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AI-POWERED ADVANCED DIABETES MANAGEMENT WITH CONTINUOUS GLUCOSE MONITORING DEVICES

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ABSTRACT

Hyperglycaemia, a sign of diabetes mellitus (DM), is a major public health issue that is spreading quickly around the world. It leads to a lot of illness, death, and economic issues. Type 1 diabetes (T1DM), type 2 diabetes (T2DM), and diabetes during pregnancy are the three main forms of diabetes mellitus. Type 2 diabetes is the most common of these. even with improvements in pharmaceutical treatments, management is still difficult and calls for ongoing observation, lifestyle changes, and preventative measures. Recent developments in technology demonstrate how machine learning (ML) and artificial intelligence (AI) are transforming the treatment of diabetes. Automated retinal screening for diabetic retinopathy, clinical decision support systems, telehealth, mobile health apps, and predictive population risk stratification are a few examples of AI uses. Furthermore, glycaemic control and patient quality of life have improved when AI is combined with controlled insulin delivery systems, pumps for insulin, and continuous blood glucose monitoring (CGM). these advances are demonstrated by devices as Glucommander, Dexcom G7, Diab loop, and Medtronic Mini Med. Mobile apps with AI capabilities, such as Glooko, mySugr, and BlueStar, improve patient adherence and engagement even more. there are still difficulties, though, such as poor data quality, little potential validation, computational limitations, and human variables. prospects for the future focus on customized care based on biomarkers, lifestyle, and genetics, deep learning models for medical imaging, and predictive analytics for problems. In general, artificial intelligence is a game-changing technology for managing diabetes, with the promise to improve patient-centred outcomes, diagnosis, treatment, and prevention.

KEYWORDS: Continuous glucose monitoring, diabetes mellitus, AI, and machine learning.

1. INTRODUCTION

A chronic metabolic illness that affects people worldwide is hyperglycemia. The International Diabetes Federation (also known as the IDF) reports that 374 million individuals within the ages of 20 and 79 have a tolerance to insulin deficiency, while 463 million people have diabetes.[1] Diabetes is one of the non-communicable diseases with the highest epidemic rate due to its rapid rise in occurrence over the last thirty years. The International Diabetes Federation (2017) estimates that 425 million people worldwide have diabetes as of 2017; by 2045, that counting is anticipated to increase by 45% to 629 million.[2,3] Numerous comorbidities and a significant rate of morbidity and mortality are associated with hyperglycemia. diabetes should be prevented and identified early in addition to being treated. Despite accounting for 10% of global health expenditures (US$760 billion), diabetes is misdiagnosed in 1 in 2 cases, making treatment challenging. Clinical support for decisions, predictive populations risk assessment, automated retinal screening, and patient self-care tools are the four main areas of diabetes treatment where artificial intelligence is essential.[4,5] Diabetes is a major global issue that is getting worse every day due to causes like population growth, age, migration, rising rates of obesity, consumption of junk food, and inactivity. Diabetic complications account for the bulk of global costs, which negatively impact both the global market and the public health system. Type2 diabetes mellitus (T2DM), type 1 diabetes mellitus (T1DM), and gestational diabetes are the three main forms of the disease. In individuals with diabetes that is type 1, the immune system destroys pancreatic beta cells, which prevents the body from producing insulin. To survive, insulin from another source substitution therapy must be given for the remainder of one's life. According to the Diabetes Atlas Second Edition, type 1 diabetes is therefore a burden on the country, the healthcare system, the patient, and their family. The age at which symptoms first appear, however, is now no longer a decisive issue. The majority of T1D diagnoses occur in children and adolescents; adults are diagnosed less frequently. T1D is a serious chronic illness that necessitates daily care and a sophisticated treatment plan Regular plasma glucose testing, insulin administration, and careful consideration of the kind, quantity, and timing of meals and exercise are all part of this regimen. People with type 1 diabetes (T1D) and those who care for them must regularly monitor the glucose levels in their blood, typically between six and ten times a day, as failing to do so can have dangerous short-term and long-term effects.[6] Type 2 diabetes mellitus (T2DM) is a serious problem in the modern period due to its high mortality rate and numerous comorbidities. there is enough evidence to show that changing one's lifestyle can protect susceptible people from type 2 diabetes's onset and progression. Diabetes mellitus frequently necessitates therapy with several drugs and long-term lifestyle modifications to avoid complications.[7]

1.1. Retrospective Evaluation Of the Rising Incidence Of Diabetes Worldwide

According to the most recent data from the International Federation of Diabetes (IDF), 537 million adults worldwide suffer from diabetes. Compared to the IDF's previous projections for 2019, this amounts to a 16% (74 million) rise. According to estimates, there would be 643 million diabetes globally in 2030 and 783 million by 2045 if current rate continues. Compared to the current scenario, this would represent a 46% rise, which is more than the 20% population growth predicted for the same time frame. The most current IDF Diabetes Atlas shows that the prevalence of diabetes has risen to 10.5% globally, with more than half (44.7%) of people still without a diagnosis. In low- and middle-income nations, over 75% of adults with diabetes live. Over 90% of people with diabetes worldwide have type 2 diabetes. Type 2 diabetes is growing more widespread due to a complex interplay of social, demographic, environmental, and genetic factors. Eighty-one percent of these individuals reside in low- and moderate-income nations. The top three nations with the highest number of people suffering from diabetes are China (116.4 million), India (77.0 million), and the United States (31.0 million), according to the IDF 2019 study.[9]

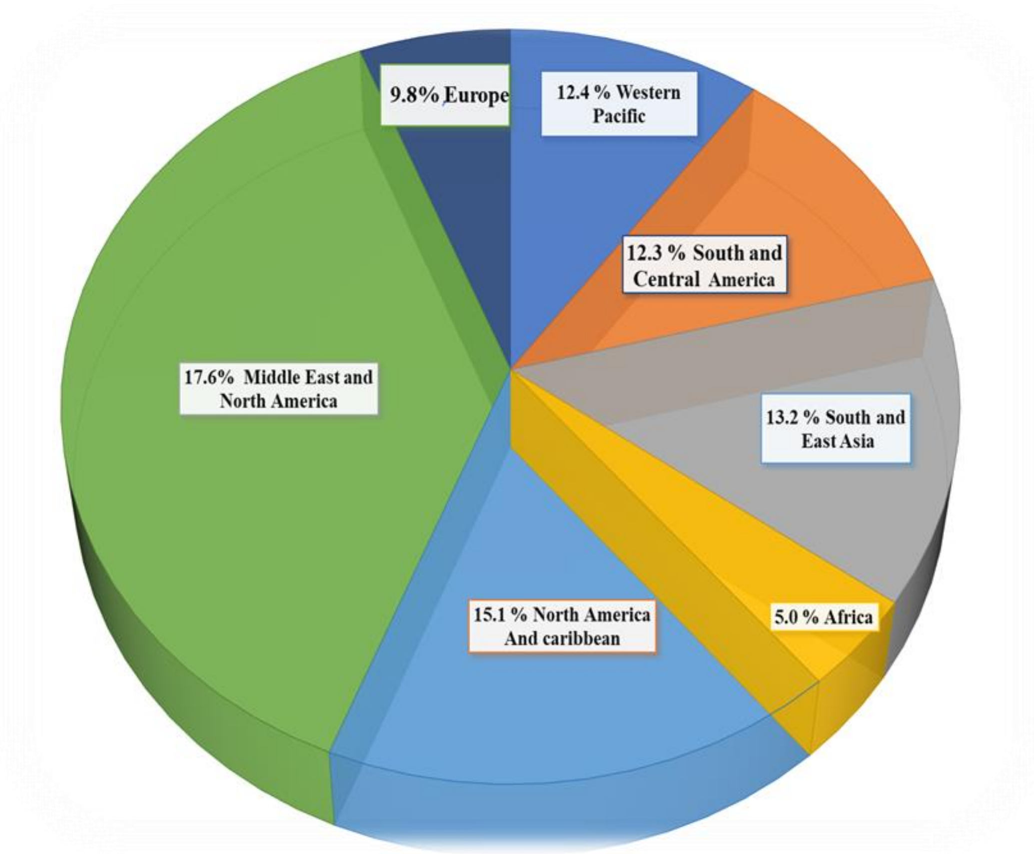

Fig. no. 1: Diabetes Mellitus Patient worldwide Status (2024).[9]

1. Artificial Intelligence in Healthcare

Afield of information technology that seeks to develop tools or systems that evaluate data and enable the management of complexities in a variety of applications. According to one definition, is artificial intelligence (AI).[10] in order to manage data effectively and develop technologies and tools for controlling the condition, it is also possible to use AI to diabetes. It is advised to have safe layouts, protection reserves, and procedure safeguards with all possible technological systems' uncertainties identified in order to produce safer technology employing AI.[11] Wearable technology, phones, and other devices that can help with ongoing surveillance and monitoring of an individual or condition's symptoms have been made possible by technological advancements. To properly manage diabetes, doctors and other healthcare providers should allow patients to select AI-assisted treatment.[12] The three main areas of management of diabetes that AI may influence and improve are patients with the condition, healthcare practitioners, and healthcare systems. (Fig.no, 2). AI has improved resource use in healthcare systems, incorporated additional aspects of diabetes patients' self-care, and given healthcare providers variable follow-ups and quick, dependable decision-making.

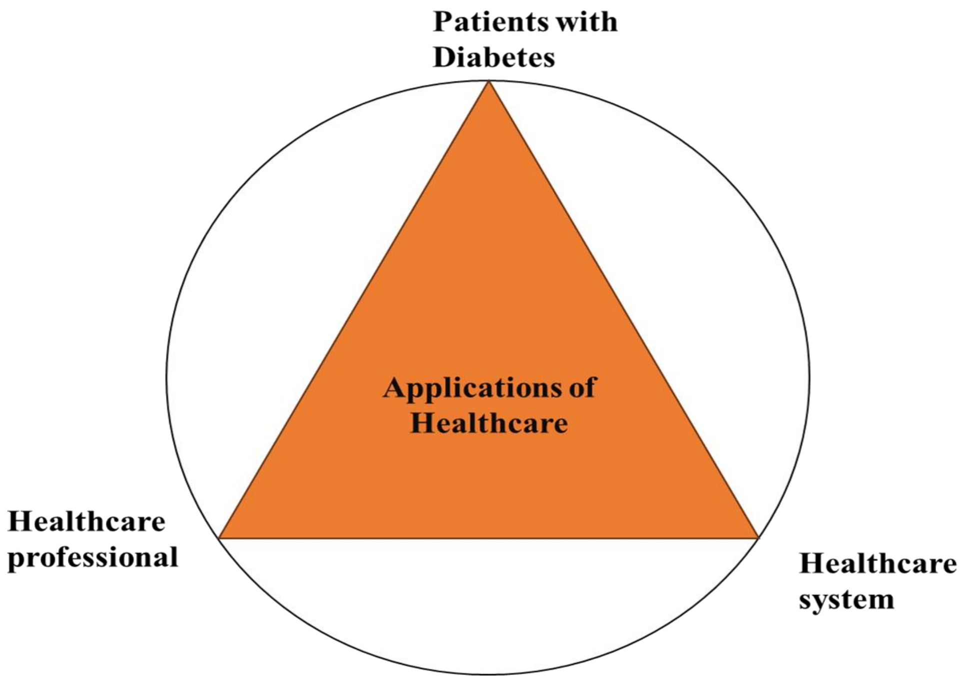

Fig. no 2: The application of machine learning(ML) and artificial intelligence(AI) to diabetes treatment.

1.1. Applications of Artificial Intelligence in Diabetes Care

Automated evaluation of the retina. Diabetic retinopathy has been diagnosed automatically using deep learning algorithms.[13] AI-based retinal scanning is a well-liked, reliable, and practical way to identify and track diabetic retinopathy. According to reports, automatic retinal screening has a high detection rate of 92.3% and an excellent specificity of 93.7%. Patient satisfaction is also high, with 96% of patients saying they are completely pleased or highly satisfied with automated testing.[14,15]

Support for Clinical Decision-Making. For patients with type 2 diabetes mellitus, supervised machine learning-based clinical decision support Tools for predicting the HbA1c response both immediately and over time after starting glucose have been developed. clinical factors that may affect a patient's HbA1c response can also be found with the aid of these tools. A general linear model based on basal HbA1c and estimated glomerular filtration rate, and which is based on elastic net regularizing, may be able to predict the HbA1c response after the introduction of insulin, according to reports. The matching AUCs were 0.81 (95% CI 0.79−0.84) and 0.80 (95% CI 0.78−0.83).[16]

Predictive Segmentation of Population Risk. A machine learning-based healthcare suggestions system (HRS) predicted a patient's risk of getting several diseases, including diabetes, by looking at their lifestyle, mental and physical health, or social media activity. Using data from 68,994 healthy people and diabetic patients, Neural networks, random forests, and choice forests have all been trained to accurately predict diabetes (accuracy = 0.8084 with all attributes).[17] using big data analytics, algorithms for prediction have been developed to evaluate the potential for issues in diabetic patients. Many models have been developed to predict the development of diabetes-related short-term (such as hypoglycaemia) and long-term (such as retinal, circulatory, and renal) issues.[18]

Other Uses. The treatment of diabetes has been transformed via telehealth. Remote monitoring reduces the time spent on subsequent appointments and allows for more real-time assessment of the patient's glycaemic status and overall health.AI has the potential to replace between 50% and 70% of normal follow-up clinical visits with remote monitoring and virtual engagements. A randomized controlled experiment including over 800 people suffering from type 2 diabetes is being conducted in sub-Saharan Africa to see whether SMS text messaging can improve medication adherence.[19]

2.2. Integration Of AI and Machine Learning for Diabetes Care

There are two primary categories into which AI approaches utilized in diabetes control and health management in general can be separated: machine learning and expert systems. An expert system is one of the most prevalent forms of artificial intelligence that helps caregivers with their daily tasks by storing expert knowledge, facts, and reasoning strategies. simulating a clinician's competence is intended to aid with decision-making. The most widely used ES in the subject of diabetes include fuzzy systems, rule- Based reasoning (RBR), and cases-based reasoning (CBR). RBR is based on transmitting expert knowledge to a computer through rules and conditions, whereas CBR applies prior knowledge to solve new issues that resemble examples from the past. on the other hand, fuzzy systems typically interpret expert knowledge and take into consideration degrees of uncertainty in class assignments. For example, a blood glucose level of 180 mg/dl is generally regarded as excessive. However, algorithms for learning (ML) refers to a machine's ability to learn over time without explicit programming. Machine learning algorithms are widely employed in the medical industry to extract useful information from enormous databases, including medical records. Among the machine learning techniques that are frequently applied in the field of diabetes management are decision trees (DT), supported vector machines (SVM), neural networks with nodes, genetic algorithmic algorithms (GA), and deep learning. In the literature, a large number of research have been carried out that predict and cure diabetes using machine learning approaches.[20] The fields of artificial intelligence and machine learning have attracted a lot of interest lately and become major topics in the technology industry. These methods, which are subsets of artificial intelligence, are used to forecast results, automate procedures, and extract knowledge from large databases. Deciphering patterns inherent in datasets is the primary focus of a sizable fraction of AI (see Fig.no. 3).This complex procedure not only enables machines to determine the best rules for behavior but also gives them the ability to adjust to changing environmental conditions.[21]

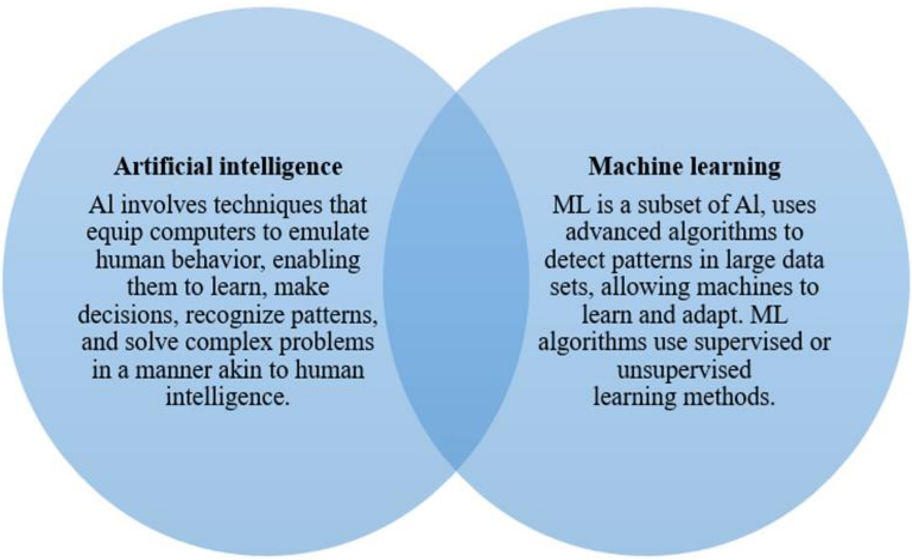

Fig. no. 3: A comparative analysis of machine learning and AI.

3. AI in Glucose Monitoring and Insulin Management

Specifically, over the past 20 years, sensors for continuous glucose monitoring, or CGM, have been created. For several days or weeks, CGM sensors monitor the interstitial blood glucose levels in the subcutaneous layer virtually constantly (for example, every one to five minutes).[22] CGM sensors de facto revolutionized interstitial glucose monitoring and opened up novel and intriguing possibilities for the daily management of diabetes.[23] In actuality, CGM sensors make it possible to monitor glucose dynamics and guarantee the timely identification of potentially asymptomatic high/low sugar events, which are challenging for SMBG to document. This contrasts with SMBG. The two primary types of CGM sensors are real-time and professional.[24] Medical providers usually prescribe professional CGM sensors for short periods of time. Since they use blinded methods to gather glucose concentration levels, the patient is unable to examine the data in real time. This allows the physician to review the patient's past glycaemic patterns and modify medication as needed. On the other hand, patients who utilize real-time CGM sensors (rtCGM) have instant access to the recorded data, which enables them to make more informed choices regarding their daily T1D therapy.[25] Furthermore, the development of multiple platforms and techniques for closed loop systems has been made possible by the combination of insulin pump devices and the growing accuracy of CGM systems, which have greatly improved the route toward automatic insulin delivery.[26] There are currently a lot of integrated CGM/insulin pumping technologies available for purchase.[27] likewise, there are a number of automated insulin delivery methods under investigation.[28] It is logical to assume that during the next five years, the switch to completely automated insulin administration systems may materialize. even with these noteworthy developments in diabetes technology, there are still enduring obstacles to the mainstream use of CGM. In the clinical context, routine integration of personal or professional CGM has not yet been optimised. This paper reviews the clinical benefits of personal and professional CGM, how it can be incorporated into daily practice, and how patients and practitioners can be barriers to wider adoption. Lastly, it proposes a straightforward, step-by-step method for reviewing and interpreting CGM data, which may be helpful for clinicians irrespective of the software or type of CGM system they use.[29]

4. AI Algorithms Used in Diabetes Care

Medtronic MiniMed 780GTM

Routine integration of professional or personal CGM has not yet been optimized in the clinical setting. The clinical advantages of personally as well as professionally CGM are reviewed in this study, along with how it might be integrated into routine practice and how both patients and healthcare providers may function as obstacles to its broader use. In addition to being a crucial tool for avoiding the negative effects of poor glucose management, new developments in diabetes technology have completely altered how diabetes is treated. Because of their increasing reliability, continuous monitoring of glucose (CGM) devices are at present the preferred method of monitoring for people with type 1 diabetes.[30] Because insulin pumps may duplicate physiologically insulin production through customized basal and bolus insulin delivery, they have been demonstrated to yield superior glycaemic results than insulin injection therapy.[31] The safety and quality of life for individuals with type 1 diabetes have been further enhanced by sensor-augmented pumps, which are the outcome of connecting pumps containing insulin with detectors to CGM (continuous glucose monitoring) systems to stop insulin delivery in the event of actual or anticipated low glucose levels.[32] A few automated insulin delivery (AID) devices have recently received approval for use in clinical settings. The first automatic insulin delivery (AID) device that was sold commercially was the Mini med TM 670G. In order to achieve a predefined sensor glucose target of 120 mg/dL, it automatically modifies the basal insulin injection rate using an altered PID (proportional integration derivative) algorithm. Glycaemic outcomes for both adult and paediatric participants have generally improved, according to data from observational studies and clinical trials.[33, 34]

Glucommander

Glytec Systems makes Glucommander available. This eGMS uses a multiplier based on the patient's weight and starting glucose target ranges to modify insulin dosage. Following that, the program suggests insulin infusion rates and blood glucose checks. Depending on how close glucose is to the target, the multipliers are changed. Numerous published research have demonstrated the effectiveness and safety of Glucommander in treating diabetes and hyperglycaemia in individuals in critical condition.[35]

Diabeloop DBLG1

Recently, automated insulin delivery has emerged as a highly promising therapy option for individuals with type 1 diabetes (T1D). following pivotal trials, regulatory bodies have approved a number of hybrid closed-loop technologies.[36, 37] The Diabeloop First Generation (DBLG1) CL device is a hybrid, single-hormone CL device with a self-learning algorithm that controls insulin supply based on CGM, CHO usage, and PA lasting more than 15 minutes.In a recent study, we demonstrated that DBLG1 totally prevented exercise-induced hypoglycemia in 14 patients who were free-living and fed an unlimited diet for three days. With its self-learning algorithm, the hybrid, single-hormone Diabeloop Generation-1 (DBLG1) CL system controls insulin delivery based on CGM, CHO consumption, and PA that lasts longer than 15 minutes. exercise-induced hypoglycaemia in 14 free-living patients who were given unlimited meals for three days was entirely reduced by DBLG1, as we have previously demonstrated.[38]

Dexcom G7

To enhance the G6 CGM's efficiency and capabilities, a seventh-generation CGM (Dexcom) was developed. The G7 uses a subcutaneous glucose oxidase-dependent sensor, which is identical to the G6 and has a 20-foot obstacle-free range. The G6 and G7 transmit data via Bluetooth with low power consumption, which may be accessed on a number of iOS and Android smart devices or on a specialized receiver. Every detector has a separate, single-use transmitter, and the G7's on-body component is 60% smaller than the G6's. Furthermore, the G7 and G6 offer autonomous session initializations, a 27-minute warm-up (as opposed to the G6's 2-hour warm-up), and a 12-hour (half-day) grace period at the conclusion of the detector's 10-day life cycle during which the glucose levels are still visible. If a gap in the data is detected by the receiver, the wearable part of the equipment may be asked to give up to 24 hours of missing information to display blood sugar levels that were unsuccessfully sent during data collection. As with G6, G7 cannot be affected by acetaminophen or ascorbic acid. Audio glucose warnings can be disabled for up to six hours, and users can modify the rate-of-change (RoC) alert settings.[39]

5. Artificial intelligence-Powered Diabetes Mobile Apps.

S.no	Apps	Descriptions	References
1.	**Blue Star (WellDoc)**	The FDA in the US authorized Welldoc, Inc.'s BlueStar diabetic management app in 2010.Its dual purpose is to encourage patients to continue their medication and hospital visits, as well as to enable physicians to efficiently monitor patients receiving home care. One patient intervention program that connects to a blood glucose monitor is called BlueStar. The effectiveness of medical consultations is increased by providing the medical team with a report on the patient's blood glucose levels, medication compliance, physical condition, and general status prior to each examination.	[40]
2.	**MySugr**	In order to help patients with the management of diabetes subjects that are recommended by the United States Association of Diabetes educators' healthy behaviours curriculum, the mySugr mobile app was developed in 2012.Glooko, A smart phone app and communication device for blood glucose meters, CGMs, and insulin pumps synchronizes with a HIPAA-compliant server.	[41,42]
3.	**Glooko (iOS and Android)**	Glooko is a smartphone software and communication tool for CGMs, insulin pumps, and blood glucose meters that interacts with a remote server that complies with HIPAA regulations. The patient's DM care team receives access to this data. Additionally, Glooko automatically integrates blood pressure, weight, and activity/exercise data with numerous popular lifestyle apps. The application for smartphones allows patients to record their insulin dosages, exercise routines, and carbohydrate intake.	[43]
4.	**Diabetes Diary**	A smartphone software called diabetes diary was created specifically for people with type 1 diabetes. In addition to serving as a bolus calculator, the software enables the wireless transfer of blood glucose (BG) readings by linking a mobile device with a Bluetooth adaptor that is attached to a BG meter. BG levels, insulin, food, and activity may all be tracked with the diabetes diary. It keeps track of past events so that patients can examine them by looking for comparable circumstances in the database.	[44]
5.	**Diabeo (Voluntis)**	A verified technique for adjusting insulin dosage based on premeal glucose levels in the blood, carbohydrate consumption, and expected physical activity is provided by Diabeo's bolus calculator. It also features an algorithm that adjusts basal insulin dosages, insulin pump infusing rates, and the diabetic/carbohydrate ratio based on postoperative or fast glucose readings. Diabeo does not provide link to electronic medical records. although it is only available in Europe at the moment, the product's developer has stated that it intends to launch it in the US. there have been reports of this product lowering A1C.	[45,46]

6. AI in the Treatment of Diabetes Complications

Diabetic Retinopathy and Macular Oedema. Diabetic retinopathy (DR) is the leading cause of preventable secondary blindness, and annual retinal exams have been advised. Among its drawbacks are the need for a qualified, experienced practitioner and the use of mydriatic drainage, which restricts the patient's schedule on that particular day of the examination. Automating the detection of diabetic eye disease and coronary risk factor monitoring has been made possible by the availability of huge retinal fundus examination datasets with specificity and sensitivity above 90%.[47,48]

Decision Support in Clinical Practice. Machine learning can forecast both the short- and long-term HbA1c responses of type 2 diabetics when they start taking insulin. A generalized linear model based on the beginning HbA1c and glomerular filtering rate and elastic network regularizing may predict both the short-term and long-term HbA1c responses.[49]

Hypo-and Hyperglycemias. Continuous glucose monitors (CGMs) and flash glucose monitors (FGMs), which have just entered the market, have demonstrated promise for efficient blood glucose control in both type 1 and insulin-requiring type 2 diabetes.[8] Real-time measurement of glucose levels changes can enhance control of rapid oscillations and management of blood sugar, particularly in patients who need frequent insulin injections, according to studies using CGM, such as the Free Style Libre (produced by Abbott Abbott Healthcare Care, Alameda, CA, USA).[50]

7. Limitations of Artificial Intelligence

Limitation of Laboratory-Based Diagnosis:-Accuracy and implementation practicality are the two primary issues that limit laboratory-based diagnosis. Potential pre-analytical mistakes include contaminated samples and faulty blood glucose strips can affect accuracy. The timing of the examination, patient medications, and environmental factors can all affect the results and cause results to be misinterpreted. For example, people with iron deficiency may have slightly elevated HbA1c readings, which could compromise the accuracy of the diagnosis. Inadequate processing or improper storage of samples can sometimes result in falsely low glucose contents.[51]

Limitations of Design:- Current AI models and their utilization in diabetes treatment were validated using retrospective data sets. If these technology developments are prospectively proven, automating diabetes care would be feasible.[52]

Human Factors:- Several research have examined the factors that impact the usage of AI in diabetic management. According to a metaanalysis of 14 randomized control trials, younger patients benefited more from diabetes care mobile apps, and the impact size increased with feedback from medical professionals.[53]

Limitations of Artificial Intelligence Models Based on DM:-The lack of clinical factors, labeling errors, poor picture quality, data imbalance, difficulties identifying the severity of the disease, lack of data, and algorithmic technical restrictions were among the drawbacks of The development of artificial intelligence-based imaging analytical models for diabetes that were examined. A variety of problems, such as poor data and imagery quality and difficulties in categorizing specific diseases, hindered the development of AI diagnostic models.[54]

Diagram Artificial Intelligence(AI) Based Medical Images in Diabetes Mellitus

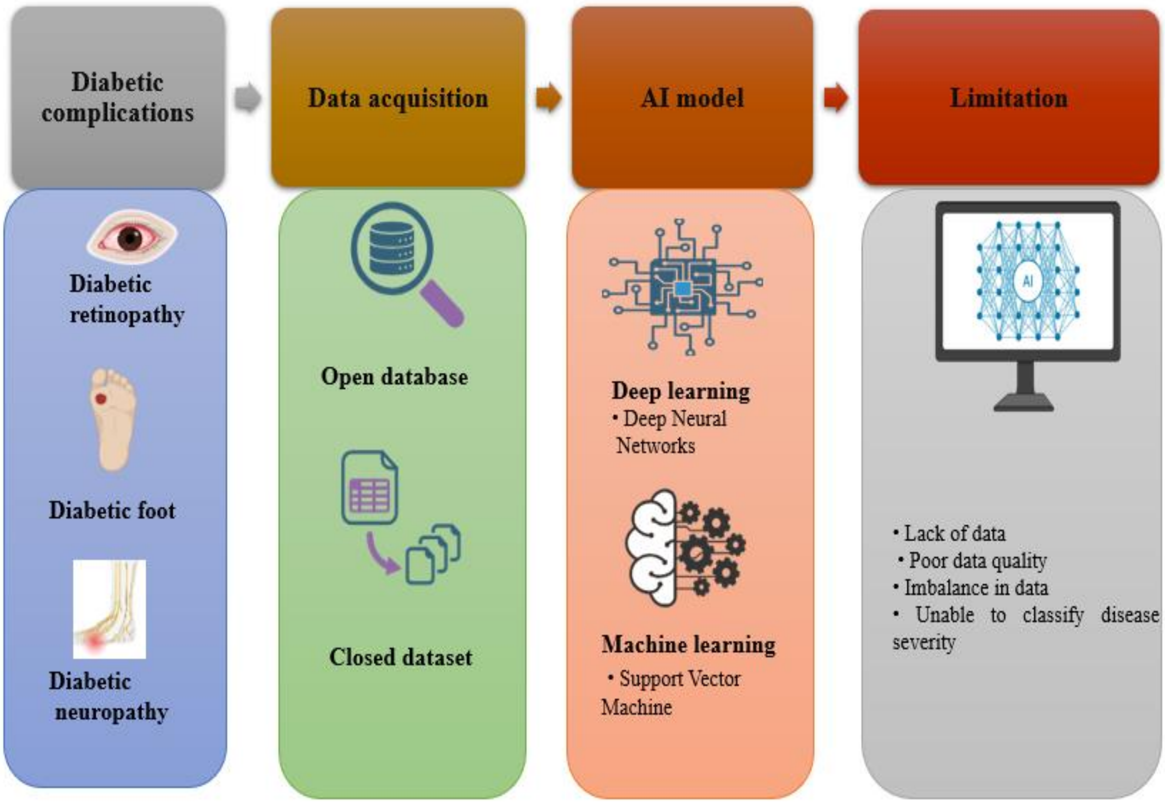

Fig. no. 4. Diagrammatic depiction of medical imaging using AI in diabetic mellitus AI = artificial intelligence.[55]

8. AI's Future Prospects in DM

The most prevalent diabetes consequence in the research this study looked at was diabetic retinopathy (DR). Open image and data data collecting were widely used in the development and validation of AI models using medical pictures. It is specifically hypothesized that certain studies on autonomous screening and diagnosis techniques are connected to DR due to a number of publicly accessible datasets. Advanced anomaly detection, which employs the recognition and segmentation of objects based on medical images to support clinical decision-making by physicians, has recently developed from the rapid and simple recognizing of diabetic complications using AI technology.[56] Deep learning methods are being researched and developed for use with medical pictures after demonstrating favourable outcomes in artificial intelligence(AI) and analysis of images tasks.[57] Apart from DR, artificial intelligence has been investigated for the diagnosis of several eye disorders, such as glaucoma, epiretinal membrane, retinal vascular occlusions, and age-related macular degeneration, which is one of the main causes of blindness.[58] Giving people individualized medical care:- customizing precision medicine to a person's genetics, environment, lifestyle, biomarkers, and other variables is the goal of personalized medicine, sometimes referred to as individualized treatment.[59] By offering focused interventions that are safe, effective, and efficient, the goal is to improve patient outcomes.[60,61]

9. CONCLUSION

Hyperglycaemia -driven diabetes mellitus is still a leading worldwide health concern, with increasing incidence, complications, and financial costs. novel approaches to diabetes care have been made possible by recent developments in artificial intelligence (AI). These include continuous glucose monitoring, insulin administration systems, clinical decision support, predictive analytics, automated retinal screening, and mobile health apps. Precision and individualized care are made possible by these technologies, which also improve glycemic control, increase early diagnosis, improve treatment adherence, and lower consequences. however, constraints including human factors, implementation viability, and data quality need to be addressed. AI has the ability to completely transform diabetes care globally when combined with clinical knowledge and patient-centred care.

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