International Journal of Advanced Research in Computational Thinking and Data Science

Journal homepage:
https://karyailham.com.my/index.php/ctds/index
ISSN: 3030-5225

Facial Expression Recognition using Stretchable Sensor and Multilayer Feedforward Backpropagation Neural Network

Siti Nur Safira Safi'e[1], Norsinnira Zainul Azlan[1,*], Zabina Tasneem[1], Osamah Ebrahim Mohammed Shweesh[1], Iswanto Suwarno[2]

[1] Department of Mechatronics Engineering, Kulliyyah of Engineering, International Islamic University Malaysia, Jalan Gombak, 53100 Kuala Lumpur, Malaysia
[2] Department of Electrical Engineering, Universitas Muhammadiyah Yogyakarta, Kampus Terpadu UMY, Jl. Brawijaya, Geblagan, Tamantirto, Kec. Kasihan, Kabupaten Bantul, Daerah Istimewa Yogyakarta, 55183, Indonesia

ARTICLE INFO

Article history:
Received 20 October 2025
Received in revised form 6 November 2025
Accepted 15 November 2025
Available online 28 November 2025

Keywords:
Facial expression recognition; stretchable sensor; multilayer feedforward backpropagation algorithm; neural network

ABSTRACT

Facial expression recognition plays a crucial role in enabling natural human–computer interaction, emotion identification systems and finds diverse applications in healthcare, security, marketing and social robotics. Traditionally, facial expression recognition relies on vision-based systems, which are often limited by sensitivity to lighting and pose variations, occlusions and high computational cost. Therefore, this study proposes a facial expression recognition system based on stretchable sensor data for controlling the movement of a robotic hand. Stretchable sensors are capable of conforming to complex and dynamic surfaces such as human skin while maintaining sensing accuracy under deformation. In this study, four stretchable sensors are placed on the forehead, upper lip, lower lip, and right cheek. The sensors are interfaced with an Arduino Mega 2560 microcontroller for data acquisition. Statistical features including mean, root mean square (RMS), variance and standard deviation are extracted and used to train a multilayer feedforward backpropagation neural network algorithm in classifying four expressions: neutral, happy, sad, and disgust. The trained model outputs are mapped to control four servo motors attached to the robotic hand's fingers and wrist, producing peace, thumbs-up, fist gestures, and wrist rotation. The validation results demonstrate that the proposed system achieved 100% accuracy in the training phase but a significantly low accuracy of 25% in the testing stage. This shows that further improvement is needed to improve the stretchable sensor-based facial expression recognition system.

1. Introduction

Facial expression recognition (FER) has become a pivotal technology in human-computer interaction, healthcare and affective computing. It enables systems to interpret and respond to human emotions through the analysis of facial cues. Traditional FER approaches have relied heavily on visual data captured by cameras and processed using advanced machine learning algorithms, such

* *Corresponding author.*
E-mail address: sinnira@iium.edu.my

https://doi.org/10.37934/ctds.7.1.4457

as multilayer perceptron (MLP) neural networks with backpropagation, which have demonstrated effectiveness in distinguishing subtle emotional states and eye conditions from facial images [1-3]. However, these methods often face challenges in real-world environments due to variations in lighting, occlusion, and pose, which can significantly degrade recognition accuracy [4,5].

Recent advancements in sensor technology have introduced stretchable, skin-conformable sensors capable of directly capturing facial muscle movements and strain patterns. These stretchable sensors are fabricated using materials like silver ink on flexible substrates. They offer high sensitivity, biocompatibility and possess the ability to conform to complex facial geometries, hence, making them ideal for continuous and unobtrusive emotion monitoring [1,4]. By integrating such sensors with neural network-based classifiers, it becomes possible to enhance the robustness and accuracy of FER systems [1,4].

The combination of stretchable sensor data with multilayer feedforward neural networks trained with backpropagation for facial expression recognition has not been fully investigated. In the integration of the sensor and algorithm, the sensor provides rich, real-time physiological signals corresponding to facial expressions, while the neural network efficiently learns to map these signals to specific emotional states through supervised learning. This approach may not only improves recognition performance but also opens new avenues for applications in telemedicine, mental health monitoring and wearable affective interfaces, addressing many of the limitations faced by conventional FER systems [1,4].

The main objective of this study is to design and develop a facial-expression recognition system based on stretchable-sensor signals to control the movement of a robotic hand. The stretchable sensors are attached at four facial locations: (1) forehead, (2) upper lip, (3) lower lip and (4) right cheek. An Arduino Mega 2560 microcontroller is used to acquire the sensors data. The mean, root mean square, variance and standard deviation features are extracted to train a multilayer feedforward backpropagation neural network for classifying neutral, happy, sad, and disgust expressions. The trained network outputs are utilized to actuate four servo motors on the robotic hand's fingers and wrist to produce predefined peace, thumbs-up, fist gestures and wrist rotation. The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 details the methodology employed in the study and Section 4 presents the results obtained. Finally, the conclusion is drawn in Section 5.

2. Literature Review

Recent studies on facial expression recognition (FER) focus on improving robustness to pose variation, occlusion and inter-class similarity. Mu *et al.* [6] addressed multi-pose conditions by combining Quantum-Inspired Firefly and Artificial Bee Colony algorithms for feature selection, followed by classification with ResNet-50. The technique achieved a high accuracy on Radboud Faces (RaF) and Karolinska Directed Emotional Faces (KDEF) datasets. Liu *et al*., [7] introduced Multi-scale Convolutional (MsC) to replace the convolutional layer of Convolutional Neural Networks (CNN) and obtained an improved accuracy of the facial expression recognition system. Ma *et al.* [8] added global compact attention and hierarchical feature interaction to overcome the different poses and occlusion problems. The results showed a superior performance on RAF and AffectNet datasets. Qingzhen *et al.* [9] designed a VR-based facial recognition system using marker tracking and mouth region segmentation for real-time FER under head-mounted display occlusion. Li *et al.,* [10] focused on applying a new technique that gave attention to the most significant areas on the picture to enhance the FER robustness.

In stretchable sensor researches, Hossain *et al.,* [11] presented a fully stretchable multi-axial sensor for tactile slip sensing, based on an ionic liquid/polymer network with CNT stretchable electrodes that resolved normal and shear forces. The sensor is capable of detecting slip across different surfaces, speeds, and load levels. A stretchable sensor with deep learning-enabled 3D force decoding was introduced by Min *et al*., [12]. It achieved an accuracy of 97% in gesture recognition, with wrist motion tracking and robotic grasp feedback. A high-gain strain transduction with additional functionalities was studied by Hong *et al.,* [13]. It could be used to monitor human's movement and to change the control underwater and in air.

Multilayer Feedforward Backpropagation algorithm is one of the methods, which can be used for recognition and classification [14-17]. Yousaf *et al.,* [16] implemented a single-layer feedforward backpropagation algorithm for identifying handwritten Latin characters and digits. Mu and Zeng [17] enhanced webpage classification using feedforward backpropagation algorithm. They implemented a better weightage approach according to the terminologies and resulted in an improved accuracy and efficiency through the strengthened feature selection and extraction.

3. Methodology

3.1 Robotic Hand Prototype

The robotic hand prototype is shown in Figure 1. The Silicone Stretch Sensor from Stretch Sense is used in this study. It is a high-quality advanced sensor developed in stretch sensing technology. The length of 2 of the sensors are 101.39 mm, while the other 2 sensors are 70 mm long. Arduino Mega 2560 is selected as the microcontroller. It is based on ATmega2560 and allows a faster transfer rate. It converts numerical values to pulse width modulation (PWM) signals for controlling the motors. It is selected primarily due to the availability of its open-source software. It can also be directly connected to the virtual COM port and can be programmed easily. Four servomotors are used to actuate the robotic hand's fingers through the strings attached, and the wrist using MATLAB

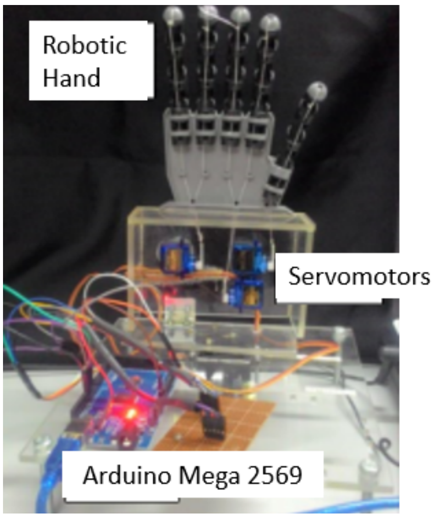


Fig.1. Robotic hand prototype

programming. The servomotors are used because of their ability to move according to the desired angle of rotation and based on the amount of signal supplied. The ready-made commercial robotic hand is selected since it is simple and looks like a human hand. Its fingers can be bent easily by the application of a small amount of force and this makes it suitable for this study.

Figure 2 shows the connection of the robotic fingers and servomotor. The thumb is connected to Servo 1 which is represented by the orange line. The index and middle fingers are attached to Servo

2, which are represented by green lines. The ring and little fingers are fixed to Servo 3 which is represented by the blue line. Servo 4 is incorporated under the hand to provide wrist movement.

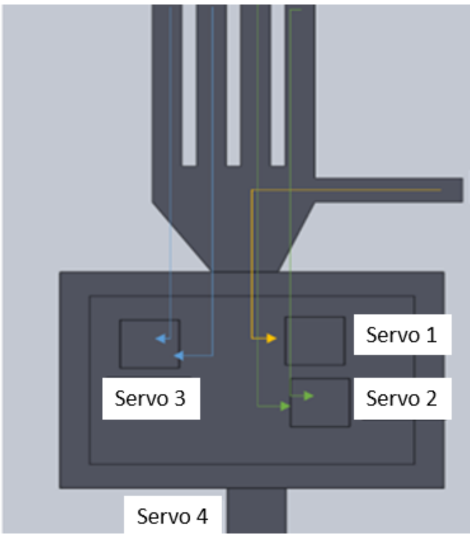
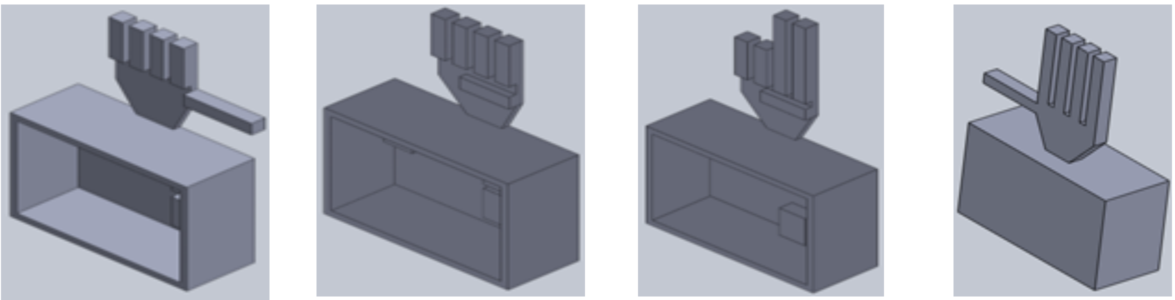


Fig. 2. Robotic hand connections with the servomotor

Four facial expressions are considered in this study, which are happy, sad, normal and disgust. When happy expression is detected, the robotic hand will show thumbs up. Servo 2 and Servo 3 will be activated to close the index, middle, ring and little fingers. If a sad face is identified, all fingers will close, showing fist. In this case, Servo 1, Servo 2 and Servo 3 will be actuated. In the event of normal expression is displayed, the robotic hand will show peace sign, where the thumb, ring finger and little finger will be encircled through the activation of Servo 1 and Servo 3. In the occasion of disgust expression is recognized, the wrist of the robotic hand will rotate while all fingers are extended. In this case, only Servo 4 will be activated. Figure 3 shows the isometric view of the robotic hand drawing in: (a) thumbs up (b) fist, (c) peace and (d) rotating positions.



(a) (b) (c) (d)

Fig. 3. Isometric view of the robotic hand drawing in (a) thumbs up (b) fist, (c) peace, (d) rotating positions

3.2 Prototype of the Facial Expression Recognition System based on Stretchable Sensor Data

The full set up of the facial expression recognition system based on stretchable sensor data is shown in Figure 4. Referring to Figure 5, the stretchable sensors are connected to the android via Bluetooth using apps 10 Channel BLE Stretch Sense. Then, the android is connected to the PC via the Bluetooth. All the servos are connected to Arduino Mega 2569 which is connected to the MATLAB in the Laptop or computer. All servos are connected to the Arduino's output port as shown in Figure 5.

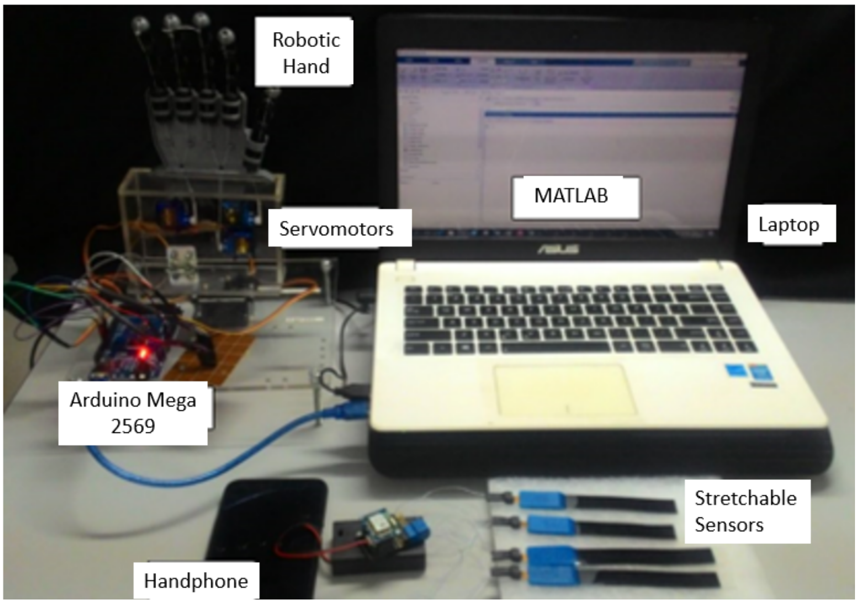


Fig. 4. Full set up of the facial expression recognition system based on stretchable sensor data

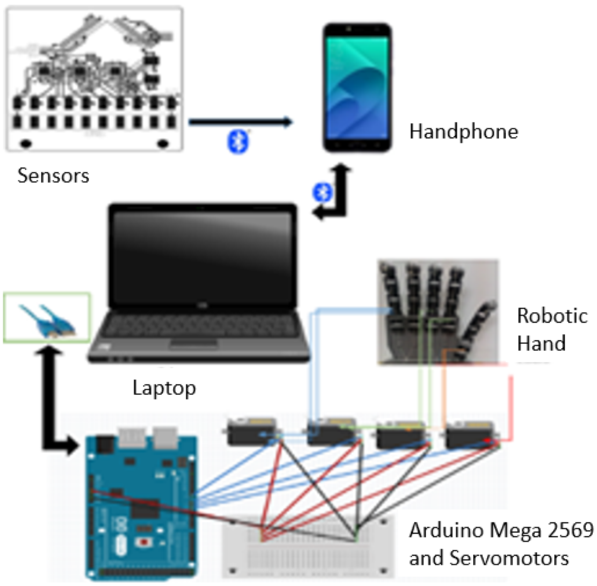


Fig. 5. Configuration of the components of the facial expression recognition system based on stretchable sensor data

The simulation works in this study is divided into two options, which are online and offline. Figure 6 shows the flow of the simulation. Sequence 1 indicate the flow for online simulation that starts with the 4 sensors acquiring the facial data through an android, and then transferred to Microsoft Excel and MATLAB on the laptop or computer, where the neural network training and recognition processes are conducted. Sequence 2 shows the offline simulation that starts from using the output of the neural network in the MATLAB. This output, which is the facial expression recognized, is then used to move the servomotors and robotic hand accordingly.

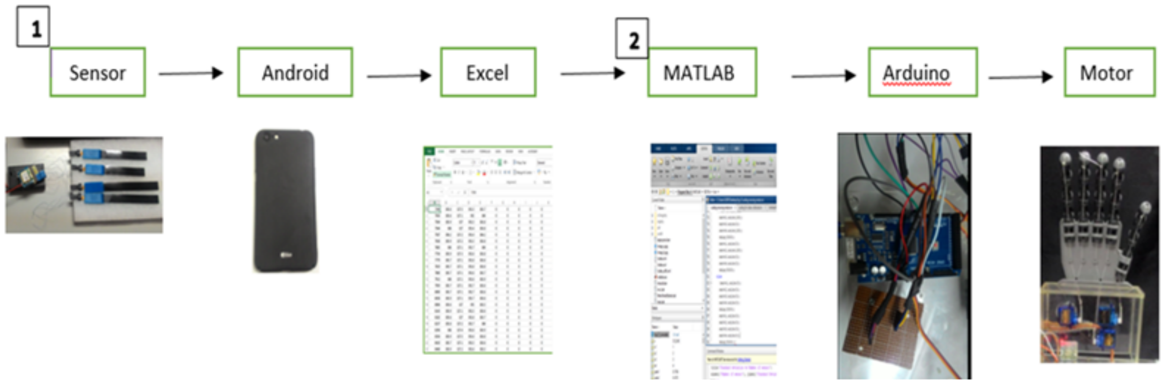


Fig. 6. Flow of simulation process in this study

3.3 *Operational Flow of the Facial Expression Recognition System based on Stretchable Sensor Data*

The operational flow of the facial expression recognition system based on stretchable sensor data is illustrated as in Figure 7.

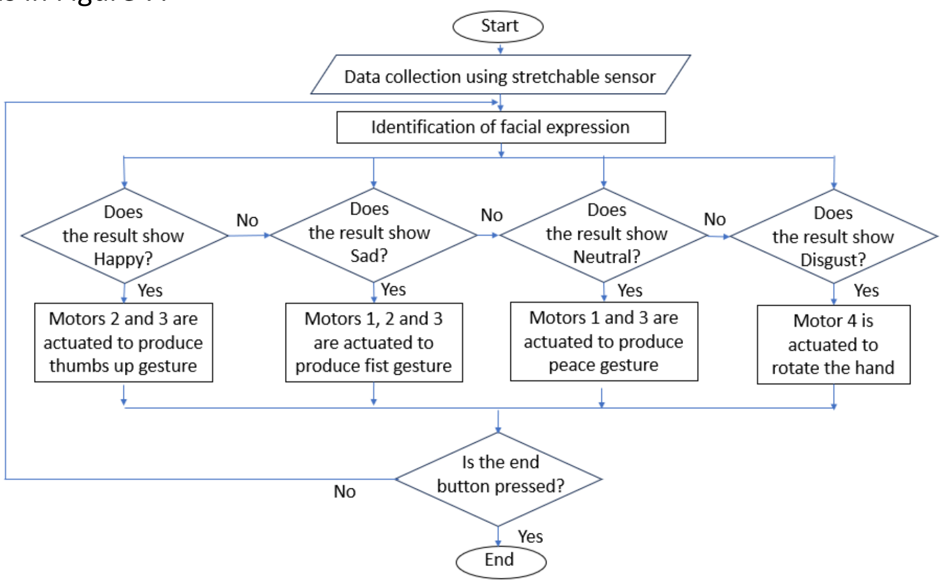


Fig. 7. Operational flow

The procedure commences with the acquisition of data from four stretchable sensors attached to the subject's face. The acquired input data and the set of output data pairs are subsequently utilized to train the neural network based on multilayer feedforward backpropagation algorithm for the classification of four facial expressions: happy, sad, neutral, and disgust. Upon the recognition of a happy expression, the Servo 2 and Servo 3 will be activated to produce a thumbs-up gesture. Detection of a sad expression results in the activation of Servo 1, Servo 2 and Servo 3 to generate a closed fist gesture. A normal expression similarly initiates a peace gesture through the actuation of Servo 1 and Servo 3, whereas the recognition of a disgust expression causes Servo 4 to rotate the hand while the robotic fingers are extended. This process operates continuously until the end button is pressed.

3.4 Data Acquisition and Features Extraction.

Four stretchable sensors are positioned at the forehead, upper lip, lower lip, and right cheek as shown in Figure 8 to classify the four facial expressions, which are happy, sad, normal and disgust.

These locations are selected because they exhibit the most evident changes across different expressions. The data are collected from 10 participants, with 5 females and 5 males to represent variability in human facial expressions. From each sensor channel, the following factures are extracted and are used in the recognition process: (i) mean, (ii) root mean square (RMS), (iii) variance (Var), and (iv) standard deviation (STD).

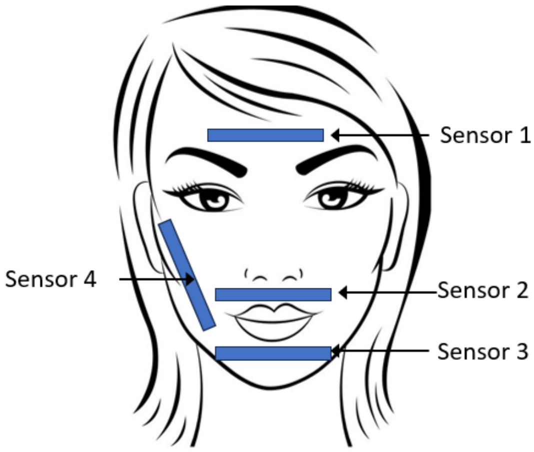


Fig. 8. Stretchable sensors placement

3.5 *Training and Testing Data*

Training and testing of the neural network based on multilayer feedforward backpropagation algorithm for facial expression recognition using the stretchable sensor data have been conducted using Neural Network Toolbox in MATLAB software. The data have been collected from healthy 10 subjects from Malay ethnicity, aged between 20-24 years old, with 5 males and 5 females. The mean, root mean square, variance and standard deviation features are extracted from the collected stretchable sensor data. The training/testing ratio is split into 80/20. The 4 features from the 4 sensors for 8 of subjects under 4 facial expressions serve as the input data to the neural network training and are arranged into 32x16 matrix. After the training has completed and the desired outputs are achieved in the validation process, the testing data with sized 8x16 from the other 2 subjects under 4 expressions are imported into the network for the testing process. For the target, a 32x2 matrix is used for the 4 expressions, 8 subjects and 2 digits of the target output. Figure 9 shows the screenshot of the input training data. In the figure, S1 until S8 which is at top of the column refers to the Subject 1 until Subject 8. While S1_MEAN until S4_MEAN, S1_RMS until S4_RMS, S1_VAR until S4_VAR and S1_STD until S4_STD represents the mean, root mean square, variance and standard deviation of Sensor 1's until Sensor 4's data respectively. Figure 10 shows the screenshot of the 2 samples of input data for the validation process after the training, which have been chosen from training data. Figure 11 illustrates the screenshot of the input data for the testing process, which is taken from the remaining 2 subjects.

International Journal of Advanced Research in Computational Thinking and Data Science
Volume 7, Issue 1 (2025) 44-57

	S1	S2	S3	S4	S5	S6	S7	S8	S1	S2	S3	S4	S5	S6	S7	S8
	NORMAL	NORMAL	NORMAL	NORMAL	NORMAL	NORMAL	NORMAL	NORMAL	HAPPY	HAPPY	HAPPY	HAPPY	HAPPY	HAPPY	HAPPY	HAPPY
S1_MEAN	0.109	0.13328	0.13912	0.15144	0.1175	0.17828	0.11224	0.10944	0.53616	0.49448	0.35316	0.2046	0.50012	2.1222	0.14	0.5448
S2_MEAN	0.1234	0.13224	0.11962	0.1464	0.135	0.234	0.12296	1.08076	0.75362	0.70696	0.58698	0.2032	0.86114	7.0656	0.4769	6.605
S3_MEAN	0.1296	0.1082	0.12654	0.14316	0.1452	0.1136	0.12684	1.08076	1.2662	1.6656	2.60796	1.006	2.77376	3.113	0.93572	4.33304
S4_MEAN	0.11244	0.11368	0.1129	0.12852	0.12648	0.09586	0.10576	5.68E-14	0.1533	0.37608	0.278	0.11636	0.44152	0.9576	0.29384	0.75344
S1_RMS	3.98E+02	3.86E+02	3.88E+02	3.83E+02	3.89E+02	4.92E+02	3.90E+02	3.85E+02	389.9328	388.7939	388.8383	384.4061	391.4614	482.9918	391.168	384.7648
S2_RMS	3.88E+02	3.84E+02	3.82E+02	3.83E+02	3.84E+02	4.57E+02	3.85E+02	4.01E+02	389.9605	389.4498	384.4017	383.5401	397.7247	453.6395	389.3554	505.8274
S3_RMS	3.87E+02	3.92E+02	3.85E+02	3.89E+02	3.87E+02	3.86E+02	3.87E+02	3.86E+02	389.5366	418.4223	393.4255	401.8322	414.7804	393.8112	399.5636	409.8855
S4_RMS	3.21E+02	3.24E+02	3.25E+02	3.27E+02	3.26E+02	3.27E+02	3.29E+02	3.91E+02	320.2771	325.7546	327.0852	327.321	328.4964	329.3618	329.3322	391.2149
S1_VAR	0.018403	0.02842	0.029991	0.038145	0.021894	0.051269	0.018792	0.018925	0.591895	0.699647	0.207228	0.082186	0.328666	6.6225	0.034117	0.600307
S2_VAR	0.024545	0.026885	0.023445	0.032121	0.027252	0.081414	0.026853	1.514799	1.143454	1.41242	0.509999	0.067475	1.36886	57.30623	0.291187	136.3016
S3_VAR	0.025156	0.019091	0.027049	0.030476	0.029495	0.024141	0.025087	0.031332	2.043277	8.71743	9.129499	1.76596	1.36886	12.90634	1.255915	31.0906
S4_VAR	0.020625	0.019979	0.019171	0.025797	0.026832	0.015001	0.018158	3.26E-27	0.038557	0.416853	0.119066	0.02107	0.292711	1.19596	0.124218	0.748489
S1_STD	0.135658	0.168583	0.173179	0.195309	0.147966	0.226426	0.137084	0.137569	0.769347	0.836449	0.455223	0.286681	0.573294	2.573422	0.184708	0.774795
S2_STD	0.15667	0.163966	0.153119	0.179224	0.16508	0.285332	0.163867	1.230772	1.069324	1.188453	0.714142	0.259759	1.169983	7.570088	0.539617	11.67483
S3_STD	0.158605	0.13817	0.164467	0.174573	0.171741	0.155375	0.158388	0.177009	1.429432	2.952529	3.021506	1.328894	3.22803	3.592539	1.120676	5.575895
S4_STD	0.143615	0.141346	0.164467	0.160614	0.163806	0.122479	0.13475	0.177009	0.196358	0.645641	0.345059	0.145154	0.541028	1.093599	0.352446	0.865153

(a)

	S1	S2	S3	S4	S5	S6	S7	S8	S1	S2	S3	S4	S5	S6	S7	S8
	SAD	SAD	SAD	SAD	SAD	SAD	SAD	SAD	DISGUST	DISGUST	DISGUST	DISGUST	DISGUST	DISGUST	DISGUST	DISGUST
S1_MEAN	13.30784	1.9213	0.2062	0.16048	0.17886	4.60952	0.44888	0.18148	0.4701	0.8164	0.3652	0.11564	0.31044	1.12744	0.14328	0.23852
S2_MEAN	0.58856	1.05892	0.1182	0.136	0.24978	12.73744	0.50472	0.60308	1.78032	0.56116	0.14072	0.1272	0.29024	2.1609	1.36022	1.62986
S3_MEAN	0.6348	2.00684	0.14424	0.29788	0.14688	0.60376	0.43064	0.14556	2.01828	0.4292	0.24108	0.4588	0.836	0.17666	1.10536	1.91404
S4_MEAN	0.14296	0.178	0.11992	0.11612	5.12E-13	0.30844	0.43952	0.26876	0.25822	0.73376	0.11192	0.212	0.184	0.296	0.12516	0.28888
S1_RMS	406.7428	384.2449	385.3701	379.3621	385.0311	488.0159	389.8083	383.6661	395.6094	380.3905	386.2402	382.771	389.0432	484.7382	391.008	382.1581
S2_RMS	387.6685	385.5829	382.09	382.842	382.9611	447.1945	387.2665	397.4066	393.3234	383.8425	381.742	383.08	385.3062	434.1038	389.132	412.762
S3_RMS	388.7556	393.7328	385.284	393.5612	387.044	388.0126	389.9443	386.894	399.4882	392.8354	385.3511	391.5403	389.6552	387.9691	392.5303	391.054
S4_RMS	320.492	323.9251	325.576	326.087	325.2	326.8222	327.6724	391.3891	321.1231	332.5975	325.652	326.4281	324.3501	329.3502	328.109	389.8462
S1_VAR	889.3455	4.602605	0.062525	0.04036	0.058322	28.527	0.275491	0.061055	0.302645	1.913794	0.183838	0.022888	0.139445	2.153438	0.030036	0.082259
S2_VAR	0.410481	1.474484	0.023333	0.027713	0.086039	185.607	0.393378	0.505014	4.295834	0.391754	0.031552	0.024444	0.132893	7.684924	2.319252	4.169951
S3_VAR	0.491793	5.427802	0.031661	0.136544	0.03562	0.45339	0.273196	0.036933	7.384908	0.32048	0.083534	0.254343	0.917055	0.058726	1.805067	5.527971
S4_VAR	0.030844	0.047955	0.024065	0.022557	2.64E-25	0.130622	0.273196	0.101999	0.095122	1.011701	0.019693	0.064865	0.053434	0.134848	0.02608	0.142307
S1_STD	29.8219	2.145368	0.25005	0.200897	0.2415	5.341067	0.524872	0.247092	0.550132	1.383399	0.428764	0.151287	0.373424	1.46746	0.17331	0.286808
S2_STD	0.640688	1.214283	0.152753	0.166473	0.293325	13.62377	0.627198	0.710643	2.072639	0.625902	0.177627	0.156347	0.364545	2.77217	1.522909	2.042046
S3_STD	0.701279	2.329764	0.177934	0.369519	0.188733	0.673342	0.522682	0.19218	2.717519	0.566109	0.289023	0.504325	0.95763	0.242335	1.343528	2.351164
S4_STD	0.175626	0.218985	0.155128	0.150188	5.14E-13	0.361417	0.507336	0.319373	0.308419	1.005833	0.140331	0.254685	0.231159	0.367217	0.161492	0.377236

(b)

Fig. 9. Input training data for (a) normal and happy, (b) sad and disgust expressions

	NORMAL	HAPPY	SAD	DISGUST	NORMAL	SAD	DISGUST	SAD
S1_MEAN	0.109	0.2046	1.9213	0.14328	0.1175	0.2062	1.12744	0.18148
S2_MEAN	0.1234	0.2032	1.05892	1.36022	0.135	0.1182	2.1609	0.60308
S3_MEAN	0.1296	1.006	2.00684	1.10536	0.1452	0.14424	0.17666	0.14556
S4_MEAN	0.11244	0.11636	0.178	0.12516	0.12648	0.11992	0.296	0.26876
S1_RMS	397.959	384.4061	384.2449	391.008	388.625	385.3701	484.7382	383.6661
S2_RMS	387.59	383.5401	385.5829	389.132	384.461	382.09	434.1038	397.4066
S3_RMS	387.164	401.8322	393.7328	392.5303	387.46	385.284	387.9691	386.894
S4_RMS	320.509	327.321	323.9251	328.109	326.006	325.576	329.3502	391.3891
S1_VAR	0.018403	0.082186	4.602605	0.030036	0.021894	0.062525	2.153438	0.061055
S2_VAR	0.024545	0.067475	1.474484	2.319252	0.027252	0.023333	7.684924	0.505014
S3_VAR	0.025156	1.76596	5.427802	1.805067	0.029495	0.031661	0.058726	0.036933
S4_VAR	0.020625	0.02107	0.047955	0.02608	0.026832	0.024065	0.134848	0.101999
S1_STD	0.135658	0.286681	2.145368	0.17331	0.147966	0.25005	1.46746	0.247092
S2_STD	0.15667	0.259759	1.214283	1.522909	0.16508	0.152753	2.77217	0.710643
S3_STD	0.158605	1.328894	2.329764	1.343528	0.171741	0.177934	0.242335	0.19218
S4_STD	0.143615	0.145154	0.218985	0.161492	0.163806	0.155128	0.367217	0.319373

Fig. 10. Input data for validation process, chosen from the training data

	HAPPY	SAD	NORMAL	DISGUST	NORMAL	DISGUST	SAD	HAPPY
S1_MEAN	0.37272	0.5558	0.11256	0.24114	0.08416	0.65456	0.3638	0.12996
S2_MEAN	0.24962	0.97416	0.12304	0.162	0.1	0.27768	0.34564	0.4084
S3_MEAN	1.70696	0.81	0.1212	0.207	0.125	2.5004	0.55026	1.1488
S4_MEAN	0.13344	0.17236	0.1199	0.13452	0.1277	0.90264	0.1368	0.27032
S1_RMS	392.0064	381.8376	387.808	386.8232	40.27213	383.3172	384.9306	386.078
S2_RMS	389.4792	328.2937	382.762	384.344	325.544	327.6842	383.6113	329.9056
S3_RMS	407.9212	394.6991	386.32	386.7391	391.743	394.5375	388.4216	329.9056
S4_RMS	320.537	382.9941	322.297	322.986	384.573	383.8773	322.5841	383.5422
S1_VAR	0.288448	0.486395	0.021956	0.139163	0.010723	0.909236	0.44697	0.024562
S2_VAR	0.121878	1.137309	0.021774	0.03764	0.01562	0.107216	0.225635	0.378258
S3_VAR	12.51128	0.848885	0.025253	0.068262	0.025708	8.400375	0.46208	2.486742
S4_VAR	0.031445	0.048246	0.024132	0.030913	0.024617	0.985883	0.032873	0.123471
S1_STD	0.537074	0.69742	0.148174	0.373045	0.103553	0.953539	0.668558	0.156721
S2_STD	0.34911	1.066447	0.147559	0.194011	0.124981	0.327439	0.475011	0.615026
S3_STD	3.537128	0.921349	0.15891	0.261269	0.160337	2.89834	0.679765	1.576941
S4_STD	0.177329	0.219651	0.155346	0.175821	0.156899	0.992916	0.181308	0.351384

Fig. 11. Input data for testing process, acquired from the remaining 2 subjects (Subject 9 and Subject 10)

In the neural network's output data, the values less than 0.5 are interpreted as 0, while the values equal to or greater than 0.5 are interpreted as 1. The resulting binary classification is mapped to specific facial expressions as follows: (1) "0 0" corresponds to the normal expression, (2) "0 1" to happy, (3) "1 0" to sad, and (4) "1 1" to disgust. Table 1 presents the target output setting for each subject in the training and validation process. The first row, labelled S1 to S8, represents Subject 1 to Subject 8, while OUT_1 and OUT_2 denote the first and second binary digits of the neural network's output, respectively.

Table 1
Digits assigned for the target output data in the training

	S1	S2	S3	S4	S5	S6	S7	S8	S1	S2	S3	S4	S5	S6	S7	S8
	NORMAL								HAPPY							
OUT_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OUT_2	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
	SAD								DISGUST							
OUT_1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
OUT_2	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1

3.6 *Multilayer Feedforward Backpropagation Neural Network Algorithm*

The facial expression recognition training is conducted using a multilayer feedforward backpropagation neural network algorithm. This study intentionally employs the fundamental algorithm to explore the implementation of stretchable sensor based facial expression recognition system using a basic neural network approach. The overall process of the algorithm is illustrated in Figure 12. First the system reads the input, target output, initial weights, minimum error and maximum number of epochs. Then, it calculates the outputs of the hidden and output layers, and the error, which is the difference between the target output and actual output. Next, if the actual error is larger than the minimum error or the number of epochs is less than the maximum number of epochs, the system calculates the weight updates for the hidden and output layers, and updates the new weights of each layer. The process continues until the error is less than the minimum error or the maximum number of epochs is reached. In this approach, selecting appropriate learning rate and momentum rate are crucial to ensure proper convergence during the training process. In this work, both the learning rate and momentum rate have been adjusted through a trial-and-error process. A relatively high learning rate with a low momentum rate has been chosen in the beginning. The momentum rate is then gradually increased and the learning rate is decreased progressively to further refine the convergence of the results.

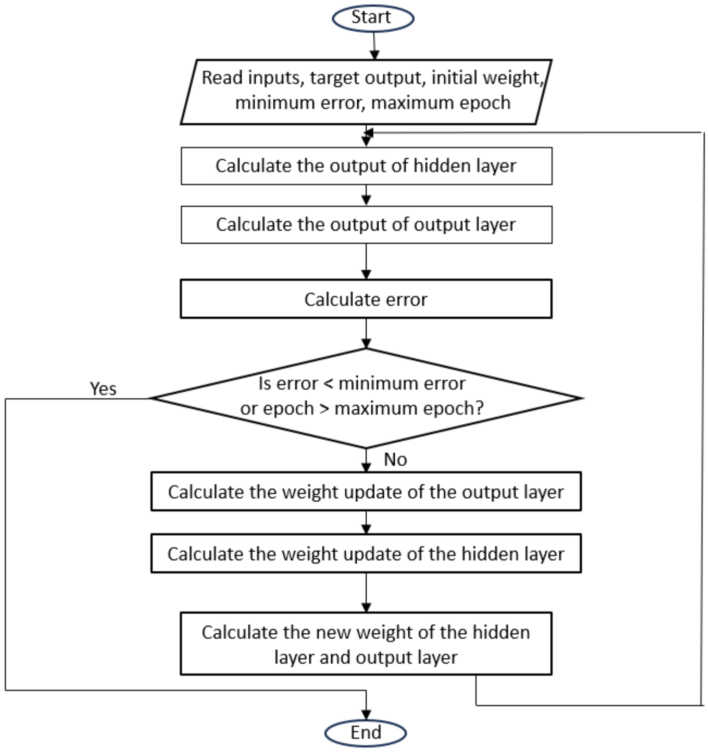


Fig. 12. Flowchart of the multilayer feedforward backpropagation neural network algorithm

4. Results and Discussions

The results after the training and testing have been recorded as shown in Figure 13 and the output matrix of the validation process has been obtained as in Table 2.

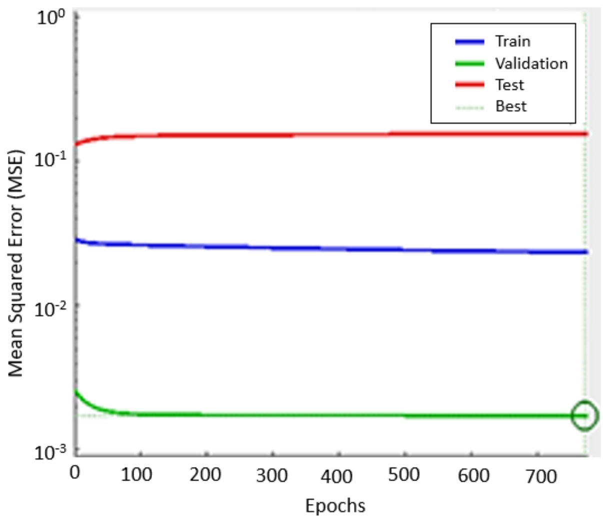


Fig. 13. Training results

Table 2
Validation results

	NORMAL	HAPPY	SAD	DISGUST	NORMAL	SAD	DISGUST	SAD
	S1	**S4**	**S2**	**S7**	**S5**	**S3**	**S6**	**S8**
OUT_1	0.0477	0.2443	0.9876	0.9219	0.2113	0.6641	0.9412	0.9411
OUT_2	0.0279	0.9768	0.0628	0.9935	0.0435	0.2346	0.9826	0.0295

Table 3
Converted validation results

	NORMAL	HAPPY	SAD	DISGUST	NORMAL	SAD	DISGUST	SAD
	S1	**S4**	**S2**	**S7**	**S5**	**S3**	**S6**	**S8**
OUT_1	0	0	1	1	0	1	1	1
OUT_2	0	1	0	1	0	0	1	0

Since any output value that is less than 0.5 is assigned as 0 and the output value that is greater than 0.5 is set to 1, the output of the validation in Table 2 has been converted as in Table 3. Based on the table, the artificial neural network (ANN) model performance can be calculated as

$$\text{ANN Performance} = \frac{\text{total number of correct recognition}}{\text{total number of recognition}} = \frac{8}{8} \times 100\% = 100\% \quad (1)$$

The accuracy of the validation process using the training data was 100%, which means all the recognition outputs are correct. Table 4 shows the result of the testing of the network using the remaining 2 subjects' data.

Table 4
Testing results

	NORMAL	HAPPY	SAD	DISGUST	NORMAL	HAPPY	SAD	DISGUST
		S9				**S10**		
OUT_1	0.4166	0.9263	0.9999	0.5923	1.0000	0.9999	0.9809	0.9999
OUT_2	0.1294	0.7007	0.9989	0.3488	0.01153	0.9999	0.9904	1.0000

Table 5
Converted testing results

	NORMAL	HAPPY	SAD	DISGUST	NORMAL	HAPPY	SAD	DISGUST
		S9				**S10**		
OUT_1	0	1	1	1	1	1	1	1
OUT_2	0	1	1	0	0	1	1	1

Similarly, since any output values less than 0.5 are categorized as 0 and those greater than 0.5 are categorized as 1, the results presented in Table 4 are transformed accordingly as illustrated in Table 5. Based on the table, only the normal facial expression of Subject 9 and the disgust appearance of Subject 10 are correct. Therefore, the accuracy of the artificial neural network (ANN) in the testing stage can be computed as

$$\text{ANN Performance} = \frac{\text{total number of correct recognition}}{\text{total number of recognition}} = \frac{2}{8} \times 100\% = 25\% \quad (2)$$

The testing accuracy of the model is significantly low, even though the validation phase demonstrates a perfect accuracy of 100%. This significant discrepancy between validation and testing performance indicates that the model may have overfitted the validation dataset, or the model may have learned its specific patterns rather than acquiring the generalized features applicable to new or unseen data. Consequently, the model exhibits poor generalization capability, which limits its effectiveness in real-world facial expression recognition tasks. The results show that there is a need for implementing a more advanced techniques and optimization strategies to enhance model robustness. Possible improvements include the use of a more advanced neural network architectures capable of capturing more complex facial features, application of machine learning or deep learning algorithms and data augmentation strategies to increase the diversity and representativeness of the training dataset.

Figure 13 presents the motor movement outcomes performed by the robotic hand in response to the output generated from the expression classification process. When the output is “0 0”, the robotic hand executes a peace gesture, which corresponds to a neutral or normal facial expression. An output of “0 1” results in a thumbs-up gesture, representing a happy expression. Conversely, when the output is “1 0,” the hand forms a fist, symbolizing a sad expression. Lastly, an output of “1 1” prompts the wrist to rotate by 180°, indicating a disgust expression.

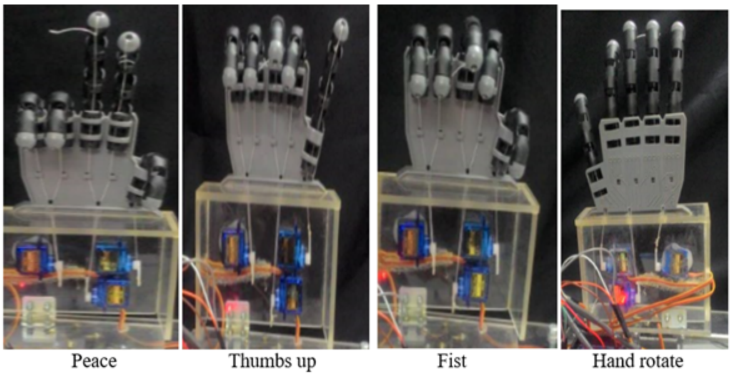


Fig. 13. Robotic hand movement based on the output of the facial expression recognition

Figure 14 depicts the motor movement profiles corresponding to each facial expression. As illustrated, for the peace gesture, only Servo 1 and Servo 3 are activated, while for the thumbs up gesture, the actuation is limited to Servo 2 and Servo 3. The fist gesture involves Servo 1, Servo 2 and Servo 3 actuations. Lastly, during the hand rotation associated with disgust expression, only Servo 4 turns. In all cases, each of the actuated servomotors undergo an angular displacement of 180°, indicating consistent servomotor behaviour across different gesture responses.

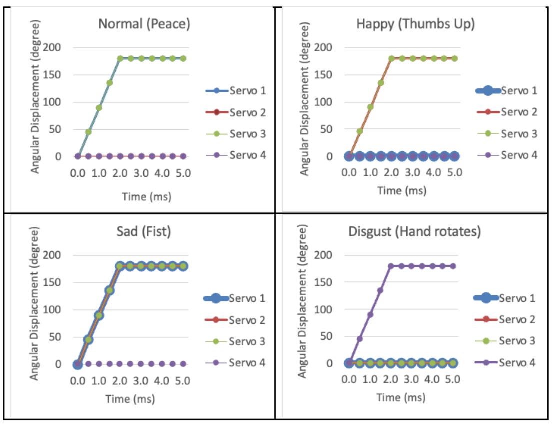


Fig. 14. Angular displacements of the servomotors for the four facial expressions

5. Conclusion

This study presents a facial expression recognition system that utilizes stretchable sensor data to control the movement of a robotic hand. The recognition process is implemented using a multilayer feedforward backpropagation neural network, which serves as the simple and basic neural network model for facial expression classification. The stretchable sensors are positioned at the key facial regions, which are at the forehead, upper lip, lower lip and right cheek to capture the skin deformations associated with different emotional expressions. The mean, root mean square (RMS), standard deviation and variance are extracted from the stretchable sensor data and employed as inputs to train the neural network model. The training and testing processes are conducted using the Neural Network Toolbox in MATLAB, chosen for its flexibility and ease of use. The validation results demonstrate a 100% accuracy in classifying happy, sad and disgust expressions, indicating strong model performance during the training phase. However, the testing phase yields significantly lower accuracy of 25% only, suggesting limited generalization capability and this highlights the shortcomings of the applied approach. Future research will focus on incorporating a more advanced computational method, including the machine learning and deep learning algorithms to enhance the training aspect of the facial expression recognition system and thus, increase its accuracy. In the future study also, the data will be acquired from a larger number of participants and a more diverse group of subjects to increase the model's robustness and therefore, will further enhance the overall performance of the stretchable sensor based facial expression recognition system.

Acknowledgement

The authors would like to thank Asian Office of Aerospace Research and Development (AOARD) for providing the financial support for the neural network part of this research under the grant number: FA2386-18-1-4105 (18IOA105).

References

[1] Gueorguieva, Natacha, George Georgiev, and Iren Valova. "Facial Expression Recognition Using Feedforward Neural Networks." In *IC-AI*, pp. 285-291. 2003.

[2] Adyapady, R. Rashmi, and B. Annappa. "A comprehensive review of facial expression recognition techniques." *Multimedia Systems* 29, no. 1 (2023): 73-103. https://doi.org/10.1007/s00530-022-00984-w

[3] Bhatti, Yusra Khalid, Afshan Jamil, Nudrat Nida, Muhammad Haroon Yousaf, Serestina Viriri, and Sergio A. Velastin. "Facial expression recognition of instructor using deep features and extreme learning machine." *Computational Intelligence and Neuroscience* 2021, no. 1 (2021): 5570870. https://doi.org/10.1155/2021/5570870

[4] Liu, Hanwei, Huiling Cai, Qingcheng Lin, Xuefeng Li, and Hui Xiao. "Adaptive multilayer perceptual attention network for facial expression recognition." *IEEE Transactions on Circuits and Systems for Video Technology* 32, no. 9 (2022): 6253-6266. https://doi.org/10.1109/TCSVT.2022.3165321

[5] Samadiani, Najmeh, Guangyan Huang, Borui Cai, Wei Luo, Chi-Hung Chi, Yong Xiang, and Jing He. "A review on automatic facial expression recognition systems assisted by multimodal sensor data." *Sensors* 19, no. 8 (2019): 1863. https://doi.org/10.3390/s19081863

[6] Panliang, Mu, Sanjay Madaan, Siddiq Ahmed Babikir Ali, Ali Khatibi, Anas Ratib Alsoud, Vikas Mittal, Lalit Kumar, and A. Johnson Santhosh. "Enhancing feature selection for multi-pose facial expression recognition using a hybrid of quantum inspired firefly algorithm and artificial bee colony algorithm." *Scientific Reports* 15, no. 1 (2025): 4665. https://doi.org/10.1038/s41598-025-85206-9

[7] Liu, Jing-Wei, Xiao-Yuan Lin, Peng-Fei Ji, Jia-Ming Chen, and Jun Zhang. "Multiscale wavelet attention convolutional network for facial expression recognition." *Scientific Reports* 15, no. 1 (2025): 22219, doi: 10.1038/s41598-025-07416-5. https://doi.org/10.1038/s41598-025-07416-5

[8] Ma, Hui, Sen Lei, Heng-Chao Li, and Turgay Celik. "FER-VMamba: A robust facial expression recognition framework with global compact attention and hierarchical feature interaction." *Information Fusion* (2025): 103371. https://doi.org/10.1016/j.inffus.2025.103371

[9] Gong, Qingzhen, Xuefang Liu, and Yongqiang Ma. "Real-Time Facial Expression Recognition Based on Image Processing in Virtual Reality." *International Journal of Computational Intelligence Systems* 18, no. 1 (2025): 8. https://doi.org/10.1007/s44196-024-00729-9

[10] Li, Jiquan, Zhiquan Liu, Wang Zhou, Amin Ul Haq, and Abdus Saboor. "FERmc: Facial expression recognition framework based on multi-branch fusion and depthwise separable convolution." *Information Fusion* (2025): 103416. https://doi.org/10.1016/j.inffus.2025.103416

[11] Hossain, Md Jarir, Shahba Tasmiya Mouna, and Jae-Won Choi. "Slip detection in robotic gripper using stretchable, soft multi-axial sensor." *Sensors and Actuators A: Physical* (2025): 116972. https://doi.org/10.1016/j.sna.2025.116972

[12] Min, Shunhua, Haoyang Geng, Yuheng He, Wensheng Liang, Shoubin Chen, Zhijun Wang, Qingzhou Liu, and Tailin Xu. "A stretchable tactile sensor with deep learning-enabled 3D force decoding for human and robotic interfaces." *Chemical Engineering Journal* (2025): 167189. https://doi.org/10.1016/j.cej.2025.167189

[13] Hong, Tianzeng, Jie Xue, Haonan Li, Yahui Wen, Xiaobo Gao, Dan Liu, and Qingbin Zheng. "Vertical graphene/carbon nanotube/polydimethylsiloxane composite films for multifunctional stretchable strain sensors." *Chemical Engineering Journal* (2025): 164747. https://doi.org/10.1016/j.cej.2025.164747

[14] Behrens, H., D. Gawronska, J. Hollatz, and B. Schurmann. "Recurrent and feedforward backpropagation for time independent pattern recognition." In *IJCNN-91-Seattle International Joint Conference on Neural Networks*, vol. 2, pp. 591-596. IEEE, 1991. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-0026732270&partnerID=40&md5=89813b9ae50a89d38d5ba286d23487c9

[15] Al Debs, Fadi, Makram El Jurdy, Elias Fares, Gaby Abou Haidar, Michel Owayjan, and Roger Achkar. "Human Activity Recognition Using Feedforward Backpropagation Neural Network." In *2024 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)*, pp. 630-635. IEEE, 2024. https://doi.org/10.1109/3ict64318.2024.10824544

[16] Yousaf, Adeel, Muhammad Junaid Khan, Muhammad Jaleed Khan, Nizwa Javed, Haroon Ibrahim, Khurram Khurshid, and Khawar Khurshid. "Size invariant handwritten character recognition using single layer feedforward backpropagation neural networks." In *2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*, pp. 1-7. IEEE, 2019. https://doi.org/10.1109/ICOMET.2019.8673459

[17] Mu, Ruihui, and Xiaoqin Zeng. "Improved Webpage Classification Technology Based on Feedforward Backpropagation Neural Network." *COMPTES RENDUS DE L ACADEMIE BULGARE DES SCIENCES* 71, no. 9 (2018): 1236-+.https://doi.org/10.7546/CRABS.2018.09.11