Body Fat Monitor Final Report

Muskaan Bhargava, Henry Chen, Ayush Dilip Gaur, Rimsha Mahmood, Mohamed Mohamed-Ali, Robert Samaskeawicz

Abstract—**Obesity is an epidemic that currently affects millions of people and is directly linked to diseases such as diabetes, heart disease, and stroke. Measuring a patient's body fat composition is essential to disease prevention, a task that is overlooked in today's market. Here we introduce an improved body fat calculator using a combination of bioelectrical impedance analysis (BIA) and machine learning (ML) to maximize device accuracy. We do so by incorporating a commonly used Arduino microcontroller to generate a 5V, 50 kHz square wave to be sent throughout the body, the device processes this signal and utilizes the Arduino to calculate body fat composition that is then displayed on an LCD. Machine model training was tested to calibrate the best fitting for our device. With BIA, we created a working device that could help improve the health of patients with poor lifestyles.**

Index Terms—**Body Fat, Electrodes, Bioelectrical Impedance Analysis, Machine Learning.**

I. Introduction

Addressing the pressing health concern of obesity affecting over 40% of the US population, a range of devices and analytical methods have emerged to quantify body fat percentage. Among these, dual-energy X-ray absorptiometry (DXA) is widely used. DXA utilizes dual-power X-ray beams to scan the entire body, distinguishing between bone, fat, and muscle for volume calculations [1]. Although widely used, DXA requires a radiology technician, involves low doses of radiation, and may not be suitable for certain patients [2]. Hydrostatic weighing, another method, immerses the patient in water and compares their weight on dry land and in water, estimating lung volume and differences in bone, muscle, and fat density [3] [4]. While effective, this method can be stressful for patients, particularly the elderly or ill, due to the need for multiple submersions. The skinfold measurement is another technique that is utilized. It measures skin thickness at specific sites using calipers and uses the measurements from the calipers to estimate body fat percentage. However, this technique requires a trained technician and is prone to errors from incorrect site measurements [5]. Another technique used to measure body fat composition is Bioelectrical impedance analysis (BIA). BIA analyzes body fat composition by passing a low-power AC current through the body, and the voltage is measured to calculate the body impedance [5] [6] [7] [8]. The relative simplicity of implementing and using devices designed using BIA makes it a popular technique for body fat composition analysis. Despite BIA's advantages, its assumption of a "cylindrical-shaped ionic conductor with homogeneous composition" poses accuracy challenges [9]. This paper focuses on designing a body fat measuring device, considering BIA's minimal equipment and training requirements, making it suitable for general public use [9] [10] [11]. To enhance accuracy and mitigate assumption-related errors, a machine learning (ML) aspect is incorporated into the device analysis. This innovative approach aims to optimize the device's performance and usability, ensuring reliable body fat percentage measurements in a safe and accessible manner for diverse user demographics. The information drawn from these sources contributes to a comprehensive understanding of existing body fat measurement methods and informs the development of an advanced and user-friendly solution.

II. Our Approach

A. Hardware Setup

Our device schematic is divided into three parts as shown in Fig.1. The first part of the circuit consists of a non-inverting amplifier that receives a 50 kHz, 5V square wave input from the microcontroller (MC). A frequency of 50 kHz is used because it is the frequency at which body fat can be measured [12]. The non-inverting amplifier behaves as our current source which supplies a constant current of about 40-50 microamps. The value of R3 is set to 100k ohms as it allows for a constant current of around 40-50 microamps to flow through the electrodes. The output of the non-inverting amplifier and its negative terminal are connected to the negative and positive input terminal of the voltage subtractor circuit respectively which forms the second part of the circuit. The voltage subtractor circuit reads the voltage across the electrodes connected to the subject. The resistors connected to the voltage divider circuit are all set to be equal in order to achieve unity gain. This allows the output of the voltage subtractor circuit to be just the voltage difference across the electrodes. The third part of our circuit consists of a simple diode circuit that provides us with a single voltage value by rectifying the signal. This is fed into the ADC input of the MC to further process and find the body fat composition which would be displayed on the LCD as seen in Fig. 2.

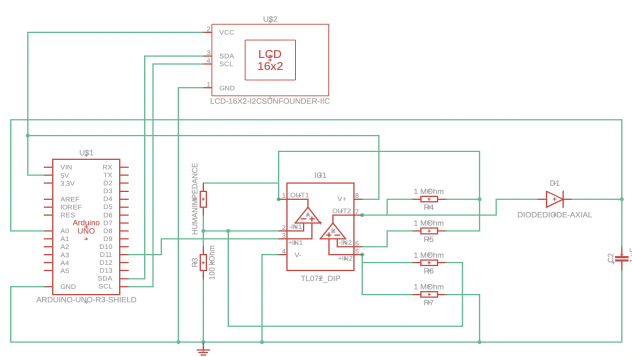


Fig. 1 Schematic Setup.

Our MC was able to generate a 5V 50 kHz square wave seen in Fig. 3 which would be sent throughout the subject's body. The voltage subtractor circuit would then record the signal across the human impedance also seen in Fig. 3. After rectifying the signal with a diode, we were able to read a DC signal as shown in Fig. 4.

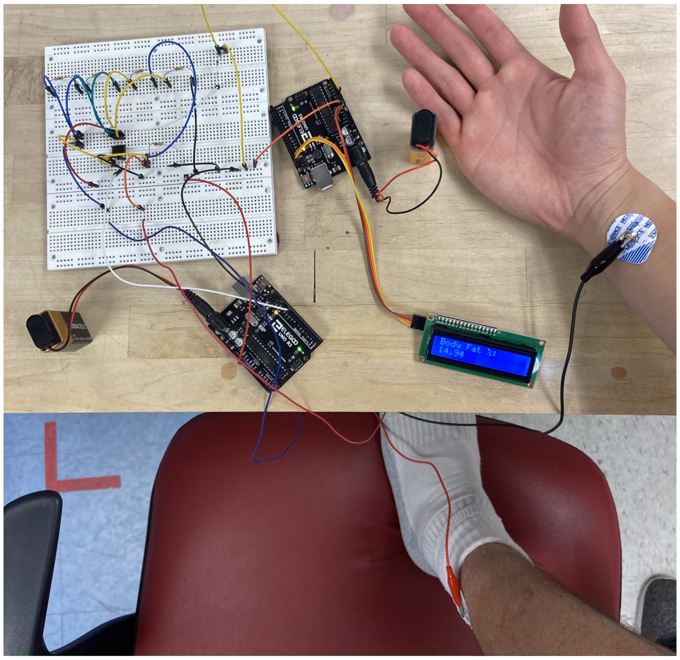


Fig. 2 Hardware Setup.

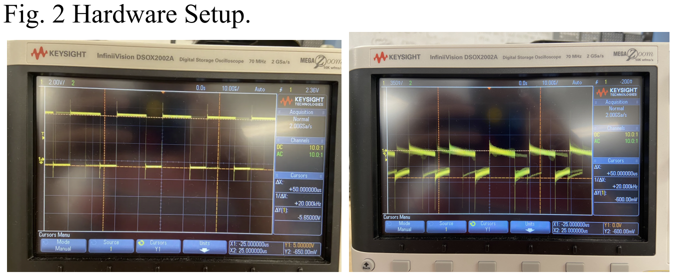


Fig. 3 Output of the MC and voltage subtractor circuit.

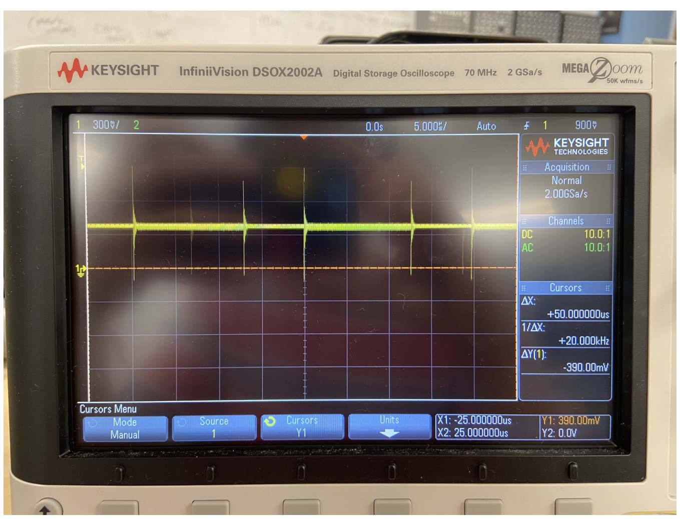


Fig. 4 Output of the diode circuit.

B. Embedded Setup

The design for our device is built around the basic BIA circuit model. Our device uses ATMEGA382P microchip, a chip known for its versatility, programmability, and low power requirements to process the device's output voltage signal and utilize it in body fat calculation. The code and the formula used to calculate the body fat percentage from the device's output voltage and the input age and weight of the user are given below in Fig. 3 and Fig . 4 respectively.

BIAInput.ino

```
const int squareWavePin = 5;  // Digital pin for square wave input
#include <LiquidCrystal_I2C.h> //opens lcd library package

LiquidCrystal_I2C lcd(0x27, 20, 4);

int weight = 170; //user input weight, changes based on subject
int age = 20; //user input age, changes based on subject


void setup() {
  Serial.begin(9600);

}

void loop() {

  float val = analogRead(A0); //analog in from A0
  float fat = 0.0923 * weight + 0.1605 * age - val/1023*5*3;
  // body fat calculation based on weight, age, and device reading
  Serial.println(fat);
  Serial.print("Body Fat % = ");
  lcd.init();
  lcd.backlight();
  lcd.setCursor(0, 0);
  lcd.print("Body Fat %: ");
  lcd.setCursor(0, 1);
  lcd.print(fat);
}
```

Fig. 5. Arduino code for calculating body fat.

Males: `body_fat = 0.0923 * weight + 0.1605 * age - 0.0263 * voltage`

Females: `body_fat = 0.1871 * weight + 0.5800 * age - 0.0920 * voltage`

Fig. 6. Formula for calculating body fat [13].

C. Device Results

After creating our device, we were able to compare our device with an existing body fat composition device on the market. We used the OMRON Body Composition Scale to compare with our data shown in Table 1. The OMRON scale included metrics such as height, age, gender, and weight to determine body fat whereas our device considered age, weight, and gender. Our device was calibrated based on the data we collected along with data from a study based on dozens of participants.

Table 1.

Device Measured Body Fat %	OMRON Scale Body Fat %	Subject's Age	Subject's Weight	Subject's Gender
11.5	13	20	145	Male
13.8	21.4	21	180	Male
14.6	13.5	20	170	Male
20.3	16.98	22	200	Male
13.6	24.3	20	141	Female
19.3	23.9	20	207	Male
13.8	12.15	20	120	Male
21.1	24.9	19	135	Male
13.3	14.9	22	168	Male
14.8	18.5	20	147	Female

D. Machine Learning

The ML model consists of 4 key components: Data Handling, Feature Selection, Model Development and Model Evaluation. To determine the most appropriate model for predicting body fat percentage, we used a mock dataset from the internet consisting of 252 sample points. This dataset was used for the sole purpose of model selection.

	Density	BodyFat	Age	Weight	Height	Neck	Chest	Abdomen	Hip	Thigh	Knee	Ankle	Biceps	Forearm	Wrist
0	1.0708	12.3	23	154.25	67.75	36.2	93.1	85.2	94.5	59.0	37.3	21.9	32.0	27.4	17.1
1	1.0853	6.1	22	173.25	72.25	38.5	93.6	83.0	98.7	58.7	37.3	23.4	30.5	28.9	18.2
2	1.0414	25.3	22	154.00	66.25	34.0	95.8	87.9	99.2	59.6	38.9	24.0	28.8	25.2	16.6
3	1.0751	10.4	26	184.75	72.25	37.4	101.8	86.4	101.2	60.1	37.3	22.8	32.4	29.4	18.2
4	1.0340	28.7	24	184.25	71.25	34.4	97.3	100.0	101.9	63.2	42.2	24.0	32.2	27.7	17.7

Fig. 7. Mock Dataset

The models under consideration are Ridge Regression, Random Forest, Support Vector Machine, Decision Tree Regression, LASSO regression and Linear Regression. The features analyzed in this mock dataset are Density, body fat, age, weight, height, neck, chest, abdomen, thigh, hip, knee, ankle, biceps, forearms and wrist. This dataset [16] consists of 252 data points and we trained all the above six mentioned models using train_test_split with a ratio of 80%:20%. The predicted output for these models was set as body fat percentage. To check the performance of each model on the mock dataset, model score was evaluated.

```
model => LR
0.9918244198502377
model => LASSO
0.9922951482590039
model => RIDGE
0.9913846291279131
model => DTR
0.9867224272378268
model => svm
0.780042728680O4
model => RFR
0.9977989577952534
```

Fig. 8. Model Scores

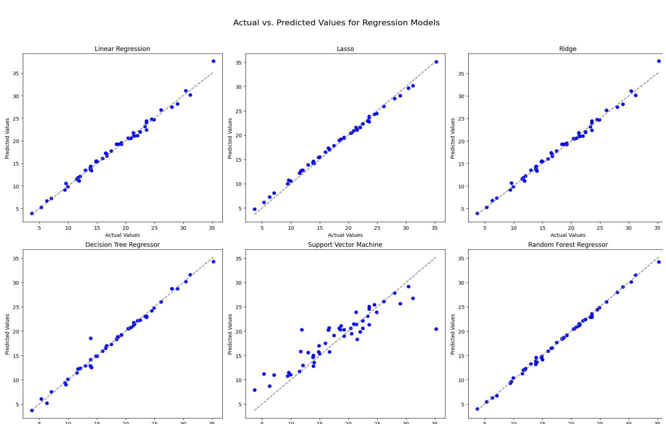


Fig. 9. Actual Values vs Predictions

Random Forest Regression (RFR) gave the highest model score out among all the considered models. To get a better understanding, we further examined the actual vs. predicted values graphs for all of the 6 machine learning models.

The line between the axes represents an ideal scenario where the predicted value of body fat percentage perfectly matches the actual value. x-coordinates represent the actual values and y-coordinates represent the predicted values. In the 6th figure corresponding to Random Forest Regression, there is the tightest clustering of points around the line which shows that it has the most accurate predictions.

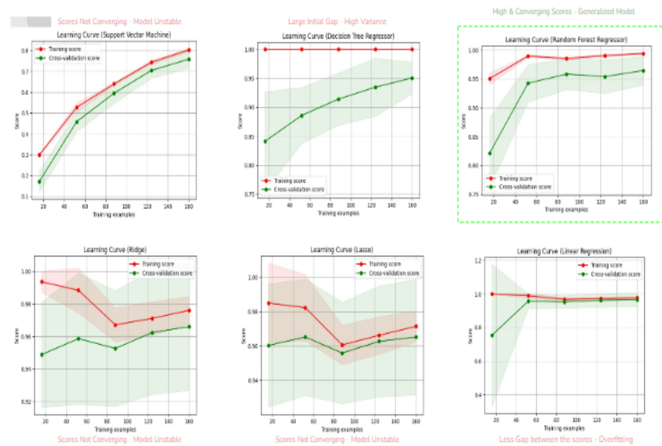


Fig. 10. Learning Curves

The learning curves are a visual representation of how effectively the model adapts to the dataset. Y-axis denotes the model score and the x-axis represents the number of training examples. In Fig. 10, the graph located in the 1st row, 3rd column, both the cross-validation and training score curves and both converge well at the end. The rest of the models either exhibit underfitting or overfitting, indicated by their learning curves.

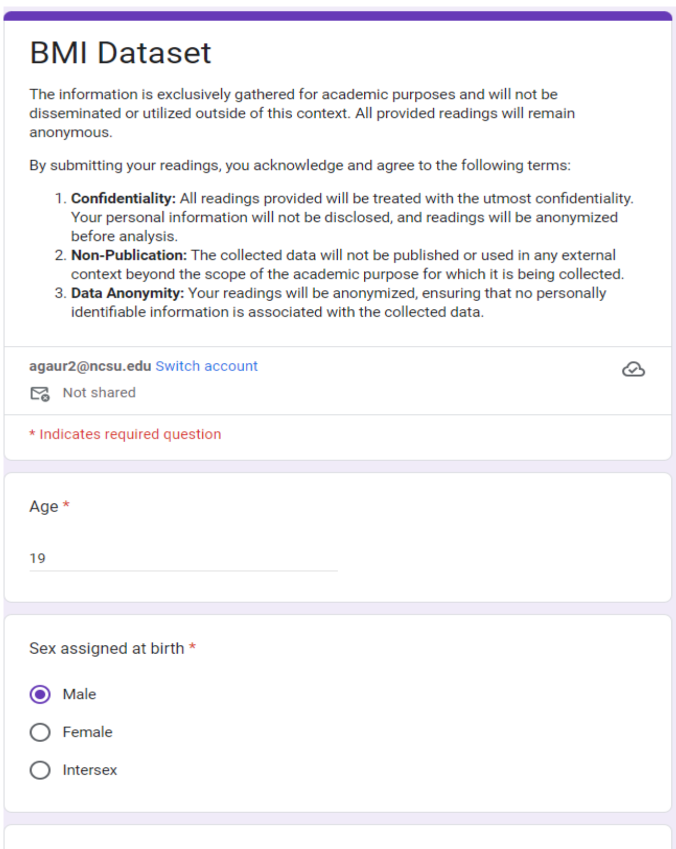
E. Data Collection

The dataset was collected using Omron's scale. The determination of the most relevant features used was made using Random Forest's inbuilt feature importance algorithm. The features include Age, height, weight, BMI, body fat, neck, wrist, knee, ankle and chest size.

Age	Height	Weight	BMI	BodyFat	Neck	Wrist	Knee	Ankle	ChestSize
19	67	171.6	23	15.2	41	18	37	23	98
19	68	149.4	22.7	14.6	41	18	41	28	96.5
19	70	163.2	23.1	16.2	41	18	38	24	97
19	72	187.8	25.5	20.6	38	18	43	28	96.5
19	72.6	166	22.5	20.5	38	15.5	40.5	20.5	91.5
19	72.6	158.8	21.2	15.6	40.5	16.5	39.5	28	87.5
18	70	171.6	22.9	19.6	43	16	38	25.5	94
19	82	208.8	27.6	24.3	48.5	19	46	30.5	98
22	72	162	21.2	14.7	35.5	16	38	27	94
20	72	175	23.7	17.3	43.5	18	41	27	95
19	73	171.6	23.1	16.5	40.5	18	42	15.5	96.5
25	65	104.6	17.1	5.3	34.5	15.5	32.5	18	30
19	68	162.8	24.4	12.2	40.5	18	38.5	28	96.5
20	66	149.2	23.7	35.9	29	18	36	27	89
20	63	137.6	23.8	36.4	38	18	36	25	99
18	69	149.8	21	14.6	38	15	38	27	94
23	67	168.8	26.9	29.9	42	15.5	43	25.5	99
23	66	111.6	17.7	5.1	37	15.5	34	22.5	56.5
23	67	158.8	24.9	23.2	39	20.5	16	28	96.5
22	69	129.6	18.9	8.6	35	18	37	28	88
21	70	140.2	20.1	13.5	35	19	37	27	94
19	72	195.6	26.5	22.3	43	20	39	25.5	102
26	70	164.8	23.3	17.2	53	19	40	25.5	100
19	67	156.6	24	20.6	43	19	38.5	25.5	95
20	79	184.8	21	16.2	42	19	42	27	98
19	72	146.6	19.7	7.9	41	18	38.5	23	89
21	68	133.8	19.9	14.4	38	18	37	25.5	87.5
21	67	187	28	22.4	41	21.5	39	27	104

Fig. 11. Actual Data

60 accurate data points for Body weight, BMI, and Body fat percentage were collected using Omron's scale, and rest of the measurements were taken using measurement tape. A Google form was designed for manual entry of the collected measurements.


BMI Dataset

The information is exclusively gathered for academic purposes and will not be disseminated or utilized outside of this context. All provided readings will remain anonymous.

By submitting your readings, you acknowledge and agree to the following terms:

1. **Confidentiality:** All readings provided will be treated with the utmost confidentiality. Your personal information will not be disclosed, and readings will be anonymized before analysis.
2. **Non-Publication:** The collected data will not be published or used in any external context beyond the scope of the academic purpose for which it is being collected.
3. **Data Anonymity:** Your readings will be anonymized, ensuring that no personally identifiable information is associated with the collected data.

agaur2@ncsu.edu Switch account

Not shared

* Indicates required question

Age *

19

Sex assigned at birth *

Male

Female

Intersex

Height (inch) *

Fig. 12. Form for Data Collection

Considering the limited size of the dataset, consisting of 60 data points, logistic regression with LASSO regularization [17] was opted. It was because of the lower complexity and improved resistance of Logistic regression to overfitting.

```
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

X = SC.fit_transform(X)

# Lasso Regression
lasso = Lasso(alpha=1.0)

# Dataset Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.6, random_state=42)

# Training Lasso Regression model
lasso.fit(X_train, y_train)

# Testing
y_pred = lasso.predict(X_test)

# Metrics
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f'Mean Absolute Error: {mae}')
print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')
```

```
Mean Absolute Error: 1.6583731448641428
Mean Squared Error: 5.002632236903221
R-squared: 0.6217812094400772
```

Fig. 13. Performance metric calculation

According to the MAE, MSE and R-squared values observed in the Fig. 13 above we can draw the conclusions below:

1. Mean Absolute Error (MAE): The value 1.6 states that the model is giving a reasonably good performance as the predictions are off by approximately 1.6 units from the actual value, which in practical scenarios is very low.
2. Mean Squared Error (MSE): The value 5 states a moderate predictive performance as MSE is a calculation of the squared differences between predicted and actual values which is desired to be small.
3. R Squared : The value of 0.62 represents that our model is able to explain around 62% of the variability in target variables, which can be considered a good performance.

```
import numpy as np
# Load the dataset
dataset = pd.read_csv("/content/BMI Dataset.csv")


dataset['BodyFat'] = pd.cut(dataset['BodyFat'], bins=[0, 10, 20, 30, 40, np.inf], labels=['Very Low', 'Low', 'Moderate', 'High', 'Very High'])

y = dataset['BodyFat'].values
X = dataset.drop(['BodyFat'], axis=1).values
SC = StandardScaler()
X = SC.fit_transform(X)

# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.6, random_state=42)

# Logistic Regression model with Lasso (L1) regularization
logreg = LogisticRegression(penalty='l1', solver='liblinear')
logreg.fit(X_train, y_train)

# Prediction
y_pred = logreg.predict(X_test)

# Display Prediction
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
```

```
Accuracy: 0.6111111111111112
```

Fig. 14. Model Accuracy Calculation

The model score defines how effectively the model has adapted to the data. We got a model score of 61.11% which is less as compared to the model score of the Random forest model when used on the Mock dataset. It's because the random forest model works well when there is plenty of data and it tends to overfit in less data. Logistic regression gave a decent model score and body fat percentage prediction when used on the real data collected from Omron’s scale.

III. Prototyping and Testing

In the realm of prototyping and testing during the project's evolution, members of the group played a central role in steering import hardware aspects. This process laid the groundwork for subsequent experimentation, wherein several iterations of breadboard circuits were purposefully designed. These varied configurations aimed to systematically explore and evaluate the output voltage characteristics of the circuit under diverse operational conditions.

The testing journey was marked by a comprehensive deployment of the Analog Discovery 2 (AD2), an invaluable instrument in the arsenal of hardware exploration. Leveraging the capabilities of the AD2, the individual orchestrated the generation of alternating current (AC) signals, encompassing both sine waves and square waves, meticulously tailored to specific frequencies and amplitudes. These signals, integral to the collaborative testing endeavor with a fellow team member, served as a linchpin in comprehensively scrutinizing the circuit's performance dynamics.

The AD2's functionalities extended to the realm of signal analysis in the time domain, offering a detailed examination of amplifier and filter outputs. This analytical dimension proved to be a critical asset, providing nuanced insights into the temporal behavior of signals and, in turn, facilitating the troubleshooting and refinement processes integral to the overarching design strategy.

Expanding the scope of analysis, the individual harnessed the AD2 channels to conduct gain measurements across an array of amplifiers. This quantitative assessment, elucidating the ratio of output voltage to input voltage, played a pivotal role in the diagnostic evaluation of circuit anomalies. Moreover, it furnished a critical lens for the comprehensive evaluation of the embedded operational amplifiers (Op Amps) within the design.

The iterative nature of the testing and analysis process, exemplified by the creation of multiple breadboard circuit versions, emerged as a linchpin in the validation and refinement paradigm. Each iteration not only substantiated the circuit's functional fidelity but also contributed significantly to the ongoing enhancements, ensuring the success and robustness of the hardware implementation. The orchestrated interplay between hands-on experimentation, collaborative testing, and analytical scrutiny exemplified a holistic and methodical approach to the prototyping and testing phase, ultimately fortifying the project's foundation.

In the software domain, the ATMEGA328P microcontroller was used and programmed. This microcontroller is a pivotal component within our system. The focus of this programming endeavor was the utilization of the microcontroller's analog-to-digital converter (ADC) functionality. Specifically, software routines were crafted to read the voltage at the output of our circuit.

This voltage data holds paramount significance in the context of the final body fat calculation—an essential metric for our project. The accuracy of this voltage reading is pivotal as it serves as a foundational input for the subsequent body fat analysis. This analysis, in turn, is designed to be benchmarked against other established body fat measurement methods, thus validating the efficacy of our devised device.

Moreover, the generated voltage values and the subsequent body fat calculations find broader applications within the scope of machine learning algorithms. The amalgamation of hardware data acquisition and software processing lays the groundwork for a comprehensive approach, contributing not only to the immediate functionality of our device but also to its potential integration into broader analytical frameworks.

To witness the integration of the Machine Learning and Body Fat Prediction, we can look at the code in Fig. 15 which shows our implementation for predicting body fat percentages using a logistic regression model. The example taken in code is from the Omron’s dataset that was collected. The actual Body fat percentage in this case was 14.6% and the logistic model gave a prediction of 14% showing that the model has effectively adapted to the data and is ready.

```python
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Loading the dataset
dataset = pd.read_csv("/content/BMI Dataset.csv")

# Creating 40 classes
bins = np.arange(1, 42)
labels = range(1, 41)

dataset['BodyFat'] = pd.cut(dataset['BodyFat'], bins=bins, labels=labels)

y = dataset['BodyFat'].values
X = dataset.drop(['BodyFat'], axis=1).values
SC = StandardScaler()
X = SC.fit_transform(X)

#Logistic Regression model with Lasso (L1) regularization
logreg = LogisticRegression(penalty='l1', solver='liblinear', multi_class='ovr')
logreg.fit(X, y)

# Input from User
age = float(input("Enter Age: "))
height = float(input("Enter Height: "))
weight = float(input("Enter Weight: "))
bmi = float(input("Enter BMI: "))
neck = float(input("Enter Neck Size: "))
wrist = float(input("Enter Wrist Size: "))
knee = float(input("Enter Knee Size: "))
ankle = float(input("Enter Ankle Size: "))
chestsize = float(input("Enter Chest Size: "))

# Prediction
user_input = SC.transform([[age, height, weight, bmi, neck, wrist, knee, ankle, chestsize]])
y_pred = logreg.predict(user_input)

# Display Prediction
print(f'Predicted Body Fat Class: {int(y_pred[0])}')
```

```
Enter Age: 19
Enter Height: 68
Enter Weight: 149.5
Enter BMI: 22.7
Enter Neck Size: 41
Enter Wrist Size: 18
Enter Knee Size: 41
Enter Ankle Size: 28
Enter Chest Size: 96.5
Predicted Body Fat Class: 14
```

Fig. 15. Body Fat Percentage Prediction (Values)

```
[21] import numpy as np
     import pandas as pd
     from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import StandardScaler
     from sklearn.linear_model import LogisticRegression
     from sklearn.metrics import accuracy_score

     # Load the dataset
     dataset = pd.read_csv("/content/BMI Dataset.csv")
     y = dataset['BodyFat'].values
     X = dataset.drop(['BodyFat'], axis=1).values
     SC = StandardScaler()
     X = SC.fit_transform(X)

     # Input from User
     age = float(input("Enter Age: "))
     height = float(input("Enter Height: "))
     weight = float(input("Enter Weight: "))
     bmi = float(input("Enter BMI: "))
     neck = float(input("Enter Neck Size: "))
     wrist = float(input("Enter Wrist Size: "))
     knee = float(input("Enter Knee Size: "))
     ankle = float(input("Enter Ankle Size: "))
     chestsize = float(input("Enter Chest Size: "))

     # Prediction
     user_input = SC.transform([[age, height, weight, bmi, neck, wrist, knee, ankle, chestsize]])
     y_pred = logreg.predict(user_input)

     # Display Prediction
     print(f'Predicted Body Fat Category: {y_pred[0]}')

Enter Age: 19
Enter Height: 68
Enter Weight: 150
Enter BMI: 23
Enter Neck Size: 41
Enter Wrist Size: 18
Enter Knee Size: 41
Enter Ankle Size: 28
Enter Chest Size: 96.5
Predicted Body Fat Category: Low
```

Fig. 16. Body Fat Percentage Prediction (Categories)

The code in Fig. 16 gives the category for predicted body fat percentages whether it is very low, low, moderate, high or very- high.

IV. Conclusion

Enhancing a patient's healthcare journey hinges on accurate diagnosis and vigilant observation. In the future, we hope to create a more compact device that will be accessible to all people. Further development of the user interface would allow easier usage of our device while maintaining the utmost accuracy. In this context, the pivotal aspect involves the precise and efficient analysis of a patient's body fat content. We propose that Bioelectrical Impedance Analysis (BIA) stands as the method through which this can be achieved. BIA offers the capability to measure body fat percentage without resorting to radiation exposure or deploying intricate and invasive techniques. By accomplishing this design, we envision not only refining the methodology for assessing body fat content but potentially advancing our comprehension of weight gain and enhancing the overall quality of life for countless patients. The completion of this device signifies a significant stride towards a more efficient and patient-friendly approach to body fat analysis, with the potential to impact healthcare practices and patient well-being on a broad scale. Also, the ML model would further help in accuracy improvement on a new device being built through the different models tested. It was learned that logistic regression and Random Forest regression can be used for body fat data analysis. Our commitment extends beyond the current design, as we envision a roadmap for ongoing enhancements and refinements. By embracing emerging technologies and staying attuned to evolving healthcare needs, our device has the potential to continually evolve, offering increasingly accurate and accessible solutions for body fat analysis. The journey toward improved healthcare practices is an ongoing one, and our device stands as a foundational step toward a future marked by innovation and heightened patient well-being.

Acknowledgment

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References

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