

Development of a measuring unit to detect poor eating habits in office workers for metabolic syndrome

Bachelor project Biomedical Engineering

Shaldon Ingmar Hartman: s4069099

Date: 17-06-2022

Department: DTPA

Supervisor: dr. Elisabeth Wilhelm

Second supervisor: dr. Taraneh Mokkafer

Abstract

Today's office workers seem to suffer increasingly from chronic diseases such as metabolic syndrome (MetS). One of the main problems is that no method is present to accurately and adequately measure one of the main risk factors related to the development of MetS: poor eating habits. This project, therefore, aimed to develop a device that can monitor the frequency of eating and that can discriminate between healthier and unhealthier food types. To make this happen a piezoelectric sensor and microphone were attached to the throat to measure the movement of the muscles in the throat and sounds during chewing and swallowing. A prototype was made and tested with apples, bananas, waffle cake and cookies. The results showed that the prototype can discriminate between apples and cookies and between bananas and waffle cake during chewing and swallowing ($p < 0.05$). Concluding that the concept and prototype have the potential to monitor and detect poor eating habits, further research and development are necessary to confirm this. With this conclusion, this research could help early detect development of metabolic syndrome, thereby preventing sick leave for employers and healthcare costs for society.

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1 Introduction

Compared to fifty years ago, the number of people having office jobs has been increasing in well-developed countries⁴⁰. With this increase in sedentary work, another public health concern has evolved simultaneously: chronic diseases, especially metabolic syndrome (MetS)². The consequences of these chronic diseases translate into a decreased quality of life and increased mortality rate¹, they also appear to have negative effects on costs for the employer and productivity of the employees⁴⁰. This motivates to find a solution for this increasing problem, however, the risk factors that are known to cause these problems are not yet measured in the office.

According to research, optimizing the prevention of risk factors directly affects the reduction of symptoms and general health of the employees, resulting in improved or restored quality of work⁴¹. Of all risk factors known for MetS, the thesis written about this topic revealed that one risk, in particular, is prone to cause chronic diseases such as MetS: eating habits. Since this risk factor is a pillar in MetS, it is worth preventing. According to research eating habits comprises the type of food taken in, as well as the amount and frequency of eating. Prolonged 'poor' eating habits consisting of unhealthy food in large amounts taken in more often than normally are a pillar in developing negative employability and quality of work^{11, 16}. However, until now, no device or method has been developed that can accurately measure and monitor eating habits and give personal feedback to employees. This project and the preliminary research done in the thesis aim to investigate and develop a device that can do this. To develop such a device capable of accurately measuring and monitoring eating habits, this project used the Methodical Design process²⁷ to investigate MetS and parameters related to food intake to answer the research question:

"Is the measurement device that is going to be constructed during the project able to monitor parameters of eating habits such as frequency and food type known to be risk factors for the development of metabolic syndrome?"

The entire project consisted of a thesis written within a three-week timeframe to get a better understanding of the syndrome and the parameters that could be used to detect risk factors⁴². The design part of the project embroidered the outcome of the thesis by focusing on eating habits. This is done by investigating what body responses there are and what type of sensors could be used to non-invasively directly measure eating habits (chapter 2), brainstorming how these sensors could be incorporated into a device (chapters 3 and 4) and developing and testing a prototype to check the potential of the device (chapter 5). The report ends with a conclusion and future recommendations in chapter 6. This report also contains an appendix, which contains the Arduino IDE code in appendix 1, the MATLAB code in appendix 2, plots of the in appendix 3, Means of the microphone in appendix 4, piezoelectric frequency means in appendix 5 and the results of the statistical analyses in appendix 6.

The results of the testing indicated that the sensors used within the prototype allow it to discriminate between two groups of food during chewing and swallowing. The prototype can distinguish during chewing and swallowing between apples and cookies and between bananas and waffle cake. With this result, the prototype shows potential in detecting other eating habits as well, however further research is needed to confirm this.

2 Analysis phase

2.1 Problem definition

2.1.1 Literature research

Metabolic syndrome is a cluster of several medical conditions that are becoming an increasing public health concern¹. Especially among office workers, the incidence of metabolic syndrome rises yearly. Nowadays the incidence ranges between 7.4% and 48.8%^{2,3}, thereby contributing 30% to the 71% of death due to non-communicable deaths⁴. Metabolic syndrome's exact cause is still unknown, what is known are the symptoms, risk factors and indications that are associated with the syndrome.

The symptoms of metabolic syndrome translate into at least three of the following conditions:

- Abdominal obesity is an excessive accumulation of fat around the abdomen and stomach and is linked to several diseases such as cardiovascular and Alzheimer's disease⁶.
- Hypertension in which long-term high blood pressure increases the risk for cardiovascular diseases such as strokes, heart failure and many more⁷.
- Hypertriglyceridemia is an accumulation of triglycerides in the blood. Hypertriglyceridemia influences diabetic control with consequences and cardiovascular disease⁸.
- Low high-density lipoprotein cholesterol (HDL-c) is related to several functions from antimicrobial, anti-inflammatory, and antithrombotic to cell membrane protection. Low levels of HDL-c affect diabetic control and cardiovascular and immunogenic properties of the body⁹.
- High fasting blood sugar manifests itself in elevated levels of blood glucose. The potential consequence of elevated blood glucose is ketoacidosis which is a life-threatening condition¹⁰.

Table 1 below shows normal and abnormal values for these medical conditions

Table 1: the symptoms of metabolic syndromes and their ranges.

Symptom	Ranges for man	Ranges for woman	Normal value
Abdominal obesity	>90 th percentile	>90 th percentile	<90 th percentile
Hypertension	Systolic blood pressure >140mmHg	Systolic blood pressure >140mmHg	Systolic blood pressure 120-130mmHg
Hypertriglyceridemia	>150mg/dl	>150mg/dl	<150mg/dl
HDL-c	<40mg/dl	<50mg/dl	>40-50 mg/dl
High fasting blood sugar	>110 mg/dl	>110 mg/dl	<110 mg/dl ⁵

Several risk factors have been determined and categorized into modifiable and unmodifiable risks depending on whether or not they can be changed through lifestyle adaptations. The risk factors involved in metabolic syndrome are:

- Stress causes an imbalanced brain and nervous system that may lead to obesity¹¹. Stress is a modifiable risk factor.
- Poor lifestyle. Poor lifestyle habits such as poor eating and little physical activity may lead to metabolic syndrome. Poor eating habits often comprise diets containing high carbohydrates (a lot of sugar), saturated fats (cream, mayonnaise, etc.) and triglycerides (alcohols, sugars, high-calorie foods, etc.)^{12,13}. This risk factor is modifiable.
- Age affects physical activity, glucose levels, cholesterol¹⁴. Age is an unmodifiable risk factor.
- Lipodystrophy is an unmodifiable risk factor the continuous loss of adipocytes leads to an accumulation of free fatty acids leading to influencing factors like insulin resistance¹⁵.

There are certain medical conditions associated or correlated to metabolic syndrome:

- Obesity is either a result or a contribution to metabolic syndrome in ways of insulin resistance, increased blood pressure, hypertriglyceridemia and high cholesterol¹⁶.
- In diabetes mellitus type 2, the chance that someone with impaired glucose tolerance or fasting glucose develops diabetes is doubled if metabolic syndrome is diagnosed¹⁷.
- Rheumatic disease¹⁸.
- Chronic obstructive pulmonary disease (COPD), is mainly associated with metabolic syndrome since these patients suffering from COPD are often also physically inactive¹⁹.
- Coronary artery disease increases triglyceride levels, one of the main symptoms of metabolic syndrome²⁰.


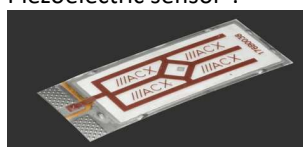
2.1.2 Market research

This project mainly focuses on early detection, therefore this part will not go into detail about current treatments. Moreover, some products are capable of detection. Detection is either indirect (in this case meaning that it measures certain blood values) or direct, meaning that it measures values outside the body, e.g., food intake. Indirect measurement has certain advantages such as easy detection, also more data and research are known to further explore these topics. However, these detection products are more capable to serve as a diagnostic product. Moreover, most current indirect measurement is invasive or minimally invasive. Since this research project is focused on early, non-invasive detection, indirect detecting products will not be discussed.

As for direct detection products, several methods or products and apps are available to early detect food intake. One of these possibilities lies in e-health. In e-health mobile fitness- and health-related apps are tools to help people monitor their food intake by letting people maintain a diary with their eating habits. This diary can be manually updated by selecting the product someone has eaten or by taking a photograph of the product. From this diary, the app gives guidelines and advice concerning certain habits. The apps also can measure physical activity, thereby collecting more data which is used to steer poor eating habits, as well as physical inactivity towards a healthier lifestyle^{21, 22}.

Other possibilities for direct detection products, especially for food intake, rely on the body's response to food intake. The body has eight responses to food intake that can all be measured using sensors. These responses and their measure modalities can be seen in table 2:

Table 2: Body's reflexes to food intake, modalities to measure them and examples of some of these modalities.

Reflex	Modalities	Examples
Swallowing: the reflex and moving of the tongue and throat can be measured	Acoustic transducers Piezoelectric sensors Capacitive sensors ²⁴	Acoustic transducer ^A :  Piezoelectric sensor ^B :  Capacitive sensor ^C :

Chewing: the sound that is produced during chewing strokes, combined with saliva content	In-ear microphones Neck-worn microphones Ear-pad microphones ²⁴ Saliva content chip.bn	<p>Saliva sensor^H:</p>
Thermic: the body's temperature increases at the liver region after food intake	Skin-contacting temperature sensor	<p>Temperature sensor^D:</p>
Cardiac: the heart rate and blood pressure change related to food intake, especially to salt and liquid intake	Electrocardiogram Blood pressure monitor	<p>ECG sensor^E:</p> <p>Blood pressure monitor^F:</p>
Gastric activity: stomach activity and bowel sounds can be measured related to food intake	Skin contacting microphones Electrogastrography (EGG) for electrical activity in the stomach ²⁵	<p>EGG^G:</p>
Intake gestures: arm-movement bringing food to the mouth	Sensor at the upper back Sensor at the lower arm ²³	-
Body composition: the amount of liquids solids changes the electrical conductance of the body	An impedance meter with electrodes, often it is a scale	-
Body weight: changes after food and liquid intake. The amount of food or liquid intake is almost linear to the increase in weight ²³	A scale	-

2.1.3 Stakeholders

Table 3 shows the stakeholders table, which all relates to the office worker that has the potential to develop metabolic syndrome. This table includes the office worker and his or her family, the employer, the medical professional, the health insurance company etc. All these stakeholders have their characteristics, expectations, potentials, or deficiencies and thus implications for the project.

Table 3: The stakeholders in this project, with their characteristics, expectations, potentials, and implications for the project.

Stakeholder	Characteristics	Expectations	Potentials and deficiencies	Implications and conclusions for the project
Office worker	Potential development of metabolic syndrome with consequences	Stay healthy as long as possible	Might not want to wear sensors, change eating habits, share health data	Product cannot be intrusive, advice need to be substantiated, the data is only available after consent of the used
Friends and family	Want optimal health for the office worker	Want the office worker to stay healthy as long as possible	Good support pillar, but their opinions might change if the product drastically alters the office workers personal life	Provide support if the product is useful and is comfortable
Employer	Wants to prevent sickness of office worker because of work absence and sick leave costs	Wants a product that prevents development of the metabolic syndrome and that drastically alters poor eating habits with little costs	Wants to widely use the product in the business. Might also want to get grip of the health data	The product must be relatively cheap or reusable. The product should not reduce office worker productivity. The product's data is only for the office worker or shared with consent
Medical professional	Prevent development of the syndrome with as little complications as possible	Easy use of product with optimal function results	Expert in the medical field, however not in the technical part of the product	The product must reduce the burden on the doctor
Health insurance	Provide optimal care with the lowest costs possible	Low cost of prevention	Supportive if data shows that the product is cost effective	Essential for the acceptance of the product
Society	Wants low costs of healthcare with the highest quality prevention	Permanent solution for the disease or permanent solution to prevent it	Supportive and useful for the test phase	Provide support if the product is useful and is comfortable
Engineer	Creates the design and sells it to the companies or hospitals	Product needs to be functional, easy to manufacture, suitable for many patients, cost-effective most of all: safe	Expert in designing products, but there is a small market, so a lot of research is needed to ensure an acceptable product	Product needs to be cost-effective, innovative, functional, and suitable for every type of office worker.
Industry	Interested if the product is innovative and developed at low costs	Profitable business	Only interested if there is a market for the product that is willing to pay more than what the industry has invested in the product	Knowledge of market and manufacturing potential.

Cause and effect diagrams

Figure 1 shows the cause and effect diagram of the worst-case scenario in which the office worker develops metabolic syndrome and is therefore not able to work leading to sick leave costs. The chain of reactions starts with risk factors such as stress, physical inactivity, age, and genes, as well as poor eating habits, on which this project will focus. These factors lead to obesity, hypertension, hypertriglyceridemia, low HDL-c, and high blood sugar, if an office worker has three or more of these factors, he/she has metabolic syndrome. Because of metabolic syndrome the chances of decreased productivity, long term illness lead to the inability to work, thereby increasing the sick leave costs.

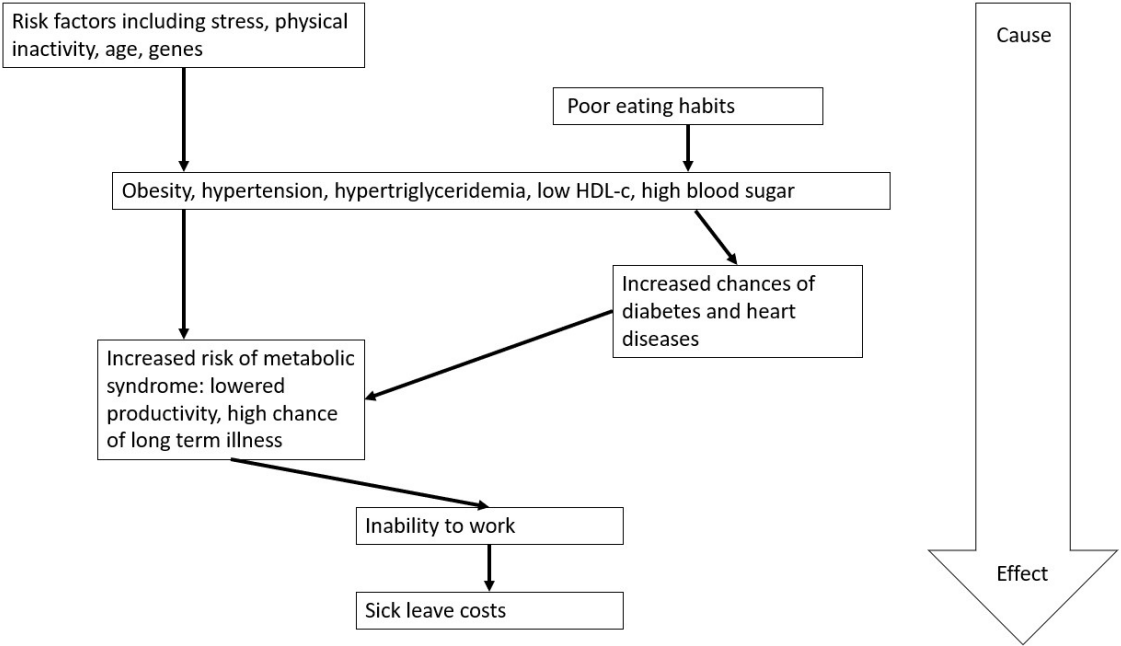


Figure 1 Negative cause-effect diagram

2.2 Goals

Figure 2 shows the positive cause and effect diagram and thereby the focus and goal of this project as well. As the figure shows many risk factors affect the potential development of the metabolic syndrome and its consequences of it. One of these factors is poor eating habits. If this project leads to a product that early detects and corrects poor eating habits, this lowers at least one risk of developing metabolic syndrome, which overall lowers the chance of developing it. The main goal of this project, therefore, is to reduce the chance of developing metabolic syndrome by designing a product that lowers the risk of a metabolic syndrome caused by poor eating habits. This product should increase the quality of life of the office worker, as well as decrease healthcare- and sick leave costs.

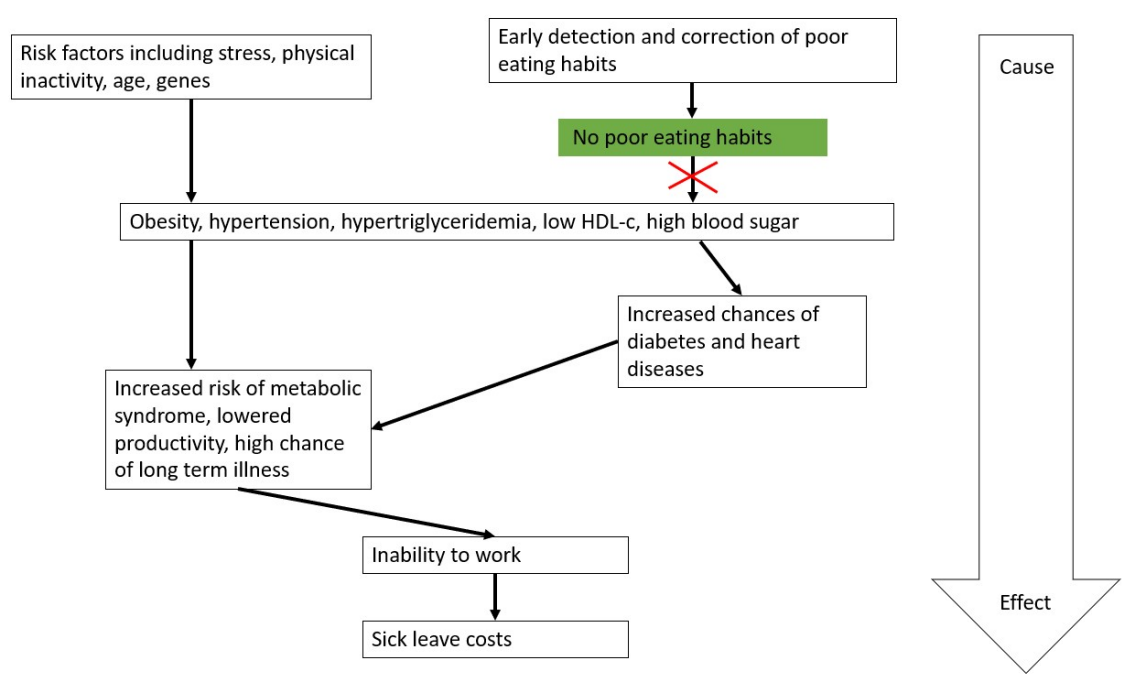


Figure 2 Positive cause-effect diagram

2.3 Design assignment

2.3.1 Strategies

The assignment given by the University of Groningen is to design a product/solution that helps to detect the potential development of metabolic syndrome in office workers. One could suggest that detecting all the risk factors of the disease at once will have a positive effect. However, this is beyond the scope of this graduation project and the current knowledge of the body, which thereby decreases any chance of succeeding. It is for this reason that this project focuses on one risk factor (poor eating habits) for detection.

Since the focus of this project will be to detect poor eating habits, the final product will have to fulfil these criteria:

- The product needs to be realisable within a timeframe of five weeks
- The chance of succeeding within the given timeframe should be realistic
- The product needs to have high acceptance from the stakeholders
- The product needs to be feasible for a third-year BME student according to their level of expertise, within the timeframe.
- The product needs to be relatively cheap to produce.
- The product needs to be non-invasive.

Now that these criteria are known, the final product should have a higher chance of succeeding. If the final product is theoretically placed in the aforementioned Cause-Effect diagram, it should decrease the chance of developing one of the conditions below. The strategy to do this is to combine or design a wearable that can be used by anyone with existing sensor technology to measure and detect poor eating habits.

2.4 Demarcation

2.4.1 Product target group

The project targets office workers that have the potential to develop metabolic syndrome, due to poor lifestyle, in this case, poor eating habits. The product is developed for the DTPA department of the University of Groningen, meaning that the specific target group consists of Dutch office workers.

2.4.2 Product characteristics

There are many types of sensors present for detection. These sensors can either be invasive in-direct or non-invasive direct detectors and are both capable of measuring symptoms related to metabolic syndrome. Given purpose of this product for office workers, it is decided that for the sake of both laws and regulations only non-invasive direct detectors are used for this project. Therefore, sensors that invasively measure food intake via blood glucose, triglycerides and HDL-c are not used in the project. The type of sensors that are used should non-invasively measure food intake, e.g., using the body's responses that are described in the market research section.

2.4.3 Design freedom

The design freedom of this project is limited due to the following reasons:

- First of all, the products should contain a sensor.
- Secondly, the sensor used in the product may not have an invasive application. The sensor and its usage may only be non-invasive.
- Thirdly, the sensor may require basic programming skills, but due to the lack of time, any advanced programming skills are not expected.
- Fourthly, the time frame of this project is five weeks. This means that there is a limit on the amount of research that is necessary to properly develop a product.
- Lastly, the programs used are Excel, Arduino IDE and MATLAB.

2.4.4 Avoidance of side effects

Side effects that may occur in the product may be related to the electronic- or sensory failure. These failures could mean that the readings/data from the sensors are compromised which also compromises the detection of potential development of the metabolic syndrome. Therefore, these side effects should be avoided.

2.5 Requirements and wishes

For this stage of the project the MoSCoW method is used to prioritize the requirements and wishes. The MoSCoW uses four categories to prioritize, namely:

- Must have: these requirements are mandatory for the product to be fulfilled.
- Should have: these requirements are not mandatory since they are not vital. However, they do add significant value to the product.
- Could have: these requirements are additions that only have a small impact if they are left out.
- Will not have: these are requirements that are not necessarily a priority for this timeframe^{26,27}.

2.5.1 Use requirements

- The product must have sensors in the system.
- The product must be able to detect food intake.
- The product must in the form of a wearable, so portable.
- The product must be designed for office workers and thus must be used able to use in the office.
- The product must be ready to be used within five minutes.
- The product must be able to be used in both sitting and standing positions.
- The product should be able to be used both in- and outdoors.

2.5.2 Functional requirements

- The product must not decrease work-productivity of the user.
- The product must weigh less than two kilograms if it is continuously worn during the day.
- The product should not be based on pre-existing, patented products.
- The product should be comfortable to wear or use.
- The product should be easy to use.
- The product should be able to be worn for eight hours straight on.
- The product should be automatic.

2.5.3 Safety requirements

- The product must not harm nor irritate the office worker using it.
- The product must not require any invasive procedures to apply it.
- The product must be non-invasive.
- The product should not cause stress or pressure on the body, that restrains the body from functioning.

2.5.4 Ergonomic and space requirements

- The product should not take up more space than an average smartphone.
- The product should not obstruct any body functions like vision and movement.

2.5.5 Time requirements

- The product should last for at least one year.
- The product should have a functioning sensor within five weeks.

2.5.6 Wishes requirements

- The office worker should be able to use the product without much prior knowledge.

2.6 Function analysis

The main function of the product is to measure food intake and to send this data to an AI sensing product. The schematic overview of this function analysis can be found in figure 3. Furthermore, figure on the bottom of the page explains the meaning of the squares used in the overview.

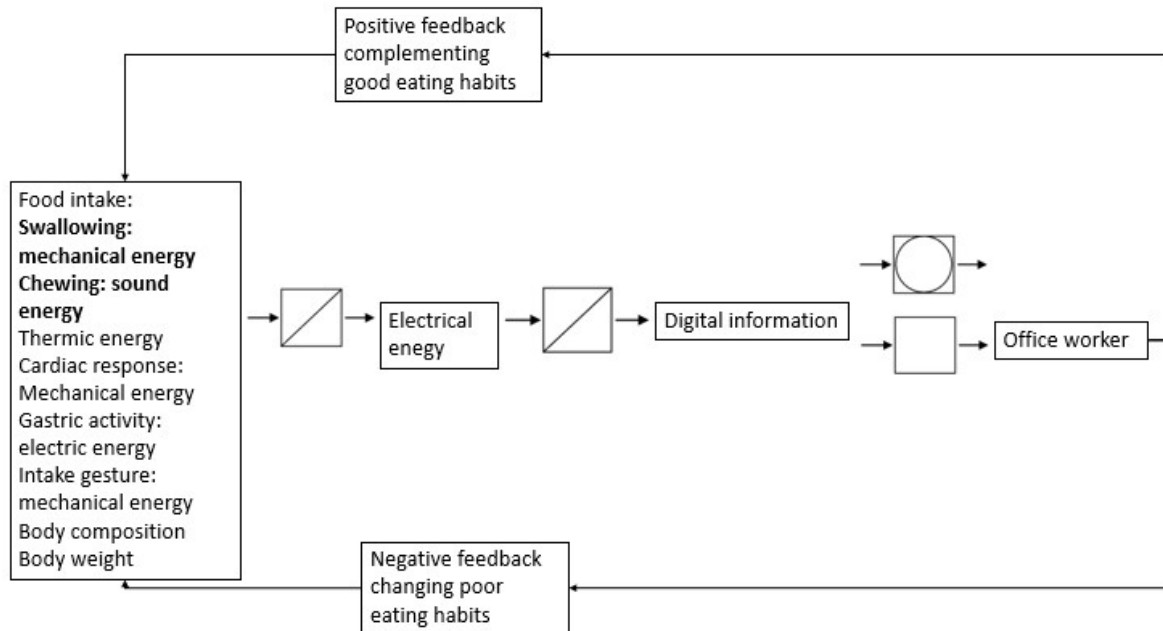


Figure 3 Function analysis of the product.

Function	Verbal meaning	Symbol
Transport	Transport, conduct, move, pump, relay	
Store	Store, keep, hold, memorise	
Connect (and separate)	Add, print, mix, connect, stir (cut, distil, scrape, read, saw, distribute)	
Transform	Flatten, grind, parse, translate, step-down, adapt	
Convert	Drive, power, time, use, control, generate, convert, burn	

Fundamental squares used to describe the function analysis!

3 Synthesis 1

3.1 Brainstorm session




















During the brainstorming session, eight pre-concepts came up. These concepts vaguely describe the following ideas:

1. A utensil like a spoon or a fork that measures certain biomarkers like triglycerides/fats/glucose in the saliva, which could also measure intake gestures.
2. A piezo-electric sensor on a necklace that measures the swallowing reflex. Thereby differentiating between solid and liquid food.
3. A laser (probably blue light) that can detect the biomarkers in vegetables and thereby measure the vegetable intake.
4. A device that contains microphones in the ear channel that measure chewing sounds, which then could be used to differentiate between different types of foods.
5. A chemical device in which the office worker disposes of saliva after food intake that measures the content of the saliva.
6. Microphones at the throat in a necklace that measures and records whether someone is swallowing and what type of food he/she is chewing on.
7. A piezo-electric sensor in a necklace that is sensitive to stretching. Meaning that if the office worker swallows, the change in diameter of the throat is measured, thereby measuring the amount volume and amount of food intake.
8. A portable EGG device that measures the gastric activity related to different food intakes.

3.2 Morphological map

To have a fully functioning device that helps detecting food intake, certain subfunction needs to be included in the concepts. These subfunctions and the possible ways to achieve them are listed in table 4 below.

Table 4: The morphological map of the pre-concepts

Function	Idea 1	Idea 2	Idea 3	Idea 4	Idea 5
Be transportable	Takes the form of a necklace 	Takes the form of an utensil 	Takes the form of a hearing aid 	Takes the form of a Holter cabinet 	Takes the form of a bowl or plate 
Transform energy/chemicals into information	Uses soundwaves to produce information 	Uses mechanical from muscle deformation energy to produce information 	Uses chemicals to produce information 	Uses light to produce information 	Uses the body's electricity to produce information 
Measure whether food intake is happening	Needs the office worker to make the indication 	Uses a body-reflex (sound, muscles moving, nervous system, etc) 	Uses light 		
Measuring what type of food is taken in	Uses the chemicals in saliva 	Uses the biomarkers food 	Uses the volume of food 	Uses the sounds different food produces 	Uses the stomachs' response to food 
Indicate the consequence of food intake	Uses an app to indicate the consequences of the food intake 				

The colours in the table correspond with the following concepts: 1: Utensil sensor, 2: Necklace sensor, 3: Laser detector, 4: Ear-microphones, 5: Saliva spitter, 6: Throat microphone, 7: Stretch sensor, 8: Portable EGG.

3.3 Pre-concepts

3.3.1 Utensil sensor

This concept is based on measuring saliva content. According to research saliva contains biomarkers that can be used for diagnostic uses such as cancer detection, drug monitoring, etc. Saliva also contains biomarkers like uric acid and insulin which play a crucial role in detecting diabetes and metabolic syndrome³⁰. The main idea behind this concept is that an utensil is designed that contains a chemical sensor that can test for these markers, thereby non-invasively measuring biomarkers that could tell something about the type of food the office workers take in every time he or they used the utensil. Technology that could be used for this concept and concept five is micro-electrical-mechanical combined with optical measurement technology³⁶.

3.3.2 Necklace sensor

This concept is based on research about piezoelectric sensors. Research indicates that during swallowing certain muscles and body-structures move in the throat. These movements can be measured with an accuracy of around 87% to determine what the type (liquid or solid food) and the number of swallowing reflexes are²⁹. The principle of this pre-concept is based on this research; instead of sticking a sensor directly to the throat, the same way as with electrodes, a necklace is designed that can be used multiple times. This necklace contains the piezoelectric sensor and measures the same values as the principal sensor design.

3.3.3 Laser detector

This concept is somewhat different from the other concepts in the way that it uses light to detect vegetable intake. According to research people with high-vegetable diets develop a yellow skin colouration due to high carotenoids concentration that is especially noticeable in the palm. This colouration gives useful information; using resonance Raman spectroscopy in which energy levels of an electron in the carotenoids after excitation by blue light can be measured³¹. This leads to the concentration of carotenoids, which directly tells something about the amount of vegetable intake. The concept comprises a wearable the office worker could wear, that contains the laser probe. This laser probe is connected to computer software that can instantly tell whether or not the levels of biomarkers for vegetables in the blood are high enough after every meal or day.

3.3.4 Ear-microphone

According to research, during chewing, meaning the opening and closing of the jaw, sounds are generated. These soundwaves are conducted through the mandible, skull, and body tissue. These sound waves could be used to produce an acoustic profile, which has the potential to classify food and the amount of time taken to eat. This concept is based on the fact that an in-ear microphone could be used to record this acoustic profile, thereby helping to classify the food the office worker takes in and the amount of time the office worker spent chewing²⁸.

3.3.5 Saliva spitter

This concept has much overlap with the utensil concept, except this concept is a plate or a bowl in which the office worker spits after he/she has eaten. The bowl then measures the saliva content for specific markers. These markers, like insulin and uric acid, then give feedback to the office worker with regards to his/her diet³⁰.

3.3.6 Throat microphone

The reflex of chewing and swallowing happens throughout the day and increases in frequency during food intake. During chewing, the soundwaves are produced that can be measured from the throat. After chewing on food, the food is converted into a bolus after which tongue movements initiate a reflex of throat muscles that propel the bolus through the throat into the oesophagus. This reflex can be measured using a throat microphone to measure chewing and swallowing sounds. This concept is based on these two types of sensors combined, to measure the amount of swallowed food via a necklace²⁸.

3.3.7 Stretch sensor

This concept is based on two responses; The first one is the fact that the oesophagus' diameter expands after a certain amount of bolus passes through and the second one is the response of muscles to the swallowing reflex. Both these responses could be used to measure how much the diameter of the neck is changing during swallowing, which then could be used to indicate the amount of food that passed through. These concepts consist of a necklace with a piezo-electric sensor in it that measures whether the diameter of the neck is increasing and how much the diameter is increasing. Although the sensor is the same as in pre-concept two the necklace sensor, the response that they measure is different. While pre-concept two measures the movement of muscles, this sensor is simpler; it only measures the diameter change.

3.3.8 Portable EGG

In electrogastrography (EGG) the gastric myoelectrical activity is measured, which can be used to measure the stomach response to different types of food. Research has already concluded that there is a relationship between EGG response and gastric sounds related to the type of food someone ingests. The concepts would consist of a Holter case with electrodes that measure the EGG response, combined with electrodes containing microphones to measure the response of the stomach²⁸.

3.4 Concept selection

3.4.1 Concept selection table

In the subchapter, the pre-concepts are scored from one to ten. Concepts that score a ten on a requirement or wish are extremely likely to fulfil the requirement, while concepts that score a one will most likely not. Also weighing factors from one to five are considered to ensure that the requirements that matter the most also weigh the most in the selection, this weighing factors is subjective because it is purely based on the insight of the designer, not on literature. Five means that a requirement or wish is important for the concept, one means that a requirement/wish is not crucial. The table with the results can be found in table 5.

Table 5: The pre-concepts and their score

Requirements	Weighting factor	C1	C2	C3	C4	C5	C6	C7	C8
Use									
The product must have sensors in the system	5	35	50	50	50	35	50	50	50
The product must be able to detect food intake and discriminate between at least two types of food	4	28	40	40	28	28	28	24	16
The product must in the form of a wearable, so portable	5	45	45	45	45	30	45	45	30
The product must be designed for office workers and thus must be used able to use in the office	5	50	50	50	35	35	50	50	30
The product must be ready to be used within five minutes	3	21	24	27	18	21	24	24	18
The product must be able to be used in both sitting and standing positions	3	30	30	30	30	30	30	30	30
The product should be able to be used both in- and outdoors	2	20	20	16	16	20	20	20	20
Functional									
The product must not decrease work-productivity of the user	5	30	35	45	30	30	35	30	35
The product must weigh less than two kilograms if it is continuously worn during the day	5	40	45	45	45	30	45	45	30
The product should not be based on pre-existing, patented products	4	24	32	32	36	24	36	32	40
The product should be comfortable to wear or use	4	28	24	36	32	24	24	24	24
The product should be easy to use	4	28	28	32	24	28	28	24	20
The product should be able to be worn for eight hours straight on	3	9	21	9	9	9	21	15	21
The product should be automatic	2	10	16	18	10	10	12	12	10
Safety									
The product must not harm nor irritate the office worker using it	5	45	40	45	30	45	40	30	30
The product must not require any invasive procedures to apply it	5	45	50	50	50	50	50	50	45
The product must be non-invasive	5	45	50	50	50	45	50	50	45
The product should not cause stress or pressure on the body	4	36	32	40	28	40	32	32	32
Ergonomic and space									
The product should not take up more space than an average smartphone	3	27	27	27	27	18	27	27	18
The product should not obstruct any body functions like vision and movement	4	36	32	40	20	36	32	32	32
Time									
The product should last for at least one year	2	8	12	18	16	16	16	8	12
The product should have a functioning sensor within five weeks	4	20	28	20	20	20	32	20	16
Wishes									
The office worker should be able to use the product without much prior knowledge	2	12	16	20	12	12	12	10	10
Total	870	672	747	785	661	636	739	684	601

3.4.2 Final concepts

The pre-concept selection showed that a maximum of 870 points could be scored, of these points concept number three, laser detection, had the highest score. The second- and third-best concepts are the necklace sensor and the microphone. Since these concepts have striking similarities, these concepts are merged into one new concept. Both the laser and the necklace are further detailed in synthesis 2.

4 Synthesis 2

4.1 Detailing

4.1.1 Laser concept

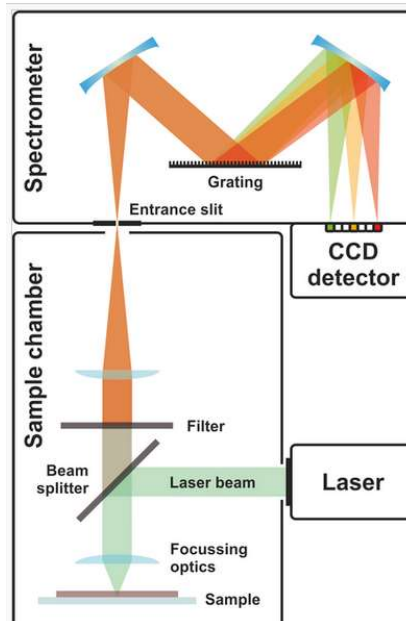
General details and materials

As described above, this concept uses resonance Raman spectroscopy (RRS) to excite electrons in carotenoids to measure the number of vegetables consumed over a certain period. The exact mechanism is as follows; the electrons in carotenoids are excited to a higher vibrational mode by absorbing the photons of the blue light laser. After the photon is absorbed, it is re-emitted with lower energy. This difference in energy is recorded as the difference in wavenumber. The wavenumber says something about the quantity of the chemical compound. The devices needed for RRS are:

- A laser is a source of photons. Nowadays research is also investigating whether other options could be used instead of a laser, since lasers may only be used in certain medical facilities due to the destructive nature of the beam if it is used more often. One of these options is a light-emitting diode (LED). Conclusions so far seem to indicate that although LEDs offer higher stability and can be used in a wider range of environmental conditions at lower costs, LEDs do not couple well into optical fibres and match poorly with grating spectrometers, resulting in data is one to two magnitudes weaker in signal than a conventional laser source³⁵.
- A detector is most often a spectrometer that collects the emitted light.
- In RRS charged coupled devices are often used (CCD) is used as detector arrays, which then convert the emitted light into data which can be sent to the computer.
- The computer with an algorithm calculates the date with the corresponding number of carotenoids in the blood³⁴. An overview of this process can be seen in the figure below.

Sketching

The overview of the basic process and systems used for RRS can be seen in the figure below. The figure shows that a laser sends a beam, this beam is split and focused onto the tissue sample. The tissue sample sends energy with a certain wavelength back, this energy is captured using the spectrometer and focused upon a CCD detector which turns the energy into data.



Basic set up for resonance Raman spectroscopyⁱ

4.1.2 Necklace concept

General details

This concept is designed in such a way that it measures two reactions. The first reaction is swallowing, during this event muscular contractions result in motion of the skin. If a sensor is placed directly on the skin, the sensor is pushed away from the body towards the outside. There are several types of sensors that are capable of measuring physical strain and convert it into a voltage output. However, for this project a piezoelectric sensor is used since it is known to convert this type of physical strain into an output^{28,32}. The second reaction is the sound that is produced during swallowing. Research has found that laryngeal microphones, stethoscopes, or accelerometers could be used for recording swallowing noises. From these sensors, accelerometers came up to be the most optimal sensors for recording at any spot on the throat. However, research also indicated that if two microphones are placed on a specific spot, these will be more optimal than accelerometers³³.

Positioning of the device

The positioning of the overall necklace is dependent on both sensors and their optimal functional position. With regards to the piezo-electric sensor, literature has suggested that the device can best be placed in certain locations on the throat, this can be seen in figure 4 in which the red dot is sensor placement with less than 50% accuracy, the yellow dots represent the sensor placement with accuracy around 70%, the green dots present sensor placement with accuracy over 80%²⁹.

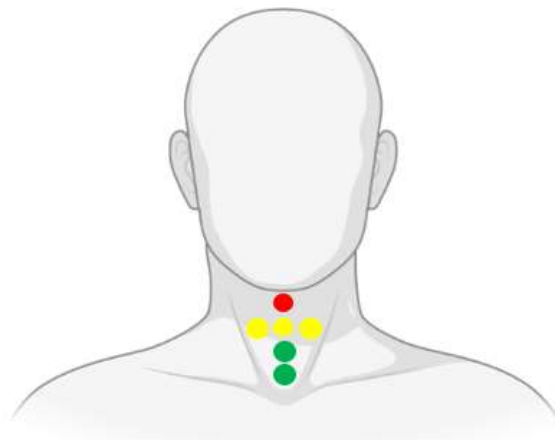


Figure 4 Piezo-electric sensor placement related to the accuracy; red 50% accurate, green is 80% accurate.

As for the microphones, since both chewing and swallowing reflexes need to be recorded, only microphones and not accelerometers are used. Research regarding the positioning of the microphones indicates that two positions have the highest accuracy, these locations can be found in figure 5 below.

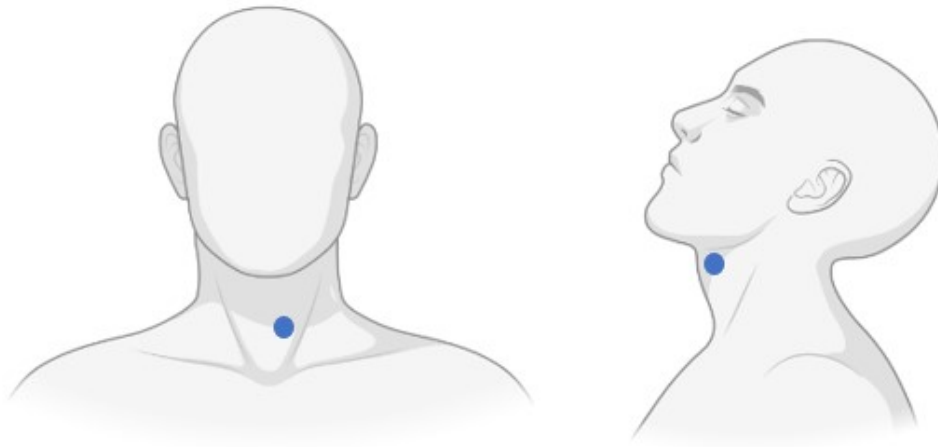


Figure 5 Positions of the microphones for the best recordings

Sketching

A corresponding schematic overview of the combined two systems would be visualized according to figure 6 and figure 7. Figure 15 shows the necklace with two piezoelectric sensors and microphones attached, for the sketch two sensors and microphones are used to show the options the team has when combining the systems. Figure 16 shows a schematic overview of the systems. In this scheme, the microphones are used to record swallowing and chewing sounds and the piezoelectric sensors are used to measure the mechanical response of the body during swallowing.

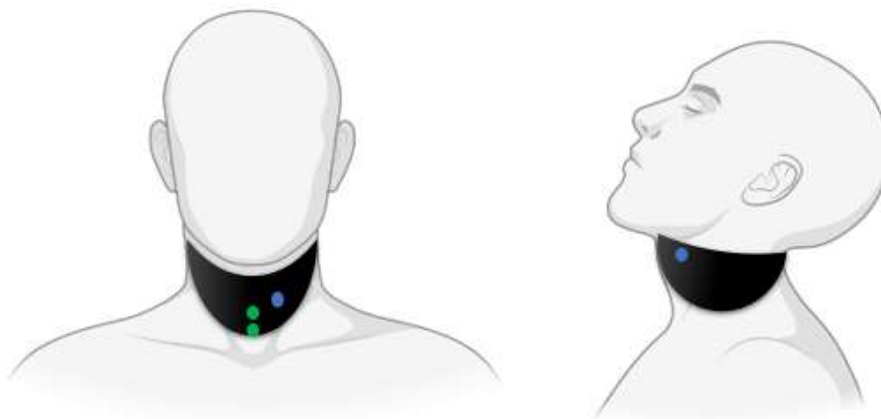


Figure 6 Overview of the positions of the piezo-electric sensors and microphones on the necklace

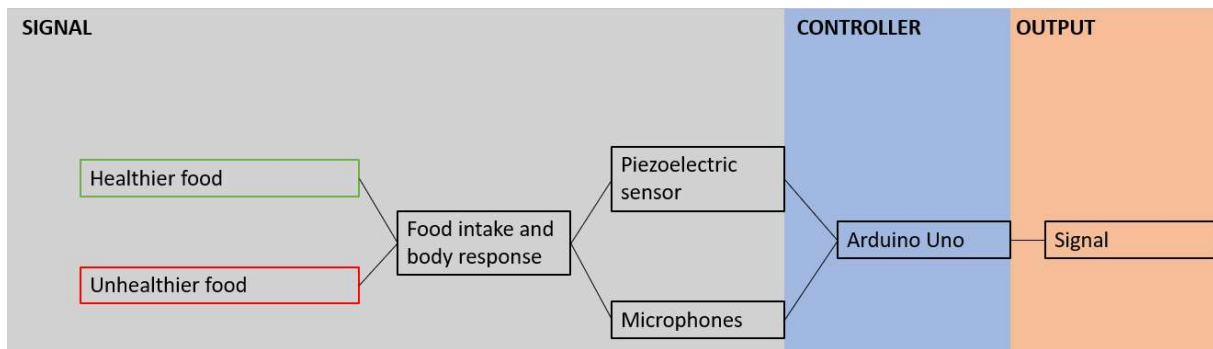


Figure 7 Schematic overview of the connection of the prototype sensors and microphones

Materials

The materials for this concept are largely theoretical, meaning that the materials used for cables, the necklace itself and others are not known but are also not the primary focus of this project. This project focuses on functioning sensors and microphones.

Many different piezoelectric sensors could be used since piezoelectric sensors come in different sizes, shapes, and functions. To select a piezoelectric sensor the main requirements, have to do with comfort and accuracy. In terms of comfort, a sensor is chosen that is thin and has a small diameter. In terms of accuracy, research similar to this project used a DT0-028 K piezoelectric sensor that is 28 micrometres thick and approximately 1 centimetre long³². The sensor used for this project will have similar dimensions.

As for the microphones MAX9814 amplifier microphones are used to record swallowing and chewing sounds.

For the software used to program both the microphone and the piezoelectric sensor, Arduino IDE is used as a controller. An overview of this system can also be found in figure 7.

4.2 Final concept selection

The normal procedure for concept selection would be to score these further detailed pre-concepts again against the requirements and wishes. In this project, it has been decided to not do this and to further detail the necklace concept. The reasons behind this are as followed; firstly, the data that is required from the laser gives accurate information, however, a timespan of 28 weeks is necessary to conclude whether or not the office worker is eating enough vegetables. Since this project is due within 10 weeks this is not achievable. Secondly, a laser is necessary to make this project work, however, lasers and the measuring equipment are not available within the given timeframe. The laser itself is also a problem, since measuring the carotenoids in the skin and thus the colour of the skin is dependent on the many different factors including ethnicity, environmental light, diet, amount of sun the office worker gets and many more factors. This project of one man simply does not have the expertise nor the time to account for all these factors. Finally, according to research, the computer needs a complex algorithm to convert data into quantities of carotenoids, this algorithm cannot be found/bought online which would delay the project. Since the expertise is not present to develop this algorithm within the time frame, this would be problematic. All these factors boil down to the following conclusion, concluding that since both concepts score high and have great potential, it is for best to further work on the concept that is the most feasible, the necklace concept.

5 Synthesis 3

5.1 Background

In this stage of the project, the final concept is translated into a functioning prototype to investigate whether or not a microphone combined with a piezoelectric sensor can discriminate between unhealthy and healthy food. However, discriminating between these food types is difficult, because healthy and unhealthy can be relative terms. An example: bananas are healthy food, they contain substances like tryptophan, leucocyanidin, potassium and many more that are known for their positive effect on mood, heartburn, heart health etc. So, eating bananas is healthy someone might suggest, however, eating ten bananas a day is not healthy since they are high caloric and also contain loads of carbohydrates³⁷. On the other hand, cookies are often considered unhealthy since they often contain high amounts of sugar, while they can also contain good fibres that help with digestion. This means that eating habits, especially poor eating habits, are not just related to the kind of food, they are also related to the frequency and amount of food taken in. This is also the starting point for synthesis three. In this testing phase, the goal is to check whether frequency (data from the piezoelectric sensor) and sound (data from the microphone) combined can help determine the eating habit. Thereby testing if the piezoelectric sensor can give conclusive data with regards to the frequency someone eats and testing whether the microphone can help discriminate between unhealthy and healthy types of food. For this phase four types of food were used to experiment with: An apple, a banana, a waffle cake, and a cookie. The apple (healthier) and the cookie (unhealthier) were chosen as opposites from each other in terms of 'health' with approximately the same texture; hard. The same is for the banana and the cake, the banana is healthier than the cake and in texture, they are approximately the same; soft.

5.2 Materials and methods

5.2.1 Hardware

As described above, in synthesis three the concept containing both the piezoelectric sensor as well as the microphone is further detailed and assessed. The set-up, thus, contained both types of hardware that are separately attached to an elastic chord that is worn around the neck. The hardware of the microphone is directly connected to the analogue side of the motherboard; the Arduino UNO R3. The piezoelectric hardware is not directly connected to the motherboard, it runs via a board that can adjust the sensitivity of the sensor. For this project, after some trial and error, a resistance of 0.714k ohm was used for the sensor. The sensitivity board is connected to the motherboard, which is connected to a laptop. The laptop has the tasks to save and process the data using the software. The hardware set-up can be seen in figure 8, 9 and 10.

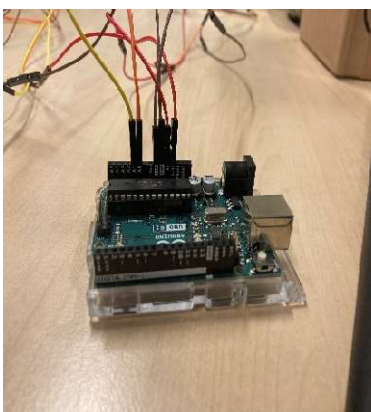


Figure 10 The motherboard: Arduino R3

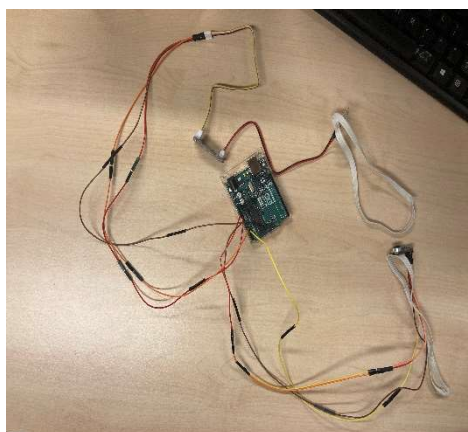


Figure 9 The hardware set-up



Figure 8 Set-up worn by tester

5.2.2 Software and programming

This project used three types of software to program the hardware, collect data, save data and to post-process the data. Arduino IDE, Excel, and MATLAB were used for these purposes and are further explained below.

Arduino IDE

Arduino IDE is a software program that can interact with the Arduino UNO R3 board and was therefore used to program the sensor and the microphone. The programming ensured that the sensitivity of the piezoelectric sensor was adequately and that the data from the sensors is collected. The programming of the Arduino IDE consisted of a series of integers, floats, a void set-up, and a void loop. The program starts with a series of integers, which have two functions; they tell which piece of hardware is connected to which analogue pin and they give the variable to store the value coming from the sensor. The Float functions are used to approximate the analogue values. So, the integers and floats are values that the software needs to orient and start functioning. After the integers and floats, a void set-up is the start of the program and tells the hardware to initialize communications at a certain sample frequency. In this case, a BAUD rate of 9600 is set as the frequency at which the communication is clocked. The void loop, as the name says it, is a loop of commands that continuously repeats itself until said otherwise. The commands in the void loop tell the hardware to do the following; it starts with counting and telling how often the hardware should measure (in this case once every millisecond), therefore the sampling frequency is 1 KHz. Then the void loop tells the system to record the data of the piezo electric sensor, convert it into voltages and send it back. After that, the void loop tells the system to record the data sent from the microphone, convert the data to voltages and send it back. The void loop ends with printing all values it has received and converted to voltages. The code of Arduino IDE can be found in appendix 1.

Excel; saving data

The next step in the process gathering and gathering data is done via Excel. While the code used in Arduino IDE is used to tell the hardware what type of data needs to be gathered and with which frequency the data needs to be gathered, Excel's main function is to organize and save the data. So, Arduino IDE gives data, this data is sent to Excel via a data streamer function. Excel then labels the data in a table; the table is saved as a CSV file.

MATLAB

The main function of MATLAB is to process the data. The data saved by Excel is imported into MATLAB and should have three columns, namely; one for time, one for piezoelectric voltage and one for microphone voltages. In MATLAB, a code is written that does the following:

- It plots the data separately and combined, with time on the x-axis and voltages on the y-axis.
- It calculates the average frequency of the piezo electric voltages per type of food.
- It calculates the mean voltage of the microphone per type of food and food sample.

The code of MATLAB can be found in appendix 2. Here the ten lines of code per food sample are used to plot the data, while the rest of the code is used to calculate averages.

Excel; processing data

The data from the microphone that MATLAB has processed is used in Excel again to alter the process of the data to run statistical analysis. The data from the microphone, like with all soundwaves moves up and down a certain base value. Since this is the case, there is no difference in the means between parts with extremely high amplitudes and parts with smaller amplitudes; the peaks are mirrored in the x-axis, making it impossible to use statistical analysis. Excel solves this problem in the following: Excel contains all data in tables, and the mean (and thus baseline) is subtracted from all values in the table. This gives positive values (peaks above the base line) and negative values (peaks below the base line).

The negative values are filtered, leaving only the positive values in the table. These positive values are then used to calculate differences between the trials of the same food type and the different food types. An example of this process can be found in figure 11. No code was written in Excel since Excel already contains automated data analysis, which includes statistical analysis. T-tests with unequal variances and ANOVA were used as statistical analysis.

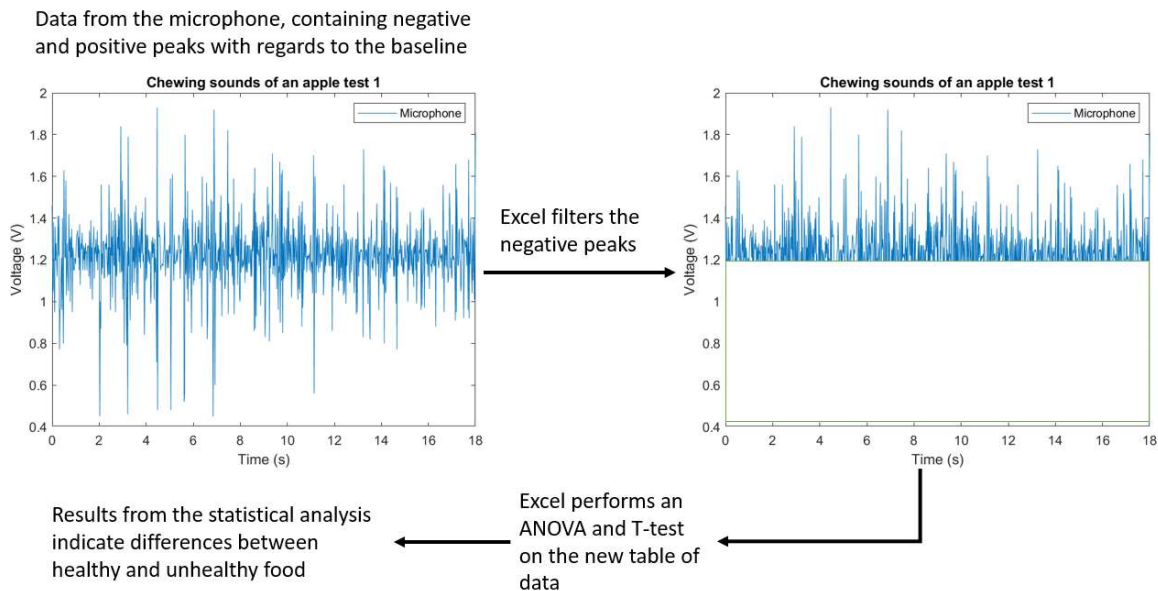


Figure 11 The post-processing of microphone data used in Excel to do a statistical analysis.

5.2.3 Measuring method

After programming the hard- and software, the next phase of the project was to evaluate the device and gather data. To assess the device, four different types of food were selected: apples, bananas, cookies, and waffle cakes. There were two types of procedures since data was recorded for chewing and swallowing. The procedure for gathering chewing data is as followed:

1. Start recording data
2. Bite from one type of food, e.g., an apple
3. Chewing on the apple until the swallowing reflex came
4. Stop recording data.
5. Redo this procedure three times, then switch to the next food type.

The procedure for gathering swallowing data is as followed:

1. Take a bit from the food type, e.g., the cake
2. Chew on the food until the swallowing reflex comes
3. Start recording data
4. Chew one more time
5. Swallow
6. Stop recording data
7. Redo this procedure three times, then switch to the next food type.

An important precaution during recording is to not connect the laptop to any power source. If something goes wrong with the power, this prevents the test person to get 230Volts on their body. After the data is recorded, the programmed software was used to analyse the data, an overview of the entire process can be found in figure 12.

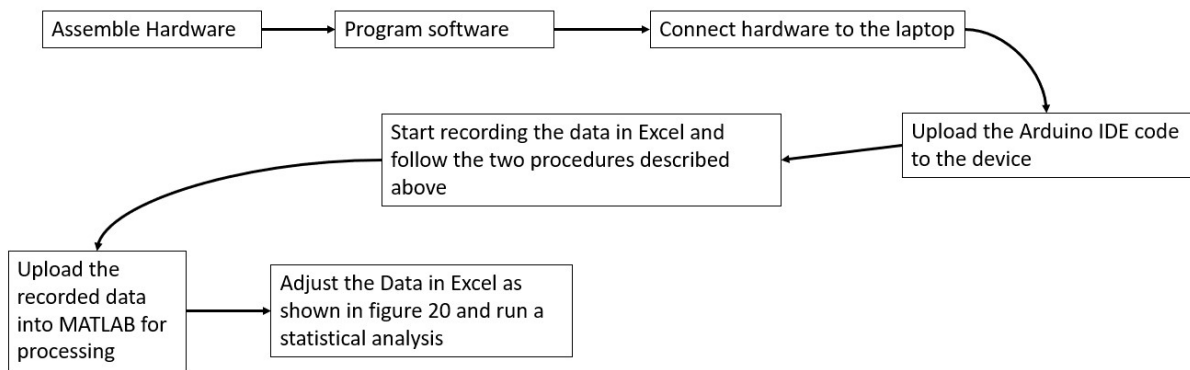


Figure 12 The overall method of testing and gathering data.

5.3 Results

The eventual experiment consisted of the four food types. Of these four food types three trials per food type were done, these trials were compared and statistically tested for divergence in variation. Furthermore, the frequencies of the piezoelectric data were calculated, as well as that of the microphone. The means can be found in appendix 4 and appendix 5. The microphone data comprises more elaborate results that include a comparison of the trials, a comparison of healthy and unhealthy food types, a comparison of all food types and finally the comparison between apples and cookies and between bananas and waffle cakes. For all statistical analyses, a normal distribution was assumed. The tables with all statistical analysis can be found in appendix 6.

5.3.1 Piezo electric results

The data from the piezoelectric sensor turned out to be binary, an example of this data can be seen in figure 13, all the plots of the piezo electric data, as well as the microphone and the combination of both, can be found in the appendix 3. Analysis of the data comprised of statistics and calculating the means of all frequencies per trial and comparing these means.

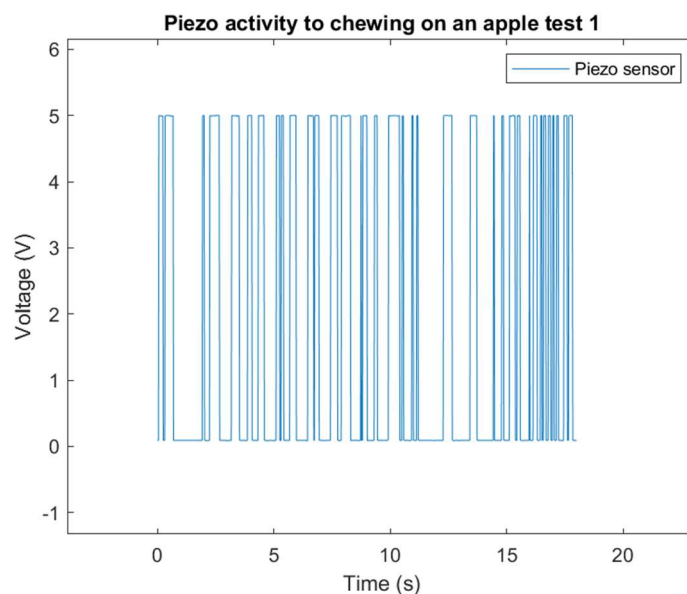


Figure 13 An example of data returned from the piezoelectric sensor

ANOVA between trials of the same food type

As described above, three trials were done per food type. Using a single factor ANOVA, the three trials were compared to check for diverging variations. Table 6 shows the result from the ANOVA test, in which the null hypothesis states that the means are the same for all food types and that the sample means differ purely because of random sampling error. For the research, it is desired that the null hypothesis is false, which can be confirmed if the P value is smaller than 0.05 or if the F value exceeds the F-critical value . The elaborate ANOVA results can be found in appendix 6.

Table 6: Summary of single-factor ANOVA tests between trials of food.

Food type	Result during chewing	Result during swallowing	Trials that caused deviation:
Apple	F > F-critical	F < F-critical	The first trial of chewing deviates from the other trials
Banana	F > F-critical	F > F-critical	The first group during chewing deviates from the other trials. During swallowing, all the groups deviate from one another, the last group with the most data points in therefore used
Waffle Cake	F < F-critical	F < F-critical	The sample means are approximately the same for the trials.
Cookie	F > F-critical	F > F-critical	The first trial during chewing deviates from the other trials. During swallowing the third trial deviates from the trials

Comparison between all food types

Table 7 below shows the result from the ANOVA test of the piezoelectric data taken from all food types during swallowing and chewing. The table shows that the relation between F-values and F-critical values ranges between 67 for chewing and 153 for swallowing, and there indicates that the null hypothesis is rejected. Meaning that there the piezoelectric data shows that there are differences between the types of food during chewing and swallowing that is not caused by random sampling error.

Table 7: ANOVA results between all food types during chewing and swallowing

Body response	F-values vs F-critical
Chewing	174 > 2.61
swallowing	400 > 2.61

T-tests

The T-tests were used to indicate whether or not there are differences between the healthier and between unhealthy food types. The T-tests were also used to test whether there could be distinguished between the 'hard' healthy and 'hard' unhealthy food (the apple and cookie) and between the 'soft' healthy and 'soft' unhealthy food (the banana and the waffle cake). Table 8 shows the results from all T-tests, if the P-value is below 0.05 it means that there is a difference between the comparison groups. If the P-value is larger than 0.05, it means that the null hypothesis is true and that there is no difference between the comparison groups. From the t-tests, it can be seen that during chewing the piezoelectric sensor cannot discriminate between apple and cookies and during swallowing the piezoelectric sensor cannot discriminate between waffle cake and cookies.

Table 8: Results from the T-test assuming equal variances

Comparison groups	Chewing (P two-tail value)	Swallowing (P two-tail value)
Apples and bananas	P<0.05	P<0.05
Cookies and waffles	P<0.05	P>0.05
Apples and cookies	P>0.05	P<0.05
Bananas and waffles cake	P<0.05	P<0.05

Comparison of the means

Figure 14 shows the result from the mean calculations. Figure 14 shows that during chewing, the piezo electric sensor registers the least amount of movement of the throat with apples, which is followed by cookies, bananas, and waffle cake. For chewing, the difference in frequency lies around 0.8 Hertz, while for bananas and waffle cake the difference lies around 1.7 Hertz.

Figure 14 also shows the differences in frequencies during swallowing. Again, swallowing an apple shows the least amount of muscle movement in the throat, which is followed by bananas, cookies, and cake. For swallowing the difference in frequency between apples and cookies lies around 3.4 Hertz, while for bananas and cake the difference lies around 12.8 Hertz.

The figure also shows the groups that are compared and are different according to the statistical analysis in from table 8, these comparison groups are marked with:

- '*' between apples and bananas
- '-' between apples and cookies
- '+' between waffle cake and cookies
- '^' between bananas and waffle cake

Overall, it can be seen that during chewing the difference in frequencies between cookies and apples, bananas and waffle cakes is relatively small. During swallowing the differences between apples and bananas compared to cookies and waffles cakes are enlarged.

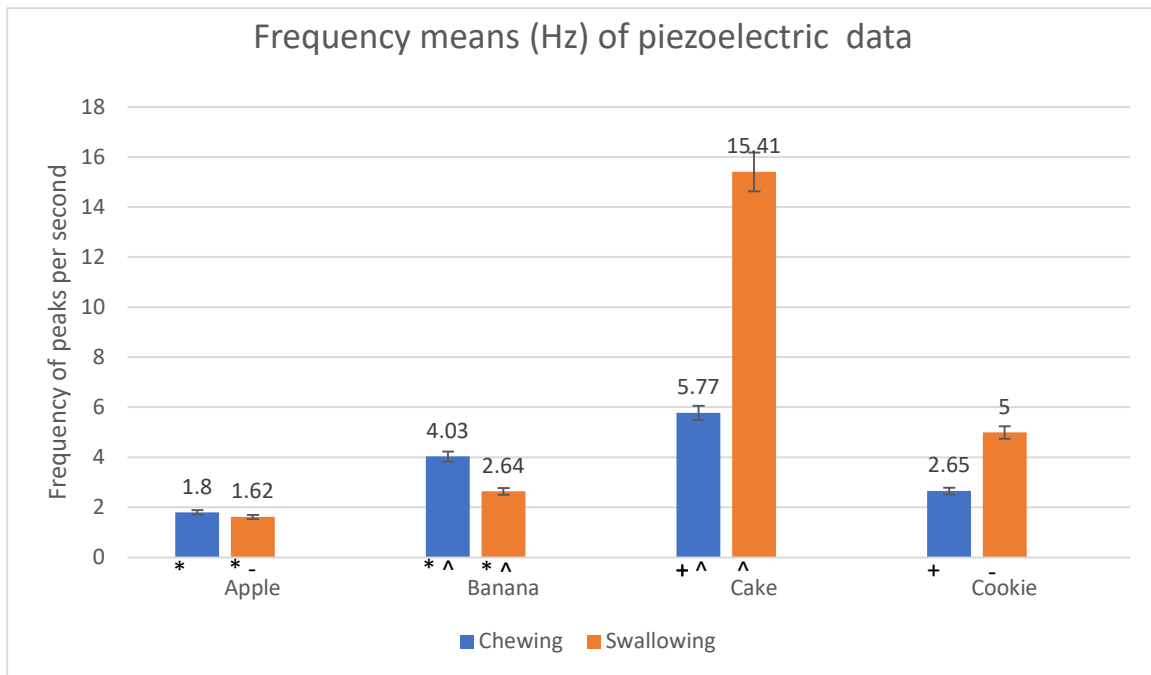


Figure 14 Comparison of the frequencies during chewing and swallowing four food types

5.3.2 Microphone results

ANOVA between trials of the same food type

Table 9 gives a summary of the appendix, the ANOVA tables can be found in appendix 6. In the ANOVA tests, the null hypothesis states that the means are the same for all food types and that the sample means differ because of random sampling error. In this case it is desired that the null hypothesis is rejected. This is confirmed if the P value is smaller than 0.05 or if the F value is larger than the F-critical value. The elaborate ANOVA results can be found in appendix 6.

Table 9: Summary of single-factor ANOVA tests between trials of food.

Food type	Result during chewing	Result during swallowing	Trials that caused deviation:
Apple	F < F-critical	F < F-critical	-
Banana	F < F-critical	F > F-critical	The third trial during swallowing deviates from the first and second trial
Waffle Cake	F < F-critical	F < F-critical	-
Cookie	F > F-critical	F < F-critical	The first trial during chewing deviates from the second and third

Comparison between all food types

Firstly, the ANOVA for all food types of the null hypothesis stated that there is no difference in frequency between the means of the different food types ($F < F\text{-critical}$) and that the sample means only differ due to random sampling error. Table 10 below shows the results from the ANOVA; all F-values are larger than the F-critical value, meaning that the null hypothesis is rejected and that there are differences during chewing and swallowing between the different types of food. Appendix 6 shows all the ANOVA results.

Table 10: ANOVA results between all food types during chewing and swallowing

Body response	F-values vs F-critical
Chewing	64.7 > 2.61
swallowing	32.7 > 2.63

Secondly, box plots of both body responses are shown in Figures 15 and 16. The boxplot in figure 24 shows that during chewing the characteristic sound that is produced by more unhealthy food (cookies and waffle cake) strongly matches, while for the healthier food (apples and bananas) the characteristic sound differs more. The whisker of the positive quartile of the healthier food varies more than for the unhealthier food and all negative quartiles. The average of the food types shows the following: the averages of bananas and apples lie near each other and are higher than that of waffle cake and cookies (who also lie near each other).

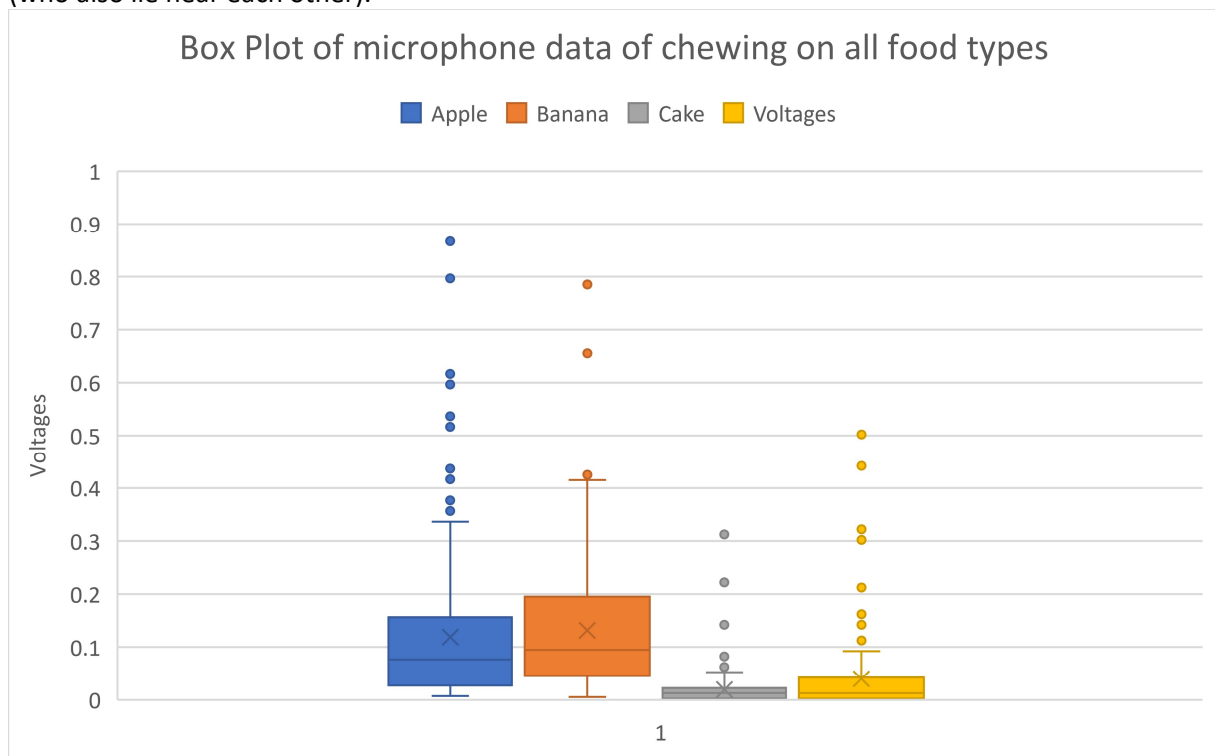


Figure 15 Boxplot, comparing all microphone data of chewing

During swallowing the characteristic sound produced by cookies and waffle cake appears to match strongly, meaning that there is not much variation when swallowing this type of food. On the other hand, for the apples and bananas, the characteristic sound does not match as strongly, thereby stating that there is more variation among these food types. As for the whiskers, the whiskers in the positive quartile of apples and bananas vary more than that of the waffle cake and cookies. Of all food types the boxplots shows that the average apples and bananas lie closer together than that of apples and bananas compared to the waffle cake and cookies. The average of the waffle cake and cookies lie near each other and is lower than that of the apples and bananas.

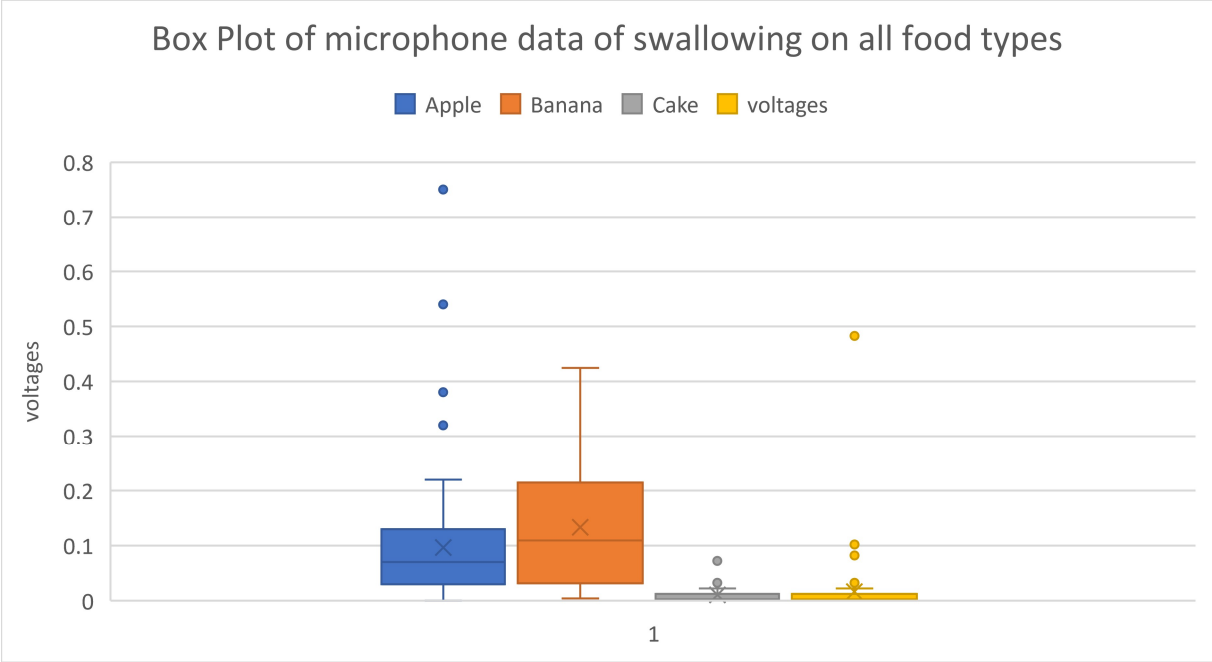


Figure 16 Boxplot, comparing all microphone data of swallowing

T-tests

After a comparison between all food types was done, several T-tests were done to investigate whether or not there are differences between more healthy and more unhealthy food and between 'hard/crispier' food and softer food. Table 11 shows the results from the T-tests, in which P-values larger than 0.05 indicate that there is no difference, while a P-value smaller than 0.05 does indicate a difference between the groups. The table indicates that during chewing the software programmes cannot discriminate between apples and bananas, but they can discriminate between waffle cakes and cookies, between apples and cookies and between bananas and waffle cake. The table shows that during swallowing the algorithm cannot discriminate between apples and bananas and between cookies and waffles cake. However, it can discriminate between apples and cookies and between bananas and waffle cake. Appendix 6 contains the more elaborate statistical results.

Table 11: Results from the T-test assuming equal variances

Comparison groups	Chewing (P two-tail value)	Swallowing (P two-tail value)
Apples and bananas	0.37 (P>0.05)	0.14 (P>0.05)
Cookies and waffles	7.1E-05 (P<0.05)	0.33 (P>0.05)
Apples and cookies	5.6E-13 (P<0.05)	9.7E-09 (P<0.05)
Bananas and waffles cake	5E0-30 (P<0.05)	6.6E-15 (P<0.05)

5.4 Discussion of the test-results

The purpose of synthesis three in this project was to investigate whether or not a microphone combined with a piezoelectric sensor can discriminate between healthier and unhealthier food. To do this, the starting point for testing was to check whether the frequency from the piezoelectric data and sound from the microphone combined can tell something about the amount and the type of food. In this discussion, the results of both pieces of hardware are discussed.

The first result, which is from the piezoelectric sensor, indicated that there are differences between the food types. The t-tests specified these differences, showing that during chewing it can differentiate between apple and bananas, between cookies and waffle cake and between bananas and waffle cake. The piezoelectric sensor can also differentiate between apples and bananas, between apples and cookies and between bananas and waffle cake during swallowing. An explanation between the different responses to the different food types during chewing could have to do with the structure of the food; the apple has a hard structure and break more easily than the banana. The banana has a soft structure that does not break easily; it tears. This translates back to the amount of effort it takes to turn the food into a bolus: it takes less effort to turn the hard food (such as the apple and the cookie) into a bolus since every time someone chews it breaks into smaller pieces. On the other side, it takes more effort to chew soft food into a bolus that can be swallowed since it does not break into smaller pieces. Therefore the muscles in the jaw and throat would have to work harder to turn soft food into a bolus, which should mean that the frequency of soft food is higher during chewing than that of hard food. Figure 14 confirms this theory by highlighting the differences in frequency²⁴. A theory that might explain the differences during swallowing could be the composition of the food types, especially the amount of water that they contain. The amount of water in apples roughly lies around 80-89%, that of bananas between 70-79% and what of cookies and waffle cake lies around 1-9%³⁸. If the food contains more water, it is more easily turned into a soft bolus, which takes less effort for the muscles surrounding the throat to swallow the bolus. For food that contains little amounts of water, more saliva is needed to turn the food into a soft bolus that can be swallowed. Because more saliva is added, if the same amount is taken in a bite, the amount of bolus is larger. Because the amount of bolus more, it takes more effort for the throat muscles to swallow it, hence the increased frequency. Figure 14 also shows this: the frequency for apples and bananas during swallowing is smaller than for cookies and waffle cake. The sensor could not discriminate between cookies and waffle cake during swallowing, which might have to do with the fact that these types of food contain approximately the same amount of water and thus need the same amount of saliva before swallowing.

The second result, from the microphone, also indicates that there are differences between the types of food. This is also confirmed by the boxplots; there are differences in the mean between the food, but there is also more variation of chewing and swallowing sounds in healthy food. An explanation of this larger variety of sounds in healthy food might be because apples and bananas come in different states. This means that apples and bananas are never the same in terms of species, and ripeness, which both translate into the structure of the fruit. The T-tests indicate that in terms of sound that is produced during chewing and swallowing, it is possible to distinguish between apples and cookies and between bananas and waffle cake. However, it is not possible to distinguish between apples and bananas during chewing and swallowing and between cookies and waffle cake during swallowing. Again, an explanation of these results might be due to the amount of water that the foods contain; according to research the amount of water plays a crucial role in acoustic sounds produced during chewing³⁹. This means that food that contains high quantities of water, such as apples and bananas, produces different sounds compared to food, such as cookies and waffles, which do not. So, this difference appears to be large enough to detect whether or not someone is eating food with high amounts of water versus food with low amounts of water. The microphone, however, needs to have types of food that have a large difference, like the bananas and the waffle and the apples and the cookies. It cannot distinguish between foods whose water percentages are similar, like the apple and banana and the cookie and waffle cake.

Besides the results from the device, which have the potential to help prevent MetS, there are also some limitations to the device and the research. One of the research's limitations is that during the examination of the results between trials of the same type of food the variations were abundant, meaning that the data was not always recorded correctly. An example: the trials with the bananas measured with the piezoelectric sensor all had more variation than an association. This resulted in fewer data points that were usable in the statistical analysis of the piezoelectric sensor. An explanation of these abundant number of variations might be explained due to a lack of constant factors. Constant factors such as taking bites from the same banana with exact the same amount of banana per bite at the same time of the day could have been better to get less unreliable data.

In addition, only three trials per food type were done, giving a certain limited amount of data points. The limitation that follows from this is that the results and conclusions are based upon a few data points which make the study less accurate. If more trials were done, it would have resulted in more data points and thus more accurate results.

The statistical analyses in this research are also considered as a limitation of the research. This research used ANOVA and T-tests assuming normal distributions for categorical variables. The reason why these tests were chosen were since they the researcher only had experience with these types of statistical analyses. The analyses with these tests limited the research in multiple ways. The first way is that ANOVA was used to compare all food types, however, not all food types contained three data points anymore since some trials were left out due to divergence. This limits the results of the ANOVA, since ANOVA needs three trial per food type to work. Another way that the research is limited due to the chosen statistical analyses is that there are many more statistical analyses that fit the data better than ANOVA and T-tests. The tests that were chosen were chosen because of convenience, which makes the result unreliable compared to statistical analyses that better fit the data.

Another limitation of the research is the kind of food that was researched. To check whether the prototype worked, this research made use of food that were on opposite sides in terms of hardness and amount of water the food contained. The research is limited since the prototype is only tested with these kinds of food while there are many more types of food in terms of hardness, softness, crispiness, amount of water, etc. Therefore, it cannot be said that the prototype can distinguish between healthier and unhealthier food; the prototype can only distinguish between hard cookies compared to apples and soft waffle cakes compared to bananas.

The device itself also had several limitations. A limitation of the device is that the piezoelectric sensor only transmits binary data, which is probably caused by the sensitivity adjuster. The problem with binary data is that it limits the results only to the frequency at which the voltage changes. Other research²⁴ used piezoelectric sensors that can give non-binary data, the non-binary data could give more information that could help distinguish, not just between more healthy and unhealthier, but more specific what type of food (e.g., fruit or vegetables, cookies, or chips), perhaps even the amount of food taken in.

This leads to the next limitation of the device; the device can distinguish whether the food type is more healthy or unhealthier, but for now, it cannot give information about the amount. To be precise, the research did not focus on how the frequencies send frequencies sent by the piezoelectric sensor relate to the amount of food taken in.

To summarize; the limitations of the research were related to the amount of data recorded, the setting in which the data was recorded, the samples used to record the data, the recorded data itself, and the amount of research done with the data. Recommendations for future research would be to record more data from more types of food in a laboratory setting with fewer factors that influences the recordings and to post-process the data using Fourier Transformations in addition to better fitting statistical analysis. Viewing the data in a domain other than time and magnitude using Fourier transformation could help extrapolate all the information the data gives, to help further distinguish between food types and why they give different signals and perhaps even get the amount of food per bite as data from the sensors.

6 Conclusion and recommendations

This project started with the goal to develop a device and create a functioning prototype that can detect food intake and discriminate between healthy and unhealthy eating habits, to help prevent the development of people, such as office workers, who have an increased risk of development of the metabolic syndrome. During the project, this goal was further defined and specified, which eventually led to the final product described and tested in synthesis 2 and 3.

To reach the goal, the final prototype is an Arduino R3 UNO connected to a microphone and piezoelectric sensor. This prototype is worn with elastic bands around the lower and upper throat and is connected to a computer. According to the data, the device can distinguish during chewing between apples and cookies and between bananas and waffle cake. The data also suggests that during swallowing it can distinguish between cookies and waffle cake, between apples and cookies and between bananas and waffle cakes. This means that the device, to some degree, can give feedback with regards to eating habits in terms of cookies, bananas, apples, and waffle cake. However, as described in the discussion above, more input and more data points are needed to get a solution that has the potential to discriminate between more types of food and thereby eating habits.

As for the requirements and wishes, all must requirements are fulfilled; the prototype is small, comfortable so that it does not affect productivity, it can be used in the office, it uses sensors and most important of all, it is non-invasive. As for the should-requirements, the prototype does not fulfil all of them, the product is not easy to use. The product still needs to be connected to wires to a laptop and is not easy to use in terms of recording data and interpreting the data it sends. Future development of the prototype could solve these problems in several ways. One of the ways to make the prototype easier to use is to use more advanced programming to ensure that only one type of program does all the work instead of manually recording data, converting it to CSV via Excel, then to MATLAB, then back to Excel. Another way to make the prototype easier to use would be to make it wireless. This could imply that the prototype uses some kind of wireless technology like Bluetooth to send data directly to one computer program. Both these modifications would make the device easier to use as well as more comfortable for the user.

To answer the research question *“How can a device help to monitor certain eating habits such as frequency and food type known to be a risk factor in developing metabolic syndrome?”* This device is capable of monitoring eating habits through mechanically measuring the movement of the throat and through recording and analysing chewing and swallowing sounds. The final concept and prototype already show great potential in detecting certain eating habits, specifically in detecting the type of food in terms of healthier and unhealthier. However, the research regarding the prototype needs to be elaborated more to confirm the data, and the prototype could use further modifications to increase comfort and usability.

Appendix

Appendix 1: the Arduino IDE code used to program the hardware

```
Analog_readerV1 $
8
9 void setup() {
10 Serial.begin(9600); // initialize serial communications
11 }
12
13 void loop() {
14   unsigned long current_time; // unsigned long is the time variable we reserve
15   current_time = millis()/1000UL; // conversion to seconds
16   Serial.print(current_time);
17   Serial.print(",");
18
19   PiezoValue = analogRead(PiezoPin) ;
20   Pval = PiezoValue*(5.0/1024);
21   //Serial.print("voltage ");
22   Serial.print(Pval);
23   Serial.print(",");
24
25
26   MicValue = analogRead(MicPin) ;
27   Mval = MicValue*(5.0/1024);
28   Serial.print(Mval);
29
30   Serial.println();
31   delay(20);
32 }
```

Appendix 2: MATLAB code

```
%% chewing apple 1
CA1 = importdata('CA1.csv');
disp(CA1);
forPlot = CA1.data;
figure()
plot(linspace(0,18,864),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of an apple test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 18]);
ylim([0 5]);

CA11 = CA1.data(1:144,3);
M1 = mean(CA11);
M1
CA12 = CA1.data(1: (145:289),3);
M2 = mean(CA12);
M2
CA13 = CA1.data(1: (290:434),3);
M3 = mean(CA13);
M3
CA14 = CA1.data(1: (435:579),3);
M4 = mean(CA14);
M4
CA15 = CA1.data(1: (580:724),3);
M5 = mean(CA15);
M5
CA16 = CA1.data(1: (725:864),3);
M6 = mean(CA16);
M6
```

```

%% chewing apple 2
CA2 = importdata('CAApple2.csv');
disp(CA2);
forPlot = CA2.data;
figure()
plot(linspace(0,21,991),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of an apple test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 21]);
ylim([0 5]);

CA21 = CA2.data(1:142,3);
M1 = mean(CA21);
M1
CA22 = CA2.data(1: (143:285),3);
M2 = mean(CA22);
M2
CA23 = CA2.data(1: (286:428),3);
M3 = mean(CA23);
M3
CA24 = CA2.data(1: (429:571),3);
M4 = mean(CA24);
M4
CA25 = CA2.data(1: (572:714),3);
M5 = mean(CA25);
M5
CA26 = CA2.data(1: (715:857),3);
M6 = mean(CA26);
M6
CA27 = CA2.data(1: (857:991),3);
M7 = mean(CA27);
M7

%% Chewing apple 3
CA3 = importdata('CAApple3.csv');
disp(CA3);
forPlot = CA3.data;
figure()
plot(linspace(0,18,870),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of an apple test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 18]);
ylim([0 5]);

CA31 = CA3.data(1:145,3);
M1 = mean(CA31);
M1
CA32 = CA3.data(1: (146:291),3);
M2 = mean(CA32);
M2
CA33 = CA3.data(1: (292:437),3);
M3 = mean(CA33);
M3
CA34 = CA3.data(1: (438:583),3);
M4 = mean(CA34);
M4
CA35 = CA3.data(1: (584:729),3);
M5 = mean(CA35);
M5
CA36 = CA3.data(1: (730:870),3);
M6 = mean(CA36);
M6

```

```

%% Chewing banana 1
CB1 = importdata('CBanana1.csv');
disp(CB1);
forPlot = CB1.data;
figure()
plot(linspace(0,15,723),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of a banana test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 15]);
ylim([0 5]);

CB11 = CB1.data(1:145,3);
M1 = mean(CB11);
M1
CB12 = CB1.data(1: (146:291),3);
M2 = mean(CB12);
M2
CB13 = CB1.data(1: (292:437),3);
M3 = mean(CB13);
M3
CB14 = CB1.data(1: (438:583),3);
M4 = mean(CB14);
M4
CB15 = CB1.data(1: (584:723),3);
M5 = mean(CB15);
M5

```

```

%% Chewing banana 2
CB2 = importdata('CBanana2.csv');
disp(CB2);
forPlot = CB2.data;
figure()
plot(linspace(0,11,440),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of a banana test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 11]);
ylim([0 5]);

CB21 = CB2.data(1:120,3);
M1 = mean(CB21);
M1
CB22 = CB2.data(1: (121:241),3);
M2 = mean(CB22);
M2
CB23 = CB2.data(1: (242:362),3);
M3 = mean(CB23);
M3
CB24 = CB2.data(1:(362:440), 3);
M4 = mean(CB24);
M4

```

```

%% Chewing banana 3
CB3 = importdata('CBanana3.csv');
disp(CB3);
forPlot = CB3.data;
figure()
plot(linspace(0,11,512),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of a banana test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 11]);
ylim([0 5]);

CB31 = CB3.data(1:140,3);
M1 = mean(CB31);
M1
CB32 = CB3.data(1: (141:281),3);
M2 = mean(CB32);
M2
CB33 = CB3.data(1: (282:422),3);
M3 = mean(CB33);
M3
CB34 = CB3.data(1:(423:512), 3);
M4 = mean(CB34);
M4

```

```

%% Chewing Cake 1
CC1 = importdata('CCake1.csv');
disp(CC1);
forPlot = CC1.data;
figure()
plot(linspace(0,13,588),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of cake test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 13]);
ylim([0 5]);

CC11 = CC1.data(1:136,3);
M1 = mean(CC11);
M1
CC12 = CC1.data(1: (137:273),3);
M2 = mean(CC12);
M2
CC13 = CC1.data(1: (274:410),3);
M3 = mean(CC13);
M3
CC14 = CC1.data(1: (411:588),3);
M4 = mean(CC14);
M4

```

```

%% Chewing Cake 2
CC2 = importdata('CCake2.csv');
disp(CC2);
forPlot = CC2.data;
figure()
plot(linspace(0,10,490),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of cake test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 10]);
ylim([0 5]);
CC21 = CC2.data(1:163,3);
M1 = mean(CC21);
M1
CC22 = CC2.data(1: (164:327),3);
M2 = mean(CC22);
M2
CC23 = CC2.data(1: (328:490),3);
M3 = mean(CC23);
M3

```

```

%% Chewing Cake 3
CC3 = importdata('CCake3.csv');
disp(CC3);
forPlot = CC3.data;
figure()
plot(linspace(0,16,750),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of cake test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 16]);
ylim([0 5]);
CC31 = CC3.data(1:125,3);
M1 = mean(CC31);
M1
CC32 = CC3.data(1: (126:251),3);
M2 = mean(CC32);
M2
CC33 = CC3.data(1: (252:377),3);
M3 = mean(CC33);
M3
CC34 = CC3.data(1: (378:503),3);
M4 = mean(CC34);
M4
CC35 = CC3.data(1: (504:629),3);
M5 = mean(CC35);
M5
CC36 = CC3.data(1: (630:750),3);
M6 = mean(CC36);
M6

```

```

%% Chewing Cookie 1
CC01 = importdata('CCookie1.csv');
disp(CC01);
forPlot = CC01.data;
figure()
plot(linspace(0,13,597),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of a cookie test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 13]);
ylim([0 5]);

CC011 = CC01.data(1:120,3);
M1 = mean(CC011);
M1
CC012 = CC01.data(1: (121:241),3);
M2 = mean(CC012);
M2
CC013 = CC01.data(1: (242:362),3);
M3 = mean(CC013);
M3
CC014 = CC01.data(1: (363:483),3);
M4 = mean(CC014);
M4
CC015 = CC01.data(1: (484:597),3);
M5 = mean(CC015);
M5

```

```

%% Chewing Cookie 2
CC02 = importdata('CCookie2.csv');
disp(CC02);
forPlot = CC02.data;
figure()
plot(linspace(0,12,588),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of a cookie test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 12]);
ylim([0 5]);
CC021 = CC02.data(1:147,3);
M1 = mean(CC021);
M1
CC022 = CC02.data(1: (148:295),3);
M2 = mean(CC022);
M2
CC023 = CC02.data(1: (296:443),3);
M3 = mean(CC023);
M3
CC024 = CC02.data(1: (444:588),3);
M4 = mean(CC024);
M4

```

```

%% Chewing Cookie 3
CC03 = importdata('CCookie3.csv');
disp(CC03);
forPlot = CC03.data;
figure()
plot(linspace(0,12,465),forPlot(:,3))
legend('Microphone')
title('Chewing sounds of a cookie test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 12]);
ylim([0 5]);
CC031 = CC03.data(1:116,3);
M1 = mean(CC031);
M1
CC032 = CC03.data(1: (117:233),3);
M2 = mean(CC032);
M2
CC033 = CC03.data(1: (234:350),3);
M3 = mean(CC033);
M3
CC034 = CC03.data(1: (351:465),3);
M4 = mean(CC034);
M4

```

```

%% chewing apple 1
CA1 = importdata('CAApple1.csv');
disp(CA1);
forPlot = CA1.data;
figure()
plot(linspace(0,18,864),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on an apple test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% chewing apple 2
CA2 = importdata('CAApple2.csv');
disp(CA2);
forPlot = CA2.data;
figure()
plot(linspace(0,21,991),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on an apple test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Chewing apple 3
CA3 = importdata('CAApple3.csv');
disp(CA3);
forPlot = CA3.data;
figure()
plot(linspace(0,18,870),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on an apple test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```
%% Chewing banana 1
CB1 = importdata('CBanana1.csv');
disp(CB1);
forPlot = CB1.data;
figure()
plot(linspace(0,15,723),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on a banana test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')
```

```
%% Chewing banana 2
CB2 = importdata('CBanana2.csv');
disp(CB2);
forPlot = CB2.data;
figure()
plot(linspace(0,11,440),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on a banana test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')
```

```
%% Chewing banana 3
CB3 = importdata('CBanana3.csv');
disp(CB3);
forPlot = CB3.data;
figure()
plot(linspace(0,11,512),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on a banana test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
```

```
%% Chewing Cake 1
CC1 = importdata('CCake1.csv');
disp(CC1);
forPlot = CC1.data;
figure()
plot(linspace(0,13,588),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on cake test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')
```

```
%% Chewing Cake 2
CC2 = importdata('CCake2.csv');
disp(CC2);
forPlot = CC2.data;
figure()
plot(linspace(0,10,490),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on cake test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')
```

```
%% Chewing Cake 3
CC3 = importdata('CCake3.csv');
disp(CC3);
forPlot = CC3.data;
figure()
plot(linspace(0,16,750),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on cake test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
```

```

%% Chewing Cookie 1
CC01 = importdata('CCookie1.csv');
disp(CC01);
forPlot = CC01.data;
figure()
plot(linspace(0,13,597),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on a cookie test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Chewing Cookie 2
CC02 = importdata('CCookie2.csv');
disp(CC02);
forPlot = CC02.data;
figure()
plot(linspace(0,12,588),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on a cookie test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Chewing Cookie 3
CC03 = importdata('CCookie3.csv');
disp(CC03);
forPlot = CC03.data;
figure()
plot(linspace(0,12,465),forPlot(:,2))
legend('Piezo sensor')
title('Piezo activity to chewing on a cookie test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Chewing banana 1
CB1 = importdata('CBanana1.csv');
disp(CB1);
forPlot = CB1.data;
figure()
plot(linspace(0,15,723),forPlot(:,3))
hold on
plot(linspace(0,15,723),forPlot(:,2))
legend('Micropphone', 'Piezo sensor')
title('Chewing sounds and piezo electric response of a banana test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Chewing banana 2
CB2 = importdata('CBanana2.csv');
disp(CB2);
forPlot = CB2.data;
figure()
plot(linspace(0,11,440),forPlot(:,3))
hold on
plot(linspace(0,11,440),forPlot(:,2))
legend('Micropphone', 'Piezo sensor')
title('Chewing sounds and piezo electric response of a banana test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Chewing banana 3
CB3 = importdata('CBanana3.csv');
disp(CB3);
forPlot = CB3.data;
figure()
plot(linspace(0,11,512),forPlot(:,3))
hold on
plot(linspace(0,11,512),forPlot(:,2))
legend('Micropphone', 'Piezo sensor')
title('Chewing sounds and piezo electric response of a banana test 3')
xlabel('Time (s)')

```

```

%% chewing apple 1
CA1 = importdata('CAppl1.csv');
disp(CA1);
forPlot = CA1.data;
figure()
plot(linspace(0,18,864),forPlot(:,3))
hold on
plot(linspace(0,18,864),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Chewing sounds and piezo electric response to an apple test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% chewing apple 2
CA2 = importdata('CAppl2.csv');
disp(CA2);
forPlot = CA2.data;
figure()
plot(linspace(0,21,991),forPlot(:,3))
hold on
plot(linspace(0,21,991),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Chewing sounds and piezo electric response to an apple test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% Chewing apple 3
CA3 = importdata('CAppl3.csv');
disp(CA3);
forPlot = CA3.data;
figure()
plot(linspace(0,18,870),forPlot(:,3))
hold on
plot(linspace(0,18,870),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Chewing sounds and piezo electric response to an apple test 3')
xlabel('Time (s)')

```

```

%% Chewing Cake 1
CC1 = importdata('CCake1.csv');
disp(CC1);
forPlot = CC1.data;
figure()
plot(linspace(0,13,588),forPlot(:,3))
hold on
plot(linspace(0,13,588),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Chewing sounds and piezo electric response of cake test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% Chewing Cake 2
CC2 = importdata('CCake2.csv');
disp(CC2);
forPlot = CC2.data;
figure()
plot(linspace(0,10,490),forPlot(:,3))
hold on
plot(linspace(0,10,490),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Chewing sounds and piezo electric response of cake test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% Chewing Cake 3
CC3 = importdata('CCake3.csv');
disp(CC3);
forPlot = CC3.data;
figure()
plot(linspace(0,16,750),forPlot(:,3))
hold on
plot(linspace(0,16,750),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Chewing sounds and piezo electric response of cake test 3')
xlabel('Time (s)')

```

```
%% Chewing Cookie 1
CC01 = importdata('CCookie1.csv');
disp(CC01);
forPlot = CC01.data;
figure()
plot(linspace(0,13,597),forPlot(:,3))
hold on
plot(linspace(0,13,597),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Chewing sounds and piezo electric response to a cookie test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% Chewing Cookie 2
CC02 = importdata('CCookie2.csv');
disp(CC02);
forPlot = CC02.data;
figure()
plot(linspace(0,12,588),forPlot(:,3))
hold on
plot(linspace(0,12,588),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Chewing sounds and piezo electric response to a cookie test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% Chewing Cookie 3
CC03 = importdata('CCookie3.csv');
disp(CC03);
forPlot = CC03.data;
figure()
plot(linspace(0,12,465),forPlot(:,3))
hold on
plot(linspace(0,13,465),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Chewing sounds and piezo electric response to a cookie test 3')
xlabel('Time (s)')
```

```
%% Swallowing apple 1
SA1 = importdata('SAApple1.csv');
disp(SA1);
forPlot = SA1.data;
figure()
plot(linspace(0,6,283),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of an apple test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 6]);
ylim([0 5]);
```

```
SA11 = SA1.data(1:94,3);
M1 = mean(SA11);
M1
SA12 = SA1.data(1: (95:189),3);
M2 = mean(SA12);
M2
SA13 = SA1.data(1: (190:283),3);
M3 = mean(SA13);
M3
```

```
%% Swallowing apple 2
SA2 = importdata('SAApple2.csv');
disp(SA2);
forPlot = SA2.data;
figure()
plot(linspace(0,3,165),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of an apple test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 3]);
ylim([0 5]);
```

```
SA21 = SA2.data(1:82,3);
M1 = mean(SA21);
M1
SA22 = SA2.data(1: (83:165),3);
M2 = mean(SA22);
M2
```

```

%% Swallowing apple 3
SA3 = importdata('SAppl3.csv');
disp(SA3);
forPlot = SA3.data;
figure()
plot(linspace(0,7,338),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of an apple test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 3]);
ylim([0 5]);

```

```

SA31 = SA3.data(1:112,3);
M1 = mean(SA31);
M1
SA32 = SA3.data(1: (113:225),3);
M2 = mean(SA32);
M2
SA33 = SA3.data(1: (226:338),3);
M3 = mean(SA33);
M3

```

```

%% Swallowing Banana 1
SB1 = importdata('SBanana1.csv');
disp(SB1);
forPlot = SB1.data;
figure()
plot(linspace(0,4,159),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of a banana test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 4]);
ylim([0 5]);

```

```

SB11 = SB1.data(1:80,3);
M1 = mean(SB11);
M1
SB12 = SB1.data(1: (81:159),3);
M2 = mean(SB12);
M2

```



```
%% Swallowing Banana 2
SB2 = importdata('SBanana2.csv');
disp(SB2);
forPlot = SB2.data;
figure()
plot(linspace(0,3,146),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of a banana test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 3]);
ylim([0 5]);
SB21 = SB2.data(1:72,3);
M1 = mean(SB21);
M1
SB22 = SB2.data(1: (73:146),3);
M2 = mean(SB22);
M2
```

```
%% Swallowing Banana 3
SB3 = importdata('SBanana3.csv');
disp(SB3);
forPlot = SB3.data;
figure()
plot(linspace(0,7,357),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of a banana test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 7]);
ylim([0 5]);

SB31 = SB3.data(1:119,3);
M1 = mean(SB31);
M1
SB32 = SB3.data(1: (120:239),3);
M2 = mean(SB32);
M2
SB33 = SB3.data(1: (240:357),3);
M3 = mean(SB33);
M3
```



```

%% Swallowing Cake 1
SC1 = importdata('SCake1.csv');
disp(SC1);
forPlot = SC1.data;
figure()
plot(linspace(0,4,174),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of cake test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 4]);
ylim([0 5]);

SC11 = SC1.data(1:86,3);
M1 = mean(SC11);
M1
SC12 = SC1.data(1: (87:174),3);
M2 = mean(SC12);
M2

```

```

%% Swallowing Cake 2
SC2 = importdata('SCake2.csv');
disp(SC2);
forPlot = SC2.data;
figure()
plot(linspace(0,3,141),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of cake test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 3]);
ylim([0 5]);

SC21 = SC2.data(1:70,3);
M1 = mean(SC21);
M1
SC22 = SC2.data(1: (71:141),3);
M2 = mean(SC22);
M2

```

```

%% Swallowing Cake 3
SC3 = importdata('SCake3.csv');
disp(SC3);
forPlot = SC3.data;
figure()
plot(linspace(0,2,127),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of cake test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 2]);
ylim([0 5]);
SC31 = SC3.data(1:127,3);
M1 = mean(SC21);
M1

```

```

%% Swallowing cookie 1
SC01 = importdata('SCookie1.csv');
disp(SC01);
forPlot = SC01.data;
figure()
plot(linspace(0,5,199),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of a cookie test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 5]);
ylim([0 5]);
SC011 = SC01.data(1:99,3);
M1 = mean(SC011);
M1
SC012 = SC01.data(1: (100:199),3);
M2 = mean(SC012);
M2

```

```

%% Swallowing cookie 2
SC02 = importdata('SCookie2.csv');
disp(SC02);
forPlot = SC02.data;
figure()
plot(linspace(0,3,164),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of a cookie test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 3]);
ylim([0 5]);
SC021 = SC02.data(1:81,3);
M1 = mean(SC021);
M1
SC022 = SC02.data(1: (82:164),3);
M2 = mean(SC022);
M2

```

```

%% Swallowing cookie 3
SC03 = importdata('SCookie3.csv');
disp(SC03);
forPlot = SC03.data;
figure()
plot(linspace(0,3,180),forPlot(:,3))
legend('Microphone')
title('Swallowing sounds of a cookie test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
xlim([0 3]);
ylim([0 5]);
SC031 = SC03.data(1:89,3);
M1 = mean(SC031);
M1
SC032 = SC03.data(1: (90:180),3);
M2 = mean(SC032);
M2

```

```

%% Swallowing apple 1
SA1 = importdata('SAppl1.csv');
disp(SA1);
forPlot = SA1.data;
figure()
plot(linspace(0,6,283),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing an apple, test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Swallowing apple 2
SA2 = importdata('SAppl2.csv');
disp(SA2);
forPlot = SA2.data;
figure()
plot(linspace(0,3,165),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing an apple, test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Swallowing apple 3
SA3 = importdata('SAppl3.csv');
disp(SA3);
forPlot = SA3.data;
figure()
plot(linspace(0,7,338),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing an apple, test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Swallowing Banana 1
SB1 = importdata('SBanana1.csv');
disp(SB1);
forPlot = SB1.data;
figure()
plot(linspace(0,4,159),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing a banana, test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% Swallowing Banana 2
SB2 = importdata('SBanana2.csv');
disp(SB2);
forPlot = SB2.data;
figure()
plot(linspace(0,3,146),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing a banana, test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% Swallowing Banana 3
SB3 = importdata('SBanana3.csv');
disp(SB3);
forPlot = SB3.data;
figure()
plot(linspace(0,7,357),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing a banana, test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Swallowing Cake 1
SC1 = importdata('SCake1.csv');
disp(SC1);
forPlot = SC1.data;
figure()
plot(linspace(0,4,174),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing cake, test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')


---


%% Swallowing Cake 2
SC2 = importdata('SCake2.csv');
disp(SC2);
forPlot = SC2.data;
figure()
plot(linspace(0,3,141),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing cake, test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')


---


%% Swallowing Cake 3
SC3 = importdata('SCake3.csv');
disp(SC3);
forPlot = SC3.data;
figure()
plot(linspace(0,2,127),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing cake, test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```
%% Swallowing cookie 1
SC01 = importdata('SCookie1.csv');
disp(SC01);
forPlot = SC01.data;
figure()
plot(linspace(0,5,199),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing a cookie, test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% Swallowing cookie 2
SC02 = importdata('SCookie2.csv');
disp(SC02);
forPlot = SC02.data;
figure()
plot(linspace(0,3,164),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing a cookie, test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% Swallowing cookie 3
SC03 = importdata('SCookie3.csv');
disp(SC03);
forPlot = SC03.data;
figure()
plot(linspace(0,3,180),forPlot(:,2))
legend('Piezo sensor')
title('Piezo electric activity in response to swallowing a cookie, test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
```



```

%% Swallowing apple 1
SA1 = importdata('SAppl1.csv');
disp(SA1);
forPlot = SA1.data;
figure()
plot(linspace(0,6,283),forPlot(:,3))
hold on
plot(linspace(0,6,283),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Swallowing sounds and piezo electric response to an apple test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Swallowing apple 2
SA2 = importdata('SAppl2.csv');
disp(SA2);
forPlot = SA2.data;
figure()
plot(linspace(0,3,165),forPlot(:,3))
hold on
plot(linspace(0,3,165),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Swallowing sounds and piezo electric response to an apple test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

%% Swallowing apple 3
SA3 = importdata('SAppl3.csv');
disp(SA3);
forPlot = SA3.data;
figure()
plot(linspace(0,7,338),forPlot(:,3))
hold on
plot(linspace(0,7,338),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Swallowing sounds and piezo electric response to an apple test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```
%% Swallowing Banana 1
SB1 = importdata('SBanana1.csv');
disp(SB1);
forPlot = SB1.data;
figure()
plot(linspace(0,4,159),forPlot(:,3))
hold on
plot(linspace(0,4,159),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Swallowing sounds and piezo electric response to a banana, test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')
```

```
%% Swallowing Banana 2
SB2 = importdata('SBanana2.csv');
disp(SB2);
forPlot = SB2.data;
figure()
plot(linspace(0,3,146),forPlot(:,3))
hold on
plot(linspace(0,3,146),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Swallowing sounds and piezo electric response to a banana, test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')
```

```
%% Swallowing Banana 3
SB3 = importdata('SBanana3.csv');
disp(SB3);
forPlot = SB3.data;
figure()
plot(linspace(0,7,357),forPlot(:,3))
hold on
plot(linspace(0,7,357),forPlot(:,2))
legend('Micropphone','Piezo sensor')
title('Swallowing sounds and piezo electric response to a banana, test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')
```



```

%% Swallowing Cake 1
SC1 = importdata('SCake1.csv');
disp(SC1);
forPlot = SC1.data;
figure()
plot(linspace(0,4,174),forPlot(:,3))
hold on
plot(linspace(0,4,174),forPlot(:,2))
legend('Micropphone', 'Piezo sensor')
title('Swallowing sounds and piezo electric response to cake, test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% Swallowing Cake 2
SC2 = importdata('SCake2.csv');
disp(SC2);
forPlot = SC2.data;
figure()
plot(linspace(0,3,141),forPlot(:,3))
hold on
plot(linspace(0,3,141),forPlot(:,2))
legend('Micropphone', 'Piezo sensor')
title('Swallowing sounds and piezo electric response to cake, test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

%% Swallowing Cake 3
SC3 = importdata('SCake3.csv');
disp(SC3);
forPlot = SC3.data;
figure()
plot(linspace(0,2,127),forPlot(:,3))
hold on
plot(linspace(0,2,127),forPlot(:,2))
legend('Micropphone', 'Piezo sensor')
title('Swallowing sounds and piezo electric response to cake, test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')

```

```

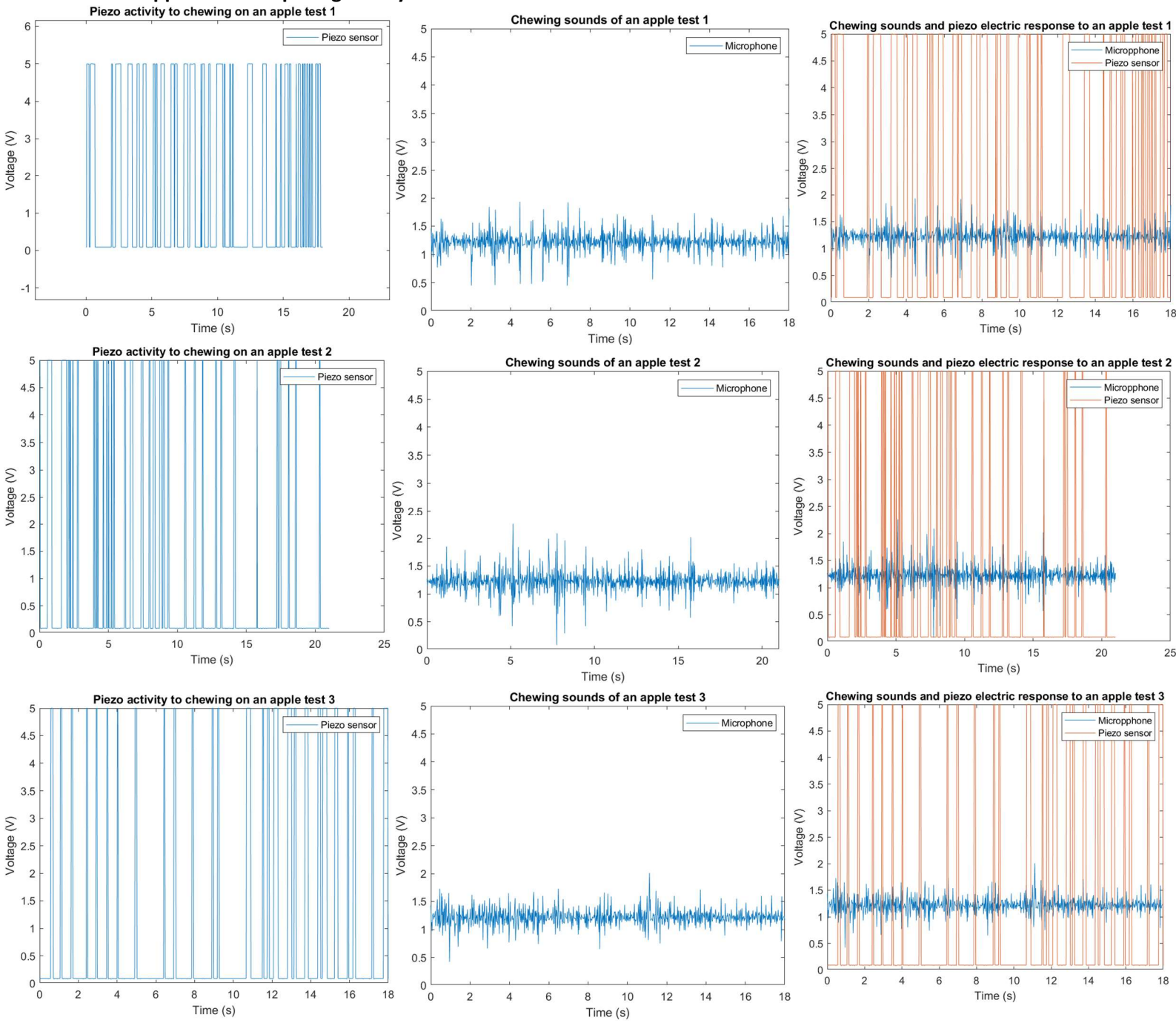
%% Swallowing cookie 1
SC01 = importdata('SCookie1.csv');
disp(SC01);
forPlot = SC01.data;
figure()
plot(linspace(0,5,199),forPlot(:,3))
hold on
plot(linspace(0,5,199),forPlot(:,2))
legend('Micropphone', 'Piezo sensor')
title('Swallowing sounds and piezo electric response to a cookie, test 1')
xlabel('Time (s)')
ylabel('Voltage (V)')

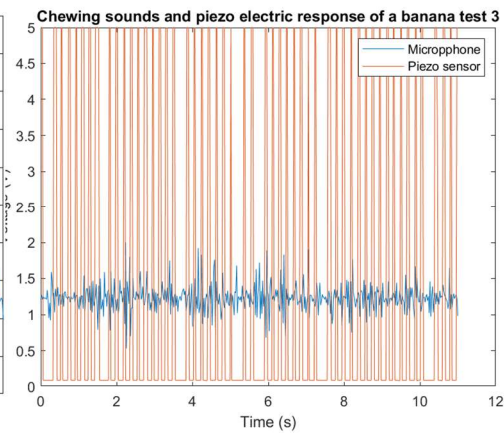
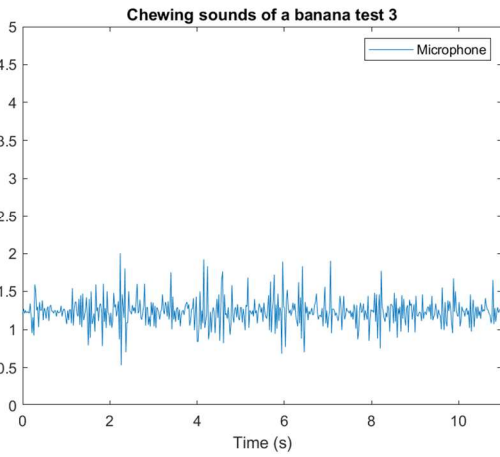
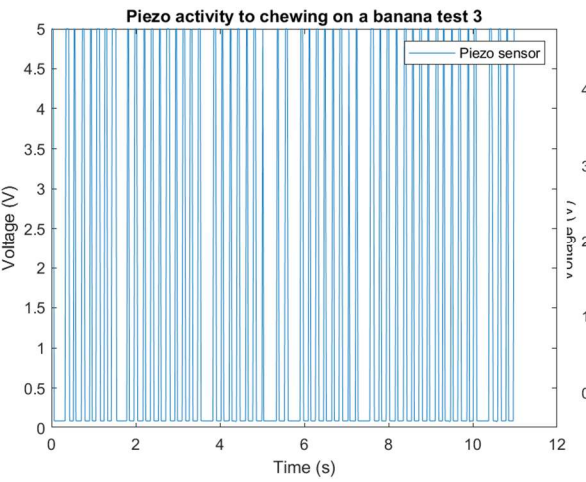
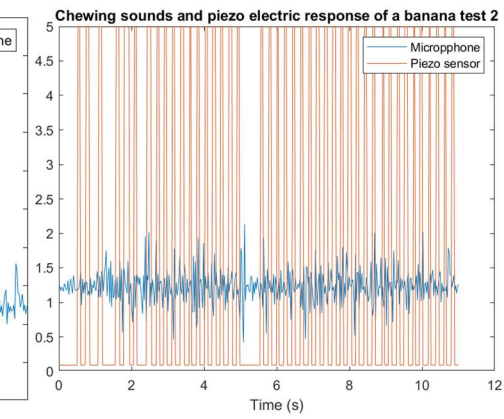
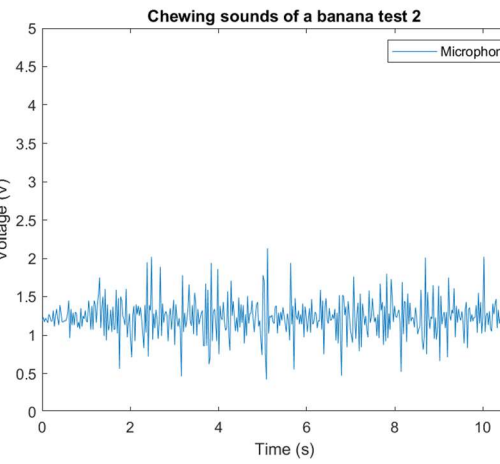
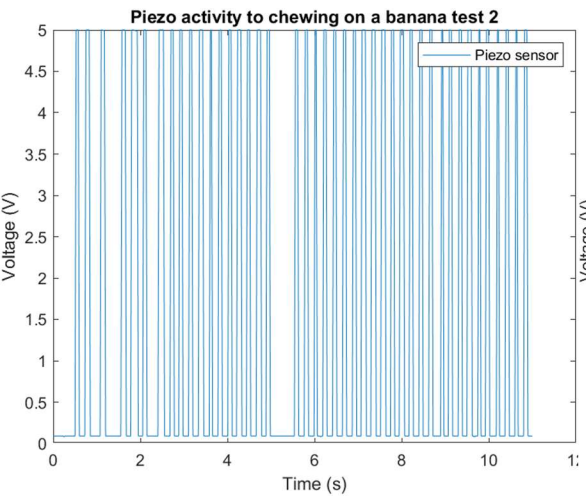
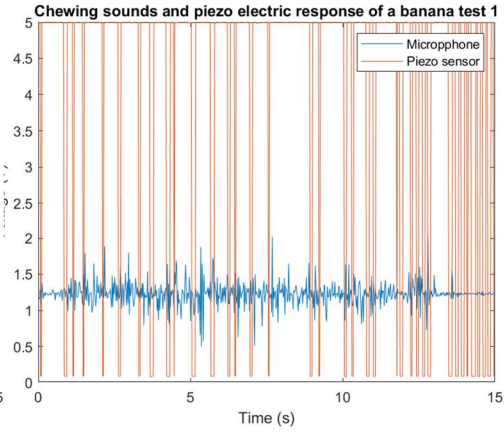
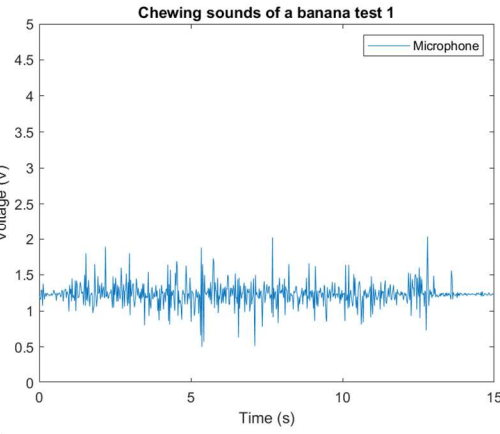
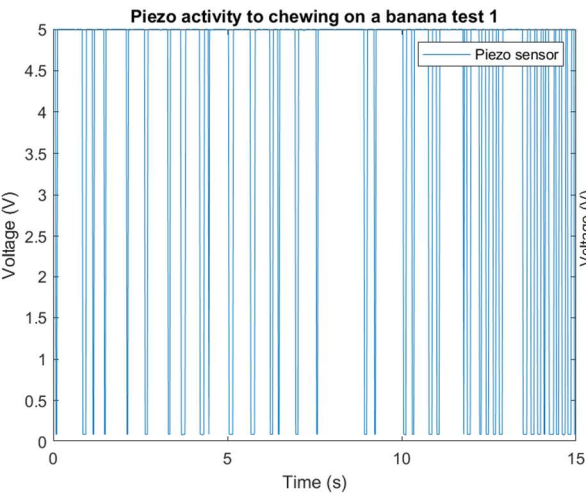
%% Swallowing cookie 2
SC02 = importdata('SCookie2.csv');
disp(SC02);
forPlot = SC02.data;
figure()
plot(linspace(0,3,164),forPlot(:,3))
hold on
plot(linspace(0,3,164),forPlot(:,2))
legend('Micropphone', 'Piezo sensor')
title('Swallowing sounds and piezo electric response to a cookie, test 2')
xlabel('Time (s)')
ylabel('Voltage (V)')

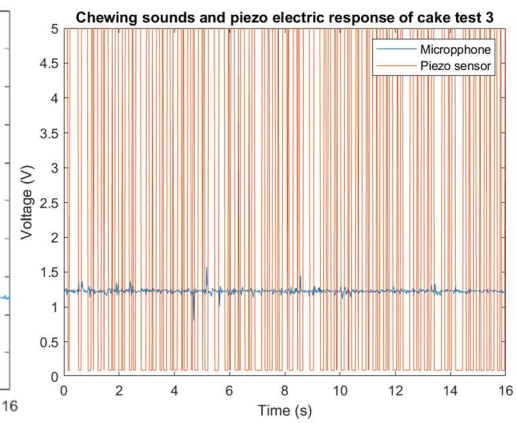
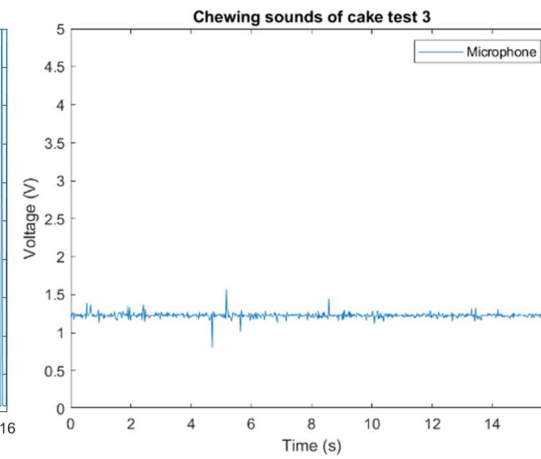
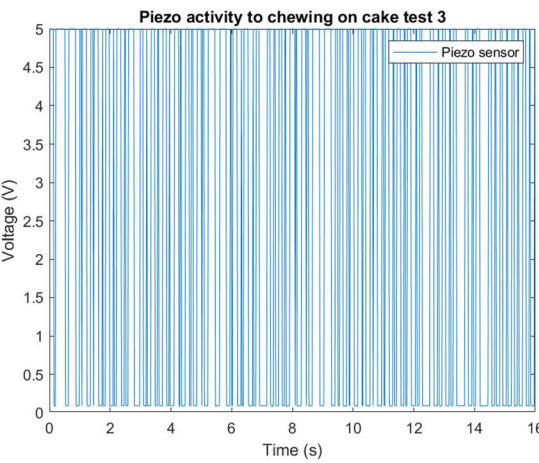
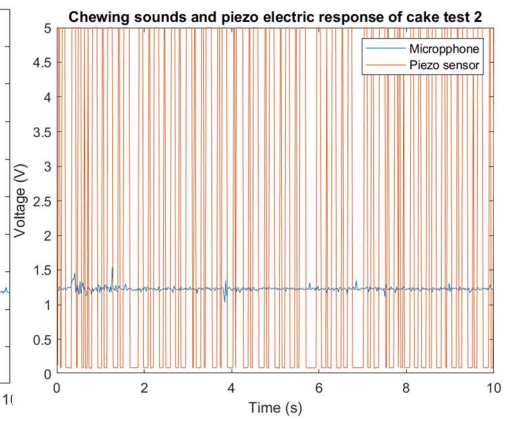
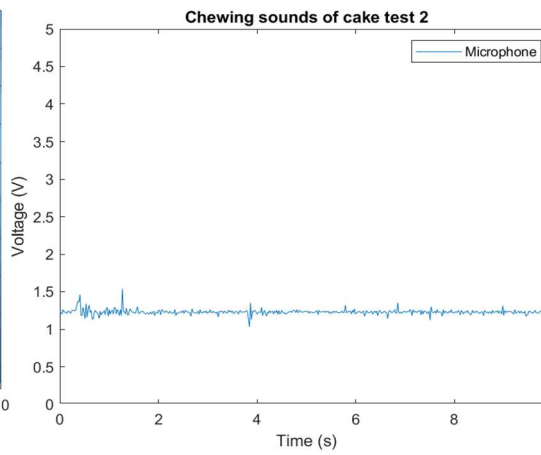
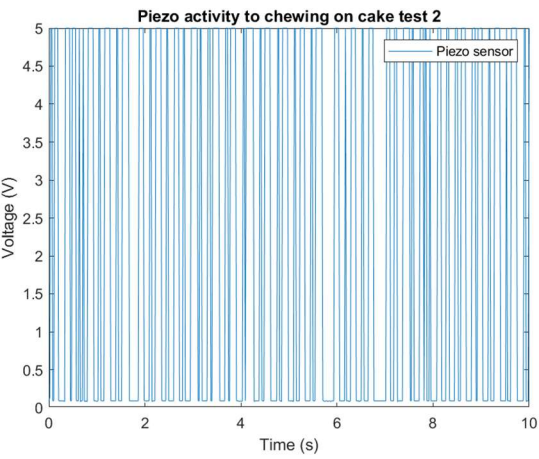
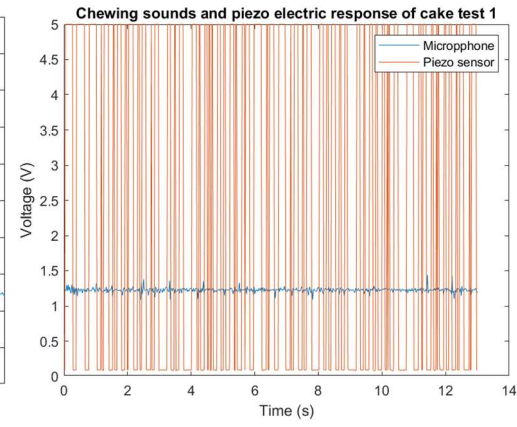
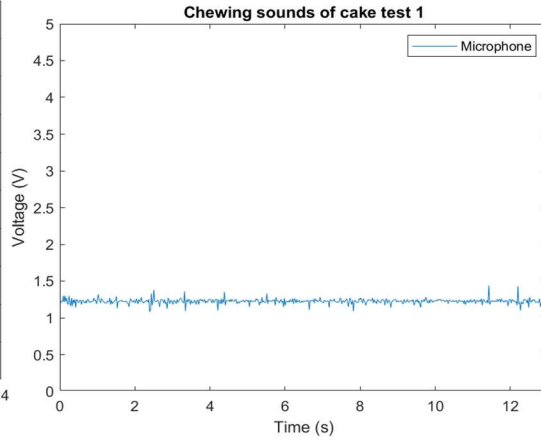
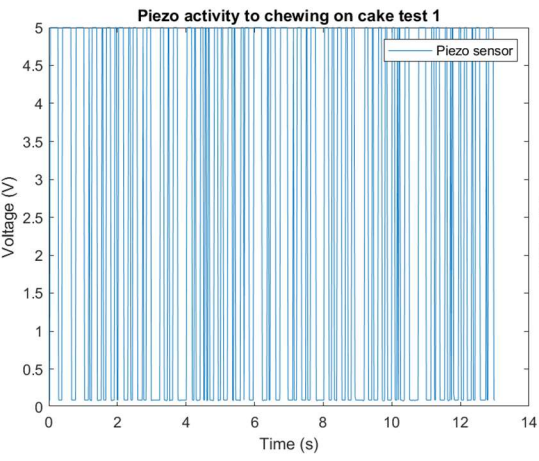
%% Swallowing cookie 3
SC03 = importdata('SCookie3.csv');
disp(SC03);
forPlot = SC03.data;
figure()
plot(linspace(0,3,180),forPlot(:,3))
hold on
plot(linspace(0,3,180),forPlot(:,2))
legend('Micropphone', 'Piezo sensor')
title('Swallowing sounds and piezo electric response to a cookie, test 3')
xlabel('Time (s)')
ylabel('Voltage (V)')

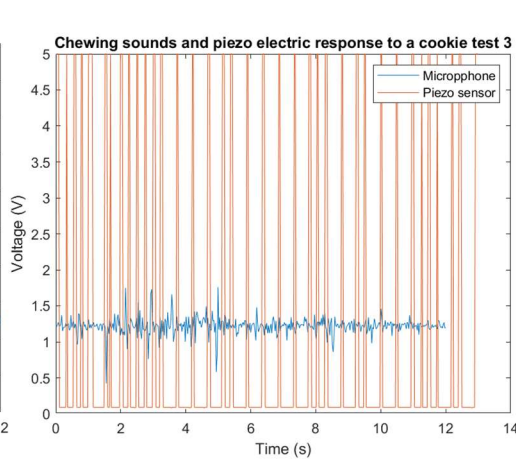
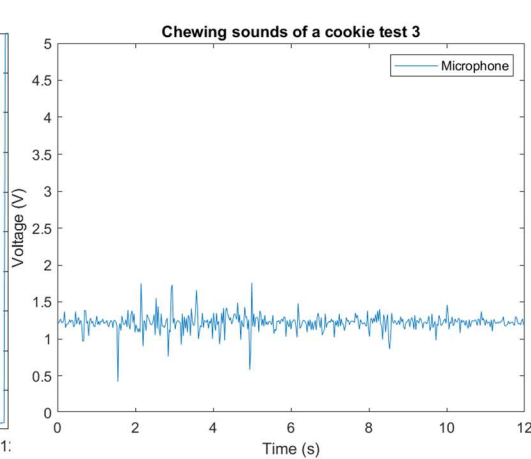
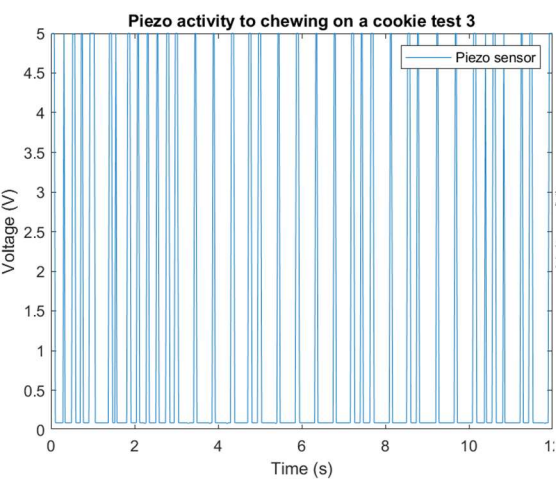
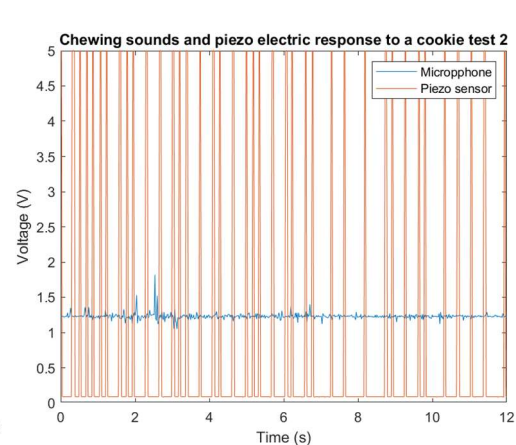
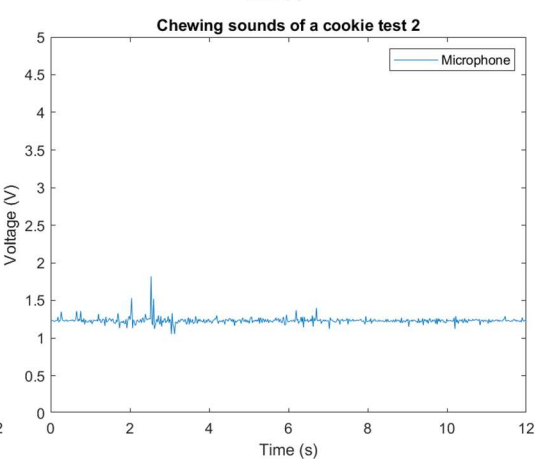
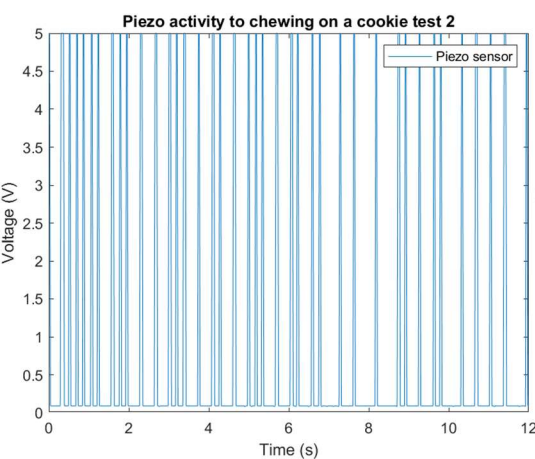
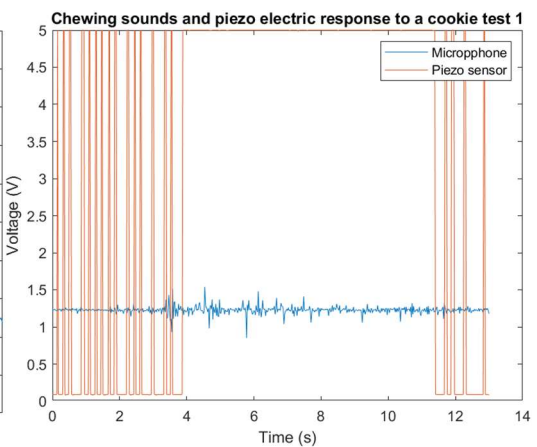
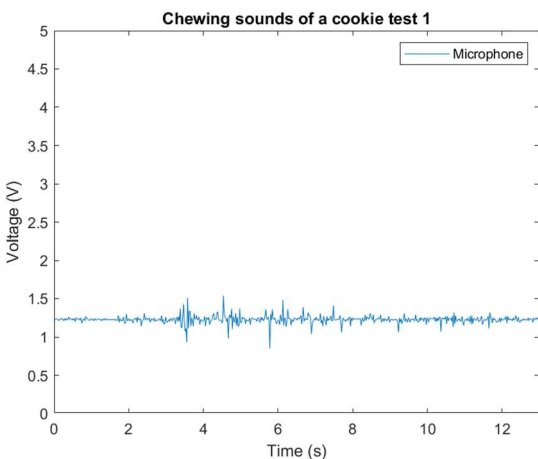
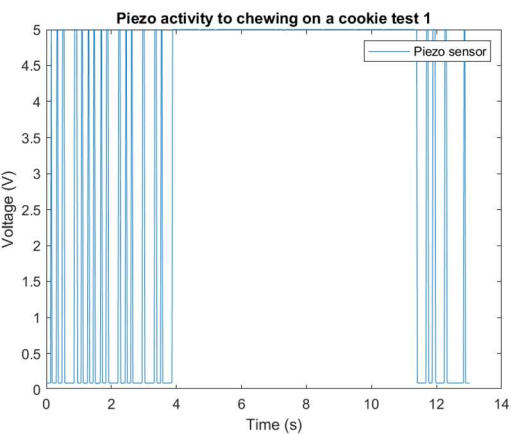
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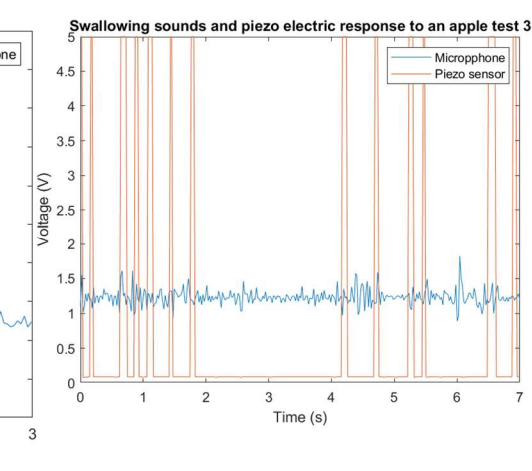
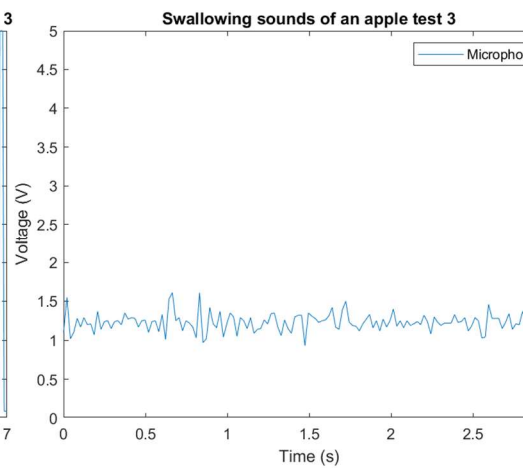
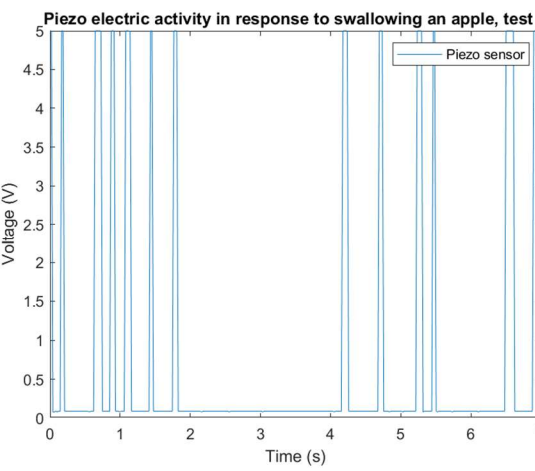
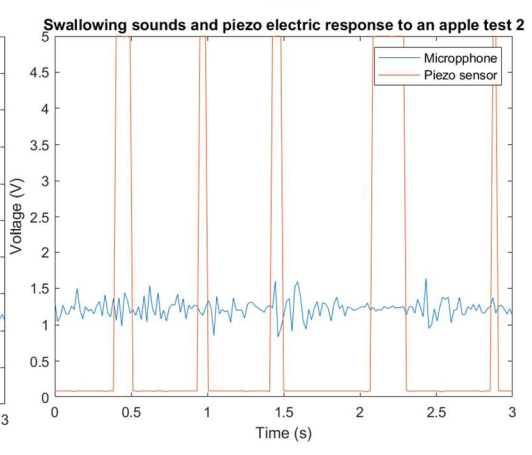
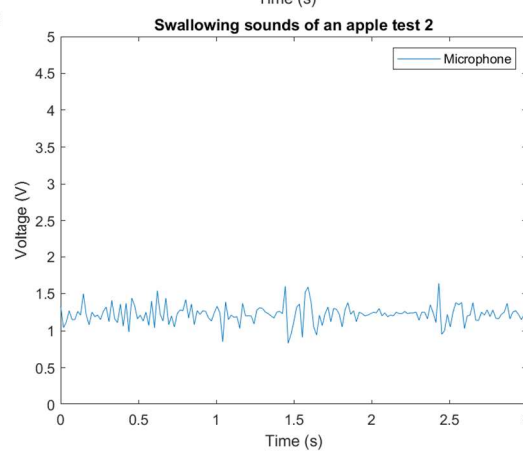
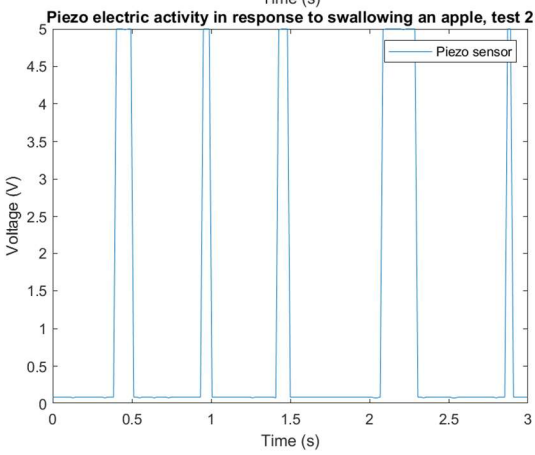
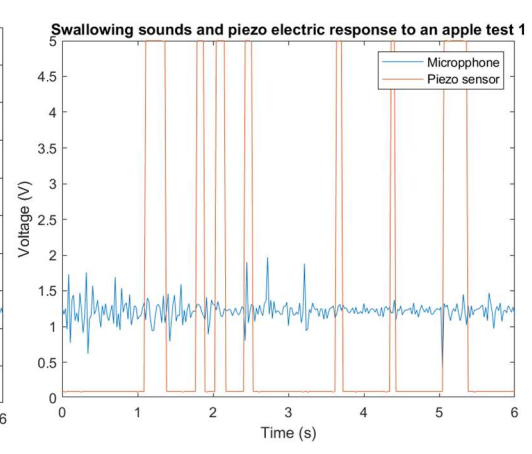
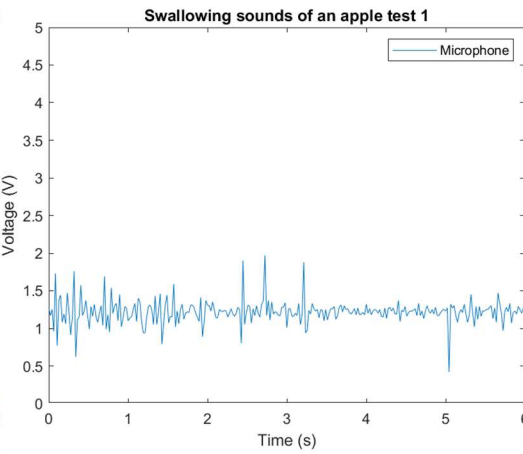
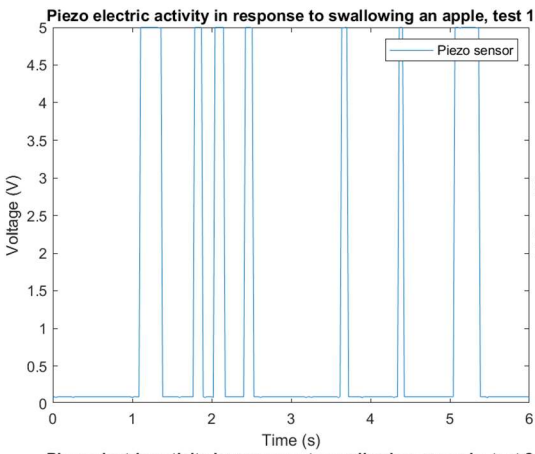
Appendix 3: All plots given by MATLAB

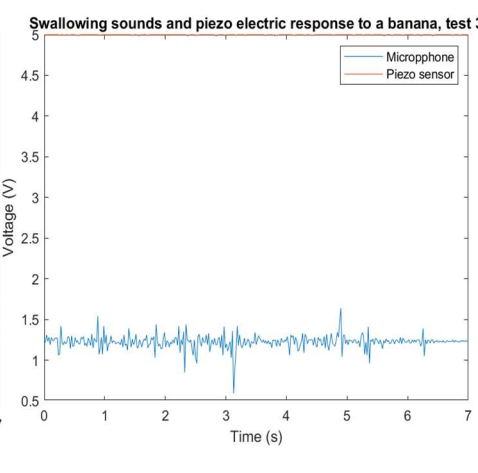
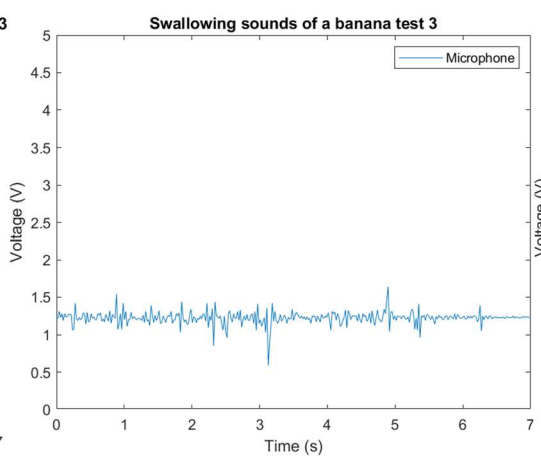
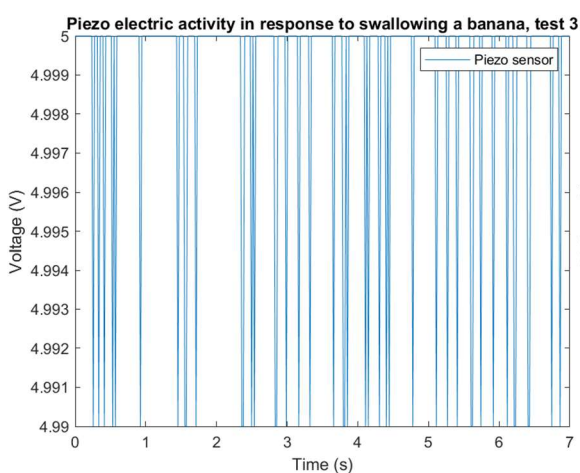
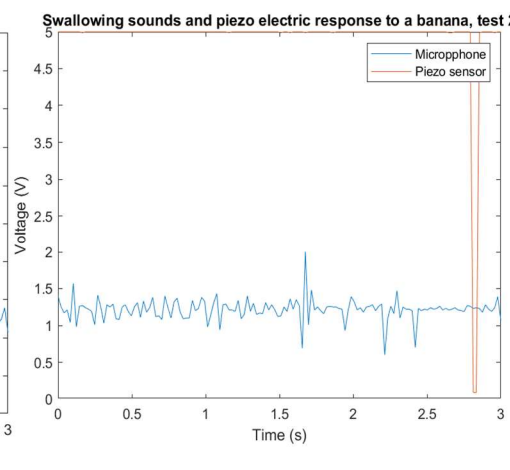
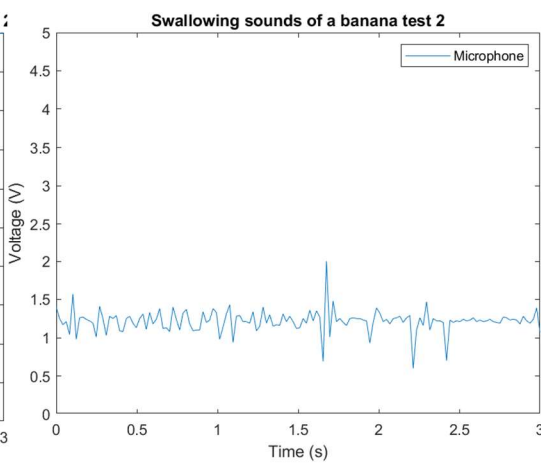
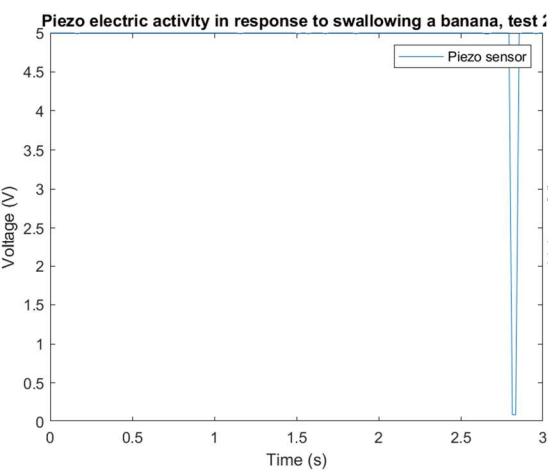
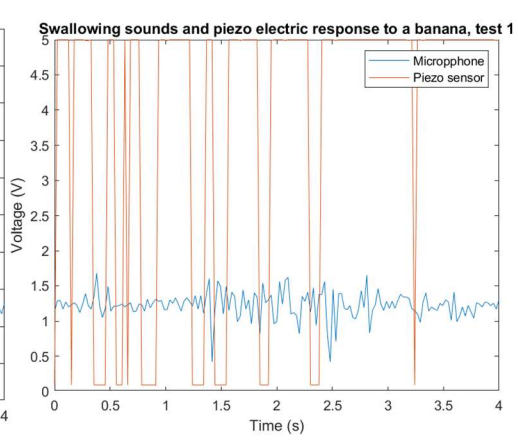
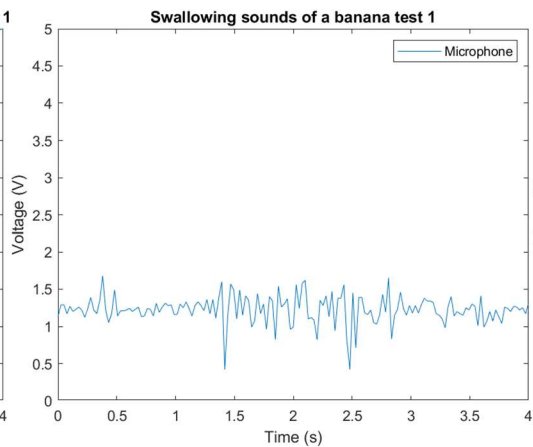
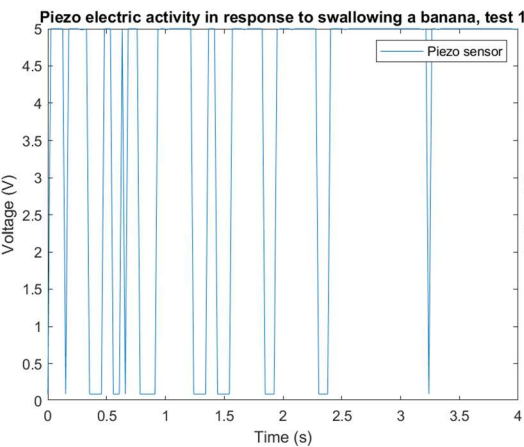


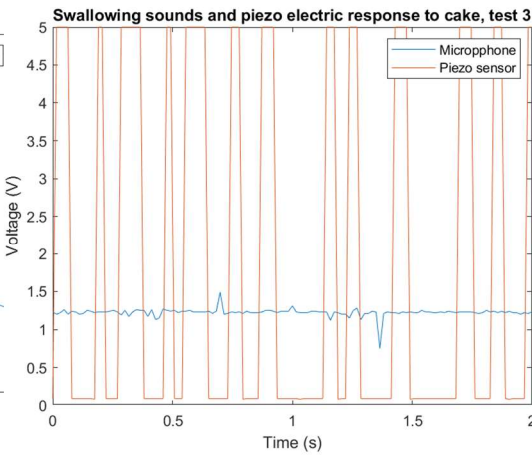
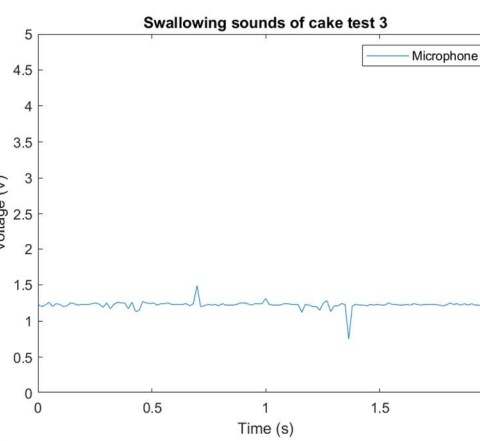
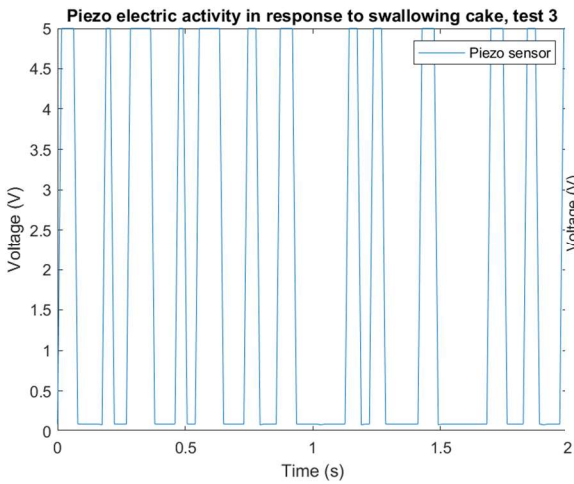
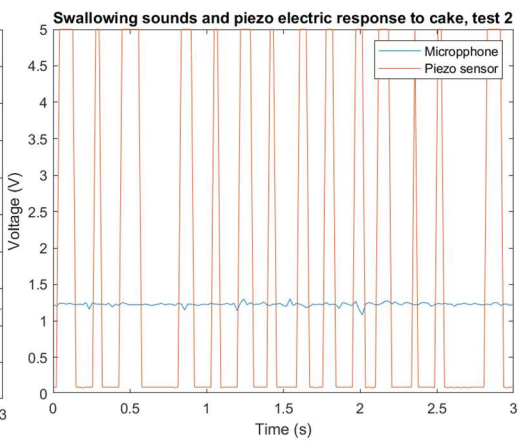
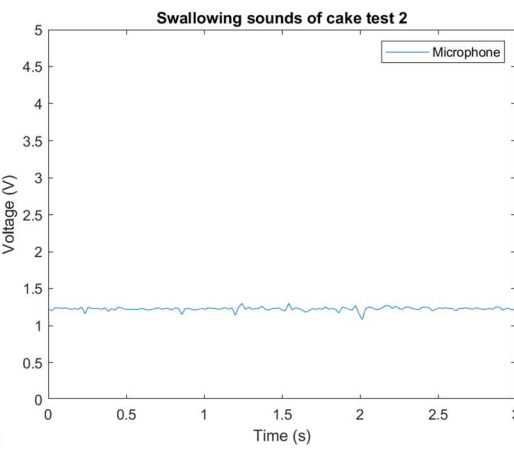
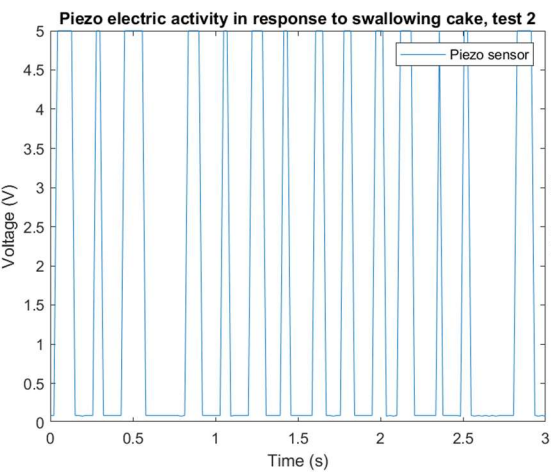
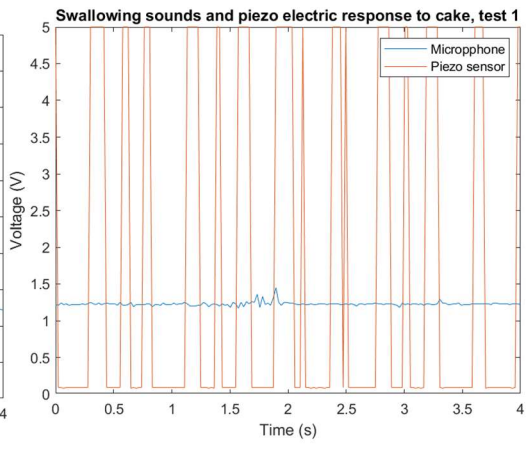
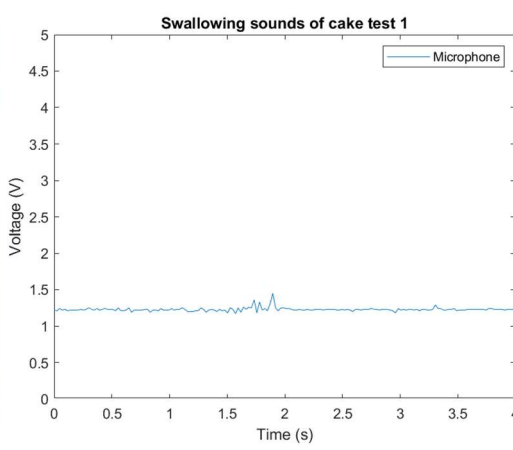
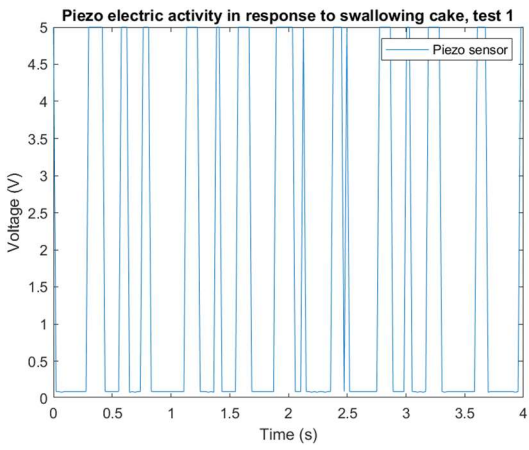


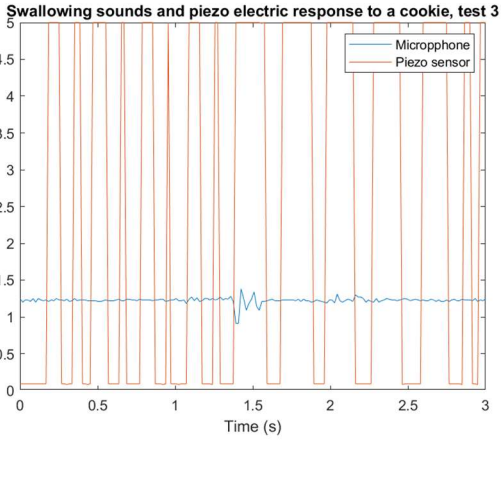
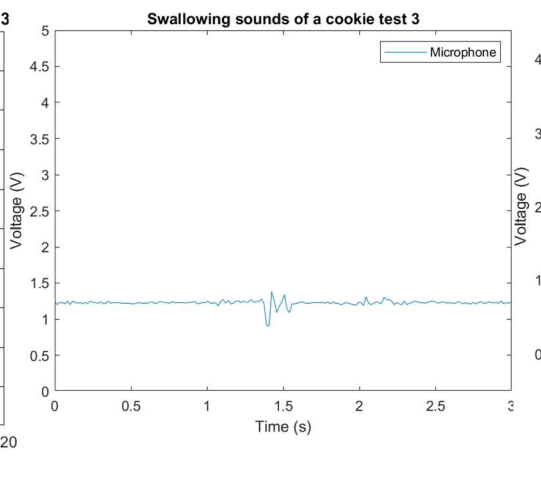
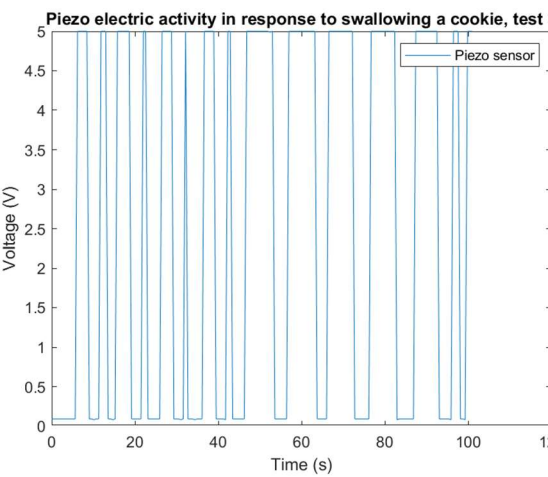
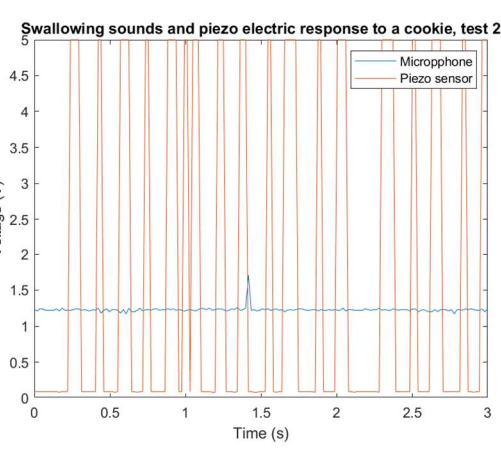
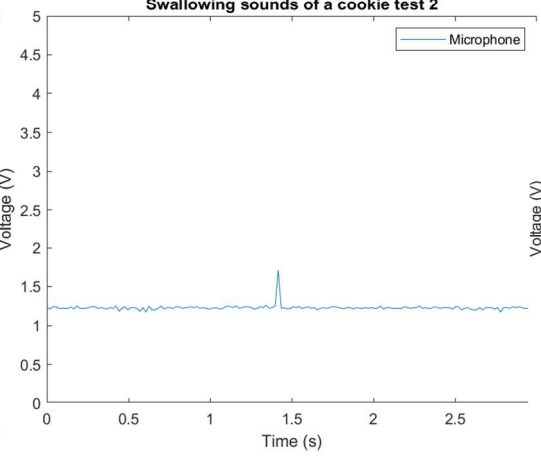
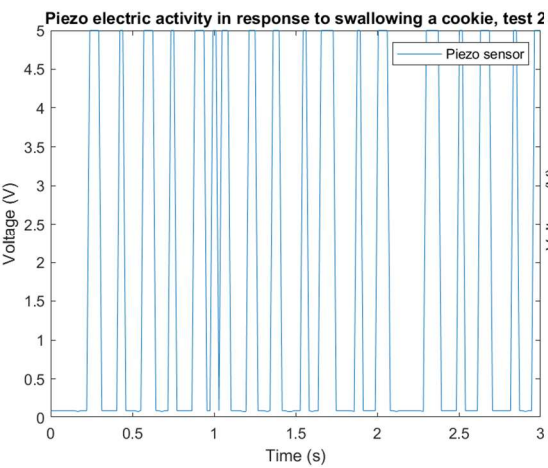
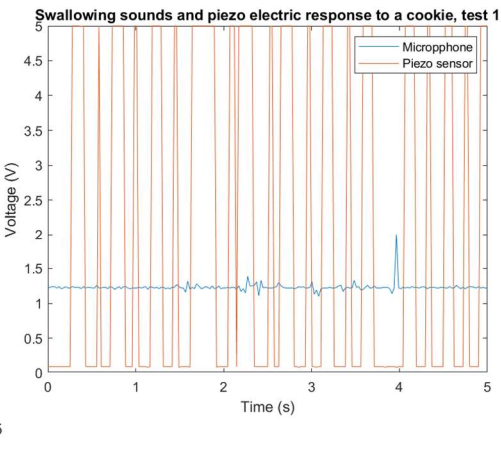
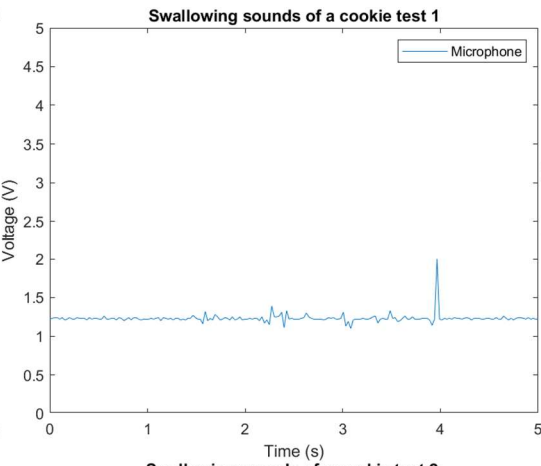
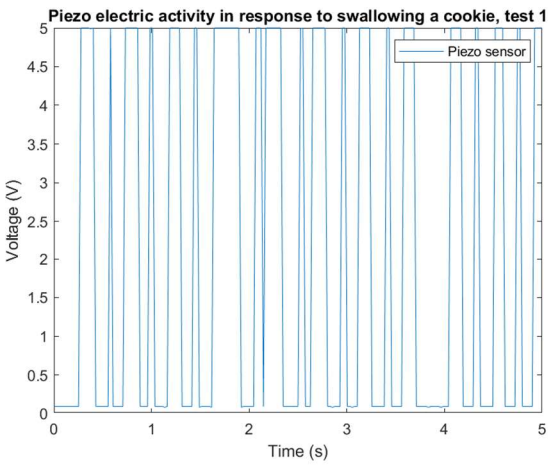












Appendix 4: Means of microphone data

Chewing

Means	Apple 1	Apple 2	Apple 3	Average
M1	1.2188	1.2242	1.2177	1.2202
M2	1.2173	1.2237	1.2184	1.2198
M3	1.2128	1.2204	1.2175	1.2169
M4	1.2170	1.2251	1.2174	1.2198
M5	1.2207	1.2250	1.2200	1.2219
M6	1.2195	1.2249	1.2208	1.2217
M7		1.2263		1.2263
Total average	1.2270	1.2242	1.2186	1.2233

Means	Banana 1	Banana 2	Banana 3	Average
M1	1.2503	1.2377	1.2351	1.2410
M2	1.2516	1.2346	1.2338	1.2400
M3	1.2366	1.2269	1.2330	1.2322
M4	1.2326	1.2259	1.2311	1.2300
M5	1.2288			1.2288
Average	1.2400	1.2313	1.2333	1.2349

Means	Cake 1	Cake 2	Cake 3	Cake 4
M1	1.2232	1.2312	1.2315	1.2286
M2	1.2229	1.2313	1.2315	1.2306
M3	1.2247	1.2285	1.2285	1.2272
M4	1.2247		1.2270	1.2259
M5			1.2263	1.2263
M6			1.2263	1.2263
Average	1.2239	1.2303	1.2285	1.2276

Means	Cookie 1	Cookie 2	Cookie 3	Average
M1	1.2278	1.2386	1.2182	1.2282
M2	1.2279	1.2386	1.2187	1.2284
M3	1.2274	1.2321	1.2222	1.2272
M4	1.2282	1.2314	1.2196	1.2264
M5	1.2280			1.2280
Average	1.2279	1.2352	1.2197	1.2276

Food type	Apple	Banana	Cake	Cookie
Average	1.2233	1.2349	1.2276	1.2276

Swallowing

Means	Apple 1	Apple 2	Apple 3	Average
M1	1.2067	1.2174	1.2307	1.2183
M2	1.2078	1.2163	1.2306	1.2118
M3	1.2206		1.2308	1.2257
Average	1.2117	1.2169	1.2307	1.2198

Means	Banana 1	Banana 2	Banana 3	Average
M1	1.2386	1.2193	1.2254	1.2278
M2	1.2426	1.2179	1.2272	1.2292
M3			1.2193	1.2193
Average	1.2406	1.2186	1.2240	1.2254

Means	Cake 1	Cake 2	Cake 3	Average
M1	1.2294	1.2259	1.2259	1.2271
M2	1.2297	1.2256		1.2277
Average	1.2296	1.2257	1.2259	1.2274

Means	Cookie 1	Cookie 2	Cookie 3	Average
M1	1.2285	1.2319	1.2222	1.2275
M2	1.2284	1.2317	1.2224	1.2275
Average	1.2285	1.2318	1.2223	1.2275

Means	Cake 1	Cake 2	Cake 3	Average
M1	1.2294	1.2259	1.2259	1.2271
M2	1.2297	1.2256		1.2277
Average	1.2296	1.2257	1.2259	1.2274

Means	Cookie 1	Cookie 2	Cookie 3	Average
M1	1.2285	1.2319	1.2222	1.2275
M2	1.2284	1.2317	1.2224	1.2275
Average	1.2285	1.2318	1.2223	1.2275

Food type	Apple	Banana	Cake	Cookie
Average	1.2198	1.2254	1.2274	1.2275

Appendix 5: Piezo electric frequency means

Chewing on an apple	Frequency (Hz) of peaks per second
Trial 1	36/18
Trail 2	36/20
Trail 3	29/18
Average	1.80

Chewing on a banana	Frequency (Hz) of peaks per second
Trial 1	38/15
Trial 2	45/11
Trial 3	60/11
Average	4.03

Chewing on cake	Frequency (Hz) of peaks per second
Trial 1	79/16
Trial 2	70/10
Trial 3	70/13
Average	5.77

Chewing on a cookie	Frequency (Hz) of peaks per second
Trial 1	19/13
Trial 2	40/12
Trial 3	38/12
Average	2.65

Swallowing an apple	Frequency (Hz) of peaks per second
Trial 1	8/6
Trial 2	13/7
Trial 2	5/3
Average	1.62

Swallowing a banana	Frequency (Hz) of peaks per second
Trial 1	11/4
Trial 2	1/3
Trial 3	34/7
Average	2.64

Swallowing cake	Frequency (Hz) of peaks per second
Trial 1	17/4
Trial 2	14/3
Trial 3	13/2
Average	15.41

Swallowing a cookie	Frequency (Hz) of peaks per second
Trial 1	20/5
Trial 2	18/3
Trial 3	15/3
Average	5.00

Summary:

Food type	Chewing frequency (Hz) of peaks per second	Swallowing frequency (Hz) of peaks per second
Apple	1.80	1.62
Banana	4.03	2.64
Cake	5.77	15.41
Cookie	2.65	5

Appendix 6: Results from the statistical analysis

Anova: Single Factor between the different chewing on apple trials						
SUMMARY						
<i>Groups</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>		
0.2367	103	11.9601	0.116117	0.012898		
0.0467	103	14.4901	0.140681	0.027536		
0.2067	103	10.1101	0.098156	0.009732		
ANOVA						
<i>Source of Variation</i>	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between Groups	0.093876	2	0.046938	2.806982	0.061943	3.025253
Within Groups	5.116915	306	0.016722			
Total	5.210791	308				

Anova: Single Factor of differences between chewing on banana trials						
SUMMARY						
<i>Groups</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>		
0.0551	57	6.0407	0.105977	0.015569		
0.0451	57	9.2407	0.162118	0.019646		
0.0451	57	5.9307	0.104047	0.013424		
ANOVA						
<i>Source of Variation</i>	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between Groups	0.124025	2	0.062012	3.824846	0.023746	3.049792
Within Groups	2.723786	168	0.016213			
Total	2.847811	170				

Anova: Single Factor of differences between chewing on cake trials						
SUMMARY						
<i>Groups</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>		
0.0724	78	1.2272	0.015733	0.000181		
0.0024	78	1.6072	0.020605	0.00188		
0.0424	78	1.5372	0.019708	0.001056		
ANOVA						
<i>Source of Variation</i>	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between Groups	0.001049	2	0.000524	0.50466	0.604375	3.034921
Within Groups	0.240017	231	0.001039			
Total	0.241065	233				

Anova: Single Factor of differences between chewing on cookie trials						
SUMMARY						
<i>Groups</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>		
0.0124	84	2.4216	0.028829	0.002308		
0.0024	84	1.4216	0.016924	0.001148		
0.0024	84	5.2816	0.062876	0.007426		
ANOVA						
<i>Source of Variation</i>	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between Groups	0.095552	2	0.047776	13.17139	3.65E-06	3.032065
Within Groups	0.90319	249	0.003627			
Total	0.998743	251				

Anova: Single Factor between chewing of all food types						
SUMMARY						
<i>Groups</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>		
Column 1	312	37.0504	0.11875	0.01684		
Column 2	116	15.2616	0.13157	0.01707		
Column 3	237	4.4888	0.01894	0.00104		
Column 4	170	6.708	0.03946	0.00475		
ANOVA						
<i>Source of Variation</i>	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between Groups	1.92701	3	0.64234	64.71	1.3E-37	2.61562
Within Groups	8.24883	831	0.00993			
Total	10.1758	834				

t-Test: Two-Sample Assuming Equal Variances of chewing on apple and banana		
	Variable 1	Variable 2
Mean	0.11875	0.13157
Variance	0.01684	0.01707
Observations	312	116
Pooled Variance	0.0169	
Hypothesized Mean Difference	0	
df	426	
t Stat	-0.9063	
P(T<=t) one-tail	0.18264	
t Critical one-tail	1.64844	
P(T<=t) two-tail	0.36527	
t Critical two-tail	1.96555	

t-Test: Two-Sample Assuming Equal Variances between chewing on waffle cake and cookies		
	Variable 1	Variable 2
Mean	0.01894	0.03946
Variance	0.00104	0.00475
Observations	237	170
Pooled Variance	0.00259	
Hypothesized Mean Difference	0	
df	405	
t Stat	-4.0135	
P(T<=t) one-tail	3.6E-05	
t Critical one-tail	1.64862	
P(T<=t) two-tail	7.1E-05	
t Critical two-tail	1.96584	

t-Test: Two-Sample Assuming Equal Variances of chewing on apple and cookie

	<i>Variable 1</i>	<i>Variable 2</i>
Mean	0.11875	0.03946
Variance	0.01684	0.00475
Observations	312	170
Pooled Variance	0.01259	
Hypothesized Mean Difference	0	
df	480	
t Stat	7.41452	
P(T<=t) one-tail	2.8E-13	
t Critical one-tail	1.64803	
P(T<=t) two-tail	5.6E-13	
t Critical two-tail	1.96492	

t-Test: Two-Sample Assuming Equal Variances of chewing on cake and banana

	<i>Variable 1</i>	<i>Variable 2</i>
Mean	0.01894	0.13157
Variance	0.00104	0.01707
Observations	237	116
Pooled Variance	0.00629	
Hypothesized Mean Difference	0	
df	351	
t Stat	-12.532	
P(T<=t) one-tail	2.5E-30	
t Critical one-tail	1.64921	
P(T<=t) two-tail	5E-30	
t Critical two-tail	1.96675	

Anova: Single Factor of piezoelectric data between trials of chewing on apples							t-Test of piezoelectric data on chewing on apples		
SUMMARY									
Groups	Count	Sum	Average	Variance				Variable 1	Variable 2
Column 1	864	1618.54	1.87331	5.579258				Mean	0.881958 0.95277
Column 2	991	874.02	0.881958	3.267246				Variance	3.267246 3.498114
Column 3	870	828.91	0.95277	3.498114				Observations	991 870
ANOVA									
Source of Variation	SS	df	MS	F	P-value	F crit			
Between Groups	544.1365717	2	272.0683	66.78218	0	2.999032	Pooled Variance		
Within Groups	11089.33416	2722	4.073966				Hypothesized Mean Difference		
Total	11633.47073	2724				df			
							t Stat		
							P(T<=t) one-tail		
							t Critical one-tail		
							P(T<=t) two-tail		
							t Critical two-tail		

Anova: Single Factor of piezoelectric data between trials of chewing on banana							t-Test of piezoelectric data on chewing on banana		
SUMMARY									
Groups	Count	Sum	Average	Variance				Variable 1	Variable 2
CBT1	723	2912.36	4.02816	3.829644				Mean	1.640773 1.420195
CBT2	440	721.94	1.640773	5.220261				Variance	5.220261 4.761396
CBT3	512	727.14	1.420195	4.761396				Observations	440 512
ANOVA									
Source of Variation	SS	df	MS	F	P-value	F crit	Pooled Variance		
Between Groups	2592.161	2	1296.08	289.3342	1.2E-108	3.001106	Hypothesized Mean Difference		
Within Groups	7489.771	1672	4.479528				df		
Total	10081.93	1674				t Stat			
							P(T<=t) one-tail		
							t Critical one-tail		
							P(T<=t) two-tail		
							t Critical two-tail		

Anova: Single Factor of piezoelectric data between trials of chewing on cake						
SUMMARY						
Groups	Count	Sum	Average	Variance		
CCT1	588	1407.93	2.394439	6.015525		
CCT2	490	1099.58	2.244041	5.949901		
CCT3	750	1834.82	2.446427	6.026919		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	12.45179	2	6.225893	1.037196	0.354656	3.000655
Within Groups	10954.78	1825	6.002618			
Total	10967.23	1827				

Anova: Single Factor of piezoelectric data between trials of chewing on cookies							t-Test of piezoelectric data on chewing on cookies		
SUMMARY									
Groups	Count	Sum	Average	Variance				Variable 1	Variable 2
CCOT1	597	1983.11	3.321792	5.432146				Mean	0.874643 1.061226
CCOT2	588	514.29	0.874643	3.243537				Variance	3.243537 3.833897
CCOT3	465	493.47	1.061226	3.833897				Observations	588 465
ANOVA									
Source of Variation	SS	df	MS	F	P-value	F crit	Pooled Variance		
Between Groups	2139.587	2	1069.793	254.6007	4.51E-97	3.001188	Hypothesized Mean Difference		
Within Groups	6920.444	1647	4.201848				df		
Total	9060.03	1649				t Stat			
							P(T<=t) one-tail		
							t Critical one-tail		
							P(T<=t) two-tail		
							t Critical two-tail		

Anova: Single Factor comparison of piezoelectric data during chewing between all food types

SUMMARY

Groups	Count	Sum	Average	Variance
CA	1861	1702.93	0.915062	3.374601
CB	952	1449.08	1.522143	4.980317
CC	1828	4342.33	2.375454	6.002862
CCO	1053	1007.76	0.957037	3.509433

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	2348.396	3	782.7987	173.5	1.2E-107	2.60647
Within Groups	25672.19	5690	4.511809			
Total	28020.59	5693				

t-Test: comparing the piezoelectric data of chewing on apples and bananas

	Variable 1	Variable 2
Mean	0.915062	1.518496
Variance	3.374601	4.972887
Observations	1861	951
Pooled Variance	3.914947	
Hypothesized Mean Difference	0	
df	2810	
t Stat	-7.65108	
P(T<=t) one-tail	1.36E-14	
t Critical one-tail	1.645396	
P(T<=t) two-tail	2.72E-14	
t Critical two-tail	1.960809	

t-Test: comparing the piezoelectric data of chewing on waffle cake and cookies

	Variable 1	Variable 2
Mean	2.375454	0.957037
Variance	6.002862	3.509433
Observations	1828	1053
Pooled Variance	5.091752	
Hypothesized Mean Difference	0	
df	2879	
t Stat	16.24804	
P(T<=t) one-tail	3.62E-57	
t Critical one-tail	1.645383	
P(T<=t) two-tail	7.24E-57	
t Critical two-tail	1.960788	

t-Test: comparing the piezoelectric data of chewing on apples and cookies		
	<i>Variable 1</i>	<i>Variable 2</i>
Mean	0.91506	0.95704
Variance	3.3746	3.50943
Observations	1861	1053
Pooled Variance	3.42331	
Hypothesized Mean Difference	0	
df	2912	
t Stat	-0.5883	
P(T<=t) one-tail	0.27818	
t Critical one-tail	1.64538	
P(T<=t) two-tail	0.55636	
t Critical two-tail	1.96078	

t-Test: comparing the piezoelectric data of chewing on bananas and waffle cake		
	<i>Variable 1</i>	<i>Variable 2</i>
Mean	1.52214	2.37545
Variance	4.98032	6.00286
Observations	952	1828
Pooled Variance	5.65281	
Hypothesized Mean Difference	0	
df	2778	
t Stat	-8.9796	
P(T<=t) one-tail	2.4E-19	
t Critical one-tail	1.6454	
P(T<=t) two-tail	4.9E-19	
t Critical two-tail	1.96082	

Anova: Single Factor of piezoelectric data between trials of swallowing apples						
SUMMARY						
Groups	Count	Sum	Average	Variance		
SAT1	200	179.88	0.8994	3.337932		
SAT2	165	147.25	0.892424	3.318821		
SAT3	338	241.38	0.714142	2.684821		
ANOVA						
Source of Varia	SS	df	MS	F	P-value	F crit
Between C	5.824037	2	2.912018	0.964555	0.381659	3.00859
Within Grc	2113.32	700	3.019028			
Total	2119.144	702				

Anova: Single Factor of piezoelectric data between trials of swallowing bananas						
SUMMARY						
Groups	Count	Sum	Average	Variance		
0.09	158	618.03	3.911582	4.182226		
5	145	715.08	4.931586	0.330129		
5	356	1779.57	4.998792	1.06E-05		
ANOVA						
Source of Varia	SS	df	MS	F	P-value	F crit
Between C	137.4134	2	68.70672	64.00837	4.03E-26	3.009455
Within Grc	704.1518	656	1.073402			
Total	841.5653	658				

Anova: Single Factor of piezoelectric data between trials of swallowing waffle cake						
SUMMARY						
Groups	Count	Sum	Average	Variance		
SCT1	174	290.49	1.669483	5.294599		
SCT2	141	238.42	1.690922	5.339984		
SCT3	127	237.23	1.867953	5.61517		
ANOVA						
Source of Varia	SS	df	MS	F	P-value	F crit
Between C	3.264543	2	1.632272	0.302212	0.739335	3.016268
Within Grc	2371.075	439	5.401082			
Total	2374.339	441				

Anova: Single Factor of piezoelectric data between trials of swallowing on cookies							t-Test of piezoelectric data on swallowing on cookies		
SUMMARY									
Groups	Count	Sum	Average	Variance			Variable 1	Variable 2	
SCOT1	199	420.42	2.112663	5.870851			Mean	2.112663	1.765793
SCOT2	164	289.59	1.765793	5.457036			Variance	5.870851	5.457036
SCOT3	180	462.92	2.571778	6.0619			Observations	199	164
ANOVA							Pooled Variance	5.684004	
Source of Varia	SS	df	MS	F	P-value	F crit	Hypothesized Mean Difference	0	
Between C	56.45238	2	28.22619	4.858819	0.008102	3.012413	df	361	
Within Grc	3137.005	540	5.809269				t Stat	1.379544	
Total	3193.458	542					P(T<=t) one-tail	0.084291	
							t Critical one-tail	1.649086	
							P(T<=t) two-tail	0.168581	
							t Critical two-tail	1.966557	

Anova: Single Factor comparison of piezoelectric data during swallowing between all food types						
SUMMARY						
Groups	Count	Sum	Average	Variance		
SA	703	568.51	0.808691	3.018723		
SB	356	1779.57	4.998792	1.06E-05		
SC	442	766.14	1.733348	5.38399		
SCO	363	710.01	1.95595	5.698184		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	4226.294	3	1408.765	399.666	2.5E-200	2.609687
Within Groups	6556.23	1860	3.524855			
Total	10782.52	1863				

t-Test: comparing the piezoelectric data of swallowing apples and bananas

	Variable 1	Variable 2
Mean	0.80869	4.99879
Variance	3.01872	1.1E-05
Observations	703	356
Pooled Variance	2.00487	
Hypothesized Mean Difference	0	
df	1057	
t Stat	-45.4921	
P(T<=t) one-tail	2E-251	
t Critical one-tail	1.6463	
P(T<=t) two-tail	4E-251	
t Critical two-tail	1.96221	

t-Test: comparing the piezoelectric data of swallong waffle cake and cookies

	Variable 1	Variable 2
Mean	1.73335	1.95595
Variance	5.38399	5.69818
Observations	442	363
Pooled Variance	5.52563	
Hypothesized Mean Difference	0	
df	803	
t Stat	-1.33692	
P(T<=t) one-tail	0.09081	
t Critical one-tail	1.64675	
P(T<=t) two-tail	0.18163	
t Critical two-tail	1.96292	

t-Test: comparing the piezoelectric data of swallowing apples and cookies

	<i>Variable 1</i>	<i>Variable 2</i>
Mean	0.80869	1.95595
Variance	3.01872	5.69818
Observations	703	363
Pooled Variance	3.93034	
Hypothesized Mean Difference	0	
df	1064	
t Stat	-8.95362	
P(T<=t) one-tail	7.5E-19	
t Critical one-tail	1.64629	
P(T<=t) two-tail	1.5E-18	
t Critical two-tail	1.9622	

t-Test: comparing the piezoelectric data of swallowing bananas and waffle cake

	<i>Variable 1</i>	<i>Variable 2</i>
Mean	4.99879	1.73335
Variance	1.1E-05	5.38399
Observations	356	442
Pooled Variance	2.98284	
Hypothesized Mean Difference	0	
df	796	
t Stat	26.5498	
P(T<=t) one-tail	5E-112	
t Critical one-tail	1.64677	
P(T<=t) two-tail	1E-111	
t Critical two-tail	1.96295	

Anova: Single Factor of differences between trials of swallowing apples						
SUMMARY						
Groups	Count	Sum	Average	Variance		
0.1502	24	3.2448	0.1352	0.030739		
0.0402	24	2.2448	0.093533	0.006632		
0.0702	24	1.4948	0.062283	0.002869		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.064236	2	0.032118	2.394464	0.098764	3.129644
Within Groups	0.925529	69	0.013413			
Total	0.989765	71				

Anova: Single Factor of differences between trials of swallowing a banana						
SUMMARY						
Groups	Count	Sum	Average	Variance		
0.0346	14	2.4444	0.1746	0.018708		
0.0346	14	1.4944	0.106743	0.007049		
0.0146	14	0.7744	0.055314	0.002669		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.100233	2	0.050117	5.289307	0.009279	3.238096
Within Groups	0.369529	39	0.009475			
Total	0.469762	41				

Anova: Single Factor of differences between trials of swallowing cake						
SUMMARY						
<i>Groups</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>		
0.0026	24	0.1924	0.008017	6.94E-05		
0.0226	24	0.3724	0.015517	0.000309		
0.0126	24	0.2124	0.00885	7.66E-05		
ANOVA						
<i>Source of Variation</i>	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between Groups	0.000811	2	0.000406	2.676764	0.075926	3.129644
Within Groups	0.010454	69	0.000152			
Total	0.011265	71				

Anova: Single Factor of difference between trials of swallowing a cookie						
SUMMARY						
<i>Groups</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>		
0.0125	31	0.5775	0.018629	0.000691		
0.0125	31	0.6575	0.02121	0.007358		
0.0025	31	0.3475	0.01121	0.000145		
ANOVA						
<i>Source of Variation</i>	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between Groups	0.001671	2	0.000835	0.305873	0.737242	3.097698
Within Groups	0.245832	90	0.002731			
Total	0.247503	92				

t-Test: Two-Sample Assuming Equal Variances between swallowing apple and bananas		
	<i>Variable 1</i>	<i>Variable 2</i>
Mean	0.0966	0.1336
Variance	0.013467	0.013382
Observations	75	30
Pooled Variance	0.013443	
Hypothesized Mean Difference	0	
df	103	
t Stat	-1.47725	
P(T<=t) one-tail	0.071329	
t Critical one-tail	1.659782	
P(T<=t) two-tail	0.142659	
t Critical two-tail	1.983264	

t-Test: Two-Sample Assuming Equal Variances between swallowing Cake and Cookies		
	<i>Variable 1</i>	<i>Variable 2</i>
Mean	0.010867	0.016771
Variance	0.000155	0.002608
Observations	75	96
Pooled Variance	0.001534	
Hypothesized Mean Difference	0	
df	169	
t Stat	-0.97821	
P(T<=t) one-tail	0.164684	
t Critical one-tail	1.65392	
P(T<=t) two-tail	0.329368	
t Critical two-tail	1.9741	

t-Test: Two-Sample Assuming Equal Variances between swallowing apple and cookies		
	<i>Variable 1</i>	<i>Variable 2</i>
Mean	0.0966	0.016771
Variance	0.013467	0.002608
Observations	75	96
Pooled Variance	0.007363	
Hypothesized Mean Difference	0	
df	169	
t Stat	6.036909	
P(T<=t) one-tail	4.84E-09	
t Critical one-tail	1.65392	
P(T<=t) two-tail	9.67E-09	
t Critical two-tail	1.9741	

t-Test: Two-Sample Assuming Equal Variances between swallowing bananas and waffle cake		
	<i>Variable 1</i>	<i>Variable 2</i>
Mean	0.1336	0.010867
Variance	0.013382	0.000155
Observations	30	75
Pooled Variance	0.003879	
Hypothesized Mean Difference	0	
df	103	
t Stat	9.122105	
P(T<=t) one-tail	3.3E-15	
t Critical one-tail	1.659782	
P(T<=t) two-tail	6.61E-15	
t Critical two-tail	1.983264	

Anova: Single Factor of swallowing all food types						
SUMMARY						
Groups	Count	Sum	Average	Variance		
Column 1	75	7.245	0.0966	0.013467		
Column 2	30	4.008	0.1336	0.013382		
Column 3	75	0.815	0.010867	0.000155		
Column 4	96	1.61	0.016771	0.002608		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.593339	3	0.19778	32.72623	4.3E-18	2.637791
Within Groups	1.643822	272	0.006043			
Total	2.237161	275				

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