BALKAN JOURNAL OF ELECTRICAL & COMPUTER ENGINEERING, Vol. 13, No. 1, March 2025
Research Article

A Novel Fuzzy Logic Based Hand Gesture Recognition System

Harun Sumbul

Abstract—**In this proposed study, a Fuzzy Logic System (FLS) was developed to classify and detect hand movements. The designed FLS system consists of a Fuzzifier, Inference Engine, Knowledge Base, and Defuzzifier. The Mamdani technique was used as the Inference Engine, and the centroid method was used for Defuzzification. Five input variables (Flex1-5) and one output variable (Sign) were used to create a rule base with 94 rules. A sensor array was placed on a glove to generate data, and a data collection circuit was established. Movements were performed through this circuit to create the rule bases. A total of 15.030 data points were analyzed to develop the FLS. According to the results, the movements (97.5%) were detected successfully.**

Index Terms—**Flex sensor, fuzzy logic, hand gesture recognition, sign language**

I. Introduction

RECENTLY, RESEARCHERS have shown increasing interest in gesture recognition due to its significant potential in various fields such as medical, military, and commercial applications. Most studies have adopted traditional learning model approaches. To achieve this, multiple interfaces such as data gloves, motion sensors, and position trackers have been developed to gather hand movement data. In recent years, the development of more robust sign language prediction for effective communication has required detecting joints in the hand, face, head, and entire body [1]. Sign language, used by deaf individuals, has been employed as a means of interaction and exchange of ideas parallel to spoken language since its inception [2]. Over 5% of the global population experiences hearing impairment, and recent projections by the World Health Organization (WHO) suggest that the prevalence of hearing impairment is expected to rise due to various factors [3].

Various communication techniques incorporating human-machine interfaces have been developed, particularly for hearing-impaired individuals. Among these, methods such as image processing [4], computer vision [5], artificial neural networks [6], deep learning [7], and machine learning [8] are frequently used, although fuzzy logic applications are also observed in similar studies. Fuzzy logic is also one of the methods that has recently become popular and is frequently utilized in significant applications [9].

In conclusion, research aimed at developing computational methods for the recognition and analysis of hand movements is a significant area of study today. This study presents a novel FLS that automates the processes of recognizing hand movements with linguistic expressions. This approach will result in time and cost savings.

To substantiate our assertions, we outline the principal characteristics of our fuzzy logic model. Section 2 offers a comprehensive description of the materials and methods utilized in developing the FLS model structure. Section 3 presents the findings and analyses derived from testing the proposed model with real-world data. In the conclusion section, we delineate the unique contributions of our study within the existing literature, provide a summary of the research, and underscore its significant findings.

II. MATERIAL AND METHOD

To provide real-time measurement of hand movements, a sensor array was placed on a plastic glove, and data were collected and digitized using a microcontroller (Arduino UNO). The sensor array consists of flexible sensors extending along each finger. This setup allows data collection from each finger during every movement, providing a stable measurement system. An overview of the measurement system architecture is illustrated in Fig. 1.

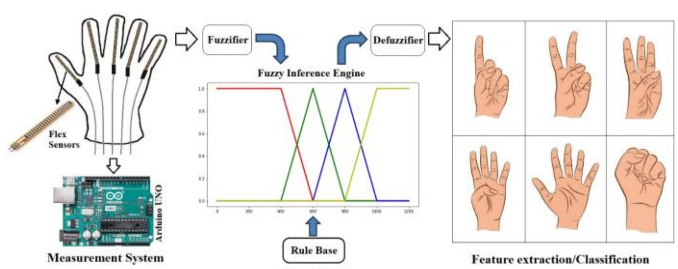


Fig.1. The methodology of the proposed study

A. Generating a hand movements dataset and labeling

Various hand movements were performed using a glove equipped with sensors, and the measured signals were recorded in real-time on a computer. To label the hand movements, six

Harun Sümbül, is with Department of Biomedical Device Technologies, Ondokuz Mayis University, Samsun, Turkey, (e-mail: harun.sumbul@omu.edu.tr).
https://orcid.org/0000-0001-5135-3410

Manuscript received Jun 20, 2024; accepted Oct 02, 2024.
DOI: 10.17694/bajece.1519693

different movements were performed (signs 1-5 and the fist-clenching movement). Each movement was labeled with a numerical digit. Fig. 2 illustrates the hand movements representing the numerical digits used in creating the database.

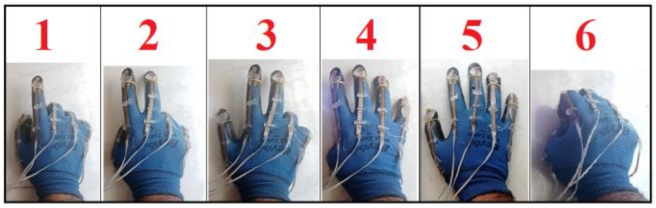


Fig.2. Hand gesture recognition from sensor arrays based on flex sensor

B. The structure of FLS

Fuzzy systems leverage fuzzy logic principles to handle imprecise and ambiguous data. These systems find applications across various fields such as healthcare, engineering, and finance. An expert system is composed of two core elements: the Inference Engine, which applies rules and logical operations for decision-making, and the Knowledge Base, which houses validated information used by the system to generate recommendations. Fig. 3 depicts the structure of the fuzzy expert system employed in this research [10].

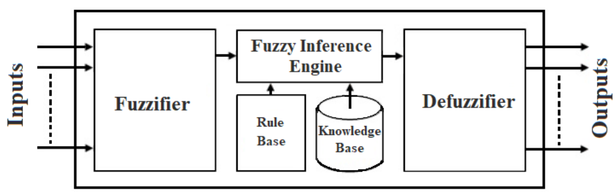


Fig.3. The structure of FLS

The components of the FLS include:

1) *Fuzzifier*: This module derives input data into a format that aligns with fuzzy logic principles, enabling it to be expressed in linguistic terms.

2) *Inference Engine*: This module generates fuzzy outputs by applying the fuzzifier's inputs to the knowledge rule base. The Mamdani method, widely employed in fuzzy logic applications, has been selected for this research.

3) *Knowledge Base*: This element organizes the results utilized for decision-making.

Various fuzzy systems implement an IF-THEN programming framework to apply knowledge. The knowledge base is divided into two sections: the database and the rule base. Rules within the knowledge base generally follow this format [11]:

IF (conditions) THEN (actions)

4) *Defuzzifier*: Commonly known as the defuzzifier, this module converts the fuzzy output from the inference engine into a precise or non-fuzzy value that is applicable for practical use.

C. Design of FLS

During finger movements, five key parameters measured with flex sensors (Flex1, Flex2, Flex3, Flex4, Flex5) were chosen as input variables for classifying and predicting the sign performed in this study. The output variable, representing the numerical value of the sign being made, is denoted as (Sign), with digits selected as follows: 1 for the sign of 1; 2 for the sign of 2; 3 for the sign of 3; 4 for the sign of 4; 5 for the sign of 5 and 6 for the fist sign. Fig. 4 illustrates the structure of the FLS regulator, including the input and output variables.

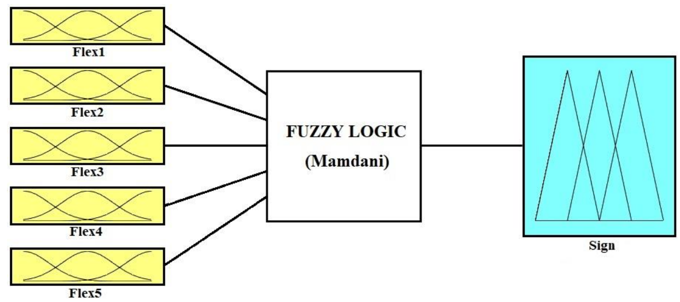


Fig.4. The architecture of FLS editor

1) Input variables

In the constructed expert system, five input variables (Flex1-5) were designated to represent the movement information for each finger. The boundary values for each fuzzy expression are detailed below. These parameters are classified symbolically. Membership functions and their degrees have been predefined in the software. Given that the same type of sensor is employed for each finger, the value ranges from 0 to 10 is divided into five fuzzy sets and variable ranges as follows:

VS (Very Slow) – S (Slow) - N (Normal) – F (Fast) - VF (Very Fast)

2) Output variables

The output variables have been divided into six fuzzy sets and variable ranges, selected empirically within the range of 0 to 6, which is considered the threshold value.

S1 ("sign 1") – S2 ("sign 2") – S3 ("sign 3") – S4 ("sign 4") – S5 ("sign 5") – S6 ("fist" sign)

Table 1 presents the input parameters, output parameters, and their corresponding linguistic expressions.

TABLE I
FUZZY SETS AND SHORT FORM LINGUISTIC EXPRESSIONS

Input Variables					*Output Variables*
Flex1	***Flex2***	***Flex3***	***Flex4***	***Flex5***	***Sign***
VS [0 2 4]	*VS [0 2 4]*	*VS [0 2 4]*	*VS [0 2 4]*	*VS [0 2 4]*	*S1 [0-2]*
S [2 4 6]	*S [2 4 6]*	*S [2 4 6]*	*S [2 4 6]*	*S [2 4 6]*	*S2 [1-3]*
N [4 6 8]	*N [4 6 8]*	*N [4 6 8]*	*N [4 6 8]*	*N [4 6 8]*	*S3 [2-4]*
F [6 7.5 9]	*F [6 7.5 9]*	*F [6 7.5 9]*	*F [6 7.5 9]*	*F [6 7.5 9]*	*S4 [3-5]*
VF [8 9 10]	*VF [8 9 10]*	*VF [8 9 10]*	*VF [8 9 10]*	*VF [8 9 10]*	*S5 [4-6]*
					S6 [5-7]

3) Rule Base

Classification uncertainties present significant challenges for deep learning models. However, fuzzy rule-based (FRB) approaches are particularly adept at managing these uncertainties. FRB methods are dependable for making inferences and are characterized by internal structures that are both efficient and straightforward to interpret [12]. Fuzzy set theory, an extension of classical crisp set theory, deals with the notion of partial truth using values that span from 0 to 1. A value of 0 denotes an entirely false statement, whereas a value of 1 signifies an entirely true statement [13]. After establishing linguistic variables, defining linguistic terms, and constructing membership functions, the final step in designing a fuzzy system is to develop a rule base. Rules verbally articulate the relationships between input and output linguistic variables according to their linguistic terms. A rule base constitutes the collection of rules for a fuzzy system [14]. In the creation of the conventional algorithm, the Rule Base and Expert System methodologies were employed as inputs for the fuzzy inference system. The initial phase in designing a fuzzy logic system typically involves the creation of an "IF-THEN" rule table. Using the membership functions we developed, a rule base consisting of 94 rules was obtained with the help of an expert. The rules derived from these membership functions are outlined in Table 2.

TABLE II
A SUMMARIZED SET OF RULES WAS DERIVED FROM THE MEMBERSHIP FUNCTIONS

Rule No:	***Rule structure***	***Input variables***					***Rule structure***	***Output variables***
	condition	*Flex 1*	*Flex 2*	*Flex 3*	*Flex 4*	*Flex 5*	*action*	***Sign***
1		*VS*	*VS*	*S*	***S***	*VS*		***S1***
2		*VS*	*VS*	*M*	*VS*	*S*		***S1***
3		*VS*	*VS*	*H*	*S*	*S*		***S1***
…		…	…	…				***…***
16		*S*	*N*	*N*	*N*	*N*		***S3***
17	***if***	*S*	*N*	*F*	*N*	*S*	***then***	***S2***
18		*S*	*N*	*F*	*F*	*F*		***S4***
…		…	…	…				***…***
92		*F*	*VF*	*N*	*VF*	*VF*		***S6***
93		*F*	*VF*	*F*	*VF*	*VF*		***S5***
94		*VF*	*F*	*VF*	*VF*	*VF*		***S6***

According to Table 2, a total of 94 fuzzy rules have been formulated, with examples provided below. The accuracy value for each rule has also been determined.

Rule 1: If (Flex1 is VF) and (Flex2 is N) and (Flex3 is VF) and (Flex4 is VF) and (Flex5 is VF) then (Sign is S1).

Rule 2: If (Flex1 is F) and (Flex2 is N) and (Flex3 is VF) and (Flex4 is VF) and (Flex5 is VF) then (Sign is S1).

…

Rule 93: If (Flex1 is F) and (Flex2 is F) and (Flex3 is VF) and (Flex4 is F) and (Flex5 is VF) then (Sign is S6).

Rule 94: If (Flex1 is F) and (Flex2 is F) and (Flex3 is VF) and (Flex4 is F) and (Flex5 is F) then (Sign is S6).

The Mamdani approach is employed as the inference engine. The degrees of validity (α) for each rule are computed using the Mamdani max-min method, as specified by the following formulas.

$\alpha_1 = min\ (Low\ (x), Slow\ (y))$
$\alpha_2 = min\ (Low\ (x), Medium\ (y))$
...
$\alpha_8 = min\ (High\ (x), Medium\ (y))$
$\alpha_9 = min\ (High\ (x), Fast(y))$

The maximum validity scores for the activated rules are computed using the formulas provided below.

$\alpha_{1,2 \ldots n} = max\ (\alpha_1, \alpha_2, \ldots \alpha_n)$

The centroid method, also known as the center-of-gravity or center-of-area technique, is utilized as the defuzzification approach in this study [15]. This method involves calculating the output of each membership function along with its associated maximum membership value (z*) using the formula specified in Equation (1). The range value relative to the centroid of the respective membership functions is represented by ž [16].

$$z^* = \frac{\sum \mu r(\check{z})\check{z}}{\sum \mu r(\check{z})} \quad (1)$$

Following the definition of the input-output parameters and their respective boundary ranges, the Triangular model depicted in Fig. 5 was employed as the method for fuzzifying membership functions, transforming the data into fuzzy sets. This model block utilizes a membership function with a triangular shape.

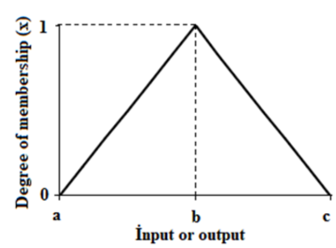


Fig.5. Triangular membership model

The defuzzification function for the triangular membership model is defined by Equation (2).

$$\mu(x) = \mu(x,a,b,c) = f(x) = \begin{cases} \frac{(x-a)}{(x-b)}, & a \leq x < b; \\ \frac{(c-x)}{(c-b)}, & b \leq x < c; \\ 0, & x > c \text{ or } x < a; \end{cases} \quad (2)$$

The membership functions for the fuzzy sets, derived using the centroid method, are aggregated using a weighted average approach. Each function is weighted by its peak membership degree. The equations governing the membership functions for both the input and output parameters are provided below. The detailed equations for the membership functions of the Flex1 variable are presented in Equations (3-7).

$$\mu_{VS}(x) = \begin{cases} \frac{(4-X)}{4}, & 0 \le x \le 4; \\ 0 & , x \ge 4 \; or \; x < 0; \end{cases} \tag{3}$$

$$\mu_{S}(x) = \begin{cases} \frac{X}{4} & , 2 \le x \le 4; \\ \frac{(6-X)}{4}, & 4 \le x \le 6; \\ 0 & , x \ge 6 \; or \; x < 0; \end{cases} \tag{4}$$

$$\mu_{N}(x) = \begin{cases} \frac{(X-4)}{4}, & 4 \le x \le 6; \\ \frac{(8-X)}{6}, & 6 \le x \le; 8 \\ 0 & , x \ge 8 \; or \; x \le 4; \end{cases} \tag{5}$$

$$\mu_{F}(x) = \begin{cases} \frac{(X-6)}{6}, & 6 \le x \le 7.5; \\ \frac{(9-X)}{7.5}, & 7.5 \le x < 9; \\ 0 & , x \le 7.5 \; or \; x \ge 9; \end{cases} \tag{6}$$

$$\mu_{VF}(x) = \begin{cases} 0 & , x \le 8; \\ \frac{(X-8)}{4}, & 8 \le x \le 10; \\ 1 & , 10 \le x \end{cases} \tag{7}$$

The membership functions for the Sign output are specified in Equations (8-13).

$$\mu_{S1}(x) = \begin{cases} \frac{(2-X)}{2}, & 0 \le x \le 2; \\ 0 & , x \ge 2 \; or \; x < 0; \end{cases} \tag{8}$$

$$\mu_{S2}(x) = \begin{cases} \frac{X}{2} & , 1 \le x \le 2; \\ \frac{(3-X)}{2}, & 2 \le x \le 3; \\ 0 & , x \ge 3 \; or \; x < 0; \end{cases} \tag{9}$$

$$\mu_{S3}(x) = \begin{cases} \frac{(X-2)}{2}, & 2 \le x \le 3; \\ \frac{(4-X)}{3}, & 3 \le x < 4; \\ 0 & , x \ge 4 \; or \; x \le 2; \end{cases} \tag{10}$$

$$\mu_{S4}(x) = \begin{cases} \frac{(X-3)}{3}, & 3 \le x \le 4; \\ \frac{(5-X)}{4}, & 4 \le x < 5; \\ 0 & , x \le 4 \; or \; x \ge 3; \end{cases} \tag{11}$$

$$\mu_{S5}(x) = \begin{cases} \frac{(X-4)}{4}, & 4 \le x \le 5; \\ \frac{(6-X)}{5}, & 5 \le x < 6; \\ 0 & , x \le 6 \; or \; x \ge 4; \end{cases} \tag{12}$$

$$\mu_{S6}(x) = \begin{cases} 0 & , x \le 7; \\ \frac{(X-7)}{7}, & 7 \le x < 5; \\ 1 & , 5 \le x \end{cases} \tag{13}$$

The graphical representation of the fuzzy input membership functions for the variable "Flex1" is shown in Fig. 6.

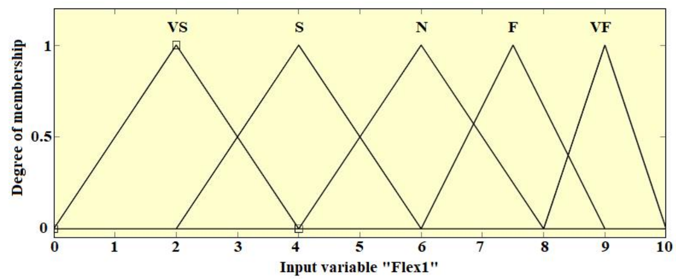


Fig.6. Graphical representation of the membership functions for the fuzzy input variable "Flex1".

Fig. 7, Graphical representation of the membership functions for the fuzzy output variable "Sign".

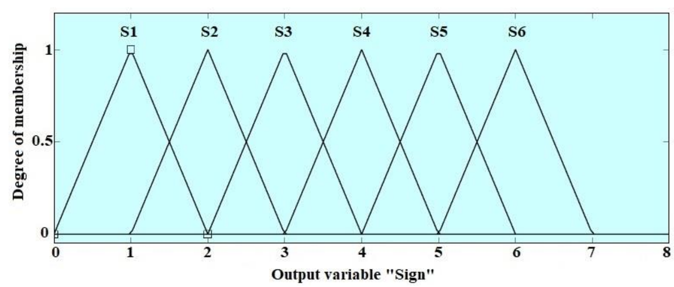


Fig.7. Graphical representation of the membership functions for the fuzzy output variable "Sign"

D. *Evaluation Metrics*

To assess the performance of our proposed method, we calculated sensitivity, specificity, and accuracy rates using the following formulas. In Equations (13-16), "TP" stands for true positives, "TN" refers to true negatives, "FP" denotes false positives, and "FN" indicates false negatives. These terms are standard in binary classification for evaluating prediction outcomes [17].

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FP + FN} \; X \; 100 \tag{14}$$

$$\text{Specificity} = \frac{TN}{TN + FP}\ X\ 100 \quad (15)$$

$$\text{Sensitivity / Recall} = \frac{TP}{TP + FN}\ X\ 100 \quad (16)$$

E. Statistical Analysis

Table 3 presents the complete list of features extracted from the hand gesture dataset along with their respective equations. Here, i ranges from 1 to K, representing K pieces of information assumed to be represented by the data u_i. Here, u denotes the mean, and n_i represents the frequency of occurrence of u_i in the dataset. The results have been statistically interpreted based on the formulas provided here.

TABLE III
DESCRIPTIVE STATISTICAL FEATURES

	Feature	*Equation*
1	***Mean***	$\frac{1}{K}\sum_{i=1}^{K} u_i$
2	***Range***	$u_{max} - u_{min}$
3	***Standard error***	$\frac{Standard\ Deviation}{\sqrt{K}} = \frac{\sqrt{\frac{1}{K-1}\sum_{i=1}^{K}(u_i - \bar{u})^2}}{\sqrt{K}}$
4	***Median***	*if K is odd:* $\left(\frac{K+1}{2}\right)^{th}$ *term* *if K is even:* $\frac{\left(\frac{K}{2}\right)^{th} term + \left(\frac{K+1}{2}\right)^{th} term}{2}$
5	***Mode***	$\{u_i: n_i = max\}, i = 1, 2, \ldots, K$
6	***Standard deviation***	$\sqrt{\frac{1}{K-1}\sum_{i=1}^{K}(u_i - \bar{u})^2}$
7	***Sample Variance***	$\frac{1}{K-1}\sum_{i=1}^{K}(u_i - \bar{u})^2$
8	***Kurtosis***	$\frac{\frac{1}{K}\sum_{i=1}^{K}(u_i - \bar{u})^4}{\left(\sqrt{\frac{1}{K-1}\sum_{i=1}^{K}(u_i - \bar{u})^2}\right)^2}$
9	***Skewness***	$\frac{\frac{1}{K}\sum_{i=1}^{K}(u_i - \bar{u})^3}{\left(\sqrt{\frac{1}{K-1}\sum_{i=1}^{K}(u_i - \bar{u})^2}\right)^3}$
10	***Maximum***	u_{max}
11	***Minimum***	u_{min}
12	***Sum***	$\sum_{i=1}^{K} u_i$

III. EXPERIMENTAL RESULTS

The developed glove model initially performed numerical signs from 1 to 5, followed by the fist clenching movement, during which the flexible sensor data were recorded in real-time on a computer for subsequent analysis. The resulting signal patterns can be seen in Fig. 8.

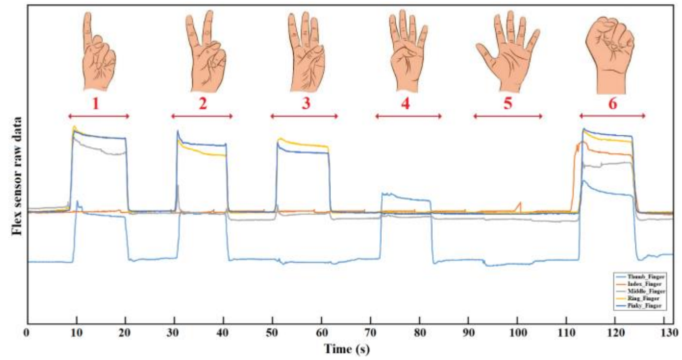
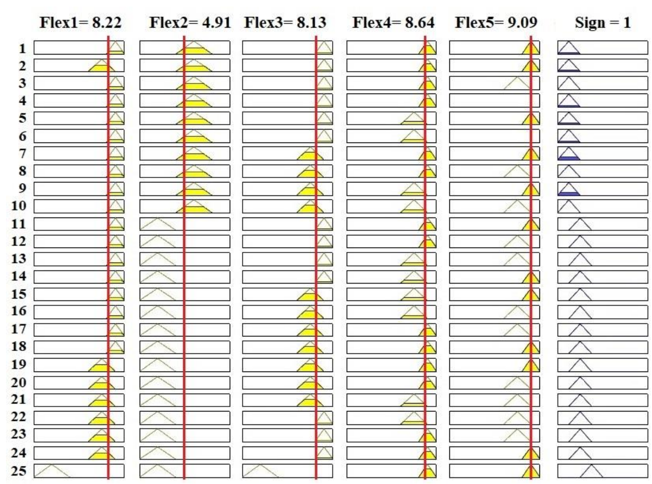
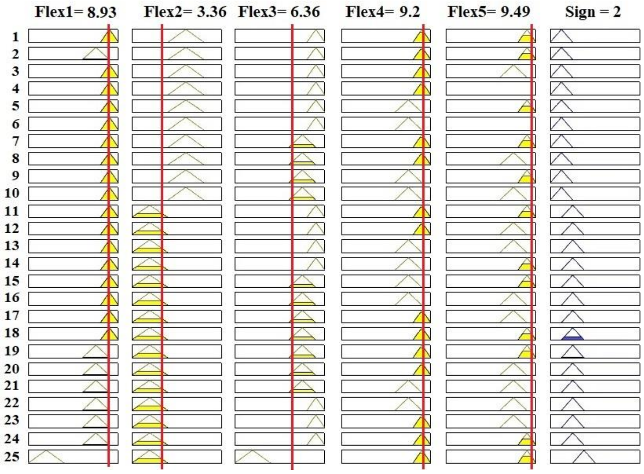


Fig.8. Flex sensor response for signs

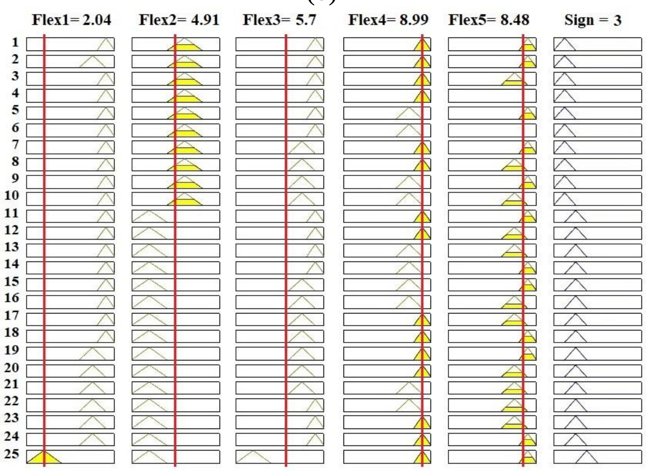
In this study, a fuzzy logic system was designed to classify and detect hand movements. The developed FLS system includes a Fuzzifier, Inference Engine, Knowledge Base, and Defuzzifier. The Mamdani technique was employed for the Inference Engine, while the centroid method was utilized for Defuzzification. A rule base comprising 94 rules was established using five input variables (Flex1-5) and one output variable (Sign). A sensor array was placed on a glove to generate data, and a data collection circuit was established. Movements were performed through this circuit to create the rule bases. A total of 15.030 data points were analyzed to develop the FLS. According to the results obtained from this study, for example, Flex1: 8.22; Flex2: 4.91; Flex3: 8.13; Flex4: 8.64; and Flex5: 9.09, the linguistic output value of Sign1 was found to be 1. This means that the sign performed according to these inputs is "1." The results obtained from fuzzy inputs for all output states (1-6) are collectively as shown in Fig. 9.



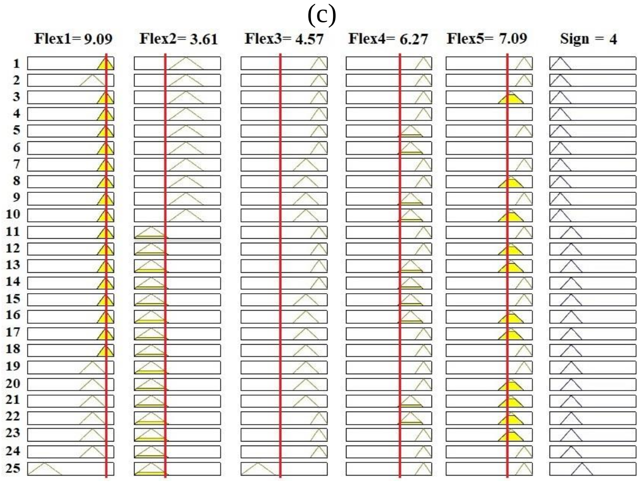
(a)



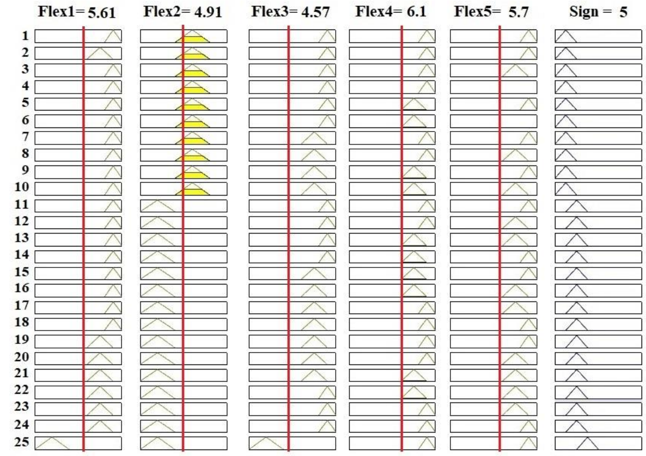
(b)



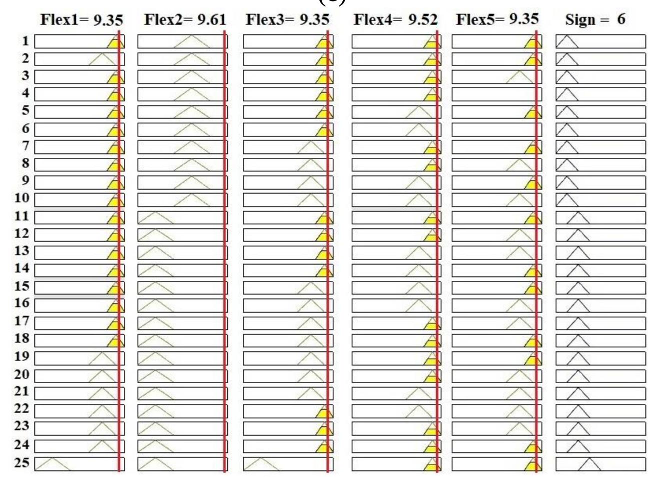
(c)



(d)



(e)



(f)

Fig.9. S1-S6 motion detection based on fuzzy inputs respectively. (Sign=1 (a), Sign =2 (b), Sign =3 (c), Sign =4 (d), Sign =5 (e), Sign =6 (f))

To test the accuracy of the measurement results, the glove was worn by different individuals, who were asked to perform 5 different movements. Accordingly, the real values and the results obtained by the FLS are comparably presented in Table 4. It was observed that the developed fuzzy model successfully identified all movements.

TABLE IV
THE COMPARISON OF RESULTS

Sign No.	*Flex1*	*Flex2*	*Flex3*	*Flex4*	*Flex5*	*FLS*	*Real*
1	***8.99***	***5.99***	***7.8***	***8.23***	***8.06***	***1***	***1***
2	***8.85***	***1.15***	***6.01***	***8.72***	***5.91***	***2.02***	***2***
3	***2.77***	***3.72***	***5.07***	***8.72***	***8.72***	***2.98***	***3***
4	***8.85***	***3.58***	***4.53***	***6.96***	***7.5***	***4.04***	***4***
5	***6.69***	***5.47***	***4.53***	***7.23***	***7.64***	***5***	***5***

According to the results, the movements (97.5%) were detected successfully. Table 5 presents the confusion matrix for the FLS across all movements.

TABLE V
THE CONFUSION MATRIX

n= 15.030	*Predicted: NO*	*Predicted: YES*
Actual: NO	*13.044*	*183*
Actual: YES	*124*	*1.679*

The results have been statistically analyzed and the results are shared in Table 6.

TABLE VI
DESCRIPTIVE STATISTICS RESULTS

	Measured	**Predicted**
Mean	232.61	202.23
Standard error	1.812	1.482
Median	332	284
Mode	354	305
Standard deviation	119.52	124.63
Sample Variance	15330.18	14222.48
Kurtosis	1.59	1.59
Skewness	0.502132	0.50223
Range	342	322
Maximum	372	319
Minimum	7	-3
Sum	128425	106452
Confidence Level (97.0%)	3.3592	3.3344

IV. DISCUSSIONS

Hearing impairment can be congenital or acquired later in life and may lead to significant communication challenges due to its impact on a large number of people worldwide. Individuals in this situation often face difficulties in social isolation, socialization, and participation in the workforce. This study presents a comprehensive framework using a new fuzzy logic model based on flexible sensors for recognizing hand movements with a prototype hand model. An intelligent hand movement classification system, based on the architecture of the fuzzy logic system, has been developed to assist deaf individuals in accurately recognizing various hand movements. The proposed community architecture achieves an impressive accuracy of 97.5%. Future work will emphasize improving recognition performance, particularly to achieve more accurate categorization results. Additionally, it is aimed to enable remote access to physiological information related to certain neurological diseases through system enhancements. Furthermore, the developed system is intended to be implemented in hospitals to address potential practical usage side effects, making it a valuable tool in clinical environments.

ACKNOWLEDGMENT

The research presented in this study was supported by the Coordinatorship of Scientific Research Projects at Ondokuz Mayis University in Samsun, Turkey. The project was identified by the project number PYO.YMY.1908.23.001.

REFERENCES

[1] Y. Zhang at all., "Mechanomyography signals pattern recognition in hand movements using swarm intelligence algorithm optimized support vector machine based on acceleration sensors", Medical Engineering and Physics 124 (2024) 104060,

[2] M.A., Rahaman, M.H. Ali, and M. Hasanuzzaman, "Real-time computer vision-based gestures recognition system for bangla sign language using multiple linguistic features analysis". Multimed Tools Appl 83, 22261–22294 (2024). https://doi.org/10.1007/s11042-023-15583-8

[3] World Health Organization (2021) Deafness and hearing loss. https://www.who.int/es/news-room/fact-sheets/detail/deafness-and-hearing-loss, 2019 Online; Accessed July 19

[4] H. Yakut, "İşaret dili harflerinin görüntü işleme yöntemleriyle taninmasi için bir uygulama", Yüksek Lisans Tezi, Firat Üniversitesi, OCAK-2013

[5] F. ShengChen, C. MingFu, C. LinHuang, "Hand gesture recognition using a real-time tracking method and hidden Markov models", Image and Vision Computing, 21(8), 1 August 2003, Pages 745-758

[6] Wu, D., Pigou, L., Kindermans, P. J., Le, N. D. H., Shao, L., Dambre, J., & Odobez, J. M., "Deep dynamic neural networks for multimodal gesture segmentation and recognition", IEEE transactions on pattern analysis and machine intelligence, 2016, 38(8), 1583-1597.

[7] O. Güler, & I. Yucedag,. "Derin öğrenme ile el hareketi tanıma üzerine yapılan çalışmaların incelenmesi", 21. Akademik Bilişim Konferansı, 2019, Ordu/TURKEY

[8] G. Devineau, F. Moutarde, W. Xi, & J. Yang, "Deep Learning for Hand Gesture Recognition on Skeletal Data", In Automatic Face & Gesture Recognition (FG 2018), 2018, 13th IEEE International Conference on (pp. 106-113), IEEE.

[9] F. Başçiftçi, H. Sümbül, "Designing an expert system for detection of tuberculosis disease with logic simplification method", e-Journal of New World Sciences Academy, NWSA Engineering Sciences, 1A0097, ISSN: 1308-7231,5(3), pp. 463-471, 2010.

[10] B. Ahmet, K. Yavuz, K. Adem, "Bulanik uzman sistem yaklaşimi ile yeşil kart başvuru değerlendirme sistemi", Atatürk Üniversitesi İktisadi ve İdari Bilimler Dergisi, Cilt: 24, Sayı: 1, 63-76, 2010

[11] H., Sümbül, A. H., Yüzer, "Design of a fuzzy input expert system visual information interface for classification of apnea and hypopnea", Multimedia Tools and Applications, 83(7), pp.21133-21152,2024 https://dx.doi.org/10.1007/s11042-023-16152-9

[12] A.B. Sargano, X. Gu, P. Angelov et al., "Human action recognition using deep rule-based classifier". Multimed Tools Appl., 2020, 30653–30667, https://doi.org/10.1007/s11042-020-09381-9

[13] B. Choi, S. Kang, K. Jun et al. "Rule-based soft computing for edge detection" Multimed Tools Appl, 24819–24831, 2017, https://doi.org/10.1007/s11042-016-4329-7.

[14] W. Bi, F. Gao, A. Zhang et al. "A framework for extended belief rule base reduction and training with the greedy strategy and parameter learning". Multimed Tools Appl, 11127–11143, 2022, https://doi.org/10.1007/s11042-022-12232-4.
[15] A. Biswas, A. Adan, P. Haldar, D. Majumder, V. Natale, C. Randler, L. Tonetti, S. Sahu, "Exploration of transcultural properties of the reduced version of the Morningness–Eveningness Questionnaire (rMEQ) using adaptive neuro-fuzzy inference system". Biological Rhythm Research. 45:6, 955-968, 2014, DOI:10.1080/09291016.2014.939442
[16] E. Allam, H.F. Elbab, M.A. Hady, S. Abouel-Seoud, "Vibration control of active vehicle suspension system using fuzzy logic algorithm". Fuzzy Information and Engineering, 2(4):361-387, 2010, https://doi.org/10.1007/s12543-010-0056-3
[17] Ö. M. Soysal, S. Shirzad and K. Sekeroglu, "Facial action unit recognition using data mining integrated deep learning," 2017 International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, 2017, pp. 437-443, doi: 10.1109/CSCI.2017.74.

BIOGRAPHIES

Harun SÜMBÜL received the B.S. degree in Electronic Sciences from the Selçuk University, Konya, Turkey, in 2008, the M.S. degree from the Selçuk University from Electrical and Electronics Engineering, Konya, Turkey, in 2011, and received the Ph.D. degree in electrical and electronics engineering from Karabük University, Karabük, Turkey. His primary areas of research are biomedical engineering and biomedical signal processing. He is currently a Lecturer at the Yeşilyurt Demir Çelik Vocational School, Department of Biomedical Device Technologies at Ondokuz Mays University, Turkey.