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DIABETES MELLITUS EARLY DETECTION DESIGN SYSTEM USING INTERNET OF THINGS (IOT)-BASED NON-INVASIVE SENSORS

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ABSTRACT

This research aims to design a diabetes mellitus early detection tool using IoT-based non-invasive sensors. This tool uses blood pressure sensors and color sensors to detect glucose levels in urine. The data obtained from these sensors is sent to the Arduino Uno microcontroller, displayed on the LCD screen, and saved to the Firebase platform for further monitoring and analysis. The test results show that this tool is able to measure and display blood pressure data and urine glucose levels accurately and in real time so that it can be used as a practical and efficient diabetes mellitus diagnostic tool. This research makes a very important contribution to the development of IoT-based health technology, especially in facilitating early detection of diabetes non-invasively.
This research aims to design a diabetes mellitus early detection tool using IoT-based non-invasive sensors.

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I. INTRODUCTION

Diabetes mellitus is a chronic disease caused by the failure of the pancreas to produce enough insulin or when the body does not use it effectively. According to some experts, diabetes mellitus is a long-standing or chronic metabolic disease characterized by elevated blood sugar levels due to abnormalities in insulin activity, insulin secretion, or abnormalities in insulin. The disease can cause many serious problems, and it is becoming increasingly common [1]. Hypertension is a condition where the blood pressure inside the blood vessels is chronically elevated, which occurs during two phases of each heartbeat: systole, which is 140 mmHg, indicating the phase of blood being pumped by the heart, and diastole. Based on. The 90 mmHg phase phase. Indicates the phase in which the blood returns to the heart [2].

The pancreas produces the hormone insulin to help control blood sugar and helps the absorption of glucose into the body's cells to control blood sugar. Glucose itself comes from carbohydrate-containing foods and is converted by the body into energy sources. Health problems such as hyperglycemia (high blood sugar) and hypoglycemia (low blood sugar) are closely related to this hormone. [3].

Diabetes mellitus (DM) has become one of the most pressing global health challenges, with a significant impact on mortality and quality of life. According to the International Diabetes Federation (IDF), in 2021, more than 537 million adults worldwide were living with diabetes, and this figure is projected to increase to 643 million by 2030 and 783 million by 2045. The alarming thing is that more than 50% of them are undiagnosed, making diabetes a “silent killer” that continues to threaten global health. Diabetes causes an estimated 6.7 million deaths every year, which translates to one death every five seconds, showing just how serious an impact the disease has on public health.[4]

Long-term complications of diabetes mellitus, if not properly managed, can lead to a range of serious conditions such as heart disease, stroke and kidney damage. This not only affects the individual but also puts a burden on the public health system, especially in low- and middle-income countries, where 81% of people with diabetes live. In Indonesia, diabetes is the leading cause of death, with prevalence reaching 10.6% in 2021, and is expected to increase to 28.6 million people by 2045.

Blood glucose levels taken from venous blood plasma can be used to screen for DM. One of the ways to perform this test is the invasive method. [5]. The results can be used to diagnose diabetic patients. The criteria for the diagnosis of DM are as follows: fasting plasma glucose of more than 126 mg/dl, plasma glucose of more than 200 mg/dl, and HbAlc of more than 6.5%. However, this method is considered less effective because it requires quite expensive costs, a long time to get results, and pain caused to the body. To overcome these problems, blood to urine samples were replaced by non-invasive methods.[6].

Every year, hypertension is the number one cause of death in the world and is one of the most dangerous diseases of diabetes. This can be caused by a number of reasons. One of them is not checking blood pressure regularly, which makes people unaware of their blood pressure condition. Therefore, in this study, an Internet of Things (IoT)-based Blood Pressure Monitoring Tool was designed and built. This tool can not only digitally measure the patient's blood pressure and read the practical measurement results, but also allows patients to monitor their condition online for 24 hours. [7].

Non-invasive detection methods, particularly those based on urine and blood pressure, are the focus of research as they offer various advantages over invasive methods. These non-invasive methods do not require blood draws, thus reducing the pain, discomfort and risk of infection usually associated with blood tests. Urine sample collection is relatively easy to perform and does not require specialized equipment, resulting in lower operational costs and more convenience for patients. Blood pressure measurements can also be performed easily at home using commercially available devices, allowing for regular monitoring without the need for frequent medical intervention. However, both methods have their own disadvantages. Urine-based methods may be less sensitive and specific than blood tests, as factors such as hydration and diet may affect the results. While blood pressure measurements are not specific to diabetes, as high blood pressure can be caused by many other conditions. These limitations indicate the need for alternative methods that can provide more accurate and reliable results. The development of better non-invasive detection methods is urgently needed to improve patient experience, increase compliance in health monitoring, and provide faster and cheaper solutions. Innovations in sensor technology and data analysis, such as those enabled by the Internet of Things (IoT), can play an important role in developing more effective and efficient non-invasive devices for early detection and monitoring of diabetes.

Previous research, as described in several studies, has often focused on specific parameters, such as examining glucose or protein levels in urine to detect diabetes. For example, studies using urine microalbumin as an indicator to detect kidney complications in diabetics showed the importance of urine analysis in kidney health monitoring. Meanwhile, your study focuses on using urine color as an early indicator of diabetes, which is a more innovative and uncommon approach in the existing literature. Urine color can reflect various metabolic conditions, including dehydration or the presence of glucose, which can be an early signal of diabetes.[8]

This research aims to design a diabetes mellitus early detection tool using IoT-based non-invasive sensors. This tool utilizes blood pressure sensors and color sensors to detect glucose levels in urine. The data obtained from the sensor is then sent to the microcontroller and then entered into farebase for classification by AI with the support vector machine method.

In previous research conducted the title Diabetes Mellitus Disease Prediction Using Support Vector Machine and Naive Bayes Methods with accuracy results of 78.04% and 76.98%[9] ,another study with the title Implementation of the C4.5 Decision Tree Algorithm for Diabetes Disease Prediction with prediction results of 70.32% [10]

The concept of SVM can be explained simply as an effort to find the best hyperplane2 that functions as a separator of two classes in the input space Support Vector Machine is a learning system that uses hypotheses in the form of linear functions in a high-dimensional feature and is trained using a learning algorithm based on the theory of optimism [11]

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II. RESEARCH METHODOLOGY

A. Research Framework

Overall, the framework of the stages of this research is depicted in the form of a diagram, which is very important as it allows to identify what stages must be achieved to produce a well-functioning system. The overall framework of this research is depicted in Figure 1 which shows the entirety of this research

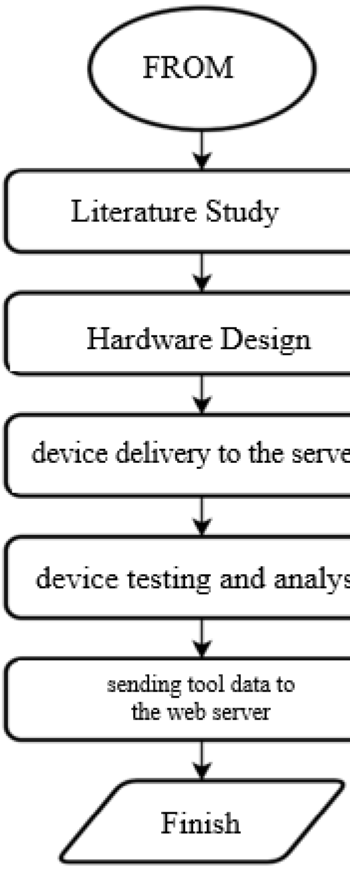

Figure 1. Research Framework

can be seen in Figure 1. explains the stages in creating a monitoring system for diabetes diagnosis tools with machine learning algorithms. Starting with collecting relevant literature through various journals and e-books, followed by hardware design including component selection, assembly, and testing. The next stage is the construction of the SVM (Support Vector Machine) algorithm model by taking clinical datasets from Palembang Hospital, storing datasets on virtual servers, creating SVM algorithms for health diagnoses, and testing models using performance indicators. After that, software design is carried out which includes web display design, implementation, and web testing on Android and IOS-based smartphones. The last stage is system testing and analysis, where hardware and software are integrated and tested by inputting patient clinical data on the web and using medical devices on patients to produce health diagnoses.

B. Device Design

This research divides hardware design and software design. Designing the block diagram of the overall system is the first step in hardware design. The block diagram is very important for the research process

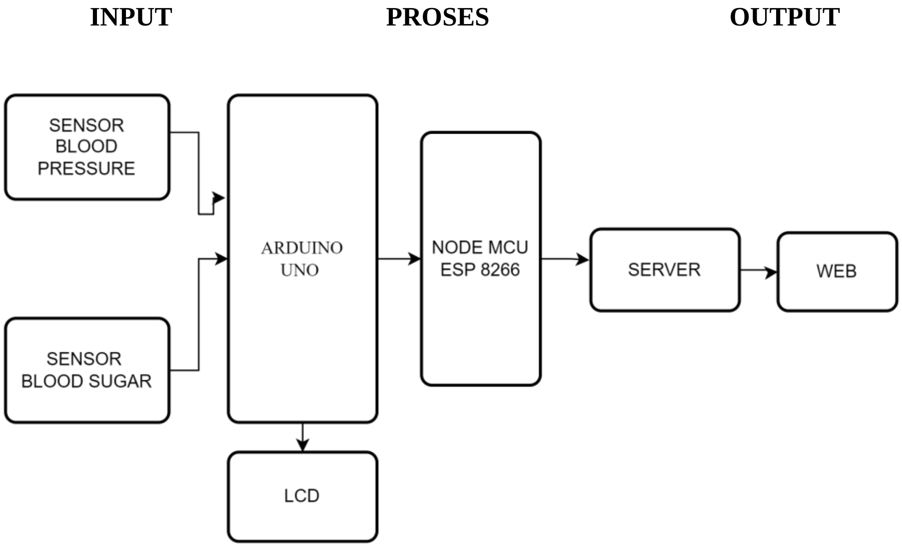

Figure 2. Block Diagram of Hardware System

can be seen in figure 2 The diagram depicts a health measurement and monitoring system consisting of several interconnected electronic components. The system uses two types of sensors, a blood pressure sensor and a blood sugar sensor, both of which are connected to an Arduino Uno microcontroller. The Arduino Uno serves as a data processing center that receives input from these two sensors. After the data from the sensor is processed by the Arduino Uno, the measurement results are displayed on an LCD screen that is also connected to the Arduino. In addition, the Arduino Uno is also connected to the NodeMCU ESP8266 module, which is a WiFi module to transmit data to the server. The data sent to the server can then be accessed via the web, allowing for online monitoring. Overall, the system is designed to measure blood pressure and blood sugar, display the results locally on the LCD, and enable remote monitoring via the internet using a server and web interface.

C. Device Circuit Schematic

The figure below represents the electronic design process, components are selected according to the needs and everything necessary for the circuit manufacturing process is prepared.

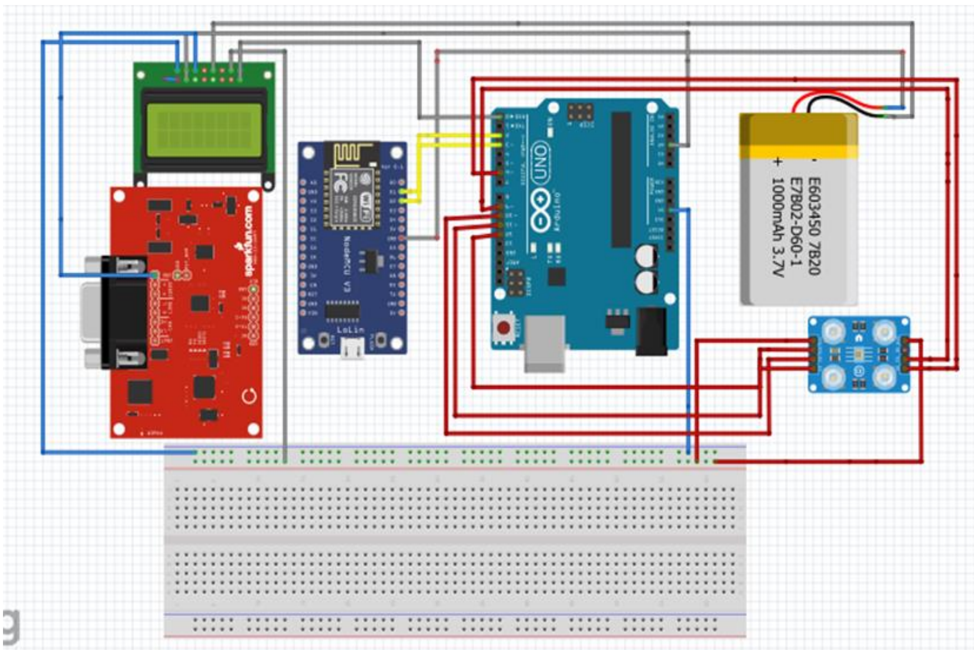

Figure 3. Hardware Schematic

Figure 3 above shows a circuit diagram of an IoT-based diabetes detection tool that uses several main components. Here is an explanation of the components seen in the image:

1. 1. LCD (Liquid Crystal Display) is a tool that functions to display a size or number, so that it can be seen and known through the crystal screen display. LCDs are used in a variety of applications, including as displays of data, characters, letters, numbers, or graphs in various electronic devices such as televisions, calculators, or computer screens elebihan dengan memanfaatkan modul I2C untuk **LCD** [12]
2. 2. Arduino Uno is the main processing unit that receives data from various sensors and input devices, processes that data, and sends the results to the LCD for display as well as to the NodeMCU for transmission. The microcontroller board is the control center of the system. The Arduino Uno is used to read data from sensors and control other devices ketika perangkat **Arduino** dijalankan, maka **Arduino** akan oleh mikrokontroller **Arduino** uno.[13]
3. NodeMCU module ESP8266 function as a Wi-Fi module that enables wireless communication with the server. This module is connected to the Arduino Uno to receive data to be transmitted to the server over the internet Wi-Fi module is used to connect the system to the in-internet network. This module allows sending data to a server or cloud for remote monitoring. NodeMCU ESP8266 secara real-time. [14]
4. LiPo battery or polymer lithium-ion battery is a type of battery that is widely used for portable electronic devices. Lithium-Ion Polymer (LiPo) batteries are a type of battery that uses a dry polymer electrolyte instead of a liquid electrolyte. This dry polymer electrolyte is shaped like a thin layer of film plastic arranged in layers between the anode and cathode. With this method, LiPo batteries can be made in a variety of shapes and sizes"[13]
5. Color Sensor Module (TCS3200): A sensor used to detect color. This sensor measures the intensity of red (R), green (G), and blue (B) colors in the tested samples, such as the color of urine in the context of this TCS 3200 Sensor project to detect the color of urine whose color parameters have been set according to the color on the BWD so that later the sensor will detect the same color [15]
6. Breadboard: A test board used to create a temporary circuit without the need for a sol-der. This breadboard is used to connect various components by using jumper cables
to assemble components[16].
7. These two voltages are given by UBEC which has an output and input section. For the input is connected to the protoboard given a voltage of 12 V, while for the output to the voltage part is 5 V [17]
8. Digital blood pressure sensor that can be used to press blood is the result of the heart's pumping activity that takes place in contraction and relaxation. [18]

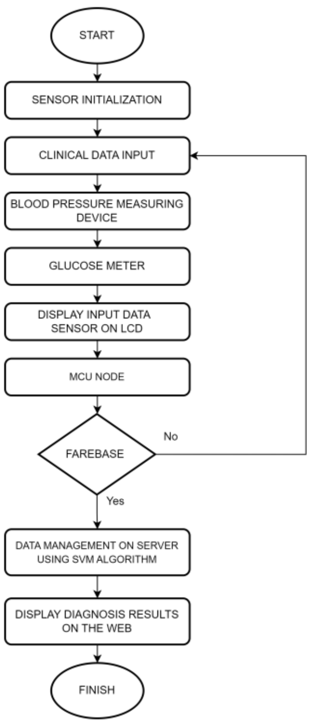

Figure 4. flowchart of system working principle

The flowchart provided explains the working principle of an IoT-based system for early detection of diabetes mellitus. The following is an explanation of the working principle based on the flowchart:

1. Start: The process starts with system initialization.
2. Sensor Initialization: The system starts by initializing the sensors that will be used to collect clinical data.
3. Clinical Data Input: Clinical data such as weight, height, age, and other data are inputted into the system.
4. Blood Pressure Measurement Device: Blood pressure measurements are taken using a blood pressure meter. The meas urement data is then sent to the system.
5. Glucose Meter: Measurement of blood glucose level is done using a glucose meter. The data from this measurement is also sent to the system.
6. Displaying Sensor Input Data on LCD: The data collected from the sensors (blood pressure and glucose) is displayed on the LCD screen for live monitoring.
7. MCU Node: Data from the sensors is sent to the Node MCU, a microprocessor in charge of connecting the hardware with the cloud platform.
8. Firebase: The data received by the MCU Node is sent to the Firebase server. Firebase acts as a data storage platform in the cloud.
9. Data Management on Server Using SVM Algorithm: The data stored in Firebase is then processed using the Support Vector Machine (SVM) algorithm to perform initial analysis and diagnosis.
10. Displaying Diagnosis Results on the Web: The analysis and diagnosis results from the SVM algorithm are displayed on the web platform, allowing easy access for users and medical personnel.
11. Finish: The process ends once the diagnosis results are displayed.

Based on the flowchart shown in Figure 3.3, it can be seen that the program flow begins with collecting patient clinical data and reading measurement data from the sensors of the health monitoring tool. In the design of this tool, the sensors used consist of blood pressure sensors, and blood sugar level sensors. In the collection of clinical data, the data collected are age, gender, height, weight, ever given birth, blood pressure, blood sugar levels.

Then both data are sent and recorded in the virtual server. If not sent, the process will return to clinical data collection. Next, the data is processed using a machine learning algorithm, namely SVM (Support Vector Machine) to determine the patient's health status. Furthermore, the processed data is displayed in the form of input and output data through a web-based smartphone display.

III. RESULTS AND DISCUSSION

A. *Design Results of Diabetes Detection Tool*

In research on diabetes detection tools, this chapter describes the stages of designing diabetes detection tools, starting from identification of needs, system analysis, hardware design to testing and evaluation of tools. The main focus of this chapter is to provide a comprehensive overview of the tool development process to ensure the tool is effective, efficient, and easy to use by users.

This study uses blood pressure parameters and urine conditions non-invasively measure a person's Blood Pressure and urine then send data to the Arduino microcontroller and then data processing Arduino microcontroller analyzes data from blood pressure and urine sensors, and compares with normal standards, The results of measurement and analysis are displayed on the LCD display. The following are the results of the device design that has been made:

Figure 5. rear view of the tool

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Figure 5 is the result of the hardware design of the diabetes detector. This device is equipped with several components consisting of an Arduino Uno microcontroller in the middle, MCU 8266 node on the side, Lipo 3s 1000 mah battery on the left side, Blood Pressure Sensor Molex kf2510, Serial / quart on the outside of the box project, Arduino calor TCS230 GY-31 TCS3200 color sensor on the outside of the right box, LCD 16x 2 on the outside of the box project, All devices are arranged and placed in accordance with the previously designed layout in order to work optimally and look more compact.

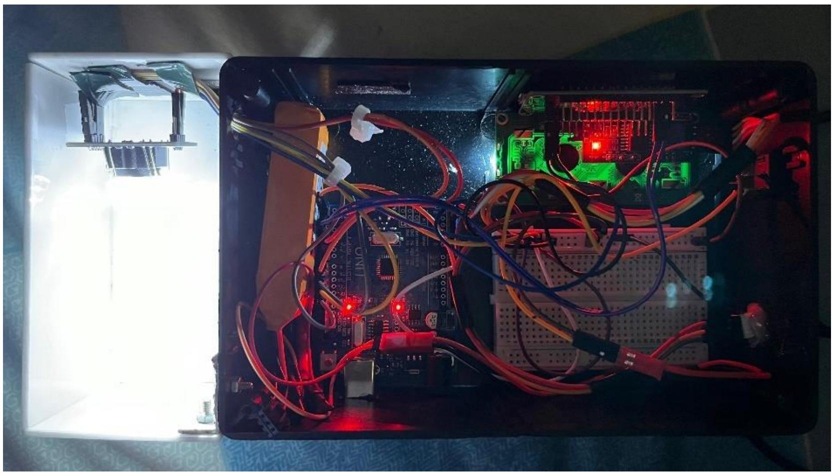

Figure 6. circuit box

In Figure 6 is an overall view of the device which consists of various components. In the inside view, there are several components such as a small seta added cover to cover the LNA component from touching so that there is no short circuit in a very sensitive LNA circuit.

B. Testing and Trial Results

This test examines the functionality of the hardware by monitoring the sensor response when reading blood pressure and urine color data. The data is sent to the Arduino Uno, which processes it into systole and diastole pressure, and measures the light intensity of the urine. The Arduino sends the data to the NodeMCU, which then sends it to Firebase. Firebase sends the data to the Web Server, which goes to the AI for classification using the Support Vector Machine (SVM) algorithm.

TABLE 1.
BLOOD PRESSURE MEASUREMENT DATA.

Sample	Type of claimant	Design tool		Tensimeter digital		Error (%)	
		Sistole	diastole	Sistole	diastole	Sistole	diastole
1.	P	130	67	128	65	2,4	2,7
2.	P	123	74	123	77	0	3,8
3.	L	120	80	123	85	2,5	8
4.	L	117	69	119	70	0	2,7
5.	L	112	85	114	86	1,6	1,2
6.	P	127	75	129	80	0,8	5,25
7.	P	108	60	107	61	0,9	1,4
8.	P	118	70	122	70	4,1	0
9.	L	135	85	110	81	8	4,8
10.	L	121	80	124	77	4,2	2,9
Average							**3,385**
Standard Deviation		**10,020**	**6,390**	**10,306**	**6,416**	**2,476**	**2,434**

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can be seen in table I .The results of blood pressure measurements from ten samples consisting of men and women. Measurements were taken using two devices, the designed device and a digital tensimeter. This table records the systole and diastole blood pressure values for each device, as well as the percentage error between the two devices.
The average measurement error for systole is 3.385%, while for diastole it is 2.434%. This shows that the designed device has good accuracy with a relatively small error rate.
Isolated systolic hypertension (HST) is an important cardiovascular risk factor in the elderly.
Two factors that can predict the development of systolic hypertension are arteriosclerosis and the initial reflection of carotid waves[19].

TABLE II
URINE COLOR SENSOR TESTING DATA

No	Sensor	R	G	B	error
1.	TCS3200	150	45	163	1,32%
	software	152	48	161	
2.	TCS3200	102	195	220	4,02%
	software	98	200	215	
3.	TCS3200	220	116	49	3,1%
	software	227	115	50	
4.	TCS3200	46	59	186	2,1%
	software	47	57	189	
5.	TCS3200	193	72	49	0,51%
	software	194	70	49	
6.	TCS3200	123	270	111	0,87%
	software	122	273	109	
7.	TCS3200	172	133	218	0,58%
	software	173	137	214	
8.	TCS3200	239	233	60	1,23%
	software	242	233	63	
	Error rata-rata				1,7%

can be seen in table II Urine Color Sensor Testing Data displays data from testing the urine color sensor using the TCS3200 sensor and Corel DRAW X7 software. This table includes several columns: the test sequence number (No), the color measurement result by the TCS3200 sensor (in red (R), green (G), and blue (B) components), the color measurement result using the eyedropper tool in the software (in the same color components), and the percentage error between the two measurement results. Each row in this table shows data from one measured urine sample. For example, in the first test, the TCS3200 sensor measured colors with components R: 150, G: 45, and B: 163, while the software measured R: 152, G: 48, and B: 161, resulting in an error of 1.32%. The other rows in the table show the differences and varying error percentages, with the highest error value reaching 4.02% in the second test. At the bottom of the table, there is a summary showing the average error of all measurements, which is 1.7%. An additional explanation at the bottom of the table states that the data measured with the TCS3200 color sensor was compared with the measurement results using the eyedropper tool in Corel DRAW X7 software[20], which was obtained by measuring the urine color using both tools.

C. Performance Indicators to Assess the Accuracy of SVM Algorithm in Diagnosing Diabetes

After successfully importing and reading the dataset used, check the dataset by looking at its contents. Here is the code:

```
df.head()
```

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	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

Figure 7. sempel data

The code above will display the top 5 data with 9 columns from the dataset.
In SVM algorithms that generally use mathematical operations, data needs to be converted into numeric data types due to practical reasons such as ease of calculation and compatibility.
Then the unnecessary column, the number column, is removed. The following is the code and results
:#Seperating the data and labels
X = data.drop(columns = 'Outcome', axis = 1)
Y = data['Outcome']

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
0	6	148	72	35	0	33.6	0.627	50
1	1	85	66	29	0	26.6	0.351	31
2	8	183	64	0	0	23.3	0.672	32
3	1	89	66	23	94	28.1	0.167	21
4	0	137	40	35	168	43.1	2.288	33
...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63
764	2	122	70	27	0	36.8	0.340	27
765	5	121	72	23	112	26.2	0.245	30
766	1	126	60	0	0	30.1	0.349	47
767	1	93	70	31	0	30.4	0.315	23

768 rows × 8 columns

Figure 8. Sample data

In the above program, to delete some columns needed by the indexing system, we use the drop() function. And to make sure the columns that are not needed are completely deleted, the info() function can be used as below:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

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Performance indicators that are often used to assess the accuracy of the SVM algorithm in diagnosing diabetes are:
Accuracy: The percentage of correct predictions out of total predictions.

$$\text{Akura}si = \frac{TP+TN}{TP+TN+FP+FN}$$

a. TP: True Positive (correctly detected positive cases)
b. TN: True Negative (correctly detected negative cases)
c. FP: False Positive (negative cases falsely detected as positive)
d. FN: False Negative (positive cases that were detected incorrectly as negative)

Confusion Matrix: A matrix that shows the number of correct and incorrect predictions in the classification. The elements are TP, TN, FP, and FN.
By using this indicator, it can evaluate how good the SVM algorithm is in diagnosing diabetes and make a decision on whether the algorithm is suitable for use in medical applications.
diabetes and make a decision on whether the algorithm is suitable for use in medical applications.

D. Results of Tool Inputs to the Web

The following are the input results of the tools that have been successfully uploaded into the web system. The data displayed includes relevant information related to the designed tool.

Table III provides an overview of the various variables measured and how they relate to the diagnosis of diabetes or not diabetes, which is the result of the tool's input to the web system. This data is useful for further analysis of the factors that influence diabetes risk.
By combining IoT and SVM technologies in a non-invasive device for early detection of diabetes, this research not only demonstrates advancements in technology but also makes a meaningful contribution to existing medical practices, improving patients' quality of life and paving the way for future innovations.

TABLE III
RESULTS OF TOOL INPUTS TO THE WEB

Umur	Jenis kelamin	Pegnancies	Glucose	Blood pressure	Skin thickness	Insulin	Berat	Tinggi	Outcome
22	p	1	148	102	11	82	58	155	Tidak diabetes
21	p	2	135	94	18	76	55	155	Tidak Diabetes
30	L	0	147	101	21	23	60	160	Tidak diabetes
50	P	6	148	72	35	0	75	150	Diabetes
35	L	0	145	80	20	60	80	170	Tidak diabetes
43	p	7	147	76	40	0	84	148	Diabetes
25	L	0	130	105	20	50	50	173	Tidak diabetes

Progress and Differences

1. Non-Invasive vs. Invasive: The non-invasive IoT devices developed in your research represent significant advances over invasive methods. The use of non-invasive sensors for diabetes detection reduces patient discomfort and allows for more frequent monitoring without direct medical intervention.
2. IoT and SVM integration: The combination of the use of IoT technology with SVM algorithms shows improvements in real-time data analysis and prediction accuracy. Previous studies may have focused only on one of these technologies, but the integration of the two could provide a more comprehensive and effective solution.
3. Real-Time Capability: The device designed in this study provides real-time monitoring capabilities that many previous methods do not have. This allows for early detection and faster treatment, which is crucial in the management of diabetes.

IV. CONCLUSION

The conclusion of this research is that the diabetes early detection device designed using blood pressure sensors and color sensors to determine glucose levels has been proven to function properly. The blood pressure sensor is able to measure systolic and diastolic pressure validly, while the color sensor can detect color changes due to chemical reactions with glucose accurately. Data from both sensors is sent to the Arduino microcontroller, processed, and the results are displayed on the LCD screen.

V. BIBLIOGRAPHY

[1] D. Diana Dewi, N. Qisthi, S. S. S. Lestari, and Z. H. S. Putri, "Perbandingan Metode Neural Network Dan Support Vector Machine Dalam Klasifikasi Diagnosa Penyakit Diabetes," *Cerdika J. Ilm. Indones.*, vol. 3, no. 09, pp. 828–839, 2023, doi: 10.59141/cerdika.v3i09.662.

[2] W. Wahyuni, S. Fatmawati, and E. Dewi Noorratri, "Penurunan Tekanan Darah Dengan Senam Hipertensi," *Profesi (Profesional Islam. Media Publ. Penelit.*, vol. 21, no. 1, pp. 47–51, 2023, doi: 10.26576/profesi.v21i1.207.

[3] U. Hasanah, "Insulin Sebagai Pengatur Kadar Gula Darah, hal," *J. Kel. Sehat Sejah.*, vol. 11, no. 22, pp. 42–49, 2013.

[4] H. S. W. Hovi, A. Id Hadiana, and F. Rakhmat Umbara, "Prediksi Penyakit Diabetes Menggunakan Algoritma Support Vector Machine (SVM)," *Informatics Digit. Expert*, vol. 4, no. 1, pp. 40–45, 2022, doi: 10.36423/index.v4i1.895.

[5] R. T. Yunardi, R. Apsari, and M. Yasin, "Comparison of Machine Learning Algorithm For Urine Glucose Level Classification Using Side-Polished Fiber Sensor," *J. Electron. Electromed. Eng. Med. Informatics*, vol. 2, no. 2, pp. 33–39, 2020, doi: 10.35882/jeeemi.v2i2.1.

[6] K. Kemalasari, M. A. Ifadah, and B. N. Iman, "Alat Pendeteksi Kadar Glukosa pada Urine dengan Metode Naive Bayes," *J. Rekayasa Elektr.*, vol. 18, no. 4, pp. 208–215, 2022, doi: 10.17529/jre.v18i4.27238.

[7] S. Hintari and A. I. Fibriana, "Hipertensi pada Penduduk Usia Produktif (15-59 Tahun) di Wilayah Kerja Puskesmas Pageruyung Kabupaten Kendal Sri," *Higeia J. Public Heal. Res. Dev.*, vol. 1, no. 2, pp. 208–218, 2023, [Online]. Available: https://journal.unnes.ac.id/sju/index.php/higeia/article/view/63472

[8] Andreas Putro Ragil Santoso *et al.*, "Deteksi Mikro Albumin Urine Sebagai Upaya Deteksi Untuk Pencegahan Diabetic Neuropati Pada Warga Desa Simo Angin-Angin," *Pros. Semin. Nas. Pengabdi. Kpd. Masy.*, vol. 3, no. 1, pp. 461–466, 2023, doi: 10.33086/snpm.v3i1.1278.

[9] N. Maulidah, R. Supriyadi, D. Y. Utami, F. N. Hasan, A. Fauzi, and A. Christian, "Prediksi Penyakit Diabetes Melitus Menggunakan Metode Support Vector Machine dan Naive Bayes," *Indones. J. Softw. Eng.*, vol. 7, no. 1, pp. 63–68, 2021, doi: 10.31294/ijse.v7i1.10279.

[10] N. Noviandi, "Implementasi Algoritma Decision Tree C4.5 Untuk Prediksi Penyakit Diabetes," *Indones. Heal. Inf. Manag. J.*, vol. 6, no. 1, pp. 1–5, 2018, [Online]. Available: https://inohim.esaunggul.ac.id/index.php/INO/article/view/142

[11] A. R. Isnain, A. I. Sakti, D. Alita, and N. S. Marga, "Sentimen Analisis Publik Terhadap Kebijakan Lockdown Pemerintah Jakarta Menggunakan Algoritma Svm," *J. Data Min. dan Sist. Inf.*, vol. 2, no. 1, p. 31, 2021, doi: 10.33365/jdmsi.v2i1.1021.

[12] S. Siswanto, G. P. Utama, and W. Gata, "Pengamanan Ruangan Dengan Dfrduino Uno R3, Sensor Mc-38, Pir, Notifikasi Sms, Twitter," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 2, no. 3, pp. 697–707, 2018, doi: 10.29207/resti.v2i3.592.

[13] D. Michael and D. Gustina, "Rancang Bangun Prototype Monitoring Kapasitas Air Pada Kolam Ikan Secara Otomatis Dengan Menggunakan Mikrokontroller Arduino," *IKRA-ITH Inform.*, vol. 3, no. 2, pp. 59–66, 2019, [Online]. Available: https://journals.upi-yai.ac.id/index.php/ikraith-informatika/article/view/319

[14] A. D. Pangestu, F. Ardianto, and B. Alfaresi, "Sistem Monitoring Beban Listrik Berbasis Arduino Nodemcu Esp8266," *J. Ampere*, vol. 4, no. 1, p. 187, 2019, doi: 10.31851/ampere.v4i1.2745.

[15] D. Sasmoko, Danang Danang, Padjar Setyo Budi, and Muhammad Agus Kurniawan, "Penggunaan Sensor TCS3200 dan NodeMCU untuk Mendeteksi Warna Daun Padi dalam Menentukan Jumlah Pupuk Urea Bebasis IoT," *Elkom J. Elektron. dan Komput.*, vol. 13, no. 1, pp. 87–102, 2020, doi: 10.51903/elkom.v13i1.174.

[16] M. F. Pela and R. Pramudita, "Sistem Monitoring Penggunaan Daya Listrik Berbasis Internet of Things Pada Rumah Dengan Menggunakan Aplikasi Blynk," *Infotech J. Technol. Inf.*, vol. 7, no. 1, pp. 47–54, 2021, doi: 10.37365/jti.v7i1.106.

[17] D. W. Hoffman, "No 主観的健康感を中心とした在宅高齢者における 健康関連指標に関する共分散構造分析Title".

[18] P. M. Sulistyawan, "Perancangan Sistem pemantau Tekanan Darah Dengan Sensor Tekanan MPX5100GP Berbasis STM32F103," *Semin. Nas. Fortei Reg. 7*, vol. 4 No.1, p. 167, 2021, [Online]. Available: https://journal.fortei7.org/index.php/sinarFe7/article/view/45

[19] A. F. Lewa, I. D. P. Pramantara, and T. B. Rahayujati, "Faktor-Faktor Risiko Hipertensi Sistolik Terisolasi pada Lanjut Usia," *Ber. Kedokt. Masy.*, vol. 26, no. 4, pp. 171–178, 2010.

[20] A. Galih Pradana and S. Nita, "Rancang Bangun Game Edukasi 'AMUDRA' Alat Musik Daerah Berbasis Android," *J. Semin. Nas. Teknol. Inf. dan Komun. 2019*, vol. 2, no. 1, pp. 49–53, 2019.