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Glucose Monitoring with AI Analytics for Diabetes Management Using Machine Learning and Smart Devices

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Abstract

Over the past few years, there has been a noticeable growth in the usage of smart devices for diabetes treatment. These technologies are meant to make life easier for people with diabetes because they have the potential to improve the stability of blood sugar monitoring and predict the onset of dangerous episodes (hypo/hyperglycemia). Notwithstanding, the primary goals of diabetic self-management are to enhance the lifestyle and quality of life of those living with the disease. This study used the literature that addressed diabetes to conduct a systematic review to monitor and control the disease effectively. The search was narrowed to include topical keywords like Artificial Intelligence (AI), technology, self-management, and diabetes, for which PubMed databases were used. There were 2655 papers in all, released between 2013 and 2023. Predicting blood glucose, identifying risk events early, automatically adjusting insulin dosages, and other diabetes care issues are the main goals of most of the chosen research. Wearable technology and AI methods were combined in these investigations. Much scientific attention has been drawn to wearable technology like Continuous Glucose Monitoring (CGM) in treating chronic illnesses like diabetes. Not only may they help avoid diabetes-related problems, but they can also aid in managing diabetes. Utilizing these gadgets has also enhanced the quality of life and treatment of sickness.

Keywords: Continues glucose monitoring, Diabetes management, Artificial intelligence, Healthcare industry, Smart devices

1. Introduction

Diabetes is linked to fasting, irregular blood glucose levels, and dysfunctions in many organ systems, such as the kidneys, eyes, neurological system, and blood circulation system. Diabetes causes heart attacks, strokes, amputations, blindness, and kidney failure. In many developed nations, it ranks as the third most common cause of death. Moreover, research indicates that nearly half of those suspected of having diabetes do not receive a diagnosis for a decade after the condition first manifests. This suggests that the actual prevalence of diabetes worldwide must be extremely high. Diabetes can be broadly divided into two types: Type I diabetes, or diabetes that is Insulin-Dependent Diabetes Mellitus (IDDM), and Type II diabetes, or Non-Insulin-Dependent Diabetes Mellitus (NIDDM). Type I diabetes mainly affects children, especially those between the ages of 12 and 15. Of all the diabetes types, type II diabetes accounts for 80–90% of cases. Compared to IDDM, NIDDM is less severe and typically affects adults over the age of 35. If diabetes is detected before it enters the danger zone, it can be cured; if not, it becomes a significant problem. Regular monitoring of

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blood glucose levels is necessary to prevent this condition. Ketone testing is essential for diabetes diagnosis [1]. Ketone level measurement aids in the efficient management of diabetes; if the body produces a lot of ketone bodies, it is thought that the condition is becoming unmanageable [2].

Consequently, to regulate blood pressure, glucose levels, and insulin levels—all of which are essential for the proper operation of the human body—a platform for diabetes self-management is required [3]. A significant portion of the Internet of Things (IoT) comprises different medical sensors, gadgets, imaging, and diagnostic tools categorized as smart objects. Diabetes monitoring services powered by the Internet of Things are anticipated to reduce expenses and improve user satisfaction. Predictive analytics is a tool that healthcare providers can use to identify patterns and project results, which may help them make well-informed decisions about patient care. For example, a novel tracking system for people with diabetes has been developed that integrates four distinct machine-learning algorithms with predictive analytics [4]. Diabetes can be detected early because smart IoT-based devices can gather patient health data in real time [1][4]. It has also been suggested that an intelligent medical monitoring system that integrates machine learning and the Internet of Things be developed to identify diabetes at an early stage [1]. These tools can help patients get better results, control their diabetes, and experience fewer complications.

With the growing application of the Internet of Things (IoT) and machine learning in healthcare, computers can generate medical records independently, forecast illness diagnoses, and continuously monitor patients in real time.

1.2. Research obstacles and novel contributions

Through non-invasive blood glucose monitoring, continuous glucose monitoring is possible inside a smart healthcare system. Ascertaining the glucose level is arguably the most challenging aspect of non-invasive testing. The existing options are expensive and require intricate mathematical models to analyze them for a prompt diagnosis. The current paper addresses the following research challenges:

- The most accurate non-invasive method for measuring glucose is identified.
- Blood glucose levels are measured using practical machine-learning algorithms.
- The smart healthcare system uses the IoMT architecture to offer continuous glucose monitoring.
- An affordable solution has to be developed for all patient types, including those who are healthy, diabetic, and pre-diabetic.

2. Review of literature

This section summarizes recent studies on intelligent sensors in glucose monitoring applications for diabetic patients. A new approach for tracking and monitoring the physical activity of the elderly or incapacitated was proposed by Ketabdar and Lyra [5]. Siddiqui et al. [6] provided an overview of painless, non-invasive blood sugar management techniques in 2018. In addition, they compare the various products made for non-invasive monitoring. The system uses smartphones to gather data. Four subject users were observed and recorded during the 320 activity instances the researchers used in their test. The accuracy of the system that was provided was 92.9%. Murakami presents a CGM system to critically ill patients in the intensive care unit [4].

A glucose client, a disposable subcutaneous diabetic sensor, and a server make up the system. The technology gathers glucose data and feeds it into a hospital information system four times daily. Doctors can check the glucose readings using the bedside monitor. An implantable glucose monitoring gadget using Bluetooth with low energy consumption (BLE) is proposed by Ali et al. [7]. The gadget gathers glucose data, which is then sent over Bluetooth LE to a PDA (mobile devices or iPads) to be viewed in text. There have been some advancements in technology that have reduced the electrical consumption of both external power units and implantable units. A model that collected and analyzed a particular population data set was put out by Zhang et al. [8] to forecast the course of an individual's disease. They obtain daily information about the diabetes patient's diet, exercise, social interactions, sleep schedule, body posture, and other habits using mobile applications. According to an examination of a research study, 1657 participants' HbA1c readings were lower due to cell phone interventions.

Additionally, statistical research revealed an excellent rate over a six-month median. The study offered compelling proof that, for individuals who self-manage their diabetes, mobile phone intervention improved glucose levels [9][10]. The idea put forth by the authors makes use of an ion-sensitive field-effect transistor coupled to a microcontroller. The measurements are transmitted to a physician via a Wi-Fi module. More investigation is needed to get beyond the sensor's contamination exposure constraint. Wireless body area networks are optimal for transmitting glucose estimations (WBAN) [11]. A patient's caregivers can monitor their progress through a web website or mobile device. Non-intrusive sensors are integrated with the IoT architecture to provide data portability and accessibility. An illustration of this interaction involves an infrared LED, which utilizes the intensity of light it receives to determine the blood glucose content. Its relationship to the design is straightforward because of how LEDs operate and are configured [12].

Another example is the suggested glucose data classification, which uses data classification techniques to test the architecture and ensure that the prediction system makes an accurate diagnosis. The writers concentrated on the proper SMS message transmission and assessing the methods employed. In most instances, this technology can address the shortcomings of conventional monitoring [13]. The majority of earlier assessments on the subject of managing diabetes concentrated on the use of mobile applications only. As seen in [Table 1], it was found that these evaluations provide a less thorough treatment of the topic. Some research solely looks at a specific age range or kind of diabetes. This study can present a more detailed analysis, even going so far as to raise doubts about certain long-held beliefs since we concentrated on analyzing each of the included studies and presenting thorough data for each.

Table 1. Past reviews that address the issue of managing diabetes (published in 2021-22)

S. No.	Title	Year	Limitations	Indexed
1.	Mobile and wearable technology for the monitoring of diabetes-related parameters: Systematic review	2021	more concerned with the gadgets than with machine learning	PubMed
2.	Implementation and impact of mobile health (mHealth) in the management of diabetes mellitus in Africa: a systematic review protocol	2021	connected to mobile health and focuses on a particular area and kind of diabetes. Furthermore, a thorough study of every piece that was presented was needed.	PubMed
4.	Mobile app interventions to improve medication adherence among type 2 diabetes mellitus patients: a systematic review of clinical trials	2021	-primarily discusses the use of mobile apps for diabetes care. -concentrating solely on one kind of diabetes.	PubMed
5.	The Impact of Wearable Technologies in Health Research.	2022	Recent studies have used reasonably priced wearable technology for medical studies.	PubMed
6.	The Impact of Wearable Technologies in Health Research: Scoping Review	2022	The present health studies use reasonably priced wearable technology.	PubMed
7.	The effectiveness of wearable activity trackers to increase physical activity and improve health: a systematic review of systematic reviews and meta-analyses	2022	Using an activity tracker might increase physical activity.	PubMed
8.	Recent Advancements in Emerging Technologies for Healthcare Management Systems: A Survey	2022	Primarily, it discusses Blockchain, AI, and wearable sensor devices combined with IoT support.	PubMed
9.	A scoping review of artificial intelligence-based methods for diabetes risk prediction	2023	Related to artificial intelligence (AI) models for T2DM risk prediction	PubMed
10.	Application of Artificial Intelligence in Assessing the Self-Management Practices of Patients with Type 2 Diabetes	2023	More concerned with Artificial intelligence and machine learning algorithms.	PubMed

3. Materials and methods

A literature review is a precise and repeatable research method that enumerates all relevant works and summarizes the state of the art at the moment to resolve one or more fundamental questions about a specific subject [14][15].

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach served as the foundation for the systematic review's methodology, which will be presented in detail in this section [16].

This paper can be divided into the following sections: techniques, which describe the conditions that must be met for an article to be included; the process of choosing data sources, the research's selection process, and data extraction methods; results, which give details about the topic, subjects, metrics, models and types of smart devices, and AI approaches used in each comprised research; as well as the conclusion, which makes suggestions for potential future paths for smartwatch research.

3.1. Standards of eligibility

[Table 2] provides a summary of the eligibility requirements for the articles that were chosen, as follows:

Table 2. An overview of the criteria for inclusion

S. No.	Standards	Explanation
1.	Paper Language	English
2.	Years taken into account	Between January 2021 to December 2022
3.	Subject	smart gadget application in diabetes care.
4.	Sector	-Artificial Intelligence (AI) -Computer -Medicine
5.	Types of Diabetes taken into account	-Diabetes Type 1 (TD1) -Diabetes Type 2 (TD2) -Gestational diabetes (GDM).
6.	Participants ages	No age-related limitations
7.	Device Type	-Portable -Mounted on the body

Since diabetes self-management technology is developing so quickly, the following restrictions apply:

- only written in English;
- only works published during the last ten years (January 2013 to December 2023);
- only articles whose primary goal is managing diabetes and its consequences;
- this only addresses type 1 or type 2 gestational diabetes;
- the only published research on the topic has used artificial intelligence (AI)-based approaches;
- Only papers discussing the use of body-mounted or portable devices for diabetes self-management were taken into consideration;

Over the past two years, there has been a rise in scientific curiosity about applying wearable technology to treat diabetes. The review's featured papers were released from 2022 to 2023. Four hundred eighty-nine papers were published over this period (in the PubMed databases), compared to just 153 publications before 2013.

The following criteria were used to weed out papers:

- they were review articles;
- they were brief conference or congress abstracts;
- they were published before 2023; or
- they were not full text available. Moreover, the review excludes studies that do not meet the criteria above.

3.2. Sources of data and search approach

A literature search was conducted using the PubMed database to find and gather papers about the areas of focus of our systematic review. These internet databases were chosen because they were pertinent to the topic and scope of research. The fields considered in search queries were the keywords, the abstract, and the title. The computerized databases of scientific articles were queried through the use of the Boolean operators (AND, either OR, and NOT) and several keywords that were inside the predetermined themes listed in the qualifying criteria. [Table 3] displays the distribution of articles in the PubMed Database by year (2013–2023), and [Figure 1] shows a graphical representation of that distribution.

Table 3. Distribution of articles by year (PubMed Database)

S. No.	Years	Publication in PubMed
1.	2013	153
2.	2014	148
3.	2015	167
4.	2016	221
5.	2017	231
6.	2018	252
7.	2019	292
8.	2020	357
9.	2021	345
10.	2022	272
11.	2023	217
		Total= 2655

Table 4. Descriptive Statistics of documents by year

Mean	250.2
Standard Error	21.68194
Median	241.5
Mode	357
Standard Deviation	68.56433
Sample Variance	4701.067
Kurtosis	-0.65329
Skewness	0.190282
Range	209
Minimum	148
Maximum	357
Sum	2502
Count	10
Largest (1)	357
Smallest (1)	148
Confidence Level (95%)	49.04796

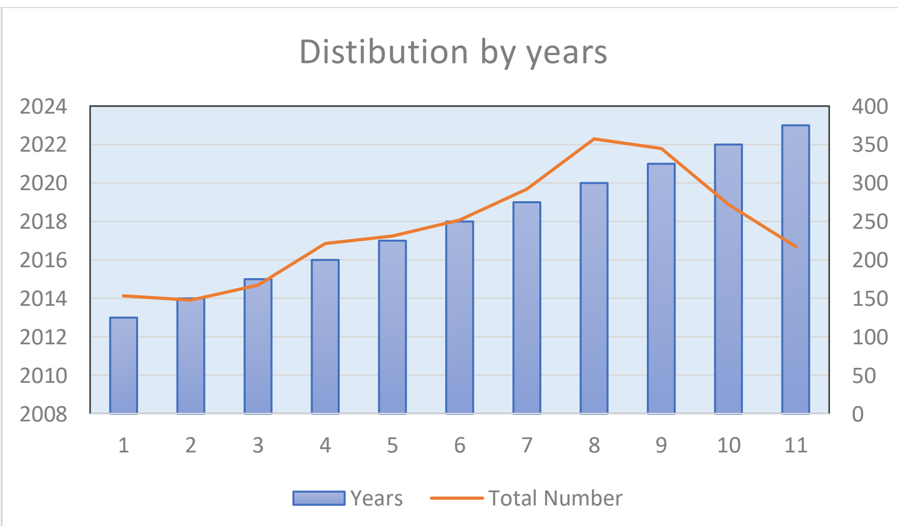

Figure 1. The distribution of documents by year (PubMed database)

Table 5. Article type and total count of publications during 2013-2023

Article Type (2013-2023)	Total Count
Systematic Review	59
Review	641
Randomized Controlled Trail	107
Meta-Analysis	55
Clinical Trail	130
Books & Documents	5

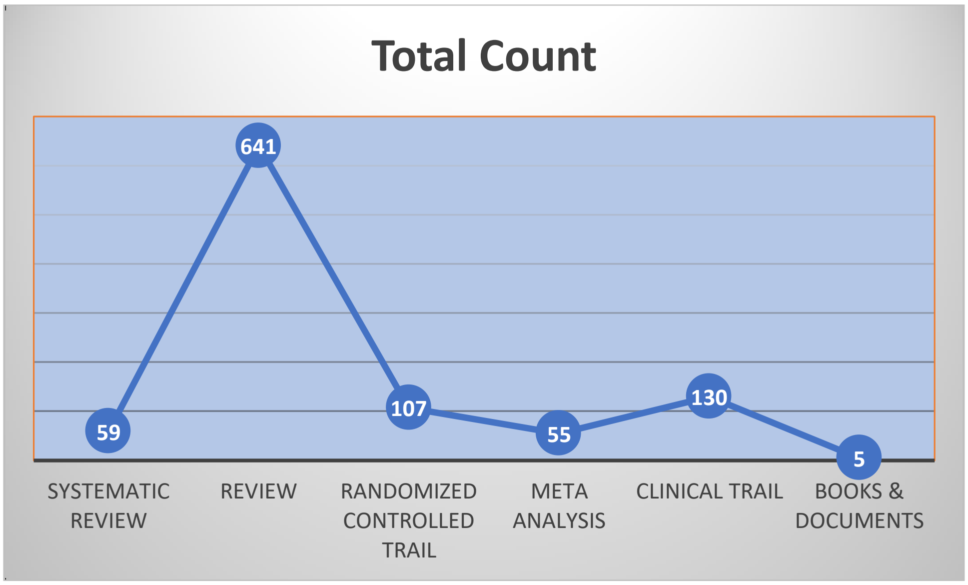

Figure 2. Article types by year (PubMed Database)

4. Results

Two thousand six hundred fifty-five research articles were published between 2013 and 2023. Most of the research on artificial intelligence-assisted diabetes management was published in 2020 (357) and 2021 (345). The fewest publications on managing diabetes were released in 2013 and 2014 [Table 2]. The distribution of texts by year is shown graphically in [Figure 1] (PubMed database). Descriptive statistics of published publications by year in the PubMed database are shown in [Table 4]. [Table 5] displays the article type and total number of publications from 2013 to 2023. [Figure 2] shows a graphical representation of this data. Clinical trials came in second, with 130 publications, while books and papers came in last, with five publications. The most significant number of publications, 641, has been released as review articles. Most of the selected research aims to solve one or more challenges associated with treating diabetes, including blood glucose prediction, early risk event detection, automated insulin dose change, etc. Wearable technologies (CGMs), diabetes monitors, and artificial intelligence approaches were combined in this investigation.

4.1. Diabetes technology

Diabetes technology refers to the tools, gadgets, and software used by individuals with the disease to control their blood sugar levels, prevent complications, lessen the stress of the disease, and improve their lives [17].

The most widely used connected devices in the diabetes space are smart scales, blood pressure, glucose monitors, and activity trackers. The growing number and variety of devices available to individuals with diabetes are expected to alter the way the illness is managed fundamentally. These devices include wearable, tiny Electrocardiographs (ECGs) connected to heart health and "smart" socks designed to monitor foot temperature and prevent ulcers and inflammation. With so much untapped potential to improve the quality of life for persons with diabetes, research on innovative technology in diabetes care is still highly promising.

4.2. Artificial intelligence techniques

4.2.1. Machine learning technique types

Four broad categories may be used to classify Machine Learning (ML) methods [38] (Figure 4). These are the following:

1. Supervised learning: the algorithm infers a function from labeled training data.
2. Unsupervised learning refers to how the training system attempts to deduce the structure of unlabelled input.
3. Semi-supervised learning: a combination of the unsupervised and supervised techniques covered above, it operates with labeled and unlabelled data.
4. Reinforcement learning: where the system interacts with a dynamic environment.

4.3. Various methods employed by ML

4.3.1. Decision tree

The Decision Tree (DT) is a classification method that consists of a node within the tree and a node on the leaf with a class label. The Decision Tree's (DT) root nodes are the highest. This method is popular as it needs no parameters and is simple to build [18].

(1) Support vector machine

Support vector machines, or SVMs, were developed in the 1990s. This method is used for machine learning (ML) tasks, which are simple yet essential processes. A set of training samples, each broken down into many categories, is provided during this procedure. Murphy [39] states that Support Vector Machine (SVM) is a machine learning technique commonly used to solve issues with regression and classification.

(2) Bayesian Classification

One type of Bayesian classifier is a statistical classifier. Naive Bayes calculates the likelihood of class membership based on a given class label [19]. It does a single data scan, which simplifies classification.

(3) K-Nearest Neighbors

One well-liked technique for categorizing data is the K-nearest neighbors' method. We can determine a distance measure from N samples used for training [37].

(4) AdaBoost

Also known as adaptive boosting is a method of ensemble learning that uses an iterative approach to help weak classifiers improve by taking lessons from their mistakes. Whereas the random forest uses a "parallel ensemble," Adaboost uses a "sequential ensemble." Combining many underperforming classifiers creates a robust classifier that achieves high accuracy.

Regarding binary classification problems, AdaBoost works best when it enhances the efficiency of both decision trees with the base estimator [20].

(5) Logistic regression (LR)

A common probabilistic-based statistical framework used for machine learning classification issues is called Logistic Regression (LR). A logistic function is typically used in logistic regression to assess probabilities. It works effectively when the dataset can be divided linearly and handle high-dimensional datasets. The assumption of linearity among independent and dependent variables is a significant drawback of logistic regression. It may be applied to resolve problems with regression and classification. The majority of the time, it is used to address categorization issues [21].

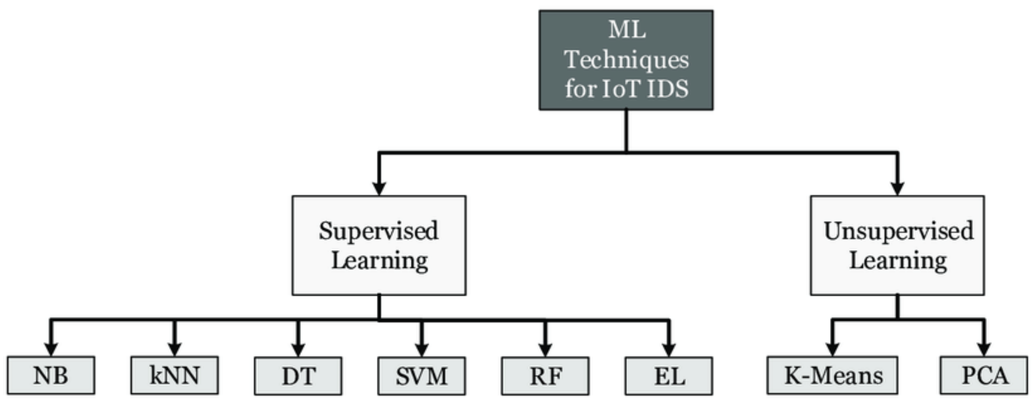

Figure 4. A taxonomy of ML techniques for IoT-based IDSs

(6) Continues Glucose Monitoring

The ecosystem surrounding diabetes management has undergone a radical change in the last ten years due to the creation of an Artificial Pancreas (AP) and the emergence of novel innovations such as Continuous Glucose Monitoring (CGM) devices and connected devices (smart watches, necklaces, patches, clothing, etc.). Additionally, the potential applications of the data collected by these new tools have revolutionized the field [22]. Strong AI techniques are available for creating models that anticipate blood glucose values, anticipate hypoglycemia, and forecast the appropriate dose of insulin to deliver. These models are intended to enhance the standard life and illness treatment for individuals with diabetes, create individualized care for every individual [23], and shield them from complications brought on by the disease and early mortality. [Figure 5] shows continuous glucose monitoring with Internet of Things (IoT) displays.

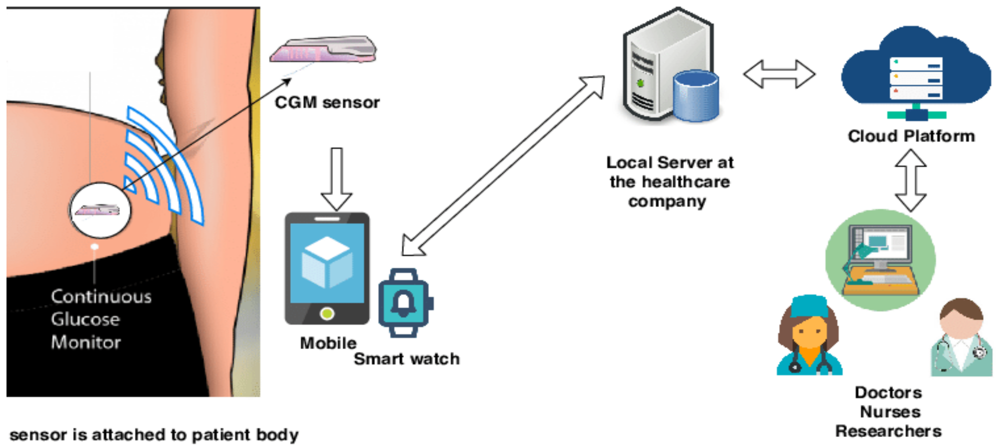

Figure 5. Continuous glucose monitoring using the Internet of Things (IoT)

Continuous Glucose Monitoring (CGM) will be used for one week every three months to measure blood glucose levels without needing a finger prick, given the low incidence of self-assessed blood glucose levels. To automatically enter biometric data, including blood pressure, weight, body fat mass, blood glucose level, and amount of exercise, into the integrated platform "Auto-check," a watch-type pedometer, scale with biological impedance evaluation, sphygmomanometer, as well as Bluetooth-enabled glucometer are used in conjunction with the platform. Medical professionals will oversee all the health data gathered and periodically give the individuals individual education and comments about nutrition, exercise, and weight control. This research aims to examine the effectiveness of an AI-based CGM system and a digital, integrated healthcare infrastructure in patients with diabetes mellitus.

Table 5. Distribution of articles by year for continuous glucose monitoring (PubMed Database)

S. No.	Year	Publication in PubMed
1.	2013	1
2.	2014	4
3.	2015	6
4.	2016	3
5.	2017	5
6.	2018	6
7.	2019	8
8.	2020	12
9.	2021	17
10.	2022	14
11.	2023	17
	Total	93

Table 6. Article type and total publications for continuous glucose monitoring during 2013-2023

Article Type (2013-2023)	Total Count
Systematic Review	2
Review	15
Randomized Controlled Trail	10
Meta-Analysis	0
Clinical Trail	12
Books & Documents	1

Between 2013 and 2023, 93 research articles on continuous glucose monitoring were published. The highest number of CGM research publications published in 2021 and 2023 was seventeen in 2022 and fourteen in 2023. The fewest publications on CGM were released in 2013 and 2016 were presented in [Table 5]. [Table 6] displays the article type and total number of publications from 2013 to 2023. A graphical depiction of this data is presented in [Figure 2]. Twelve papers involving clinical trials were published; the lowest number of publications was two systematic reviews, and the highest number of publications was fifteen review articles.

The goals and conclusions of the study are shown in [Table 7]. Out of the ten studies, eight (80%) dealt with patients. The database contained images of different meal components because one of the three remaining studies involved developing a smartphone application to help people with type 1 diabetes count the carbohydrates in their diet; the other two studies used virtual subjects to predict critical events and blood glucose levels.

Table 7. Summary of each selected article

S. No.	Authors	An overview of the study's findings
	Zecchin et al. [27]	This research discussed the development of a technology that can accurately predict blood glucose levels in diabetic patients for 30 minutes. This method relies on a feed-forward neural network, whose inputs are connected directly to the output neuron and the first hidden layer. The amount of carbs the patient supplies with their meal and the CGM data are the inputs for this method. The outcomes demonstrated that this approach offers a very accurate estimate of glucose concentration.
	Nuryani et al. [28]	This research develops a hybrid swarm-based support vector machine, or SVM, a technique that uses ECG readings as inputs to diagnose hypoglycemia. This method suggests using the Particle Swarm Optimization (PSO) strategy to improve the SVM and detect hypoglycemia. Our new SVM-RBF swarm-based hypoglycemic detection approach beats the competition with a sensitivity of 70.68%.
	Anthimopoulos et al. [29]	Creating a smartphone app to help type 1 diabetics keep track of their daily carb intake. Using the photographs captured by the smartphone, the prior outcomes, and the information supplied by the USDA nutritional database, the various components of the plate are identified, the portions of the multiple components are calculated, and the caloric intake of the meals is estimated. A mean absolute percentage error of 10 ± 12% was found in assessing the suggested carbohydrate measurement method.
	Allam et al. [30]	This paper proposes a new approach for predicting future levels of glucose using a prediction horizon (PH) of 15, 30, 45, and 60 minutes, utilizing an RNN (recurrent neural network) along with information from a CGM (continuous glucose monitoring) device. These predicted glucose levels can be used to develop early hypoglycemia/hyperglycemia alarms and to calculate suitable insulin doses. The feed-forward neural network prediction model (NNM) outcome is compared and contrasted with the outcomes of the suggested approach. The findings show that the RNN outperforms the NNM in predictions for relatively large prediction scopes.
	Cappon et al. [31]	the development of an innovative, creative way to classify postprandial glycemic states during meals (low blood sugar, high blood sugar levels, and euglycemia) and use its prediction to adjust the insulin bolus's delivery during meals. The XGB (extreme gradient boosted tree) model is the classification methodology used in this approach. It forecasts the future level of glucose in the postprandial

		period using data from CGM readings, estimates of carbohydrate consumption, and records of insulin infusion. The suggested XGB algorithm might be readily included in the insulin pumps already used or used as a standalone mobile application.
	Stolfi et al. [32]	This article examines the various variables contributing to the onset and progression of diabetes. To do this, the scientists created a computer model that resembles the immunological and metabolic alterations linked to the disease and outlines its origin. This approach will make it possible to identify early indicators of the disease's development and provide people with diabetes with a tool for self-evaluation. To create such a model, researchers employed 46,170 virtual participants.
	Tsai et al. [33]	To establish a connection between blood sugar levels (BGL) and the optical signals gathered, this study used wearable technology to collect PPG data from nine Type 2 diabetes patients. The study's findings demonstrated that glucose predictions may be made with 90% accuracy. An Adaboost model and the random forest regression algorithm were created to achieve this.
	Rghioui et al. [34]	Using sensors built into various portable devices, an intelligent system is being developed to enable continuous monitoring of diabetic patients' physiological conditions and allow physicians to remotely monitor these patients' health status (smartphones, smart watches, etc.). In addition to classifying blood glucose events, this system can forecast future blood glucose levels and assess the severity of different scenarios. Sequential minimum optimization, or SMO, OneR, ZeroR, J48, random trees, and naïve Bayes (NB) were the categorization techniques employed in this work. Several test results demonstrated 99.17% accuracy, 99.47% sensitivity, and 99.32% precision.
	Maritsch et al. [35]	illustrate the system's outstanding performance based on the J48 algorithm. This work suggests a machine-learning technique for identifying hypoglycemia using heart rate sensor variability data in smartwatches. A blood sugar level that is low (positive) or a blood glucose level that is normal (negative) is the binary choice that this hypoglycemia alert system must make to classify data. According to the gradient boosting tree of decisions (GBDT), the prediction model used for this assignment has a mean accuracy of 82.7%.
	Bunescu et al. [36]	A machine learning model was created that may notify patients about upcoming changes to blood sugar levels roughly 30 to 60 minutes in advance, assisting them in taking preventive action. An SVR model, or support vector regression, was used for this. The continuous glucose monitoring (CGM) device's past blood glucose readings, as well as regular occurrences like meals and insulin injections, are included in this approach.

5. Discussion

The design of Artificial Pancreas (AP) and the introduction of novel technologies such as wearables (smartwatches, bracelets, clothes, patches, etc.) and Continuous Glucose Monitoring (CGM) devices have completely changed the landscape of diabetes treatment in the last ten years [22]. Powerful AI techniques are available for creating models that predict blood glucose values, anticipate hypoglycemia, and determine the appropriate dose of insulin to deliver. These models are intended to improve the standard of life and illness management of individuals with diabetes, create individualized care for each patient, and protect them from complications from the disease and early death [23][24]. Providing optimal CGM technology integration in clinical practice poses many obstacles for healthcare professionals. Doctors must learn to use several brand-specific reports and software applications when working with personal or professional CGM systems. Despite efforts to standardize CGM review and interpretation, providers cannot access formal "CGM education courses" or systematic, standardized procedures [25]. Additional difficulties include the requirement for support personnel to upload CGM and pump systems and the time required to sort through several reports to get pertinent data and alter patients' regimens during the sometimes-constrained period of an office visit.

One of the best preventive measures for diabetics in high-risk persons is physical activity. Daily activity levels may be recorded with wearables that log steps taken and the length and intensity of activities. These devices make it possible to track daily activity, which might motivate someone to include exercise into their schedule to control their blood sugar levels better. Yom-Tov et al. [26] created a reinforcement-learning algorithm-based approach that customizes messages to each patient's unique situation to motivate patients to engage in physical activity. Acknowledging that longitudinal research will be necessary for further therapeutic applications to quantify intra- and inter-subject variability is imperative. However, because wearable can be expensive and technically challenging to install widely, conducting such research might take a lot of work.

6. Conclusion

The last 20 years have seen a significant increase in scientific interest in wearable technology in the healthcare industry, particularly for patients with chronic illnesses like diabetes. They can help avoid complications related to diabetes and aid in its treatment. Furthermore, both quality of life and diabetes management have improved using these devices. Patients must get proper training to benefit from CGM treatment fully. This training should cover topics including insertion techniques, calibration procedures for systems that still need them, and frequency and ideal timing of calibrations. Regular usage of CGMs and involvement in data evaluation and report notifications are essential to promote. It is best to set alarms and notifications gradually. Depending on the demands of each patient, it can be wise to put up hyperglycemia alerts later and solely hypoglycemia alerts during training to prevent alarm fatigue.

An extensive analysis of intelligent systems created as tools for managing diabetes is given in this article. In summary, big data-based analytics, the integration of artificial intelligence with diabetes data, and recent technology advancements are poised to bring about a paradigm shift in the treatment, prevention, and management of diabetes and its related conditions.

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