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A machine learning approach to predict foot care self-management in older adults with diabetes

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Abstract

Background Foot care self-management is underutilized in older adults and diabetic foot ulcers are more common in older adults. It is important to identify predictors of foot care self-management in older adults with diabetes in order to identify and support vulnerable groups. This study aimed to identify predictors of foot care self-management in older adults with diabetes using a machine learning approach.

Method This cross-sectional study was conducted between November 2023 and February 2024. The data were collected in the endocrinology and metabolic diseases departments of three hospitals in Turkey. Patient identification form and the Foot Care Scale for Older Diabetics (FCS-OD) were used for data collection. Gradient boosting algorithms were used to predict the variable importance. Three machine learning algorithms were used in the study: XGBoost, LightGBM and Random Forest. The algorithms were used to predict patients with a score below or above the mean FCS-OD score.

Results XGBoost had the best performance (AUC: 0.7469). The common predictors of the models were age (0.0534), gender (0.0038), perceived health status (0.0218), and treatment regimen (0.0027). The XGBoost model, which had the highest AUC value, also identified income level (0.0055) and A1c (0.0020) as predictors of the FCS-OD score.

Conclusion The study identified age, gender, perceived health status, treatment regimen, income level and A1c as predictors of foot care self-management in older adults with diabetes. Attention should be given to improving foot care self-management among this vulnerable group.

Keywords Foot care, Older adults, Self-management, Machine learning, Diabetes

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Background

Diabetes mellitus is a chronic disease affecting 537 million people worldwide [1]. Diabetes mellitus is a chronic condition that can result in acute or chronic complications if not effectively managed. These complications have a negative impact on patients' quality of life, increase mortality rates, require additional healthcare workforce and increase healthcare costs. Diabetic foot is one of the common complications in people with diabetes. The risk of developing diabetic foot ulcers over a lifetime is between 19% and 34% among individuals with diabetes [2].

Maintaining healthy blood glucose levels and preventing complications are the main objectives of diabetes management. Foot care plays a crucial role in the prevention of diabetic foot. Studies have shown that foot care helps to reduce the incidence of diabetic foot ulcers. Bus and Netten (2016) reported that an integrated foot care can prevent 75% of foot ulcers in people with diabetes [3]. Similarly, Chellan et al. (2012) reported that the incidence of diabetic foot ulcers was 9% among patients who practiced diabetic foot care, while the incidence was 39.8% among patients who did not practice diabetic foot care [4].

Despite the evidence of the importance of foot care in diabetes, foot care practices were reported to be underutilized in older adults [5]. It has been reported that older adults with DFUs are more vulnerable to frailty and physical disability in activities of daily living compared to those without DFUs [6]. Older people with DFUs were also reported to have lower health-related quality of life [7]. In a study by Costa et al. (2017), it was reported that older age was associated with higher mortality and amputation rates in patients with DFUs [8]. It is important to prevent DFUs in older adults because of the above consequences of DFUs in older adults.

Improving foot care practices in older adults is important for the prevention of DFUs. Foot care practices in older adults may be affected by physical limitations, health status, and cognitive or psychosocial factors [9]. Matricciani et al. (2015) reported that foot self-care is underutilized by older adults with diabetes as a primary prevention measure, adopted only after complications occur [5]. It is therefore important to predict the ability of older adults to self-manage their foot care.

Predicting foot care self-management in older adults could help identify at-risk groups. However, the studies on predicting foot care self-management in older adults are limited. In recent years, machine learning has commonly been used to construct predictive models capable of capturing intricate patterns and understanding relationships within data, all with minimal human interference. Machine learning has demonstrated great success in analysing complex patterns in healthcare [10]. This study aimed to identify predictors of lower levels of foot care self-management in older adults with diabetes using a machine learning approach. The identification of predictors of foot-care self-management in older adults will facilitate the identification of vulnerable groups within healthcare settings and society. Consequently, a focus on this group to improve self-management will be implemented. This will, in turn, help to enhance foot-care self-management in older adults.

Methods

The study had a cross-sectional design and data were collected between the November 2023-February 2024 and aimed to identify predictors of lower levels of foot care self-management in older adults with diabetes using a machine learning approach. The study was conducted and presented in line with Strengthening the reporting of observational studies in epidemiology (STROBE) guideline.

Study setting and sample

The study was conducted in a public hospital in Istanbul, Turkey, between November 2023 and January 2024. Patients admitted to the endocrinology and metabolic disorders department of the hospital were included in the study. Convenience sampling was used for the study. The inclusion criteria were as follows: age 65 years or older, diagnosis of diabetes for at least six months or more, absence of cognitive disorders, and willingness to be part of the study. Patients who were diagnosed with diabetic foot ulcers and who had a history of diabetic foot ulcers or amputation were excluded from the study. Forty-two patients were excluded from the study because of a history of diabetic foot ulcers. Two patients were excluded from the study because of a history of cognitive impairment. Both patients were diagnosed with dementia by a neurologist, which was confirmed by the patient's electronic records. Written permission was obtained from the medical research ethics committee of Uskudar University under protocol number 2023-54.

Data collection

Data were collected by the researchers in the outpatient clinic of The Department of Endocrinology and Metabolic Disorders at a university hospital. For the sociodemographic and disease-related characteristics of the patients, a patient introduction form was developed by the researchers in accordance with the literature. The Foot Care Scale for Older Diabetics (FCS-OD) was used to assess foot care self-management skills in older adults.

Patient identification form the form included 18 items and was developed by the researchers in accordance with relevant literature [11–14]. The patient's age, gender, education, marital status, income level, place of residence, duration of diagnosis, type and duration of treatment, HbA1c level, smoking and alcohol consumption, comorbidities, hospital admissions, and follow-ups are recorded in the form. Additionally, the patients self-assessed their overall health status and quality of life on a scale of 0 (worst) to 100 (best).

Foot Care Scale for Older Diabetics (FCS-OD) The tool was developed for use with older Japanese adults. Sable-Morita et al. (2021) developed the scale, which has two versions: the long version and the short version. The long version comprises 22 items and six subscales: skin condition, nail clipping, attention to wounds, relationships with others, attention to feet, and self-efficacy. The short version consists of nine out of 22 items and four subscales; skin condition, nail clipping, attention to wounds and relationships with others. The scales' Cronbach's Alpha values were 0.797 for the short version and 0.879 for the long version [14]. The scale was adapted to the Turkish population by Toygar et al. (2024). The long version of the scale was used in this study to predict the foot care self-management ability of older adults. No cut-off score was reported for the scale, therefore in order to identify patients with low levels of self-management, the mean score of the population was used as a reference point in this study.

Data analysis

The study presents the sociodemographic and disease-related characteristics of the patients using percentages (%), numbers (n), means (m), and standard deviations (SD). To compare the sociodemographic and disease-related characteristics between the patients who had an FCS-OD score below or above the average, chi-square and independent sample t-tests were used. IBM SPSS v27 was used to compare the frequency and mean scores between the groups.

The machine learning analyses were conducted using Ddsv4-series Azure Virtual Machines with 32 vCPUs and 128 GiB of memory. The results and parameters of the best model obtained from the analyses conducted in Azure Automated ML. Three models were used to predict foot care self-management: XGBoost, LightGBM, and Random Forest.

We have evaluated predictive model performance with 10-fold cross validation (a training set 70% and a test set 30%) [15] and all ML algorithms' parameters optimized hyperparameters optimization method [16].

XGBoost

In the context of gradient boosting for regression, the fundamental building blocks are regression trees. Each regression tree maps an input data point to one of its leaf nodes, where a continuous score is assigned. XGBoost employs an objective function that undergoes regularization through the inclusion of both L1 and L2 terms. These regularization terms are integrated into XGBoost's objective function to control the complexity of individual trees, mitigating overfitting and promoting model generalization.

The objective function unites a convex loss function, responsible for quantifying the disparity between predicted and target outputs, with a penalty term aimed at addressing model complexity, specifically the functions represented by the regression trees.

The training process in XGBoost unfolds iteratively. It commences with the addition of new trees that predict the residuals or errors of previous trees. Subsequently, these new trees are harmoniously integrated with the existing ensemble of trees to make the final prediction. The term 'gradient boosting' is aptly attributed to XGBoost as it harnesses a gradient descent algorithm to minimize the loss when introducing these new models [17] (Fig. 1).

It generally provides very high accuracy rates. Trees are optimized sequentially using Gradient Boosting. It is fast due to optimization techniques and hardware accelerations (e.g., using GPU). It can work with various loss functions and offers a streamlined model-building process. Hyperparameter tuning can be complex and time-consuming. Due to its high flexibility, there is a risk of overfitting if not carefully adjusted [18].

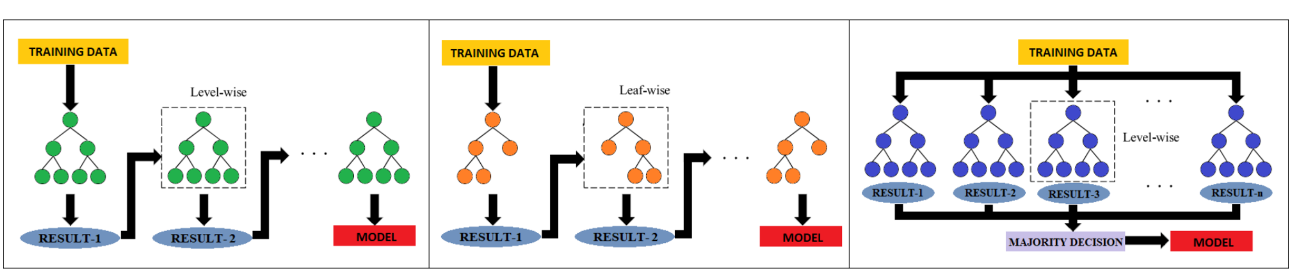

Fig. 1 Training and classification phases of different machine learning models

LightGBM

LightGBM is a high-performance gradient boosting algorithm that utilizes a tree-based learning approach. It was developed by Microsoft Research Asia as part of the Distributed Machine Learning Toolkit (DMTK) project in 2017 (source: https://lightgbm.readthedocs.io/en/latest). This algorithm presents several advantages over other boosting algorithms, including more effective resolution of prediction problems related to big data, efficient utilization of resources (RAM), high prediction performance, and parallel learning. Its rapid processing speed is reflected in its name, "Light." In the article titled "A Highly Efficient Gradient Boosting Decision Tree," LightGBM was found to be 20 times faster than other algorithms [19] (Fig. 1).

This algorithm provides high-speed training thanks to its histogram-based algorithm, which is especially effective on large data sets. It works very well with large and high-dimensional datasets. It may be less effective than other methods on small data sets, where it separates the data points into groups. Tuning hyperparameters can be complex and requires careful optimization [18].

Random Forest

The Random Forest is an ensemble learning algorithm extensively employed for both classification and regression tasks in machine learning. It functions by creating numerous decision trees during training and provides the mode of the classes for classification tasks or the mean prediction for regression tasks based on the individual trees' outputs [20] (Fig. 1).

Random Forest is a simple and easy-to-use algorithm. It is easier to tune hyperparameters when performing model optimization compared to other algorithms. It is an algorithm that is robust to overfitting because it increases the generalization ability of the model by averaging multiple decision trees. Since each tree is created independently, it can be calculated in parallel, which reduces the computation time. On the contrary, it can be slow due to the approach of creating a large number of decision trees in large data sets. Due to the number of trees, the model can be large, and memory usage increases [18].

Results

In this study, data of 213 patients were evaluated. The participants were divided into two groups according to their total FCS-OD score for machine learning prediction. Thus, there were two groups in the study; below average and above average. There were statistically significant differences between the groups in terms of gender, place of residence, income level, treatment regimen, presence of comorbidities, and adherence to follow-up (Table 1).

There were statistically significant differences between the groups regarding age, A1c, perceived health status and perceived quality of life. Those with a lower-than-average FCS-OD score was older, had higher A1c levels, and had lower scores for perceived health status and perceived quality of life (Table 2).

Three machine learning models were used to predict the FCS-OD scores (Fig. 2). The XGBoost model had the highest AUC and precision scores, while the Random Forest model had the highest accuracy, recall, F1 score, and Mathews' correlation coefficient. The AUC graphs of the models are presented in Fig. 2. The common predictors of the models were age, gender, perceived health status, and treatment regimen. The XGBoost model, which had the highest AUC value, also identified income level and A1c as predictors of the FCS-OD score (Table 3) (Fig. 2).

Discussion

Foot care is one of the most important practices for preventing diabetic foot ulcers. Predicting the foot care self-management ability in older adults with diabetes is important for preventing diabetic foot ulcers. This study utilised machine learning approaches to identify predictors of foot care self-management in older adults with diabetes.

Age was a common predictor in three models and the top predictor in two models. The patients who scored below the average on FCS-OD were older than those who scored above the average. Abdelhamid et al. (2018) reported that there is a negative correlation between the age and foot care practices and knowledge [21]. It has been reported that many older adults with diabetes fail to achieve glycemic control and adherence to self-management because of the complex activities they require [22]. It is common for older adults to experience difficulties when performing foot care, because it requires the ability to bend over, adequate visual acuity, and fine motor skills to cut toenails [23]. It was reported that 89% of hospitalized older adults with diabetes had problems in cutting toenails [23]. Maintaining foot care self-management can be challenging for older adults due to physiological changes that occur with age. Therefore, special attention is required to improve foot care for these patients. Healthcare professionals should be aware of the increased risk for older adults as they age.

Gender was another common predictor of the models. Of the males, 62.6% scored below the average, while 65.7% of females scored above it. Older male adults were more likely to have poor self-managed footcare in this study. Rossaneis et al. (2016) reported that males with diabetes had greater deficits in self-care and foot care than did their female counterparts [24]. It was reported that males care less about their feet [25]. In another study

Table 1 Comparison of the sociodemographic and disease-related categorical characteristics of the participants in the groups

		FCS-OD Below the Average n (%)	FCS-OD Above the Average n (%)	Total n (%)	Test statistics; *p*-value
Gender	**Male**	72 (62.6)	43 (37.4)	115 (100)	**$X^2 = 17.914$ $p < 0.001$**
	Female	37 (34.3)	71 (65.7)	108 (100)	
Education Level	**Illiterate**	15 (41.7)	21 (58.3)	36 (100)	X^{2*}=9.229 $p = 0.052$
	Literate	5 (83.3)	1 (16.7)	6 (100)	
	Primary school	78 (53.4)	68 (46.6)	146 (100)	
	High school	7 (29.2)	17 (70.8)	24 (100)	
	Associate or higher degrees	4 (36.4)	7 (63.6)	11 (100)	
Place of residence	**City**	101 (52.1)	93 (47.9)	194 (100)	**$X^2 = 6.048$ $p = 0.014$**
	Town/Village	8 (27.6)	21 (72.4)	29 (100)	
Income level	**Income is equal to the expense**	20 (35.7)	36 (64.3)	56 (100)	**$X^2 = 5.186$ $p = 0.023$**
	Income is less than the expense	89 (53.3)	78 (46.7)	167 (100)	
Marital Status	**Married**	82 (49.7)	83 (50.3)	165 (100)	$X^2 = 0.170$ 0.761
	Single	27 (46.6)	31 (53.4)	58 (100)	
Treatment regimen	**Combined**	17 (58.6)	12 (41.4)	29 (100)	**$X^2 = 17.568$ $p < 0.001$**
	Oral antidiabetics	21 (28.8)	52 (71.2)	73 (100)	
	Insulin	71 (58.7)	50 (41.3)	121 (100)	
Smoking status	**Yes**	12 (40.0)	18 (60.0)	30 (100)	$X^2 = 1.094$ $p = 0.331$
	No	97 (50.3)	96 (49.7)	193 (100)	
Alcohol consumption	**Yes**	1 (20.0)	4 (80.0)	5 (100)	X^{2*}=1.707 $p = 0.370$
	No	108 (49.5)	110 (50.5)	218 (100)	
Comorbidity	**Yes**	92 (54.4)	77 (45.6)	169 (100)	**$X^2 = 8.631$ $p = 0.005$**
	No	17 (31.5)	37 (68.5)	54 (100)	
Unscheduled hospital admission in last six months	**Yes**	62 (52.1)	57 (47.9)	119 (100)	$X^2 = 1.060$ $p = 0.303$
	No	47 (45.2)	57 (54.8)	104 (100)	
Adherence to the follow-ups	**Yes**	69 (54.8)	57 (45.2)	126 (100)	**$X^2 = 4.012$ $p = 0.045$**
	No	40 (41.2)	57 (58.8)	97 (100)	
Hospitalization in last year	**Yes**	15 (62.5)	9 (37.5)	24 (100)	$X^2 = 1.997$ $p = 0.158$
	No	94 (47.2)	105 (52.8)	199 (100)	

X^2: Chi square test statistics; X^{2*}: Exact test statistics; $p < 0.05$ Significance level

Table 2 Comparison of the sociodemographic and disease-related continuous characteristics of the participants in groups

	Below the Average		Above the Average		Test statistics; *p*-value
	Mean ± SD	**Med [min-max]**	**Mean ± SD**	**Med [min-max]**	
Age	75.02 ± 5.09	75 [67–86]	70.42 ± 3.51	70 [65–85]	**U = 2887.00 $p < 0.001$**
Diagnosis duration	168.21 ± 109.35	144 [12–480]	166.39 ± 97.53	168 [18–384]	U = 6076.00 $p = 0.776$
Treatment duration	152.67 ± 101.7	132 [1-420]	157.98 ± 96.91	156 [8-372]	U = 5925.50 $p = 0.550$
A1c	9.57 ± 2.01	10 [6–15]	8.95 ± 1.94	9 [6–15]	**U = 5115.50 $p = 0.021$**
Perceived health status (0-100)	49.4 ± 14.14	50 [20–80]	59.51 ± 14.96	60 [10–90]	**U = 3775.50 $p < 0.001$**
Perceived QoL (0-100)	47.94 ± 12.19	50 [10–70]	52.5 ± 13.27	50 [10–80]	**U = 4831.00 $p = 0.003$**

U: Mann Whitney U test statistics; $p < 0.05$ Significance level

conducted in the same country as the current study, it was found that males had lower levels of foot care behaviour compared to females [26]. As in the literature, this study found gender differences in foot care self-management among older adults with diabetes. As in the literature, this study revealed gender differences in foot care self-management among older adults with diabetes. To improve foot care self-management, we recommend using gender-specific approaches.

Patients treated with insulin or combination therapies (insulin + oral antidiabetics) had lower FCS-OD scores. In most cases, insulin is not the first treatment option for

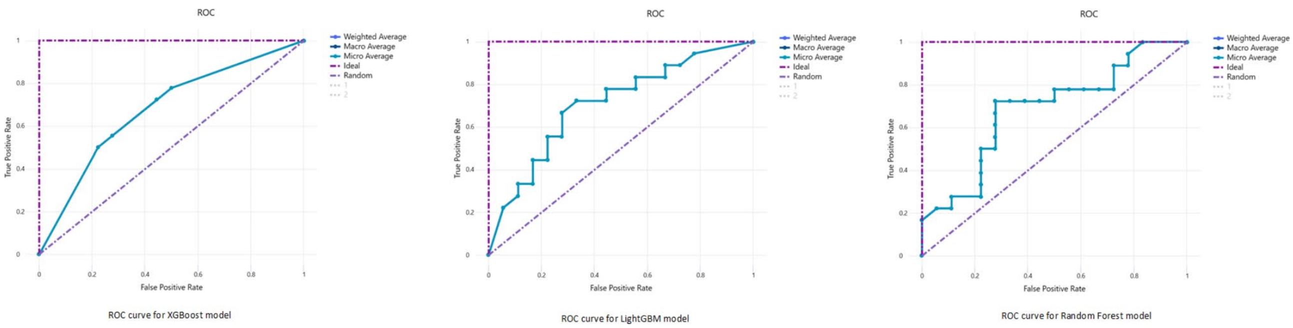

Fig. 2 The ROC curves of the different machine learning classification models

Table 3 Variable importance and performance metrics of machine learning models

Model 1. XGBoost			
Variables	**Importance**	**Performances Metrics**	**Values**
Age	0.0534	Accuracy	0.6667
Perceived health status	0.0218	AUC	0.7469
Income Level	0.0055	Precision	0.7561
Gender	0.0038	Recall	0.6700
Treatment regimen	0.0027	F1 score	0.6630
A1c	0.0020	Mathews' Correlation	0.3419
Model 2. LightGBM			
Variables	**Importance**	**Performances Metrics**	**Values**
Age	0.7410	Accuracy	0.6667
Gender	0.3551	AUC	0.7346
Perceived health status	0.3238	Precision	0.7122
Treatment regimen	0.2407	Recall	0.6666
A1c	0.0649	F1 score	0.6625
Perceived QoL	0.0180	Mathews' Correlation	0.3419
Diagnosis duration	0.0067		
Model 3. Random Forest			
Variables	**Importance**	**Performances Metrics**	**Values**
Gender	**0.7267**	Accuracy	0.7222
Treatment regimen	**0.4279**	AUC	0.7160
Age	**0.3442**	Precision	0.7250
Perceived health status	**0.2343**	Recall	0.7222
Income Level	**0.0557**	F1 score	0.7213
Unscheduled hospital admission in last six months	**0.0401**	Mathews' Correlation	0.4472
Perceived QoL	**0.0273**		
Adherence to the follow-ups	**0.0241**		
Diagnosis duration	**0.0239**		
Marital status	**0.0185**		

patients with type 2 diabetes. The American Association of Clinical Endocrinologists (AACE) recommends insulin therapy as initial or add-on therapy for patients with an A1c above 9% [27]. Insulin is an option in the management of type 2 diabetes for those who do not achieve their A1c target with diet, exercise and oral antidiabetics [27]. Sayampanathan et al. (2017) reported that general degree of self-care, presence of comorbidities restricting the ability to self-care and age were predisposing factors for proper diabetic foot care while diabetic sensory neuropathy and complexity of disease were the factors affecting proper diabetic foot care [28]. Insulin as a main or additional therapy is more common in these patients. Therefore, we believe that insulin treatment by itself was not a predictive factor. Our conclusion for this finding is that the patients who have comorbidities and problems in complying with disease management were treated with insulin and had lower levels of foot care self-management.

Perceived health status and perceived quality of life were greater in those with a higher-than-average FCS-OD score. A systematic review investigating patient and practitioner perceived barriers to accessing foot care services reported that patients focused on patient-level factors, while practitioners focused on the health care system [29]. Similarly, Yıldırım Usta et al. (2019) reported that illness perception and health beliefs are predictors of foot care behaviours [26]. Ezeamama et al. (2016) reported that resilience improves the self-rated health and there is a positive relationship between the resilience and self-rated health. In the same study, it was reported that resilience predicted lower healthcare utilization [30]. Resilience also has a positive relationship with self-care in people with chronic conditions [31]. We believe that patients who rate their overall health and quality of life higher are more resilient and therefore more compliant with their foot care. However, further studies are needed to investigate this relationship.

Income level and A1c were also identified as predictors of FCS-OD score by the XGBoost model, which had highest AUC. Income level has been reported to be one of the factors influencing diabetes self-management [32]. Dietz et al. (2023) reported that patients earning between $25,000 and $50,000 per year had a lower number of days to perform their foot care than those earning less than $25,000 per year [32]. However, in the current study, self-management scores were higher among those who reported that their income was equal to their expenditure than among those who reported that their income was less than their expenditure. We thought this might be related to health insurance and purchasing power in the countries surveyed. Access to healthcare in Turkey is free, except in private clinics. However, there is no reimbursement for most of the disease-specific products such as shoes, socks or nail clippers. However, in the United States, healthcare costs increase with chronic disease or complications. We believe that patients in Turkey have a higher level of self-management of foot care as their income increases, but patients in the United States are focused on preventing complications to avoid hospital admission. For this reason, patients with a lower income level in the United States performed foot care more regularly. However, this explanation for the difference between Turkey and the United States is the authors' assumption. There is a need for further studies to investigate the reason for this difference. Yang et al. (2016) reported that knowledge of A1c is a predictor of diabetes self-management [33]. On the other hand, there are studies reporting the effect of diabetes self-management on A1c [34, 35]. There is a two-sided interaction between the diabetes self-management and A1c. Beard et al. (2010) reported that patients with a good understanding of A1c exhibited a lower A1c level (7.5%) compared to those with a poor understanding of A1c (8.9%). Furthermore, in the same study by Beard et al. (2010), it was also reported that good understanding of A1c is associated with better foot-care self-care scores and foot care self-efficacy scores [36]. Foot care self-management is a component of self-management activities in diabetes. Kurniwawan et al. (2011) reported that a self-management education programme is also effective in diabetic foot care behaviours [37]. Conversely, in both disease self-management and foot care self-management, maintaining a healthy blood glucose level is a crucial element. Consequently, it is anticipated that patients with a lower A1c level will exhibit higher self-management and foot care scores. Furthermore, it is expected that there will be a decrease in the A1c level in patients who comply with the foot care self-management activities. In the current study, this interaction was found to be similar between foot care self-management and A1c.

Machine learning and deep learning have been extensively studied in the literature for diagnosing diabetic foot ulcers. Puneeth et al. proposed utilizing the EfficientNet, a deep neural network model, for early detection and prognosis of diabetic foot ulcers. Their study involved analyzing a dataset consisting of 844 foot images, comprising both healthy and diabetic ulcer feet. The EfficientNet model outperformed several popular models such as AlexNet, GoogleNet, VGG16, and VGG19, achieving maximum accuracy, F1-score, recall, and precision of 98.97%, 98%, 98%, and 99%, respectively. Mousa et al. focused on 19 significant attributes, including medical history and foot images, affecting diabetic foot ulcers. They proposed two classifiers, a feedforward neural network, and a decision tree, for predicting foot ulcers. The experimental results indicated that the artificial neural network outperformed the decision tree, achieving an accuracy of 97% in automating the prediction of diabetic foot ulcers. This study suggested that diabetic outpatient clinics should consider developing health education and follow-up programs to prevent complications associated with diabetes. Wang et al. developed an optimal predictive model for hard-to-heal DFUs (ulcers failing to decrease by >50% at 4 weeks) based on clinical characteristics using machine learning algorithms. Their findings identified the NB model as the most generalizable, with an AUC of 0.864, a recall of 0.907, and an F1-score of 0.744. Machine learning and deep learning algorithms have achieved impressive prediction results by utilizing clinical characteristics and images [38–40].

Limitations

The study was conducted in Turkey and the generalizability of the results is limited to Turkey. The participants were the patients admitted to the hospital. We recommend conduction of the similar studies in other countries. Creating a data pool and real-time analysis on the predictors can also help to extend the generalizability of the study thanks to the further studies in other societies.

In this study, foot care self-management was evaluated via self-reported data. There is a need for the prediction with clinical self-management outcomes.

The present study was limited by the absence of a cut-off score for the FCS-OD. In order to identify the group with a lower level of self-management, the authors employed the mean score as a cut-off point. However, the mean score is specific to this population, thereby limiting the generalisability of the study. Although the mean score provides an indication of the low scores observed in the population under study, further research is required to determine a specific cut-off score for the scale.

Conclusion

This study employed three machine learning analyses to predict foot care self-management in older adults and concluded that age, gender, perceived health status, treatment regimen, income level and A1c were predictors. The majority of these predictors were not modifiable. However, they are important for identifying vulnerable groups. The practices to improve foot care self-management should be implemented for all patients; however, there is a need for a specific focus on patients with these characteristics. Further studies are recommended to evaluate the effectiveness of interventions to improve self-management in vulnerable groups. It is also recommended that future studies adopt a community-based design and include larger groups. It is further recommended that future studies be conducted on different samples and in different settings. The creation of a data pool and subsequent real-time analysis of this data pool will facilitate the updating of the generalisability of the results. Therefore, it is recommended that the data pool be created with the further studies in other samples and countries.

Abbreviations

AACE	American Association of Clinical Endocrinologists
AUC	Area under curve
DFUs	Diabetic foot ulcers
DMTK	Distributed Machine Learning Toolkit
FCS-OD	Foot Care Scale for Older Diabetics
LightGBM	Light Gradient-Boosting Machine
ML	Machine Learning
STROBE	Strengthening the reporting of observational studies in epidemiology
XGBoost	eXtreme Gradient Boosting
QoL	Quality of Life

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Author contributions
Su Özgür: Conceptualization, Methodology, Formal Analysis, Writing - Original Draft, Investigation Serpilay Mum: Conceptualization, Methodology, Data Curation, Writing - Original Draft, Investigation Hilal Benzer: Conceptualization, Methodology, Data Curation, Writing - Original Draft, Investigation Meryem Koçaslan Turan: Conceptualization, Methodology, Data Curation, Writing - Original Draft, Investigation İsmail Toygar: Conceptualization, Methodology, Validation, Formal analysis, Writing - Original Draft, Supervision, Visualization, Writing - Review & Editing,

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Written permission was obtained from the medical research ethics committee of Uskudar University (protocol: 2023-54). Informed consent was read and signed by each participant. The study complied with the principles of the Declaration of Helsinki "Recommendations Guiding Physicians in Biomedical Research Involving Human Subjects", adopted by the 18th World Medical Assembly, Helsinki, Finland, June 1964 (and its successive amendments).

Competing interests
The authors declare no competing interests.

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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. 2021:109119.
2. Edmonds M, Manu C, Vas P. The current burden of diabetic foot disease. J Clin Orthop Trauma. 2021;17:88–93.
3. Bus SA, van Netten JJ. A shift in priority in diabetic foot care and research: 75% of foot ulcers are preventable. Diab/Metab Res Rev. 2016;32:195–200.
4. Chellan G, Srikumar S, Varma AK, Mangalanandan T, Sundaram K, Jayakumar R, et al. Foot care practice–the key to prevent diabetic foot ulcers in India. Foot. 2012;22(4):298–302.
5. Matricciani L, Jones S. Who cares about foot care? Barriers and enablers of foot self-care practices among non-institutionalized older adults diagnosed with diabetes: an integrative review. Diabetes Educ. 2015;41(1):106–17.
6. Bôas NCRV, Salomé GM, Ferreira LM. Frailty syndrome and functional disability among older adults with and without diabetes and foot ulcers. J Wound Care. 2018;27(7):409–16.
7. Khunkaew S, Fernandez R, Sim J. Health-related quality of life among adults living with diabetic foot ulcers: a meta-analysis. Qual Life Res. 2019;28:1413–27.
8. Costa RHR, Cardoso NA, Procópio RJ, Navarro TP, Dardik A, de Loiola Cisneros L. Diabetic foot ulcer carries high amputation and mortality rates, particularly in the presence of advanced age, peripheral artery disease and anemia. Diabetes & Metabolic Syndrome: Clinical Research & Reviews. 2017;11:S583-S7.
9. Ahmad Sharoni SK, Abdul Rahman H, Minhat HS, Shariff-Ghazali S, Azman Ong MH. The effects of self-efficacy enhancing program on foot self-care behaviour of older adults with diabetes: a randomised controlled trial in elderly care facility, Peninsular Malaysia. PLoS ONE. 2018;13(3):e0192417.
10. Stiglic G, Kocbek P, Fijacko N, Zitnik M, Verbert K, Cilar L. Interpretability of machine learning-based prediction models in healthcare. Wiley Interdisciplinary Reviews: Data Min Knowl Discovery. 2020;10(5):e1379.
11. Kır Biçer E. Diyabetli Hastalarda ayak bakım uygulamaları ve öz etkililiğin değerlendirilmesi. İstanbul: İstanbul University; 2011.
12. Kır Biçer E. Ayak Bakım Davranışı Ölçeği Türkçe formu geçerlik ve güvenirliği. Diyabet Obezite ve Hipertansiyonda Hemşirelik Forumu Dergisi. 2014;6(2):35–9.
13. Bakir E, Samancioglu S. Dıyabetık Ayakta Öz Bakim Davranişi Ölçeği'Nın Türkçe Geçerlılık ve Güvenılırlığı. Karya J Health Sci. 2021;2(2):39–43.
14. Sable-Morita S, Arai Y, Takanashi S, Aimoto K, Okura M, Tanikawa T et al. Development and testing of the Foot Care Scale for Older Japanese Diabetic patients. Int J Low Extrem Wounds. 2021:15347346211045033.
15. Microsoft. Configure training, validation, cross-validation and test data in automated machine learning 2024 https://learn.microsoft.com/

en-us/azure/machine-learning/how-to-configure-cross-validation-data-splits?view=azureml-api-1#k-fold-cross-validation
16. Microsoft. Hyperparameter tuning a model (v2) 2023 https://learn.microsoft.com/en-us/azure/machine-learning/how-to-tune-hyperparameters?view=azureml-api-2
17. Inoue T, Ichikawa D, Ueno T, Cheong M, Inoue T, Whetstone WD, et al. XGBoost, a machine learning method, predicts neurological recovery in patients with cervical spinal cord injury. Neurotrauma Rep. 2020;1(1):8–16.
18. Suenaga D, Takase Y, Abe T, Orita G, Ando S, editors. Prediction accuracy of Random Forest, XGBoost, LightGBM, and artificial neural network for shear resistance of post-installed anchors. Structures: Elsevier; 2023.
19. Özgür S, Orman M. Application of deep learning technique in next generation sequence experiments. J Big Data. 2023;10(1):160.
20. Rigatti SJ. Random forest. J Insur Med. 2017;47(1):31–9.
21. Abdelhamid FM, Taha NM, Mohamed EH, EL-Khashab MN. Effect of self-management support program on improving Diabetic Foot Care behaviors. Int J Pharm Res Allied Sci. 2018;7(4).
22. Tan CCL, Cheng KKF, Wang W. Self-care management programme for older adults with diabetes: an integrative literature review. Int J Nurs Pract. 2015;21(S2):115–24.
23. James K, Orkaby AR, Schwartz AW. Foot Examination for older adults. Am J Med. 2021;134(1):30–5.
24. Rossaneis MA, Haddad MCFL, Mathias TAF, Marcon SS. Differences in foot self-care and lifestyle between men and women with diabetes mellitus. Rev Latinoam Enferm. 2016;24.
25. Navarro-Peternella FM, Lopes APAT, de Arruda GO, Teston EF, Marcon SS. Differences between genders in relation to factors associated with risk of diabetic foot in elderly persons: a cross-sectional trial. J Clin Translational Endocrinol. 2016;6:30–6.
26. Usta YY, Dikmen Y, Yorgun S, Berdo İ. Predictors of foot care behaviours in patients with diabetes in Turkey. PeerJ. 2019;7:e6416.
27. Sterrett JJ, Bragg S, Weart CW. Type 2 diabetes medication review. Am J Med Sci. 2016;351(4):342–55.
28. Sayampanathan AA, Cuttilan AN, Pearce CJ. Barriers and enablers to proper diabetic foot care amongst community dwellers in an Asian population: a qualitative study. Annals Translational Med. 2017;5(12).
29. McPherson M, Carroll M, Stewart S. Patient-perceived and practitioner-perceived barriers to accessing foot care services for people with diabetes mellitus: a systematic literature review. J Foot Ankle Res. 2022;15(1):92.
30. Ezeamama AE, Elkins J, Simpson C, Smith SL, Allegra JC, Miles TP. Indicators of resilience and healthcare outcomes: findings from the 2010 health and retirement survey. Qual Life Res. 2016;25:1007–15.
31. Jin Y, Bhattarai M, Kuo W-c, Lisa B. Relationship between resilience and self-care in people with chronic conditions: a systematic review and meta-analysis. J Clin Nurs. 2023;32(9–10):2041–55.
32. Dietz C, Sherrill W, Ankomah S, Rennert L, Parisi M, Stancil M. Impact of a community-based diabetes self-management support program on adult self-care behaviors. Health Educ Res. 2023;38(1):1–12.
33. Yang S, Kong W, Hsue C, Fish AF, Chen Y, Guo X, et al. Knowledge of A1c predicts diabetes self-management and A1c level among Chinese patients with type 2 diabetes. PLoS ONE. 2016;11(3):e0150753.
34. Cunningham AT, Crittendon DR, White N, Mills GD, Diaz V, LaNoue MD. The effect of diabetes self-management education on HbA1c and quality of life in African-Americans: a systematic review and meta-analysis. BMC Health Serv Res. 2018;18(1):1–13.
35. Chrvala CA, Sherr D, Lipman RD. Diabetes self-management education for adults with type 2 diabetes mellitus: a systematic review of the effect on glycemic control. Patient Educ Couns. 2016;99(6):926–43.
36. Beard E, Clark M, Hurel S, Cooke D. Do people with diabetes understand their clinical marker of long-term glycemic control (HbA1c levels) and does this predict diabetes self-care behaviours and HbA1c? Patient Educ Couns. 2010;80(2):227–32.
37. Kurniwawan T, Sae-Sia W, Maneewat K, Petpichetchian W. The effect of a self-management support program on the achievement of goals in diabetic foot care behaviors in Indonesian Diabetic patients. Nurse Media J Nurs. 2011;1(2):195–210.
38. Thotad PN, Bharamagoudar GR, Anami BS. Diabetic foot ulcer detection using deep learning approaches. Sens Int. 2023;4:100210.
39. Mousa KM, Mousa FA, Mohamed HS, Elsawy MM. Prediction of Foot Ulcers using Artificial Intelligence for Diabetic patients at Cairo University Hospital, Egypt. SAGE Open Nurs. 2023;9:23779608231185873.
40. Wang S, Xia C, Zheng Q, Wang A, Tan Q. Machine Learning Models for Predicting the Risk of Hard-to-Heal Diabetic Foot Ulcers in a Chinese Population. Diabetes, Metabolic Syndrome and Obesity: Targets and Therapy. 2022:3347-59.

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