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Review

Artificial Intelligence Based Prediction of Diabetic Foot Risk in Patients with Diabetes: A Literature Review

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Abstract: Diabetic foot is a prevalent chronic complication of diabetes and increases the risk of lower limb amputation, leading to both an economic and a major societal problem. By detecting the risk of developing diabetic foot sufficiently early, it can be prevented or at least postponed. Using artificial intelligence, delayed diagnosis can be prevented, leading to more intensive preventive treatment of patients. Based on a systematic literature review, we analyzed 14 articles that included the use of artificial intelligence to predict the risk of developing diabetic foot. The articles were highly heterogeneous in terms of data use and showed varying degrees of sensitivity, specificity, and accuracy. The most used machine learning techniques were support vector machine (SVM) (n = 6) and K-Nearest Neighbor (KNN) (n = 5). Future research is recommended on larger samples of participants using different techniques to determine the most effective one.

Keywords: artificial intelligence; machine learning; thermography; diabetic foot prediction; diabetes; diabetes care; diabetic foot; literature review

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1. Introduction

Diabetes mellitus (DM) is a chronic disease that requires constant monitoring and management, not just blood glucose control. Worldwide, around 422 million people have diabetes, most of them in low- and middle-income countries, and 1.5 million deaths a year are directly related to diabetes [1]. The disease causes several chronic complications that can have a significant impact on the quality of life of patients, burden the healthcare system through hospitalizations and contribute to an increase in mortality [2]. Many people with diabetes are expected to develop diabetic foot ulcers (DFU) [3], which causes a high rate of amputations in diabetic patients [4], usually due to poor glycemic control, underlying neuropathy, peripheral vascular disease, or poor foot care. DFU can occur at any age but are most common in diabetic patients aged 45 and over [5]. Mortality rates associated with the development of diabetic foot are estimated at 5% in the first 12 months and 42% at 5 years [6]. The annual incidence of diabetic foot ulcers worldwide is between 9.1 and 26.1 million [5,7].

The characteristics of a DFU, such as anatomical location, depth of the wound, infection, and ischemia of the foot lesion at presentation, as well as glycemic control, influence the outcome [8–10]. People at the highest risk of ulcers can be identified by a clinical examination of the feet [11]. Therefore, prevention strategies, including annual diabetic foot examinations, have been implemented to enable early identification of diabetic patients at high risk of diabetic foot complications [12]. Predicting who will develop an ulcer means that preventive therapies can be targeted appropriately [13]. Grading the severity of the ulcer is crucial in the care of patients with DFU and has been reported to have a greater impact on the ultimate success of treatment than the site of the ulcer [8,14].

Artificial intelligence (AI) includes a description of the use of computers and technology to simulate intelligent behavior and critical thinking [15]. Different methods cope with different and increasing amounts of health data, allowing for greater patient autonomy and personalized treatment [16]. Some research has been carried out to diagnose and predict diabetic mellitus and its complications, such as diabetic foot [17]. The automation of healthcare management has led to a transformation in the field by introduction of artificial intelligence-based solutions, due to the ease of mass data collection and powerful computational processing. It has the potential to prevent delayed diagnosis and identify preventive treatments [18]. Clinical practice can use these predictive models to better determine which high-risk people with diabetes should be monitored more closely and treated more intensively [19]. Thermography is also one of the non-invasive methods that can be used to predict risk, as temperature differences in the foot can indicate problems associated with diabetic foot [20].

The aim of this rapid review is to answer the research question: which AI techniques are most effective in predicting the risk of developing diabetic foot?

2. Materials and Methods

A literature review [21,22] was used to describe the current AI based approaches to diabetes and diabetic foot prediction. The first step included a review of the scientific literature on predictive models for diabetic foot ulcer risk using the keywords and synonyms diabetic foot ulcers, prediction model, and artificial intelligence. The full search string was ("diabetic foot" OR "diabetic foot ulcers") AND ("artificial intelligence" OR AI OR "predictive models" OR "predictive modeling" OR "prediction model"). Based on the keywords and the search string, a systematic literature review was performed in the following databases: PubMed, CINAHL/MEDLINE, Web of Science, Scopus, and SAGE. We also reviewed the relevant research in Google Scholar. In the next step, two reviewers independently screened the titles and abstracts and analyzed them according to the inclusion/exclusion criteria. All types of research articles in English were included. We excluded duplicates, commentaries, books, protocols, editorials, etc. The articles that were included in the follow-up were downloaded in full and screened.

The analyzed articles were presented using a characteristics table (author, year, study aim, sample, data collection strategies, techniques, main findings, and limitations). Based on the content of the articles, we divided them into two groups: articles for predicting diabetic foot risk based on a prediction model and articles for predicting diabetic foot risk based on thermography. Based on a literature review and an analysis of articles, we have presented a graphical representation of the most frequently used AI techniques.

3. Results

Based on the search string and considering the search limitations, the following hits were extracted from the databases (Table 1): PubMed (n = 152), CINAHL/MEDLINE (n = 134), Scopus (n = 118), SAGE (n = 75), and Web of Science (n = 121).

Table 1. Searches in the database.

#	Key Words	PubMed	MEDLINE/ CINAHL	Web of Science	Scopus	SAGE
1	("diabetic foot" OR "diabetic foot ulcers")	14,752	26,197	13,055	21,671	2844
2	("artificial intelligence" OR AI OR "predictive models" OR "predictive modeling" OR "prediction model")	1,138,539	277,910	955,062	726,455	30,477
3	("diabetic foot" OR "diabetic foot ulcers") AND ("artificial intelligence" OR AI OR "predictive models" OR "predictive modeling" OR "prediction model")	152	134	121	118	75

After an additional Google Scholar search, we added 12 more reports. Then, we used the Rayyan, computational tool to remove duplicates (n = 310). We screened the remaining articles (n = 290) and excluded articles that were not predicted DFU, that were full-text available, were not included artificial intelligence, and papers written in other languages. Finally, 14 studies were included in the analysis (Figure 1).

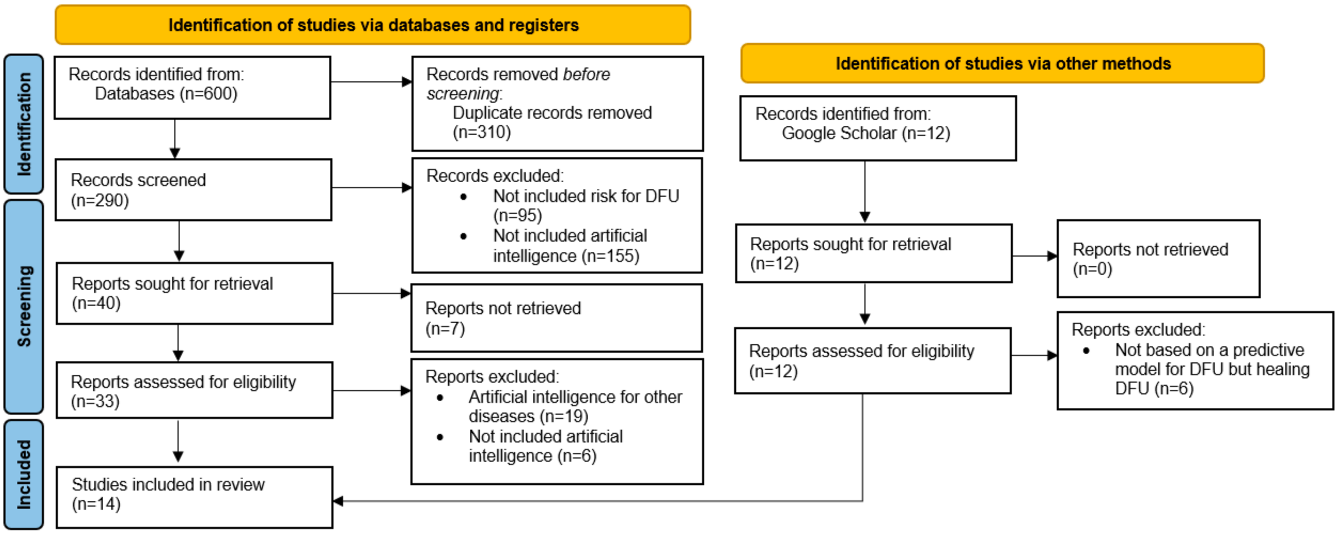

Figure 1. PRISMA flow diagram.

Table 2 presents the basic characteristics of the included studies.

Table 2. Basic characteristics of the included studies.

Author, Year	Study Aim	Sample	Data Collection Strategies	Techniques	Main Findings	Limitations
Articles for predicting diabetic foot risk based on a prediction model						
Ferreira et al., 2020 [23]	The aim of this study is to automatically identify patients with DM who have a high risk of developing diabetic foot, via an unsupervised machine learning technique.	250 patients diagnosed with diabetes.	Risks were recorded by expert nurses based on an interview, a self-care habits questionnaire, a socio-demographic questionnaire, and measurements.	Artificial Neural Network (ANN)	• In a competitive neural layer (CNL) training, more importance is given to the most discriminatory variables and less importance to the least discriminatory variables. • The ANN method was validated on available test data and achieved a sensitivity of 71%, a specificity of 100%, and an accuracy of 90%. • The proposed algorithm suggested the most important variables. These variables are age, type of diabetes, body mass index, food control, physical activity, smoking, presence of hypertension and circulatory problems, sensation of shock in the feet and legs, presence of bunions, vision changes, problems with the habit of washing the feet, presence of pimples on the feet, and presence of a wound and/or amputation.	The authors point out the limitation due to the subjective information obtained from patients with diabetes. They also point out that the research findings did not prove whether patients who were classified as at risk for developing diabetes really developed diabetic foot.
Nanda et al., 2022 [24]	This study aims is to find out the association between various clinical and biochemical risk factors and DFU using different machine learning algorithms. Eighty each of type 2 diabetes mellitus (T2DM) with DFU and T2DM without DFU were enrolled for this observational study.	160 patients, of whom 80 patients diagnosed with type 2 diabetes with DFU and 80 patients diagnosed with type 2 diabetes without DFU.	Patients with DFU were classified based on the Wagner classification system for ulcers. Data were based on blood sample (5 mL) for FPG, PPPG, lipid profile, renal function tests, HbA1C, ApoA1, and cytokines such as IL-10 and TNF-α.	Support Vector Machine (SVM), K-nearest neighbour (KNN), Naive Bayes (NB)	• New risk factors such as ApoA1 and IL-10 have been identified for the development of DFU in diabetes. IL-10 together with uric acid could discriminate ulcer rates according to its severity. • VM-PolyK (0.875) and F-measure (0.938) outperformed all other algorithms closely followed by RF, which was superior to SVM-PolyK in terms of area under the curve (AUC: 0.969). • The performance of KNN and Naive Bayes is comparable to each other as they both performed below random forest (RF) and SVM-PolyK. • The strategy of clustering decisions using the Stacking C algorithm resulted in higher prediction accuracy for both classification levels, which can be used as a complementary method for computational screening of DFUs.	The authors mention small sample sizes as a limitation.

Table 2. *Cont.*

Author, Year	Study Aim	Sample	Data Collection Strategies	Techniques	Main Findings	Limitations
Ohura et al., 2019 [25]	This study investigated whether segmentation of DFU and venous leg ulcer (VLU) wounds using a CNN is feasible after being trained with pressure ulcer (PU) datasets.	Data from 440 patients (images of 400 pressure ulcers, 20 diabetic foot ulcers, and 20 venous leg ulcers).	The images were extracted from a digital wound image database. Wounds were photographed under controlled lighting conditions with cameras at a distance of approximately 30 to 40 cm from the plane of the wound.	CNNs: SegNet, LinkNet, U-Net and U-Net_VGG16	• CNNs with different algorithms and architectures (SegNet, LinkNet, U-Net, and U-Net with VGG16 Encoder Pre-Trained on ImageNet) were produced. • U-Net had the best results, showing the second highest accuracy in terms of area under the curve (0.997) and high specificity (0.943) and sensitivity (0.993).	The data are based on Japanese patients, so it cannot be generalized to patients of other races.
Reddy et al., 2021 [26]	The aim of this study was to predict DFU using an effective neural network algorithm on a suitable dataset that consists of risk factors and clinical outcomes of the disease.	133 instances.	The data consisted of 22 attributes (21 predictors, 1 target) obtained from the data warehouse.	Extreme learning machine (ELM), K-Nearest Neighbor (KNN), Support Vector Machine (SVM) with Gaussian kernel, and Artificial Neural Network (ANN) are also considered.	• Five evaluation metrics were used to compare the algorithms: accuracy, zero loss, Threat/Critical Success Index (TS/CSI), Failure Rate (FOR), and False Discovery Rate (FDR). • After comparison, it was found that ELM outperformed KNN, SVM with Gaussian kernel, and ANN in terms of all metrics. • The values of accuracy, loss of 0–1, TS/CSI, FOR, and FDR obtained for ELM are 96.15%, 0.0385, 0.95, 0, and 0.05 respectively.	The authors recommend that future research should focus on better techniques for predicting foot ulcers and other side effects and risks associated with diabetes.
Schäfer et al., 2020 [27]	They analyzed the data of 246,705 patients with diabetes to assess some of the main risk factors for developing DFU/amputation. They further use machine learning techniques to assess the practical usefulness of such risk factors for predicting foot ulcers and amputation.	246,705 patients with diabetes.	The data were based on socioeconomic information and past medical history of patients born between 1900 and 1968 obtained from the Danish national registries.	Applaying Machine Learning Mehods: logistic regression (LR) and random forest (RF). Statistic model: Time-Varying Cox (TVC) Model, The Aalen Johansen Model	• Patients with lower household income have a higher risk of developing DFU. The Cox PH model estimates the conditional probability of developing DFU or amputation. This model is useful for qualitatively assessing the increase in risk due to other complications. • The Aalen Johansen model is a non-parametric approach to calculate the cumulative hazard rate. After assessing the different risk factors, machine learning is used to predict the occurrence of DFU/amputation at different time intervals. • Compared to the classification task, the ROC curve clearly shows worse performance. Based on the results of the classifier, the features used in the study can be used for predictive models but are not sufficient to accurately predict DFU/amputation.	The authors mention the need to use more engineering functions and to obtain more information on the medical and physiological history of patients.

Table 2. *Cont.*

Author, Year	Study Aim	Sample	Data Collection Strategies	Techniques	Main Findings	Limitations
Tulloch et al., 2020 [28]	The aim of this study is to assess the utility and accuracy of machine learning (ML) in interventional care and treatment of DFU.	37 papers.	Systematic review.	Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Support Vector Machine (SVM)	• Image segmentation and classification, raw data analysis, and risk assessment are all applications where ML has had a positive impact on data analysis and DFU outcomes. In small sample sizes and study conditions, ML offers an efficient and accurate solution to guide the analysis and extraction of data from interventions designed to care for DFUs. • Although neural networks and SVMs cannot be trained on large datasets, they can achieve a high level of accuracy and specificity.	The authors define methodological bias as the main limitation of the study.
Zhang et al., 2022 [29]	This study aims to predict the occurrence and prognosis of DFUs based on data from lower extremity computed tomography angiography (CTA) and clinical data.	203 patients with diabetic foot ulcers (138 patients in the low Wagner Score group and 65 patients in the high Wagner Score group).	Clinical and lower extremity CTA data.	Artificial neural networks (ANN) model	• Based on clinical and lower limb CTA data, the ANN model can predict the occurrence and prognosis of DFU. The overall performance of the ANN model had a sensitivity of 92.3%, a specificity of 93.5%, a positive predictive value of 87,0%, a negative predictive value of 94.2%, and an area under the curve of 0.955. The DFU was predicted with 91.6% accuracy by the proposed model. The PPV, NPV, and sensitivity of the model were calculated by retained sample analysis and were 88.9%, 90.0%, 88.5%, 75.0%, and 95.8%, respectively. The ANN outperformed the logistic regression. • The variables included are age, sex, body mass index, duration of diabetes, duration of diabetic foot ulcer, limb symptoms, degree of lower limb arterial stenosis, segment of lower limb arterial stenosis, arterial calcification, and comorbidities.	The data were collected from different staff at different hospitals. Individual hospitals did not have specialized equipment to measure patients' ankle–brachial index (ABI).

Table 2. *Cont.*

Author, Year	Study Aim	Sample	Data Collection Strategies	Techniques	Main Findings	Limitations
Articles for predicting diabetic foot risk based on a thermography						
Cruz-Vega et al., 2020 [30]	To analyze the use of artificial intelligence and deep learning (DL) for the classification of diabetic foot thermograms and to analyze the advantages and limitations of this method.	110 thermograms of patients with diabetes.	The data were obtained from a public thermogram database.	Multilayer Perceptron (MLP), Support Vector Machine (SVM), metrics of accuracy (ACC), Artificial Neural Network (ANN), and convolutional neural network (CNN)	• The results obtained with the DL method had better performance than the other models and saved time, as they have a short training time. The results of CNN methods such as GoogLeNet and AlexNet were not satisfactory. • The paper proposed a new CNN design with simple structure but better design. The proposed DFTNet provides satisfactory results with measures of sensitivity, specificity, accuracy, and AUC values.	The authors state that they aim to obtain more images of the thermograms in future studies.
Eid et al., 2018 [31]	To propose a new system for early diagnosis of diabetic foot using thermal imaging.	50 subjects.	The resulting database consisted of 500 images.	K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Decision Tree	• The Fine KNN achieved a maximum accuracy of 96.8%, a sensitivity of 88.3%, a specificity of 99.1%, and a loss score of 0.004. • The proposed system is accurate, with a low time in the learning and testing phase, which allows to automatically diagnose diabetic foot and discriminate between them.	The authors propose to include more subjects in the study and classify the system using a deep learning algorithm without feature extraction.
Filipe et al., 2022 [32]	To develop a functional methodology for the analysis and classification of different thermal changes in the plantar region in diabetic and healthy individuals, to enable use by healthcare professionals in a clinical setting.	167 individuals (122 with diabetes and 45 without diabetes).	Public dataset of thermal images.	Support Vector Machine (SVM) and K-Nearest Neighbor (KNN)	• The two proposed models performed well, but compared to model 1 (thermogram), model 2 outperforms model 1 as it allows a better classification of healthy individuals and diabetics into the first class. • The SVM algorithms performed second best with similar results, followed by the Weighted KNN algorithm; however, this was better than the 3-NN algorithm.	The authors cite as a limitation that the data obtained from the public dataset were unbalanced, resulting in under-representation of some classes.

Table 2. *Cont.*

Author, Year	Study Aim	Sample	Data Collection Strategies	Techniques	Main Findings	Limitations
Goyal et al., 2020 [33]	To propose applications of traditional computer vision features with DFU classification. The DFU classification problem classifies skin into two classes: normal skin (healthy skin) and abnormal skin (DFU).	292images of patient's with DFU.	Color images of the stpal of different patients collected from a database of the last five years with the hospital. The images were taken with a Nikon D3300 at a distance of approximately 30–40 cm with parallel to the ulcer plane.	Faster R-CNN with InceptionResNet V2, BayesNet, Random Forest, InceptionV3, and ResNet	• To identify differences in features between healthy skin and DFU, a new convolutional neural network architecture, DFUNet, which improved feature extraction were proposed. • With 10-fold cross-validation, DFUNet achieved an AUC score of 0.961, outperforming the tested machine learning and deep learning classifiers.	In the future, the authors recommend the development of an automatic annotator that can automatically delineate and classify images of the feet without the help of doctors, the development of automatic detection, recognition, and classification of ulcers using these classifiers, and the implementation of a method to identify different pathologies and to perform different user-friendly software tools.
Gururajarao et al., 2019 [34]	To present the use of soft computing techniques for the analysis of medical images based on infrared thermography, for the assessment of diabetic foot complications, and the challenges that need to be addressed when using infrared thermography for diagnostic purposes.	62 patients with diabetes (38 men and 24 women) and 20 without diabetes.	Dimension of mage 320 × 240 and 320 × 240 pixels.	Artificial Neural Network (ANN)	• The ANN model was used to predict the risk of diabetic foot without complications, healthy foot, or diabetic foot with complications. A temperature difference of 2.2 °C was observed in the presence of a complication. • The CNN classified an image of a diabetic foot without any complications with a probability of 87,43%. Testing all images, an average accuracy of 91% was achieved for each class. • Although 62 diabetic and 20 healthy participants were included in the study, it is not clear how the classification performance was calculated.	In the future, the authors plan to develop the model from the initial step to have more control over the parameters to classify and quantify the complication rates in the different categories more accurately.
Muralidhara et al., 2022 [35]	To present a novel, holistic classification approach that considers thermograms of non-diabetic and diabetic subjects based on a CNN.	122 diabetic patients and 45 controls.	Asymmetric analysis on a butterfly pattern of the temperature distribution, where the asymmetry in this distribution indicates an anomaly. The data of analysis were collected from a publicly available database.	Convolutional neural network (CNN)	• A comprehensive multiclass classification of thermal imaging of the feet for the prediction and classification of patients with diabetes mellitus were presented. • The model achieved the best performance with an overall accuracy of 0.9827, a baseline sensitivity of 0.9684, and a baseline specificity of 0.9892.	The authors present a limitation due to publicly available data, which is often unbalanced and leads to over-represented classes and low sensitivity to under-represented classes.

Table 2. *Cont.*

Author, Year	Study Aim	Sample	Data Collection Strategies	Techniques	Main Findings	Limitations
Vardasca et al., 2018 [36]	Assess the risk of ulceration based on thermal images.	56 patients in the early stage of DFU.	The image was captured using an infrared camera under predefined conditions (a 10-min acclimatization period was previously used and the room was acclimatized at a temperature of about 22 °C).	K-Nearest Neighbor (KNN)	• Infrared thermal images were captured from 56 patients with early-stage DFU, processed and classified using an intelligent data mining method (KNN), achieving an accuracy of 92.5%. • The authors propose to evaluate the performance of the model on a larger sample.	The authors do not present any limitations.

Tulloch et al., in 2020 [29], reviewed articles that addressed the topic of prevention, diagnostician, and treatment of DFU using ML alone. In the case of our review, we did not limit ourselves to these models. We included seven articles that included variable-based prediction of DFU risk and a prediction model, and seven articles that addressed the possibility of DFU based on thermal images.

The most frequently used AI models were SVM (n = 6) and KNN (n = 5), followed by ANN and CNN (each n = 4) and RF (n = 2) (Figure 2).

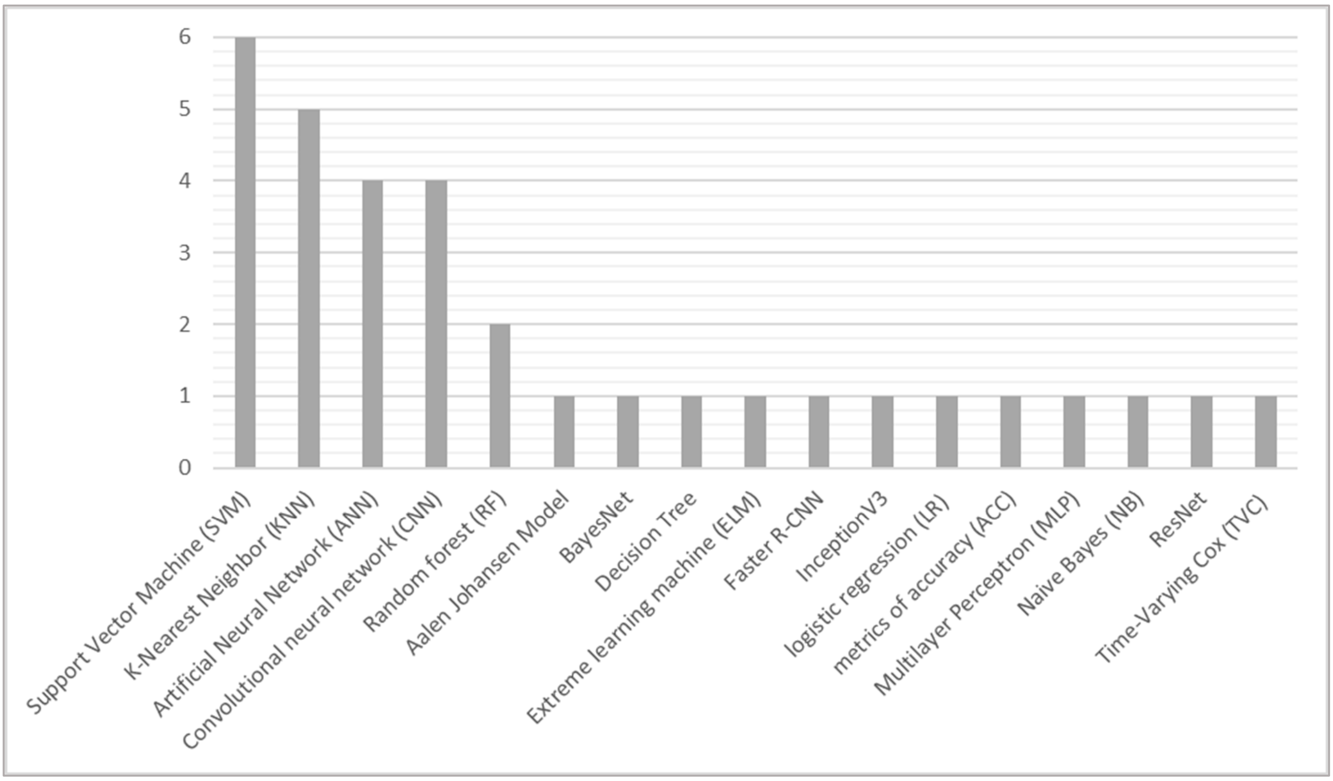

Figure 2. Artificial intelligence prediction techniques for risk of developing diabetic foot.

4. Discussion

Diabetic foot ulcers are costly and debilitating and have serious consequences for people with diabetes [37]. All diabetic patients should be carefully and thoroughly educated about preventive measures and foot care [5]. However, the traditional process of diagnosis of DFU by clinicians and DFU specialists is very expensive and time-consuming. Therefore, deep learning in medical imaging opens corridors for the automatic diagnosis of DFU [38]. Given the complex nature of DFUs, AI methodologies seem well suited to address aspects such as timely screening to identify the risk of foot ulcers (or worse, amputation) based on appropriate sensor technologies [39].

Our review of the papers found that DFUs can be identified in different ways. The most used classifiers in the reviewed papers are SVM and KNN. Nanda et al. [24] found that SVM is better than the other algorithms in point of MCC, which is 0.875, and F-measure, which is 0.938. The performance of KNN and Naive Bayes were comparable to each other. In the study, RF was the most efficient in terms of sensitivity and SVM was the most efficient in terms of highest specificity, which was 93.8%. Reddy et al. [26] included ELM and ANN in the research, in parallel to SVM and KNN. The ELM achieved the highest accuracy, followed by the SVM with 92.31%. The ANN and KNN were comparable, both achieving an accuracy of 84.62%. In a literature review by Tulloch et al. [28], all included models achieved accuracies above 90%. SVM and KNN have also been used for risk prediction based on thermography. In a study by Cruz-Vega [30], although the SVM model obtained satisfactory results, it did so after a feature extraction procedure, which we would like to avoid. Eid et al. [31] found that KNN achieved the highest performance, improving classification accuracy by 4.3% compared to using SVM. Another effective technique for interpreting the learned features of CNN layers is t-distributed stochastic neighborhood embedding (t-SNE) [40], which has been used to visualize clusters of heart rate data with respect to glucose levels. The use of t-SNE can also be generalized to other CNN applications, such as DFU detection, in order to qualitatively analyze the extracted feature maps. In addition, a recent study has also verified the consistency of neural network models with respect to glucose and insulin dynamics [41]. Similar approaches can be used to analyze the performance of DNNs and further improve interpretability [42].

The most common variables included in the prognostic model are age, type of diabetes, body mass index (BMI), and type of diabetes. In the studies by Ferreira et al. [23] and Zhang et al. [29], only ANN models were used. In the first study, they reported a sensitivity of 71%, a specificity of 100%, and an accuracy of 90%. In the second study, they report that the model had a sensitivity of 92.3% and a specificity of 93.5%.

Many authors attempt to classify foot thermograms using asymmetric analysis, which consists of comparing the temperature of the foot with that of the contralateral foot [31]. Several papers report that thermography is useful for detecting changes in sole temperature that could increase the risk of pressure ulcers. Cruz-Vega et al. (2020) discovered that the CNN classifiers require an additional data augmentation step for three structures (GoogLeNet, AlexNet, and DFTNet) [30]. The highest values of sensitivity, specificity, AUC (area under the curve), and accuracy were obtained with classifiers such as SVM and for the CNN structures in almost all pairs of classes compared, especially in the well-separated classes. The best results of DFNet can be attributed to the specific network design for this type of images. Although the GoogLeNet and AlexNet network structures are more complex and supposed to be better classifiers, they were trained with a different type of images. This work presents a comparison of conventional classifiers such as ANN, SVM, and currently important classifiers such as CNN [30]. The works by Muralidhara et al. [35] use techniques that only allow binary classification of thermograms (which corresponds to the first case).

Improving AI-based systems improves the accuracy and efficiency of diagnosis and treatment in different areas [43], and thus, the safety of care [44]. Using AI and data sources also reduces the frequency of errors in different areas of patient care [44].

The main limitation is the heterogeneity of the research, as we have included different types of research with different prediction models. By using balanced datasets with a significant number of samples, classification models can achieve more accurate predictions. Expanding the dataset should not only mean including more detailed clinical information on the subjects studied, but should also include a wide range of the most common variables included in the prognostic models. The images used in the studies analyzed were usually taken with a smartphone or tablet and did not require the high-tech imaging available only in research and industrial settings. The use of hand-crafted imaging features and raw clinical attributes in the prediction algorithm facilitates better insight for both clinicians and patients. With more samples and research, it is expected that accuracy will increase and that it could be performed in specialized units in daily practice for early DFU, allowing rapid care and avoiding further costs and consequences for the patient. Different Al models have been applied in these areas, achieving better experimental performance than previous conventional machine learning methods. On the other hand, several challenges have been identified in the literature, including data availability, feature processing, and interpretability of models. In the future, there is considerable potential to address these challenges by applying recent advances in deep learning technologies to massive multimodal diabetes treatment data. We expect that deep learning technologies will be widely deployed in clinical settings and will greatly improve the treatment of people living with diabetes. In the discussion, we compared the numerical values of the performance of the models reported in the reviewed papers. The papers did not use the same dataset for training and testing, which could be a serious limitation in some studies. We also limited our search to

English articles only, thus leaving open the possibility that we did not include all relevant studies in the review.

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