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The Internet Of Things On Neural Networks Provides Intelligent Healthcare Management For Diabetic Patients

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Abstract: A newly developed health system for a diabetic is described in this study, which tracks their health based on blood sugar levels, heart rate, food consumption, sleep duration, and activity. To explain, this technology is continually receiving variables via sensors and processes them using a neural network to analyze the data, yielding four things like health threats: minimal, moderate, extreme, and severe. The spectrum of genetic risk varies depending on the customer's kind and past health histories. Furthermore, if a patient's health state is at high or extreme danger, an instantaneous phone call/SMS notice is made to the patient's family, including the patient's position. In addition, it alerts patients to the nearest hospital if they are in danger. This technique has been successfully tested on 25 people with diabetes, with reliability of 84.41 percent in determining the appropriate level of risk, which is a highly adequate standard of determining risk factor status.

Keywords: Diabetic Treatment, ehealth, Neural Networks, Internet of Things

1. INTRODUCTION

Extended waiting times and health monitoring equipment is now possible due to the Internet of Things (IoT). Diabetics must queue for years in hospitals and care centers for a fasting blood glucose test and blood pressure. The development of a smart health care system for diabetics, which can be utilized for everyday routine diabetic monitoring, became a need. Until now, an enormous number of solutions for diabetes monitoring of patients have been created. With the aid of the IoT, these technologies may simply and effectively address this problem of diabetes patient monitoring, benefiting a large number of people across the world. Designers have emphasized our system in this article, which would be capable of providing automated monitoring and alerting solutions for diabetic patients utilizing sensors. We looked at and analyzed current systems, as well as the gaps among them, to come up with a decent option for diabetic patients.

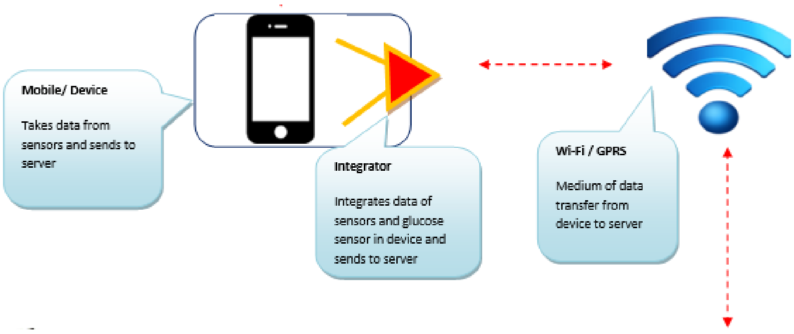
A great deal of research has gone into developing smart health care systems for a variety of medical problems. The authors of the article [1] suggested design requires sensors to collect physiological signals from the patient's body and delivers them to a near-central node, which may be a mobile device with a graphical user interface, an alarm signaling, and a sensor control unit. By monitoring, the base station sends the signal or alert to an emergency and health clinic. An evaluation of the analysis and simulating of a health surveillance system [2] has been completed.

2. RELATED WORKS

The working method of a wireless networking temperature and pulse tracking system employing sensors detecting patient conditions operated via microprocessors is described in an IoT system [3], which can assist a person in an unexpected crisis. IoT has just been utilized in [4] to assist patients with their emotional and physical wellness. The authors have described architecture utilizing IoT for remote health care [5]. They used equipment such as an ECG sensor, a temperature, a glucometer, Wi-Fi modules, and an Arduino to consider bodily data. The researchers of article [6] developed an IoT-based Smart Healthcare Monitoring System that takes into account people's health concerns in remote and distant locations, such as diabetes, respiratory oximetry, and renal function, temperature, and cardiovascular health [7].

3. METHODOLOGY

Diabetics aren't continually monitored as patients would be in a hospital, but instead cope with the illness mostly on their own, causing them to be concerned about their health state frequently. The suggested decision-making support system's fundamental design is based on different IoT devices. To give an example, the program includes wireless or wired devices to collect data on blood sugar, sleep time, activity, and GPS data from diverse sensors. The mobile phone compiles all of the health information into an app and transmits it to the server that stores it in data.



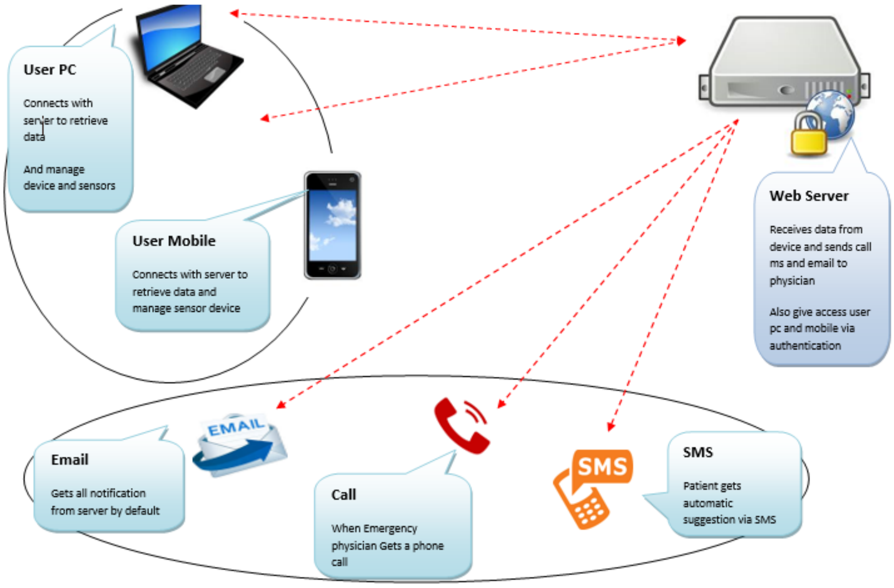


Figure 1: The Proposed Design in IoT

This management information system is also connected with an e-mail, mobile network to notify a relative's nearby hospital about the patient's health status. The application will automatically contact and deliver an SMS to the client's family, informing them of the client's present position. In the worst-case scenario, the system will transfer the patient to the nearest hospital for emergency care. Figure 1 depicts the general structure of the suggested model of diabetic health monitoring.

The systems are a collection of interconnected neurons that communicate with one another. The network may be adopted consistently based on the inputs and outputs, making it appropriate for deep classification. The input image, the input neurons, and the output unit are the three principal elements of the collecting. Dense layers refer to the three layers that make up the network. These layers do not communicate with the outside world, but they have a significant influence on the ultimate product.

The input image of our suggested system has seven neurons: the patient's age, gender, blood sugar level, and activity or calorie burn. Nevertheless, we possess 4 neurons in our output nodes that will determine a customer's level of risk, which are severe, high, moderate, and minimal. Having so very few neurons in the hidden units, on the other hand, will result in class imbalance. Likewise, regularization can occur when more neurons are used in the hidden units. Overfitting happens whenever the neural platform's data processing capability is so great that the training set's small percentage of the population is insufficient.

To enhance our system, researchers first must determine what inaccurate our forecasts were. Then, to reduce the error margin, designers modify the ensure adherence. Backpropagation calculations happen for each "level" in the same way that forward dispersion estimates do. We'll start by adjusting the weights of the hidden and output layers. The increase in temperature to these values is calculated in two steps: 1) Designers take out all the required changes in the output total by calculating the delta output total even by hidden state outcomes, and 2) we recover the increase in values by combining the delta outputs total by the hidden state outcomes.

$SUM\ Error$ = Forcast – observations ------ (1)

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4. RESULT AND DISCUSSION

Because of the IoT-based platform, designers collected original data using an array of devices and IoT devices. To test the device, we took 25 diabetes patients and collected data through continuous monitoring. These patients were chosen for their age and gender diversity, as well as the fact that they have been diabetic for at 5 years. Nevertheless, we gathered data for two months and extracted six (six) relevant timestamps for each patient on a given day.

Monitoring systems and IoT applications provide inputs for this data collecting process, including sugar levels and sleep hours. However, to create the Decision Model in our suggested system, we employed a few more features; that information was physically obtained via a survey. Food consumption data, for instance, was obtained from the sufferers' everyday routine and translated to a quantitative for further processing.

For example, for males and women, the sex has been assigned a value of 1 and 0. We produced a significant quantity of data, with around 9001 packets; one section is displayed in Table 1.

Table 1. Data from an investigation for a health-monitoring platform

Patient	Day	Timestamp	Age	Sex	Sugar Level (mg/dL)	Blood Pressure Systolic (mmHg)	Blood Pressure Diastolic (mmHg)	Food Intake (Kcal)	Sleep (Hrs.)	Exercise (Kcal)
P1	D1	07:30:25	39	F	87	140	69	200	7	250
		12:22:00			90	146	77	0	0	150
		17:15:26			76	161	75	120	2	300
	D4	06:30:23			81	145	72	0	6	200
		14:22:56			91	140	76	50	0	0
		18:17:32			97	162	68	100	0	240
		21:43:23			79	152	65	0	0	170
P7	D2	06:12:17	45	M	189	138	68	60	6	200
		10:16:56			199	143	65	200	2	0
	D5	07:24:24			172	167	67	0	8	200
		14:53:35			300	164	68	300	0	0
		18:26:42			218	168	69	0	2	350
	D7	06:46:35			102	162	56	0	7	240
		11:46:53			110	158	64	120	0	0
		13:42:23			150	156	76	250	0	0
		18:43:29			180	146	69	50	0	500
	D9	08:30:24			91	148	69	100	8	250
		10:23:57			82	140	71	250	0	0
		16:34:45			78	147	80	0	1	200
P15	D16	08:32:13	56	M	50	141	67	0	8	250
		10:02:54			67	146	65	240	0	600
	D23	09:45:17			56	133	84	370	8	350
		14:17:23			62	153	77	0	0	0
		19:14:26			68	157	69	50	1	50
		21:46:12			57	143	68	0	0	315
	D24	07:56:53			57	146	78	0	7	200
		09:57:25			69	151	67	200	0	0
P20	D11	06:46:43	29	F	58	136	64	0	8	200
		12:24:32			62	140	62	0	0	0
		19:43:23			57	138	68	120	0	120
	D17	08:31:20			62	140	72	220	9	0
		13:42:20			67	148	62	300	0	0
P23	D25	06:54:31	47	M	51	139	86	0	6	260
		10:00:01			68	143	72	200	0	0
		12:51:53			59	136	68	0	0	0
		15:52:23			56	142	69	300	1	0

The data from each individual then was blended with the advice of specialized doctors in the next phase. To demonstrate, professional doctors analyzed this data for each patient to determine the patient's level of risk based on the seven categories of input data. Finally, the neural network was trained using a whole set of data shown in Table 2.

Table 2 shows a sample of data from a 52-year-old female client with varying amounts of exposure

Sugar	Systolic BP	Diastolic BP	Food Intake	Exercise	Sleep	Risk
75	141	69	0	300	8	L
134	165	68	220	50	6	M
142	161	67	350	0	5	H
85	155	65	200	240	6	L
57	140	72	0	200	6	L
106	153	69	240	0	7	M
139	145	68	290	0	6	M
75	139	76	50	250	9	L
134	143	63	150	100	7	M
196	145	68	350	50	5	H
57	137	76	80	0	8	L
179	142	66	250	280	6	M
120	120	84	30	90	7	M
152	155	87	350	0	4	H
199	163	76	260	0	5	H
135	127	68	100	250	7	M

5. IMPLEMENTATION

There are two levels to the entire system: a mobile application and a web service. This online application, on the other hand, uses a decision support system and a neural network to analyze data. The Model-View-Control (MVC) paradigm has been used to create this app, which increases data security by separating the model (system data) from the target audience. MVC also will outperform other state-of-the-art patterns when it comes to scalability for an IoT-based software application. Furthermore, this method can control a large amount of data for the decision support tool by including additional IoT devices or sensors.

Likewise, the Smartphone app part was developed for Android OS, with data gathered from the patient and the medical devices being stored using Java and SQLite. Sending Web applications from the phone to the health gateway servers, which replies with a JSON structured acknowledgment message, synchronizes data between both the app data and the distant healthcare gateway data. The user dashboard, which allows them to see and control many aspects of the system.

5.1 Experimental Protocol

In this study, researchers employed convolutional neural networks to determine risk levels from a dataset. The data has been split into 2 phase: upper class, which contains data of severe and dangerous conditions, and lower class, that has data with low and medium risks. Researchers had used 9000 data points from 25 patients to train our neural network. We selected 10 individuals' data for 7 days at random and used it as the testing data. We repeated our tests ten times to reduce the impact of randomly picked samples on the outcomes. Then, in terms of effectiveness, sensitivities, and range, we took the average of the key performance indicators. Table 3 shows the number of actual diagnoses made by doctors and the number of assumptions made by the planned NN.

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Table 3. Actual and forecast level of risk

	Actual Diagnosis by Doctor	Prediction by Proposed Method
Extreme	6	5
High	28	23
Medium	14	11
Low	22	20

As shown in Figure 2(a), the low potential risk has been accurately detected with the highest percentage of 90%. The accurately recognized rate for severe and high instances, but on the other side, is 82 percent and 81 percent, respectively. The medium forecast accuracy is 79 percent for moderate found to be correct danger levels. We've also determined the sensitivities, precision, and accuracy of the outcomes to assess our program's efficiency.

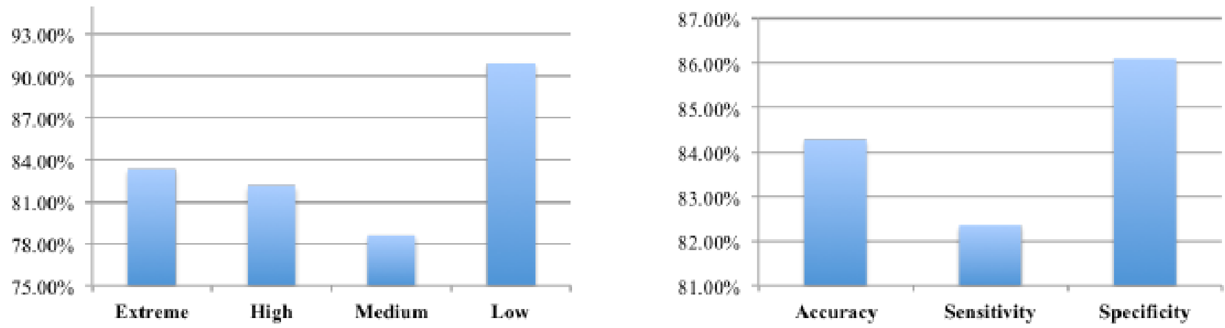

Figure 2(a) and (b): a) Performance of NN based on Risk b)Efficiency is extremely good when compared with the existing system

If these metrics are high, the network performance can be considered good in this situation. Figure 2 (b) shows that our system has an efficiency of 84.29 percent, a sensibility of 82.35 percent, and a specific of 86.11 percent, which is extremely good.

6. CONCLUSION

The use of IoT health tracking for a diabetic is addressed, to change the phase from a traditional to a patient-centered approach. A novel Decision Support design using a NN to determine risk level. It is accomplished by collecting patient data remotely using various IoT equipment and then determining the customer's particular level of risk to use a recommendation system. The findings of a pilot software system that considered end-to-end capabilities, including a smooth, safe, and precise data transmission from IoT, besides a system-based overall risk determination.

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