi: 10.1177/193229681100500124 [published Online First: 20110101]
26. El Sayed NA, Aleppo G, Aroda VR, et al. Classification and diagnosis of diabetes: Standards of care in diabetes-2023. Diabetes Care. 2023;46(Suppl 1):S19-S40. doi: 10.2337/dc23-S002
27. Ohde S, Moriwaki K, Takahashi O. Cost-effectiveness analysis for HbA1c test intervals to screen patients with type 2 diabetes based on risk stratification. BMC Endocr Disord. 2021;21(1):105. doi: 10.1186/s12902-021-00771-0 [published Online First: 20210522]
28. Heidt B, Siqueira WF, Eersels K, et al. Point of care diagnostics in resource-limited settings: A review of the present and future of PoC in its most needed environment. Biosensors (Basel) 2020;10(10) doi: 10.3390/bios10100133 [published Online First: 20200924]
29. Gregg EW, Sattar N, Ali MK. The changing face of diabetes complications. Lancet Diabetes Endocrinol. 2016;4(6):537-47. doi: 10.1016/S2213-8587(16)30010-9 [published Online First: 20160504]
30. Herman WH, Ye W, Griffin SJ, et al. Early detection and treatment of type 2 diabetes reduce cardiovascular morbidity and mortality: a simulation of the results of the anglo-danish-dutch study of intensive treatment in people with screen-detected diabetes in primary care (ADDITION-Europe). Diabetes Care. 2015;38(8):1449-55. doi: 10.2337/dc14-2459 [published Online First: 20150518]
31. Lindstrom J, Tuomilehto J. The diabetes risk score: a practical tool to predict type 2 diabetes risk. Diabetes Care. 2003;26(3):725-31. doi: 10.2337/diacare.26.3.725
32. Mohan V, Deepa R, Deepa M, et al. A simplified Indian diabetes risk score for screening for undiagnosed diabetic subjects. J Assoc Physicians India. 2005;53:759-63.
33. McGregor MS, Pinkham C, Ahroni JH, et al. The American Diabetes Association risk test for diabetes. Diabetes Care. 1995;18(4):585-6. doi: 10.2337/diacare.18.4.585b
34. Sulistiowati E, Pradono J. Development of a validated diabetes risk chart as a simple tool to predict the onset of diabetes in Bogor, Indonesia. J ASEAN Fed Endocr Soc. 2022;37(1):46-52. doi: 10.15605/jafes.037.01.09 [published Online First: 20220427]
35. Noble D, Mathur R, Dent T, et al. Risk models and scores for type 2 diabetes: systematic review. BMJ. 2011;343:d7163. doi: 10.1136/bmj.d7163
36. Martinez-Millana A, Argente-Pla M, Valdivieso Martinez B, et al. Driving type 2 diabetes risk scores into clinical practice: Performance analysis in hospital settings. J Clin Med. 2019;8(1) doi: 10.3390/jcm8010107 [published Online First: 20190117]
37. Wang L, Zhang Y, Wang D, et al. Artificial intelligence for COVID-19: A systematic review. Front Med (Lausanne). 2021;8:704256. doi: 10.3389/fmed.2021.704256 [published Online First: 20210930]
38. Amisha, Malik P, Pathania M, Rathaur VK. Overview of artificial intelligence in medicine. J Family Med Prim Care. 2019;8(7):2328-31. doi: 10.4103/jfmpc.jfmpc_440_19
39. Aijaz SF, Khan SJ, Azim F, et al. Deep learning application for effective classification of different types of psoriasis. J Healthc Eng. 2022;2022:7541583. doi: 10.1155/2022/7541583 [published Online First: 20220115]
40. Chuang CL. Case-based reasoning support for liver disease diagnosis. Artif Intell Med. 2011;53(1):15-23. doi: 10.1016/j.artmed.2011.06.002 [published Online First: 20110714]
41. Owais M, Arsalan M, Choi J, et al. Artificial intelligence-based classification of multiple gastrointestinal diseases using endoscopy videos for clinical diagnosis. J Clin Med. 2019;8(7) doi: 10.3390/jcm8070986 [published Online First: 20190707]
42. Yildirim O, Plawiak P, Tan RS, Acharya UR. Arrhythmia detection using deep convolutional neural network with long duration ECG signals. Comput Biol Med. 2018;102:411-20. doi: 10.1016/j.compbiomed.2018.09.009 [published Online First: 20180915]
43. Kanegae H, Suzuki K, Fukatani K, et al. Highly precise risk prediction model for new-onset hypertension using artificial intelligence techniques. J Clin Hypertens. (Greenwich) 2020;22(3):445-50. doi: 10.1111/jch.13759 [published Online First: 20191209]
44. Luo H, Xu G, Li C, et al. Real-time artificial intelligence for detection of upper gastrointestinal cancer by endoscopy: a multicentre, case-control, diagnostic study. Lancet Oncol. 2019;20(12):1645-54. doi: 10.1016/S1470-2045(19)30637-0 [published Online First: 20191004]
45. Ghaffar Nia N, Kaplanoglu E, Nasab A. Evaluation of

artificial intelligence techniques in disease diagnosis and prediction. Discover Artificial Intelligence 2023;3(1):5. doi: 10.1007/s44163-023-00049-5

46. Al Kuwaiti A, Nazer K, Al-Reedy A, et al. A review of the role of artificial intelligence in healthcare. J Pers Med. 2023;13(6) doi: 10.3390/jpm13060951 [published Online First: 20230605]
47. Wu X, Liu X, Zhou Y. Proceedings of 2021 chinese intelligent systems conference: review of unsupervised learning techniques in lecture notes in electrical engineering. Singapore: Springer; 2022.
48. Woldaregay AZ, Arsand E, Walderhaug S, et al. Data-driven modeling and prediction of blood glucose dynamics: Machine learning applications in type 1 diabetes. Artif Intell Med. 2019;98:109-34. doi: 10.1016/j.artmed.2019.07.007 [published Online First: 20190726]
49. Williams BM, Borroni D, Liu R, et al. An artificial intelligence-based deep learning algorithm for the diagnosis of diabetic neuropathy using corneal confocal microscopy: a development and validation study. Diabetologia. 2020;63(2):419-30. doi: 10.1007/s00125-019-05023-4 [published Online First: 20191112]
50. Fregoso-Aparicio L, Noguez J, Montesinos L, García-García JA. Machine learning and deep learning predictive models for type 2 diabetes: a systematic review. Diabetol Metab Syndr. 2021;13(1):148. doi: 10.1186/s13098-021-00767-9 [published Online First: 20211220]
51. Khanna NN, Maindarkar MA, Viswanathan V, et al. Economics of artificial intelligence in healthcare: Diagnosis vs. treatment. Healthcare. 2022;10(12):2493.
52. Wolff J, Pauling J, Keck A, Baumbach J. The economic impact of artificial intelligence in health care: Systematic review. J Med Internet Res. 2020;22(2):e16866. doi: 10.2196/16866
53. Ayesha S, Kashif M, Talib R. Overview and comparative study of dimensionality reduction techniques for high dimensional data. Information Fusion. 2020;59 doi: 10.1016/j.inffus.2020.01.005