Blood Glucose Level Prediction Using ARMAX and ARMAX-ANN Models

Intan Maisarah Abd Rahim[1], Herlina Abdul Rahim[1*], Nur Athirah Syafiqah Noramli[2]

[1*] Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 Skudai, Johor, Malaysia
[2] School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Shah Alam, Selangor. Malaysia

Corresponding author* email: herlina@utm.my
Available online 30 June 2024

ABSTRACT

Diabetes is a serious medical condition that can lead to complications such as stroke, heart disease, blindness, and obesity. An estimated 347 million people were affected by diabetes, with approximately 3.4 million deaths attributed to high blood sugar levels. Researchers have explored various non-invasive techniques to measure blood glucose levels, including ultrasonic sensors, multisensory systems, absorbance and transmittance methods, bio-impedance, voltage intensity, and thermography. The development of non-invasive glucose monitoring methods continues to be a significant area of interest in the medical field.

This study investigates the application of near-infrared (NIR) spectroscopy for glucose level measurement, alongside the use of linear and non-linear system identification models to predict output data from NIR measurements. While NIR spectroscopy has been utilized in previous studies, the optimal wavelength range remains a topic of debate among researchers. To assess the feasibility of a linear approach, the Autoregressive Moving Average Exogenous (ARMAX) model was applied to predict NIR measurement outcomes. Additionally, a non-linear model combining ARMAX with an Artificial Neural Network (ANN) was implemented, allowing for a comparative analysis of the performance of both linear and non-linear prediction methods.

Keywords: Diabetes, Glucose level, Near-infrared (NIR), ARMAX, ANN.

1. Introduction

Glucose, often referred to as the central carbohydrate, originates from the Greek word glykys, meaning "sweet." It exists in two optical isomers: D-glucose and L-glucose [1]. In the human body, glucose plays a vital role, and regular monitoring of blood glucose levels is crucial for diabetic patients to maintain a normal clinical range of 3.5–6.1 mmol/L [2]. However, diabetes can develop due to poor dietary management and lifestyle choices. In 2004, approximately 347 million people worldwide were affected by diabetes, with an estimated 3.4 million deaths attributed to complications arising from high blood sugar levels [3].

According to some references, blood glucose levels can be classified as follows [4]:
Diabetic classification:

$$Diabetic = \begin{cases} 0, & 4\ mmol/L \leq BGL \leq 7\ mmol/L \\ 1, & BGL > 7\ mmol/L \end{cases} \quad (1)$$

where:
0 = Non-diabetic individual
1 = Potential diabetic patient

For individuals with severe diabetes, continuous monitoring and management are crucial. If blood glucose levels exceed the normal range, it strongly indicates the presence of diabetes. Regular diabetes management helps regulate sugar levels within a safe range, preventing serious health complications. Proper control is essential to avoid severe conditions caused by prolonged high blood sugar levels. Without effective management, long-term complications such as kidney failure, heart disease, and stroke may develop [5].

Many diabetic patients express concerns about traditional blood glucose testing, describing it as painful due to frequent finger pricking. Continuous monitoring, particularly for critical patients, often requires multiple finger pricks

per day, which can be exhausting and uncomfortable. The process becomes even more challenging for individuals with dexterity limitations, a fear of pain (algophobia), or anxiety disorders. Since diabetes is an incurable, life-threatening metabolic disorder, frequent monitoring is essential, especially for those with severe conditions [6].

2. Methodology

This study involves data acquisition using both a conventional glucose meter as the reference device and NIR spectroscopy as the input data source. The collected data is analyzed using the Autoregressive Moving Average Exogenous (ARMAX) model, a linear system identification approach, to evaluate its effectiveness in predicting blood glucose levels based on NIR wavelengths. Prior to analysis, the dataset undergoes a pre-processing stage to enhance its features and improve prediction accuracy.

2.1 Data Acquisition

The data was collected from three groups: individuals diagnosed with diabetes, non-diabetic individuals, and a control group without a prior diagnosis. The data collection process was conducted under the supervision of medical personnel at the Outpatient Department (OPD) of Hospital Universiti Sains Malaysia (HUSM) in Kubang Kerian, Kelantan, Malaysia.

Among the optimal measurement sites, human fingertips were selected due to their thinner skin and higher concentration of observable blood vessels, making them ideal for accurate readings. The dataset comprises 135 samples obtained from the three subject groups, with variations in gender, age, race, and medical condition (critical or non-critical). The study was conducted in accordance with ethical principles outlined in the Good Clinical Practice guidelines and the Declaration of Helsinki [7,8]. Figure 1 illustrates the setup of the NIR spectrometer during data measurement.

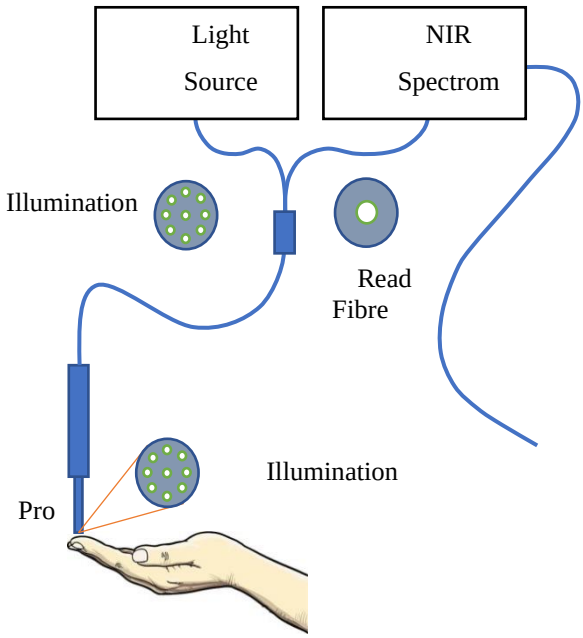

Figure 1. The illustration of the NIR spectroscopy instrument

2.2 NIR Penetration on Skin

The penetration of near-infrared (NIR) light through the skin is influenced by several factors, including wavelength, energy, attenuation coefficient, area of irradiance, coherence, and pulsing. Generally, longer wavelengths and higher power densities result in deeper penetration depths [6],[9]. Human skin is composed of three primary layers: the epidermis, dermis, and subcutaneous layer, each of which interacts differently with NIR light.

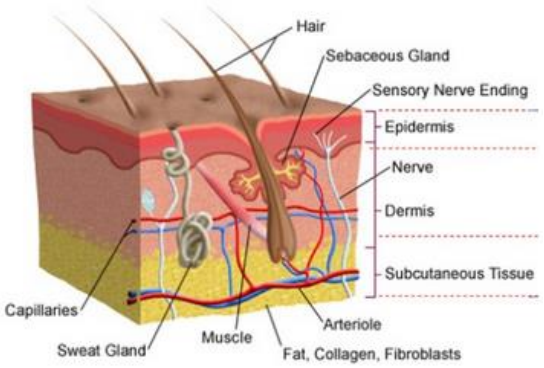

Figure 2. The cross section of skin layer [10]

The dermis layer of human skin contains blood vessels, nerve endings, sweat glands, and hair follicles. Figure 2 presents a cross-section of the epidermis and dermis layers of the skin. Based on this illustration, it is concluded that for effective measurement, NIR light must penetrate the skin deep enough to reach the dermis layer, where blood vessels are located, to obtain relevant information [11].

Figure 3 depicts the penetration depth of NIR light through the skin, progressing from the epidermis layer to the dermis and hypodermis layers [9]. For accurate data collection, NIR diffusion must reach at least the dermis layer. As shown, starting from a wavelength of 600 nm, NIR can penetrate the dermis layer. However, as the wavelength increases, the penetration gradually decreases.

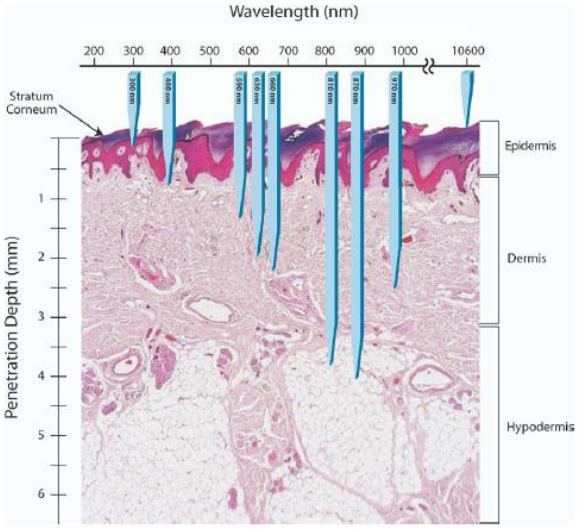

Figure 3. The penetration of NIR on human skin

2.3 Data Pre-processing

In this research, data pre-processing methods included noise filtering, data sampling, interval correction, and data distribution. The collected data may contain multiple variables that can influence each other, making it challenging to integrate models effectively [12-14]. However, modified baseline correction has been proven effective in predicting NIR spectra for human serum analysis.

To enhance data quality, the Savitzky-Golay filter was applied to remove unwanted noise from the wavelength data. The data sampling process then extracted only the relevant wavelength information to be used as input. Following this, interval correction was applied to selected peaks in the NIR spectrum to refine the dataset. Finally, the data distribution process was implemented, randomly dividing the dataset into training, testing, and validation sets. Figure 2 illustrates the flow of the data pre-processing stage.

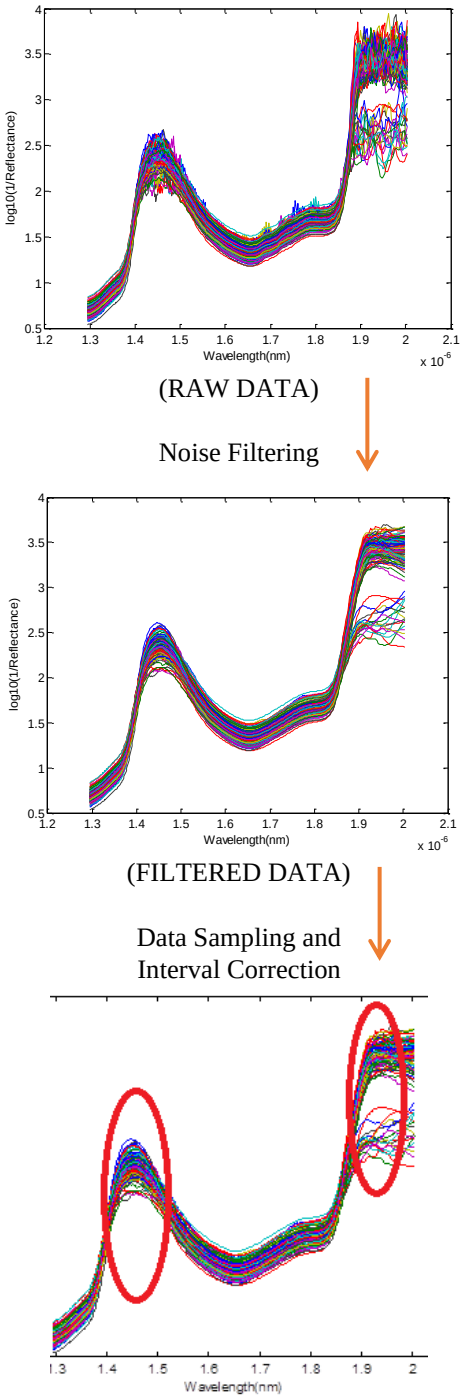

Figure 4. The flow of data pre-processing

3. System Identification

System identification is a process of developing mathematical models of dynamic systems based on observed input-output data. These models can be either linear or nonlinear, depending on the nature of the system being studied.

Linear system identification involves developing models that assume a linear relationship between the input and output of a system. These models are simpler, computationally efficient, and often provide a good approximation for systems that operate within a limited range.

Nonlinear system identification is used when the relationship between input and output is inherently nonlinear. These models are more complex but can capture a wider range of system behaviors, especially for systems with nonlinear dynamics.

3.1 Linear System Identification Model

In this study, the linear model used is the Autoregressive Moving Average Exogenous (ARMAX) model. Autoregressive Moving Average Exogenous (ARMAX) model is defined as:

$$G(z,p) = \frac{B(z)}{A(z)}, H(z,p) = \frac{1}{A(z)} \quad (2)$$

where $A(z) = 1 + a_1 z^{-1} + \cdots + a_{n_a} z^{-n_a}, B(z) = b_1 z^{-1} + \cdots + b_{n_b} z^{-n_b}$

$G(p,z)$ and $H(p,z)$are filters of finite order and functions of a parameter vector p,

$$p = [a_1 \ldots . a_{n_a} \;\; b_1 \ldots . b_{n_b}]^T \quad (3)$$

The un-regularized and regularized ARMAX models are both implemented to determine the optimum testing result of the system.

3.2 Non-Linear System Identification Model

In this study, the non-linear model used is the combination of the Autoregressive Moving Average Exogenous (ARMAX) model and the Artificial Neural Network (ANN) model. The result from the linear system ARMAX from previous process was fed to the ANN model using the Levernberg Marquardt (LM) Algorithm.

4. Model Validation

The Clarke Error Grid Analysis is a widely recognized reference for assessing the clinical accuracy of glucose level estimations in blood, particularly when compared to conventional invasive methods [5, 15–17]. This approach is used in this study to validate the linear system identification model as shoen in Table 1. The output data set and reference data set are plotted to analyze the distribution regions and evaluate the model's accuracy [18].

Table 1. Region distribution

Region	Description
Region A	within 20% of the reference sensor (clinically accurate).
Region B	outside of 20% but would not lead to an inappropriate treatment (clinically acceptable).
Region C	leading to unnecessary treatment (overcorrection).
Region D	indicating a potential dangerous failure to detect hypoglycaemia or hyperglycaemia (dangerous failure to detect).
Region E	confuse treatment of hypoglycaemia for hyperglycaemia and *vice versa* (serious error).

5. Results

The prediction results of the ARMAX model, as illustrated in Figures 5 and 6, present the regression outcomes for both un-regularized and regularized ARMAX methods. When converted into percentage form (R^2), the accuracy of the un-regularized model is only 47.8%, whereas the regularized model achieves an accuracy of 74.2%. Given its superior performance, the regularized model was selected for further analysis.

However, the results from this linear model did not meet the desired level of accuracy. To improve performance, the output from the regularized ARMAX model was fed into the non-linear ANN model. As shown in Figure 7, the regression

result for the regularized ARMAX-ANN model is 0.91705, corresponding to an accuracy of 84.1%, demonstrating a significant improvement over the linear model.

To further validate the model's effectiveness, the results were analyzed using Clarke Error Grid (CEG) Analysis, a crucial validation method in medical applications. Figure 8 displays the distribution of the regularized ARMAX model on the CEG, while Figure 9 presents the distribution of the regularized ARMAX-ANN model. The results indicate that the regularized ARMAX-ANN model shows a marked improvement in accuracy and reliability compared to the regularized ARMAX model.

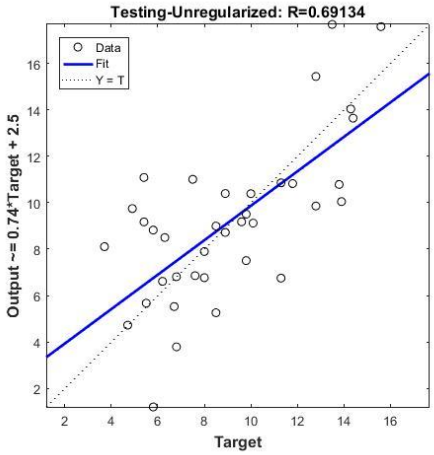

Figure 5. The regression result of un-regularized ARMAX.

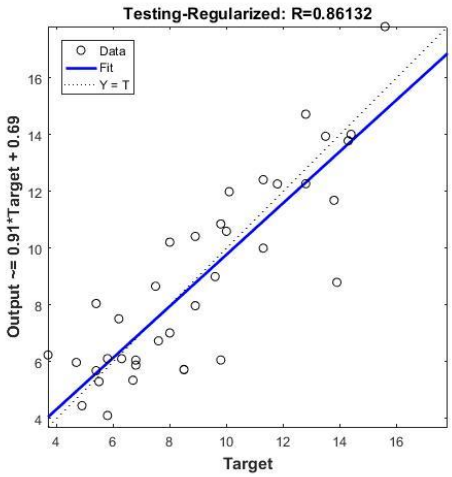

Figure 6. The regression result of regularized ARMAX.

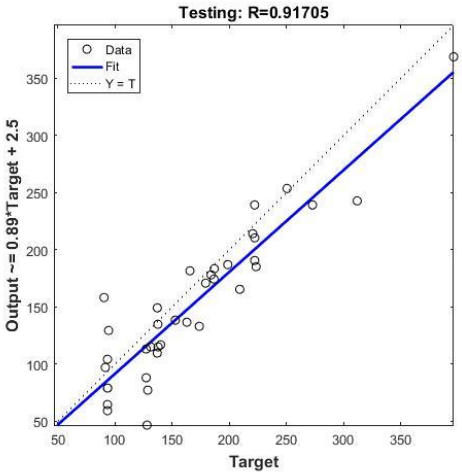

Figure 7. The regression result of regularized ARMAX combined with ANN.

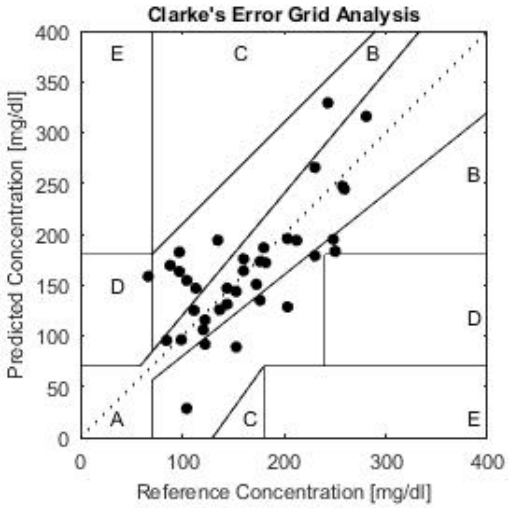

Figure 8. The CEG distribution of regularized ARMAX model

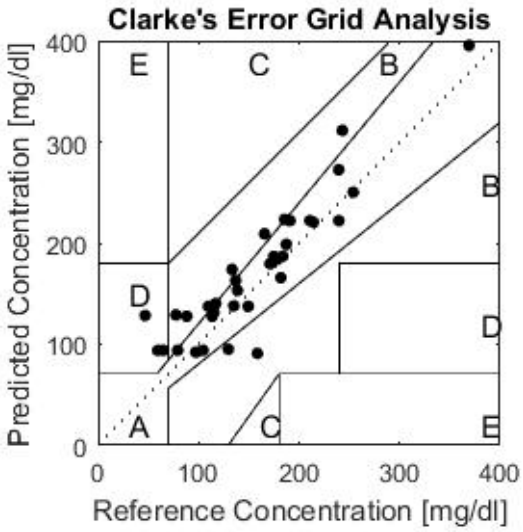

Figure 9. The CEG distribution of regularized ARMAX-ANN model.

6. Conclusion

Diabetes is a critical medical condition with severe complications, including stroke, heart disease, blindness, and obesity, affecting millions worldwide and contributing to significant mortality rates. The development of non-invasive glucose monitoring techniques has become a crucial area of research to improve patient care and reduce the risks associated with invasive methods. This study explored the application of NIR spectroscopy for blood glucose measurement, coupled with linear and non-linear system identification models to predict glucose levels from NIR data. While NIR spectroscopy has shown promise in previous studies, the optimal wavelength range for accurate glucose measurement remains a subject of ongoing research.

ARMAX model was employed to evaluate the feasibility of a linear approach for glucose prediction. Additionally, a hybrid non-linear model combining ARMAX with an ANN was implemented to enhance prediction accuracy. The comparative analysis of these models highlights the strengths and limitations of both linear and non-linear methods in predicting glucose levels from NIR measurements. While the linear ARMAX model provided a foundational understanding, the non-linear ARMAX-ANN hybrid model demonstrated improved performance, underscoring the potential of non-linear approaches in capturing the complex dynamics of glucose measurement.

This study contributes to the ongoing efforts to develop reliable non-invasive glucose monitoring techniques. The findings suggest that non-linear models, such as the ARMAX-ANN hybrid, hold significant promise for improving the accuracy of glucose level predictions. Future research should focus on optimizing wavelength selection, refining non-linear models, and validating these methods in larger and more diverse patient populations to advance the field of non-invasive glucose monitoring.

Acknowledgment

The authors would like to express our deepest gratitude to all parties who have contributed to this research, especially Universiti Teknologi Malaysia and the Outpatient Department, Hospital Universiti Sains Malaysia (USM), Kubang Kerian Kelantan for the their utmost cooperation.

References

[1] T. Denisova, L. Malinova, *Glucose, in: Handb. Opt. Sens. Glucose Biol. Fluids Tissues*, Taylor & Francis, 2008: pp. 1–40. doi:doi:10.1201/9781584889755.ch1.

[2] E.M.A. A. Trabelsi, M. Boukadoum, C. Fayomi, "Blood glucose sensor implant using NIR spectroscopy: Preliminary design study", in: Microelectron. (ICM), *2010 Int. Conf. On, Cairo*, pp. 176–179, 2010.

[3] C.I. Examinations, Facts and figures about diabetes, (2016) 2016. http://www.cie.org.uk/images/268776-facts-and-figures-about-cambridge-international-examinations.pdf (accessed January 01, 2014).

[4] C.F. So, K.S. Choi, J.W.Y. Chung, T.K.S. Wong, "An extension to the discriminant analysis of near-infrared spectra", *Med. Eng. Phys.* 35, 172–177, 2013, doi:10.1016/j.medengphy.2012.04.012.

[5] L. Ben Mohammadi, T. Klotzbuecher, S. Sigloch, K. Welzel, M. Göddel, T.R. Pieber, et al., "In vivo evaluation of a chip based near infrared sensor for continuous glucose monitoring", *Biosens. Bioelectron*, 53, 99–104, 2014. doi:10.1016/j.bios.2013.09.043.

[6] S. Sivanandam, M. Anburajan, B. Venkatraman, M. Menaka, D. Sharath, "Estimation of blood glucose by non-invasive infrared thermography for diagnosis of type 2 diabetes: An alternative for blood sample extraction", *Mol. Cell. Endocrinol*. 367, 57–63, 2013, doi:10.1016/j.mce.2012.12.017.

[7] C. Review, S. Communication, G. Principles, World Medical Association Declaration of Helsinki. "Ethical principles for medical research involving human subjects", *Nurs. Ethics*, 9, 105–109, 2002.

[8] A. Caduff, M. Mueller, A. Megej, F. Dewarrat, R.E. Suri, J. Klisic, et al., "Characteristics of a multisensor system for non invasive glucose monitoring with external validation and prospective evaluation", *Biosens. Bioelectron*, 26, 3794–3800, 2011. doi:10.1016/j.bios.2011.02.034.

[9] J. Workman, *NIR Spectroscopy Calibration Basics, in: Handb. Near-Infrared Anal*. Third Ed., CRC Press, 2007: pp. 123–150. doi:doi:10.1201/9781420007374.ch7.

[10] P. Hindle, *Historical Development*, in: Handb. Near-Infrared Anal. Third Ed., CRC Press, 2007: pp. 3–6. doi:doi:10.1201/9781420007374.pt1.

[11] J. Workman, D. Burns, *Commercial NIR Instrumentation*, in: Handb. Near-Infrared Anal. Third Ed., CRC Press, 2007: pp. 67–78. doi:doi:10.1201/9781420007374.pt2.

[12] K.S. Chia, *Predictive Models and Shortwave Near Infrared Spectroscopy Analysis in Non-Destructive Soluble Solids Content Assessment of Pineapples*, 2014.

[13] J. Sundaram, C.V. Kandala, C.L. Butts, "Application of near infrared spectroscopy to peanut grading and quality analysis: Overview", *Sens. Instrum. Food Qual. Saf.* 3,156–164, 2009. doi:10.1007/s11694-009-9081-5.

[14] L. Leon, J.D. Kelly, G. Downey, "Detection of apple juice adulteration using near-infrared transflectance spectroscopy", *Appl. Spectrosc*. 59, 593–599, 2005. doi:10.1366/0003702053945921.
[15] A. Caduff, M.S. Talary, M. Mueller, F. Dewarrat, J. Klisic, M. Donath, et al., "Non-invasive glucose monitoring in patients with Type 1 diabetes: A Multisensor system combining sensors for dielectric and optical characterisation of skin", *Biosens. Bioelectron*. 24, 2778–2784, 2009. doi:10.1016/j.bios.2009.02.001.
[16] E. Monte-Moreno, "Non-invasive estimate of blood glucose and blood pressure from a photoplethysmograph by means of machine learning techniques", *Artif. Intell. Med*. 53, 127–138, 2011. doi:10.1016/j.artmed.2011.05.001.
[17] M. Aloraefy, J.T. Pfefer, C.J. Ramella-Roman, E.K. Sapsford, "In Vitro Evaluation of Fluorescence Glucose Biosensor Response", *Sensors*, 14, 2014. doi:10.3390/s140712127.
[18] W.L. Clarke, D. Cox, L. a Gonder-Frederick, W. Carter, S.L. Pohl, "Evaluating clnical accuracy of systems for self-monitoring of blood glucose", *Diabetes Care*. 10, 622–628, 1987.