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IOT Based Continuous Glucose Monitoring for Diabetes Mellitus using Deep Siamese Domain Adaptation Convolutional Neural Network

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Abstract—The phrase "Internet of Things" (IoT) refers to the forthcoming generation of the Internet, which facilitates interaction among networked devices. IoT functions as an assistant in medicine and is critical to a variety of uses that monitor healthcare facilities. The pattern of observed parameters can be used to predict the type of the disease. Health experts and technologists have developed an excellent system that employs commonly utilized technologies like wearable technology, wireless channels, and other remote devices to deliver cost-effective medical surveillance for people suffering from a range of diseases. Network-connected sensors worn on the body or put in living areas collect large amounts of data to assess the patient's physical and mental wellbeing. In this Manuscript, IoT -based Continuous Glucose Monitoring for Diabetes Mellitus using Deep Siamese Domain Adaptation Convolutional Neural Networ k (CGM-DM- DSDACNN) is proposed. The goal of the work that has been described to investigate whether Continuous Glucose Monitoring System (CGMS) on the basis of IoT is both intrusive also secure. The job at hand is for making an architecture based on IoT that extends from the sensor model to the back-end and displays blood glucose level, body temperature, and contextual data to final users like patients and doctors in graphical and text formats. A higher level of energy economy is also attained by tailoring the Long range Sigfox communication protocol to the glucose monitoring device. Additionally, analyse the energy usage of a sensor device and create energy collecting components for it. Present a Deep Siamese Domain Adaptation Convolutional Neural Network (DSDACNN) as a last resort for alerting patients and medical professionals in the event of anomalous circumstances, like a too -low or too-high glucose level.

Keywords-1.Diabetes Mellitus, 2.Deep Siamese Domain Adaptation Convolutional Neural Network - , 3.Long range sigfox communication protocol, 4.Social Networking Sites

I. INTRODUCTION

The IoT can be thought of as a dynamic network that connects both real-world and virtual objects[1, 2].The Internet of Things (IoT), includes cutting-edge technology like Wireless Sensor Networks (WSN), Artificial Intelligence (AI) &Cloud Computing (CC), is crucial in a variety of industries, including robotics, logistics, transportation, and medical caring [3]. One method for distant and present e-health observing, for instance, is provided by IoT-based health care systems that include sensors, WSN, smart gateways, and Cloud [4]. The creation of e-health and wellness applications now has a creative foundation thanks to WSN advancements [5]. Smart houses, ambient assisted living, and ambient intelligence are all gaining popularity. These may be coupled with other health solutions such applications for tracking food or nutrition, managing chronic diseases, and exercise and wellbeing [6, 7]. Instead than being divided into monitoring and decision-making processes, the new initiatives frequently integrate into the ecosystem of patient information.

Potential advantages of an ageing population include the ability to monitor and treat older persons in the convenience of their own homes [8, 9]. Wireless technologies for fully autonomous health monitoring offer a wide range of practical uses [10]. The measuring of glucose levels for diabetics is one of these applications. A significant health risk is diabetes. In 2012, more than 1.5 million people died for diabetes-related causes, and the WHO estimates that there are over 422 million people worldwide who have the disease [11]. Diabetes was listed as one of the top 10 causes of death by the WHO. Both an individual's and society's well-being are significantly impacted by diabetes [12]. Unfortunately, diabetes currently has no recognized long-term remedy. To finish the loop with the proper insulin administration, this issue can be addressed by continually monitoring blood glucose levels.

The UK Prospective Diabetes Group's statistics shows, CGM can cut long-term problems among 40% &75%. As a result, CGM with warning systems can assist patients in taking remedial action(s), like decisions regarding food, exercise routine, and medication administration timing [13]. This work's goal is to investigate whether intrusive and secure CGMS can be used with IoT [14, 15]. The task is to create a framework on the basis of IoT from a sensor model to the back-end method to final-users like patients and doctors in graphical and text formats [16]. Additionally, the study adapts long-range Sigfox communication to be compatible with glucose monitoring systems and to achieve great energy efficiency [17,18].

Additionally, analyze the energy usage of sensor model and create energy collecting components for it. Present a push notification facility to alert patients and medical personnel in the event of abnormal circumstances, like a very-low or very-high blood glucose level [19]. Review of the relevant IoT-based patient health monitoring systems' existing body of work. According to the analysis, it has been determined that the traditional healthcare systems' drawbacks are getting worse [20]. Second, the expense of human resources goes up since medical staff must be on the patient's property at all times. The cost of the patient's hospital stay is then charged, and it is not less expensive. The expense of inpatient care for an individual is high. Last but not least, searching for, retrieving, and updating patient information data takes time due to the habit of managing health records on paper. To face this issue, some resolutions required to solve this problem. The existing methods cannot provide required accurateness for detection, so we are planned to do this research work. Subsequently, IoT-based Continuous Glucose Monitoring for Diabetes Mellitus using Deep Siamese Domain Adaptation Convolutional Neural Network is incorporated in this work for getting better results in continuous Glucose Monitoring for Diabetes Mellitus. These motivate us to carry out this research work.

In this Manuscript, IoT-based Continuous Glucose Monitoring for Diabetes Mellitus using Deep Siamese Domain Adaptation Convolutional Neural Network (CGM-DM-DSDACNN) is proposed. The goal of the work that has been described is to investigate whether an IoT-based CGMS is both secure &intrusive. The task is to develop a framework based on IoT from the sensor model to the back-end scheme to display blood glucose level, body temperature, and contextual data to final -users.

Furthermore, the study customizes the Long range sigfox communication procedures for compatibility with glucose monitoring system and excellent energy efficiency. In addition, evaluate the energy usage of sensor device and construct energy collecting modules for it. Lastly, using Deep Siamese Domain Adaptation Convolutional Neural Network (DSDACNN), the study enables several sophisticated facilities at the gateway, like a push notification facility to inform patients and doctors in abnormal conditions like as very low or very high glucose levels. The suggested gateway gathers information from wireless sensor models and sends it to Cloud server. Finally, Doctor may remotely view real-time data on the Cloud using a web browser or an application for mobile devices.

At last, show a DSDACNN for informing the patient and doctors in the event of an unusual scenario, like a low or high glucose level. Generally Deep Siamese Domain Adaptation Convolutional Neural Network has no evidence of the use of optimization models to calculate ideal parameter to ensure reliable intrusion detection in cloud applications.

II. LITERATURE SURVEY

Various research works were suggested in the literature based on deep learning based Continuous Glucose Monitoring for Diabetes Mellitus; some recent works are reviewed here. In 2021, Sivakumar, N.R, et.al.,[21] have Presented big data framework using equidistant heuristic and duplex deep neural network for diabetic disease prediction on the basis of IoT. The evaluation technique for forecasting diabetes illness must be accelerated to give early analysis in keeping with DLs' expectations for large data applications from an electric device. This research suggests an Equidistant Heuristic and Duplex Deep Neural Network (EH- DDNN) as a strategy to predict early diabetes illness. Create an IoMT-capable wearable model with a less- cost, low-power scheme on the chip enabling Bluetooth connection, edge computation, real-time BG forecasting, and predictive hypoglycemia diagnosis to implement the embedded model. Using an evidentiary recurrent neural network based on attention, propose a novel deep learning methodology. Additionally, developed desktop, cloud, and mobile applications to display BG trajectories and projections, as well as systems to back up data and enhance models. It provides higher accuracy and lower specificity.

In 2022, Zhu, T,, et.al.,[22] have Presented IoMT-enabled real-time blood glucose prediction with deep learning and edge computing. To implement the embedded model, create an IoMT-capable wearable model that has less-cost, less-power scheme on a chip. Utilizing an attention-based evidential Recurrent Neural Network, propose a novel deep learning methodology. Additionally, we developed desktop, cloud, and mobile applications to display BG trajectories and projections, as well as systems to back up data and enhance methods. The embedded method was analyzed using data from

3 medical dataset involving 47 T1D subjects. It provides higher sensitivity and lower accuracy.

In 2022, Naveena S, et.al.,[23] have Presented A new design of diabetes detection and glucose level forecasting with moth flame-based crow search deep learning. The vital objective of this study is to apply an intelligent system to detect diabetes &prediction of glucose level. PIMA and UCI datasets, two significant benchmark datasets, are initially consulted for the data. Deep feature extraction is performed with hybrid meta-heuristic-based Convolutional Neural Network (CNN) with 2 max pooling and 2 convolutional layers. Deep feature extraction, diabetes diagnosis, and glucose level prediction have all been improved by a brand-new, state-of-the-art algorithm known as MF-CSA, which can handle multi-objective optimization difficulties. The main contribution is, Moth Flame-based Crow Search Algorithm (MF-CSA), which combines Deep Learning methods such as CNN with MFO& CSA to accomplish the optimal feature selection. Hybrid MF- CSA was utilized to maximize unseen neurons count in CNN's 2 convolutional layer to get lowest correlation among features and eliminate the use of duplicate information. A modified fuzzy classifier with membership optimization may diagnose diabetes thanks to these characteristics. The output therefore has either a high or less level of glucose. After the levels have been classified, the improved RNN, which is depends on the presented MF-CSA, forecasts range of the levels. It provides higher precision and lower accuracy.

In 2021, Nasser, A.R., et.al.,[24] have Presented IoT and cloud computation in health-care: innovative wearable technology with a deep learning cloud approach to monitor diabetes. Diabetes is a chronic disorder that can harm a person's health if their blood sugar levels were elevated over what is referred to as the hyperglycemia range. When a specified critical threshold is surpassed, the continuous glucose monitoring (CGM) devices now in use alert the individual with type-1 diabetes. To decrease the level of glucose, this may force patient's body to function at high levels up until the medicine is taken, increasing the risk of major health issues if the intake is delayed. To offer patients with a prognosis of their future glucose levels, prediction model's implementation and its integration with the wearable CGM model are also being investigated. Due to its superior characteristics regarding improved prediction accuracy, a cascaded RNN-RBM DL method depends on RNN and restricted Boltzmann machines (RBMs) has been recognized between more DL techniques in state-of-the-art (SoTA). It provides higher accuracy and lower precision.

In 2021, Hossain, M.I, et.al.,[25] have Presented Factors influencing adoption method of continuous glucose monitoring model for IoT healthcare. In this an adoption method for CGMs devices by merging features from many ideas in earlier works of wearable medical models. In order to give customers advice for purchasing the CGMs device, the suggested adoption model also considers the existing situation. 97 actual CGMs device users provided information for our research. Partial least squares and structural equation modelling were employed for study's measurement and model evaluation. The experiment found that interpersonal impact and trustworthiness are the most important variables in determining how someone would feel about a wearable gadget. It provides higher precision and lower sensitivity.

In 2021,Swapna, G., et.al.,[26] have Presented Diabetes detection and sensor-based continuous glucose monitoring a DL approach. This article discusses utilizing deep learning to treat and diagnose diabetes. Diabetic neuropathy causes a reduction in heart rate variability (HRV). As a result, a reduced HRV indicates diabetic neuropathy. Impulses from an electrocardiogram (ECG) are utilized to construct the HRV parameter. The ECG of a person was recorded non-invasively. Heart conditions can be identified by anomalies in the P-wave and ST segment of the ECG waveform, among other parts of the waveform. These features, aside from variations in heart rate, rely on size &shape of ECG waveform, and it was exceedingly hard to understand the morphological variations. Deep learning algorithms may be used to analyze the sensor data in a distributed fashion, allowing all imaginable minute details to be recovered, even to the point of delivering valuable information about the prognosis of the condition. It provides higher precision and lower energy efficiency.

In 2022,Faura, G , et.al.,[27] have Presented Colorimetric and Electrochemical Screening for Early Detection of Diabetes Mellitus (DM) and Diabetic Retinopathy(DR)Application of Sensor. This article includes several papers on identification of biomarkers for DM and DR, with an intention of supporting as well as motivating researchers to create sensor-array ML-supported models to detect accurate, speedy, and reasonably priced early diagnosis of terrible disease. Firstly underline how important it was for society to establish organized screening programmers for various disease and how sensor- arrays and machine learning algorithms help with primary detection. A range of studies provided on colorimetric and electrochemical detection of biomarkers linked with DM &DR utilizing non- invasive sample, with a focus on certain already- existing sensor arrays and ML approaches. It gives high specificity and low sensitivity.

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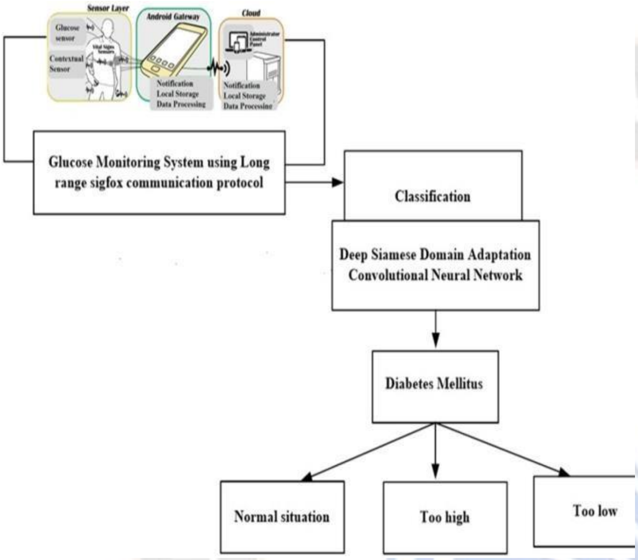
III. METHODOLOGY

In this section, IoT-based continuous glucose monitoring for Diabetes Mellitus using Deep Siamese Domain Adaptation Convolutional Neural Network (CGM-DM-DSDACNN) is discussed. This section presents the clear description about the research methodology used for the glucose monitoring for Diabetes Mellitus. The block diagram of the proposed CGM-DM-DSDACNN is represented in Figure 1. Thus, the detailed description about CGM-DM- DSDACNN is given below,



<Figure 1>Block Diagram of the proposed CGM-DM-DSDACNN methodology

3.1 Glucose monitoring system using Long range sigfox communication protocol

In this section, Long range sigfox communication protocol [28]is proposed to glucose monitoring and attaining higher level of energy efficacy. Data from microcontroller is sent to the gateway via a sigfox transmitter using the long range sigfox communication protocol. The block has an inbuilt antenna and an RF sigfox transceiver IC for 2.4GHz ISM band. Sigfox fully satisfies the criteria for transmission of data rates in the CGM model because it supports 2Mbps. Sigfox transmission data rates may be set to various levels of energy economy. When providing glucose, temperature, and contextual data, for instance, a data rate of 256kbps can be utilized to save electricity rather than 2Mbps.

Additionally, Sigfox can transmit across small and long distances of a few centimetres to 100 meters. The gearbox range and gearbox power can be customized for different purposes. Sigfox uses less energy while communicating over a short distance. The signal produced by Sigfox technique may also be used to easily cover a wide region and penetrate to things that are situated underneath. Large swaths of territory, on the list of tens of kilometers in the countryside and some kilometers in the city, may now be connected by the Sigfox communication technology. Transmission is sent at a slow pace, with the highest transmission rate being around 100bps and allowing either 4, 8, or 12 bytes. SDR (Software Defined Radio) gateway modules are used, and the network is often established in collaboration with mobile carriers. The radio frequency layer consists of Sigfox communiqué. Sigfox communication channels are part of the radio frequency layer, the physical layer contains the updated system, medium access control, finding of error, and access of channel, and application layer is determined by needs of users. Data is broadcast 3 times on three separate channel (to guarantee frequency variety) at three times as part of the transmission process, which exploits redundancy. The communication is more resistant to interferences thanks to its redundancy. Only node to Gateway connection (uplink) was allowed in first setup of Sigfox, which is a single way communication link. Later, a downlink mechanism from the gateway to the nodes was introduced to guarantee a two-way communication protocol. Node will transmit the maximum of 140 messagefor a day with payload of 12 bytes size&get a maximal of 4 message per day through application by Gateway with payload of 8 bytes size.

Same to a LoRaWAN class A model, application will have to wait for reception time slot to be assigned before it can send a message to node. A SigFox end-device is permitted to transfer 36 seconds every hour, or around 6 seconds each transmission. As a result, there will only be 6 messages every day.As a result, there will only be 6 messages every hour with a payload of 12 bytes and a packet delay of 2.08 seconds. After twenty seconds the node transfer a message, this slot becomes active. The node waits for an indication from Gateway within a receiving window that lasts for 20.1–44.5 seconds. Through the closest Gateway, application delivers a notification to the node. For a higher Quality of Service to be achieved, random access is a crucial component.

The Gateway module receives the packet, which will then be forwarded through an IP-based network to Sigfox Cloud. Sigfox Cloudis a middle man among Sigfox users and partners, is used in architecture. Cloud provides network devices control for consumer accounts as well as services for map coverage estimates. According to the literature of Sigfox technique, Sigfox Cloud is an OSS. Small packets are used by the Sigfox technology, hence a frame with a payload of 12 bytes will have a frame size of 26 bytes. The network bandwidth is increased while the process cost is drastically decreased and a lightprocedureframe is used. The deep learning approach is then utilized to classify data. Then , process of classification done with the deep learning based algorithm.

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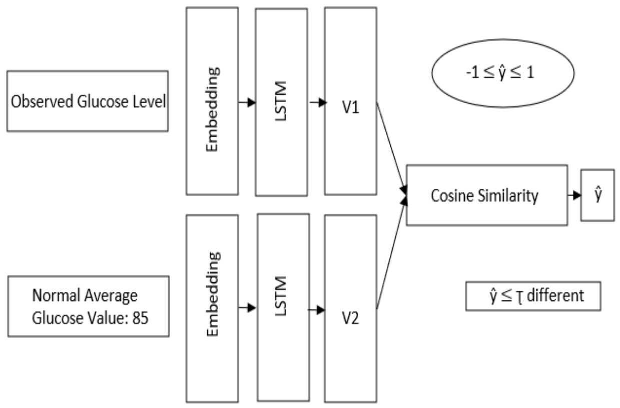
Health monitoring system using DSDACNN In this section, DSDACNN [29] is proposed to notify patient and doctor in case of unusual conditions.In order to display glucose level in blood, body temperature, and contextual data to final-user like patient and doctor, DSDACNN will develop IoT-based model framework from sensor model to back-end device. A higher level energy economy is also attained by tailoring the Sigfox communication protocol to the glucose monitoring device. Additionally, analyze the energy usage of sensor model and create energy collecting components for it. Present a push notification facility to alert patients too-high blood glucose levels and medical personnel in the event of abnormal circumstances, like a too-low or too-high.

3.2 Siamese neural network

A Siamese neural network (sometimes called a twin neural network) is an artificial neural network that contains two or more identical subnetworks which means they have the same configuration with the same parameters and weights. Usually, we only train one of the subnetworks and use the same configuration for other sub-networks. These networks are used to find the similarity of the inputs by comparing their feature vectors.



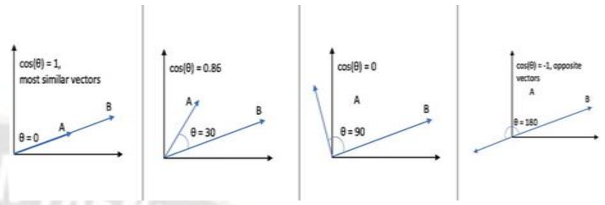
<Figure 2> Architecture Diagram of the proposed CGM-DM-DSDACNN methodology

In figure 2, input for the first subsystem is observed glucose level from the patient, input to the second subsystem is Average Glucose value when it is normal(85). Both the inputs are passed through the system and at output of Siamese neural network it converts into vectors. These vector outputs from both the subsystems are passed as inputs to find the Cosine similarity. The below given formula shows to find the cosine value

3.2.1Cosine Similarity

DSDACNN will notify patients & doctors in anomalous conditions like very low or very high level of glucose. The vector values coming from both the subsystems are plotted in the graph(A&B).

if both goes same direction(angle value 0) then both are most similar vectors, concluding that patient is in the normal condition. if both goes reverse direction(angle value 180) then both are most similar vectors, Positive, energy efficiency and AUC was looked at in order to assess performance.



<Figure 3> Diagram of Cosine Similarity Values

If cosine similarity value is -1, then the patient is abnormal affected with severe illness and need to send notification to the patient and doctor mobiles. Otherwise if the cosine similarity value is +1, then no notification will be send, since patient is in normal condition.

IV. RESULTS AND DISCUSSION

The obtained results of the proposed CGM-DM-DSDACNN method are analyzed with the existing methods such as CGM-DM-EH-DDNN - Equidistant Heuristic and Duplex Deep Neural Network

CGM-DM-RMSE - Root Mean Square Error, and

CGM-DM-MF-CSA - Moth Flame-based Crow Search Deep Learning

4.1 Confusion matrix

This matrix makes clear not only how often the model predictions were correct, but also in which ways it was correct or incorrect. True Positives(TP): It is the output in which the actual and the predicted values are Positive.True Negatives(TN): It is also known as TN. It is the output in which the actual and the predicted values are Negative.False Positives(FP): It is also known as FP. It is the output in which the actual value is Negative but the predicted value is Positive. False Negatives(FN): It is the output in which the actual value is Positive but the predicted value is Negative.

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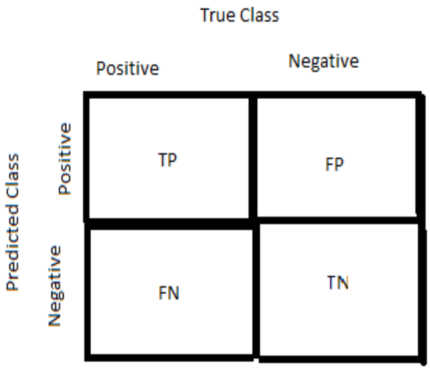


<Table 1> Confusion Matrix

Building a model that detects whether a person has diabetes or not.

After the train-test split, a test set of length 100, out of which 70 data points are labeled positive (1), and 30 data points are labeled negative (0).

TPR (True Positive Rate) = (True Positive / Actual Positive)

TNR (True Negative Rate) = (True Negative/ Actual Negative)

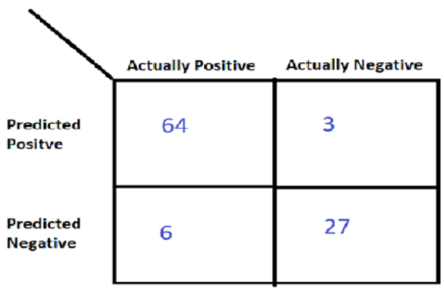
FPR (False Positive Rate) = (False Positive / Actual Negative)

FNR (False Negative Rate) = (False Negative / Actual Positive)

If a model to be smart, then, model has to predict correctly.

TPR & TNR should be very high whereas

FPR & FNR should be very low,



For diabetes detection model, ratios:

TPR = 91.4%

TNR = 90%

FPR = 10%

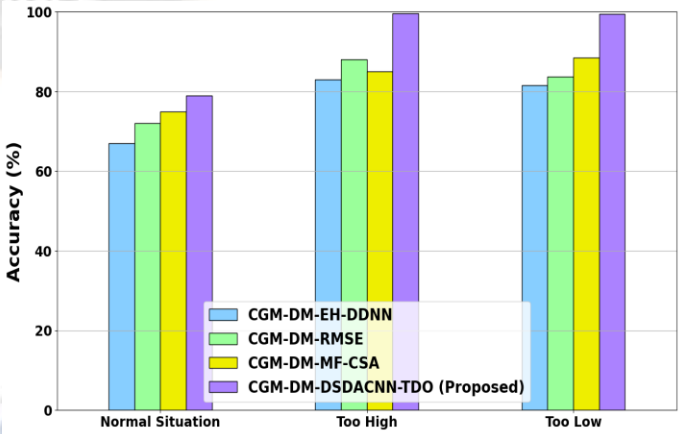
FNR = 8.6%

Accuracy

Accuracy is the difference among the actual value concluding that patient is in the abnormal condition.

T(P) and evaluated value T(N) .If higher the accuracy is, the evaluation approach is better. This is scaled by equation (1),

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

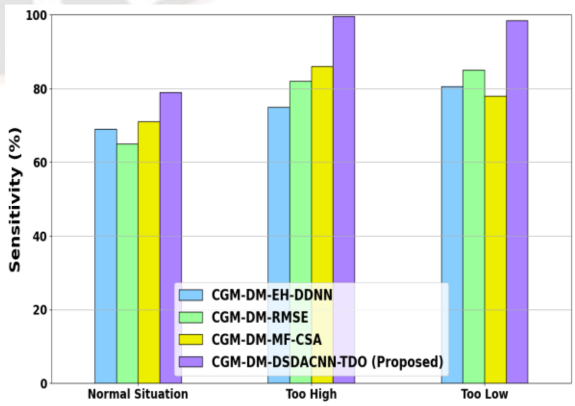


Here, the proposed method provides 34.34%, 27.3% and 33.56% higher accuracy for normal situation; 31.45%, 22.34% and 34.2% higher accuracy for Too high;21.45%, 32.34% and 14.2% higher accuracy for Too low

Sensitivity

It is referred to the true positive rate and indicates the count of actual positives that are accurately detected.

$$Sensitivity = \frac{TP}{(TP + FN)}$$



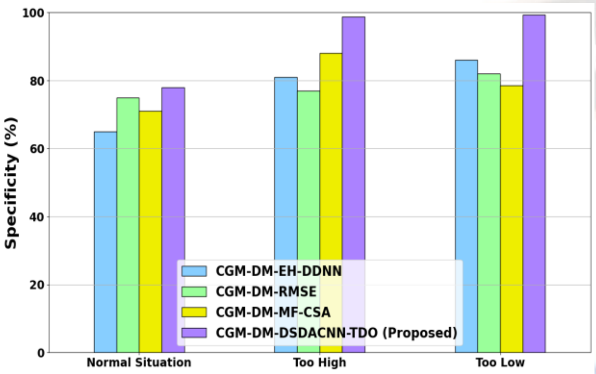
Here, CGM-DM-DSDACNN method provides

24.34%, 31.3% and 25.56% higher specificity for normal situation; 21.45%, 31.34% and 23.2% higher sensitivity for Too high; 31.45%, 21.34% and 23.2% higher sensitivity for Too low

Specificity

It is also known as the real negative rate and provides an estimate of the actual negatives that are accurately detected.

$$Specificity = \frac{(TN)}{(FP+TN)}$$



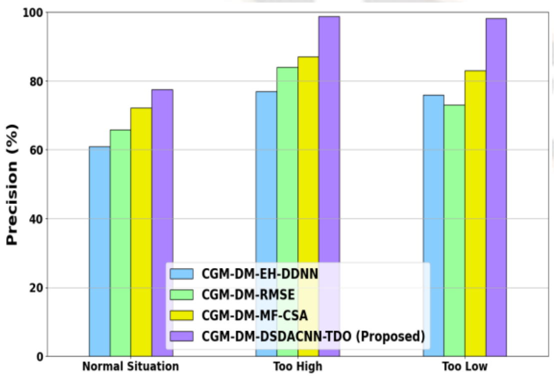
the proposed method provides 34.34%, 27.3% and 33.56% higher specificity for normal situation; 31.45%, 22.34% and 34.2% higher specificity for Too high; 35.45%, 32.34% and 34.2% better specificity for Too low

Precision

Precision is the percentage of points claimed to be positive which are truly positive

The precision value lies between 0 and 1.

$$Precision = \frac{TP}{TP+FP}$$



the proposed method provides 34.34%, 21.3% and 31.56% higher precision for normal situation; 32.45%, 24.34% and 26.2% higher precision for Too high; 22.45%, 34.34% and 26.2% higher precision for Too low

F Score

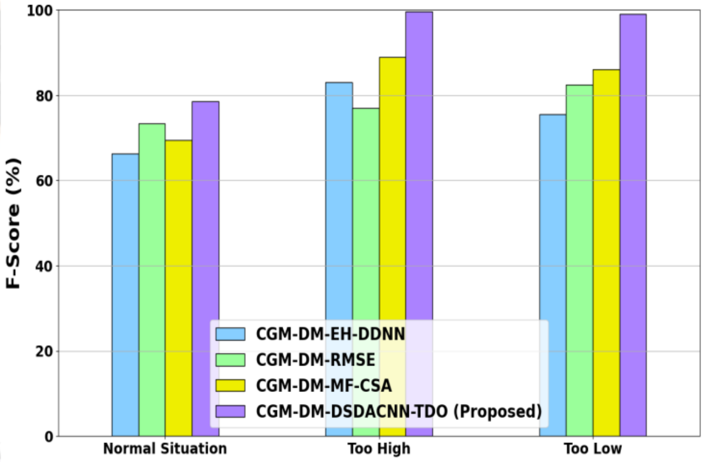
It's described as the "harmonic mean of precision and recall."

$$F1 = \frac{sensitivity \times precision}{Precision + Sensitivity}$$

It returns score between 0 and 1

1 means best score

0 is the worst



The proposed method provides 24.34%, 31.3% and 25.56% higher F-Score for normal situation; 21.45%, 31.34% & 23.2% high F-Score for Too high; 21.45%, 31.34% &13.2% better F-Score for Too low

V. CONCLUSION

The successful implementation of the first objective that is IoT-based continuous glucose monitoring for Diabetes Mellitus using the Deep Siamese Domain Adaptation Convolutional Neural Network (CGM-DM-DSDACNN) has been achieved.Results highlight the effectiveness of the proposed CGM-DM-DSDACNN approach in enhancing the accuracy and sensitivity of continuous glucose monitoring for Diabetes Mellitus compared to the existing methods.

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