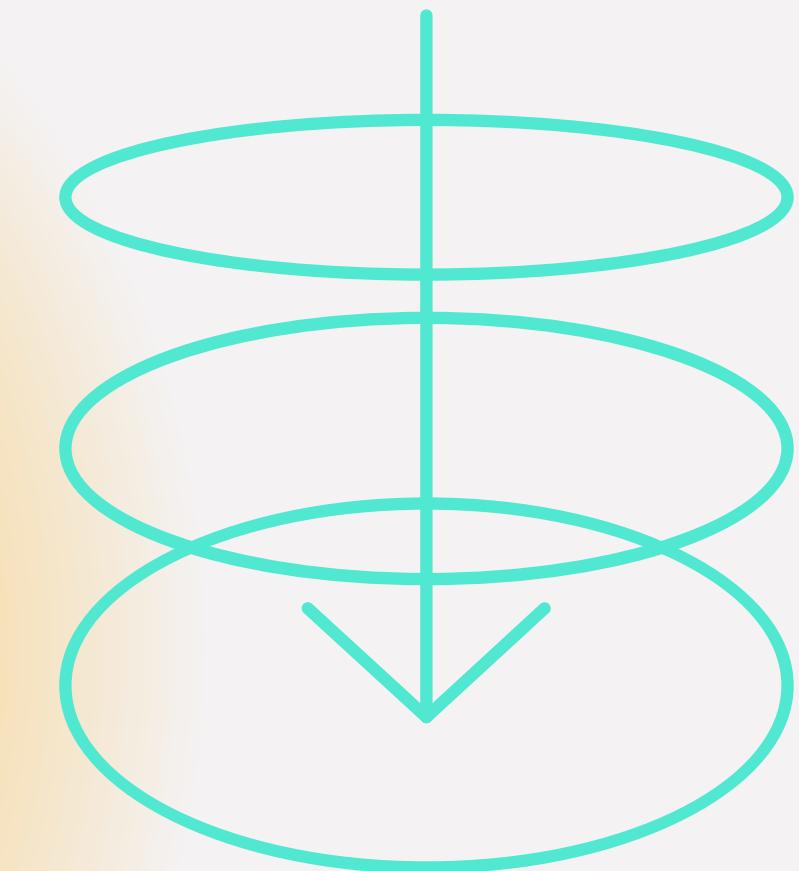


RevolutionD

Painless blood glucose monitoring during exercise



Sensors

Application

Servers

Websites

Table of contents

- Introduction/Recap
- Prototype
- Application
- Model
- Server & Website
- **DEMO**
- Conclusion

10 Mins



Introduction/Recap

Chosen Problem, **Type 2 Diabetes**:

- Exercise for diabetic patients pose a risk of their blood sugar spiking
- Monitoring blood sugar levels during exercise is painful and bothersome

Our idea:

- A non-invasive blood glucose monitor
- Uses sweat and movement to measure blood glucose
- Suitable for tracking blood glucose during exercise



Research

International Journal of Nanoelectronics and Materials
Volume 13 (Special Issue) May 2020 [9-16]

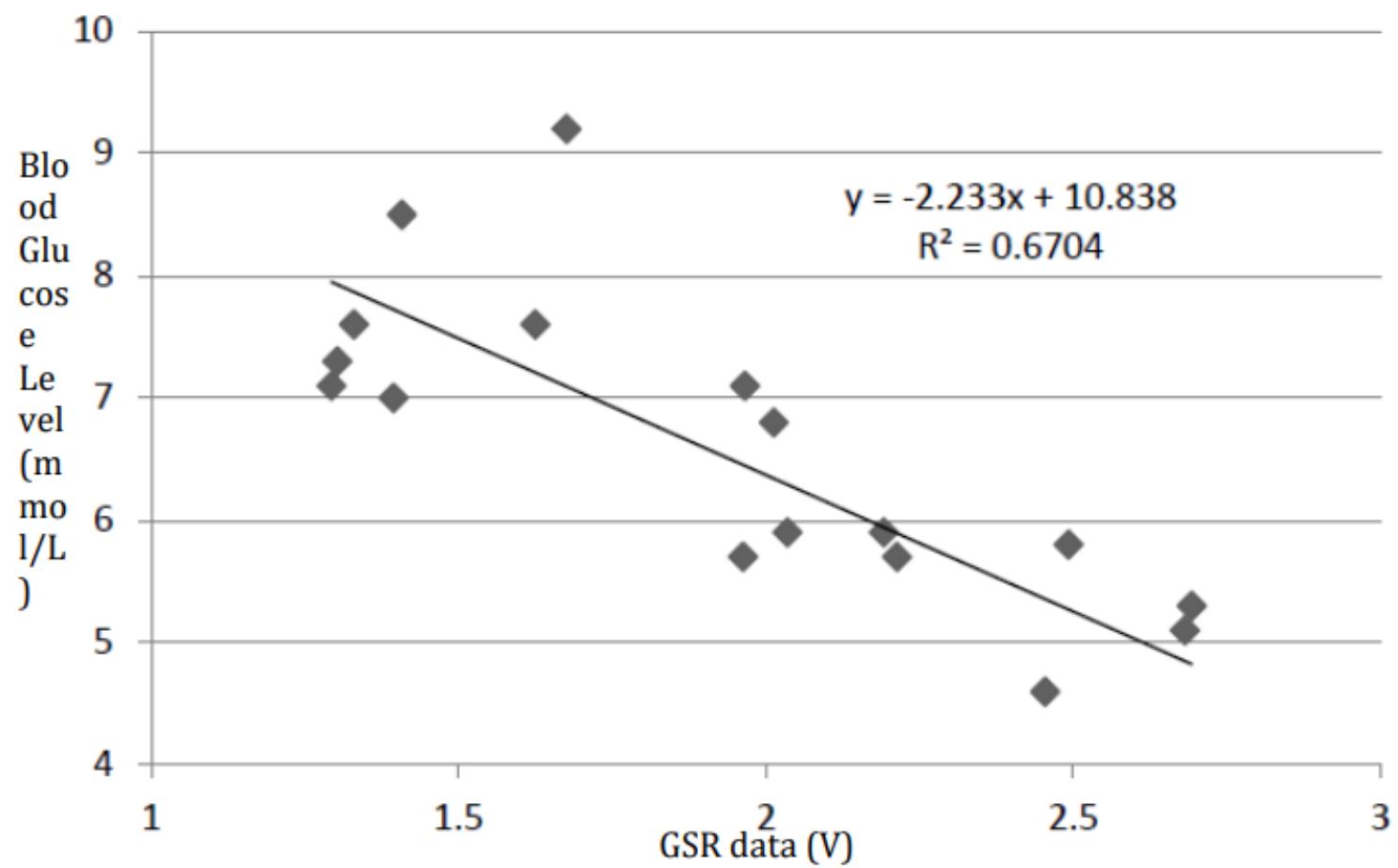


Figure 7. Correlation between blood glucose level and GSR readings.

A study shows that the correlation between blood glucose level and GSR data reading is determined as inversely proportional to each other with a correlation factor of **0.67**. [1]

Research

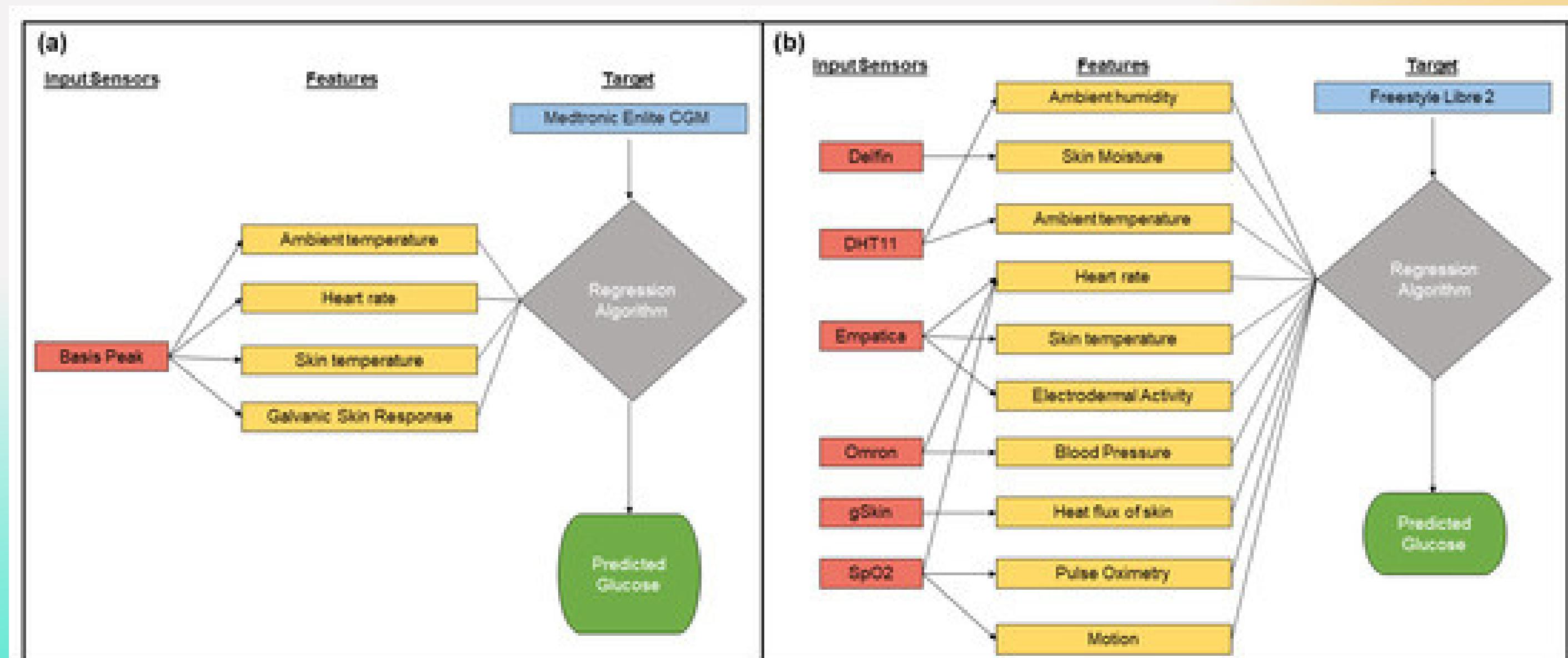


Figure 1. Sensors and their features for the (a) OhioT1DM and (b) UofM datasets.

The results of another study show that the combination of fourteen noninvasive biometric measurements with ML algorithms is able to accurately predict blood glucose levels

Our Idea

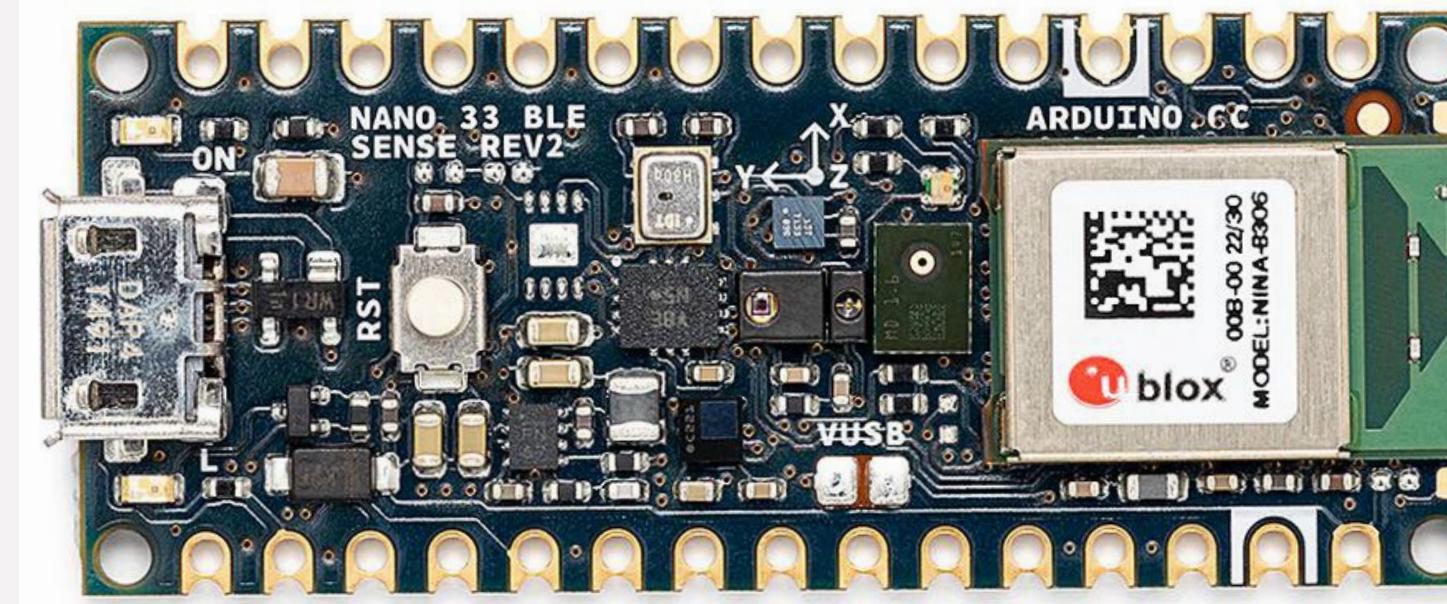
Using multiple sensors to track several physiological factors, predict their blood glucose levels in real-time.

Prototype

Prototype

Sensors

Arduino Board



SpO₂ Sensor

GSR Sensor

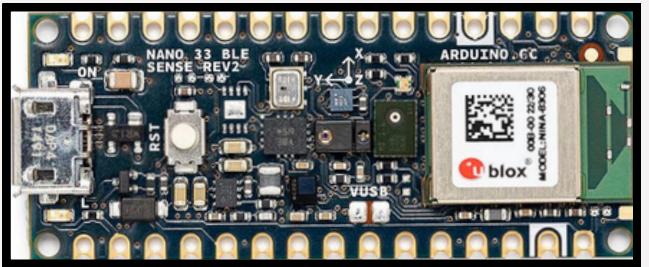
Arduino Nano 33 BLE Sense Rev2

- Transfer data to application
- Measures *motion*
- Measures *ambient heat*
- Measures *ambient temperature*

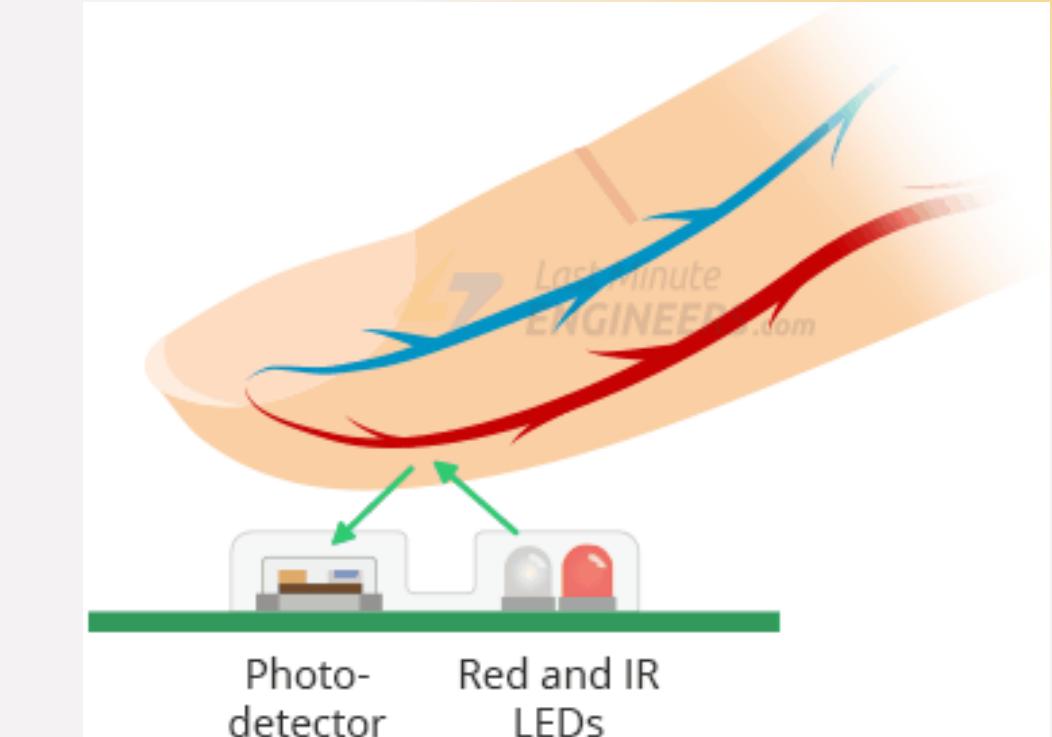
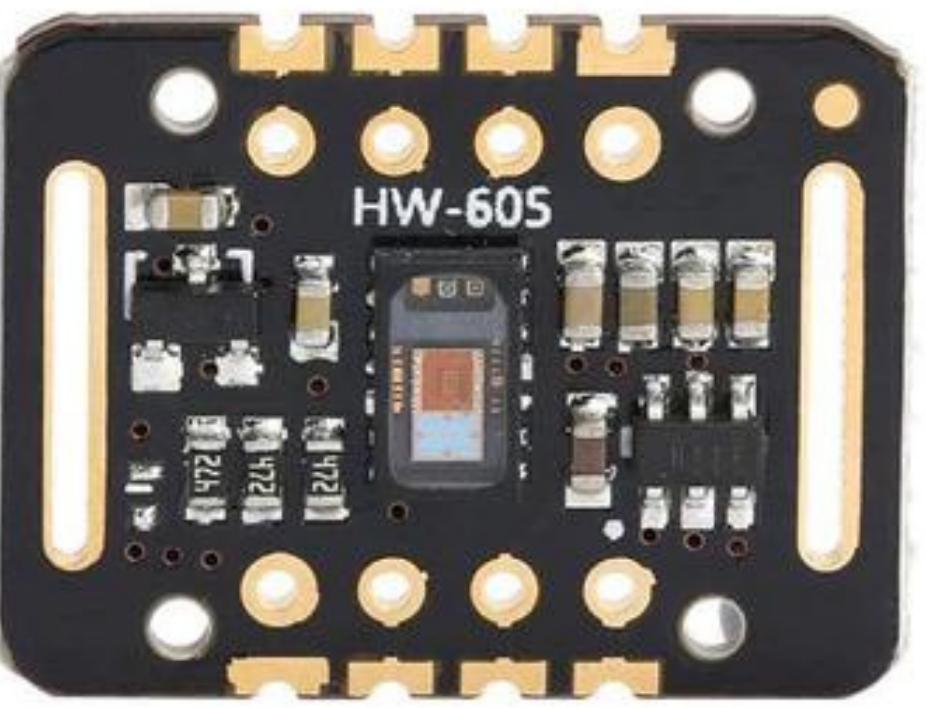
Prototype

Sensors

Arduino Board



SpO₂ Sensor



GSR Sensor

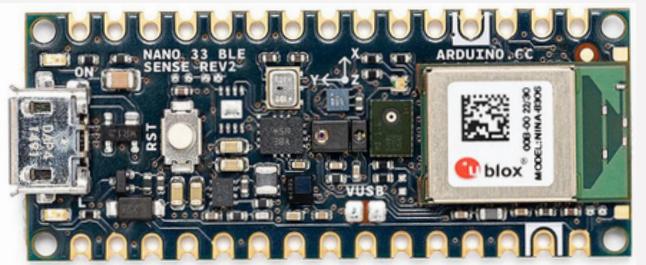
MAX30102 Pulse Oximeter & Heart Rate Sensor

- Measures *Heart Rate*
- Measures *Oxygen Saturation (SpO₂)*

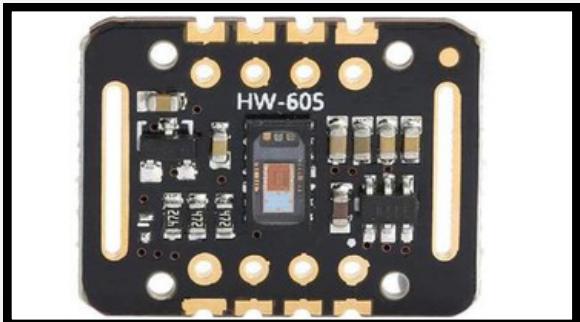
Prototype

Sensors

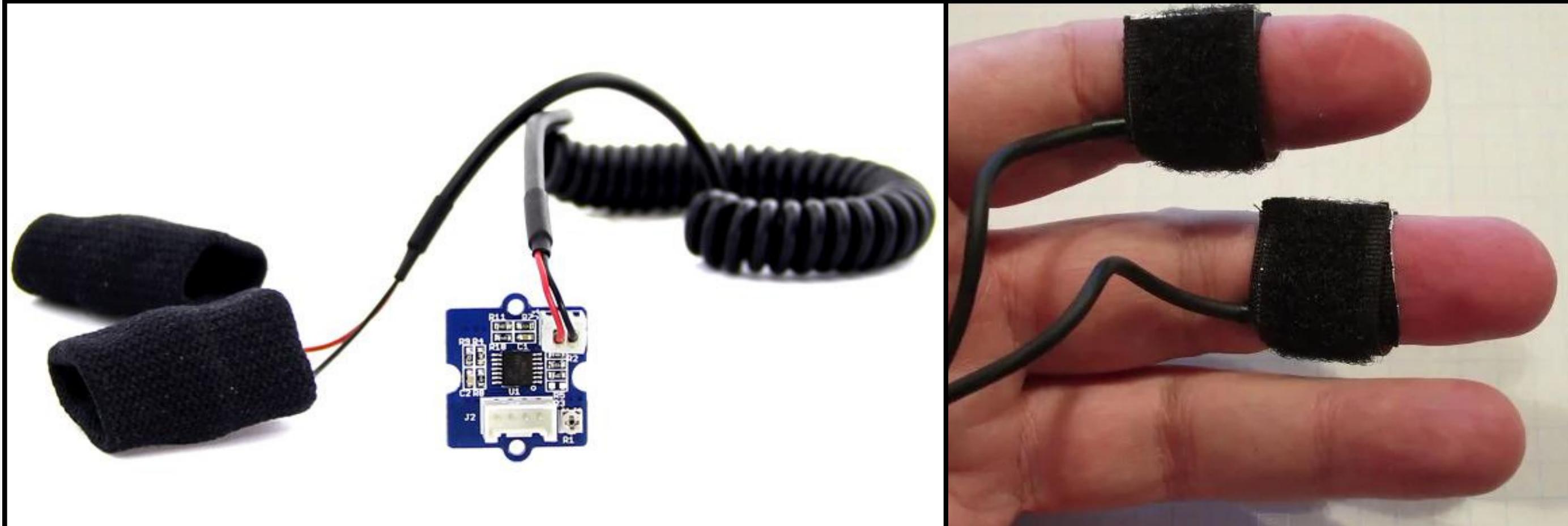
Arduino Board



SpO₂ Sensor



GSR Sensor

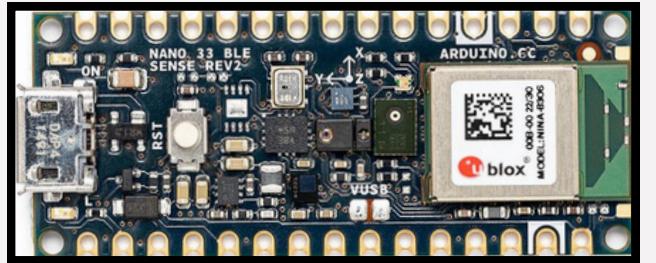


Galvanic Skin Response Sensor

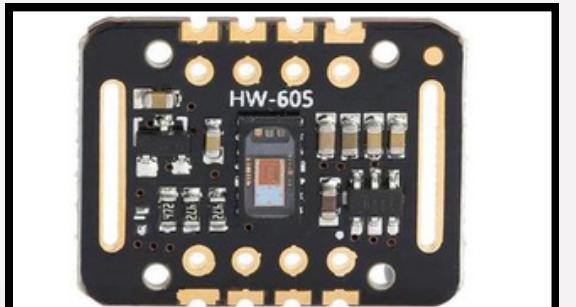
- Measures eda in sweat produced during exercise

Prototype

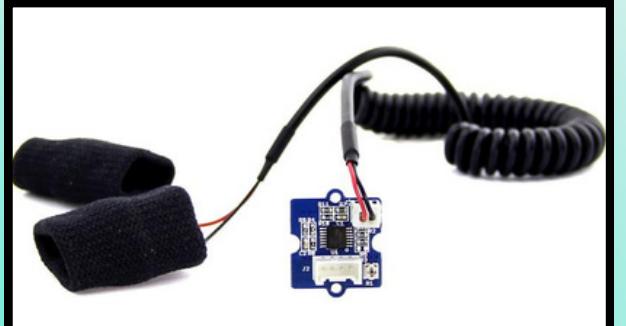
Arduino Board



SpO₂ Sensor



GSR Sensor



Sensors

Housing



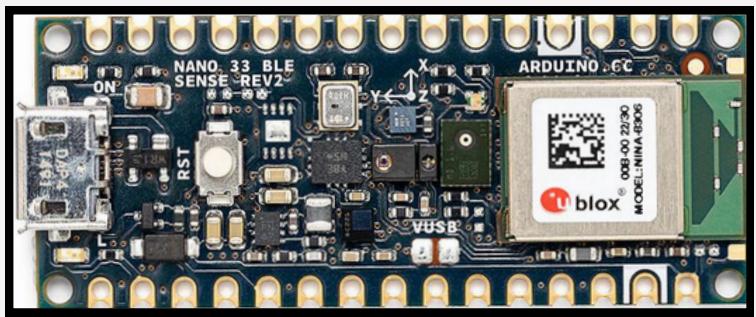
Prototype

Sensors

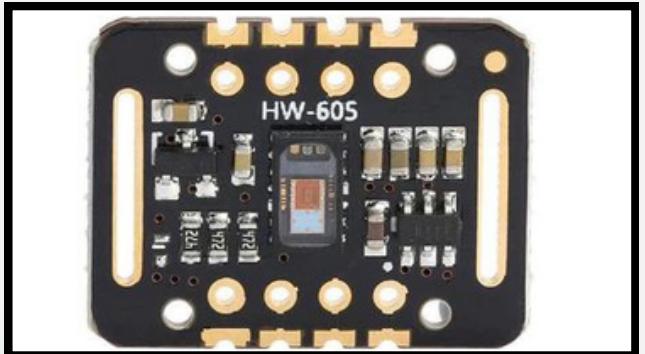
Housing

Product

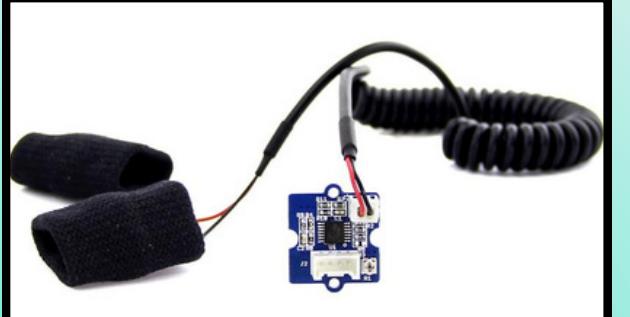
Arduino Board



SpO2 Sensor

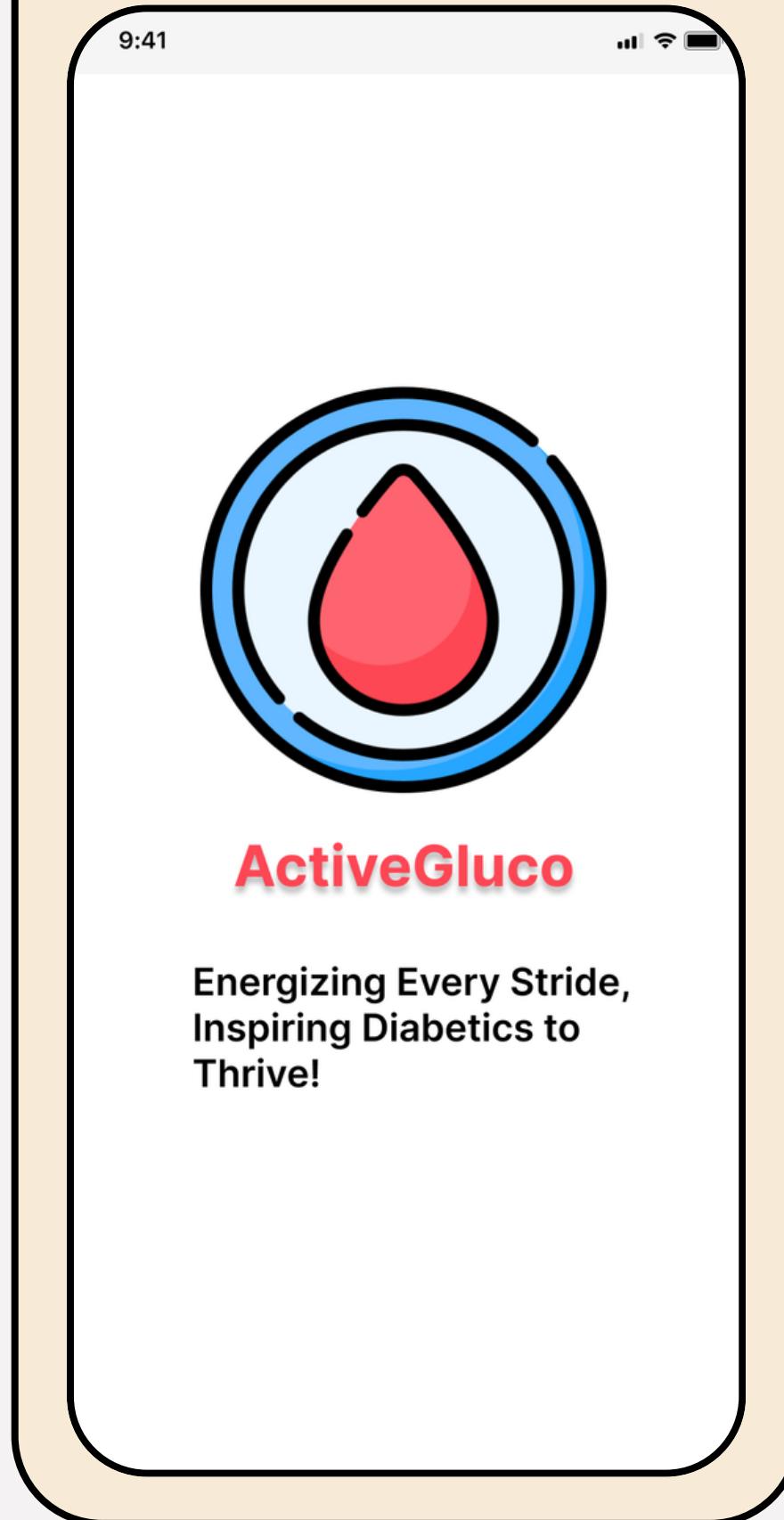


GSR Sensor



Application

Splash Page



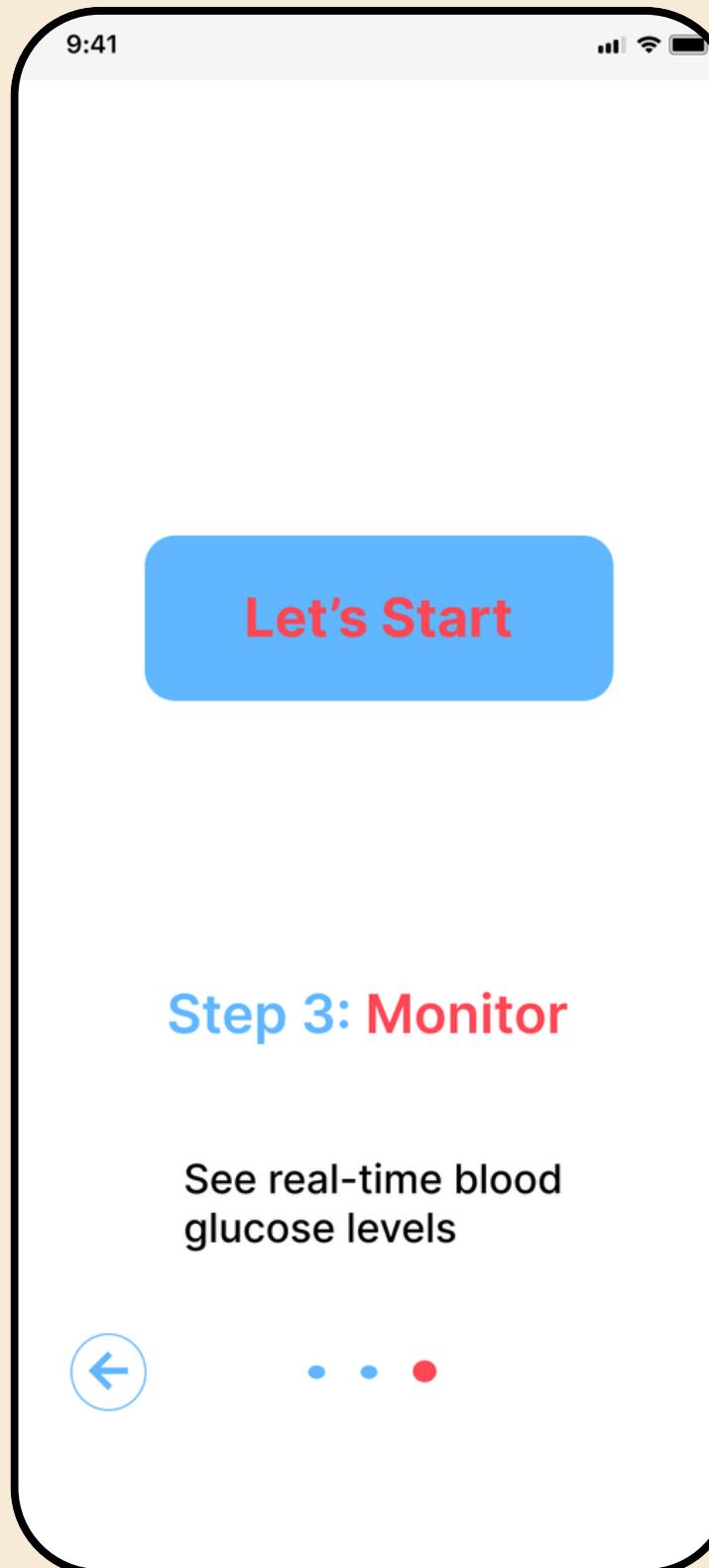
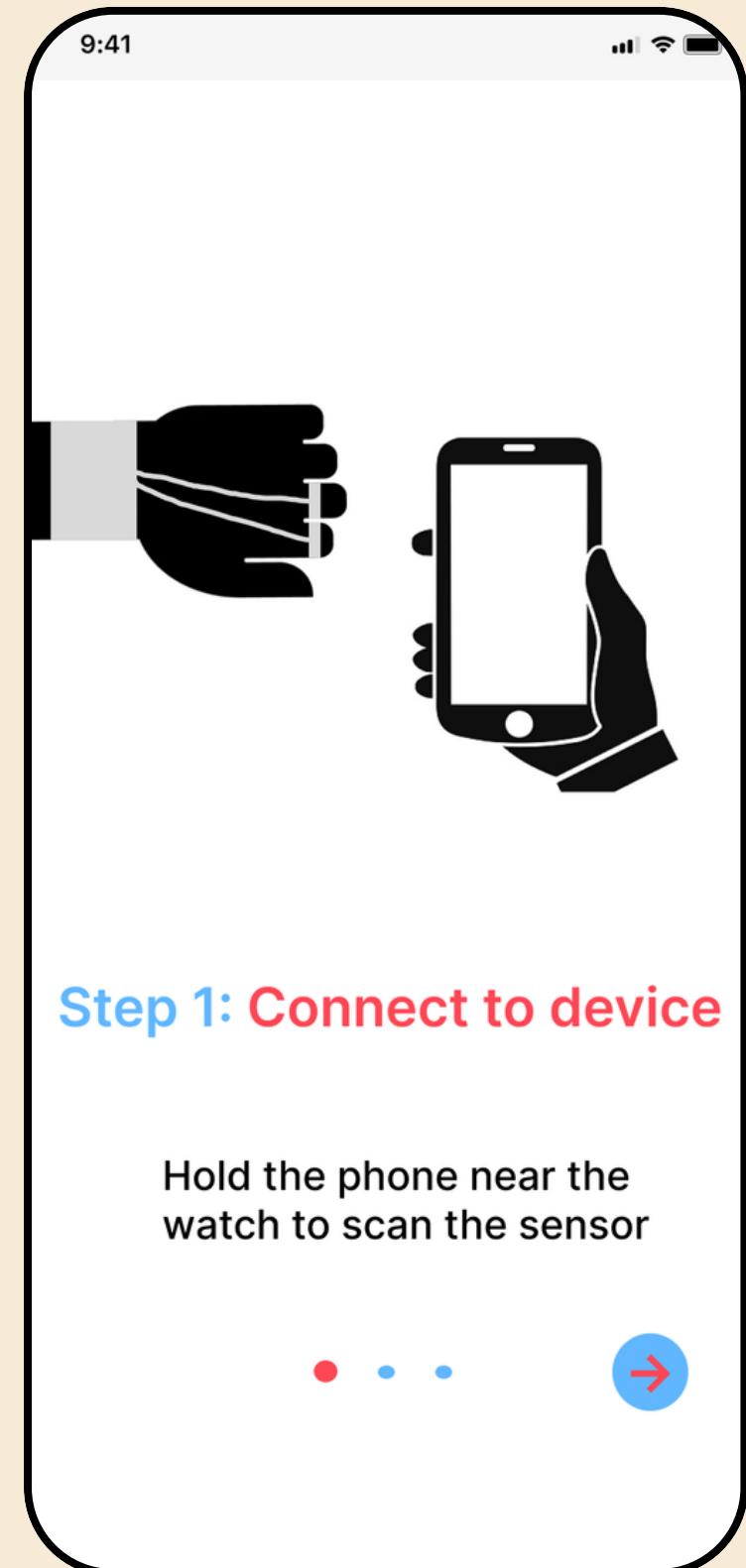
App (ActiveGluco)

- Track and monitor real-time blood glucose levels while exercising

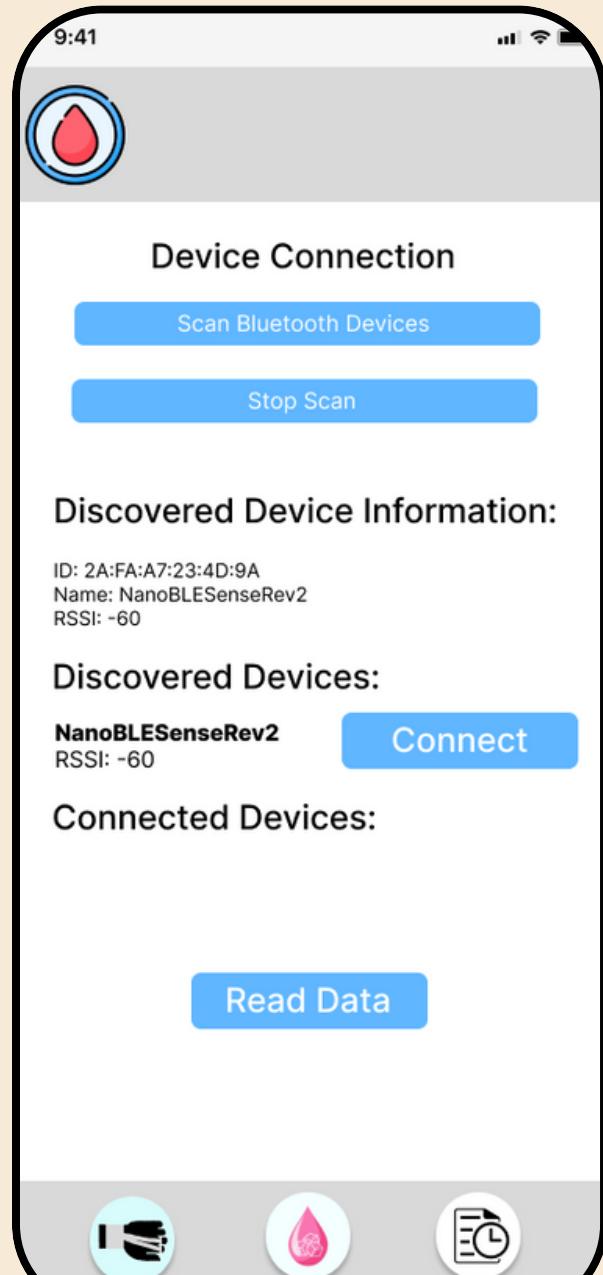
Did you know?

- Exercise helps diabetics better regulate blood glucose levels and reduce the need for external insulin administration

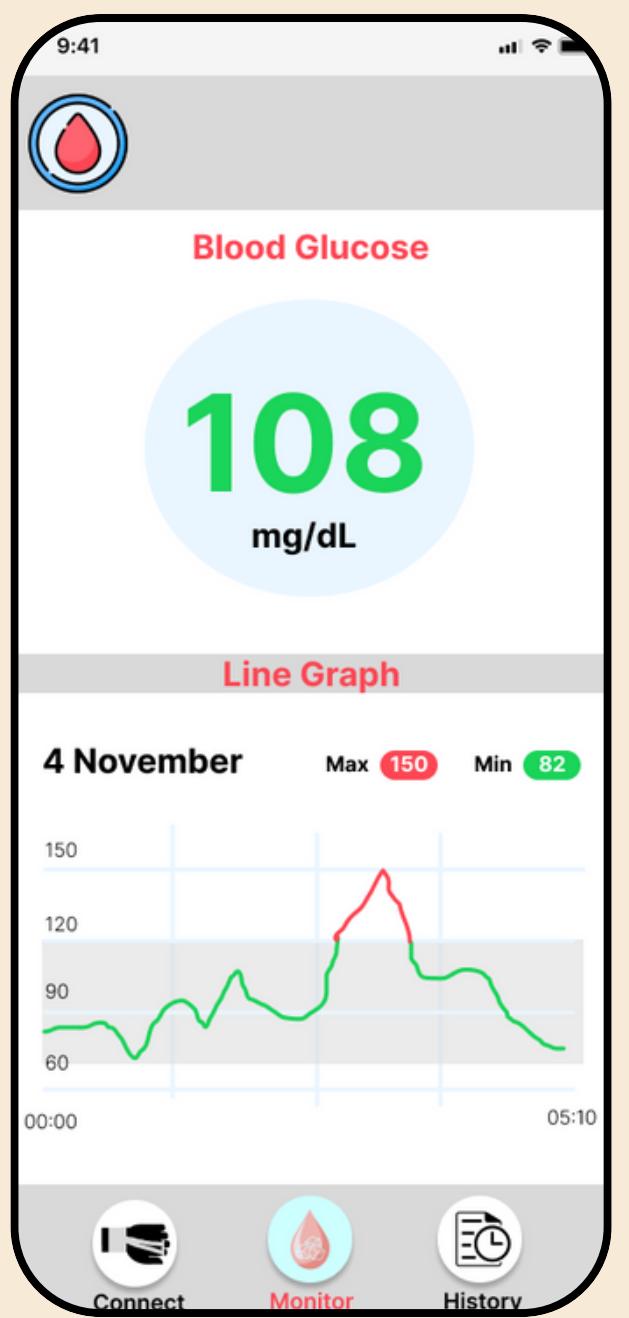
Simple step by step process:



Connect Page



Monitor Page



History Page

The History Page displays a header with a blood drop icon and the time 9:41. The main content is a table titled "History" showing a list of blood glucose measurements with columns for Date, Duration, and Avg. The data is as follows:

Date	Duration	Avg
1 November	10 mins	96 mg/dL
26 October	23 mins	88 mg/dL
22 October	8 mins	104 mg/dL
20 October	30 mins	87 mg/dL
18 October	15 mins	119 mg/dL

At the bottom, there is a navigation bar with icons for Connect, Monitor, and History.

Purpose

- Users can exercise safely by monitoring real time blood glucose level

How it works

- Fetch real-time data from Arduino and send to server
- Server will process the received data through a machine learning model
- App will get the predicted blood glucose levels from the server and display it in a line graph



Machine
Learning
Model

Statistics from UofM dataset, subject 2:

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9100498/pdf/sensors-22-03534.pdf>

Features	Glucose	SpO2	Heart rate	Motion	Amb. Humidity	Amb. Temp.	Moisture: Ventral	Moisture: Dorsal	Heat Flux	BVP	IBI	Skin Temp	EDA	Systolic	Diastolic
Glucose	1.00														
SpO2	0.40	1.00													
Heart rate	-0.37	-0.48	1.00												
Motion	-0.32	-0.31	0.62	1.00											
Amb. Humidity	0.08	-0.12	0.05	0.08	1.00										
Amb. Temp.	-0.06	0.09	-0.27	-0.09	0.47	1.00									
Moisture: Ventral	-0.21	-0.33	0.55	0.34	-0.04	-0.29	1.00								
Moisture: Dorsal	-0.28	-0.10	0.32	0.19	0.06	0.20	-0.05	1.00							
Heat Flux	0.12	-0.01	-0.02	-0.02	0.45	-0.09	-0.01	0.11	1.00						
BVP	0.25	0.20	-0.10	-0.03	-0.05	0	-0.13	-0.04	-0.03	1.00					
IBI	0.06	0.18	-0.27	-0.05	-0.14	-0.10	-0.16	-0.14	-0.18	-0.11	1.00				
Skin Temp.	-0.61	-0.40	0.58	0.42	-0.06	0.02	0.38	0.36	0.13	-0.10	-0.23	1.00			
EDA	-0.38	-0.37	0.87	0.54	-0.07	-0.43	0.62	0.33	-0.01	-0.01	-0.13	0.57	1.00		
Systolic	-0.18	-0.51	0.84	0.52	0.01	-0.43	0.53	0.22	-0.10	-0.05	-0.11	0.32	0.84	1.00	
Diastolic	-0.36	-0.43	0.83	0.53	-0.04	-0.39	0.59	0.29	-0.07	-0.05	-0.08	0.48	0.87	0.85	1.00

Table 5. Statistical analysis of Subject 2 from the UofM dataset

Finding Datasets

Generating Data

Training Model

Implementation

Defining data statistics
(Mean, StDev, Min, Max)

Defining correlations

Generating 20,000 samples

Write to CSV

```
import numpy as np
import pandas as pd

# Define the parameters for each feature
params = {
    'Glucose': {'mean': 113.75, 'std': 23.18, 'min': 84.00, 'max': 172.00},
    'SpO2': {'mean': 96.14, 'std': 1.66, 'min': 86.00, 'max': 98.33},
    'Heart Rate': {'mean': 77.83, 'std': 14.96, 'min': 57.00, 'max': 121.63},
    'Motion': {'mean': 2.81, 'std': 2.24, 'min': 0.00, 'max': 10.87},
    'Amb. Humi.': {'mean': 43.86, 'std': 5.40, 'min': 23.85, 'max': 52.60},
    'Amb. Temp.': {'mean': 22.04, 'std': 3.59, 'min': 10.70, 'max': 29.20},
    'EDA': {'mean': 4.47, 'std': 7.20, 'min': 0.08, 'max': 22.47}
}

# Define the correlation matrix
correlation_matrix = np.array([[1.0, 0.40, -0.37, -0.32, 0.08, -0.06, -0.21],
                               [0.40, 1.0, -0.48, -0.31, -0.12, 0.09, -0.33],
                               [-0.37, -0.48, 1.0, 0.62, 0.05, -0.27, 0.55],
                               [-0.32, -0.31, 0.62, 1.0, 0.08, -0.09, 0.34],
                               [0.08, -0.12, 0.05, 0.08, 1.0, 0.47, -0.04],
                               [-0.06, 0.09, -0.27, -0.09, 0.47, 1.0, -0.29],
                               [-0.21, -0.33, 0.55, 0.34, -0.04, -0.29, 1.0]])

# Generate random samples based on the provided parameters
sample_size = 20000
sample_data = np.random.multivariate_normal(mean=np.zeros(len(params)), cov=correlation_matrix, size=sample_size)

# Adjust samples to meet the provided minimum and maximum values for each feature
for i, (feature, param) in enumerate(params.items()):
    sample_data[:, i] = np.clip(sample_data[:, i] * param['std'] + param['mean'], param['min'], param['max'])

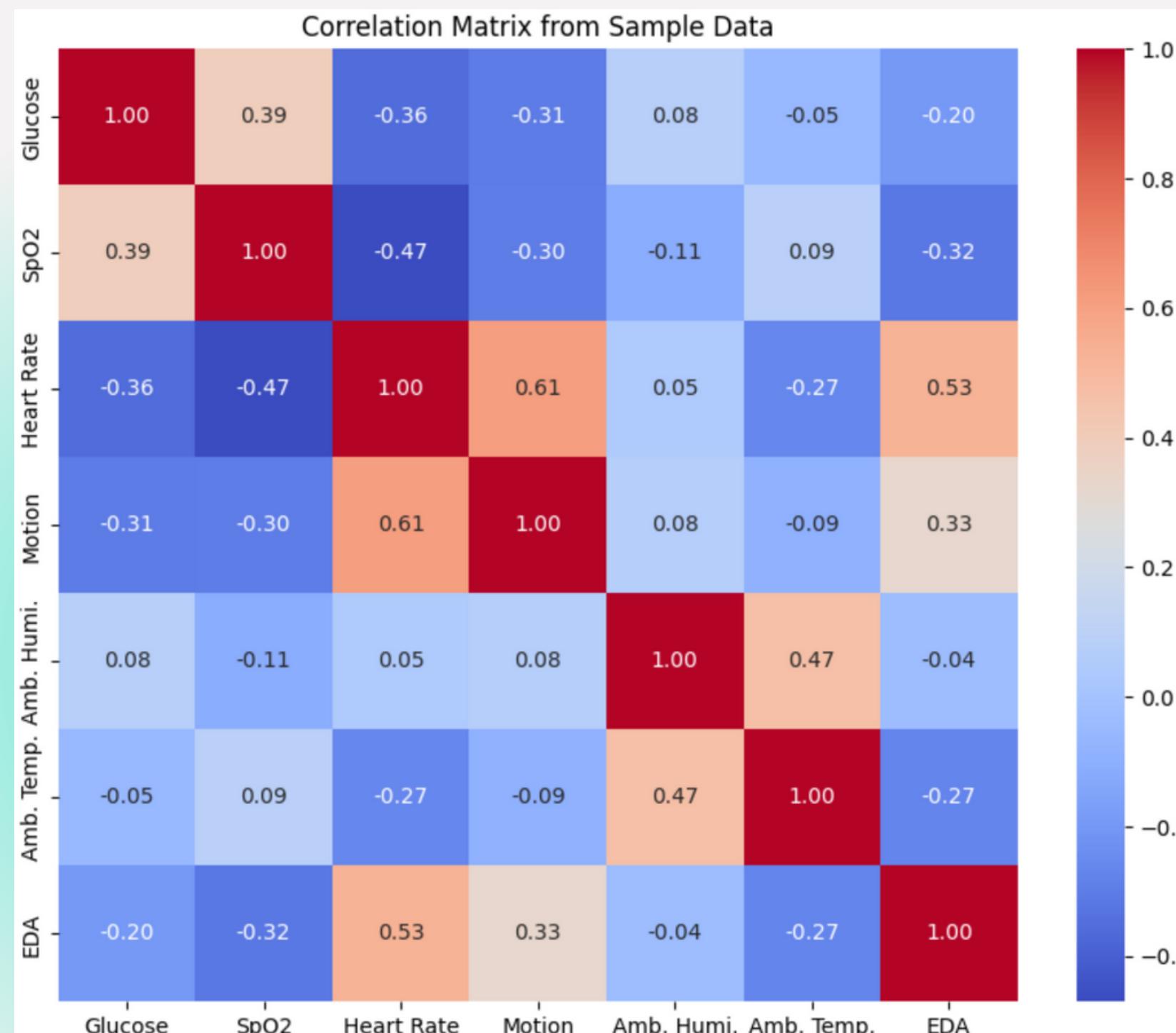
# Create a DataFrame from the generated sample data
df_sample = pd.DataFrame(sample_data, columns=params.keys())

# Write the DataFrame to a CSV file
df_sample.to_csv('sample_data.csv', index=False)

print("Sample data has been written to 'sample_data.csv'.")
```

Sample data has been written to 'sample_data.csv'.

From generated data, we get almost identical statistics and correlation



Statistics from Sample Data:

	Glucose	SpO2	Heart Rate	EDA	Motion	Amb. Humi.	Amb. Temp.
mean	114.923818	96.071605	78.421644	5.655576	2.931086	43.740685	22.016715
max	172.000000	98.330000	121.630000	22.470000	10.870000	52.600000	29.200000
min	84.000000	89.361406	57.000000	0.080000	0.000000	23.850000	10.700000
std	21.109669	1.523305	13.932304	5.524003	2.040517	5.133837	3.509732

Considerations for model:

1. The model needs to predict values quickly

- Sensor will constantly stream data
- Model must be able to keep up
- If model is slow, the application will either be inaccurate, or slow.

2. The model needs to be accurate

- Accurate readings lead to correct responses by the user
- Inaccurate readings could lead user to taking wrong medical action, causing harm



Linear Regression Model results

Clarke's Error Grid predictions:

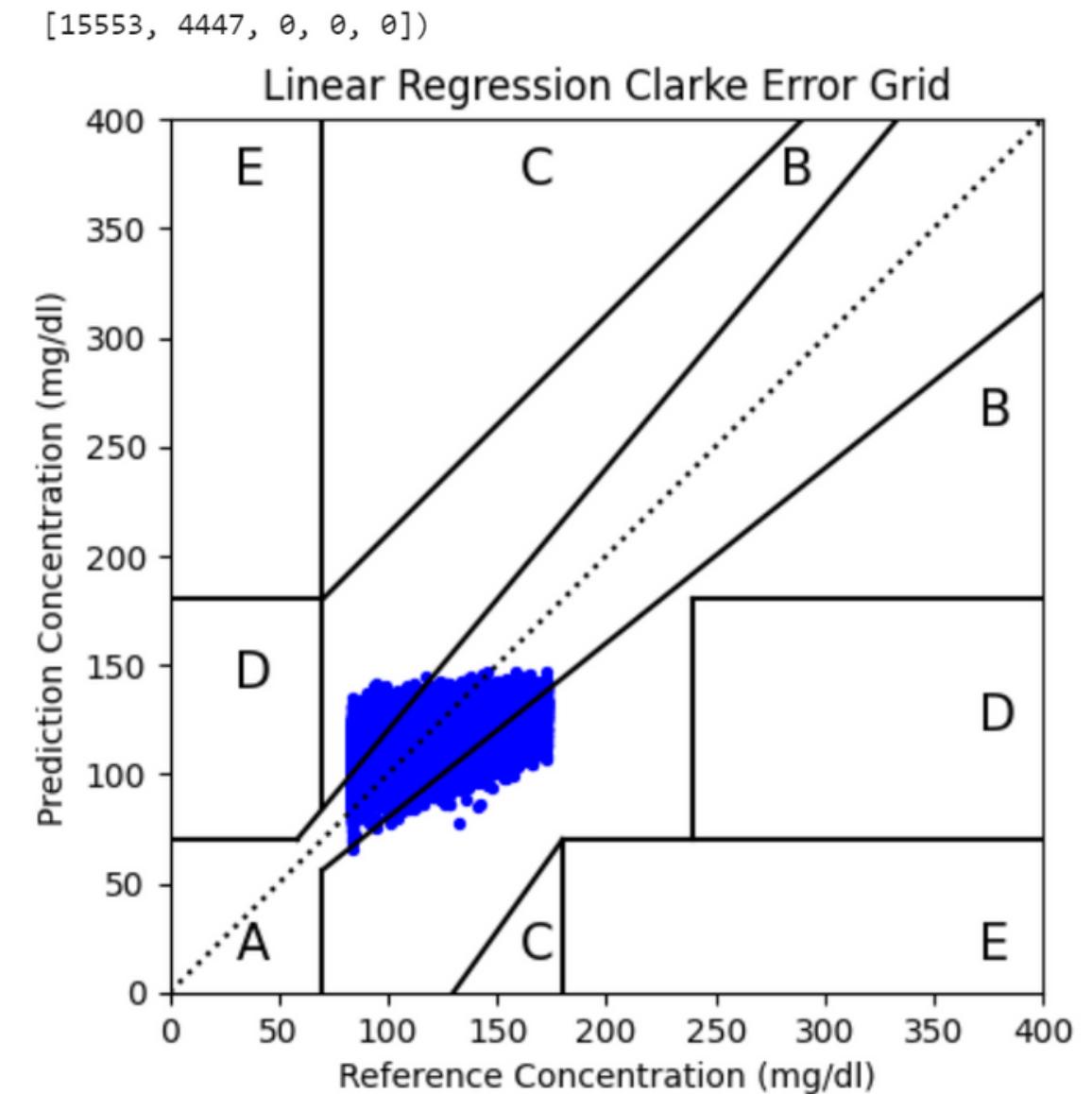
- 75% land in A range
- 25% land in B range
- None in C, D or E

Clarke's Error Grid:

- Region A are those values within 20% of the reference sensor,
- Region B contains points that are outside of 20% but would not lead to inappropriate treatment,
- Region C are those points leading to unnecessary treatment,
- Region D are those points indicating a potentially dangerous failure to detect hypoglycemia or hyperglycemia, and
- Region E are those points that would confuse treatment of hypoglycemia for hyperglycemia and vice versa.

Scores:

- Low R2 score
- Low Mean Squared Error
- Low Root Mean Squared Error



R2 Score: 0.268

MSE: 14.6660714

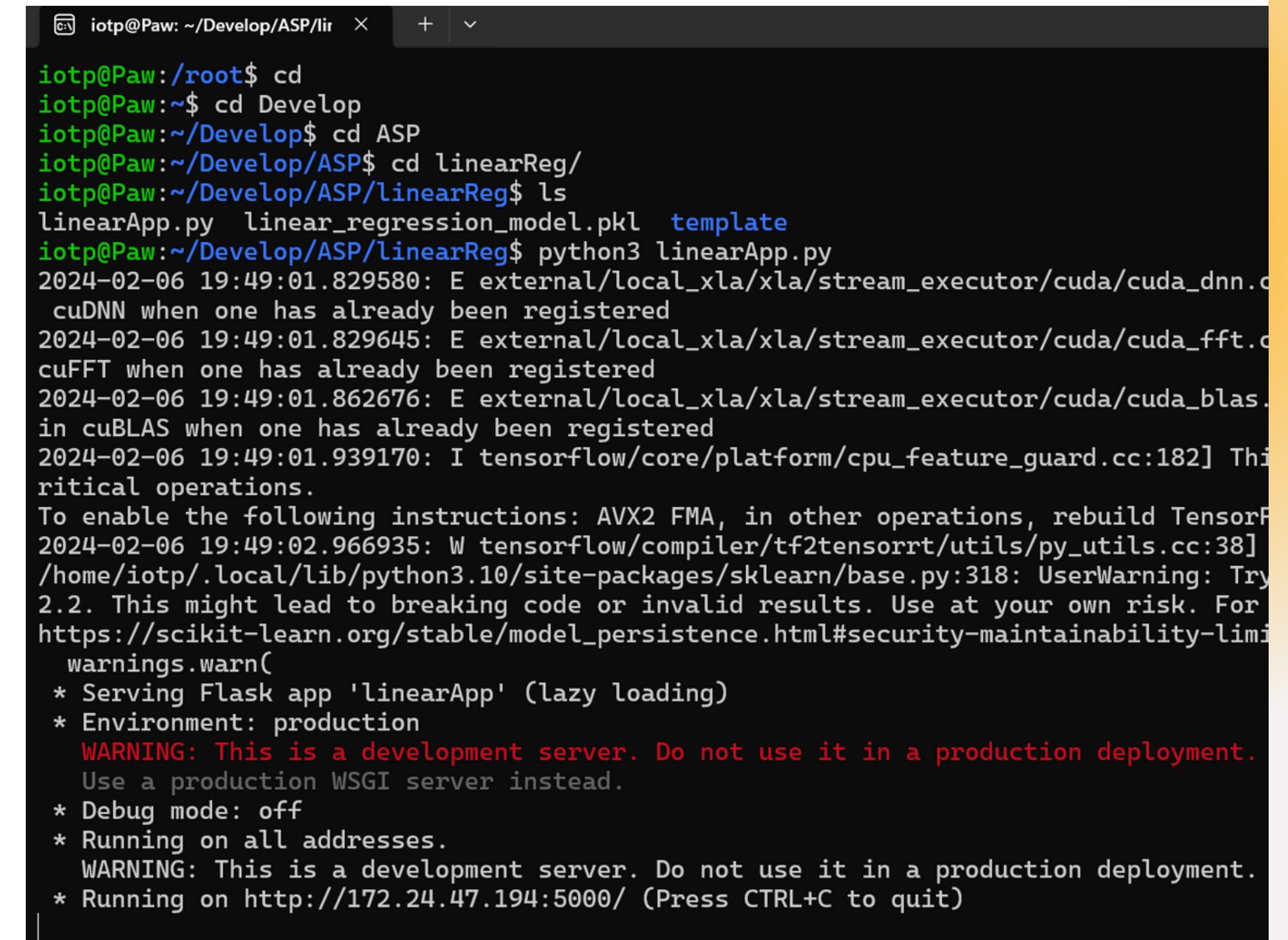
RMSE: 18.090384

Implementation

Step 1: Local Flask Server

Flask server contains various GET and POST methods to send and receive data

```
@app.route('/send', methods=['POST'])  
@app.route('/predict', methods=['GET'])  
@app.route('/getData', methods=['GET'])
```



A terminal window showing the startup logs of a Flask application named 'linearApp'. The logs indicate the application is running on port 5000 and provide several warning messages about development server usage and TensorFlow operations.

```
iotp@Paw:~/Develop/ASP/lir> cd Develop  
iotp@Paw:~/Develop> cd ASP  
iotp@Paw:~/Develop/ASP> cd linearReg/  
iotp@Paw:~/Develop/ASP/linearReg> ls  
linearApp.py linear_regression_model.pkl template  
iotp@Paw:~/Develop/ASP/linearReg> python3 linearApp.py  
2024-02-06 19:49:01.829580: E external/local_xla/xla/stream_executor/cuda/cuda_dnn.cuDNN when one has already been registered  
2024-02-06 19:49:01.829645: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cuFFT when one has already been registered  
2024-02-06 19:49:01.862676: E external/local_xla/xla/stream_executor/cuda/cuda_blas.in cuBLAS when one has already been registered  
2024-02-06 19:49:01.939170: I tensorflow/core/platform/cpu_feature_guard.cc:182] This critical operations.  
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow.  
2024-02-06 19:49:02.966935: W tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] /home/iotp/.local/lib/python3.10/site-packages/scikit-learn/base.py:318: UserWarning: Try 2.2. This might lead to breaking code or invalid results. Use at your own risk. For https://scikit-learn.org/stable/model_persistence.html#security-maintainability-limits  
warnings.warn(  
    * Serving Flask app 'linearApp' (lazy loading)  
    * Environment: production  
      WARNING: This is a development server. Do not use it in a production deployment.  
      Use a production WSGI server instead.  
    * Debug mode: off  
    * Running on all addresses.  
      WARNING: This is a development server. Do not use it in a production deployment.  
    * Running on http://172.24.47.194:5000/ (Press CTRL+C to quit)
```

Implementation

Step 2: Public Flask Server

Using ngrok, the flask server can be hosted on a Public & Static domain

```
iotp@Paw: /root          (Ctrl+C to quit)
ngrok
Build better APIs with ngrok. Early access: ngrok.com/early-access

Session Status               online
Account                      TPolyRay (Plan: Free)
Version                      3.5.0
Region                       Asia Pacific (ap)
Latency                      7ms
Web Interface                http://127.0.0.1:4040
Forwarding                   https://jawfish-touched-supposedly.ngrok-free
Connections
    ttl     opn     rt1     rt5      p50      p90
    0       0       0.00    0.00    0.00    0.00
```

Data Storage

Server → Data Storage → *Website*

Flask Server

```
iotp@Paw:~/root      + v
ngrok

Build better APIs with ngrok. Early a

Session Status
Account
Version
Region
Latency
Web Interface
Forwarding

Connections

online
TPolyRa
3.5.0
Asia Pa
7ms
http://
https:/

ttl
0
```

WAMP Framework

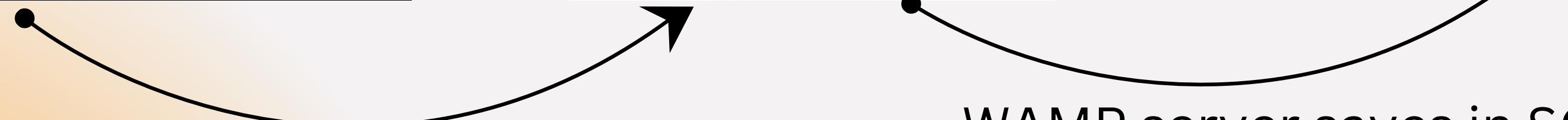


SQL Database



Server sends data to WAMP server

WAMP server saves in SQL



Server → Data Storage → Website

Screenshot of the phpMyAdmin interface showing the 'blood_glucose' database and 'healthdata' table.

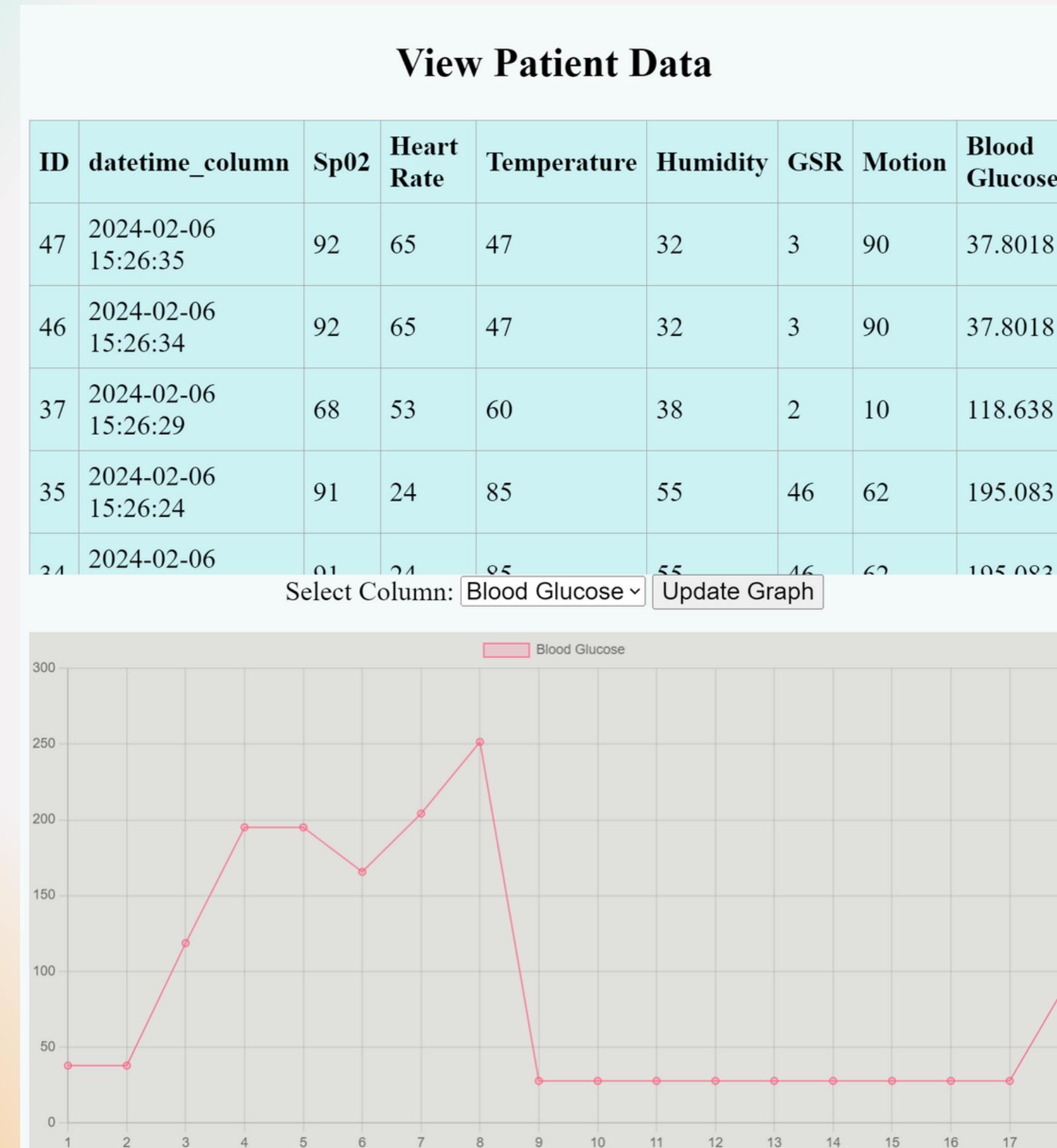
The 'Current server' dropdown is set to MySQL. The 'Recent' tab is selected.

The 'blood_glucose' database is highlighted in green.

The 'healthdata' table is selected. The table structure is as follows:

	Edit	Copy	Delete	Id	DateTime	SP02	Heart_Rate	Temperature	Humidity	GSR	Motion	Blood_Glucose
<input type="checkbox"/>	Edit	Copy	Delete	37	2024-02-06 15:26:29	68	53	60	38	2	10	118.638
<input type="checkbox"/>	Edit	Copy	Delete	35	2024-02-06 15:26:24	91	24	85	55	46	62	195.083
<input type="checkbox"/>	Edit	Copy	Delete	34	2024-02-06 15:26:24	91	24	85	55	46	62	195.083
<input type="checkbox"/>	Edit	Copy	Delete	33	2024-02-06 15:26:22	92	40	40	28	29	91	165.7
<input type="checkbox"/>	Edit	Copy	Delete	32	2024-02-06 15:26:21	46	70	13	76	10	79	204.184
<input type="checkbox"/>	Edit	Copy	Delete	30	2024-02-06 15:26:19	65	55	9	45	100	69	251.475
<input type="checkbox"/>	Edit	Copy	Delete	29	2024-02-06 15:26:18	5	17	94	98	55	8	27.7007
<input type="checkbox"/>	Edit	Copy	Delete	28	2024-02-06 15:26:17	5	17	94	98	55	8	27.7007

Data Storage —> Website



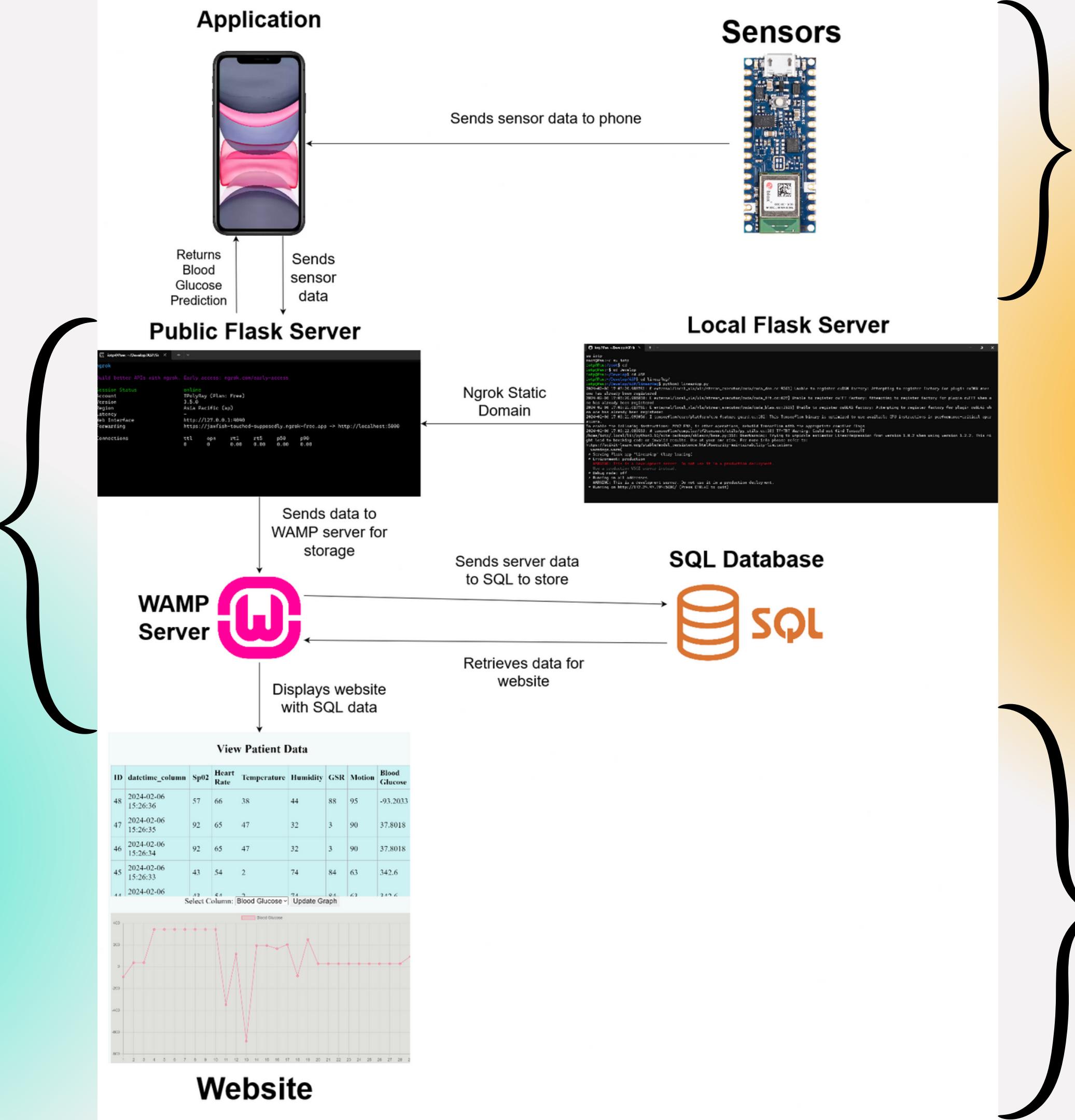
The patient's data can be seen using a website

Graphs can be used to improve analytics of patient's condition

Conclusion

Summary with Demo

Server Layer



Device Layer

Website

QnA



Q. Why is the model implemented on the flask server instead of the mobile application?
A. By hosting the model on a server, we can take advantage of the faster computational speeds using a computer and reduce the load on the application.

Q. Why did you choose linear regression for your model?
A. The accuracy among all the models i tested (Linear, SVR, KNR, RF, DecisionTree, Bagging, AdaBoost) are similar, therefore I picked the simplest and fastest one out of the models which is LinearRegression

Q. Why did you choose these features? (Sp02, motion, temp, humidity, heart rate, gsr)
A. These selected features are critical indicators that changes during physical activity and are closely associated with blood glucose levels.

References

- [1] W. Saad et al., “Analysis on Continuous Wearable Device for Blood Glucose Detection Using GSR Sensor,” International Journal of Nanoelectronics and Materials, vol. 13, 2020, Accessed: Feb. 1, 2024. [Online]. Available: <http://dspace.unimap.edu.my/bitstream/handle/123456789/67952/Analysis%20on%20Continuous%20Wearable%20Device.pdf?sequence=1&isAllowed=y>
- [2] B. Bogue-Jimenez, X. Huang, D. Powell, and A. Doblas, “Selection of Noninvasive Features in Wrist-Based Wearable Sensors to Predict Blood Glucose Concentrations Using Machine Learning Algorithms,” Sensors, vol. 22, no. 9, p. 3534, May 2022, doi: <https://doi.org/10.3390/s22093534>.