Development of Cost-Effective Portable Diabetes Monitoring Device for Sub-Saharan Africa

Sreesamhitha Bhamidipati
Rutgers University (New Brunswick)
NJ GSET
Bergen County, New Jersey

Sanjit Kakarla
Rutgers University (New Brunswick)
NJ GSET
Mercer County, New Jersey

Gajan Mohan Raj
Rutgers University (New Brunswick)
NJ GSET
Monmouth County, New Jersey

Daniel Park
Rutgers University (New Brunswick)
NJ GSET
Middlesex County, New Jersey

Shriram Vasudevan
Rutgers University (New Brunswick)
NJ GSET
Morris County, New Jersey

Weronika Wasniowska*
*Corresponding Author
Biomedical Engineering PhD Student
Rutgers University
New-Brunswick, New Jersey
Email: wkw11@gsbs.rutgers.edu

***Abstract*—Diabetes mellitus is a chronic medical condition characterized by high blood glucose levels that can lead to severe complications. Sub-Saharan African has more than 24 million cases of this condition. This prevalence is exacerbated by a lack of cost-effective glucose monitoring devices. In this paper, GlucoVision is proposed as a novel diabetes monitoring framework tailored for Sub-Saharan Africa. GlucoVision utilizes near-infrared (NIR) spectroscopy within a durable wristwatch. By utilizing a this technique along with machine learning, GlucoVision would be able to calculate glucose readings (mg/dL) using voltage readings (mV). Both a KNN model with an average error of 2.45% and a prototype with correct behaviour were constructed, demonsrating the promise of the proposed device.**

I. Introduction

Diabetes Mellitus is a medical condition where an individual has elevated blood glucose levels, frequently leading to disastrous health implications. This condition has proven to be a severe global concern for decades with an estimated 537 million people suffering globally in the year 2021, up 214% from 2000 [1], [2]. Projections from the International Diabetes Federation also starkly emphasize that approximately 783 million adults, or 12.5% of the adult population, will be living with diabetes by the year 2045, an increase of 46%. Reports suggest that 75% of adults with diabetes live in low and middle-income countries [1].

Despite medical advancements, Sub-Saharan African (SSA) nations often struggle with acquiring and utilizing proper diabetes monitoring devices due to high production and delivery costs, technological shortcomings, and a lack of medical infrastructure to distribute devices and educate residents [3]. As of 2021, there were an estimated 23.6 million cases in SSA, a number expected to rise to 54.9 million in 2045 [4]. With the rise in rapid demographic changes attributed to growing urbanization and a lack of care over noncommunicable diseases, SSA is facing an epidemiological turning point with diabetes projected to burden communities more than ever before [5]. This shift to urbanization is worsened by a lack of access to healthcare resources and pr eventative measures in these regions. In order to better diagnose and treat those with diabetes in SSA, we propose GlucoVision, a glucose monitoring device that is cost-efficient and uses suitable materials for SSA's environment. GlucoVision is a wearable device utilizes near-infrared (NIR) spectroscopy to measure glucose levels in mg/dL in a non-invasive fashion.

II. Background

A. Diabetes

Diabetes mellitus refers to a group of conditions characterized by high glucose levels (hyperglycemia) due to insufficient insulin production or inefficient insulin use. [6].

Over a period of time, excess amounts of glucose in the blood can damage blood vessels of the heart, eyes, kidneys, and nerves, leading to catastrophic conditions such as retinopathy, neuropathy, and heart failure [7]. Diabetes has been linked with heart complications such as heart attack, stroke, and heart failure. Thus, monitoring devices are essential for early detection. [6].

B. Case-study: Diabetic Patients in Sub-Saharan Africa

This paper specifically focuses on a cost-effective portable diabetes monitoring device for patients in SSA. Diabetes management in SSA is particularly difficult, leading to the high prevalence of the condition. Having the largest population in Africa, SSA has seen the age-adjusted case counts of diabetes grow steadily from around 2,530,000 cases in 2000 to around 23.6 million cases in 2021[8]. Despite this high prevalence, an estimated 54% in SSA remain undiagnosed [9]. The high costs ranging from $80-$100 of existing glucose monitoring devices are prohibitive for Sub-Saharan Africans, and this is an issue as monitoring devices are crucial for diabetes management.

In designing a portable glucose monitoring framework, the following factors served as criteria for engineering the design to satisfy patients in SSA:

1). Functionality: The design must be able to monitor glucose levels in mg/dL for standardized data sharing and easy interpretation.

2). Cost: The design must cost less than $30 and reusable. Existing glucose-monitoring devices cost $80-$100 making them cost prohibitive.

3). Durable: The design must be durable to withstand everyday use, high temperatures, and accidental collisions while maintaining functioning.

C. Existing Monitoring Products

The most common form of glucose monitoring in use today is finger-prick devices, using a lancet to prick the fingertip and extract a drop of blood. This blood is then placed on a test strip with enzymes, causing a reaction that produces an electrical current, the strength of which is proportional to the amount of glucose in the blood [10].

The downside with these devices comes with the fact that they are invasive, painful, and prone to contamination [?]. In Sub-Saharan Africa, cross-contamination with blood should be avoided due to the high presence of communicable diseases such as HIV/AIDS, tuberculosis, and malaria alongside the large number of deaths to these diseases per year (around 3 million people) [11].

The transdermal patch approach for diabetes monitoring relies on microneedles for gauging glucose levels while also releasing insulin through the skin. This approach utilizes a system of drug-based microneedles to enter into skin layers along with biosensors to function optimally. Although promising, there are serious concerns about device accuracy and contamination with claims that the system would face difficulties differentiating blood glucose from other inner bodily fluids [12].

D. Infrared Absorption Spectroscopy for Glucose Monitoring

The optical method for glucose monitoring involves emitting light at various frequencies to detect glucose in the skin. In infrared absorption spectroscopy for glucose monitoring, the intensity of a reflected beam of infrared light is measured after it is emitted on a skin area [13].

With near-infrared (NIR) light (wavelength between 0.7 – 2.5 µm), 90-95% of the light passes through the outer layers of skin easily, allowing for more specific detection of glucose molecules [13].

A benefit of using the optical method as opposed to invasive methods or other noninvasive approaches such as the transdermal method is that its use causes less irritation and poses lower chances of infection. Near-infrared spectroscopy (NIR) is the most effective optical method since it employs the optimal wavelength to penetrate the outer skin layers and target glucose molecules [13]. NIR spectroscopy has been tested in various studies and it has been proven that there is a correlation of at least r = 0.91 between NIR spectroscopy readings and actual glucose levels [13]. It is also convenient to use NIR light in areas of thin skin, such as the wrist; this shows that NIR has the potential to be leveraged in a watch-like glucose monitoring device that would detect concentrations in the wrist [14].

A 940 nm wavelength is found to be optimal as higher wavelengths in the NIR region have a greater penetration depth of light, though above 1000 nm, water predominantly absorbs light, making it difficult to differentiate between absorption due to glucose and absorption due to water [15].

III. Methodology

A. CAD Design

In designing our wearable glucose monitor watch, we considered durability, user comfort, and ease of use. We also considered conditions specific to Sub-Saharan Africa, such as high temperatures and the growing need to make our device cost-effective. Our design includes optimal space for an LCD display to show glucose readings to the user, a Micro USB port to recharge the device, a button to activate the NIR sensor, and a detachable compatible watch strap connector. Our design was created through AutoCAD Fusion 360, a software tool for product modeling and simulation before an eventual 3D print.

B. Technological Specifications

The base of the device features a near-infrared (NIR) Light Emitting Diode (LED) that emits at a 45 degree angle 2.5 mm left of the center which emits monochromatic light at 940 nm, a wavelength known to be an absorption peak for glucose molecules [16]. The intensity of the NIR light that is reflected, or unabsorbed by Glucose in the blood, is picked up by a Photodiode 2.5 mm right of the center [17].

The photodiode signal is sent to an integrated module that combines both the capabilities of an analog-to-digital Converter (ADC), which converts data from an analog format to a digital one, and an Analog Front End (AFE), which can enhance the quality of the signal. The module run a low-pass filter to attenuate high-frequency noise [18].

GlucoVision would use a microcontroller such as the ESP32-S0WD to input the clean data into the calibration model and run it. The estimated glucose concentration outputted by the model is displayed on the monochrome LCD, as shown in Figure 1. A PCB to connect the electrical components would be powered by a 3.85 Lithium Polymer Round Battery.

C. Machine Learning for Calibration

The clean digital voltage values (mV) collected from the photodiode need to be converted to glucose values (mg/dL)for display on the Monochrome LCD. This conversion can be done using machine learning algorithms. Data on voltage values (mV) from a NIR glucose monitoring system and corresponding glucose values (mg/dL) from 80 diabetic patients were taken and sourced from a 2022 study "Non-Invasive Glucose Monitoring Using NIR Spectroscopy" by Reddy et. al. [19]. To prevent overfitting and underfitting, the dataset of 80 diabetics was split with 80% of the data (64 diabetic patients) for the training set and 20% of the data (16 diabetic patients) for the testing set.

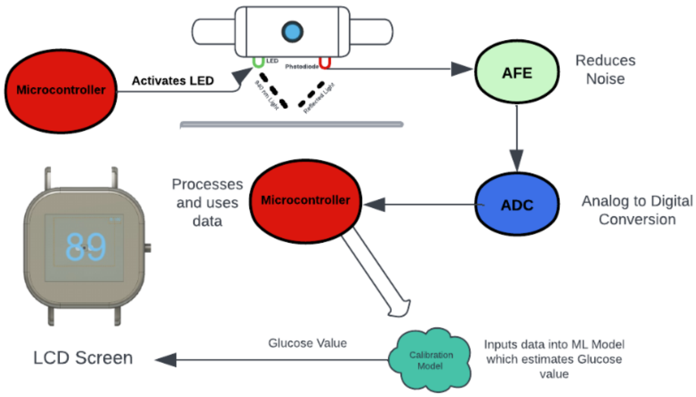

Figure 1. Pipeline of GlucoVision

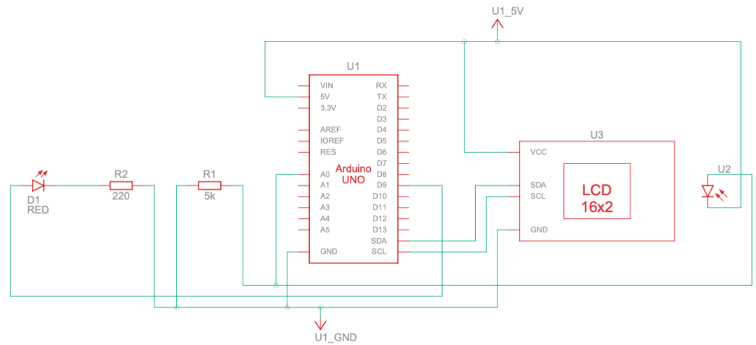

Figure 2. Circuit Schematic

Six different ML regression algorithms were trained and tested for this conversion task from voltage values to glucose values: linear regression, polynomial regression, decision trees, random forest, support vector regression, and K-Nearest Neighbors regression. The primary metrics of evaluation for the models are the R^2 and RMSE values. The ML model with the highest R^2 value and lowest RMSE value will be selected to be implemented for GlucoVision to convert collected voltage values to glucose values, which will be displayed clearly on the Monochrome LCD.

D. Materials

GlucoVision will be constructed with a simple list of parts to minimize the manufacturing cost yet ensure the device is well-functioning. It will be made of a 3.85 V polymer round battery, a micro USB charging board, a monochrome LCD, an ESP 32 microcontroller, an analog-to-digital converter (ADC), a 940 nm NIR LED, and a photodiode for the electrical components.

For the main base of the watch, a blend of recyclable thermoplastic materials such as ABS, polystyrene, polycarbonate, and more will be used since they can easily be thermoformed to the specific watch shape. Thermoforming is a common method of plastic manufacturing where parts are formed by heating a heat-malleable sheet into the desired shape using a mold [20]. This recycleable plastic will be durable for daily use and survive through light accidents since the average tensile strength of three of the most common thermoplastics (polycarbonate, polyvinyl chloride, and polyethylene terephthalate) is around 106.67 MPa [21]. The strap of the watch will be made of locally sourced cotton, which can have a tensile strength of up to 150 MPa, meaning that it is a strong material that can withstand the daily usage of GlucoVision [22].

E. Proof of Concept

To demonstrate the potential viability of the device, a setup using an Arduino UNO R4 (which provides the same functions as the ESP32 and ADC), 940 nm LED, 940 nm Photodiode, and an LCD screen was built. A circuit schematic can be seen in Figure 2. An experiment was created in which a container of water was filled, and increasing amounts of pure glucose were dissolved in it. The LED and Photodiode were positioned as shown in Figure 3, and light intensity values were recorded. A TSL2561 was used to measure broadband light levels over tests, allowing us to ensure consistency in conditions.

IV. Results

A. Machine Learning Modeling Results

The six different ML models (linear regression, polynomial regression, decision trees, random forest, support vector regression, and K-Nearest Neighbors regression) were trained and tested on the dataset of 80 diabetics (their voltage values [mV] paired up with their respective glucose values [mg/dl]) provided by past work on leveraging NIR spectroscopy for glucose monitoring [19]. The R^2 value and RMSE of each model on the test dataset are detailed below in Table I.

Table I
Machine Learning and Regression Analysis

ML Model	R^2 **Value**	**RMSE**
Polynomial Regression Model - Past Work [19]	0.9399	8.2221
Linear Regression Model	0.9289	8.9409
Polynomial Regression Model	0.9358	8.4978
Decision Trees	0.7030	18.2692
Random Forests - 100 Estimators	0.8874	11.2520
Support Vector Regression	0.9477	7.6649
K-Nearest Neighbors - 14 neighbors	0.9695	5.8571

Of the six models created as well as the original polynomial regression model determined by past work [19], the KNN model achieved the highest R^2 value of 0.9695 and lowest RMSE of 5.8571. The R^2 value of 0.9696 indicates that the KNN regression model explains approximately 97% of the variance in glucose values based on the voltage measurements. Additionally, the RMSE of 5.8571 indicates that the predicted glucose values differ from true glucose values by approximately 5.8571 mg/dL, on average. If this value is normalized, giving a value between 0 and 1, the normalized RMSE is 0.0245. Thus, the average error of GlucoVision is 2.45%. The actual glucose values compared to the predicted glucose values for the KNN model are depicted in Figure 8.

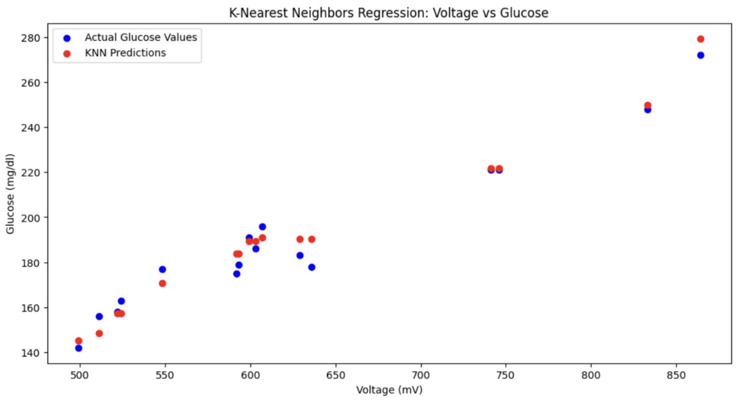

Figure 3. Graphical Depiction of KNN Algorithm

B. CAD Model

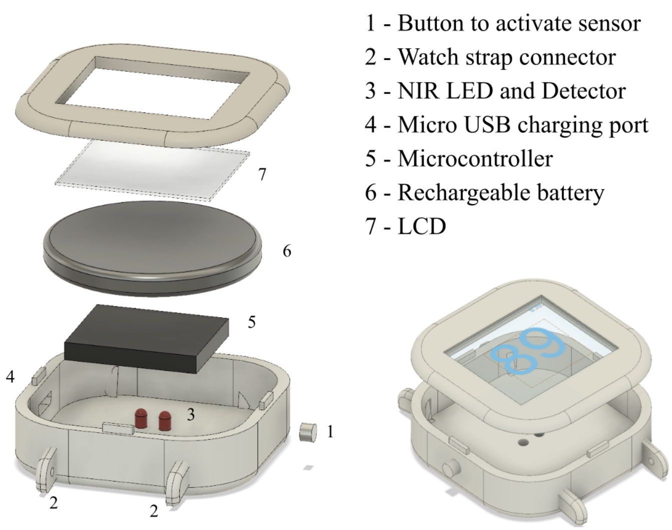

Figure 4. V3 Diagram Component View and Top View

The watch consists of two separate components, a main body to store all electrical and functional parts and a top face that can be detached and reattached for assembly and repairs. Four snap-fit connections secure the top face to the main body. The connection between the main body and strap is a standard fit, compatible with the majority of watch straps. The overall dimensions of the watch is 40 mm by 40 mm by 12 mm.

C. Proof of Concept Results

Table 2 shows the light intensity values for ten trials over the different glasses, as well as the broadband light levels, to show consistency in conditions over trials.

V. Discussion

A. Analysis of ML Results

Assuming the voltage data is properly obtained and cleaned, the KNN model is expected to estimate blood glucose levels accurately. The R^2, which represents how well the model fits the data, is 0.9696. This high value indicates that the KNN model is applicable for glucose calibration.

Since the RMSE represents the average error in a model's predictions, it is an accurate descriptor of how well the model predicts glucose concentration. After normalization, the RMSE was 0.0245. A value as low as 0.0245 suggests that the model has low error, making it a promising predictor of glucose values.

Table II
Costs of Guaranteed Materials

Name of Material	**Price**
ESP 32 Microcontroller	$1.03
Near-infrared LED and photodiode	$0.049
Monochrome LCD display	$0.92
Locally sourced Cotton Canvas watch strap	$0.01
Rechargeable Polymer Round Battery	$4.64
Battery to micro usb charger port adapter	$0.13
Analog-to-digital convertor	$2.96
Total Price:	**$9.74**

B. Cost Analysis

After determining all of the final materials for GlucoVision, it can be determined that the estimated price for the device will be more affordable than existing monitoring devices. The total cost of the materials described is around $9.73 or 15,515.07 Nigerian Naira, 783.70 Ethiopian Birrs, or 27,973.75 Congolese Francs; without factoring in shipping and manufacturing costs, per watch (Table II). The plastic used will also be obtained for a minimal if not zero cost when using recyclable thermoplastics collected across Africa. The cost of the PCB circuit is also tentative but it will likely only add $1 at most to device cost. After minimizing manufacturing and shipping costs and utilizing bulk pricing, we safely ensure that each watch can cost less than $30 to produce, reducing the cost of a NIR light-powered glucose monitoring device by around $55 or 60%, compared to previous models priced at around $85 [16].

Since our device is a one-time cost of around $9.73 that can aid in the detection of diabetes before symptoms worsen, compared to the currently available products, GlucoVision will be far more affordable and suitable for diabetic patients in SSA.

C. Analysis of Proof of Concept Results

The results in the table show that light intensity values were lower over the sugar filled glass. This behaviour is correct, as more of the light was absorbed by sugar, meaning less was reflected back. This experiment shows that our proposed materials can produce proper behaviour, making them promising for usage in an actual device.

The next steps would be collect our own training data in the same fashion as Reddy et. al. We would use these to train our own KNN Model that would work with GlucoVision's light intensity values.

VI. Conclusion

Using near-infrared spectroscopy at the 940 nm wavelength, the GlucoVision device can specifically target glucose molecules when emitting near-infrared light from the bottom of the watch. By using near-infrared light for the monitoring, glucose detection can occur without invasive methods, avoiding risk of transfer of communicable diseases prevalent in Sub-Saharan Africa. We discerned glucose concentrations through a regression analysis using a dataset of correlations between voltages and glucose concentrations that a K-Nearest Neighbors regression model is optimal for the device's machine-learning approach to detecting glucose concentrations. We created multiple CAD model iterations of the proposed device scaled to actual proportions, depicting the inner electronic components and a sample glucose reading on the screen. The final device also uses materials researched to be cost-effective, assuring that it will be accessible. Therefore, our research shows that a portable, affordable diabetes monitoring device can be created specifically for use in Sub-Saharan Africa.

VII. Acknowledgement

The authors of this paper gratefully acknowledge the following: Dean Jean Patrick Antoine, project mentor Weronika Wasniowska, Residential Teaching Assistant Norene Williams, Dean Jean Patrick Antoine, Rutgers University, The Rutgers School of Engineering, and the New Jersey office of the Secretary of Higher Education.

References

[1] International Diabetes Federation, "Diabetes facts & figures," 2024, accessed: 2024-07-18. [Online]. Available: https://idf.org/about-diabetes/diabetes-facts-figures/

[2] S. Wild, G. Roglic, A. Green, R. Sicree, and H. King, "Global prevalence of diabetes: Estimates for the year 2000 and projections for 2030," *Diabetes Care*, vol. 27, no. 5, pp. 1047–1053, 2004.

[3] M. Zimmermann, C. Bunn, H. Namadingo, C. M. Gray, and J. Lwanda, "Experiences of type 2 diabetes in sub-saharan africa: a scoping review," *Global Health Research and Policy*, vol. 3, pp. 1–13, 2018.

[4] A. N. Wade, I. Maposa, G. Agongo, G. Asiki, P. Boua, S. S. R. Choma, F. X. Gómez-Olivé, E. Maimela, L. K. Micklesfield, S. F. Mohamed, E. A. Nonterah, S. A. Norris, H. Sorgho, M. Ramsay, N. J. Crowther, AWIGen, and the H3Africa Consortium, "Diabetes care cascade and associated factors in 10 700 middle-aged adults in four sub-saharan african countries: a cross-sectional study," *BMJ Open*, vol. 13, no. 4, p. e069193, 2023.

[5] D. T. Jamison *et al.*, "Disease and mortality in sub-saharan africa," 2006.

[6] P. Hantzidiamantis, A. Awosika, and S. Lappin, "Physiology, glucose," in *StatPearls*, updated 2024 apr 30 ed. Treasure Island (FL): StatPearls Publishing, 2024, accessed: 2024-07-18. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK545201/

[7] World Health Organization, "Diabetes," 2024, accessed: 2024-07-18. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/diabetes

[8] I. D. Federation, "Africa diabetes report 2000—2045," https://diabetesatlas.org/data/en/region/2/afr.html, 2021, accessed: 2024-08-05. [Online]. Available: https://diabetesatlas.org/data/en/region/2/afr.html

[9] S. Scutti, "Facing the challenge of undiagnosed diabetes in africa," https://www.fic.nih.gov/News/GlobalHealthMatters/may-june-2023/Pages/facing-challenge-undiagnosed-diabetes--africa.aspx, 2023, accessed: 2024-08-05. [Online]. Available: https://www.fic.nih.gov/News/GlobalHealthMatters/may-june-2023/Pages/facing-challenge-undiagnosed-diabetes--africa.aspx

[10] MIT Engineering, "How do glucometers work?" 2024, accessed: 2024-07-18. [Online]. Available: https://engineering.mit.edu/engage/ask-an-engineer/how-do-glucometers-work/

[11] National Institute of Allergy and Infectious Diseases, "Niaid research in sub-saharan africa," 2024, accessed: 2024-07-18. [Online]. Available: https://www.niaid.nih.gov/research/niaid-research-sub-saharan-africa

[12] M. R. Prausnitz and R. Langer, "Transdermal drug delivery," *Nature Biotechnology*, vol. 26, no. 11, pp. 1261–1268, 2008.

[13] N. Oliver, C. Toumazou, A. Cass, and D. Johnston, "Glucose sensors: A review of current and emerging technology," *Diabetic Medicine*, vol. 26, no. 3, pp. 197–210, 2009.

[14] J. Yadav, A. Rani, V. Singh, and B. M. Murari, "Prospects and limitations of non-invasive blood glucose monitoring using near-infrared spectroscopy," *Biomedical signal processing and control*, vol. 18, pp. 214–227, 2015.

[15] T. A. Henderson and L. D. Morries, "Near-infrared photonic energy penetration: can infrared phototherapy effectively reach the human brain?" *Neuropsychiatric disease and treatment*, pp. 2191–2208, 2015.

[16] S. Rajeswari and P. Vijayakumar, "Development of sensor system and data analytic framework for non-invasive blood glucose prediction," *Scientific Reports*, vol. 14, no. 1, p. 9206, 2024.

[17] E. Hub, "Photodiode: Working, characteristics, and applications," 2024, accessed: 2024-07-20. [Online]. Available: https://www.electronicshub.org/photodiode-working-characteristics-applications/

[18] X. Engineer, "Low pass filter," 2024, accessed: 2024-07-20. [Online]. Available: https://x-engineer.org/low-pass-filter/

[19] P. S. K. Reddy, D. Mahesh, C. U. Teja, M. Janaki, and K. Mannem, "Non-invasive glucose monitoring using nir spectroscopy," in *Journal of Physics: Conference Series*, vol. 2325, no. 1. IOP Publishing, 2022, p. 012021.

[20] Formlabs, "Thermoforming 101: Learn the basics of thermoforming plastics," 2024, accessed: 2024-07-20. [Online]. Available: https://formlabs.com/blog/thermoforming/#

[21] SpecialChem, "What are the tensile strength at break values of several plastics?" 2024, accessed: 2024-07-20. [Online]. Available: https://omnexus.specialchem.com/polymer-property/strength-at-break-tensile

[22] M. El Messiry, A.-B. Mito, A. Al-Oufy, and E. El-Tahan, "Effect of fabric material and tightness on the mechanical properties of fabric–cement composites," *Alexandria Engineering Journal*, vol. 53, no. 4, pp. 795–801, 2014.

VIII. Appendix

A. Code

The following Github link contains the code for the machine learning algorithms and proof of concept: https://github.com/gajanm/GSET-Development-of-a-Cost-Effective-Portable-Diabetes-Monitoring-Device-for-Sub-Saharan-Africa