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Integration of strain gauge sensor in biceps muscle movement detection using LabView

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ABSTRACT

Muscle injuries caused by sports can have a serious impact on sportsmen, to avoid injuries during sports can be prevented by detecting the wrong movement using a strain gauge sensor attached to the muscle which in this study is devoted to the biceps muscle. The strain gauge will detect muscle movement, and the output generated at the strain gauge will be converted into the form of voltage and current which will be used to be processed using machine learning to get data patterns so that they can be grouped into data patterns of wrong movements and correct movements. The strain gauge movement pattern here is simulated using LabView by using a gauge resistance of 120 Ω, strain configuration quarter bridge 1, gauge factor 2.05, Vex is the excitation voltage given to the Wheatstone bridge is 5 V and the initial voltage -180.08 μV, the strain gauge output pattern is obtained in the form of Excel and with this data can be converted into voltage and current.

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1. INTRODUCTION

Sports injuries are a pressing health issue, with a significant impact on athletes and physically active individuals. Muscle damage that occurs due to sports movement errors can lead to serious injuries that require appropriate and timely medical intervention. Understanding the movement patterns that cause muscle injuries and developing effective detection systems are crucial steps in addressing this issue. Skeletal muscle tissue has the largest mass in the human body, accounting for 45% of total body weight. A deep understanding of the biomechanics of body movements is key to developing an effective detection system [1], [2]. By combining knowledge of potentially harmful movement patterns with data obtained from strain gauge sensors, we can improve our understanding of muscle injury risk and design more effective prevention strategies. Muscle movements that cause injury generally occur when the muscle is overstretched or over-contracted, especially in eccentric movements or when the muscle stretches while bearing weight. Muscle injuries can occur due to a variety of factors, including overuse in sports or physical activities, excessive strain, lack of warm-up, or use of incorrect technique [3]–[7]. Muscle injuries can occur due to a variety of factors, including overuse in sports or physical activities, excessive strain, lack of warm-up, or use of incorrect technique. Joint angle, torque, and strength, as well as the length of the hamstring muscle-tendon unit calculated using a three-dimensional biomechanical model, are necessary to improve the specificity of rehabilitation [8]–[11].

In Benfica *et al.* study [12], [13], differences in muscle strength can be observed based on age, gender, and whether measurements were taken on the dominant or non-dominant side. For example, for the age groups 20-29 to 60-69 years, the reference values of muscle strength ranged from 167 ± 23.4 to 281.8 ±

50.7 N. In addition, for handgrip isometric strength, the reference values ranged from 9.5 ± 1 to 91.3 ± 18.5 pounds for the age groups 60-69 and 70-74 years. Men tend to have higher muscle strength than women, and the dominant side tends to have higher muscle strength than the non-dominant side. This can be used as a basis for classifying muscles that move correctly with muscles that move incorrectly in performing sports movements.

Some of the previous studies were presented in real-time and visually. Maskeliūnas *et al.* integrate camera technology to enrich the real-time patient monitoring experience in the BiomacVR system. Our system uses a convolutional pose machine (CPM) model, trained with a sequence of images from a depth sensor, to identify human movements and accurately evaluate the effectiveness of physical training. However, the camera integration enhances the system's ability to provide more timely visual feedback to the patient. The integration of the camera extends the system's ability to better distinguish between healthy subjects and those suffering from low back pain. Thus, this study confirms that the use of cameras in the BiomacVR system not only improves real-time interaction between patients and therapists but also enriches overall monitoring in the context of remote patient rehabilitation. Using a strain gauge is expected to be able to provide data from strain gauge sensors that utilize strain and stress so that the resulting data will be collected to become a data set, which will then be processed using machine learning so that it can provide muscle detection results when an error occurs in performing the exercise [14]–[17].

The initial resistance value of the strain gauge sensor is 350 Ω for the strain gauge used for the transducer, but 120 Ω for the strain gauge that is directly mounted or attached to the surface of the object to be measured. As we know, the resistance value or resistance of the strain gauge sensor will change along with the change in the shape of the object to be detected. Flexible and stretchable sensors for measuring muscle contraction and tracking elbow movement. The strain gauges used in this study are TA120-6AA models that have a sensitive grid size and use a special material (annealed Constantan Foil) that allows measurement of deformation up to 20% with a Gage Factor of about 2.00-2.20 <0×D3> <0×07> 1%. These strain gauges are integrated into Dragon Skin silicone rubber, which has a Young's modulus close to the Young's modulus of human skin and can stretch to several times its original size and return to its original shape without distortion, according to authors [18]–[21].

In response to this challenge, this research proposes the use of strain gauges as a solution to movement error detection in sports. Strain gauges are sensors that are sensitive to small changes in tension and compression, making it possible to monitor changes in muscle structure as body movements are performed. By utilizing this technology, it is expected that we can identify movement patterns that have the potential to cause muscle injuries more accurately and in a timely manner. The development of detection technologies such as strain gauges offers great potential in improving the diagnosis and management of muscle injuries. By understanding the biomechanical mechanisms of body movements and strain patterns associated with injuries, healthcare practitioners can design more targeted and effective interventions and reduce the risk of complications associated with muscle injuries.

The main objective of this research is to develop a detection system that can assist in preventing muscle injuries in sports. By utilizing strain gauge technology, it is hoped that we can improve the understanding of potentially harmful movement patterns and reduce the risk of muscle injury for athletes and physically active individuals. By integrating a detection system using strain gauges as a solution in this research, it is hoped that we can make a new contribution to the prevention and management of muscle injuries in the context of sports.

2. METHOD

This research builds a system that can detect the wrong muscles when doing sports movements. This system requires a sensor to capture strain data from the muscles, then the data is collected to produce data that is ready to be stored and processed using a microcontroller, where the data forms a data set that will be processed by machine learning so that the data can be used as material to find out the wrong muscle movements in sports so that athletes can avoid movements that can cause injury or as evaluation material when injured in sports so that injuries that occur in muscles can be evaluated when medical treatment will be carried out. The system that will be built is like the block diagram in Figure 1.

The muscle strain output of the sensor to be analyzed is the change in resistance that occurs when the sensor is pulled or pressed, which is then measured as a voltage change. This change can then be converted into muscle strength generated by muscle contraction, according to Alvarez *et al.* [15], [22]–[24]. The data from the muscle strain will be stored and processed using a microcontroller to become a data set that will be processed using machine learning. The flow of data to produce decisions used to classify muscles with correct movements with muscles with incorrect movements in exercise is shown in Figure 2.

The change in resistance when the strain gauge sensor is pulled and pressed is then measured as a voltage change that will be processed by machine learning so that it becomes data for analyzing muscle conditions that can be classified to get a decision that the muscle movement is wrong or right when doing sports. Collecting data from strain gauge output to form a dataset can be done using various measurement methods and techniques. Here are some common steps and methods to collect data from strain gauges, first attach the strain gauge to the surface of the object being measured in the muscle to be measured for strain, then set the measuring instrument to be connected to the strain gauge, monitoring the stress resulting from the muscle deformation captured by the strain gauge, applying a variety of muscle movements that cause muscle deformation, calibration to change the voltage or resistance data from the strain gauge, repeating measurements with variations in muscle movement to obtain sufficient data, analyzing data to evaluate the strain gauge response to variations in deformation to obtain data analysis methods and the last is data validation to ensure the consistency and reliability of measurement results and comparison with other measurement methods or sources can be done for verification. The following are the stages of machine learning in the process of processing data sets that have been generated from sensor data collection in Figure 3.

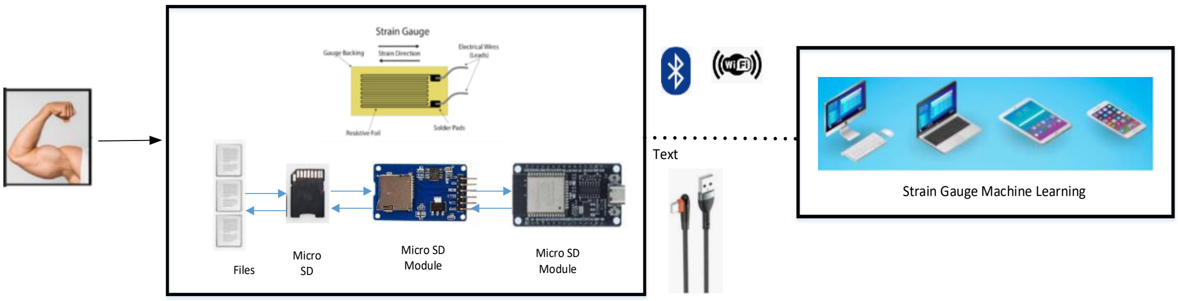

Figure 1. Architecture system

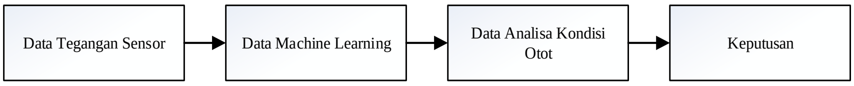

Figure 2. Data flow

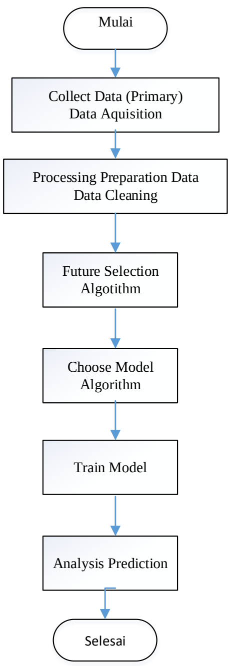

Figure 3. Machine learning stages

The data analysis process begins with the first step of data collection (primary data acquisition), where data required for analysis is collected from various sources. After that, the data is prepared (data preparation) by performing processes such as duplicate removal and handling missing values. The next step is data cleaning, where errors or discrepancies in the data are identified and corrected. Next, a feature selection algorithm is performed to select the most relevant variables for inclusion in the model. Once the appropriate features are selected, the next step is the model selection algorithm (choose model algorithm), where the most suitable model or algorithm is chosen for the specific data analysis. Once the model is selected, the model is trained (train model) using the previously prepared data. Finally, prediction analysis is performed by using the trained model to make predictions or estimates on new data that has not been seen before. By following this sequence of steps, it is hoped that accurate and informative analysis can be produced based on data that has been properly collected and processed.

3. RESULTS AND DISCUSSION

To find out the characteristics of the strain gauge sensor, a simulation is carried out using LabView, which will produce the output value of the strain. In this study, the output of voltage and current is desired, which is the response of the strain gauge. Therefore, a simulation is carried out using LabView to see the response of the strain gauge.

3.1. Strain setup

The component whose value is entered in the LabView simulation is the strain value, which is set using the Rg value of 120 Ω, using the strain configuration quarter bridge 1, gauge factor 2.05, Vex is the excitation voltage given to the Wheatstone bridge is 5 V, and the initial voltage -180.08 µV is found in Figure 4. Strain values can be positive or negative because strain gauge sensors are used to measure deformation or strain in a material. Its working principle is based on the change in electrical resistance that occurs when the sensor is strained. Strain is a change in the shape of a material due to the stress (force) applied to it. Strain is usually expressed as a change in length per unit initial length (relative deformation), positive strain (tensile strain) occurs when the material is pulled so that its length increases, and negative strain (compressive strain) occurs when the material is pressed so that its length decreases.

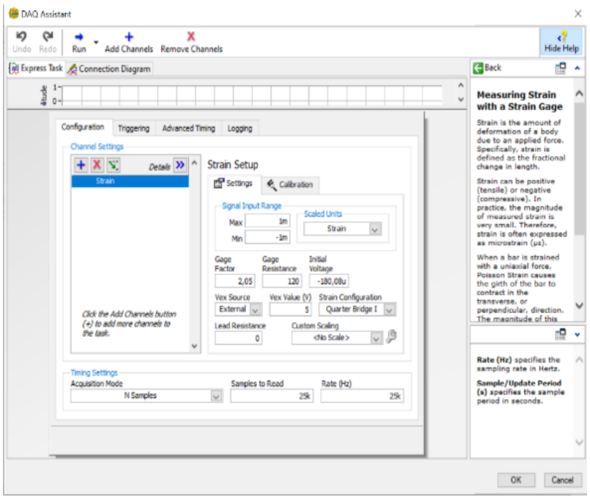

Figure 4. Strain setup with quarter bridge I

3.2. Setting Young's modulus quarter bridge I

To give the same elasticity effect as human skin, the role of Young's modulus will be decisive; therefore, Young's modulus value similar to human skin is sought. Young's modulus of human skin varies depending on many factors, such as location on the body, age, and individual health conditions. But in general, it is often used in scientific literature based on age, where at a young age it is 4.2×10 N/m^2, and for old age, it is 8.5×105 N/m^2 [25]–[28]. The Young modulus value that is close to human skin is found in silicon dragon skin, which has a Young modulus value between 0.24 MPa and 0.74 MPa [29], [30]. The dragon skin was used for the experiment, using RTV-52 as its embedded system. With Young's modulus data from dragon skin, the strain value can be calculated, which will be converted in the form of stress. Young's modulus is a key parameter in understanding the elasticity of materials, and strain gauges are an important tool for measuring the deformation associated with that elasticity because strain gauges measure strain, and Young's modulus is needed to convert that strain to stress, so we can understand how materials behave under certain loads. Figure 5 is the Young's modulus setting in LabView.

In Young's modulus setting in LabView, as in Figure 5, on the stress side, because the mass is in kg, it is multiplied by the acceleration of gravity, which is 9.81 m/s^2. Young's modulus is a fundamental parameter that describes the elastic properties of materials, specifically how they respond to applied stress. Young's modulus (also known as the modulus of elasticity) is a measure of the stiffness of a material. In this case because the strain gauge will be placed on the biceps muscle which requires the same Young modulus as human skin.

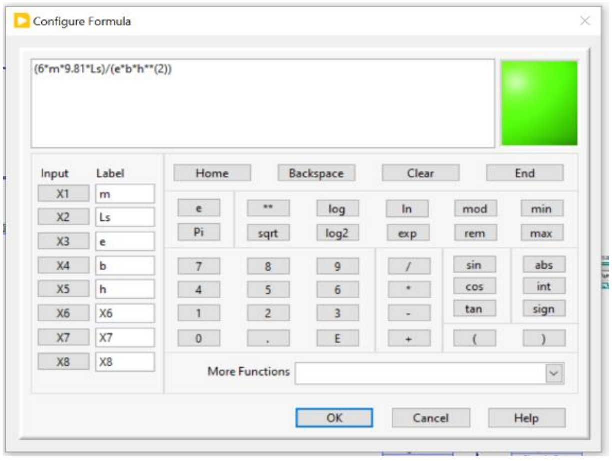

Figure 5. Setting Young's modulus quarter bridge I

3.3. Design of strain gauge characteristics of quarter bridge I

Define the ratio between stress and strain within the elastic limit of the material, which is the region where the material will return to its original shape after the applied force is removed. In practical applications, when materials are tested or monitored using a strain gauge, Young's modulus is used to interpret the strain measurement results. Without knowing Young's modulus, we cannot accurately convert strain measurements into information about the stress or strength experienced by the material. The results of the designed circuit are as shown in Figure 6.

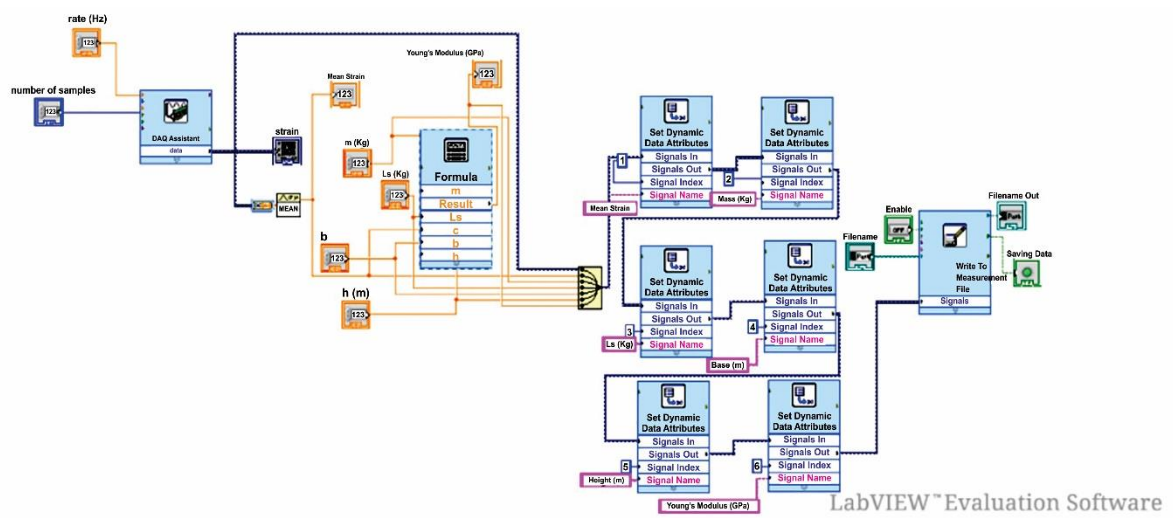

Figure 6. Design of strain gauge characteristics of quarter bridge I

In the simulation using LabView in the formula block is a formula that can be inputted as an indicator that affects the strain gauge in tension and stretching. There are 6 indicators that are used as formulas, namely mean, Young's modulus, m (Kg), Ls (Kg), b and h (m). This attribute data can later be entered in Figure 7, so that the output can be displayed with the design in Figure 6 and the data set can be retrieved as in Figure 8.

3.4. Simulation circuit of strain gauge characteristics of quarter bridge I

After the characteristic circuit of the strain gauge, the results of the circuit can be run and can be displayed with the desired values of the desired stress and strain as shown in Figure 7 of the LabView simulation. In Figure 7 attribute data can be filled in according to the needs of strain and strain gauge stress, so that the strain gauge graph in the form of strain will come out according to the attribute data entered. The average strain will appear as a nominal along with the strain graph that appears. Young modulus will come out as an indicator of the elasticity value of the stretched strain.

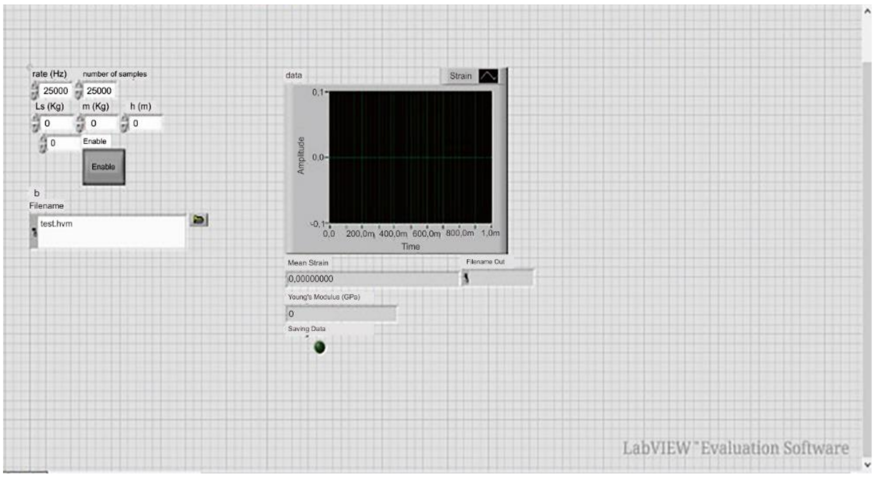

Figure 7. Simulation circuit of strain gauge characteristics of quarter bridge I

3.5. Setting Young's modulus quarter bridge I

The simulation of the characteristics of the strain gauge can be displayed in Excel for the strain results in Figure 8. From the Excel data, it can be seen that the strain value obtained can be positive and can also be negative according to the change in length per unit initial length (relative deformation) and positive strain (tensile strain). The values of Ls, mass (m), and height (m) can be adjusted as needed.

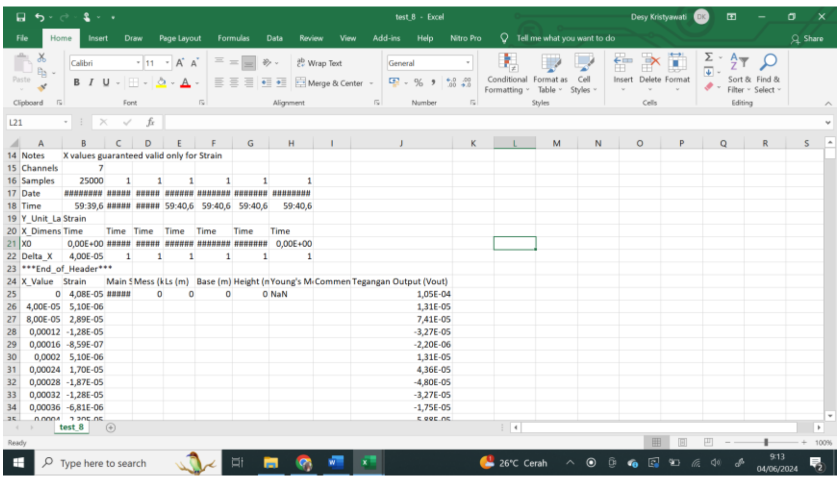

Figure 8. Excel data strain value

3.6. Strain gauge voltage (Wheatstone bridge)

Based on simulations in LabView using quarter bridge 1, gauge factor 2.05, Vex, namely the excitation voltage given to the Wheatstone bridge is 5V and the initial voltage is -180.08 µV and Rg 120 Ω in Figures 4, 5, 6, 7, and 8, the strain gauge value is obtained in excel form. The strain value obtained can be positive or negative, depending on the change in length relative to the initial length (relative deformation), with a positive strain referred to as a tensile strain. The strain data obtained from the LabView simulation in Figure 8, can be used as a reference to get the stress value, then with the calculation results by the value entered in the LabView simulator using quarter bridge 1 which is assumed to be like using a Wheatstone bridge with a Gauge factor value of 2, 05 where the gauge factor value here is a constant that connects the change in strain gauge resistance with strain, the value of the resistance Gauge (Rg) used is 120 Ω, the initial voltage is -180.08 µV, the excitation voltage (Vex) is 5 V and one of the strain data using LabView is 4.08×10^{-5} then if it is derived from the Wheatstone bridge $Vout$ formula obtained by being derived in the equation.

$$Gf = \frac{\Delta R/_{R}}{\varepsilon}$$

$$\frac{\Delta R}{R} = Gf \times \varepsilon$$

$$Vout = \left(\frac{\Delta R}{R}\right)\left(\frac{Vex}{4}\right)$$

$$Vout = Gf \times \varepsilon \times \left(\frac{Vex}{4}\right)$$

$$Vout = 2.05 \times 4.08 \times 10^{-5} \times \left(\frac{5}{4}\right)$$

$$Vout = 1.05 \times 10^{-4} V$$

$$Vout = 0.105\, mV$$

The following data is taken based on the strain gauge simulation generated by LabView. The data below is sampled from some strain data from LabView, which is calculated to be a strain. Calculation data for some strain data can be seen in Table 1.

Table 1. Calculation of stress response to strain

Strain	Output voltage ($Vout$) volt	Current ampere
4.08E-05	1.05E-04	8.75E-07
5.10E-06	1.31E-05	1.09E-07
2.89E-05	7.41E-05	6.18E-07
-1.28E-05	-3.27E-05	-273E-07
-8.59E-07	-2.20E-06	-1.83E-08
5.10E-06	1.31E-05	1.09E-07
1.70E-05	4.36E-05	3.63E-07
-1.87E-05	-4.80E-05	-3.99E-07
-1.28E-05	-3.27E-05	-2.73E-07
-6.81E-06	-1.75E-05	-1.46E-07
2.30E-05	5.88E-05	4.91E-07
-1.87E-05	-4.80E-05	-3.99E-07
-6.81E-06	-1.75E-05	-1.46E-07
5.10E-06	1.31E-05	1.09E-07
1.70E-05	4.36E-05	3.63E-07
3.49E-05	8.94E-05	7.45E-07
2.89E-05	7.41E-05	6.18E-07
1.11E-05	2.83E-05	2.37E-07
2.30E-05	5.88E-05	4.91E-07
2.30E-05	5.88E-05	4.91E-07
-2.47E-05	-6.32E-05	-5.28E-07
5.10E-06	1.31E-05	1.09E-07
2.30E-05	5.88E-05	4.91E-07
3.49E-05	8.94E-05	7.45E-07

From the data results in Table 1, it can be seen that the response of changes in voltage and current from the strain gauge placed on the biceps muscle when it is contracting or relaxing. Where the strain value obtained can be positive or negative, depending on the change in length relative to the initial length (relative deformation), with positive strain referred to as tensile strain. By conducting experiments on a strain gauge that has been integrated with the RTV-52, where the RTV-52 is pulled along 0 to 5 cm with a ruler indicator to see. When not pulled or 0 cm can be seen, the voltage results on the LCD and Multimeter, which is 7 mV as in Figure 9.

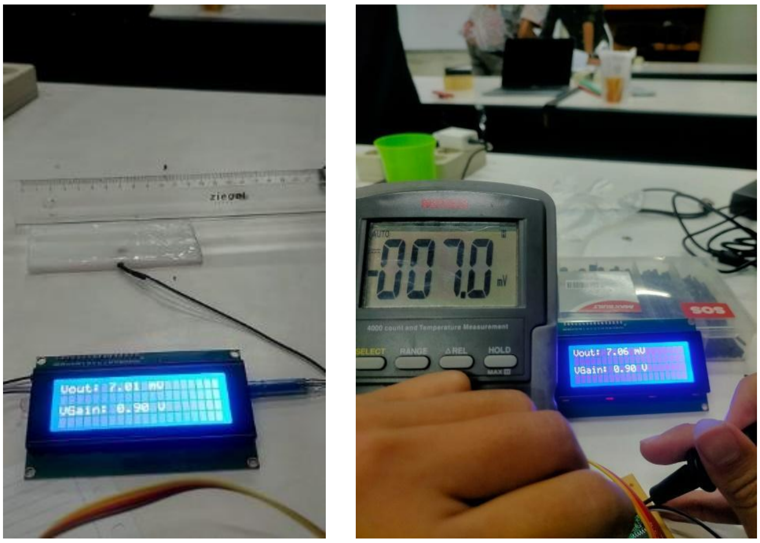

Figure 9. Strain gauge withdrawal experiment on RTV-52 as embedded system

Table 2 shows the measurement results when the strain gauge is pulled with a strain between 0 to 5 cm, which describes the contraction and relaxation movements in the biceps muscle. From the table, it can be concluded that the greater the strain, the smaller the voltage. The measurement results displayed on the LCD and multimeter are slightly different but not significant.

Table 2. Strain Gauge voltage testing

Size (cm)	Measured voltage using multimeter (mV)	Output voltage on LCD (mV)
0	7.00	7.01
1	6.86	6.86
2	6.70	6.70
3	6.51	6.52
4	6.35	6.38
5	6.20	6.26

4. CONCLUSION

Calculation of the stress response to strain in the strain table, can be seen in the response of changes in voltage and current from the strain gauge placed on the biceps muscle when it is contracting or relaxing. Where the strain value obtained can be positive or negative, depending on the change in length relative to the initial length (relative deformation), with positive strain referred to as tensile strain. These stresses and current values will later be processed using machine learning to get the wrong and correct exercise movement patterns in the biceps muscle. In the test, the strain gauge that has been integrated with the RTV-52 as an embedded system is pulled up to 5 cm and will produce the resulting output voltage seen on the LCD and also the multimeter, which will later be applied to the biceps muscle.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Robby Kurniawan Harahap	✓	✓			✓		✓							

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This study did not require ethical approval as it did not involve human participants, animal subjects, or sensitive data.

DATA AVAILABILITY

The data supporting this study's findings are available from the corresponding author, upon reasonable request.

REFERENCES

[1] T. L. Fernandes, A. Pedrinelli, and A. J. Hernandez, “Muscle injury – physiopathology, diagnosis, treatment and clinical presentation,” *Revista Brasileira de Ortopedia (English Edition)*, vol. 46, no. 3, pp. 247–255, 2011, doi: 10.1016/s2255-4971(15)30190-7.

[2] J. Paulo, C. Santanna, T. L. Fernandes, A. Pedrinelli, and A. J. Hernandez, “Muscle Injury : Pathophysiology , Diagnosis , and Lesão muscular : Fisiopatologia , diagnóstico e tratamento,” 2022.

[3] S. L. Boye *et al.*, “Preclinical studies in support of phase I/II clinical trials to treat GUCY2D-associated Leber congenital amaurosis,” *Molecular Therapy - Methods & Clinical Development*, vol. 28, pp. 129–145, Mar. 2023, doi: 10.1016/j.omtm.2022.12.007.

[4] S. G. Jacobson *et al.*, “Safety and improved efficacy signals following gene therapy in childhood blindness caused by GUCY2D mutations,” *iScience*, vol. 24, no. 5, p. 102409, 2021, doi: 10.1016/j.isci.2021.102409.

[5] F. Babatunde, J. MacDermid, and N. MacIntyre, “Characteristics of therapeutic alliance in musculoskeletal physiotherapy and occupational therapy practice: A scoping review of the literature,” *BMC Health Services Research*, vol. 17, no. 1, 2017, doi: 10.1186/s12913-017-2311-3.

[6] F. A. Aragão, G. S. Schäfer, C. E. de Albuquerque, R. F. Vituri, F. M. de Azevedo, and G. R. F. Bertolini, “Neuromuscular efficiency of the vastus lateralis and biceps femoris muscles in individuals with anterior cruciate ligament injuries,” *Revista Brasileira de Ortopedia (English Edition)*, vol. 50, no. 2, pp. 180–185, 2015, doi: 10.1016/j.rboe.2015.03.010.

[7] R. De Marche Baldon, F. V. Serrão, R. S. Silva, and S. R. Piva, “Effects of functional stabilization training on pain, function, and lower extremity biomechanics in women with patellofemoral pain: A randomized clinical trial,” *Journal of Orthopaedic and Sports Physical Therapy*, vol. 44, no. 4, pp. 240–251, 2014, doi: 10.2519/jospt.2014.4940.

[8] A. G. Schache, T. V Wrigley, R. Baker, and M. G. Pandy, “Biomechanical response to hamstring muscle strain injury,” *Gait and Posture*, vol. 29, no. 2, pp. 332–338, 2009, doi: 10.1016/j.gaitpost.2008.10.054.

[9] E. S. Chumanov, A. G. Schache, B. C. Heiderscheit, and D. G. Thelen, "Hamstrings are most susceptible to injury during the late swing phase of sprinting," *British Journal of Sports Medicine*, vol. 46, no. 2, p. 90, 2012, doi: 10.1136/bjsports-2011-090176.

[10] A. G. Schache, T. W. Dorn, P. D. Blanch, N. A. T. Brown, and M. G. Pandy, "Mechanics of the human hamstring muscles during sprinting," *Medicine and Science in Sports and Exercise*, vol. 44, no. 4, pp. 647–658, 2012, doi: 10.1249/MSS.0b013e318236a3d2.

[11] B. C. Heiderscheit, D. M. Hoerth, E. S. Chumanov, S. C. Swanson, B. J. Thelen, and D. G. Thelen, "Identifying the time of occurrence of a hamstring strain injury during treadmill running: A case study," *Clinical Biomechanics*, vol. 20, no. 10, pp. 1072–1078, 2005, doi: 10.1016/j.clinbiomech.2005.07.005.

[12] P. do A. Benfica, L. T. Aguiar, S. A. F. de Brito, L. H. N. Bernardino, L. F. Teixeira-Salmela, and C. D. C. de M. Faria, "Reference values for muscle strength: a systematic review with a descriptive meta-analysis," *Brazilian Journal of Physical Therapy*, vol. 22, no. 5, pp. 355–369, 2018, doi: 10.1016/j.bjpt.2018.02.006.

[13] R. W. Bohannon, "Considerations and practical options for measuring muscle strength: A narrative review," *BioMed Research International*, vol. 2019, 2019, doi: 10.1155/2019/8194537.

[14] R. Maskeliūnas, R. Damaševičius, T. Blažauskas, C. Canbulut, A. Adomavičienė, and J. Griškevičius, "BiomacVR: A Virtual Reality-Based System for Precise Human Posture and Motion Analysis in Rehabilitation Exercises Using Depth Sensors," *Electronics (Switzerland)*, vol. 12, no. 2, 2023, doi: 10.3390/electronics12020339.

[15] O. Glauser, D. Panozzo, O. Hilliges, and O. Sorkine-Hornung, "Deformation capture via soft and stretchable sensor arrays," *ACM Transactions on Graphics*, vol. 38, no. 2, 2019, doi: 10.1145/3311972.

[16] V. Bijalwan, V. B. Semwal, G. Singh, and T. K. Mandal, "HDL-PSR: Modelling Spatio-Temporal Features Using Hybrid Deep Learning Approach for Post-Stroke Rehabilitation," *Neural Processing Letters*, vol. 55, no. 1, pp. 279–298, 2023, doi: 10.1007/s11063-022-10744-6.

[17] T. A. Heiyanthuduwa, K. N. U. Amarapala, K. V. B. Gunathilaka, K. S. Ravindu, J. Wickramarathne, and D. Kasthurirathna, "VirtualPT: Virtual reality based home care physiotherapy rehabilitation for elderly," *ICAC 2020 - 2nd International Conference on Advancements in Computing, Proceedings*, no. December, pp. 311–316, 2020, doi: 10.1109/ICAC51239.2020.9357281.

[18] C. Zizoua, S. Achiche, S. Boukhenous, M. Attari, and M. Raison, "Wearable bio-instrument for detecting body movement based on strain gauges," *Canadian Conference on Electrical and Computer Engineering*, pp. 18–21, 2017, doi: 10.1109/CCECE.2017.7946640.

[19] C. Zizoua, M. Raison, S. Boukhenous, M. Attari, and S. Achiche, "Detecting muscle contractions using strain gauges," *Electronics Letters*, vol. 52, no. 22, pp. 1836–1838, 2016, doi: 10.1049/el.2016.2986.

[20] A. Ancans, M. Greitans, R. Cacurs, B. Banga, and A. Rozentals, "Wearable sensor clothing for body movement measurement during physical activities in healthcare," *Sensors*, vol. 21, no. 6, pp. 1–16, 2021, doi: 10.3390/s21062068.

[21] N. A. Demidenko *et al.*, "Flexible strain-sensitive silicone-CNT sensor for human motion detection," *Bioengineering*, vol. 9, no. 1, p. 36, Jan. 2022, doi: 10.3390/bioengineering9010036.

[22] J. T. Alvarez *et al.*, "Toward Soft Wearable Strain Sensors for Muscle Activity Monitoring," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 2198–2206, 2022, doi: 10.1109/TNSRE.2022.3196501.

[23] H. Wang, D. Li, W. Zhong, L. Xu, T. Jiang, and Z. L. Wang, "Self-Powered Inhomogeneous Strain Sensor Enabled Joint Motion and Three-Dimensional Muscle Sensing," *ACS Applied Materials and Interfaces*, vol. 11, no. 37, pp. 34251–34257, 2019, doi: 10.1021/acsami.9b12195.

[24] J. Tolvanen, J. Hannu, and H. Jantunen, "Stretchable and washable strain sensor based on cracking structure for human motion monitoring," *Scientific Reports*, vol. 8, no. 1, pp. 1–10, 2018, doi: 10.1038/s41598-018-31628-7.

[25] A. Kalra and A. Lowe, "An overview of factors affecting the skins Youngs modulus," *Journal of Aging Science*, vol. 4, no. 2, 2016, doi: 10.4172/2329-8847.1000156.

[26] A. Kalra, A. Lowe, and A. M. Al-Jumaily, "Mechanical behaviour of skin: a review," *Journal of Material Science & Engineering*, vol. 5, no. 4, pp. 1–8, 2016, doi: 10.4172/2169-0022.1000254.

[27] H. Zahouani, C. Pailler-Mattei, B. Sohm, R. Vargiolu, V. Cenizo, and R. Debret, "Characterization of the mechanical properties of a dermal equivalent compared with human skin in vivo by indentation and static friction tests," *Skin Research and Technology*, vol. 15, no. 1, pp. 68–76, 2009, doi: 10.1111/j.1600-0846.2008.00329.x.

[28] G. Boyer, L. Laquièze, A. Le Bot, S. Laquièze, and H. Zahouani, "Dynamic indentation on human skin in vivo: Ageing effects," *Skin Research and Technology*, vol. 15, no. 1, pp. 55–67, 2009, doi: 10.1111/j.1600-0846.2008.00324.x.

[29] F. De Tommasi, C. Romano, D. Lo Presti, C. Massaroni, M. Carassiti, and E. Schena, "FBG-Based Soft System for Assisted Epidural Anesthesia: Design Optimization and Clinical Assessment," *Biosensors*, vol. 12, no. 8, 2022, doi: 10.3390/bios12080645.

[30] F. De Tommasi, D. Lo Presti, F. Virgili, C. Massaroni, E. Schena, and M. Carassiti, "Soft system based on fiber bragg grating sensor for loss of resistance detection during epidural procedures: In silico and in vivo assessment," *Sensors*, vol. 21, no. 16, 2021, doi: 10.3390/s21165329.

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