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Smart wearable glove for enhanced human-robot interaction using multi-sensor fusion and machine learning

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ABSTRACT

Hand gesture recognition (HGR) using flexible sensors (flex-sensor) and the MPU6050 sensor has proved to be a key area of research in human-machine interaction, with major applications in biasing, rehabilitation, and assisted robotics. This paper proposes a wearable intelligent glove designed to operate a robotics arm in real time, relying on multi-sensor fusion and machine learning methods to enhance the system's responsiveness and precision. The proposed system enables the intuitive reproduction of hand movements and precise control of the robotic arm. In the context of Industry 4.0 and internet of things (IoT), the classification of gestures is necessary for maintaining operational efficiency. To guarantee gesture recognition, data signals from the smart glove are collected and trained by a recurrent neural network (RNN), which achieves 98.67% accuracy for real-time classification of seven gestures. Beyond industrial applications, the wearable smart glove can be exploited in a recognized circuit of all systems, including rehabilitation exercises that involve recording the progression of muscular activity for the assessment of motor functions and serve as a tool for patient recovery.

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1. INTRODUCTION

Today, as connectivity, automation and embedded intelligence redefine our relationship with interactive systems, the development of advanced human-machine interaction (HMI) solutions is a fundamental pillar of technological research. Among these solutions, wearable gesture interfaces are gaining in popularity, as they enable intuitive, contactless and adaptive communication between the user and digital systems [1].

The integration of flexible sensors and inertial measurement units (IMUs) into smart gloves offers a promising way to accurately capture hand gestures, while reducing hardware complexity. Recent approaches have exploited these sensors to drive robotic arms via sensory object internet of things (IoST) platforms, with encouraging results in terms of cost and efficiency [2]. Other works have proposed combinations of micro-electro-mechanical systems (MEMS) sensors, convolutional neural networks or Bayesian models to improve the robustness of the recognition system [3], [4]. A number of limitations remain despite these advances: Some flexible gloves are expensive and require frequent calibration [5], IMUs alone are sensitive to temporal drift [6], electromyographic (EMG) and piezoresistive devices require precise wearing conditions and complex interpretation [7], Finally, deep learning algorithms on powerful platforms (Jetson, GPU) are not easily embedded [8], [9]. Faced with these challenges, the problem of this study is as follows: *How can we design a lightweight, low-cost, wearable gesture interface combining passive and inertial sensors with real-time embedded processing to control a robotic arm accurately and robustly?*

This work proposes an answer through the development of a multimodal smart glove combining resistive flexion sensors, an MPU6050 IMU, and an ESP32 board for on-board processing. Gesture recognition is provided by optimized supervised models, enabling dynamic hand movements to be predicted and a robotic arm to be controlled in real time. Our contributions are as follows: The hardware design of a low-cost, energy-efficient smart glove, integrating flex sensors and IMU. An embedded software architecture on ESP32, capable of processing sensor signals locally and sending gesture commands. A multi-sensor data fusion method to improve the accuracy and stability of gesture classification. Integration of the system with a robotic arm, validated by experiments reproducing complex gestures in an Industri 4.0 type environment. A benchmarking study with existing approaches, demonstrating the relevance of our solution in terms of latency, cost and accuracy.

The experimental results obtained show that our solution provides reliable recognition and smooth control, with an angular error of less than ±0.15° on all three axes (roll, pitch, yaw). Compared with more complex or costly systems, our approach represents a good compromise between hardware simplicity, gestural precision and robotic integration [10]. Some flexible gloves based on soft piezoresistive sensors, such as those based on polydimethylsiloxane-carbon black (PDMS-CB), have demonstrated good sensitivity, but pose challenges of durability and long-term reproducibility [11]. Recent work has proposed EMG models embedded on edge artificial intelligence (AI) architectures, enabling dynamic gesture recognition with good performance, but still requiring user-specific tuning [12].

The remainder of this article is structured as follows: Section 2 presents related work and comparative approaches in the literature. Section 3 details the system architecture and proposed methodology. Section 4 presents the experimental results and their comparison with existing approaches. Finally, section 5 concludes the implications of our solution and proposes avenues for improvement.

2. RELATED WORK

2.1. Wearable device for manipulator control: human-computer interaction

Human-computer interaction systems have been revolutionized by wearable sensors, providing an intuitive and efficient means of communication between humans and machines. The many applications of these sensors help to enhance the user environment through gesture recognition, physiological monitoring, and haptic feedback. This section presents the main features of human-machine interaction systems based on wearable sensors and their application in the literature review. Recent innovations in sensor technologies have significantly improved gesture recognition and human-machine interaction while opening up new prospects for ergonomic applications.

Triboelectric sensors, flex sensors, and dielectric elastomer matrices: Triboelectric sensors, such as the triboelectric drum nanogenerator (DS-TENG), have proved particularly effective at detecting light pressure signals, with a detection limit set at 3.9 Pa and an accuracy rate of up to 92% in gesture recognition [13]. At the same time, the integration of dielectric elastomer matrices in textiles enables continuous interaction with the user while achieving a predictive efficiency of at least 80%, thanks to highly sophisticated machine learning algorithms [14]. The research for the comfort and personalization of wearable devices is greatly focused on the integration of flexible sensors, such as EMG signals [15], IMU sensors [16], flex sensors [2], or textile sensors [5].

Applications in ergonomics and human-machine interaction: In the field of intelligent wearables, artificial intelligence-assisted exo-skeletons make industrial tasks easier by reducing muscular fatigue and maximizing posture. Such devices integrate machine-learning models to offer real-time personalized support [3], [9]. In addition, enabling systems combining triboelectric sensing and pneumatic feedback enhance the user experience by providing realistic touch sensations, with applications in virtual reality (VR) and rehabilitation [13]. Despite these advances, challenges remain, particularly in terms of sensor accuracy, comfort, and energy efficiency. Further miniaturization and user adaptability are crucial areas of research to ensure optimal integration in a variety of application contexts [1]. In addition, the widespread adoption of wearable sensors may be hampered by concerns about data privacy, cybersecurity, and over-reliance on digital technologies.

2.2. Hand movement recognition based on signal

Signal-based recognition of hand gestures, in particular signals from flexion or EMG sensors, has attracted growing interest in a variety of applications, especially prosthetics, robotic arm control, and human-computer interface. The implementation of machine learning technology helped increase the accuracy and efficiency of recognizing hand gestures from signal-based data. This technology not only enhances human-computer interaction but also serves as a vital tool for individuals with hearing impairments.

Flex sensor technology: Flex sensors have an important role to play in gesture recognition, measuring the degree of finger flexion and providing real-time data on hand movements. Their integration with other sensing systems, such as IMUs, significantly enhances the accuracy of gesture recognition [17]. Machine learning has optimized gesture classification by exploiting various algorithms, including convolutional neural networks (CNN), Gaussian naive Bayes, random forest, k-nearest neighbors (KNN), and support vector machine (SVM) [18]. Multimodal data analysis, which combines flexion sensor signals with other data sources, has proved a major enhancement to the effectiveness of classification models. These advances facilitate interaction with the environment and help to overcome physical limitations. However, despite the progress made in the design of flexible sensors and their combination with advanced machine learning techniques, gesture recognition still suffers from a certain lack of variety in training datasets. Wider data collection on diverse sensors remains essential to improve model robustness and generalization.

EMG signal acquisition and processing: The acquisition and analysis of EMG signals is an important step in the recognition of hand movements. The signals are captured via electrodes attached to the skin, allowing detection of the electrical activity generated by muscle contractions [19]. To improve signal processing and recognition accuracy, various pre-processing steps are implemented, notably, interference filtering, extraction of relevant segments, and feature normalization. In real-time, hand gestures are identified by acceleration sensors and gyroscopes, which send the information to control applications via ad-hoc wireless communication [20]. Feature extraction constitutes a key phase in signal interpretation in general. Various techniques have been adopted, such as time-synchronous averaging [21]–[23], time-domain descriptors, and wavelet transformations, to better distinguish the value of each signal.

Table 1. Overview of studies on model-based approaches and sensor technologies for gesture recognition

Year	Ref.	Model/Classifier	Performance metrics	Gesture/Purpose	Sensors	Controlled robotics
2019	[5]	Neural network (NN) / Dynamic time warping (DTW) algorithm	Data from 4 males aged 24 volunteers, Recognition accuracy: 98.5% for 2000 static digits gestures, 98.3% for 180 CSL word samples.	Chinese CSL; data have been collected with 2000 static digit and 9 CSL word samples.	RGO-coated textile data-glove.	×
2020	[11]	Finite element method (FEM)	Stretchable PDMS-CB strain sensors are validated to accommodate larger deformations (>30%)	Controls the motion of robot fingers remotely	PDMS-CB strain sensors	✓
2021	[15]	Teager-Kaiser energy operator (TKEO) / (mean absolute value, zero crossings)	3 EMG signals from 4 healthy subjects. Accuracies: 74–98%. The best model had 96.67% accuracy, 99.66% recall, and 96.99% precision.	Classifying upper arm movements using EMG signals. Controlling a 2-DoF robotic arm effectively.	Three EMG sensors	✓
2022	[24]	Bayesian FC-DenseNets	4.7% increase in mIoU compared with Ego hands	Human-robot collaboration (HRC) dataset from 3 human agents/recorded the HRC image data using a camera	--	✓
2023	[16]	Gaussian Naive Bayes and random forest	3300 samples from 10 subjects performing hand gestures. cascaded classifier with high accuracy (92%) and low latency (7.5 ms recog. time)	Asynchronous hand gesture detection and recognition method	6DoF IMUs, data glove	✓
2023	[17]	Dynamic time warping (DTW) fusion algorithm	recognition accuracy was 85.21%	American ASL; data have been collected with 20 ASL words	Inertial and bending sensors	×
2024	[25]	MOA/SConv/Bi-LSTM/GRU model	Accuracy, Precision, Recall, F1-Score (≈ 0.9866)	16,000 Samples, 4 Individuals, 20 Gestures	--	✓
2025	[26]	Integration of SWCNTs within PDMS matrix.	Achieving a 70% strain range and a gauge factor of 73	Movements of diff. Fingers	SWCNTs/PDMS composite strain sensors	✓

2.3. Real-time robotic arm controlling

Real-time control of robotic arms via smart gloves or wearable devices uses the power of advanced sensor technologies in synergy with machine learning algorithms for natural, intuitive human-machine interaction. These systems detect hand gestures, which are interpreted and converted into commands for robotic arms in a variety of applications, from rehabilitation and gaming to industrial automation. Smart glove systems integrate various technologies to enhance robot command. The integration of multimodal tactile perception enables smart gloves to analyze tactile information and build models of the world in the sense of object shapes and grip states, using pressure, bending, and also heat sensors [27]. By integrating deep learning into flexible smart gloves, it is possible to determine finger movement intentions early on, thus reducing communication latency and enhancing robot control [28]. On the other hand, by using surface EMG (Electromyogram) signals, it is possible to exceed certain efficiency thresholds in gesture recognition, thus enabling a minimal mode of operation to better control robotic arms [15]. Gesture-controlled robotic arms are increasingly applied in manufacturing and teaching, streamlining operations and enhancing learning experiences. This enables fine-grained recognition to control robotic devices [29].

3. MATERIALS AND METHOD

Hand gestures have two main functions: to convey information and to enable functional interaction. Wearable interfaces can facilitate gesture recognition in both these areas, enabling seamless communication between humans and machines and even between individuals. This improves the quality of life and creates more intuitive interactions. Humans generally use their hands and fingers to perform specific tasks or express ideas. However, keyboards can limit this expression, restricting direct and intuitive communication due to hardware constraints. Hand gestures often involve coordinated movements of all five fingers and can be complex, involving actions such as finger flexion/extension, abduction/adduction, wrist rotation, deviation, and hand positioning. In many applications, it is not necessary to capture every possible hand pose; instead, defining a specific set of gestures can provide adequate performance for the intended purpose.

Figure 1 shows the overall architecture of the proposed system, divided into four main modules: data collection, pre-processing, gesture recognition and robotic arm control. The smart glove captures real-time data from the flexion sensors and IMU (accelerometer and gyroscope), transmitted wirelessly for processing. The data is then normalized, filtered and segmented to extract features useful for training a RNN model. Finally, recognized gestures are translated into precise commands for robotic arm control, demonstrating fluid, real-time interaction. The ESP32 is a portable card using an ATmega328 CPU with a single 8-bit chip, an operating voltage of 5 V, and a processing clock of 16 MHz. The board has 8 analog pins for connecting the various types of sensory input used in this work. The second part involves receiving and pre-processing input data from the flex sensors, which are processed and digitized in the MCU, where the movements are recognized and transmitted to a laptop via the ESP32's built-in Wi-Fi module to control the robotic arm.

Figure 2 illustrates the operational process of the continuous loop system. After initialization, data from the flexion sensors and MPU6050 are acquired and pre-processed (filtered and normalized). Each detected gesture is classified in real time, then converted into a specific command transmitted via Wi-Fi to the ESP32 to control the robotic arm. The system remains on standby for continuous gesture analysis until a stop condition is triggered.

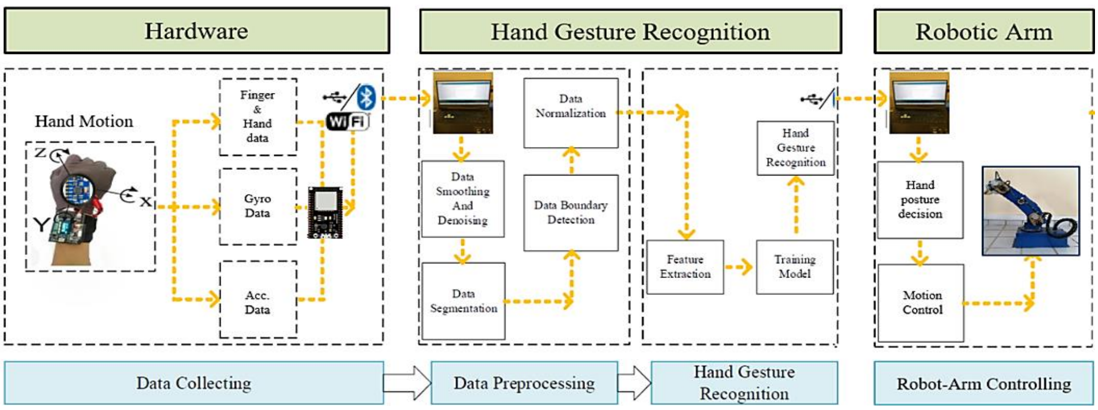


Figure 1. A proposed architecture for the gesture recognition and intelligent glove control system for the robotic arm

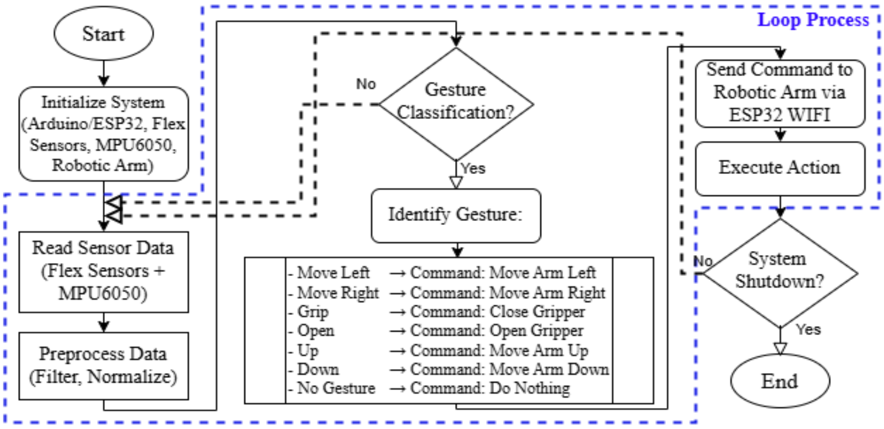
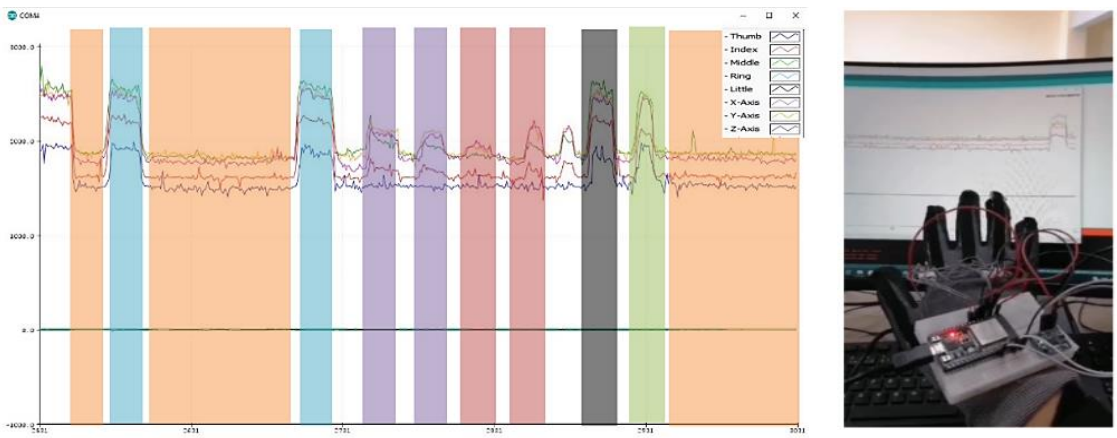


Figure 2. Flowchart of the gesture recognition and robotic arm control process

3.1. Smart glove capturing device

The wearable technology of the intelligent glove, in which the gesture capture device represents an essential advance, is confronted with gesture recognition, enabling intuitive interaction between man and machine. Using sensors of all kinds, this device captures upper limb movements and transforms them into commands that can be used for a variety of applications, from games to medical rehabilitation. Hand gesture data to control the robotic arm is captured using a smart wearable glove. The Smart-Glove assembles hand gesture data from 5 bending sensors and an MPU6050, which are mounted to the top of our prototype glove as shown in Figure 3(a) shows the temporal evolution of signals from the five flexion sensors (thumb, index finger, middle finger, ring finger and little finger), as well as the inertial axes (X, Y, Z), for different gesture sequences. Colored areas identify segments corresponding to distinct recognized gestures. Figure 3(b) shows the smart glove in actual operation, with sensor wiring visible and the signal visualization interface displayed on screen. This experimental configuration validates the glove's ability to capture fine variations in movement in real time.



(a) (b)

Figure 3. Smart-glove capturing device: (a) visualization of multisensory data collected, and (b) the smart glove during gesture execution

3.2. Robotic arm system

As the smart glove performs movements, it delivers signals related to the angle of the flex sensors as well as acceleration via MPU6050. To characterize this relationship, a wearable sensor glove was designed by integrating flexible sensors and an MPU6050 to track hand movements. After calibration, five analog values from the flexible sensors and three analog input values from the accelerometer were collected simultaneously. These values were converted to digital data (10 bits) via the ESP32's ADC using (1):

$$V_i = \frac{V_d}{2^n} \times V_{cc} \tag{1}$$

Here, V_i represents the input voltage, V_d corresponds to the digital voltage reading from the ESP32's, V_{cc} denotes the supply voltage, and n is the ADC resolution. The resistance of each flex sensor was then determined using the voltage divider formula (2), which is used to estimate the resistance of the flexible sensor R_{flex} as a function of the measured voltage V_i, the reference resistance R_d, and the supply voltage V_{cc}, according to (2):

$$R_{Flex} = \frac{R_d}{V_i - 1} \times V_{cc} \tag{2}$$

The output voltage V_{out} is in effect fixed by the circuit configuration, where R_2 corresponds to the variable resistance of the flex sensor (R_{flex}), R_1 representing a known reference resistance between 33-45 k ohm, and V_{in} the input voltage of 5 V. V_{out} is recorded using the ESP32's 10-bit ADC (analog-to-digital converter), so the resistance of the bending transducers can be directly deduced from the digital values supplied by the ADC, by applying (3) previously considered under the assumption that the variations measured correspond to variations Flexion degree:

$$V_{out} = V_{in}\left(\frac{R_1}{R_1 + R_2}\right) \tag{3}$$

The wearable sensor glove also integrates an accelerometer, which converts its Analog input values (Axe *x*, Axe *y,* and Axe *z*) into digital values using the esp32's internal 10-bit ADC. These data were used directly in the study. Table 2 shows the averages of the values measured (in millivolts) by the five flexible sensors and the raw accelerometer values (X, Y, Z axes) for each control gesture. These data provide a useful baseline for segmentation and labeling during classification model training. They highlight the distinction between gestures through specific signal variations, enabling reliable recognition via machine learning.

Figure 4 illustrates the complete architecture of the gesture recognition model based on a RNN, applied to the temporal data acquired by the smart glove. Flexible sensors measure finger curvature, while the MPU6050 sensor provides three-axis acceleration and rotation data. These data are collected continuously and organized in time sequences.

Table 2. Sensor value ranges corresponding to each action

#Samples	Flexible sensors data (mVoltage)					Accelerometer data		
	Flex 1	Flex 2	Flex 3	Flex 4	Flex 5	Axe X	Axe Y	Axe Z
Grip Pince	639	709	702	959	958	16,208	-824	3,944
Open Pince	652	801	770	981	976	15,292	1,204	5,916
Up	657	784	748	926	930	12,348	-7,512	7,972
Down	661	807	750	975	976	10,560	2,684	11,336
Move left	644	849	791	953	955	15,980	-1,780	4,128
Move right	656	786	741	974	971	8,908	11,924	-7,828
Nothing	665	732	701	965	968	15,536	-1,216	6,436

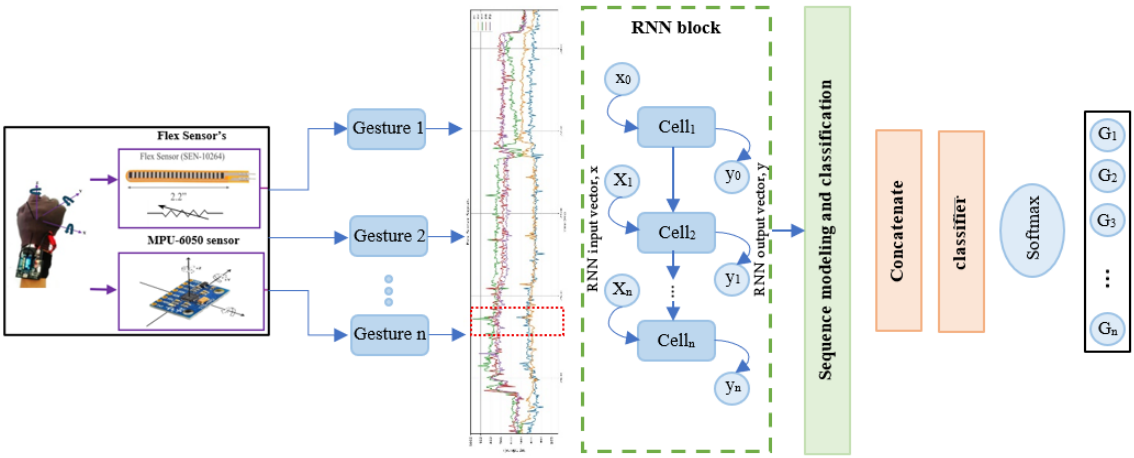


Figure 4. Visualization of multisensory data collected by the smart glove during gesture execution

Each sequence corresponds to a candidate gesture, represented by a multivariate vector entering the RNN block, which models temporal dependencies via recurrent cells. The RNN outputs are then aggregated and processed by a classifier and a SoftMax activation function to identify the most likely gesture among the predefined gestures. This pipeline enables efficient, real-time recognition of dynamic gestures, with the accuracy demonstrated in our experimental results as shown in Figures 5 and 6. Its lightweight, sequential structure is particularly well suited to resource-constrained embedded systems such as the ESP32.

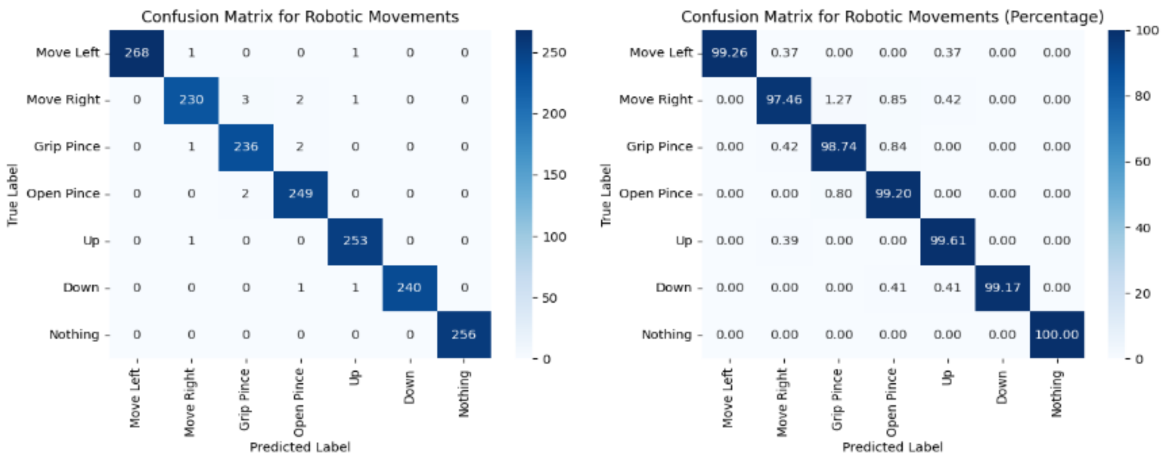


Figure 5. Classifier performance evaluation for robotic movements

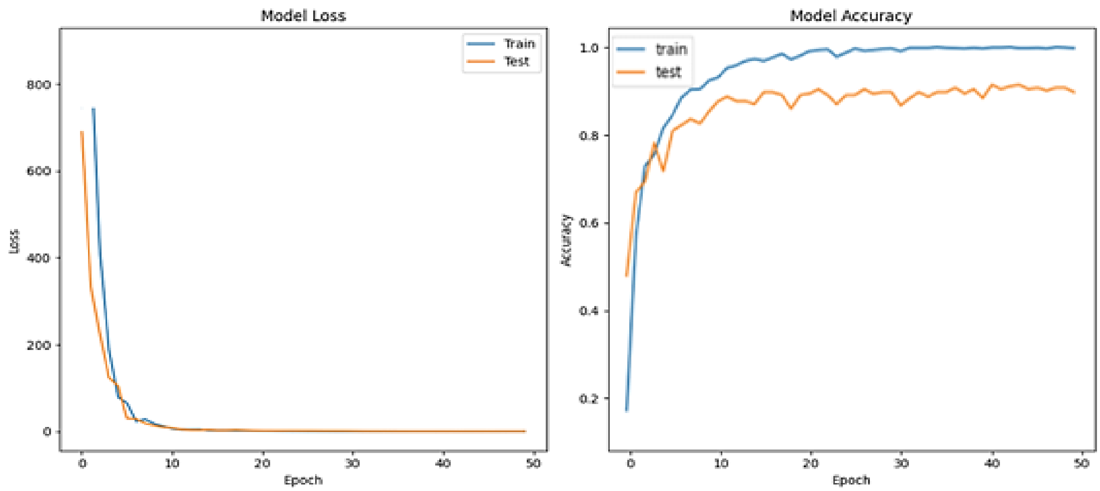


Figure 6. Evolution of loss function and accuracy during training

4. RESULTS AND DISCUSSION

Gesture control has become a very promising approach in the field of human-machine interfaces, particularly for rehabilitation, teleoperation, and robotic assistance applications [4]–[7], [10]. However, real-time gesture recognition still poses challenges due to environmental interference, the variability of human movements, and the hardware limitations of on-board sensors. In this research, the performance of the suggested and developed solution is assessed by comparing it with works in the literature [10], [15], [16], as shown in Table 3.

The selection of the operating mode for robotic arm control is based on the use of movement dictionaries detectable by flexible sensors and an accelerometer MPU6050. Machine learning applied to this classification requires a training phase using datasets generated from relevant features in smart glove signals extracted for each gesture. In this study, we propose motion dictionaries based on the analysis of signals from an MPU6050 accelerometer as well as from five flexion sensors integrated into the smart glove. By exercising movements through our smart glove, we have defined repertoires of usable gestures. Figure 7 shows the six hand gestures detectable by the smart glove and their direct correspondence with the movements of the robotic arm. Each gesture - such as pinching, hand opening, up/down and left/right movements - is captured by the flexible sensors and inertial unit (MPU6050), then interpreted into specific commands. This gesture dictionary guarantees intuitive, natural control of the robotic arm via wireless gesture interaction.

Table 3. A performance comparison with other studies

Publications, Year	Type of sensor	Learning model	Controlled robotics	Raw Data	# Gestures	Accuracy
Lu *et al.* [16], 2023	IMUs	Bi-LSTM	✓	5 (IMUs)	10	92%
Laksono *et al.* [15], 2021	EMGs	KNN	✓	3 (EMG)	4	96.67% accuracy, 99.66% recall, 96.99% precision.
Cruz *et al.* [10], 2023	EMG + IMU	DQN	✓	EMG-IMU sensor	6	97.45 ± 1.02% and 88.05 ± 3.10%
Proposed approach	MPU6050 + Flex	RNN	✓	5 (flex) + 1 (IMU)	7	98.67%

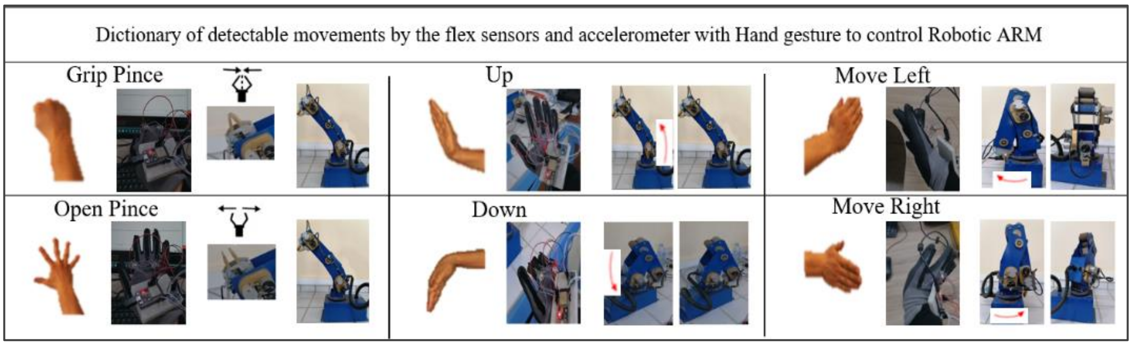


Figure 7. Dictionary of gestures recognized for robotic arm control using flexion and inertial sensors

Hand gesture recognition algorithms can be categorized into two main types: i) classification of hand poses and trajectories, aimed at identifying specific gestures (for example, recognition of the Grip Pence gesture or cyclic hand movement), and ii) continuous parameter regression, enabling variables such as finger flexion angle or hand trajectory or wrist deviation to be estimated in real time.

Figure 8 illustrates the entire processing pipeline, from the acquisition of sensory data by the smart glove (flexions + IMU) to the final decision by a classifier based on a deep neural network. After signal visualization, normalization and filtering, the extracted features are transmitted to the deep learning module, where a neural network and a SoftMax classifier enable real-time gesture prediction. The example presented shows recognition of a closed grip with 99% accuracy.

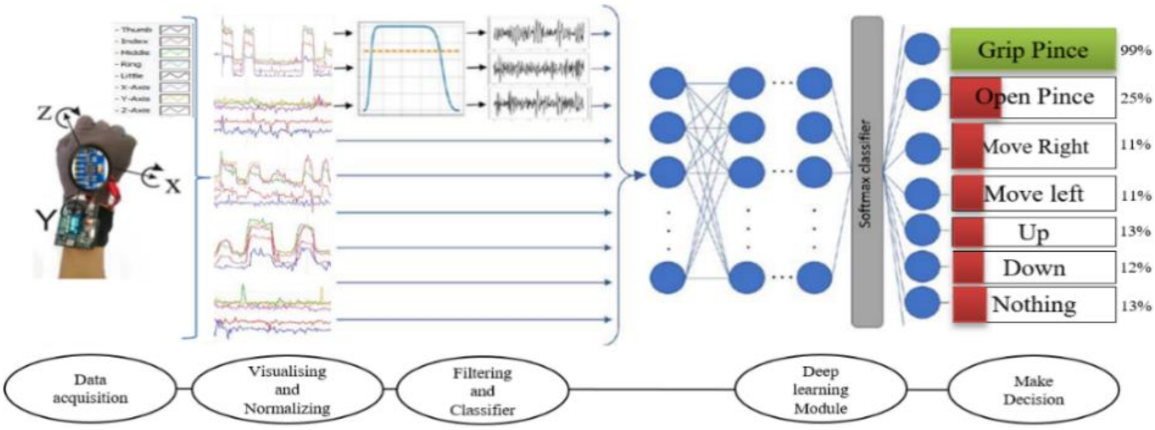


Figure 8. Signal processing chain and gesture classification via deep learning

Figure 5 shows two confusion matrices illustrating the performance of the classification model for seven gestures: “Move Left”, “Move Right”, “Grip Pince”, “Open Pince”, “Up”, ‘Down’ and “Nothing”. On the left, the absolute value matrix shows the number of correct predictions per class, while on the right, the normalized percentage matrix shows that the average accuracy of the model reaches 98.67%, with perfect recognition for the “Nothing” gestures and rates above 97% for the majority of classes. These results validate the robustness of our deep learning approach for real-time control of the robotic arm.

Figure 6 illustrates the convergence of the model during training over 50 epochs. The left-hand curve shows a rapid decrease in loss from the very first iterations, reaching stability at a low level for both the training and test sets. The right-hand curve reveals accuracy above 90% as early as the 10^{e} epoch, and reaching almost 98.67% for training, attesting to the network's learning efficiency. This stability indicates a good bias-variance compromise, with little overlearning.

Table 3 comparison highlights that our approach using only low-cost sensors (MPU6050 + flexible sensors) achieves accuracy superior or equivalent to other more complex systems based on EMG or deep Q-learning (DQN). It combines efficiency, low cost and robustness for real-time robotic control. This study presents several limitations that merit further investigation. Firstly, the recognition process was trained and validated with data from a single participant, requiring a recalibration and re-training phase for each new user, which may affect the generalizability and scalability of the model. In addition, the current implementation has not yet been tested in an embedded system for remote classification, a key step in assessing its practical integration as well as non-cutting-off during long-distance control. Finally, the study was limited to a restricted set of gestures and a single user; future work will need to expand the database by integrating a greater diversity of gestures and participants involved in evaluating the adaptability and performance of the model in different populations.

5. CONCLUSION

In this study, we designed and implemented a wearable smart glove integrating flexion sensors and an MPU6050 inertial sensor, combined with an RNN-based deep learning model for real-time gesture recognition. The proposed hardware and software architecture enables fluid and intuitive interaction with a robotic arm, achieving a classification accuracy of 98.67% on seven distinct gestures. Experimental results demonstrate the robustness and reliability of the proposed system. Multi-sensor fusion, accompanied by a pre-processing process including data boundary detection, normalization and learning based on recurrent networks, enables accurate interpretation of dynamic gestures. A comparison with other recent approaches highlights the high performance of our system, despite its lighter architecture and low-cost hardware.

This work thus contributes to the advancement of wearable human-machine interfaces, with potential applications in the fields of assisted robotics, medical rehabilitation and Industry 4.0. Thanks to its ability to interpret gestures in real time, while ensuring precise control of the robotic arm, our solution effectively meets the requirements of interactive embedded systems.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author N.H. on request.

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