International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2
DOI: https://doi.org/10.17762/ijritcc.v11i2.6109
***Article Received**: 12 December 2022 **Revised**: 17 January 2023 **Accepted**: 24 January 2023*

SDAV 1.0: A Low-Cost sEMG Data Acquisition & Processing System For Rehabilitation

[1]Rajendra Kachhwaha, [2]Ajay P Vyas, [2]Rajesh Bhadada, [3]Rajendra Kachhwaha
[1]Department of CSE, MBM University
Jodhpur, India
e-mail: rajendra1983@gmail.com
[2]Department of ECE, MBM University
Jodhpur, India
e-mail: ajaypvyas@gmail.com, rajesh_bhadada@rediffmail.com
[3]Department of Physiotherapy, Narayan Hrudayalaya Institute of Physiotherapy
Bengaluru, India
e-mail: rajendra.physio88@gmail.com

Abstract— Over the last two decades, myoelectric signals have been widely used in fields including rehabilitation devices and human-machine interfaces. This study aimed to develop an algorithm for surface electromyography (sEMG) data acquisition utilizing low-cost hardware and validate its performance using English vowels as silent speech content. The sEMG data were collected from the three facial muscles of one healthy subject. The sEMG signals were pre-processed, and various time-domain and statistical features were extracted in real time. The raw data and features were then used to train and test three customized machine learning classifiers: k-nearest neighbor (KNN), support vector machine (SVM), and artificial neural network (ANN). All customized classifiers achieved almost equivalent accuracy rates of 0.83 ± 0.01 in recognizing the English vowels with an improvement of 27.27% (KNN), 3.75% (SVM), and 51.85% (ANN) utilizing the same low-cost data acquisition hardware. Our findings are substantially closers to the results of commercial hardware setups, which raise the possibility of potential usage of low-cost sEMG data acquisition systems with the proposed algorithm in place of commercial hardware setups for rehabilitation devices and other related sectors of human-machine interaction.

Keywords- Surface electromyography (sEMG); Low-cost data acquisition system; Silent speech; English vowels; Classification; Rehabilitation;

I. INTRODUCTION

During the past two decades, rehabilitation devices, clinical prostheses, and human-machine interfaces (HMIs) have all made substantial use of myoelectric control signals to assist people with impairments in regaining the ability to manage items in their daily lives. Hand prostheses, deaf interpreters, silent voice interfaces, human-computer interfaces, and many more come under this category. Myoelectric is based on the physiological idea that when human muscle contracts or flexes, a small electrical signal is created from which signature-like information may be retrieved to identify the action [1, 2]. Electromyography (EMG) records electrical activity caused by muscle contractions acquired by putting electrodes on the skin's surface. This non-invasive recording of electromyograms is known as surface electromyography (sEMG) [3, 4]. Such myoelectric signals are sophisticated and non-stationary and can be expressed as equ (1) [5, 6]:

$$s(t) = \sum_{j} \mathrm{MUAP\ T_j(t)} + \mathrm{n(t)}$$
$$= \sum_{j}\sum_{i} \mathrm{k_j}\, f_{\mathrm{i}}\left(\frac{t - \Theta_{\mathrm{ij}}}{\alpha_{\mathrm{j}}}\right) + \mathrm{n(t)} \qquad (1)$$

where: k_j is an amplitude factor for the j^{th} motor unit, f(i) the shape of the action potential discharge, Θ_{ij} the occurrence time of motor unit action potential (MUAP), α_j a scaling factor, and n(t) represents the additive noise.

sEMG signals can be measured in various ways, including single differential, bipolar, and common mode rejection. Single differential measurement involves placing two electrodes on the skin surface above the muscle, with one electrode recording the electrical potential and the other serving as a reference. Bipolar measurement involves placing two electrodes on the skin surface above the muscle, with one electrode measuring the electrical potential between the two electrodes. Common mode rejection is a technique that eliminates noise and interference from the sEMG signal by subtracting the electrical potential at one electrode from the electrical potential at the other. sEMG is commonly used in various fields, including medicine, sports science, rehabilitation, and ergonomics, to evaluate muscle function, diagnose muscle disorders, monitor muscle activity during physical activity, and design ergonomic equipment. Fig 1 demonstrates the general approach for generating assistive devices utilizing sEMG signals. It is critical to consider the four primary cascade modules: identifying the exact muscle

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2
DOI: https://doi.org/10.17762/ijritcc.v11i2.6109
***Article Received**: 12 December 2022 **Revised**: 17 January 2023 **Accepted**: 24 January 2023*

pickup point, data acquisition followed by pre-processing, feature extraction, and classification.

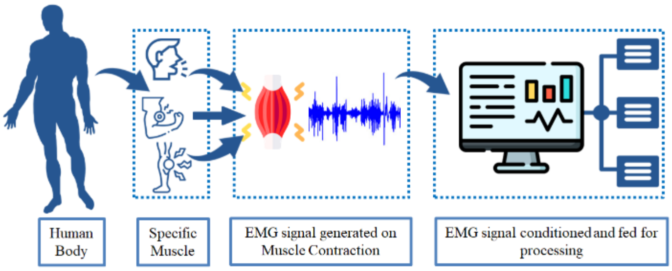


Figure. 1 Stage of sEMG signal processing

In order to improve real-time data gathering and feature computation using commercial or low-cost hardware, several methods have been developed. The raw data or chosen features are the key kernels utilized in studying EMG signals to gain improved classification accuracy. The system's primary goal would be to quickly and precisely record data for all actions and respond accordingly.

Regarding sEMG data acquisition, most research groups depended on various commercial products available for sEMG data acquisition, including MyoResearch XP Master Edition, Delsys Trigno wireless EMG system, Gtec g.USBamp, Bagnoli EMG system, the Noraxon, the Myon GmbH Myon wireless EMG system, and the TMSi wireless sEMG systems. These systems typically include the sEMG sensors and amplifiers and may also include data analysis and visualization software [5, 6]. However, several Arduino-based/ Raspberry Pi-based low-cost products are available for sEMG data acquisition systems. Software packages like EMG Works, OpenViBE, and MyoLua can use low-cost sEMG sensors and amplifiers to create a low-cost data acquisition system. It is worth noting that the cost of the system is not the only factor to consider when choosing an sEMG data acquisition system; the quality of the data obtained and the required features of the system should also be taken into account. Improved sEMG pattern recognition classification performance relies on feature extraction for sEMG analysis. This requires converting the raw EMG signals into a feature vector. The three principal kinds of features utilized in the analysis of sEMG data are time-domain (TD) features, frequency-domain (FrD) features, and time-frequency-domain (TFD) features. In the case of TD features, feature assessment is based on the amplitude of a time-varying signal. The signal amplitude during analysis is affected by muscle states and types. Furthermore, no further signal alteration is necessary to use these features. FrD features, unlike TD features, are created using parametric approaches or a periodogram and contain the power spectrum density (PSD) of the signals being analyzed. In contrast, TFD characteristics are described as a combination of time and frequency data. Because of their capacity to represent information at varied frequencies across multiple time locations, TFD features may characterize a richness of non-stationary data in the analyzed signals [6]. Various research groups have investigated the complicated structure of sEMG signals using commercial or low-cost setups. Witman et al. [7, 8] examined it for recognizing finger movement and interpreting the alphabet of sign language; Kumar et al. [9], Arjunan et al. [10, 11], Naik et al. [12], Meltzner et al. [13], Larraz et al. [14], Agnihotri et al. [15], Vyas et al. [16], Kachhwaha et al. [17], and Chandrashekhar [18] explored it for silent speech content recognition; Russo et al. [19] studied it for a prosthetic robotic hand; Sidik et al. [20] and Kareem et al. [21] probed it to acquire lower arm motion, and Crawford et al. [22] used it to capture facial expressions. Due to its non-invasive, safe, and effective method for measuring muscle activity, sEMG is a valuable tool for evaluating muscle function, diagnosing muscle disorders, monitoring muscle activity during physical activity, and designing ergonomic equipment. Several studies have been conducted on low-cost sEMG data acquisition systems, focusing on various aspects such as data collection, sensor design, signal processing, feature extraction, and data analysis. According to research findings presented by [16, 20, 21], authors recommend that complex algorithms capable of performing many jobs concurrently were required to gather accurate data in low-cost setups. According to [7, 8, 16], individuals have difficulty computing features and their storage in real-time as data is captured utilizing low-cost equipment. This real-time feature vector computation task encourages us to develop an algorithm utilizing low-cost hardware for sEMG data acquisition. This allows us to capture sEMG data, compute customized features as soon as data is acquired, and store the computed features and raw data in a CSV(comma-separated values) file to disk for further classification. In addition to the low-cost option for collecting sEMG data, we looked at MyoWare Muscle (MWM) sensor from Advancer Technologies [23-25] to help the general public. The MWM sensor is a small, low-cost, and flexible sensor that can be placed directly on the skin to detect the electrical activity of a muscle. Several research findings [7, 8, 18-22] have shown the MWM sensor's dependability and suitability for usage in sEMG data acquisition. The MWM sensor has the added benefit of being far less expensive than the commercial sEMG recording setup. To showcase the efficacy of our proposed solution, we picked the field of silent speech recognition (SSR) since it is the most natural and powerful form of human communication, and there is a significant amount of research on the topic. The field of study known as SSR examines what happens when subjects do not use their spoken voices while completing tasks designed to test their comprehension of a particular language. This phenomenon has been studied in recent years as a way to

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2
DOI: https://doi.org/10.17762/ijritcc.v11i2.6109
***Article Received**: 12 December 2022 **Revised**: 17 January 2023 **Accepted**: 24 January 2023*

improve communication, particularly in noisy environments or for people with speech impairments. The detection of silent speech is typically accomplished using sEMG and studied by various research groups, including [9-18]. The primary muscles involved in silent speech are the submental muscles, which are located under the chin. These muscles include the genioglossus, which elevates the tongue, and the hyoglossus, which depresses the tongue. Other muscles involved in silent speech include the orbicularis oris, which controls the movement of the lips, and the mentalis, which controls the movement of the lower lip. In addition, the larynx muscles, such as the cricothyroid muscle and the thyroarytenoid muscle, are also involved in silent speech. These muscles control the vocal cords' tension and the larynx's position, which are essential for speech production. Fig 2 depicts typical muscle locations of a human face [3].

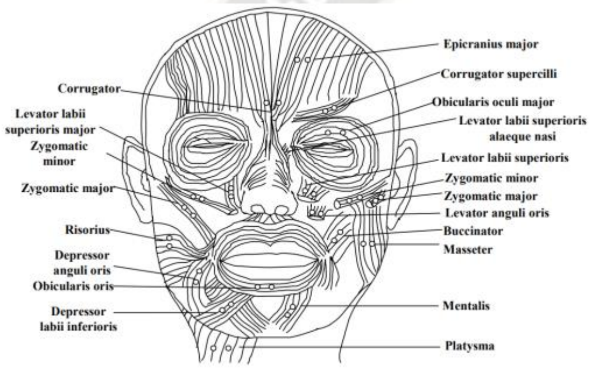


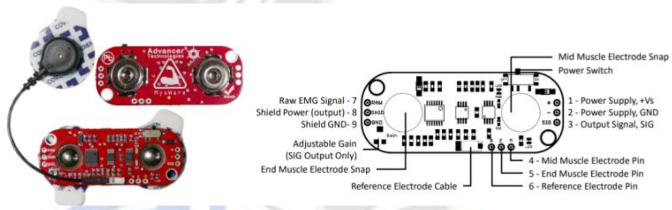
Figure 2: Facial muscles location for Humans [3]

For the initial investigation, we collected silent speech sEMG signal of English vowels from a single muscle Orbicularis Oris (M1), which is further extended for two other muscles, i.e., the Masseter (M2) and the Digastric (M3). To summarise the rest of the paper's structure, here it is: in section 2, we describe the detailed methodology, which includes details about the sensor, validation vocabulary, details of muscles under observation, data collection technique, the process of dataset preparation, and employed customized classification techniques. Section 3 presents the observations and results. Finally, section 4 presents our conclusions.

II. METHODOLOGY

A. Sensor Details

We utilize an MWM sensor with an Arduino Uno R3 Microcontroller to develop our initial single-channel (extended to three-channel) sEMG data acquisition to meet the objective of ease of availability, accessibility, low cost, and experimentation on the human face and neck. Fig 3 depicts the MWM sensor's details [22, 23]. We selected the MWM sensor (AT-04-001), a wearable sensor with a single supply (+2.9V to +5.7V), two output modes, and an adjustable gain; such features are helpful for a prosthetic, orthosis, and other control systems. It may be expanded using a sensor cable and cable shield (with a 3.5mm TRS jack connector), eliminating the need to physically join the sensor pads to the MWM Sensor. When the MWM sensor is connected to the human body, it produces a value between 0 to 1023 based on the amount of muscle contraction, which is then supplied to Arduino's analog pins (A0, A1, and A2). The Arduino normalizes these values between 0 to 5 and sends the result via serial port to the software. For this work, we used disposable Ag/Agcl electrodes shaped rectangle dimensions 40mm x 32mm, gel area of 201 mm^2, and sensor area of 80 mm^2 to pick sEMG signals from facial muscles.



(a) (b)

Figure 3: (a) Actual sensor image (b) Details of pin layout [23]

B. Validation Vocabulary

For validation, the proposed sEMG data acquisition system was subject to testing by acquiring the English language's silent speech data of five vowels < A, E, I, O, U >. Along with these five vowels, we recorded the "Silence" samples when the subject did not speak. That makes six different samples investigated during this study. To uniquely identify a category of each recorded instance inside the collection, each class is automatically represented by an integer number during recordings and presented in Table 1.

Table 1: Vocabulary codes

Syllabus	Silence	A	E	I	O	U
Unique Number	0	1	2	3	4	5

C. Muscles Under Observation

As shown in Fig 2, different facial muscles have been used to obtain sEMG data for silent speech. For the initial investigation, we collected silent speech sEMG data by placing sensors over Orbicularis Oris (M1) facial muscle, which is circular around human lips. Over this single muscle, data acquisition and validation were carried out for five vowels of the English language. After that, it was performed for two other muscles used in speech generation, i.e., the Masseter (M2) and the Digastric (M3), a muscle on the neck

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2
DOI: https://doi.org/10.17762/ijritcc.v11i2.6109
***Article Received**: 12 December 2022 **Revised**: 17 January 2023 **Accepted**: 24 January 2023*

area. The Masseter muscle comes from the zygomatic arch and connects to the mandibular ramus' angle and lateral surface. In the neck, the Digastric muscle pushes the mandible downward to open the jaw and lifts the hyoid bone for stability. The digastric muscle was selected to establish the involvement of the neck muscle in silent speech generation. Figure 4 depicts actual electrode placements on the subject's left side of the face.

Figure 4: Actual placement of disposable Ag/Agcl electrodes on human face during experimental sessions

The subject was made aware of the recording process and technique. Data recordings were made by making the subject sit over an isolated chair in front of a computer screen. Care was taken to maintain room temperature between 24-26 °C to avoid perspiration. Initially, data from individual muscles on the face of the subject were collected. After that, signals were picked simultaneously on all three muscles, corresponding to five quietly spoken vowels and one for silence (subject sitting silence, i.e., no speaking). Each vowel was pronounced independently, and our software captured and recorded sEMG signals over muscles under test.

D. Data Processing Technique

We collectively gathered sEMG data from face muscles using the proposed data processing technique after estimated muscle identification. We placed the electrodes on the facial and neck muscles and connected them with microcontroller hardware & a computer. After that, with due appropriate settings & initialization, the recording was started via the python-based application. The obtained data with defined features were instantly attached to the CSV file. The overall schematic diagram of our approach is presented in Fig 5.

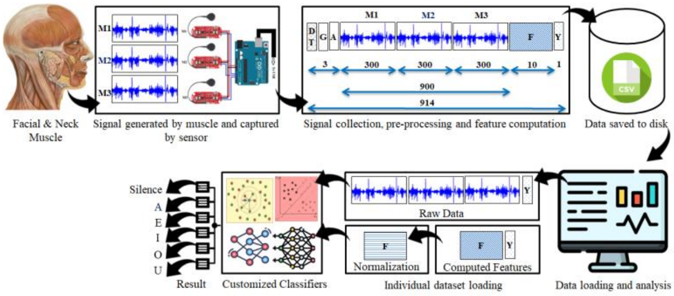


Figure 5: Schematic diagram of our approach: Muscle activities from a healthy man were captured from various muscles using an MWM sensor. The signal is collected, pre-processed, feature computed, and directly written into a CSV file. Machine learning classifiers utilized raw data and features individually for silent speech recognition.

Before starting, we need to set a few constants, such as *gender* (the subject's gender) to' M' (male) and *age* (the subject's age) to 39 (years). The parameters under measurement were initialized as per Table 2 during the software run.

Table 2: Measurement parameters with default values & range

Parameter	Description	Initialized Value	Range
port	At which hardware gets connected	COM4	COM1 to COM4
brate	Baud rate at which serial communication performed	9600 bps	9600/ 19200/ 38400
frame_size	Length of each sample that we want to record	300 samples	300 to 1000
offset	Length of an offset left before and after the actual sample	06 samples	6 to 20
muscle	Name of the muscle	'M1M2M3'	M1/M2/M3/ M1M2M3
sensors	Number of sensors connected as per '*muscle*'	3	1 or 3
sample_no	Number of samples to be recorded	5	5 or 10 or 20
sample_count	The number of samples recorded	0	5 or 10 or 20
master_list	Keep captured data	Empty	As per *frame_size*
y	Target class	0	0 to 5

In our data collection approach, we kept appending sEMG data we received from *port* to *master_list* till its length was not becoming equal to *frame_size*. We kept a provision to consider *offset* before and after a silent speech by subject. During the software run, when the length of *master_list* became equal to *frame_size*, we kept appending the *datetime*, *gender*, and *age* along with *master_list*, *feature_vector*, and *y* as a row to a CSV file. Our algorithm is presented below:

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2
DOI: https://doi.org/10.17762/ijritcc.v11i2.6109
***Article Received**: 12 December 2022 **Revised**: 17 January 2023 **Accepted**: 24 January 2023*

Algorithm:

```
Start
Initialize path to file location to save results
Initialize port ← 'COM4', brate ← 9600, gender ← 'M', age ← 40
    ▷ gender can be F, M
Initialize sample_no ← 5, muscle ← 'M1M2M3'
    ▷ muscle can be M1, M2, M3, M1M2M3
Initialize sensors ← int(len(muscle)/2)
Initialize frame_size ← 300 ∗ sensors, offset ← int(frame_size ∗ 0.02)
Initialize statements ← {0: 'Silence',1: 'A',2: 'E',3: 'I',4: 'O',5: 'U'}
Initialize fname as sequence of path, datetime, gender, age and muscle.
if (Hardware is connected at port) then
    for y in statements do
        ▷ Iterate over each value in statements
        sample_count ← 0
        while sample_count ≤ sample_no do
            ▷ check record count
            Initialize master_list ← [ ]
            while len(master_list) ≠ frame_size do
                if len(master_list) == 0 then
                    Display 'Ready to Speak'
                end if
                Read a line from port, decode it and append decoded
                content to master_list
                if len(master_list) == offset then
                    Display 'Speak Now'
                end if
                if len(master_list)== frame_size − offset then
                    Display 'Stop'
                end if
            end while
            data ← [datetime, gender, age]
            ▷ Create a list of datetime, gender, age
            Transpose master_list and add to the end of data.
            Compute feature_vector for each master_list
            Add feature_vector to the end of data.
            Add value of y as target class to the end of data.
            Append data as a row to CSV file fname and Do
            sample_count ← sample_count + 1
        end while
    end for
    Display a message 'Thanks'
else
    Display a message 'Hardware not connected'
end if
Stop
```

We focused on a few TD and statistical features and their horizontal fusion used as feature vectors to reduce computational complexity. The mathematical representation of these features is presented in Table 3.

Table 3: Mathematical representation of features

Feature No	Extracted Feature	Mathematical Equation
F1	Maximum of EMG (MAX)	$MAX = \max\,(x_1, x_2, \ldots .\, x_N)$
F2	Minimum of EMG (MIN)	$MIN = \min\,(x_1, x_2, \ldots .\, x_N)$
F3	Mean Absolute Value (MAV)	$MAV = \frac{1}{N}\sum_{n=1}^{N} \lvert x_n \rvert$
F4	Median of EMG (MED)	$MED = \text{median}\,(x_1, x_2, \ldots .\, x_N)$
F5	Standard Deviation of EMG (STD)	$STD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N} x_n^2}$
F6	Variance of EMG (VAR)	$VAR = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2$
F7	Skewness of EMG (SKW)	$SKW = \text{skewness}\,(x_1, x_2, \ldots .\, x_N)$
F8	Kurtosis of EMG (KUR)	$KUR = \text{Kurtosis}\,(x_1, x_2, \ldots .\, x_N)$
F9	Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}$
F10	Energy (ENG)	$ENG = \frac{1}{N}\sum_{n=1}^{N} x_n^2$

E. Dataset Preparation

Using the suggested data collection approach, at least 55 recordings for each vocabulary letter were gathered during experimental sessions, using either a single muscle (M1 or M2, or M3) or all three muscles combined (M1+M2+M3). This procedure yielded four master datasets, including raw sEMG data with calculated features (F1 to F10) and other attributes. Each channel's sEMG data length was restricted to a minimum of 300 samples, resulting in 900 sample values for three channels. The whole recording was saved as a CSV file. We developed the application to allow sample length customization for easy testing and expansion. We chose a dataset comprising recordings of all three muscles (M1+M2+M3) and ten calculated features (F1 to F10) with the desired value (output class) for this investigation. Table 4 describes the datasets' properties.

Table 4: Dataset characteristics

Feature	Description
Date	Date time at which the sample gets recorded
Gender	Gender of subject
Age	Age of subject
c1-c900	Sample values of length 900 (for three muscles)
F1-F10	Computed features
Target	The output class

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2
DOI: https://doi.org/10.17762/ijritcc.v11i2.6109
***Article Received**: 12 December 2022 **Revised**: 17 January 2023 **Accepted**: 24 January 2023*

To detect content from sEMG recordings, we selected 50 rows from the gathered datasets for (i) the raw dataset (RD) of 901 columns [(c1-c900), Target] and (ii) the feature dataset (FD) of 11 columns [(F1-F10), Target].

F. Classification Techniques

The recorded sample from each dataset is immediately fed into our bespoke classifier (with 80% - 20% as training-testing data) to discover patterns in the recorded sEMG. Individually, we studied the RD and FD using modified versions of k-nearest neighbors (KNN), support vector machines (SVM), and artificial neural networks (ANN). The KNN classifier is a non-parametric approach, making no assumptions about the data's underlying probability distribution. The main principle underlying KNN is to categorize a new observation based on its k closest neighbors' majority class. SVM, on the other hand, is a supervised machine-learning technique that finds a hyperplane in the feature space that best separates the distinct classes. ANN is a non-linear statistical technique inspired by the structure and function of the human brain. ANNs are made up of linked nodes known as artificial neurons that are grouped into layers. ANNs work by altering the weights of the connections between neurons to learn a mapping from input to output data. Many studies have emphasized the ANN classifier in sEMG classification because it can represent linear and non-linear connections derived from the sEMG data under consideration. Table 5 summarizes the customization information for deployed classifiers.

Table 5: Classifiers customization details

Classifier	Hyper-parameters
KNN	n_neighbors=6, weights='uniform', p=2, algorithm='auto', metric='minkowski', leaf_size=30
SVM	C=100.0, kernel='rbf', degree=3, random_ state=7
ANN (100)	hidden_layer_sizes=(100), max_iter=500, solver='adam', activation='relu', learning_rate_init=0.001, random_state=7
ANN (100,100)	hidden_layer_sizes=(100,100), max_iter=500, solver='adam', activation='relu', learning_rate_init=0.001, random state=7

To evaluate how well the gathered datasets were able to be classified, we used accuracy as an assessment parameter. The proportion of properly identified samples relative to the total number of samples is accuracy, and it is defined as (2):

$$\text{Accuracy} = \frac{\text{Number of correct classified samples}}{\text{Number of total samples}} \quad (2)$$

III. OBSERVATIONS & RESULTS

This section describes the classification results of 50 syllables using defined customized classifiers. Fig 6 (a), (b) illustrates a few screenshots of our sEMG data acquisition process. It shows the *port* at which the hardware is connected and the *gender* and *age* of the subject. A message corresponding to the recording sample (with *sample_no*) is shown to the user to inform when to start and when to stop indication. By displaying '*Frame recorded….and..Appended*', the subject is also informed about that particular sample with defined features gets appended to a file. In one iteration, the program records a total of samples equal to *sample_no* for each vocabulary content.

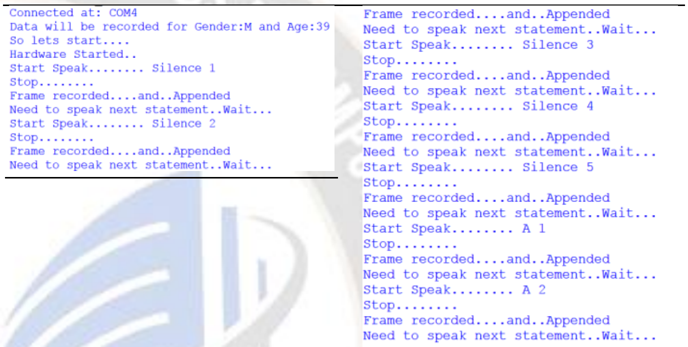


Figure 6: Screenshots of the data acquisition process

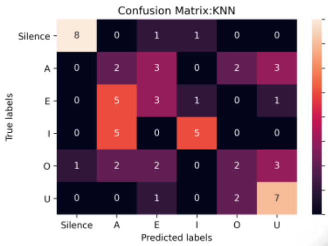
Following recording sessions, the RD and TD datasets were separated from the master dataset and fed into deployed classifiers independently. Table 6 shows the categorization results in terms of accuracy for RD and FD. Except for one example (0.67) of RD, all customized classifiers had accuracies equal to or better than 0.72 for each vocabulary content with RD and FD. Each classifier's mean recognition rates are 0.828, 0.827, 0.825, and 0.837, respectively.

Table 6: Accuracy for each classifier utilizing RD and FD

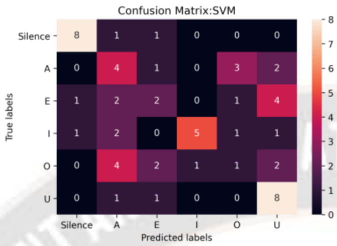
Vocabulary	Dataset Type	Customized Classifiers			
		KNN	SVM	ANN (100)	ANN (100, 100)
Silence	RD	0.95	0.93	0.97	0.97
	FD	1.0	0.98	0.93	0.95
A	RD	0.67	0.73	0.72	0.82
	FD	0.77	0.77	0.78	0.77
E	RD	0.77	0.78	0.82	0.87
	FD	0.87	0.83	0.88	0.82
I	RD	0.88	0.90	0.78	0.82
	FD	0.80	0.78	0.77	0.80
O	RD	0.80	0.77	0.83	0.80
	FD	0.77	0.77	0.72	0.75
U	RD	0.83	0.82	0.82	0.83
	FD	0.83	0.87	0.88	0.85

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2
DOI: https://doi.org/10.17762/ijritcc.v11i2.6109
***Article Received**: 12 December 2022 **Revised**: 17 January 2023 **Accepted**: 24 January 2023*

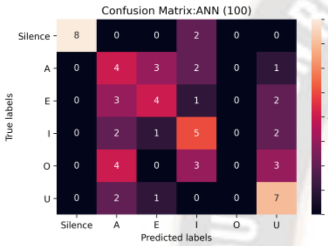
The confusion matrices derived by each classifier are shown in Fig 7 and 8 for RD and FD, respectively, to highlight the outcomes of each classifier further. We received higher values along the diagonal in these matrices for successful recognition and lower numbers for poor recognition. This value is also connected to a color map (from lower to higher range) for better display.



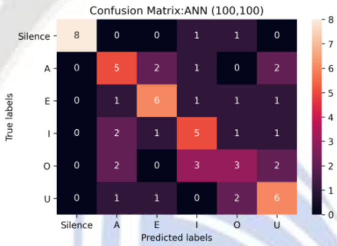
(a) For KNN



(b) For SVM

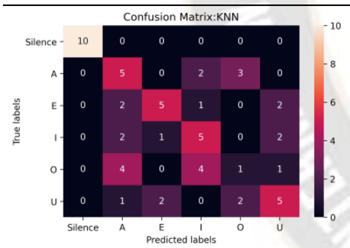


(c) For ANN (100)

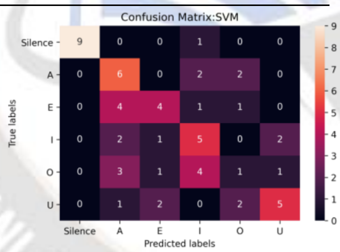


(d) For ANN (100, 100)

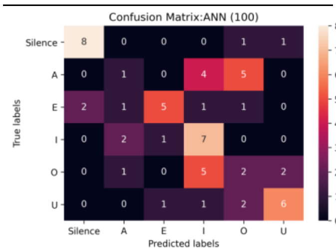
Figure 7: Confusion matrix obtained for RD utilizing deployed classifiers



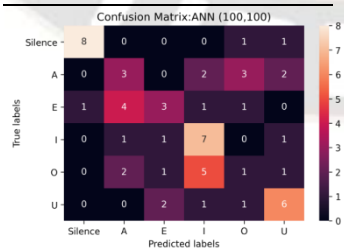
(a) For KNN



(b) For SVM



(c) For ANN (100)



(d) For ANN (100, 100)

Figure 8: Confusion matrix obtained for FD utilizing deployed classifiers

Furthermore, the accuracies for each word item and classifier using RD and FD are displayed in Fig 9. The RD has a broad range of accuracies ranging from 0.67 to 0.97 for each lexical content with various classifiers. At the same time, FD shows a more steady and promising range of accuracies from 0.72 to 1.0 with less variance.

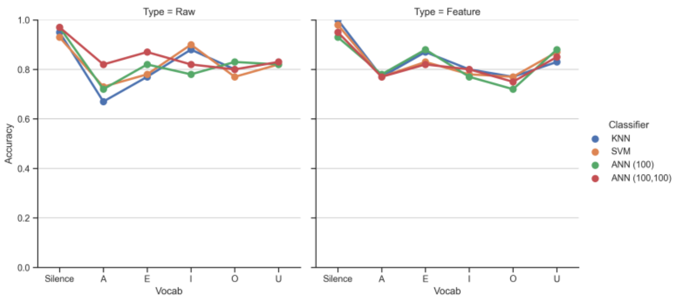


Figure 9: Accuracy scores obtained

In addition, we compare our RD and FD findings to those of Larraz et al. [14]. Larraz et al. employed English vowels RD and FD and found mean accuracies of 0.53 and 0.75, respectively [14]. Our mean accuracies for RD and FD are 0.82 and 0.83, respectively, with RD being 54.71% and FD being 10.6% improved. We also compare our findings acquired using FD to comparable work performed with commercial or low-cost setups employing feature datasets. Table 7 compares the accuracies achieved for sEMG English vowels FD in terms of hardware type, hardware utilized, and classifier applied.

Table 7: Comparison of accuracies for FD with commercial and low-cost setups

Ref	Hardware Type	Hardware Used	Classifiers employed		
			KNN	SVM	ANN
[9]	Commercial	MEGAWIN	-	-	0.88 (↓ 6.82)
[10]	Commercial	MEGAWIN	-	-	0.92 (↓ 10.87)
[11]	Commercial	MEGAWIN	-	-	0.86 (↓ 4.65)
[12]	Commercial	MEGAWIN	-	-	0.60 (↑36.67)
[14]	Commercial	Gtec g.USBamp	-	-	0.75 (↑ 9.33)
[15]	Commercial	BIOPAC	-	-	0.84 (↓ 2.38)
[18]	Low-cost	MWM Sensor	0.66 **(↑ 27.27)**	0.80 **(↑ 3.75)**	0.54 **(↑ 51.85)**
Our	**Low-cost**	**MWM Sensor**	**0.84**	**0.83**	**0.82**

The percentage up or down is denoted by the up or down arrow with previous findings in Table 7. We improved 27.27% in KNN, 3.75% in SVM, and 51.85% in ANN compared to low-cost hardware type [18] and denoted by an up arrow with percentage improvement. Compared to previous work done with commercial hardware sets by [9-12, 14, 15], our identification rate using the ANN classifier is closer to the

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 2
DOI: https://doi.org/10.17762/ijritcc.v11i2.6109
***Article Received**: 12 December 2022 **Revised**: 17 January 2023 **Accepted**: 24 January 2023*

recognition rates of commercial hardware. The percentage up or down is denoted by the up or down arrow with previous findings in the ANN column of Table 7. This indicates the feasibility of using low-cost sEMG data-collecting devices with the proposed algorithm instead of commercial hardware configurations for silent speech recognition and other human-machine interaction-related applications.

IV. CONCLUSION

In conclusion, this work effectively designed and validated an algorithm for sEMG data collecting using low-cost hardware employing English vowels as speech content. The sEMG data were acquired from three face muscles of one healthy person and pre-processed to extract different characteristics. The raw and feature datasets were individually used to train and evaluate three machine learning classifiers: KNN, SVM, and ANN. The findings demonstrated that the devised sEMG data collection technique performed well. Using the same low-cost data-collecting hardware, all customized classifiers obtained almost comparable accuracy rates of 0.83 ± 0.01 in detecting English vowels, with improvements of 27.27% (KNN), 3.75% (SVM) and 51.85% (ANN) from existing available work. Our results are significantly closer to those of commercial hardware setups, raising the possibility of using low-cost sEMG data acquisition systems with the proposed algorithm instead of commercial hardware setups for silent speech recognition, rehabilitation, and other human-machine interaction-related fields. However, this research has numerous limitations, including incorrectly muttered data and just one form of speech content (English vowels) for validation. A GUI-based data collection system with real-time display of produced sEMG signals may be included as a future scope during data collecting with the record or discard option. More research with diverse forms of speech material is required to generalize the findings and enhance the system's performance. Furthermore, deep learning approaches may increase the system's performance and versatility.

REFERENCES

[1] J. V. Basmajian, "Muscles alive. their functions revealed by electromyography," Academic Medicine, vol. 37, no. 8, p. 802, 1962.
[2] C. J. De Luca, "Physiology and mathematics of myoelectric signals," IEEE Transactions on Biomedical Engineering, vol. BME-26, no. 6, pp. 313–325, 1979.
[3] A. J. Fridlund and J. T. Cacioppo, "Guidelines for human electromyographic research," Psychophysiology, vol.23, no.5, pp. 567–589, 1986.
[4] C. J. De Luca, "Surface electromyography: Detection and recording," DelSys Incorporated, vol. 10, no. 2, pp. 1–10, 2002.
[5] B. Lapatki, D. Stegeman, and I. Jonas, "A surface emg electrode for the simultaneous observation of multiple facial muscles," Journal of neuroscience methods, vol. 123, no. 2, pp. 117–128, 2003.
[6] A. Merlo, D. Farina, and R. Merletti, "A fast and reliable technique for muscle activity detection from surface emg signals," IEEE transactions on biomedical engineering, vol. 50, no. 3, pp. 316–323, 2003.
[7] A.-D. Witman, B. Meneses-Claudio, F. Flores-Medina, P. Condori, N. I. Vargas-Cuentas, and A. Roman-Gonzalez, "Acquisition and classification system of emg signals for interpreting the alphabet of the sign language," International Journal of Advanced Computer Science and Applications, vol. 10, no. 8, 2019.
[8] A.D. Witman, M.C. Brian, and R.G. Avid, "Electromyography signal acquisition and analysis system for finger movement classification," Electromyography, vol.10, no.6, 2019.
[9] S. Kumar, D. K. Kumar, M. Alemu, and M. Burry, "Emg based voice recognition," in Proceedings of the 2004 Intelligent Sensors, Sensor Networks and Information Processing Conference, 2004., pp. 593–597, 2004.
[10] S. P. Arjunan, D. K. Kumar, W. C. Yau, and H. Weghorn, "Unspoken vowel recognition using facial electromyogram," in International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 2191–2194, 2006.
[11] S. P. Arjunan, H. Weghorn, D. K. Kumar, and W. C. Yau, "Vowel recognition of english and german language using facial movement (semg) for speech control based HCI," in Proceedings of the HCSNet workshop on Use of vision in human-computer interaction - Volume 56, pp. 13–18, 2006.
[12] G. R. Naik, D. K. Kumar, and S. P. Arjunan, "Reliability of facial muscle activity to identify vowel utterance," in TENCON 2008- IEEE Region 10 Conference, pp. 1–6, IEEE, 2008.
[13] G. S. Meltzner, G. Colby, Y. Deng, and J. T. Heaton, "Signal acquisition and processing techniques for semg based silent speech recognition," in Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 4848–4851, 2011.
[14] E. Lopez-Larraz, O. M. Mozos, J. M. Antelis, and J. Minguez, "Syllable-based speech recognition using emg," in Annual International Conference of the IEEE Engineering in Medicine and Biology, pp.4699–4702, 2010.
[15] U. Agnihotri, A. S. Arora and A. Gard, "Vowel recognition using facial movement (semg) for speech control based HCI," in International Journal of Engineering Research Technology ACMEE, vol. 4, no. 15, pp. 1–5, 2016.
[16] A. P. Vyas and R. Bhadada, "Feature extraction cum frequency analysis system for facial surface electromyography signals based human speech recognition," International Journal for Research in Applied Science and Engineering Technology, vol.5, no.12, pp. 1998–2006, 2017.
[17] R. Kachhwaha, A. P. Vyas, and R. Bhadada, "Adaptive threshold-based approach for facial muscle activity detection in silent speech emg recording," in Proceedings of

6th International Conference on Recent Trends in Computing, pp.83–98, Springer Singapore, 2021.

[18] V. Chandrashekhar, "The classification of emg signals using machine learning for the construction of a silent speech interface," The Young Researcher, vol.5, no.1, pp.265–283, 2021.

[19] R. E. Russo, J. G. Fern´andez, R. R. Rivera, M. G. Kuzman, J. M. Lopez, W. A. Gemin, and M. A. Revuelta, "Algorithm of myoelectric signals processing for the control of prosthetic robotic hands," Journal of Computer Science and Technology, vol. 18, no. 1, pp. 28–34, 2018.

[20] M. Sidik, S. Ghani, and M. M. Padzi, "Development of a wireless surface electromyography (semg) signal acquisition device for power-assisted wheelchair system," International Journal of Engineering and Advanced Technology, vol. 8, no. 6, pp. 3414–3418, 2019.

[21] F. R. Kareem, M. H. A. E. Azeem, M. Genedy, A. Mohamed, and A. Abdeldayem, "Classification of emg signals of lower arm (forearm\hand) motion patterns in different ages group," International Conference on ICT in Our Lives, pp. 89–94, 2017.

[22] L. E. Crawford, D. T. Vavra, and J. C. Corbin, "Thinking outside the button box: Emg as a computer input device for psychological research," Collabra: Psychology, vol.3, no.1, 2017.

[23] K. Hartman, "Getting started with myoware muscle sensor," Adafruit Industries, pp. 1–13, 11 2021.

[24] A.Technologies, "Myoware muscle sensor kit", https://learn.sparkfun.com/tutorials/myoware muscle-sensor-kit/all. Online accessed 13-01-23.

[25] A.Technologies, "Myoware muscle sensor datasheet", https://cdn.sparkfun.com/datasheets/Sensors/Biometric/MyowareUserManualAT-04-001.pdf, 2015. Online accessed 13-01-23.