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APPLICATION OF CLOSED-LOOP THEORY IN DEEP LEARNING TRAINING GUIDED BY HIGH-STRENGTH INTELLIGENT MACHINERY

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Abstract. Artificial intelligence (AI) algorithms and continuous monitoring technologies have the potential to transform the way chronic illnesses are managed. We will also talk about the problems and potential that AI technology presents for CGM in individualised and preventive medicine. Furthermore, we assessed the AHCL system's usefulness in patients with impaired awareness of hypoglycemia (IAH) and those who correctly recognised hypoglycemia symptoms. The participants' ages varied from 37 to 15, and they had received diabetes medication for an average of 20 to 10 years. IAH was seen in 12 individuals (27%) with a Clarke's score of less than 3. Patients with IAH were older than those who did not have IAH. The baseline CGM readings and A1c were the same, but the estimated glomerular filtration rate (eGFR) was lower. Despite prior insulin treatment, the AHCL system resulted in an overall drop in A1c (from 6.9 0.5% to 6.7 0.6%, P 0.001). Only three patients (7%) received Clarke's three scores after six months on the AHCL system, resulting in a 20% absolute risk decrease for IAH (95% confidence interval: 7-32).

Key words: Artificial intelligence, machine learning, glucose monitoring in a closed loop.

1. Introduction. In recent years, deep learning technology has made significant breakthroughs in various fields, from natural language processing to computer vision, as well as autonomous driving. However, to make machines more intelligent, more high-strength intelligent machinery is needed to guide the deep learning process. In this context, the application of closed-loop theory has become particularly important. Closed loop control is a method of controlling a system by continuously monitoring and adjusting the system's output to achieve specific goals or maintain the system's operation in the desired state. This theory has been widely applied in automation, engineering, and control systems, but its application in the field of deep learning is still in the exploratory stage. Diabetes mellitus is a worldwide and chronic disease caused by a difficulty with glucose metabolism. By 2030, it is expected that there will be 439 million adult diabetes globally, costing roughly $490 billion USD. Diabetes and its complications are mostly caused by abnormalities in glucose metabolism. However, such monitoring cannot immediately detect the functions of hyperglycemia. The growth of continuous glucose monitoring (CGM) is a developing area of interest, which will rely heavily on technological advancements that have taken decades to perfect. Wearable CGM biosensors have recently experienced tremendous growth in popularity, with sales exceeding $1 billion. When controlling diabetes, CGM has a few advantages to finger stick blood glucose monitoring [8, 9]. First, CGM has several advantages over the traditional capillary blood glucose measuring method, including the removal of psychological and physical pain. Despite the rapid advancement of CGM technology, several barriers, like cost, lag time, the need for calibration, and others, still prevent its widespread usage. The main topics have been well-reviewed. The evolution of CGM and wearable CGM biosensors is examined in this article. Unfortunately, patients with IAH are underrepresented in clinical studies, and more research is required on how to use automated insulin delivery systems to restore hypoglycaemia awareness. To better understand this, we examined a prospective cohort of 46 T1D patients who had transitioned to an autonomous insulin administration device and then underwent CGM or flash glucose monitoring (FGM) [7, 4].

Several types of type 2 diabetes mellitus are available. They can be used in various ways, including evaluating long-term clinical outcomes, assessing the costs of clinical trials, and assisting in choosing the most appropriate interventions for these populations. The Dexcom system was regarded as a helpful study aid. The effectiveness of a new, powerful algorithm-equipped Dexcom was evaluated. Suitable modelling techniques are used to anticipate future glucose concentrations. The high-precision and real-time data transmission of the

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Dexcom system helps to ensure the accuracy of research data. This is crucial for the reliability of the research results. The Dexcom system not only provides current blood sugar levels, but also monitors blood sugar trends. This is very useful for studying the triggering and duration of hypoglycemic or hyperglycemic events. The real-time data transmission of the Dexcom system allows patients to more easily monitor their blood sugar without the need for frequent fingertip blood sugar tests. This can improve patient engagement and research execution. With time, the continuous glucose monitor's accuracy and consistency increased, with the most significant improvement. The results show that signal processing-induced time delays have been reduced, and low plasma glucose performance has been improved [12, 1, 6, 22, 10]. Performance enhancements for sensor systems are envisaged as a result of these upgrades. Thanks to this application, which keeps blood glucose levels steady, reaction times are slowed when glucose is consumed. The results of this study can also be used to improve closed-loop systems and provide data for insulin pumps. Future work may have a foundation thanks to these findings. People with long-term diabetes become more mindful of how low blood sugar affects their bodies. This programme can assist in preventing hypo and restless periods since it can identify hypo and hyper periods even before the drop or rise in blood glucose level has fully begun. It can, however, also result in an unexpected change in consciousness. This application successfully maintains a constant blood glucose level because glucose eating reduces blood glucose level reaction times. After testing this application with real-time data from a continuous glucose monitor, the algorithm will be enhanced. A single programme that covers every available sensor would also be the ideal use case. The outcomes of this study can also be used to teach insulin pumps and improve closed-loop systems [18, 11, 20, 13].

2. Literature Survey. An autoimmune condition known as type 1 diabetes mellitus necessitates ongoing patient care. We demonstrated the viability of a model-based Reinforcement Learning strategy for a fully automated artificial pancreas that is safe for humans. The architecture used can control blood sugar levels without the requirement for meal notification because it doesn't need to know how much CHO was consumed. The average results demonstrate that the created controller can automatically and effectively regulate blood glucose levels for simulations lasting up to 12 hours and incorporating two meals. It is feasible to look into this exploratory work further [2].

This study differs from others in that it makes use of artificial intelligence. Technology in a supply chain and reverse logistics' garbage recycling section. In this paper, a design for CLSC pomegranates is proposed. The corresponding logistics network, developed for years, includes producers, distribution centres, customers, and compost end consumers. In the current study, a MOO model of a sustainable CLSC is presented. Reduced network costs and energy consumption are the chain's reverse logistic operations' goals, including rubbish recycling. An effort has been made to evaluate and validate the identified issue through a case study on pomegranates in Iran. The fruit is transformed as planned along the supply chain into food, pharmaceuticals, and concentrate after delivery and distribution. Through reverse logistics, the pomegranate waste is also transformed into recycled goods like compost, an organic fertiliser, and ethanol, which may be used as a sustainable energy source and alternative fuel for vehicles—several methods used to produce pomegranates. Automation cuts personnel costs and shipping expenses, which significantly lowers chain pricing. Using image processing to diagnose pomegranate quality ensures compliance with international standards. Manufacturers have also experienced severe problems with waste and damaged products. The organization's economic, social, and environmental aims can all be accomplished through this framework. The findings of this study may be helpful to businesses and managers who work with food, crops, and other items that have a chance of failing [25].

Two meta-heuristic methods are employed. The three answers are compared, and the problem is also addressed using the GAMS program.

- This will modify the research's findings. The mathematical model is then built using the data that was collected.

Also, here are a few suggestions for future research:

- Using the fuzzy set technique to estimate the degree of ambiguity in pomegranate demand
- Solving the given model using a sound optimization technique and treating it as a scenario-based model.
- Consider a cooperative game between pomegranate growers and the government from the game theory perspective [5].

Based on these forecasts, patients choose the optimal strategy to control their blood sugar levels, considering things like insulin dosage and other relevant factors. Machine learning (ML) techniques can be used to model glucose level trends to forecast this variable accurately. It is challenging to directly run complex machine learning algorithms on restricted devices due to their poor processing capabilities. Machine learning (ML) technology can be used to simulate trends in blood sugar levels to accurately predict this variable. The ML algorithm can train models based on past blood glucose data, lifestyle factors, dietary habits, medication treatment, and other factors to predict future blood glucose levels. This model can help patients with diabetes better manage their blood sugar, predict potential hyperglycemia or hypoglycemia events, and take corresponding measures to avoid dangerous situations. Performance, edge computing, and the usage of lightweight machine learning techniques. Despite these limitations, feature extraction and pre-processing allow machine learning techniques to be applied to constrained devices. It is crucial to compare the computational needs of machine learning methods for forecasting as this might significantly impact how well-suited they are to restricted devices. A capable device could easily handle the computational requirements of the random forest technique for short datasets. Many times, with some limitations, random forest-based forecasting tasks can be managed by restricted devices. Given the characteristics of the volunteers, the present study, which collected measurements from 40 patients with diabetes, may have some limitations. Although the glycaemic control levels in our sample ranged widely, it is possible that individuals who performed inaccurately could hurt the standard of diabetes management. It might lead to more individualised and accurate glucose level projections, enabling more effective management of diabetes [19].

3. Materials and Methods.

3.1. Research plan. In our prospective study, 46 T1D patients who frequently attended the diabetic outpatient clinic at an academic hospital in Madrid, Spain, and were monitored by CGM or FGM took part. (ClinicalTrials.gov identifier: NCT04900636). Extending invitations to all T1D patients who met the research eligibility requirements, we used consecutive sampling to reduce sample bias. Approved national laws carried out the study, the 1964 Helsinki Declaration, and its following amendments [17].

3.2. Study participants. Consecutively, we sought out adults at least 18 years old, had had T1D for more than a year, and were closely watched by CGM or FGM. Prior episodes of ketoacidosis and diabetic autoimmune disease were required for the diagnosis of T1D, and the usage of insulin was essential for survival after them American Diabetes Association standards. The following were listed as exclusion criteria:

1. Identifying forms of diabetes mellitus outside type 1 diabetes (T1D).
2. Lack of ability to receive the instruction or learn the information necessary to operate a computerized insulin delivery device [15, 14].

4. Experimentation and Results.

4.1. Data gathering and evaluation.

4.1.1. Hypoglycaemia with diminished awareness as measured by the Clarke score. A hypoglycaemia incident is a hypoglycaemic episode requiring outside help to administer therapy. A hypoglycemic event, also known as a hypoglycemic episode, refers to a decrease in blood sugar levels to a dangerous level that requires external intervention or treatment to correct the condition. Under normal circumstances, the blood sugar level in the human body fluctuates within a certain range, but when the blood sugar level is too low, it may lead to a series of physical and neurological reactions that may endanger the patient's health. The Clarke questionnaire has already been verified using hypoglycaemic clamping, both prospective and retrospective records of extreme hypoglycaemia in the T1D patient group, according to L. Nattero-Chavez et al. Diabetes Research and Clinical Practice 199 (2023) 110627. The participants' knowledge of hypoglycaemia symptoms was assessed using a reliable and validated 8-item survey, and the results were used to determine Clarke's score. The frequency of hypoglycaemic episodes that participants had encountered in the two months prior and their symptoms' during hypoglycaemia was disclosed. Each response received either an "A" for awareness or an "R" for cognitive impairment. Each R response was worth 1, compared to each A [3, 16, 21, 23, 24]. Figure 3.1 describes the schematic of artificial intelligence used to manage diabetes. Continuous glucose monitoring, or CGM.

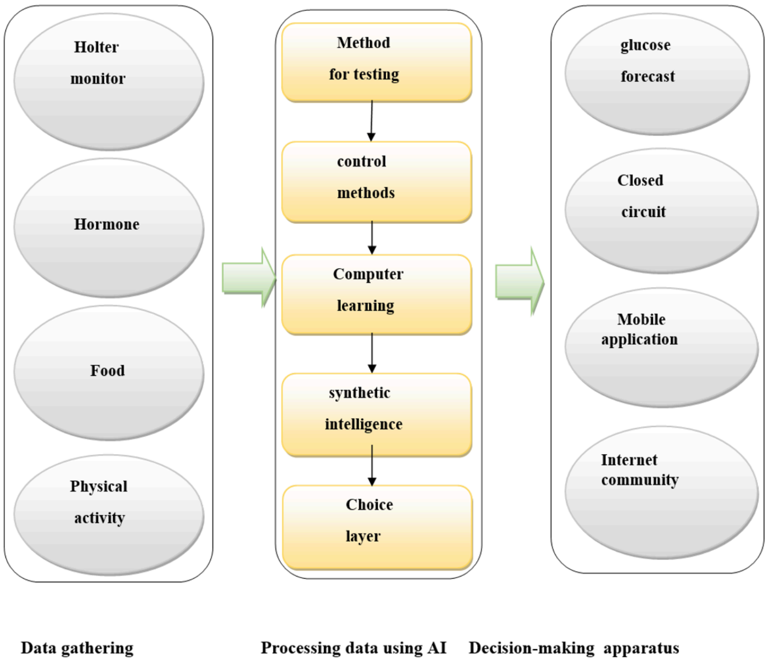

Fig. 3.1: Schematic of artificial intelligence used to manage diabetes. Continuous glucose monitoring, or CGM.

4.1.2. Artificial intelligence for CGM biosensors. Instead of conventional screening methods, artificial intelligence is being utilised to diagnose diabetic macular oedema and moderate diabetic retinopathy. Several diabetes control application scenarios have shown potential for combining CGM and machine learning. The artificial intelligence application of continuous glucose monitoring (CGM) biosensor is an important technology that can help diabetes patients better manage their blood glucose levels. The resources for patient self-management, an automated retinal screening, closed-loop control, and calibration are all included. A biosensor with artificial intelligence that continuously monitors the amount of glucose is shown in Figure 4.1. Patients put on a continuous glucose monitor (CGM) sensor that wirelessly feeds data to a smartphone while continuously checking glucose.

4.2. Algorithms for closed-loop controls. The closed-loop control algorithm, also known as feedback control algorithm, is an automatic control method in a control system. Its basic principle is to adjust the input based on the output feedback information of the system to achieve the desired goal or maintain stable operation of the system in the expected state. These algorithms are widely used in automation, engineering, medical equipment, and other fields, where real-time adjustments are required to the system to respond to changes or maintain performance. People with T1D must use insulin therapy and frequently adjust their dosage to meet their glycemic goals [10]. Hence, closed-loop control systems. The MPC algorithm predicts glucose levels and modifies insulin delivery using a dynamic model based on fictitious output data [6, 10]. Even though a closed-loop technology that automatically regulates blood glucose has been commercially accessible, some patients may still find using an artificial pancreas unreliable and potentially stressful. Figure 4.2 defines an advanced hybrid closed-loop system for hypoglycaemia awareness was implemented, and baseline and six months later results were compared and Figure 4.3 deals with an variations in the concentration of glycated haemoglobin (A1c) were seen six months after switching to an advanced hybrid closed-loop system (means SD).

Data represent mean SD.

Observable variations between T0 and T2 -x

There are notable distinctions between T0 and T6-y

Differences that are statistically significant between T2 and T6-z

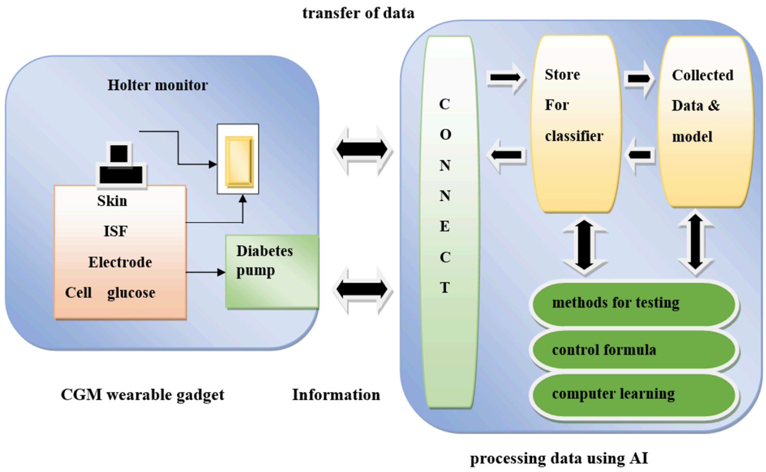

Fig. 4.1: A biosensor with artificial intelligence that continuously checks the level of glucose. Patients apply a continuous glucose monitor (CGM) sensor to their skin, which wirelessly transmits data to a smart phone while constantly monitoring glucose l.

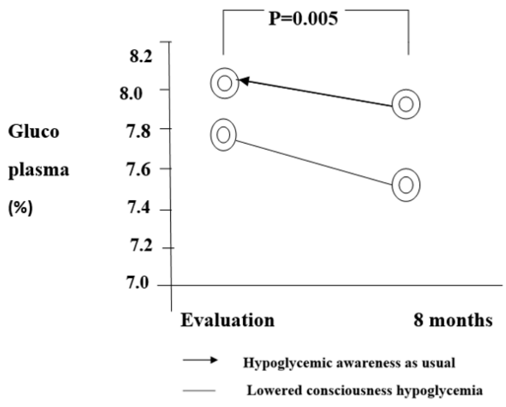

Fig. 4.2: An advanced hybrid closed-loop system for hypoglycaemia awareness was implemented, and baseline and six months later results were compared.

Substantial variations between the IAH group and the regular IH group=w

5. Conclusion. In its conclusion, this research analysed the advancement of CGM and emphasized the interaction between CGM performance and AI. CGM biosensors aim to revolutionize patient care for treating diseases like diabetes. The primary barriers to the widespread use of CGM biosensors are the cost of supplies (35.3%), accuracy (30.1%), and discomfort with having devices on one's body (29.7%). However, the evolution of CGM technology is moving in the direction of adaptability, downsizing, and long-term closed-loop systems. The goal of developing AI-powered CGM biosensors is being met. First, it should be emphasised that the physiological lag time and the CGM sensor's effectiveness impact the well-known lag between blood glucose and ISF glucose. An additional factor for T1D is the price. Closed-loop decision-making based on CGM sensors, as well as data adaptation and learning, are essential. But even before the next technology revolution, AI is being created for biosensors, opening the door to medical advancements. We've already covered the enormous amounts of data created by continuous monitoring and the three ways AI enhances CGM performance. They

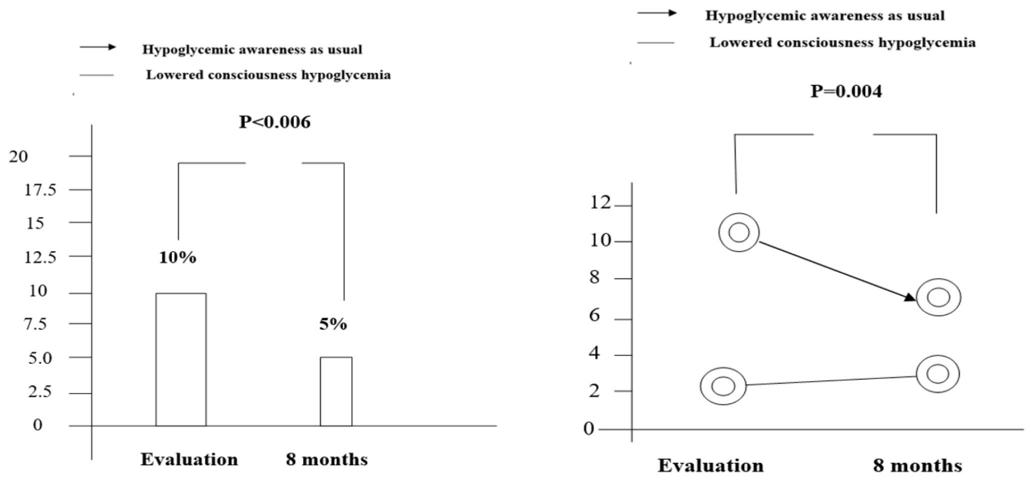

Fig. 4.3: Variations in the concentration of glycated haemoglobin (A1c) were seen six months after switching to an advanced hybrid closed-loop system (means SD).

Table 4.1: Based on the presence or absence of impaired awareness of hypoglycemia (IAH), maintains glucose monitoring metrics, biochemical parameters, and insulin dosages at baseline (T0), two months later (T2), and six months later (T6). After switching to an advanced hybrid closed-loop system, this is done.

Factor	Baseline(T0)		After 3 months (T2)		After 8 months (T6)		P
	Normal IAH n=18	AH n=44	Normal IAH n=18	AH n=44	Normal IAH n=18	AH n=44	
variables for continuous glucose tracking							
TBR <80 mg/dL	0.4±0.9	0.9±0.12	0.7±0.89	0.12±0.12	0.2±0.89	0.2±0.1	NS
TBR <100 mg/dL^{x,y}	10±15	9±9	80±19	9±7	60±1	4±4	0.02
Total TBR <100 mg/dL^{x,y}	10±15	9±9	18±65	5±9	8±5	5±9	0.013
TIR 100 and 210 mg/dL^{x,y}	90±10	80±20	50±40	40±90	90±0.10	4±20	<0.004
TAR >210 mg/dL^{x,y}	30±8	35±20	50±7	33±70	5±9	33±70	<0.004
TAR >300 mg/dL	6±9	4±9	8±10	3±10	6±40	1±40	NS
Total TAR >210 mg/dL^{x,y}	40±20	34±23	80±30	3±7	8±0.3	3±67	>0.003
Other results							
Average sensor use(%)	120±10	100±4	0.9±0.56	02±0.12	0.9±0.56	0.3±0.2	0.003
GMI(%)	8.1±0.6	29±4	90±49	5±7	90±49	4±70	0.001
ordinary sensor glucose^{x,y}	200±23	45±5	38±85	2±7	38±85 70±20	4±7	0.004
sensor glucose CV(%)^{x,y}	28±20	67±9	70±20	50±97	7±6	67±7	NS
sensor glucose SD(mg/dL)^{x,y}	53±13	78±12	7±6	35±80	4±1	5±0.4	0.007
closed-loop system duration(%)	-	4±6	4±1	3±90	90±40	6±0.60	0.008
everyday carbohydrate intake(gr/d)^{W}	-	-	90±40	7±7		4±2	NS
Biochemical factors							
fasting blood sugar(mg/dl)	230±45	56±6	-	-	40±5	56±6	0.05
eGFR(mL/min/2.35 m^2)^{y}	120±5	67±6	-	0.5	10±70	67±6	0.065
UACR(mg/g)	15±3	7±3	-	1	1±2	7±3	NS
A1c(%)$^{y^{W}}$	9±0.9	35±8	-	0.2	67±012	35±8	NS
BMI & daily insulin dosage							
Daily total insulin dose(U/kg)^{z}	0.66±0.32	0.6±0.78	0.6±0.32	0.1±0.38	0.6±0.2	0.6±0.8	0.056
Daily basal insulin(U/kg)*	0.50±0.90	0.90±0.10	0.90±0.10	0.10±0.10	0.5±10	0.9±0.10	NS
Daily bolus insulin(U/kg)^{y}	0.6±0.67	0.40±0.87	0.10±0.7	0.01±0.6	0.4±0.7	0.5±0.67	0.090
Bolus of automatic correction(U/kg)^{z}	-	-	-	-	-	-	0.056
Normal BMI(Kg/m^2)	39.6±6.8	0.9±0.5	17.6±6.8	0.20±0.5	39.6±6.8	0.9±0.2	0.001

will probably soon open the door for individualised care. Ultimately, closed-loop therapeutic technology is the best amalgamation of CGM and AI, providing many clinical possibilities and scientific advancements in artificially intelligent biosensors and medicine. It's critical to underline the clinical relevance of these findings. Although we have made some encouraging progress, the application of closed-loop theory in deep learning is still an evolving field. Future research can explore more complex closed-loop control methods and more advanced machine intelligence systems to further improve performance.

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