REVIEW ARTICLE

AI-Powered Innovations in Diabetes: A Narrative Review

Pei Kuan Lai[1], Sivalingam Nalliah[2]

[1] Institute for Research, Development and Innovation (IRDI), IIMU University, No.126, Jalan Jalil Perkasa 19, Bukit Jalil, 57000 Kuala Lumpur, Malaysia
[2] School of Medicine, IMU University, Clinical Campus Seremban, Jalan Rasah, Bukit Rasah, 70300 Seremban, Negeri Sembilan, Malaysia

ABSTRACT

Artificial intelligence (AI) has been increasingly used in diabetes care with promising results of improved outcomes. This is a narrative review on the application of AI in *diabetes mellitus* (DM) management in Malaysia. Bibliographic search with the search terms of "*diabetes mellitus*", "artificial intelligence", "machine learning" and "Malaysia" was conducted on PubMed, Scopus, and Google Scholar. A final list of 65 publications were included for analysis in this review. Most of the studies (n=28, 43.1%) were done with the focus on DM in general. The types of AI most employed by the studies were neural network (n=15, 23.1%), supervised learning together with neural network (n=13, 20.0%), and supervised learning (n=12, 18.5%). AI was most applied in the classification (n=15, 23.1%), prediction (n=15, 23.1%), detection (n=11, 16.9%), diagnosis (n=9, 13.8%), and identification (n=7, 11.0%) of DM. High levels of accuracy, sensitivity, specificity, and precision (more than 90%) were reported in the included studies.
Malaysian Journal of Medicine and Health Sciences (2025) 21(5): 267-282. doi:10.47836/mjmhs.21.5.30

Keywords: Artificial intelligence (AI), *Diabetes mellitus*, Applications, Malaysia, Review

Corresponding Author:
Dr Lai Pei Kuan, PhD
Email: laipeikuan@imu.edu.my
Tel :+60128017383

INTRODUCTION

Described as "a pandemic of unprecedented magnitude spiralling out of control" (1), *diabetes mellitus* (DM) stands as one of the most prevalent non-communicable chronic diseases, leading to elevated blood glucose levels (2). DM is caused by a deficiency of insulin secretion or resistance to insulin resulting in hyperglycemia in the body (3). Of late, DM has been recognised as one of the fastest growing global health emergencies of the 21st century. It was estimated that 537 million people reportedly have DM in 2021. This figure is projected to reach 643 million by 2030, and 783 million by 2045 (1). Gaining its reputation as a disease of 'over-sweetness', DM marks the highest prevalence rate in Asia and one of the highest in the world. To exacerbate the situation, the prevalence of DM continues to rise relentlessly worldwide. In Malaysia, the prevalence of DM has doubled over the past 10 years and now includes rapidly rising numbers of children and adolescents (4). To date, 1 in 5 adults (about 3.9 million people) aged 18 and above in Malaysia have DM (5), making this country the 'sweetest nation in Asia'. Seven million Malaysian adults are projected to have DM by 2025, a worrying trend that leads to a prevalence rate of 31.3% for adults aged 18 years and above (1 in 3 adults) (6).

Artificial intelligence (AI) has become an integral part of our daily lives, simplifying complex tasks and improving efficiency (7). AI utilizes algorithms to generate results and enables computers to model intelligent behaviour with minimal human intervention, performing tasks that typically demand human intelligence, including reasoning, learning, and self-improvement (8-10). They mimic human cognitive functions, enabling prediction, automation, and the resolution of intricate tasks historically undertaken by humans (10).

AI, machine learning, deep learning and neural networks constitute of a series of AI systems from the largest to the smallest, each encompassing the next (Fig. 1). In this system, AI is the overarching system; machine learning is a subset of AI; followed by deep learning as a subfield of machine learning, and lastly neural networks make up the backbone of deep learning algorithms (10). (Fig. 1).

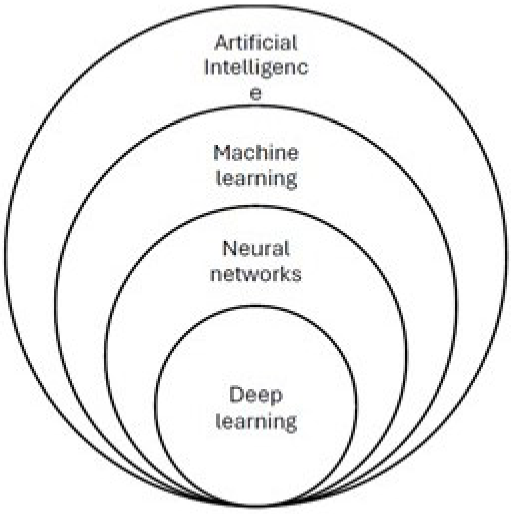

Fig. 1: Artificial intelligence, machine learning, neural networks, and depp learning[10]

Poorly controlled DM could lead to a wide range of microvascular and macrovascular complications such as retinopathy, nephropathy, and neuropathy (microvascular) as well as ischemic heart disease, peripheral vascular disease, and cerebrovascular disease (macrovascular) which are the major cause of morbidity and mortality amongst individuals (11, 12). DM could be better managed and handled with early diagnosis and treatment which will also potentially delay or prevent major complications and even fatality (13). Recent face-paced advancements in AI and machine learning methods have paved the way for researchers to conduct more cutting-edge research for more effective and improved early diagnosis, treatment and management of DM (14).

Machine learning has the potential to assist both health professionals and patients by offering initial insights into DM based on routine physical examination outcomes. These insights serve as crucial guidance for physicians in their decision-making process (13). Machine learning and data mining techniques play a pivotal role in DM research, enabling the extraction of valuable insights from the extensive volume of DM-related data at our disposal. With the burgeoning data landscape in medical science research on DM, AI-based methods such as machine learning and data mining prove immensely valuable in facilitating the diagnosis, management, and various clinical facets of DM treatment.

AI or machine learning serves as a powerful tool in understanding *diabetes mellitus* (DM) as a complex disease and providing tailored diagnosis and treatment regimens to the patients with diabetes (15). Ultimately, it will help the patients, healthcare teams, and hospital administrators in managing DM holistically in terms of prevention, prediction, and cost-management more effectively (15). One of the main challenges in applying machine learning to DM research and diagnosis is in selecting the most relevant features (variables or attributes) and choosing the appropriate algorithm to effectively analyse and make predictions from DM-related data. This critical aspect of machine learning in healthcare requires careful consideration to develop effective machine learning solutions for DM-related tasks (13).

To the best knowledge of the authors, there has been no published paper in Malaysia to narrate on the applications of AI in DM in the Malaysian context. The aim of this review is to take a narrative approach on how AI has been applied in DM management in Malaysia. The review findings will provide an overall picture of the types of AI and its utilisation in the management or treatment of DM.

MATERIAL AND METHODS

A comprehensive, systematic literature search was conducted with the search terms of "*diabetes mellitus*", "artificial intelligence", "machine learning" and "Malaysia" in online bibliographic databases which included PubMed, Scopus, and Google Scholar. Development of this review was guided by Preferred Reporting Items for Systematic Review and Meta-analyses Protocols (PRISMA-P) (16). Study criteria are outlined in the following sub-sections based on the PICOTS framework (17).

Participants (P)
Studies that involved patients with all types of DM, including type 1 diabetes (T1DM), type 2 diabetes (T2DM), gestational diabetes and its complications and management were included in this review. There were no eligibility restrictions on age, population, gender, ethnicity, geographical location of participants to give a more comprehensive review of the usage of AI in diabetes. Studies on other DM complications were also included in this analysis.

Interventions (I)
Malaysian studies which involved any type of AI and machine learning, such as supervised and unsupervised learning, neural network, and deep learning were included in the reference.

Outcome (O)
Studies related to the applications of AI in DM were included in this review.

Time (T)
There was no limit to the year of publication for included studies.

Settings (S)
Only studies published in Malaysia and with one of the affiliated authors from Malaysia were included for analysis.

The inclusion criteria for eligible studies in this analysis were as follows:
• Studies with at least one author affiliated in Malaysia.
• Studies involving any type of diabetes (type 1, 2, or gestational).
• Studies employing any form of AI or machine learning.
• Only original articles.
• Only cross-sectional studies.

The exclusion criteria for articles in this review were:
1.Review articles, conference proceedings, books, book chapters, reports, case reports, editorials, commentaries, theses or dissertations, abstracts, study protocols, and letters are excluded from analysis in this review.

The literature search was performed from inception up till 31st May 2023. The retrieved references were managed using EndNote X8 citation manager (18). Two researchers screened the retrieved papers and consensus on the final papers to be included was reached after discussion when disputes arose.

Joanna Briggs Institute (JBI) Checklist for Analytical Cross-sectional Studies was employed to assess the quality of the included studies (19). The checklist was specifically designed for cross-sectional studies and has reportedly high methodologic rigour (20). There has been no generally decided threshold for an 'acceptable' JBI score (21). Nonetheless, studies with < 4/8 (50%) total '✓' were excluded from this review, suggesting high likelihood of poor study qualities (21). (Table I)

Table I: Risk of Bias of studies included in this review

No	Authors	Criteria 1	Criteria 2	Criteria 3	Criteria 4	Criteria 5	Criteria 6	Criteria 7	Criteria 8	Total (%)
1	Ahmed WR 2011[17]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
2	Nadeem MW 2021[18]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
3	Amith K 2021[19]	✓	✓	✓	✓	✓	X	✓	✓	**7 (87.5%)**
4	Aghila R 2022[20]	✓	✓	✓	✓	✓	X	✓	✓	**7 (87.5%)**
5	Amith K 2022[21]	✓	✓	✓	✓	✓	X	✓	✓	**7 (87.5)**
6	Maher TA 2022[22]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
7	Nilashi M 2018[23]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
8	Farah MMG 2020[24]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
9	Tang MCS 2022[25]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
10	Thirumalaimuthu TR 2022[26]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
11	Nilashi M 2017[27]	✓	✓	✓	✓	X	X	✓	✓	**6 (755)**
12	Kumarmangal R 2021[2]	✓	✓	✓	✓	✓	X	✓	✓	**7 (87.5%)**
13	Vimala B 2011[28]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
14	Tutut H 2014[29]	✓	X	✓	✓	X	X	✓	✓	**5 (62.5%)**
15	Ozal Y 2019[30]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
16	Acharya UR 2017[31]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
17	Acharya UR 2013[32]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
18	Sarni SR 2016[33]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
19	Aibinu AM 2010[34]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
20	Khan A 2022[35]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
21	Zulkifli MFY 2022[36]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
22	Shakeel PM 2018[37]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
23	Suhaimi N 2012[38]	✓	✓	✓	✓	✓	X	✓	✓	**7 (87.5%)**
24	Sim R 2023[13]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
25	Alex SA 2022[39]	✓	✓	✓	✓	✓	X	✓	✓	**7 (87.5%)**
26	Rosli MM 2020[40]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
27	Abbas SL 2009[41]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
28	Hasliza AH 2020[42]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
29	Ayuni Z 2022[43]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
30	Butt MM 2022[44]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
31	Fahmida H 2021[45]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
32	Kakudi HA 2018[46]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
33	Yap CW 2021[47]	✓	✓	✓	✓	✓	X	✓	X	**6 (75%)**

CONTINUE

Table I: Risk of Bias of studies included in this review (CONT.)

No	Authors	Criteria 1	Criteria 2	Criteria 3	Criteria 4	Criteria 5	Criteria 6	Criteria 7	Criteria 8	Total (%)
34	Abbood SH 2022[48]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
35	AL-Behadili HNK 2021[49]	✓	✓	✓	✓	X	X	✓	X	**5 (62.5%)**
36	Rahmat MAA 2017[50]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
37	Albadr MAA 2022[51]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
38	Abbood SH 2022[52]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
39	Abdullah L 2017[53]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
40	Sampathkumar A 2022[54]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
41	Yusuf N 2015[55]	✓	✓	✓	✓	✓	X	✓	✓	**7 (87.5%)**
42	Chowdhury MNH 2023[56]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
43	Khaled A 2017[57]	✓	✓	✓	✓	✓	X	✓	✓	**7 (87.5%)**
44	Kasim S 2022[58]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
45	Fahmida H 2022[59]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
46	Butt UM 2021[60]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
47	Sonia JJ 2023[61]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
48	Chew JT 2022[62]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
49	Chan KK 2019[63]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
50	Ramanathan TT 2022[64]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
51	Tang MCS 2021[65]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
52	Minarul I 2020[66]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
53	Ali MS 2016[67]	✓	✓	✓	✓	✓	X	✓	✓	**7 (87.5%)**
54	Liyana S 2015[68]	✓	✓	✓	✓	✓	X	✓	✓	**7 (87.5%)**
55	Chowdhury NH 2021[69]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
56	Fahmida H 2021[70]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
57	Zuraida K 2020[71]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
58	Sumathy B 2022[72]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
59	Azit NA 2022[73]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
60	Shahid A 2023[74]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**
61	Usama A 2022[75]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
62	Sapon MA 2011[76]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
63	Hafiz MFAR 2020[77]	✓	✓	✓	✓	X	X	✓	✓	**6 (75%)**
64	Farhan NMN 2020[78]	✓	✓	✓	✓	✓	X	✓	✓	**7 (87.5%)**
65	Amith K 2022[79]	✓	✓	✓	✓	✓	✓	✓	✓	**8 (100%)**

Criteria 1: Were the criteria for inclusion in the sample clearly defined?
Criteria 2: Were the study subjects and the setting described in detail?
Criteria 3: Was the exposure measured in a valid and reliable way?
Criteria 4: Were objective, standard criteria used for measurement of the condition?
Criteria 5: Were confounding factors identified?
Criteria 6: Were strategies to deal with confounding factors stated?
Criteria 7: Were the outcomes measured in a valid and reliable way?
Criteria 8: Was appropriate statistical analysis used?
Yes = ✓, No = X

After finalising the studies to be included for analysis, full texts of all the included eligible studies were retrieved. Data was extracted from the full texts and exported into a pre-determined data extraction form in Excel sheet which contained the following information: (1) type of diabetes; (2) type of AI; (3) applications of AI; (4) findings.

The extracted data was analysed with descriptive statistics using IBM SPSS Statistics software (version 28). The data was computed using number, percentage, mean, and standard deviation, and subsequently presented graphically in tables, figures, and charts.

RESULTS

Search Results

An online database search using the terms "*diabetes mellitus*", "artificial intelligence", "machine learning", and "Malaysia" was conducted on 31st May 2023 and yielded 879 results. After removing 250 duplicates from the list, 629 potential studies were subsequently filtered by reviewing titles and abstracts. A final list of 65 publications were included for analysis after excluding irrelevant studies such as studies not affiliated with Malaysian institutions, conference abstracts, study protocols, reviews, theses, and studies not utilising any AI or machine learning algorithms. (Fig. 2)

Studies included in this review

A total of 65 studies published between 2009 and 2023 were included in this review. All were original articles and cross-sectional studies. Characteristics of the included studies are summarised in Table II.

It is important to note that the studies utilized various statistical methods to assess accuracy, specificity, sensitivity, and precision, tailored to the specific scope of each AI application. As a result, variances in the findings of accuracy, specificity, sensitivity, and precision exist amongst the included studies.

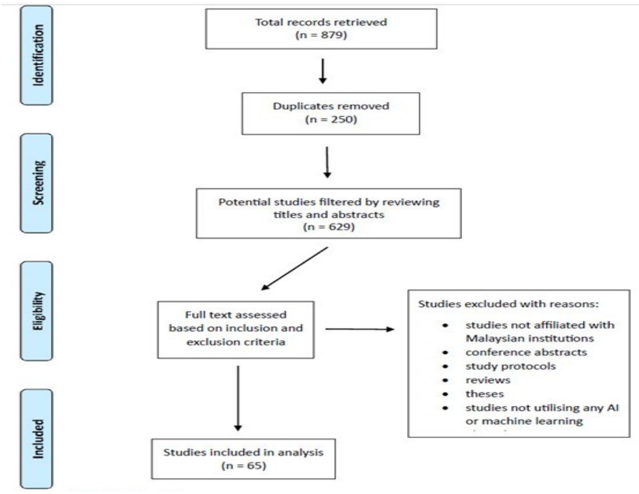

Fig. 2: PRISMA Flow Diagram

Table II: Characteristics of studies included in this review

No	Authors	Area of Diabetes	Type of AI	Sub-category of AI	Application of AI	Findings
1	Ahmed WR 2011[17]	Non-proliferative diabetic retinopathy (NPDR)	Reinforcement learning	Decision making	Screening of early stage of diabetic retinopathy	Accuracy = 97%
2	Nadeem MW 2021[18]	Diabetes	Supervised learning & Neural network	Classification & artificial neural network	Identification/classification of diabetes and prediction of the onset of critical events	Accuracy = 94.67%
3	Amith K 2021[19]	Diabetic foot	Supervised learning & Neural network	Classification & convolutional neural network	Identification of diabetic foot	F1 scores of 95% and 97%
4	Aghila R 2022[20]	Diabetes	Neural network	Artificial neural network	Diabetes prediction	Accuracy = 80%
5	Amith K 2022[21]	Diabetic foot ulcers	Unsupervised learning & Neural network	Clustering & convolutional neural network	Diabetic foot severity classification	Accuracy = 94.47%, precision = 94.45%, sensitivity = 94.47%, F1 score = 94.43%, and specificity = 93.25%
6	Maher TA 2022[22]	Diabetes	Neural network	Neural network	Diabetes diagnosis	Accuracy = 92.77%
7	Nilashi M 2018[23]	Diabetes	Supervised & unsupervised learning	Classification & Clustering	Diabetes disease classification	-
8	Farah MMG 2020[24]	Type 2 diabetes mellitus	Supervised learning & Neural network	Regression & Multilayer perceptron (MLP) neural network	To classify the major factors associated with creatinine in dyslipidemia and type 2 diabetes mellitus patients.	-
9	Tang MCS 2022[25]	Proliferative Diabetic Retinopathy (PDR)	Deep learning	Deep learning	Neovascularization detection	Accuracy = 91.57%, sensitivity = 85.69%, specificity = 97.44%, and precision = 97.10%
10	Thirumalaimuthu TR 2022[26]	Diabetic retinopathy	Neural network	Deep learning	Identification of diabetic retinopathy	Accuracy = 95%
11	Nilashi M 2017[27]	Diabetes	Unsupervised learning & Neural network	Clustering, Principal Component Analysis & neural network	Diabetes disease classification	-
12	Kumarmangal R 2021[2]	Type 2 diabetes mellitus	Supervised learning & neural network	Classification & artificial neural network	Type 2 diabetes classification	Accuracy = 98%
13	Vimala B 2011[28]	Diabetes	Machine learning	Rule-based reasoning	Diabetes diagnosis	-
14	Tutut H 2014[29]	Diabetes	Unsupervised learning	Clustering	Clustering diabetics dataset	-
15	Ozal Y 2019[30]	Diabetes	Deep learning	Deep learning	Automated diagnosis of diabetes	Accuracy = 97.62%, sensitivity = 100%

CONTINUE

Table II: Characteristics of studies included in this review (CONT.)

No	Authors	Area of Diabetes	Type of AI	Sub-category of AI	Application of AI	Findings
16	Acharya UR 2017[31]	Diabetic macular edema (DME)	Supervised learning, neural network	Classification, probabilistic neural network (PNN)	Automated detection of diabetic macular edema (DME)	Accuracy = 100% (private) and 97.01% (public) (MESSIDOR) databases
17	Acharya UR 2013[32]	Diabetes	Supervised learning & Neural network	Classification & probabilistic neural network (PNN)	Identification of diabetes heart rate	Accuracy = 90%, sensitivity = 92.5%, specificity = 88.7%.
18	Sarni SR 2016[33]	Diabetic retinopathy and maculopathy	Fuzzy logic	Fuzzy logic	Automatic detection of diabetic retinopathy and maculopathy	-
19	Aibinu AM 2010[34]	Diabetes	Unsupervised learning	Regression	Blood glucose level prediction	-
20	Khan A 2022[35]	Diabetes	Supervised learning	Classification	Cardiovascular and diabetes disease classification	Accuracy = 97.35%
21	Zulkifli MFY 2022[36]	Diabetic peripheral neuropathy (DPN)	Neural network	Artificial neural network	Detection of neuropathy based on the myoelectric signal	Accuracy = 98.6%
22	Shakeel PM 2018[37]	Diabetes	Unsupervised learning	Clustering	Diabetes diagnosis	-
23	Suhaimi N 2012[38]	Type 2 diabetes mellitus	Neural network	Artificial neural network	Identifying risk factors contributing to blood glucose level among T2DM patients	Accuracy = 77.3%, sensitivity = 78.4%, specificity = 71.8%.
24	Sim R 2023[13]	Type 2 diabetes mellitus	Supervised learning	Regression	Prediction of development of chronic kidney disease among T2DM patients	-
25	Alex SA 2022[39]	Diabetes	Neural network	Deep learning	Diabetes prediction	Accuracy = 99.64%
26	Rosli MM 2020[40]	Gestational diabetes	Methods not clearly stated	Methods not clearly stated	Self-monitoring application for meal intake prediction among gestational diabetes	-
27	Abbas SL 2009[41]	Diabetes	Natural language processing	Natural language processing	Virtual diabetes physician/ doctor consultation	-
28	Hasliza AH 2020[42]	Proliferative Diabetic Retinopathy (PDR)	Neural network	Convolutional neural network (CNN)	Detection of Proliferative Diabetic Retinopathy in Fundus Images	Accuracy = 73.81%, sensitivity = 76%, specificity = 69%.
29	Ayuni Z 2022[43]	Diabetes	Supervised learning	Classification	Diabetes disease classification	Accuracy = 78.62%
30	Butt MM 2022[44]	Diabetic retinopathy (DR)	Neural network	Convolutional Neural Network (CNN)	Detection of diabetic retinopathy	Accuracy = 97.8%
31	Fahmida H 2021[45]	Diabetic Sensorimotor Polyneuropathy (DSPN)	Fuzzy logic	Fuzzy logic	Classification of diabetic Sensorimotor Polyneuropathy severity	-
32	Kakudi HA 2018[46]	Metabolic syndrome (MetS) (Type 2 diabetes)	Supervised learning	Classification	Diagnosing the risk of metabolic syndrome	Area under the receiver operating characteristic curves (AUC) = 86.42 % (young female), 87.04 % (middle-aged female), 91.08 % (young male), 89.24 % (middle-aged male).
33	Yap CW 2021[47]	Diabetic Retinopathy (DR)	Supervised learning	Classification	Auto Detecting Diabetic Retinopathy (DR)	Sensitivity = 85.1%
34	Abbood SH 2022[48]	Diabetic Retinopathy (DR)	Deep learning	Deep learning	Diagnosis of diabetic retinopathy lesions	Accuracy = 98.4%
35	AL-Behadili HNK 2021[49]	Diabetes	Fuzzy logic	Fuzzy logic	Diabetes classification	-
36	Rahmat MAA 2017[50]	Diabetes	Internet of Things (IoT)	Internet of Things (IoT)	Monitoring glucose level	Percentage error = 7.2%
37	Albadr MAA 2022[51]	Diabetic retinopathy	Supervised learning	Classification & regression	Diabetic retinopathy detection	Accuracy of 96.21% for multi-class and 99.47% for binary using APTOS-2019 dataset as well as 96.15% for multi-class and 99.04% for binary using IDRiD dataset.
38	Abbood SH 2022[52]	Diabetic retinopathy	Deep learning	Deep learning	Diabetic retinopathy diagnostic	-

CONTINUE

Table II: Characteristics of studies included in this review (CONT.)

No	Authors	Area of Diabetes	Type of AI	Sub-category of AI	Application of AI	Findings
39	Abdullah L 2017[53]	Diabetes	Fuzzy logic	Fuzzy logic	Identification of risk factors for diabetes	-
40	Sampath-kumar A 2022[54]	Diabetes	Internet of Medical Things (IoMT)	Internet of Medical Things (IoMT)	Diabetes prediction	
41	Yusuf N 2015[55]	Diabetic foot	Supervised learning & Neural network	Classification & Probability neural network	Identification of the causative bacteria responsible for diabetic foot infection	Accuracy = up to 90%
42	Chowdhury MNH 2023[56]	Type 1 diabetes mellitus	Supervised learning & neural network	Classification, regression, deep learning, multi-layer perceptron (MLP) neural network	Predicting the risk of chronic kidney disease in type 1 diabetes patients	Accuracy = 97%, specificity = 98%, sensitivity/recall = 96%, precision = 98%, F1 score = 97%, Kappa and MCC score = 94%, AUROC = 99%, Precision-Recall curve = 99%.
43	Khaled A 2017[57]	Diabetic macular edema (DME)	Supervised & unsupervised learning	Classification & principal component analysis (PCA)	Diabetic macular edema (DME) classification	Sensitivity = 87.5%, specificity = 87.5%.
44	Kasim S 2022[58]	Diabetes	Supervised learning	Classification & regression	Prediction of in-hospital mortality risk among heterogenous STEMI patients with diabetes	AUC = 90%
45	Fahmida H 2022[59]	Diabetic neuropathy (DN), Diabetic foot ulceration (DFU)	Supervised learning	Classification	Identification of diabetic neuropathy and diabetic foot ulceration	Accuracy = 96.18% (EMG analysis), accuracy = 98.68% (GRF analysis)
46	Butt UM 2021[60]	Diabetes	Supervised learning, neural network	Classification, regression, multilayer perceptron (MLP) neural network	Classification, early-stage identification, and prediction of diabetes; monitoring blood glucose	Accuracy = 86.08% (MLP) & 87.26% (LSTM)
47	Sonia JJ 2023[61]	Type 1, 2, and gestational diabetes	Neural network	Deep learning	Prediction of risk	Specificity = 95%, sensitivity = 97%, accuracy = 97%.
48	Chew JT 2022[62]	Diabetes	Neural network	Convolutional neural network	Mobile Food Journalling Application / food logging	-
49	Chan KK 2019[63]	Type 2 diabetes mellitus	Fuzzy logic	Fuzzy logic	Mobile dietary logging application / food journaling	-
50	Ramanathan TT 2022[64]	Type 2 diabetes mellitus	Supervised learning & fuzzy logic	Classification & fuzzy logic	Diabetes classification	Accuracy = 90.26%
51	Tang MCS 2021[65]	Proliferative Diabetic Retinopathy (PDR)	Neural network	Convolutional neural network	Neovascularization detection and localization in fundus images	Accuracy = 99.48%, sensitivity = 87.72%, specificity = 99.76%, precision = 86.96%, Jaccard similarity = 76.43%, Dice similarity = 84.66%
52	Minarul I 2020[66]	Diabetes	Neural network	Deep artificial neural network	Detection of blood glucose concentration level non-invasively	Accuracy = 88%
53	Ali MS 2016[67]	Diabetes	Neural network	Deep artificial neural network	Detection of blood glucose concentration level non-invasively	Accuracy = 82%
54	Liyana S 2015[68]	Diabetes	Neural network	Neural network	Diabetes classification	-
55	Chowdhury NH 2021[69]	Type 1 diabetes mellitus	Supervised learning	Classification & clustering	To diagnose CKD in T1DM patients	Accuracy = 0.96 (±0.01), sensitivity = 0.98 (±0.01), specificity = 0.93 (±0.02)
56	Fahmida H 2021[70]	Diabetic Sensorimotor Polyneuropathy (DSPN)	Supervised learning & Neural network	Classification & artificial neural network (ANN)	Diabetic sensorimotor polyneuropathy severity classification	-
57	Zuraida K 2020[71]	Diabetic retinopathy	Supervised learning & Neural network	Regression, classification, artificial neural network	Predicting the presence of diabetic retinopathy among Type II diabetic patients & to determine its risk factors	Sensitivity = 50.0%, specificity = 79.03%, accuracy = 66.36%.
58	Sumathy B 2022[72]	Diabetic retinopathy	Supervised learning	Classification & regression	Prediction of diabetic retinopathy using health records	Accuracy = 90.1% (boosted tree) & 88.9% (KNN)
59	Azit NA 2022[73]	Type 2 diabetes mellitus	Supervised learning & neural network	Classification, regression, artificial neural network	Prediction of hepatocellular carcinoma risk in type-2 diabetes patients	Accuracy = 85.28%, AUC = 91.4% (SVM)

CONTINUE

Table II: Characteristics of studies included in this review (CONT.)

No	Authors	Area of Diabetes	Type of AI	Sub-category of AI	Application of AI	Findings
60	Shahid A 2023[74]	Type 2 diabetes (Amyloid proteins (AMYs))	Supervised learning	Classification	Prediction of amyloid proteins in T2DM patients	Accuracy = 93.10% (training sequences) and 89.67% (independent sequences)
61	Usama A 2022[75]	Diabetes	Supervised learning, neural network, fuzzy logic	Classification, artificial neural network, fuzzy logic	Diabetes prediction	Accuracy = 94.87%
62	Sapon MA 2011[76]	Diabetes	Neural network	Artificial neural network	Diabetes prediction	Accuracy = 88.8%
63	Hafiz MFAR 2020[77]	Type 2 diabetes mellitus	Supervised learning	Classification	Classification of type 2 diabetes mellitus (T2DM); Prediction model	Accuracy = 87%, sensitivity = 90%, specificity = 80%, precision = 90%, F1-score = 90% and AUC value = 93% (random forest).
64	Farhan N M N 2020[78]	Diabetic Retinopathy	Transfer learning, supervised learning	Transfer learning, classification	An automated detection method to diagnose the diabetic retinopathy	Accuracy = 99% (training), 99% (testing) and 96% validation processes.
65	Amith K 2022[79]	Diabetic foot	Neural network, supervised learning	Convolutional neural network, classification	Classification of diabetic foot thermogram image	Accuracy = 90.1%

AUC = area under the curve; AUROC = area under the receiver operating characteristic curve; MCC score = Matthews Correlation Coefficient score.

Key Areas for Study Focus

The majority of the studies (n=28, 43.1%) focused on *diabetes mellitus* (DM) in general. This was followed by nine (13.8%) studies done on diabetic retinopathy (DR) and type 2 *diabetes mellitus* (T2DM) respectively. Four (6.2%) studies were done on diabetic foot and three (4.6%) studies were on proliferative diabetic retinopathy (PDR). Subsequently, six (9.3%) studies were conducted on diabetic macular oedema (DME), and diabetic sensorimotor polyneuropathy (DSPN), and type 1 *diabetes mellitus* (T1DM) with 2 (3.1%) studies in each area respectively. The remaining seven (10.8%) studies were each done on diabetic neuropathy (DN) together with diabetic foot ulceration (DFU), diabetic peripheral neuropathy (DPN), diabetic retinopathy and maculopathy, gestational diabetes, metabolic syndrome (MetS), as well as non-proliferative diabetic retinopathy (NPDR).

Types of Artificial Intelligence

Out of the 65 eligible studies, majority of the studies (15, 23.1%) were conducted using neural network, out of which four (26.7%) studies were done using artificial neural network, four (26.7%) convolutional neural network, three (20.0%) deep learning, two (13.3%) neural network, and two (13.3%) deep artificial neural networks.

A total of 13 (20.0%) studies had employed both supervised learning and neural network, with three (23.1%) studies using classification together with artificial neural network, three (23.1%) studies using classification together with probabilistic neural network, two (15.4%) studies using classification together with convolutional neural network, and two (15.4%) studies using classification together with regression and artificial neural network. Meanwhile, one (7.7%) study employed classification together with regression and multilayer perceptron (MLP) neural network. One (7.7%) study was using classification together with regression, deep learning, and multi-layer perceptron (MLP) neural network. Also, another one (7.7%) study was using regression together with multi-layer perceptron (MLP) neural network.

Twelve studies (18.5%) employed supervised learning, with the majority - seven studies (58.3%) - utilizing classification techniques. Three (25.0%) studies employed both classification and regression. One (8.3%) study employed both classification and clustering while the remaining one (8.3%) study employed regression.

The remaining studies employed fuzzy logic (n=5, 7.7%), deep learning (n=4, 6.2%), supervised learning (n=3, 4.6%), unsupervised learning together with neural network (n=2, 3.1%), as well as both supervised and unsupervised learning (n=2, 3.1%).

Eight studies (12.3%) each employed a combination of the Internet of Things (IoT), the Internet of Medical Things (IoMT), machine learning, rule-based learning, natural language processing, reinforcement learning (decision-making), supervised learning (classification), fuzzy logic, and transfer learning. Lastly, there was one study (1.5%) in which the employed AI method was not clearly stated.

Applications of AI

A total of 15 (23.1%) studies were conducted on classification of diseases applying AI and 15 (23.1%) studies were on disease prediction. This is followed by 11 (16.9%) studies done with AI applied on disease detection and nine (13.8%) studies done with AI applied on the diagnosis of the disease. Seven (11.0%) studies were done on identification of the disease or the risk factors for DM. The remaining six (9.2%) studies were each conducted with the application of AI on clustering, blood glucose monitoring, screening, virtual consultation, classification together with identification, prediction, and monitoring, as well as identification together with classification and prediction.

Classification

From the 65 included studies, 15 (23.2%) were related to classification of DM, out of which nine (60.0%) studies (2, 22-30) were classified DM generally and two studies (31, 32) were on classification of the severity of diabetic sensorimotor polyneuropathy. The remaining four studies were each conducted on classification of diabetic macular oedema (DME) (33), severity of the diabetic foot (34), and diabetic foot thermogram image (35). Lastly, one study was conducted to classify the major factors associated with creatinine in dyslipidemia and T2DM patients (36).

From these studies, the accuracy levels reported ranged from 78.6-98%. The levels of precision were reportedly ranging from 90-95.1% while sensitivity levels were ranging from 87.5-95.1%. Besides, the specificity levels recorded were from 80-97.2%.

Prediction

Besides, 15 (23.2%) studies were related to prediction, out of which five (33.3%) studies (37-41) were conducted on the prediction of DM. Two (13.3%) studies (14, 42) were on the prediction of development of chronic kidney disease among individuals with DM and another two (13.3%) studies (43, 44) were on the prediction of diabetic retinopathy among DM patients. Another study also developed a new mobile application for gestational diabetes patients to self-monitor their blood glucose levels based on the meal intake recommendation (45). The remaining five (33.3%) studies were each on the prediction of blood glucose levels (46), amyloid proteins (AMYs) (47), risk of DM based on DM categorisation (48), in-hospital mortality risk among heterogenous ST-elevation myocardial infarction (STEMI) patients with DM (49), and hepatocellular carcinoma risk among T2DM patients (50).

The levels of prediction accuracy reported amongst these studies ranged from 66.4-99.6%. Levels of specificity were between 79.0-98.0%. Meanwhile, levels of sensitivity were between 50-97% and a precision level of 98% was reported in one study.

Detection of *Diabetes mellitus*

A total of 11 (16.9%) studies were done on detection which encompassed three (27.3%) studies (51-53) were on the detection of diabetic retinopathy, two (18.2%) studies (54, 55) were on the detection of blood glucose levels non-invasively, and two (18.2%) studies (56, 57) were on neovascularisation detection. The remaining four studies related to detection were each conducted on the detection of diabetic macular edema (DME) (58), neuropathy based on the myoelectric signal (59), proliferative diabetic retinopathy in fundus images (60), and diabetic retinopathy together with maculopathy (61).

The levels of accuracy among the detection studies ranged from 73.8-100%. The levels of sensitivity reported ranged from 76.0-87.8%. Meanwhile, levels of specificity were from 69.0-99.8% and the precision levels ranged from 87.0-97.1%.

Diagnosis of *Diabetes mellitus*

Nine (13.8%) studies were related to diagnosis, with the majority of 4 (44.4%) studies (62-65) on the diagnosis of DM and three (33.3%) studies (66-68) were done on the diagnosis of diabetic retinopathy. One (11.1%) study (69) was on the diagnosis of the risk of metabolic syndrome and one (11.1%) study (70) was on the diagnosis of chronic kidney disease among T1DM patients.

The levels of accuracy in diagnosis amongst the eleven studies ranged from 92.8-99.0%. However, none of the eleven studies reported on sensitivity, specificity, and precision.

Identification of risk factors and complications

Seven (10.8%) papers were related to identification, which included two (28.6%) papers on identification of risk factors for DM (71, 72), two (28.6%) papers on identification of diabetic foot (73, 74), one (14.3%) paper on identification of diabetic retinopathy (75), one (14.3%) paper on identification of diabetes heart rate (76), and one (14.3%) paper on identification of diabetic neuropathy (DN) together with diabetic foot ulceration (DFU) (77).

The levels of accuracy reported by these seven studies ranged from 69.9-98.7%, while the levels of sensitivity ranged from 50.0-92.5% and the levels of specificity were between 70.4-88.7%. None of the seven studies reported level of precision.

For the remaining eight papers, two (3.1%) papers (78, 79) deliberated on the incorporation of AI into food journaling mobile application for dietary food management, one (1.5%) paper (80) was on screening of early stage of non-proliferative diabetic retinopathy (NPDR), one (1.5%) paper (81) was on clustering of diabetics dataset, one (1.5%) paper (82) was on designing an AI chatbot as virtual diabetes doctor providing virtual consultation, one (1.5%) paper (83) was on creation a non-invasive method to monitor blood glucose levels, one (1.5%) paper (84) was related to the identification or classification of DM and prediction of the onset of critical events, and lastly one (1.5%) paper (85) was regarding classification, early-stage identification, and prediction of DM together with the monitoring of blood glucose levels.

Amongst these eight studies, the accuracy levels reported ranged from 86.1-97.0% and one study reported a percentage error of 7.2%.

DISCUSSION

AI technologies and applications have been increasingly and widely adopted in Malaysia for the classification, prediction, detection, diagnosis, and identification of signs and symptoms as well as risk factors of DM. While the application and utilization of AI technologies in DM remain somewhat niche, recent developments are accelerating its adoption, leading to a gradual increase in its utilization over time. From the analysis of the selected study in this review, these applications and new developments have showed high levels of accuracy, sensitivity, specificity, and precision.

AI and machine learning algorithms can serve as valuable tools to assist medical professionals in diagnosing patients as either diabetic or non-diabetic, and subsequently, these algorithms can be employed to assess and identify the most accurate predictive model for DM (25). Integrated flexible individual classifiers have better performance and less likelihood of misclassifying a single instance (24). From our analysis, many of the proposed hybrid intelligent systems for classification of DM has improved accuracy of prediction as high as 99% and reduced computational time as compared to the non-incremental approaches (22, 24, 27). A proposed classifier also has the capability of automatically diagnosing possible patients with DM (27). A newly proposed intelligent severity classifier also helps health professionals to diagnose and stratify diabetic sensorimotor polyneuropathy (DSPN) based on both signs and symptoms and electrophysiological changes (31). The efficacy of fuzzy logic as a classifier in analysing DM patterns across all classification criteria has been conclusively demonstrated (26).

Based on the included studies, it is evident that the proposed classifiers yield promising results when classifying potential patients with DM (27). Hence, the newly created AI applications can be of tremendous help for the medical practitioners in the healthcare practice as a decision support system in assisting medical professionals in making the right treatment decisions (22, 25, 27).

Additionally, new methods of blood glucose level modelling and prediction using AI based techniques have been proposed. The new hybrid AI technique can predict the next blood glucose levels with higher accuracy, helping to avoid critical emergencies while also allowing for timely preparation of insulin injections and appropriate meals for patients with *diabetes mellitus* (DM) (46). The prediction algorithm of new self-monitoring mobile application for patients with diabetes to self-monitor their blood glucose levels based on meal intakes have also successfully predicted the next meal intake according to the patient blood glucose levels (45). In addition, new predictive models using AI algorithms have also been proposed such as DM prediction with cardiac risk prediction based on the damage in blood vessels and cardiac nerves and subsequently predicting the risk for a cardiac attack (39), while another study proposed a machine learning approach for chronic kidney disease risk prediction among T1DM patients (42). A study on the prediction of in-hospital mortality risk among heterogenous ST-elevation myocardial infarction (STEMI) patients with DM using a combination of machine learning approaches demonstrated promising outcomes and highlighted that the approaches will improve prognostic outcomes particularly in the Asian multiethnic population (49). Predictive models with high accuracy have offered a glimpse of hope in early detection of carcinomas among patients with DM with a simple and yet highly accurate AI predictive model being proposed to detect hepatocellular carcinomas among T2DM patients (50). Moreover, several novel predictive models have shown promise in the early detection of diabetic retinopathy, a condition that can lead to permanent blindness in individuals with long-standing DM (43, 44).

From our analysis, various predictive models show reliable performance in risk predictions and prediction of DM. Applications of AI for the prediction of DM can yield high accuracy levels as high as 99.64%, and maximum specificity, sensitivity, and precision levels of 98%, 97%, and 98% respectively. This strongly suggests that the proposed predictive models using AI or machine learning approaches are efficient and workable to be implemented in the medical practice (48). Early prediction results and outcomes may help the medical professionals and patients themselves to take the necessary precautions to overcome the risk (42). The high predictive capability will also be useful for scientists and play a vital role in future drug development and academic research (47).

DM is a chronic condition and a silent killer which requires systematic management to keep blood glucose level under control (54). Hence, regular glucose levels monitoring is a routine task for a patient with DM (55). The conventional way involves pricking the patients physically to collect blood frequently and this inevitably inflicts discomfort or even pain to the patients. To overcome such distress and inconveniences, non-invasive blood glucose measurement is crucial and AI has offered the solution to detect blood glucose concentration level non-invasively without withdrawing blood physically from the patients (54, 55). This method not only exhibits high accuracy in detecting glucose concentration in blood plasma non-invasively, but also is safe, comfortable, user-friendly, and affordable (54).

Certainly, early detection of DM should be coupled with precise and accurate diagnosis of the disease conditions as well for the utmost benefits of the patients. From our analysis, different AI diagnostic models and intelligent diagnostic system for DM have been developed and they have showcased promising outcomes with DM diagnoses being done accurately, precisely, and rapidly (62, 63). The levels of accuracy for diagnosis attained by the AI models and intelligent systems were as high as 97.62% and even recorded a sensitivity level of 100% (64). On top of that, different AI applications have also been in place to diagnose complications related to DM including diabetic retinopathy (66, 67), metabolic syndrome (69), as well as chronic kidney disease in diabetic patients (70). With high levels of accuracy up to 99% achieved, this strongly suggests that AI applications can be used to support medical practitioners in accurate and early diagnosis of DM complications (69). AI applications with high diagnostic reliability could be utilised widely for clinical assessment in the future of sophisticated technological healthcare (66).

AI applications have also been successfully utilised to identify risk factors for DM which serve as predictors for the disease conditions (71, 72), albeit relatively lower levels of accuracy (77.3%), sensitivity (78.4%), and specificity (75.3%) were reportedly attained. Meanwhile, several studies have focused on identifying complications of *diabetes mellitus* (DM), such as diabetic foot ulcers (DFUs) and diabetic retinopathy. These studies reported accuracy levels as high as 97% in their findings (73, 74). Interestingly, a study by Acharya et al. has proposed a non-invasive diagnostic support system which identifies heart rate signals and cardiac health of a patient and subsequently determines whether or not DM is present (76). This system has reportedly yielded an average accuracy of 90%, sensitivity of 92.5%, and specificity of 88.7%. Lastly for identification, a study had applied machine learning models for identifying diabetic neuropathy (DN) together with diabetic foot ulcers (DFU) which was the first work demonstrating that DN and DFU can be identified with higher accuracy with the help of machine learning.

On top of that, AI is helpful in identifying modifiable risk factors for diabetes such as high blood pressure, high blood cholesterol, tobacco smoking, lack of physical activity, obesity, and bad diet habits (86, 87). From the identified modifiable risk factors, precise, personalised, and early interventions could be planned and implemented for each patient with DM (87). This is a crucial step to help prevent further complications among the patients with modifiable risk factors as well as to refer patients with severe complications for medical treatment at an early stage.

Nowadays, there has been increasing need for personalised treatment and management for diabetes as the personal characteristics of each patient vary such as age, health condition, duration of disease, weight, height, and haemoglobin A1c (88). It is crucial to utilize information from an individual's genetic makeup to tailor strategies for the prevention, detection, treatment, and monitoring of *diabetes mellitus* (DM) (88). In this regard, AI algorithms stand at the forefront of revolutionising diabetes care by analysing individual patient data, predicting blood glucose levels, optimising insulin dosages, predicting risk of complications, and customising treatment plans leading to more tailored, individualised, and effective diabetes treatment plans (89, 90). The data-driven approach adopted by AI also shows promising results in enhancing patient care and outcomes with advanced diagnostics, predictive modelling, personalised treatment plan (90).

In Malaysia, AI has been integrated to the Malaysian healthcare system in various ways, enhancing the efficiency, accuracy, and accessibility of medical services (91). For instance, the Ministry of Health (MOH) of Malaysia has been collaborating with tech companies and research institutions to develop and implement AI-based healthcare solutions. AI has also been used to analyse medical images with higher accuracy in predicting and diagnosis diseases. Several private hospitals and clinics in Malaysia have adopted AI technologies for diagnostics, treatment planning, and patient management. Many public and private universities and research centers are also in the ongoing efforts to conduct and research of developing AI applications to cater to various healthcare needs.

Nevertheless, integration of AI in healthcare also involves robust collection of users' private data or large datasets which leads to data privacy issues of privacy leakage or data breaches due to data sharing and cross-utilisation (92, 93). There is not only the risk of data leakage without the awareness of the users but also data being abused for potentially discriminatory affairs (93). Hence, the developments of policies, ethical frameworks, legal regulations are warranted to protect user data privacy and ensure responsible AI usage (92).

In view of this, existing statutes have been implemented as guidelines for best practices, including the torts law, Consumer Protection Act 1999 ("CPA"), Personal Data Protection Act 2010 ("PDPA"), Sale of Goods Act 1957 ("SGA"), and Contracts Act 1950 ("CA"). The Malaysian government are also continuously improving the existing legislation and formulate national framework to regulate the usage of AI. Besides, governance laws on data protection should be in place as larger datasets are easily subjected to severe breaches leading to unauthorised access and the landing of significant amounts of personal data unto unlawful parties (94). The Malaysian government is also considering further regulatory measures and initiatives have been ongoing to develop an AI Governance Framework, establish policy on cybersecurity, create AI Code of Ethics, and collaborate with different industry partners to create privacy, security, and ethical measures (94). Also, the

Malaysian Digital Economy Corporation (MDEC) which is leading the National Big Data Analytics Framework is also developing a national AI framework, and the government is considering adopting a national data-sharing and AI policy (94).

Medico-legal Implications of AI Assisted Decision Making and Treatment
The implications of medico-legal aspects in the integration of AI in DM management are of equal importance. Liability and accountability concerns arise when adverse outcomes occur in AI assisted decision making. Conventional medical practice is based on informed consent and good clinical practice based on current clinical practice guidelines. AI assisted decision making may perpetuate treatment biases. These factors have ethical implications. Safe usage is based on regular updates of practice guidelines. AI applications are required to synchronize with current practices. Regulatory compliance is in vogue in institutions and safe usage requires oversight bodies. There is always the issue of malpractice when quality of care is suspected due to AI assisted decision making and treatment. Data privacy and security are other issues to contend with. Additionally, continuous education and training for healthcare professionals are essential with evolution of new applications and knowledge. Collaboration among all stakeholders including healthcare professionals, regulatory bodies, and legal experts on the subject is essential as health care and standard of care requires continuous adaptation of the legal framework in the country to keep astride of evolving technology. (95)

Limitations of this study
There are a few limitations arising in this review which are worth taking note. Firstly, this review was based solely on local Malaysian studies and hence it only depicts the applications of AI technologies in DM in the Malaysian context. Besides, many of the proposed AI applications are still in the early stage of development. Therefore, more studies are warranted to explore further the AI applications, particularly those with accuracy and precision levels exceeding 95%, on a national scale. This is to ensure that the newly proposed applications are safe to be utilised amongst patients with DM with minimised health risks inflicted.

CONCLUSION

This narrative review shows some promise for the increased use of AI applications in the classification, prediction, detection, diagnosis, and identification of signs and symptoms as well as risk factors related to DM yielding high levels of accuracy, sensitivity, specificity, and precision. As a result, there is an expectation that AI technology applications will progressively inspire greater confidence among medical professionals, patients, and stakeholders in the field. Nevertheless, further research is essential to explore additional applications and advanced utilization of AI in this field, aiming to provide DM patients with enhanced benefits, including earlier and more accurate detection, improved disease management, and more effective treatment outcomes. The findings will also provide essential guidance for policymakers and stakeholders in shaping the future of AI adoption in diabetes care in Malaysia.

ACKNOWLEDGEMENT

We would like to sincerely express our gratitude and appreciations to Dr Tan Ee Xion and Dr Chuah Tong Kuan for their guidance and enlightenment on the type of AI and help in categorising the type of AI of all the included studies.

REFERENCES

1. Sun H, Saeedi P, Karuranga S, Pinkepank M, Ogurtsova K, Duncan BB, et al. IDF Diabetes Atlas: Global, regional and country-level diabetes prevalence estimates for 2021 and projections for 2045. Diabetes Res Clin Pract. 2022;183:109119. DOI: 10.1016/j.diabres.2021.109119.
2. Roy K, Ahmad M, Waqar K, Priyaah K, Nebhen J, Alshamrani SS, et al. An enhanced machine learning framework for type 2 diabetes classification using imbalanced data with missing values. Complexity. 2021;2021:1-21. DOI: https://doi.org/10.1155/2021/9953314.
3. Dzakiyullah N, Burhanuddin M, Ikram RR, Ghani K, Setyonugroho W. Machine learning methods for diabetes prediction. Int J Innov Technol Explor Eng [Internet] Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM), Melaka, Malaysia. 2019;8:2199-205. DOI: 10.35940/ijitee.L2973.1081219
4. Mustapha FI, editor Current Burden of Diabetes in Malaysia. National Oral Health Research Conference; 2014; Kuala Lumpur, Malaysia.
5. National Health and Morbidity Survey 2019. Technical Report - Volume I. NCDs - Non-Communicable Diseases: Risk Factors and other Health Problems. Institute for Public Health, Ministry of Health, Malaysia.
6. Tee ES, Yap RWK. Type 2 *diabetes mellitus* in Malaysia: current trends and risk factors. Eur J Clin Nutr. 2017;71(7):844-9. DOI: 10.1038/ejcn.2017.44.
7. Hamet P, Tremblay J. Artificial intelligence in medicine. Metabolism. 2017;69S:S36-S40. DOI: 10.1016/j.metabol.2017.01.011.
8. Great Learning. What is Artificial Intelligence in 2023? Types, Trends, and Future of it? 2023. Available from: https://www.mygreatlearning.com/blog/what-is-artificial-intelligence/.
9. Benko A, L6nyi CS. History of artificial intelligence. Encyclopedia of Information Science and

Technology, Second Edition: IGI global; 2009. p. 1759-62.
10. IBM. AI vs. Machine Learning vs. Deep Learning vs. Neural Networks: What's the difference? 2023. Available from: https://www.ibm.com/blog/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks/.
11. Cade WT. Diabetes-related microvascular and macrovascular diseases in the physical therapy setting. Phys Ther. 2008;88(11):1322-35. DOI: 10.2522/ptj.20080008.
12. Aikaeli F, Njim T, Gissing S, Moyo F, Alam U, Mfinanga SG, et al. Prevalence of microvascular and macrovascular complications of diabetes in newly diagnosed type 2 diabetes in low-and-middle-income countries: A systematic review and meta-analysis. PLOS Glob Public Health. 2022;2(6):e0000599. DOI: 10.1371/journal.pgph.0000599.
13. Hatmal MM, Abderrahman SM, Nimer W, Al-Eisawi Z, Al-Ameer HJ, Al-Hatamleh MAI, et al. Artificial Neural Networks Model for Predicting Type 2 *Diabetes Mellitus* Based on VDR Gene FokI Polymorphism, Lipid Profile and Demographic Data. Biology (Basel). 2020;9(8). DOI: 10.3390/biology9080222.
14. Sim R, Chong CW, Loganadan NK, Adam NL, Hussein Z, Lee SWH. Comparison of a chronic kidney disease predictive model for type 2 *diabetes mellitus* in Malaysia using Cox regression versus machine learning approach. Clin Kidney J. 2023;16(3):549-59. DOI: 10.1093/ckj/sfac252.
15. Omar N, Nazirun NN, Vijayam B, Wahab AA, Bahuri HA. Diabetes subtypes classification for personalized health care: A review. Artificial Intelligence Review. 2023;56(3):2697-721. DOI: 10.1007/s10462-022-10202-8.
16. Moher D, Shamseer L, Clarke M, Ghersi D, Liberati A, Petticrew M, et al. Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. Syst Rev. 2015;4(1):1. DOI: 10.1186/2046-4053-4-1.
17. Riva JJ, Malik KM, Burnie SJ, Endicott AR, Busse JW. What is your research question? An introduction to the PICOT format for clinicians. The Journal of the Canadian Chiropractic Association. 2012;56(3):167.
18. EndNote X8. London: Clarivate Analytics; 2020.
19. JBI. Critical Appraisal Tools: Checklist for Analytical Cross Sectional Studies. Adelaide, Australia: Joanna Briggs Institute, 2024.
20. Migliavaca CB, Stein C, Colpani V, Munn Z, Falavigna M, Prevalence Estimates Reviews - Systematic Review Methodology G. Quality assessment of prevalence studies: a systematic review. J Clin Epidemiol. 2020;127:59-68. DOI: 10.1016/j.jclinepi.2020.06.039.
21. Lai PK, Teng CL, Mustapha FI. Diabetes knowledge among Malaysian adults: A scoping review and meta-analysis. Malaysian Family Physician: the Official Journal of the Academy of Family Physicians of Malaysia. 2024;19:26. DOI: https://doi.org/10.51866/rv.304
22. Nilashi M, Bin Ibrahim O, Mardani A, Ahani A, Jusoh A. A soft computing approach for diabetes disease classification. Health Informatics J. 2018;24(4):379-93. DOI: 10.1177/1460458216675500.
23. Nilashi M, Ibrahim O, Dalvi M, Ahmadi H, Shahmoradi L. Accuracy improvement for diabetes disease classification: a case on a public medical dataset. Fuzzy Information and Engineering. 2017;9(3):345-57. DOI: https://doi.org/10.1016/j.fiae.2017.09.006.
24. Khan A, Khan A, Khan MM, Farid K, Alam MM, Su'ud MBM. Cardiovascular and Diabetes Diseases Classification Using Ensemble Stacking Classifiers with SVM as a Meta Classifier. Diagnostics. 2022;12(11):2595. DOI: https://doi.org/10.3390/diagnostics12112595.
25. Darmawan MF, Zamri A, Hatim SM, Firdaus AFA, Osman MZ. Diabetec Disease Classifier Based on Three Machine Learning Models. Mathematical Sciences and Informatics Journal. 2022;3(2):25-34. DOI: 10.24191/mij.v3i2.20118.
26. Al-Behadili HNK, Ku-Mahamud KR. Fuzzy unordered rule using greedy hill climbing feature selection method: An application to diabetes classification. Journal of Information and Communication Technology. 2021;20(3):391-422. DOI: https://doi.org/10.32890/jict2021.20.3.5.
27. Ramanathan TT, Hossen J, Sayeed S. Naпve Bayes Based Multiple Parallel Fuzzy Reasoning Method for Medical Diagnosis. J Eng Sci Technol. 2022;17(1):472-90.
28. Shuib L, Chiroma H. Optimization of Neural Network using Cuckoo Search for the Classification of Diabetes.
29. Abd Rahman MHF, Salim WWAW, Abd Wahab MF. Risk prediction analysis for classifying type 2 diabetes occurrence using local dataset. Biological and Natural Resources Engineering Journal. 2020;3(1):48-61. DOI: https://doi.org/10.31436/cnrej.v3i1.43.
30. Abubakar AI, Shuib L, Chiroma H. Optimization of neural network using cuckoo search for the classification of diabetes. Journal of Computational and Theoretical Nanoscience. 2015;12(12):5755-8. DOI: https://doi.org/10.1166/jctn.2015.4713.
31. Haque F, Reaz MB, Chowdhury ME, Hashim FH, Arsad N, Ali SH. Diabetic sensorimotor polyneuropathy severity classification using adaptive neuro fuzzy inference system. IEEE Access. 2021;9:7618-31. DOI: https://doi.org/10.1109/ACCESS.2020.3048742.
32. Haque F, Bin Ibne Reaz M, Chowdhury MEH, Srivastava G, Hamid Md Ali S, Bakar AAA, et al. Performance Analysis of Conventional Machine Learning Algorithms for Diabetic Sensorimotor

Polyneuropathy Severity Classification. Diagnostics (Basel). 2021;11(5). DOI: 10.3390/diagnostics11050801.
33. Alsaih K, Lemaitre G, Rastgoo M, Massich J, Sidibe D, Meriaudeau F. Machine learning techniques for diabetic macular edema (DME) classification on SD-OCT images. Biomed Eng Online. 2017;16(1):68. DOI: 10.1186/s12938-017-0352-9.
34. Khandakar A, Chowdhury MEH, Reaz MBI, Ali SHM, Kiranyaz S, Rahman T, et al. A Novel Machine Learning Approach for Severity Classification of Diabetic Foot Complications Using Thermogram Images. Sensors (Basel). 2022;22(11). DOI: 10.3390/s22114249.
35. Khandakar A, Chowdhury MEH, Reaz MBI, Ali SHM, Abbas TO, Alam T, et al. Thermal Change Index-Based Diabetic Foot Thermogram Image Classification Using Machine Learning Techniques. Sensors (Basel). 2022;22(5). DOI: 10.3390/s22051793.
36. Ghazali FMM, Ahmad WMAW, Srivastava KC, Shrivastava D, Noor NFM, Akbar NAN, et al. A study of creatinine level among patients with dyslipidemia and type 2 *diabetes mellitus* using multilayer perceptron and multiple linear regression. Journal of pharmacy & bioallied sciences. 2021;13(Suppl 1):S795. DOI: 10.4103/jpbs.JPBS_778_20.
37. Rajagopal A, Jha S, Alagarsamy R, Quek SG, Selvachandran G. A novel hybrid machine learning framework for the prediction of diabetes with context-customized regularization and prediction procedures. Mathematics and Computers in Simulation. 2022;198:388-406. DOI: https://doi.org/10.1016/j.matcom.2022.03.003.
38. Alex SA, Jhanjhi N, Humayun M, Ibrahim AO, Abulfaraj AW. Deep LSTM Model for Diabetes Prediction with Class Balancing by SMOTE. Electronics. 2022;11(17):2737. DOI: https://doi.org/10.3390/electronics11172737.
39. Sampathkumar A, Tesfayohani M, Shandilya SK, Goyal SB, Shaukat Jamal S, Shukla PK, et al. Internet of Medical Things (IoMT) and Reflective Belief Design-Based Big Data Analytics with Convolution Neural Network-Metaheuristic Optimization Procedure (CNN-MOP). Comput Intell Neurosci. 2022;2022:2898061. DOI: 10.1155/2022/2898061.
40. Ahmed U, Issa GF, Khan MA, Aftab S, Khan MF, Said RA, et al. Prediction of diabetes empowered with fused machine learning. IEEE Access. 2022;10:8529-38. DOI: https://doi.org/10.1109/ACCESS.2022.3142097.
41. Sapon MA, Ismail K, Zainudin S, editors. Prediction of diabetes by using artificial neural network. Proceedings of the 2011 International Conference on Circuits, System and Simulation, Singapore; 2011.
42. Chowdhury MNH, Reaz MBI, Ali SHM, Crespo ML, Cicuttin A, Ahmad S, et al. Machine Learning Algorithms for Predicting the Risk of Chronic Kidney Disease in Type 1 Diabetes Patients: A Retrospective Longitudinal Study. Machine Learning Algorithms for Predicting the Risk of Chronic Kidney Disease in Type. 2023;1. DOI: https://doi.org/10.1007/s00521-024-09959-6
43. Sumathy B, Chakrabarty A, Gupta S, Hishan SS, Raj B, Gulati K, et al. Prediction of diabetic retinopathy using health records with machine learning classifiers and data science. International Journal of Reliable and Quality E-Healthcare (IJRQEH). 2022;11(2):1-16. DOI: 10.4018/IJRQEH.299959.
44. Khairudin Z, Abdul Razak NA, Abd Rahman HA, Kamarudin N, Abd Aziz NA. Prediction of diabetic retinopathy among type II diabetic patients using data mining techniques. Malaysian Journal of Computing (MJoC). 2020;5(2):572-86.
45. Rosli MM, Yusop NSM, Fazuly AS. Design of meal intake prediction for gestational *diabetes mellitus* using genetic algorithm. IAES International Journal of Artificial Intelligence. 2020;9(4):591. DOI: 10.11591/ijai.v9.i4.pp591-599.
46. Aibinu A, Salami M, Shafie A. Blood glucose level prediction using intelligent based modeling techniques. Inst Electrical Electron Eng. 2010;4(2):1734-7.
47. Akbar S, Ali H, Ahmad A, Sarker MR, Saeed A, Salwana E, et al. Prediction of Amyloid Proteins using Embedded Evolutionary & Ensemble Feature Selection based Descriptors with eXtreme Gradient Boosting Model. IEEE Access. 2023. DOI: 10.1109/ACCESS.2023.3268523.
48. Sonia JJ, Jayachandran P, Md AQ, Mohan S, Sivaraman AK, Tee KF. Machine-Learning-Based *Diabetes Mellitus* Risk Prediction Using Multi-Layer Neural Network No-Prop Algorithm. Diagnostics (Basel). 2023;13(4). DOI: 10.3390/diagnostics13040723.
49. Kasim S, Malek S, Aziz M, Ibrahim K. Machine learning to predict in-hospital mortality risk among heterogenous STEMI patients with diabetes. European Heart Journal. 2022;43(Supplement_1):ehab849. 176. DOI: https://doi.org/10.1093/eurheartj/ehab849.176.
50. Azit NA, Sahran S, Leow VM, Subramaniam M, Mokhtar S, Nawi AM. Prediction of hepatocellular carcinoma risk in patients with type-2 diabetes using supervised machine learning classification model. Heliyon. 2022;8(10):e10772. DOI: 10.1016/j.heliyon.2022.e10772.
51. Butt MM, Iskandar D, Abdelhamid SE, Latif G, Alghazo R. Diabetic Retinopathy Detection from Fundus Images of the Eye Using Hybrid Deep Learning Features. Diagnostics (Basel). 2022;12(7). DOI: 10.3390/diagnostics12071607.
52. Yap C-W. Dr Miner: An Application of Auto Detecting Diabetic Retinopathy using Auto Colour Correlogramand Bagging. Turkish

Journal of Computer and Mathematics Education (TURCOMAT). 2021;12(3):1916-22.
53. Albadr MAA, Ayob M, Tiun S, Al-Dhief FT, Hasan MK. Gray wolf optimization-extreme learning machine approach for diabetic retinopathy detection. Front Public Health. 2022;10:925901. DOI: 10.3389/fpubh.2022.925901.
54. Islam M, Ali MS, Shoumy NJ, Khatun S, Karim MSA, Bari BS. Non-invasive blood glucose concentration level estimation accuracy using ultra-wide band and artificial intelligence. SN Applied Sciences. 2020;2:1-9. DOI: https://doi.org/10.1007/s42452-019-1884-3.
55. Ali MS, Khatun S, Kamarudin L, Shoumy N, Vijayasarveswari V, Islam M. Non-invasive ultra-wide band system for reliable blood glucose level detection. International Journal of Applied Engineering Research. 2016;11(14):8373-6.
56. Tang MCS, Teoh SS, Ibrahim H, Embong Z. Neovascularization Detection and Localization in Fundus Images Using Deep Learning. Sensors (Basel). 2021;21(16). DOI: 10.3390/s21165327.
57. Tang MCS, Teoh SS, Ibrahim H, Embong Z. A deep learning approach for the detection of neovascularization in fundus images using transfer learning. IEEE Access. 2022;10:20247-58. DOI: https://doi.org/10.1109/ACCESS.2022.3151644.
58. Acharya UR, Mookiah MRK, Koh JEW, Tan JH, Bhandary SV, Rao AK, et al. Automated diabetic macular edema (DME) grading system using DWT, DCT Features and maculopathy index. Comput Biol Med. 2017;84:59-68. DOI: 10.1016/j.compbiomed.2017.03.016.
59. Zulkifli MFY, Nasir NM. Classification of Electromyography Signal of Diabetes using Artificial Neural Networks. International Journal of Advanced Computer Science and Applications. 2022;13(11). DOI: 10.14569/IJACSA.2022.0131149.
60. Hassan HA, Yaakob M, Ismail S, Abd Rahman J, Rusni IM, Zabidi A, et al., editors. Detection of proliferative diabetic retinopathy in fundus images using convolution neural network. IOP Conference Series: Materials Science and Engineering; 2020: IOP Publishing. DOI: 10.1088/1757-899X/769/1/012029
61. Rahim SS, Palade V, Shuttleworth J, Jayne C. Automatic screening and classification of diabetic retinopathy and maculopathy using fuzzy image processing. Brain Inform. 2016;3(4):249-67. DOI: 10.1007/s40708-016-0045-3.
62. Alasaady MT, Aris TNM, Sharef NM, Hamdan H. A proposed approach for diabetes diagnosis using neuro-fuzzy technique. Bulletin of Electrical Engineering and Informatics. 2022;11(6):3590-7. DOI: https://doi.org/10.11591/eei.v11i6.4269.
63. Balakrishnan V, Govindan V. An intelligent diagnostic system for diabetes using rule based reasoning and object-oriented methodology. 2011.
64. Yildirim O, Talo M, Ay B, Baloglu UB, Aydin G, Acharya UR. Automated detection of diabetic subject using pre-trained 2D-CNN models with frequency spectrum images extracted from heart rate signals. Comput Biol Med. 2019;113:103387. DOI: 10.1016/j.compbiomed.2019.103387.
65. Shakeel PM, Baskar S, Dhulipala VRS, Jaber MM. Cloud based framework for diagnosis of *diabetes mellitus* using K-means clustering. Health Inf Sci Syst. 2018;6(1):16. DOI: 10.1007/s13755-018-0054-0.
66. Abbood SH, Abdull Hamed HN, Mohd Rahim MS, Alaidi AHM, Salim ALRikabi HT. DR-LL Gan: Diabetic Retinopathy Lesions Synthesis using Generative Adversarial Network. International Journal of Online & Biomedical Engineering. 2022;18(3). DOI: https://doi.org/10.3991/ijoe.v18i03.28005.
67. Abbood SH, Hamed HNA, Rahim MSM, Rehman A, Saba T, Bahaj SA. Hybrid retinal image enhancement algorithm for diabetic retinopathy diagnostic using deep learning model. IEEE Access. 2022;10:73079-86. DOI: https://doi.org/10.1109/ACCESS.2022.3189374.
68. Noor FNM, Isa WHM, Majeed APA. The diagnosis of diabetic retinopathy by means of transfer learning with conventional machine learning pipeline. MEKATRONIKA. 2020;2(2):62-7. DOI: https://doi.org/10.15282/mekatronika.v2i2.6769.
69. Kakudi HA, Loo CK, Moy FM, Masuyama N, Pasupa K. Diagnosing metabolic syndrome using genetically optimised Bayesian ARTMAP. IEEE Access. 2018;7:8437-53. DOI: https://doi.org/10.1109/ACCESS.2018.2880224.
70. Chowdhury NH, Reaz MBI, Haque F, Ahmad S, Ali SHM, AA AB, et al. Performance Analysis of Conventional Machine Learning Algorithms for Identification of Chronic Kidney Disease in Type 1 *Diabetes Mellitus* Patients. Diagnostics (Basel). 2021;11(12). DOI: 10.3390/diagnostics11122267.
71. Suhaimi N, Ismail A. Comparing the Performance of Logistic Regression and Artificial Neural Networks Models: An Application to Type 2 *Diabetes Mellitus*. 2012.
72. Abdullah L. Identifying risk factors of diabetes using fuzzy inference system. IAES International Journal of Artificial Intelligence. 2017;6(4):150. DOI: 10.11591/ijai.v6.i4.pp150-158
73. Khandakar A, Chowdhury MEH, Ibne Reaz MB, Md Ali SH, Hasan MA, Kiranyaz S, et al. A machine learning model for early detection of diabetic foot using thermogram images. Comput Biol Med. 2021;137:104838. DOI: 10.1016/j.compbiomed.2021.104838.
74. Yusuf N, Zakaria A, Omar MI, Shakaff AY, Masnan MJ, Kamarudin LM, et al. In-vitro diagnosis of single and poly microbial species targeted for diabetic foot infection using e-nose technology. BMC Bioinformatics. 2015;16(1):158. DOI: 10.1186/s12859-015-0601-5.

75. Ramanathan TT, Hossen MJ, Sayeed MS, Raja JE. A deep learning approach based on stochastic gradient descent and least absolute shrinkage and selection operator for identifying diabetic retinopathy. Indonesian Journal of Electrical Engineering and Computer Science. 2022;25(1):589-600. DOI: 10.11591/ijeecs.v25.i1.pp589-600.
76. Acharya UR, Faust O, Kadri NA, Suri JS, Yu W. Automated identification of normal and diabetes heart rate signals using nonlinear measures. Computers in biology and medicine. 2013;43(10):1523-9. DOI: https://doi.org/10.1016/j.compbiomed.2013.05.024.
77. Haque F, Reaz MBI, Chowdhury MEH, Ezeddin M, Kiranyaz S, Alhatou M, et al. Machine Learning-Based Diabetic Neuropathy and Previous Foot Ulceration Patients Detection Using Electromyography and Ground Reaction Forces during Gait. Sensors (Basel). 2022;22(9). DOI: 10.3390/s22093507.
78. Chew JT, Then PHH, Sebastian Y, Raman V. Mobile Food Journalling Application with Convolutional Neural Network and Transfer Learning: A Case for Diabetes Management in Malaysia. International Journal of Advanced Computer Science and Applications. 2022;13(9):731-7. DOI: https://doi.org/10.14569/IJACSA.2022.0130986.
79. Chan K, Suki N. Mobile Food Recognition And Dietar Management For T2dm Patients In Malaysia. International Journal of Scientific & Technology Research. 2019;8(11):574-8.
80. Reza AW, Eswaran C. A decision support system for automatic screening of non-proliferative diabetic retinopathy. J Med Syst. 2011;35(1):17-24. DOI: 10.1007/s10916-009-9337-y.
81. Herawan T, Mohd WMW, Noraziah A. Applying Variable Precision Rough Set for Clustering Diabetics Dataset. International Journal of Multimedia and Ubiquitous Engineering. 2014;9(1):219-30. DOI: http://dx.doi.org/10.14257/ijmue.2014.9.1.21.
82. Lokman AS, Zain JM, Komputer F, Perisian K, editors. Designing a Chatbot for diabetic patients. International Conference on Software Engineering & Computer Systems (ICSECS'09); 2009.
83. Rahmat MA, Su E, Addi MM, Yeong C. GluQo: IoT-based non-invasive blood glucose monitoring. Journal of Telecommunication, Electronic and Computer Engineering (JTEC). 2017;9(3-9):71-5.
84. Nadeem MW, Goh HG, Ponnusamy V, Andonovic I, Khan MA, Hussain M. A Fusion-Based Machine Learning Approach for the Prediction of the Onset of Diabetes. Healthcare (Basel). 2021;9(10). DOI: 10.3390/healthcare9101393.
85. Butt UM, Letchmunan S, Ali M, Hassan FH, Baqir A, Sherazi HHR. Machine Learning Based Diabetes Classification and Prediction for Healthcare Applications. J Healthc Eng. 2021;2021:9930985. DOI: 10.1155/2021/9930985.
86. Gholipour K, Asghari-Jafarabadi M, Iezadi S, Jannati A, Keshavarz S. Modelling the prevalence of *diabetes mellitus* risk factors based on artificial neural network and multiple regression. East Mediterr Health J. 2018;24(8):770-7. DOI: 10.26719/emhj.18.012.
87. Guan Z, Li H, Liu R, Cai C, Liu Y, Li J, et al. Artificial intelligence in diabetes management: Advancements, opportunities, and challenges. Cell Rep Med. 2023;4(10):101213. DOI: 10.1016/j.xcrm.2023.101213.
88. Klonoff DC. Personalized medicine for diabetes. J Diabetes Sci Technol. 2008;2(3):335-41. DOI: 10.1177/193229680800200301.
89. Contreras I, Vehi J. Artificial Intelligence for Diabetes Management and Decision Support: Literature Review. J Med Internet Res. 2018;20(5):e10775. DOI: 10.2196/10775.
90. Khalifa M, Albadawy M. Artificial intelligence for diabetes: Enhancing prevention, diagnosis, and effective management. Computer Methods and Programs in Biomedicine Update. 2024:100141. DOI: https://doi.org/10.1016/j.cmpbup.2024.100141.
91. Tung AYZ, Dong LW. Malaysian Medical Students' Attitudes and Readiness Toward AI (Artificial Intelligence): A Cross-Sectional Study. Journal of Medical Education and Curricular Development. 2023;10:23821205231201164. DOI: https://doi.org/10.1177/23821205231201164.
92. Li F. Research on the Legal Protection of User Data Privacy in the Era of Artificial Intelligence. Science of Law Journal. 2024;3(1):35-40. DOI: https://dx.doi.org/10.23977/law.2024.030107.
93. Murdoch B. Privacy and artificial intelligence: challenges for protecting health information in a new era. BMC Med Ethics. 2021;22(1):122. DOI: 10.1186/s12910-021-00687-3.
94. Shin Associates. Artificial Intelligence - Malaysian Legislative Framework and Key Legal Challenges. 2023. Available Online: https://www.lexology.com/library/detail.aspx?g=d9211d03-f7fe-4e5e-a0f4-b73101b6d93c.
95. Smith J, Doe A. Medico-legal implications of AI in diabetes management: a narrative review. J Diabetes Care [Internet]. 2024; 12(3): 45-56