

Cost-effective Flex Sensor Glove-based Bangla Sign Language (BdSL) Interpreter for Resource-limited Settings

Md. Sayzar Rahman Akash^{1,2}, Rethwan Faiz¹, Mohammad Hasan Imam^{1,2}, G.M. Tanvirul Islam¹, Sheikh Tanvir Alam¹, Jhon Dev¹, and Nuzat Nuay Alam¹

¹Department of Electrical & Electronic Engineering, American International University-Bangladesh, Dhaka, Bangladesh

²Center for Biomedical Research (CBR), D2A21, American International University-Bangladesh, Dhaka, Bangladesh

Article Info

Article history:

Received Jul 11, 2025

Revised Apr 9, 2026

Accepted Jun 29, 2026

Keywords:

Bangla Sign Language (BdSL)
Flex Sensor Glove
Wearable Technology
Sign Language Interpreter
MPU 6050 Gyroscope
Threshold-Based Rule Classifier (TRC)

ABSTRACT

In Bangladesh, approximately 13 million individuals experience hearing loss, including nearly 3 million with severe to profound impairments, creating significant communication barriers for the deaf and mute community. Most existing Bangla Sign Language (BdSL) interpretation systems rely on image-based approaches. However, these systems are sensitive to environmental conditions, require substantial computational resources, and often involve high implementation costs. To address these limitations, this paper presents a low-cost wearable BdSL interpreter based on flex sensor gloves and inertial sensing. The proposed system utilizes ten flex sensors to capture finger bending and two MPU6050 gyroscope modules to measure hand orientation. Sensor data are processed using a Threshold-Based Rule Classifier (TRC) algorithm running on an Arduino Mega 2560, eliminating the need for computationally intensive machine learning or image-processing techniques. The developed prototype recognizes a total of 25 BdSL gestures, comprising 10 numerals, 10 alphabet letters, and 5 commonly used words. The system provides both text and speech outputs to facilitate communication for hearing and visually impaired users. Experimental evaluation involving five volunteers demonstrated an overall recognition accuracy of 91.2%, with recognition accuracies of 98% for numerical gestures, 80% for alphabetical gestures, and 100% for word-level gestures. Confusion matrix analysis showed macro-F1 and weighted-F1 scores of 0.9798 for numerical gestures and 0.7991 for alphabetical gestures. The complete prototype was developed at a cost of approximately 100 USD using commercially available hardware components sourced from the local market. By avoiding dependence on cameras and high-performance computing platforms, the proposed system provides robust real-time performance under diverse environmental conditions while maintaining affordability and portability. The results demonstrate the potential of low-cost wearable technology to improve accessibility and promote inclusive communication for Bengali-speaking deaf communities in resource-limited settings.

Copyright © 2026 Institute of Advanced Engineering and Science.
All rights reserved.

Corresponding Author:

Mohammad Hasan Imam,
Faculty of Engineering,
American International University-Bangladesh,
408/1, Kuratoli, Khilkhet, Dhaka 1229, Bangladesh
Email: hasan.imam@aiub.edu

1. INTRODUCTION

Communication is fundamental to human interaction, serving as the exchange of ideas, thoughts, and experiences that allows people to express emotion, share knowledge, and build relationships. Speech is generally the most effective means of doing so, but for individuals who are deaf or mute, speech is not an option, and sign language becomes their primary means of communication instead [1]. Sign language conveys meaning through structured hand gestures, body movement, and facial expression, making it a powerful alternative for individuals with hearing and speech impairments.

Physical disabilities such as deafness, muteness, and blindness affect millions of people worldwide. According to World Health Organization (WHO) statistics, approximately 285 million people are blind, 300 million are deaf, and over 1 million are mute, with many experiencing a combination of these disabilities [2]. In Bangladesh alone, an estimated 13 million people have some degree of hearing loss, 3 million of them severe to profound. Chronic Otitis Media (CSOM) and otitis media effusion are the most common acquired causes of deafness in the country, with CSOM alone accounting for over 12% of cases [3].

Bangladesh's Population and Housing Census 2022 [4] and the National Survey on Persons with Disabilities (NSPD) 2021 [5] both point to significant challenges in addressing disability in a country of 165.16 million people, particularly among deaf and mute individuals. The Census puts overall disability prevalence at 1.43%, including 0.07% with hearing disabilities and 0.12% with speech disabilities. The NSPD 2021, based on a sample of 36,000 households (78.50% rural, 21.50% urban), reports a higher prevalence: 2.80% with at least one disability, 0.36% with hearing disabilities, and 0.32% with speech disabilities. Taken together (Table 1), these figures point to a clear need for accessible, low-cost communication tools such as the flex sensor glove-based BdSL interpreter proposed here, particularly in resource-limited settings.

Table 1. Hearing and speech disability prevalence in Bangladesh by gender. Data from the Population and Housing Census 2022 and NSPD 2021

Type of Disability	Both (%)	Male (%)	Female (%)
Population & Housing Census 2022.			
The total population of Bangladesh is 165.16 million.			
Total (with at least one disability)	1.43	1.63	1.23
Hearing Disability	0.07	0.07	0.07
Speech disability	0.12	0.14	0.11
National Survey on Persons with Disabilities (NSPD) 2021.			
Household sample coverage = 36,000, where Rural 28,261 and Urban 7,739 sampled households.			
Total (with at least one disability)	2.80	3.28	2.32
Hearing Disability	0.36	0.37	0.34
Speech disability	0.32	0.37	0.27

The Department of Social Services (DSS) [6] puts the number of registered persons with disabilities in Bangladesh at more than 3.65 million. The government supports this population through the Disability Allowance Programme, which in fiscal year 2025-2026 covers 3.45 million beneficiaries at a monthly allowance of BDT 900, with a total budget allocation of BDT 3752.08 crore. This reflects a genuine commitment to social inclusion, but the limited purchasing power it affords many beneficiaries points to a continued need for affordable assistive technology. Low-cost, locally implementable communication aids, such as the Bangla Sign Language recognition glove proposed here, are therefore essential to improving accessibility and social participation among hearing and speech-impaired individuals.

Researchers have responded to these challenges by developing sign language recognition systems intended to bridge the communication gap between hearing and non-hearing communities. These systems translate sign language gestures into text or speech to facilitate interaction, and sensory gloves are among the most promising approaches. Fitted with sensors that capture hand movement, orientation, and position, such gloves pair with gesture recognition algorithms to convert manual signs into a form that hearing individuals can understand [7]. This approach addresses a genuine need for inclusive communication tools and carries a practical advantage as well. Unlike computer vision-based systems, sensory gloves do not depend on ambient lighting, making them more reliable in many real-world scenarios. They can also be designed to be affordable and portable, which matters most in low- and middle-income countries, where preventable conditions such as ear infections account for a disproportionate share of hearing impairment [2].

Despite this potential, most recent BdSL research has focused on image-based approaches where deep learning and camera systems with complex, sophisticated processing were utilized. These methods can achieve high accuracy, but that accuracy depends on lighting and camera angle. Recent studies [8] for instance, reports strong results that are nonetheless constrained by environmental factors. Wearable systems are a promising alternative but remain far less common, particularly for specific sign languages like BdSL. One wearable system for Chinese Sign Language recognition reports 95.85% accuracy on isolated signs using a convolutional neural network [9]. On the image-based side, a CNN approach for real-time BdSL character recognition and translation achieves 99.57% validation accuracy [10], though its computational demands leave it impractical for resource-limited settings. However, it remains impractical for resource-limited settings.

This work addresses that gap directly, with a flex sensor glove-based interpreter built specifically for BdSL that recognizes 20 two-handed gestures and produces both text and speech output. The design is intended to be reliable and practical for Bangladesh's BdSL community. Technology alone cannot close this gap, however a parallel need for educational and social measures, including raising awareness of the diversity of

sign languages and training hearing individuals as interpreters, so that deaf and mute individuals can participate fully in social life rather than simply communicate within it [11]. Systems like these extend beyond easing day-to-day communication, opening access to education, healthcare, and professional opportunities that would otherwise be harder to reach. Future progress is likely to come from advances in dynamic gesture recognition, more cost-effective designs, and improved portability. A systematic review [12] reaches a similar conclusion, identifying accessibility, diversity, inclusion, and awareness as central priorities for using this technology to support individuals with hearing impairments. This work follows that framing, aiming for an interpreter that is affordable, portable, and built specifically around the BdSL standard.

Bangla Sign Language (BdSL), also referred to as Bengali or Bangladesh Sign Language, is thought to have originated at the Kolkata Deaf and Dumb School in 1893, where students developed an independent signing system that later spread across West Bengal and Bangladesh [13]. Following Bangladesh's independence in 1971, the signs in these regions diverged into West Bengal Sign Language (WBSL) and BdSL due to reduced migration between the two areas. Efforts to standardize BdSL include the publication of a sign language dictionary in 1994 and its recognition as an official language of Bangladesh in 2009. Additionally, February 7 has been celebrated as Bangla Sign Language Day since 2013 [14]. In Fig. 1. i)-vi), Fig. 2. i)-xxx), and Fig. 3. i)-x) below, selected examples of vowel signs, consonant signs, and numerical signs in Bangla Sign Language (BdSL) are illustrated with ISO 15919 Romanisation of the Bengali language, which is a transliteration of the Bengali script [15], respectively.

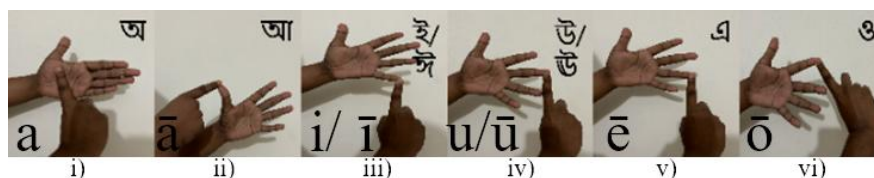


Figure 1. Example postures of the BdSL Bengali vowel alphabet letters are shown from i) to vi) with ISO 15919 Romanisation of the Bengali language

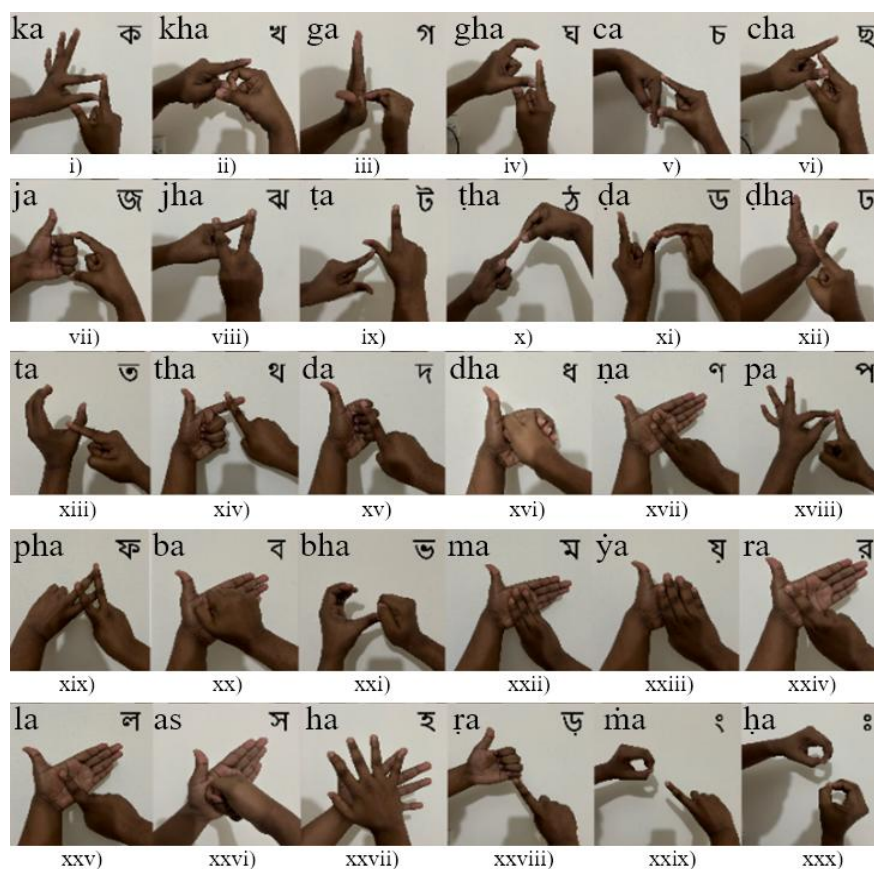


Figure 2. Example postures of the BdSL Bengali consonant alphabet letters are shown from i) to xxx) with ISO 15919 Romanisation of the Bengali language

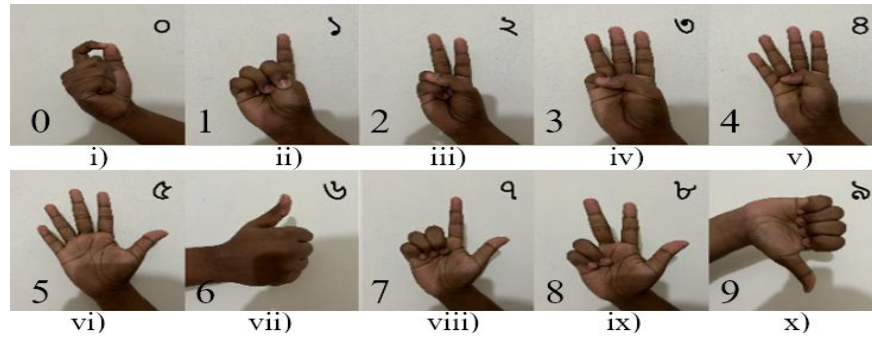


Figure 3. Example postures of BdSL Bengali numeral signs. The numerals 0, 1, 2, 3, 4, 5, 6, 7, 8, 9 are shown from i) to x) in the Bengali language

Over the past few decades, researchers have developed various approaches to address communication challenges faced by individuals with speech disabilities, focusing on sign languages such as American Sign Language (ASL), Indian Sign Language (ISL), Chinese Sign Language (CSL), and other major sign languages. Among these, Bangla Sign Language (BdSL) is unique, with limited studies implementing it on wearable devices. Most BdSL research has focused on computer vision, machine learning, and deep learning algorithms. There is a notable gap in studies involving smart wearable devices that follow the BdSL dataset. This section discusses various techniques for sign language recognition systems. It emphasizes recent improvements and their significance to BdSL.

1.1 Research on Sign Languages & Interpreter Techniques

Wearable translation systems for sign language have moved steadily toward multi-sensor data gloves designed to improve recognition accuracy, usability, and accessibility. Most combine flex sensors, accelerometers, and gyroscopes with neural network classifiers to capture hand gestures and convert them into text or speech. The studies below are grouped by the sensing approach and processing technique each one relies on, since these choices largely determine both the accuracy and the practicality of the resulting system.

1.1.1 Sensor-Based Systems

Flex sensors remain the most common building block for gesture recognition because they detect finger curvature directly and cheaply. Sengupta et al. [16] built a glove that paired flex sensors with accelerometers and streamed the data over Bluetooth to a smartphone, which converted the readings into Malaysian text and speech. Jadhav and Tripathy [17] developed a low-cost system using flex sensors alone, driving an Android phone's audio output for more accessible translation. Working on Pakistan Sign Language, Shaheen and Mehmood [18] combined accelerometers and flex sensors with a Bluetooth-linked microcontroller to produce spoken translations efficiently. Shubankar et al. [19] extended the flex-sensor glove concept for American Sign Language by adding Optical Character Recognition for blind users and a GSM module for emergency communication.

1.1.2 Integration of Advanced Sensors

Adding gyroscopes and IMUs to the sensor stack has generally improved both accuracy and real-time responsiveness. Mori and Toyonaga [20] used a gyro sensor to capture the palm-turning motions specific to Japanese Sign Language, producing an affordable training tool for beginners. Rewari et al. [21] combined flex sensors, gyroscopes, and accelerometers on an Arduino platform to interpret Indian Sign Language with improved accuracy. Diliberti et al [22] went further with a full motion-capture glove built on IMU sensors, reaching 98% accuracy on both dynamic and static gestures using a lightweight convolutional neural network.

1.1.3 Machine Learning and Neural Networks

Machine learning has become the default classifier across most recent gesture-recognition gloves, though the specific techniques vary widely. Rizwan et al. [23] paired flex sensors with machine learning classifiers to recognize American Sign Language with high accuracy, while Villagomez et al. [24] instead combined fuzzy logic with neural networks and reported a 92.58% recognition rate. Meier et al. [25] took a different sensing path altogether, using magnetic field sensors alongside neural networks to build a cost-effective, wear-free system. Cassim et al. [26] focused on portability and affordability, reaching 85.51% repeatability accuracy for American Sign Language. Within Bangla Sign Language specifically, Islam et al. [27] applied transfer learning to static signs and recorded validation accuracies between 84.95% and 99.92% depending on the model configuration. Huang et al. [28] moved away from conventional flex sensors entirely, coating fibers in reduced graphene oxide to reach over 98% accuracy on Chinese Sign Language gestures. Begum et al. [29] proposed a deep learning sensory glove for Bangla Sign Language built on CNN-LSTM architectures, testing two model variants that reached 90.34% and 94.73% accuracy, respectively.

1.1.4 Low-Cost and Accessibility-Oriented Solutions

Cost-effective solutions have been a focal point for enhancing accessibility to those most in need from underserved communities. Saleh et al. [30] built a low-cost glove for Arabic Sign Language that converts gestures into both speech and text, reaching 90% recognition accuracy. Using entirely open-source hardware, Tze How et al. [31] designed a Malaysian Sign Language glove to keep costs down. McCaw et al. [32] tracked finger bending with capacitive strain sensors in a design meant to scale easily to larger production runs, while Mehra et al. [33] built a gesture-to-speech pipeline around low-cost sensors and Python, calibrating the system against American Sign Language for ease of use.

1.1.5 Hybrid Approaches and Novel Applications

A few of the systems above stand out for combining technologies in ways that extend beyond straightforward gesture recognition. Shubankar et al.'s [19] pairing of flex-sensor gesture capture with OCR opened the glove up to visually impaired users specifically. Huang et al. [28] showed that RGO-coated fibers could improve wearability without sacrificing accuracy. Diliberti et al. [22] demonstrated that convolutional neural networks could classify gestures in real time, pointing toward broader human-computer interaction applications beyond translation alone.

1.2 Research on Bangla Sign Language (BdSL)

Efforts to translate BdSL have used sensor-integrated smart gloves, achieving notable accuracy and functionality. Sarker and Hoque [34] combined flex sensors with an accelerometer and gyroscope to reach 99.5% accuracy across 248 samples. Islam et al. [27], discussed above, pushed validation accuracy as high as 99.92% using transfer learning. Md. Yeasin et al. [35] built a wearable glove with flex sensors and a gyroscope driven by an Arduino Nano, targeting real-time BdSL-to-speech conversion with an emphasis on ease of use. Tanim Rahman et al. [36] added GPS and GSM modules to a single-handed gesture system, reaching 99% accuracy across eight signs while foregrounding safety alongside usability. Despite this sensor-based work, image-based recognition still dominates the recent BdSL literature. Siddique et al. [8] trained a deep learning model on a Jetson Nano across 49 gesture categories, though performance suffers under inconsistent lighting. The BAUST Lipi dataset from Hadiuzzaman et al. [37] contributed 18,000 images in 2024 to support further image-based work. Pranto and Siddique [38] reached 94% accuracy with a computer vision approach, but like other camera-based systems, it stays dependent on environmental conditions such as lighting and background. Wearable, sensor-based approaches to BdSL are comparatively rare in the literature, and this gap is exactly what the present system addresses by recognizing 20 two-handed gestures with dual text and speech output, performing consistently regardless of lighting. Table 2 summarizes the accuracy rates reported across these systems along with the sensing and modelling approaches behind them.

Table 2. Summary of the sign language recognition systems based on different approaches and technologies from the available literature works

Author(s) and Year	Sign Language	Methodology/Device	Key Features	Results/Accuracy	Ref.
Mori & Toyonaga (2018)	Japanese Sign Language	Data glove with gyro sensor	Captures palm-turning gestures, cost-effective, simplifies training for beginners	Greater than 50% accuracy	[20]
Sengupta et al. (2019)	Malaysian Sign Language	Glove with flex sensors, accelerometer	Detects finger curvature and hand orientation, Bluetooth transmission, smartphone processing to convert gestures into text and speech	60% - 100% Accuracy	[16]
Jadhav & Tripathy (2018)	American Sign Language	Flex sensor gloves connected to an Android phone via Bluetooth	Converts hand gestures into speech, uses 8051 microcontroller and ADC, real-time translation	Not specified	[17]
Shubankar et al. (2019)	American Sign Language	IoT device with flex sensors, OCR, and GSM	Converts gestures into audio/visual outputs, includes OCR for blind users and live tracking	Not specified	[19]
Shaheen & Mahmood (2018)	Pakistan Sign Language	Sensor gloves with accelerometers and flex sensors	Bluetooth transmission, energy-efficient, uses a lookup algorithm for gesture recognition	Efficiency of 93.4%	[18]
Saleh et al. (2020)	Arabic Sign Language	Low-cost smart glove with flex sensors and tilting sensing module	Translates gestures into speech and text via an Android app, facilitates interaction	90% recognition rate	[30]

Rewari et al. (2018)	Indian Sign Language	Glove with flex sensors, accelerometer, gyroscope controlled by Arduino Uno	Translates ISL gestures into audio, integrated with standardized ISL dictionary	Not specified	[21]
McCaw et al. (2018)	American Sign Language	Soft capacitive strain sensors	Measures finger bending and fingertip pressure, utilizes low-cost materials, scalable	95% confidence bounds	[32]
Mehra et al. (2019)	American Sign Language	Glove with flex sensors, accelerometer, gyroscope	Cost-effective, user-friendly, Python-based algorithm enhances accuracy	96% for 100 iterations	[33]
Tze How et al. (2018)	Malaysian Sign Language	Low-cost dataglove with open-source hardware	Captures gestures, interprets with microcontroller, wireless communication	66.67% - 100% Accuracy	[31]
Rizwan et al. (2019)	American Sign Language	Wireless glove with flex sensors and accelerometer	Gesture classification using machine learning, portable, cost-effective, Bluetooth communication	Around 95% accuracy	[23]
Villagomez et al. (2019)	American Sign Language	Sensors in gloves, fuzzy logic, and neural networks	Hybrid approach for improved recognition accuracy, reduces errors	92.58% recognition rate	[24]
Diliberti et al. (2019)	General Application	Custom gloves with IMU sensors	Uses 3D rotation data, lightweight CNN for efficient classification	98% accuracy	[22]
Meier et al. (2019)	General Sign Numbers	Magnetic field sensing system	Robust against environmental factors, cost-effective, and wear-free	99.7% - 99.8% from confusion matrix	[25]
Huang et al. (2019)	Chinese Sign Language	Flexible data glove with reduced graphene oxide (RGO)-coated fibers	High recognition accuracy for static/dynamic gestures, comfortable fit, simple fabrication	98.5% for static, 98.3% for CSL	[28]
Cassim et al. (2022)	American Sign Language	Glove-based with three-axis accelerometer	Used machine learning approach with five different algorithms. Low-cost pricing of \$35	85.51% repeatability accuracy	[26]
Liu et al. (2023)	Chinese Sign Language	Stretchable strain sensors, IMU, CNN	Recognizes 48 CSL words, high accuracy	95.85% for word, 84% for sentence	[9]
Islam et al. (2022)	Bangla Sign Language	Recognizing multiclass Static Sign Language words of BdSL	Used transfer learning techniques named VGG16, VGG19, AlexNet and InceptionV3 on datasets	84.95% to 99.92% from different techniques	[27]
Sarker et al. (2018)	Bangla Sign Language	Smart gloves with flex sensors, accelerometer, gyroscope	Bluetooth transmission, high accuracy with a dataset of 248 samples	99.5% accuracy	[34]
Alam et al. (2021)	Bangla Sign Language	Two-dimensional CNN trained on 4600 hand-sign webcam-captured images, real-time prediction	CNN for classification and translation to Bangla text	validation accuracy of 99.57%, validation loss of 0.56%	[10]
Yeasin et al. (2019)	Bangla Sign Language	Smart gloves with flex sensors and gyroscope	Arduino Nano processing, real-time translation, user-friendly	Not specified	[35]
Rahman et al. (2024)	Bangla Sign Language	Smart glove with flex sensors, MPU6050, GPS, GSM	Gesture translation and location tracking, high recognition accuracy	99% recognition for 8 single-handed signs	[36]
Siddique et al. (2023)	Bangla Sign Language	Deep learning on Jetson Nano	Trained with 49 categories, image-based, limited by lighting	94.91% mAP@.5 for detectron2 model	[8]
Hadiuzzaman et al. (2024)	Bangla Sign Language	Deep learning, image-based dataset	18,000 images for 36 symbols, camera-dependent	97.92% accuracy rate	[37]
Pranto et al. (2024)	Bangla Sign Language	Mediapipe Holistic, LSTM, computer vision	Real-time detection, image-based	94% accuracy rate	[38]
Begum et al. (2024)	Bangla Sign Language	5 flex sensors, MPU6050, Raspberry Pi; CNN and CNN-LSTM architectures	41 Bengali word-level signs, wearable glove, two proposed models	94.73% (CNN-LSTM), 90.34% (CNN)	[29]

This study is structured as follows: Section 2 presents the proposed research method and implementation, including the selection of a total of 25 BdSL gestures, the design of the flex sensor glove-based system, the recognition algorithm based on a simple Threshold-Based Rule Classifier (TRC), and the

Cost-effective Flex Sensor Glove-based Bangla Sign Language (BdSL) Interpreter for...(Akash et al)

simulation and hardware prototyping carried out using MATLAB Simulink, Proteus software, and the physical prototype. Section 3 discusses the experimental results, providing accuracy measurements, a cost analysis, comparisons with state-of-the-art systems, and showing limitations. In the final part, Section 4 concludes the research work by restating the objectives, summarizing the main findings, and suggesting directions for future work.

2. RESEARCH METHOD

The proposed system is a flex sensor glove-based Bangla Sign Language (BdSL) interpreter built to recognize 25 two-handed gestures, made up of 10 numerals, 10 alphabet letters, and 5 commonly used words, while producing both text and speech output for more accessible communication. This work was carried out at the Center for Biomedical Research (CBR), Dr. Anwarul Abedin Institute of Innovation (D2A2I), under American International University-Bangladesh. All ethical and experimental procedures and protocols were approved by the Institutional Review Board (IRB) at American International University-Bangladesh and carried out in line with the Declaration of Helsinki [39].

The core system comprises three main sections, an input section, a processing section, and an output section. Its working principle is simple. Sensor data is collected in the input section, processed by a microcontroller, and converted into corresponding letters, words, or audio files if the data matches predefined values.

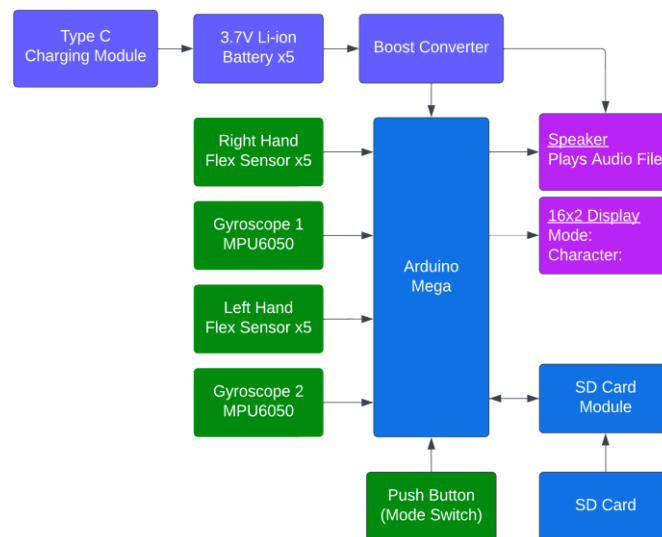


Figure 4. Block diagram of the proposed system

2.1 Input Section

Forming a BdSL sign involves bending the fingers and moving the hands, and since standard BdSL gestures typically use both hands, the input section is built to capture hand signs from both sides at once, using a pair of gloves fitted with sensors. Flex sensors record finger bending, while gyroscopes track hand orientation, together giving a complete picture of each gesture.

2.1.1 Flex Sensor

Flex sensors [40] are variable resistors, which change their resistance with bending angles. The flex sensor is made of material that has a property called piezo resistivity. They use the principle of piezo resistivity, where the electrical resistance varies with mechanical deformation (e.g., bending or flexing). It means that it changes its electrical resistance when it is mechanically deformed.

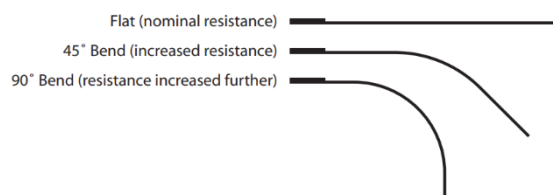


Figure 5. Resistance changes based on the bending angle

As Fig. 5 shows, the sensor's conductive material offers a relatively low-resistance path when it sits flat and unflexed. Bending the sensor increases the distance between its conductive particles, which raises the resistance in turn.

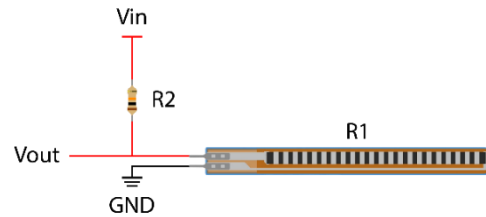


Figure 6. Connection diagram of the flex sensor

$$V_{out} = V_{in} \left(\frac{R_1}{R_1 + R_2} \right) \quad (1)$$

As shown in Fig. 6, the flex sensor sits in a voltage divider circuit, wired in series with a fixed resistor (R_2) so the output voltage (V_{out}) can be measured directly. The flex sensor's changing resistance (R_1) shifts the voltage across the network, producing an analog signal tied to the degree of bending, as equation (1) describes. Ten flex sensors in a 2.2-inch (56 mm) form factor make up the system, each with a total length of 7 cm and an ultra-thin profile just 0.43 mm high. They sit directly on top of each finger joint on the glove. As a finger straightens or bends, its sensor follows along, moving from a flat resistance of $30 \text{ k}\Omega \pm 30\%$ down to a minimum bend resistance of $20 \text{ k}\Omega \pm 30\%$ at a full 180° pinch. Each sensor draws 0.5 Watts continuously (1 Watt at peak) and is rated for more than 1 million bend cycles, making the design durable enough for extended glove use.

2.1.2 Gyroscope Sensor

To track hand orientation, two MPU6050 sensor modules are integrated into the middle of each glove, as shown in Fig. 7. The MPU6050 is a 6-axis MEMS motion tracking device built around a 3-axis gyroscope and a 3-axis accelerometer. Suspended proof masses inside the chip shift under acceleration or rotation, and that mechanical movement is converted into precise electrical signals through internal 16-bit ADCs. Its programmable full-scale ranges run from $\pm 250^\circ/\text{s}$ to $\pm 2000^\circ/\text{s}$ for the gyroscope and $\pm 2\text{g}$ to $\pm 16\text{g}$ for the accelerometer, sensitive enough to map both small gestures and fast movements. The module communicates over a standard I²C interface and draws an active operating current of under 3.9 mA, making it well suited to wearable, glove-based data collection.

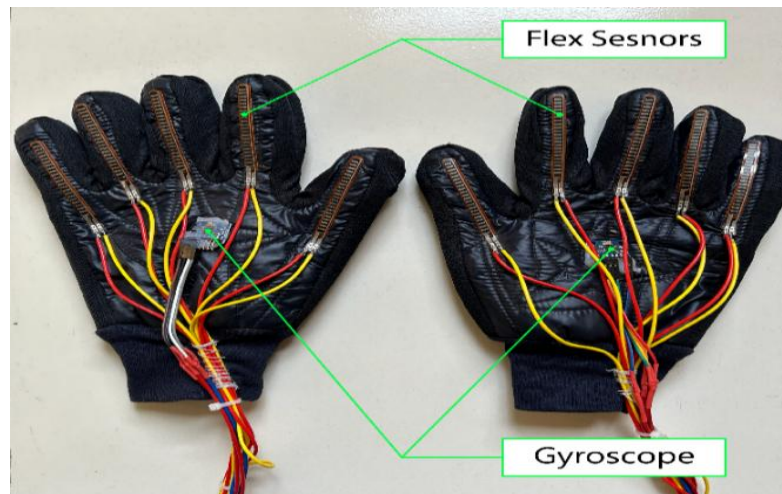


Figure 7. Flex and gyroscope sensors are placed on the wearable gloves

Fig. 7 shows the gloves once the flex and gyroscope sensors are in place. This dual-sensor design (flex sensors for the fingers, gyroscopes for orientation) sets the system apart and allows precise two-handed BdSL gesture recognition, unlike the single-handed systems common in recent literature, such as Rahman et al. [36].

2.2 Processing Section

The input section generates two types of signals: analog from flex sensors and digital from MPU6050 gyroscopes. We selected the Arduino Mega 2560 microcontroller for its ability to process both signal types, affordability, and availability of at least ten analog pins to accommodate all flex sensors. Based on the

ATmega2560, it features 54 digital I/O pins (15 PWM outputs), 16 analog inputs, 4 UARTs, a 16 MHz crystal oscillator, USB connection, power jack, ICSP header, and a reset button.

2.2.1 Data Acquisition

To get the data from all the flex and gyroscope sensors, a data acquisition system is developed. For programming the Arduino Mega 2560, we used the Arduino IDE software. As shown in Fig. 6 & Fig. 7, the Vout of each flex sensor is connected to the analog pin of the Arduino Mega microcontroller to measure the voltage changes of each sensor independently. Because flex sensors create analog signals, they must be converted into digital signals before they can be processed. Here, the microcontroller's built-in ADC converts the analog signals from the sensors to digital values for its understanding. The maximum and minimum voltage ranges of all of the flex sensors are not identical to the ADC values. That's why, after getting the ADC values, they are mapped between 0-100 as shown in Fig. 8 for better understanding.

```
int flex1_pos;
int finger1_pos;
flex1_pos = analogRead(flex1);
finger1_pos = map(flex1_pos, 850, 900, 0, 100);
finger1_pos = constrain(finger1_pos, 0, 100);
```

Figure 8. Mapping of the flex sensor values

2.2.2 Threshold-Based Rule Classifier (TRC)

Threshold-Based Rule Classifier (TRC) was developed to simplify the interpretation and recognition of Bengali Sign Language (BdSL) gestures from the flex sensors and MPU6050 modules. The TRC simplifies the interpretation of finger positions and hand orientations by assigning numerical identifiers based on predefined threshold values. For the flex sensors, a threshold value of 50 is selected to distinguish between bent and straight finger positions. Each finger state is represented using a binary identifier, where a bent finger is assigned a value of 0 and a straight finger is assigned a value of 1. The thresholding criteria for the flex sensors are presented in Table 3.

Table 3. Threshold-Based Rule Classifier (TRC): Level of finger bending based on ADC values

Range of Mapped ADC Value	Level of Finger Bending	Numeric Identifier
finger_pos > 50	Bend	0
finger_pos < 50	Straight	1

Similarly, the MPU6050 measurements are discretized using a threshold value of 5.8. Based on the measured orientation along each axis, the sensor output is encoded as -1, 0, or 1, as summarized in Table 4.

Table 4. Threshold-Based Rule Classifier (TRC): Orientation of the MPU6050 gyroscope

Axis	Condition	Numeric Identifier
x	L X > 5.8	L X V = 1
	-5.8 < L X < 5.8	L X V = 0
	L X < -5.8	L X V = -1
y	L Y > 5.8	L Y V = 1
	-5.8 < L Y < 5.8	L Y V = 0
	L Y < -5.8	L Y V = -1
z	L Z > 5.8	L Z V = 1
	-5.8 < L Z < 5.8	L Z V = 0
	L Z < -5.8	L Z V = -1

The encoded flex-sensor and orientation states are combined to form a feature vector representing the current hand configuration. Each BdSL gesture is associated with a predefined rule set stored in the microcontroller program memory. During recognition, the generated feature vector is evaluated against these predefined rules, and the corresponding gesture label is returned when the required conditions are satisfied. The complete recognition procedure of the proposed TRC is presented in Algorithm 1 (Figure 9).

In Algorithm 1, as shown in Figure 9, (A[1..10]) denotes the mapped outputs of the ten flex sensors positioned on both hands. (Y[1..m]) represents the set of MPU6050 orientation measurements used for gesture recognition, where each element corresponds to an orientation parameter obtained from the sensor axes. The binary variables F[i] represent the bending state of the i-th finger, where each value is assigned according to the threshold criteria listed in Table 3. Likewise, R[j] represents the discretized orientation state obtained from

the corresponding MPU6050 measurement $Y[j]$, taking values of 1, 0, or 1 based on the threshold conditions summarized in Table 4. The complete feature vector, Z , is generated by combining the finger-bending and hand-orientation states. The predefined gesture rules stored in the microcontroller memory are represented by $T[1..n]$, while $G[k]$ denotes the gesture label associated with the k -th rule. During recognition, the generated feature vector is compared sequentially with the stored gesture rules. A gesture is identified when all conditions of a predefined rule are satisfied; otherwise, the input is classified as an unknown pattern.

Algorithm 1 Threshold-Based Rule Classifier (TRC) for BdSL Gesture Recognition

```

1: procedure CLASSIFYGESTURE( $A[1..10]$ ,  $Y[1..m]$ ,  $T[1..n]$ )
2:   for  $i = 1$  to 10 do
3:     if  $A[i] > 50$  then
4:        $F[i] = 0$ 
5:     else
6:        $F[i] = 1$ 
7:     end if
8:   end for
9:   for  $j = 1$  to  $m$  do
10:    if  $Y[j] > 5.8$  then
11:       $R[j] = 1$ 
12:    else if  $Y[j] < -5.8$  then
13:       $R[j] = -1$ 
14:    else
15:       $R[j] = 0$ 
16:    end if
17:  end for
18:   $Z = [F[1], F[2], \dots, F[10], R[1], R[2], \dots, R[m]]$ 
19:  for  $k = 1$  to  $n$  do
20:    if  $Z$  satisfies rule  $T[k]$  then
21:      return  $G[k]$ 
22:    end if
23:  end for
24:  return "Unknown"
25: end procedure

```

Figure 9. Algorithm 1: The pseudo-code for the Threshold-Based Rule Classifier (TRC) of the designed BdSL gesture recognition system

As illustrated in Algorithm 1, the proposed TRC first converts the raw sensor readings into discrete states, constructs a feature vector, and then performs rule-based gesture matching. Because the algorithm is based on predefined decision rules instead of computationally intensive model training, it is well suited for implementation on resource-constrained embedded platforms while providing real-time gesture recognition. After defining these identifiers, the processed sensor outputs are displayed in the Arduino serial monitor to facilitate data collection and verification of BdSL gestures, as illustrated in Fig. 10.

```

:::41:06.990 -> finger1: 1 finger2: 1 finger3: 1 finger4: 1 finger5: 1 finger6: 0 finger7: 1 finger8: 1 finger9: 1 finger10: 1
:::41:07.129 -> Accelerometer Right X: 0, Y: 0, Z: 1 Accelerometer Left X: 0, Y: 0, Z: 1
:::41:07.221 ->
:::41:07.221 ->
:::41:08.435 -> finger1: 1 finger2: 1 finger3: 1 finger4: 1 finger5: 1 finger6: 0 finger7: 1 finger8: 1 finger9: 1 finger10: 1
:::41:08.574 -> Accelerometer Right X: 0, Y: 0, Z: 1 Accelerometer Left X: 0, Y: 0, Z: 1
:::41:08.667 ->
:::41:08.667 ->
:::41:09.672 -> finger1: 1 finger2: 1 finger3: 1 finger4: 1 finger5: 1 finger6: 0 finger7: 1 finger8: 1 finger9: 1 finger10: 1
:::41:10.013 -> Accelerometer Right X: 0, Y: 0, Z: 1 Accelerometer Left X: 0, Y: 0, Z: 1
:::41:10.106 ->
:::41:10.106 ->
:::41:11.310 -> finger1: 1 finger2: 1 finger3: 1 finger4: 1 finger5: 1 finger6: 0 finger7: 1 finger8: 1 finger9: 1 finger10: 1
:::41:11.449 -> Accelerometer Right X: 0, Y: 0, Z: 1 Accelerometer Left X: 0, Y: 0, Z: 1
:::41:11.542 ->
:::41:11.542 ->
:::41:12.747 -> finger1: 1 finger2: 1 finger3: 1 finger4: 1 finger5: 1 finger6: 0 finger7: 1 finger8: 1 finger9: 1 finger10: 1
:::41:12.887 -> Accelerometer Right X: 0, Y: 0, Z: 1 Accelerometer Left X: 0, Y: 0, Z: 1
:::41:12.992 ->
:::41:12.992 ->

```

Figure 10. Acquiring serial monitor data for all sensors

2.2.3 Creation of Bangla Characters for 16x2 Display

As the 16x2 screen doesn't have a support library for Bangla characters/letters, the Bangla alphabet letters were manually created to show them on screen. For the creation of custom characters for the display, an array in the program code was created for the Arduino. The procedure for arranging the bits for creating a custom character (here, for the number '২') is shown in Fig. 11. The other Bangla characters that are included in this project have also been created in the same way. For each character, the display has 5x8 pixels. To light up a pixel, the bit is set to '1' and to turn off a pixel, '0' is set in its place.

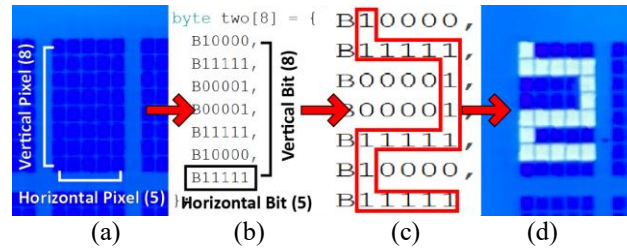


Figure 11. Creation of Custom Letters in Display. (a) horizontal and vertical pixels in the display, (b) array code, (c) position of bits to create characters, (d) the final character

2.2.4 Data Processing

The data acquisition stage described how the flex sensor and gyroscope outputs were converted into numerical identifiers. For example, a bent finger position was assigned the identifier '0', whereas a straight finger position was assigned the identifier '1'. After data acquisition, these numerical identifiers were utilized to simplify the programming process. Initially, the processed sensor values were displayed on the Arduino serial monitor, as shown in Fig. 10. While wearing the glove, the predefined BdSL hand signs were performed, and the corresponding numerical values displayed on the serial monitor were recorded. Based on these recorded values, a dataset representing the corresponding BdSL gestures was established. This dataset was subsequently used to program the Arduino Mega 2560 for gesture recognition using the proposed Threshold-Based Rule Classifier (TRC). The program also controlled the audio output. Voice files corresponding to each predefined gesture were stored on an SD card connected to the microcontroller through an SD card module. Whenever a gesture was recognized, the corresponding Bangla character was displayed on the LCD, and the associated voice file was retrieved from the SD card and played through a speaker connected via a 3.5 mm audio jack. Although the proposed processing method is based on a simple rule-based approach, it provides reliable recognition for the selected 25 BdSL gestures while emphasizing affordability, portability, and suitability for resource-limited environments.

2.3 Output Section

The proposed system provides two output modes: visual output and audio output. For visual output, a 16×2 I²C LCD display compatible with the Arduino Mega 2560 microcontroller was employed. The recognized Bengali numerals, letters, or words corresponding to the performed hand signs are displayed on the LCD, as shown in Fig. 12.

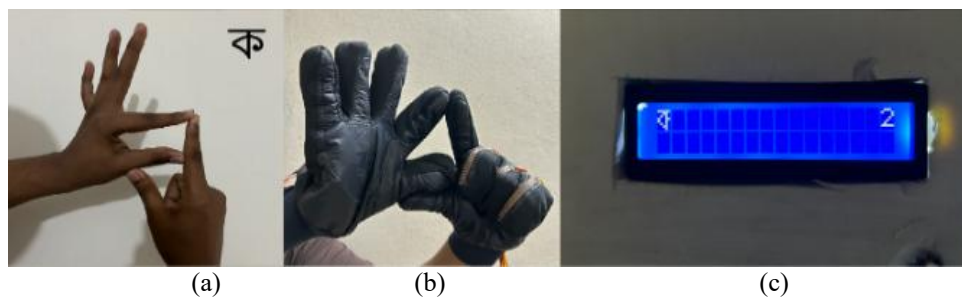


Figure 12. Output is displayed for corresponding hand gestures. (a) BdSL hand sign (b) Hand Sign with gloves on (c) Visual output in display

For audio output, a 3.5 mm audio jack was incorporated into the system. A pair of speakers was connected through the audio jack to provide voice output, while headphones or earphones can also be connected as an alternative output device. Voice files corresponding to each predefined BdSL gesture were stored on an SD card and retrieved whenever a gesture was recognized. The selected voice file was then played through the connected audio device, enabling audible communication of the recognized gesture.

2.4 Simulation

To verify the functionality of the proposed BdSL glove-based interpreter, simulations were performed using both MATLAB Simulink and Proteus design software. These simulations helped model the electronic behavior of the flex sensors, assess current and voltage variations, and visualize how the Arduino microcontroller processes sensor data for real-time gesture recognition and display.

2.4.1 MATLAB Simulink Simulation

The MATLAB Simulink software has been utilized to simulate the proposed model system. It is a valuable tool for design engineers, commonly employed in Windows applications for simulating systems, designing control algorithms, and analyzing dynamic models. The circuit schematic is shown in Fig. 13.

The flex sensor is represented in the Simulink software with variable resistors since the working principles are essentially the same. Connected to the variable resistor, the constant block is used to set the resistive value. For every variable resistor, voltage and current measurement blocks are used. These blocks display the voltage and current across each variable resistor based on variations in the resistive value in the constant block that is connected to the variable resistor. Every variable resistor is linked in parallel to the power source, which in this case is the battery. The current flowing through each resistor will fluctuate in response to changes in resistance. The Arduino microcontroller is then represented by a MATLAB function block that receives the current values. The output of each variable resistor is processed before being connected to the 16x2 display, which is shown in this example by the display block. Each flex sensor has a slider switch that allows it to switch between bent and straight modes.

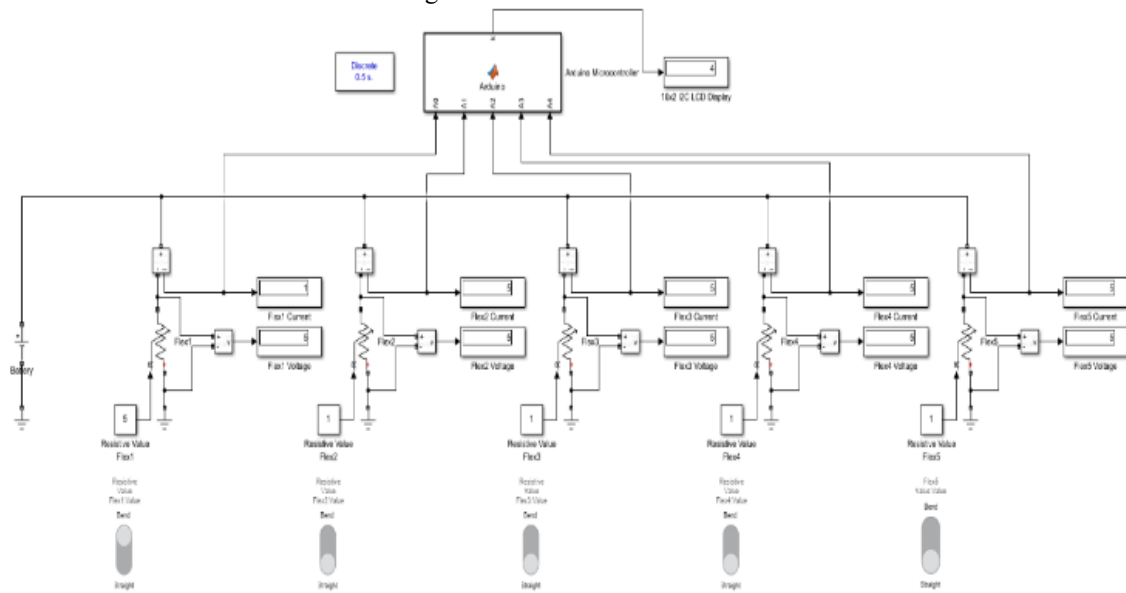


Figure 13. Simulation of the system in MATLAB Simulink software

2.4.2 Proteus Simulation

The Proteus design suite has also been used to simulate the proposed model. It is a helpful piece of software for design engineers that is utilized in Windows applications for simulation, designing PCB (Printed Circuit Board) layouts, and capturing schematics. The schematic of the circuit is shown in Fig. 14.

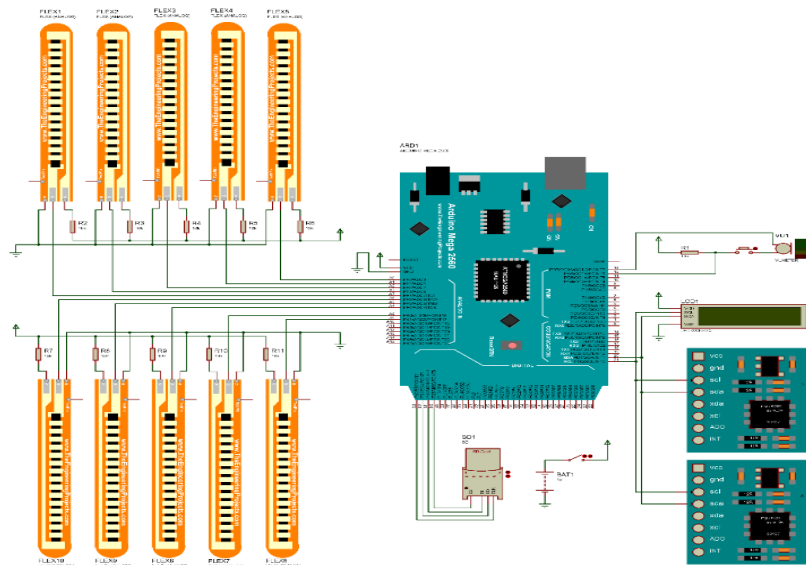


Figure 14. Schematic diagram of the system in Proteus 8 simulation software

In Figure 14, the actual circuit diagram of the system is replicated using Proteus 8 software. There are ten flex sensors, each of them connected to the analog pins of the Arduino Mega 2560 microcontroller through 10k ohm resistors in series. Both the MPU6050 gyroscope's and the 16x2 I2C LCD display's SDA and SCL pins are connected in parallel with the microcontroller's SDA and SCL pins. The SD card's pins are connected to the digital pins of the microcontroller. A 5V battery is used in the simulation system to power the whole system.

2.5 Hardware Model

The connection diagram of the proposed system is already shown in the Proteus simulation section in Fig. 14. The 3D design of the proposed system is shown in Fig. 15. Here, SOLIDWORKS, a 3D design software, was used to create the 3D model of the system.

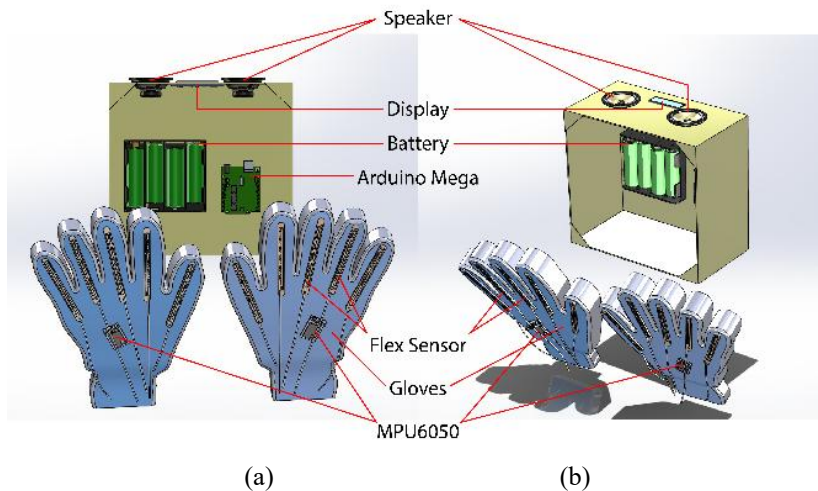


Figure 15. 3D design of the proposed system. (a) top view and (b) side view

The dimensions of the main control unit box are 12x12x5 inches. The Arduino Mega microcontroller, display, speakers, batteries, and other components are placed inside the main control unit. Two sets of wires are coming out from the control unit, and each of them is connected to the sensor glove. The prototype of the proposed model is shown in Fig. 16.

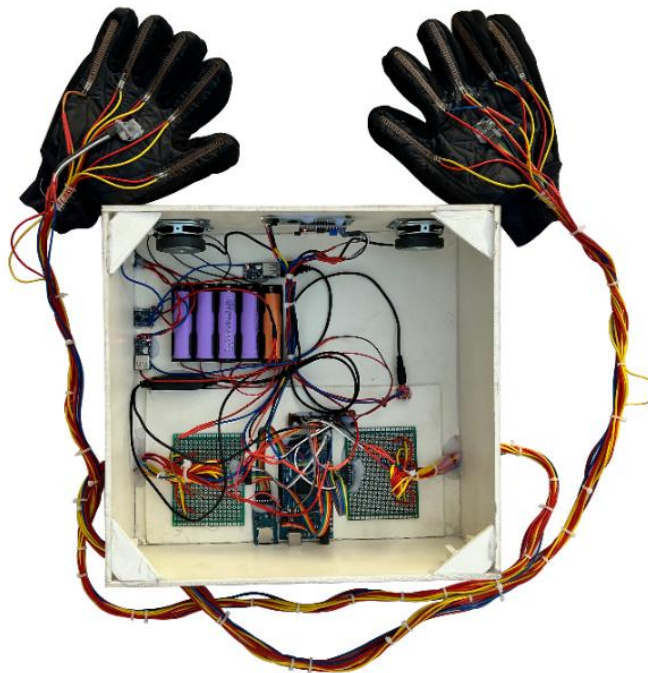


Figure 16. Implementation of the hardware prototype with wearable gloves

The main control unit is the housing of all the processing and power supply components. The circuitry connection of the designed prototype is shown in Fig. 17. This hardware design ensures portability and cost-effectiveness, aligning with recent trends towards accessibility in low-resource settings.

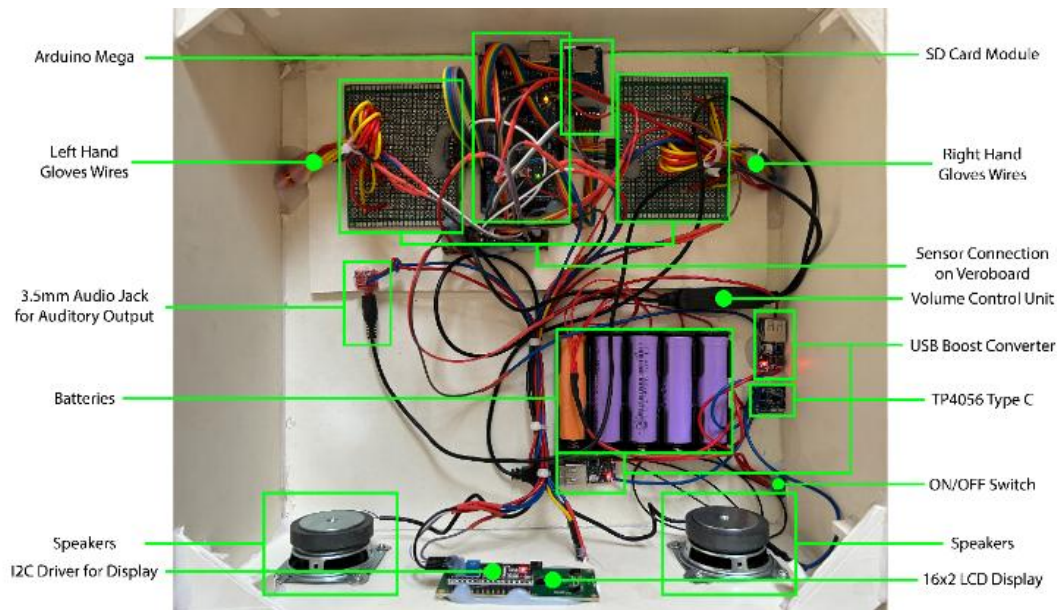


Figure 17. Hardware components & circuitry connection inside the implemented prototype

3. RESULTS AND DISCUSSION

To validate the effectiveness of the proposed flex sensor glove-based BdSL interpreter, experiments were conducted to evaluate its ability to recognize 20 official BdSL gestures and 5 predefined word gestures. The system performance was evaluated through a series of experimental tests. This section describes the experimental setup, presents the obtained results, and compares the proposed system with recent BdSL recognition studies to demonstrate its practical applicability in resource-limited settings.

3.1 Sensor Data and Gesture Recognition

The proposed glove incorporates ten flex sensors to capture finger movements by measuring the corresponding changes in voltage and resistance between the straight and maximum bend positions. These measurements form the basis of gesture recognition, as the analog voltage signals are converted into digital values using the built-in analog-to-digital converter (ADC) of the Arduino Mega 2560.

Table 5. Voltage, resistance, and current readings on the bend and straight positions from the 10 flex sensors of two wearable hand gloves

Angle	V & R	Flex1	Flex2	Flex3	Flex4	Flex5	Flex6	Flex7	Flex8	Flex9	Flex10
Maximum Bend Position	Volt (V)	3.92	3.79	3.59	3.81	3.71	3.74	3.71	3.64	3.71	3.89
	R (k Ω)	2.76	3.19	3.93	3.12	4.48	3.37	3.48	3.74	3.48	2.85
	I (mA)	1.42	1.19	0.91	1.22	1.07	1.11	1.07	0.97	1.07	1.36
Straight Position	Volt (V)	4.06	4.08	3.91	4.01	3.89	4.06	4.08	4.23	4.03	4.01
	R (k Ω)	2.32	2.25	2.79	2.47	2.85	2.32	2.25	1.82	2.41	2.47
	I (mA)	1.75	1.81	1.40	1.62	1.36	1.75	1.81	2.32	1.67	1.62

The maximum and minimum voltage, current, and resistance ranges for each flex sensor are shown in Table 5, which is also shown in a scatter plot below. Fig. 18 shows the voltage ranges across all flex sensors, highlighting distinct patterns for different hand positions.

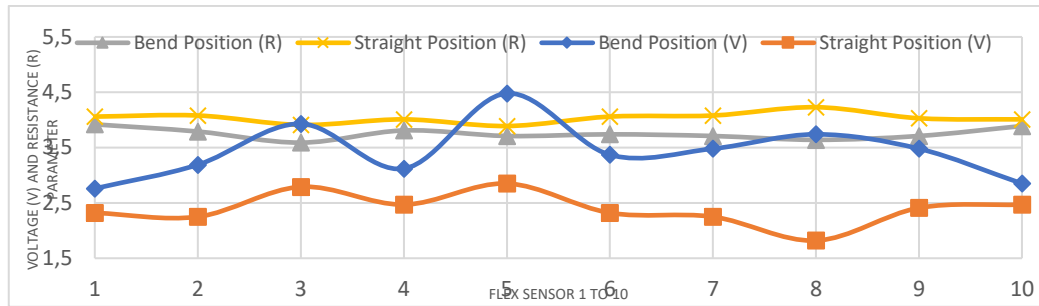


Figure 18. Voltage and resistance characteristics of the flex sensors under straight and bend conditions

The maximum and minimum voltage and resistance values obtained from each flex sensor play an important role in defining the gesture dataset. Since the sensors provide analog voltage signals, the Arduino Mega 2560 converts these signals into digital values through its embedded ADC. The resulting digital values are then used to establish the threshold ranges required for gesture recognition and dataset generation. The ADC values that we get from the microcontroller are also shown in Fig. 19.

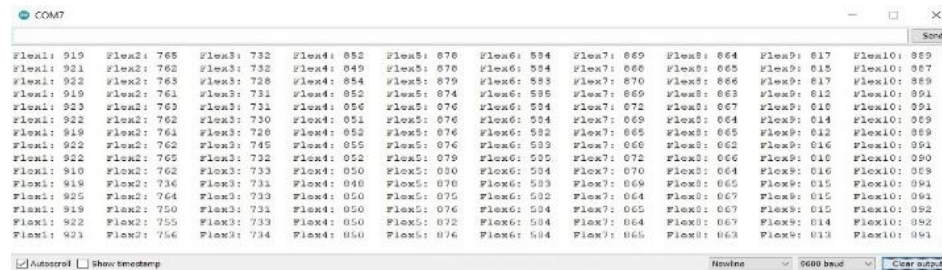


Figure 19. Acquiring the maximum and minimum values of each flex sensor from the serial monitor

For specific BdSL gestures, such as the letters 'य' and 'व', unique resistance profiles emerge across the flex sensors (Fig. 20). These profiles form the basis of our gesture dataset, enabling the system to differentiate between signs using a simple 'if-else' conditioning method.

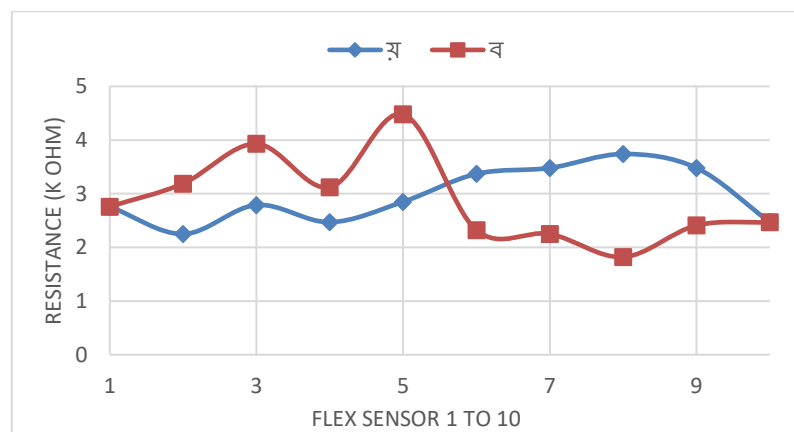


Figure 20. Resistive values of each flex sensor for the letters 'य' and 'व'

These resistances are unique to these specific hand signs for corresponding letters. That's why this voltage data can be used to create a data set for these letters. All the other letters also have this kind of voltage variation. With this type of data set of resistances unique to each BdSL hand sign, the output can be created in the same way as mentioned earlier.

3.2 Accuracy of the System

Accuracy was used as the primary metric to evaluate the performance of the proposed prototype. To assess the robustness of the glove across different users, the system was tested by five volunteers, including

three male and two female participants. The same glove was used for all participants, and the wrist fit was adjusted with Velcro straps before each trial to ensure proper sensor placement. Each participant completed two evaluation rounds consisting of 10 numerals, 10 alphabet letters, and 5 words, with each gesture repeated 10 times. The evaluation was conducted in accordance with the ethical principles of the Declaration of Helsinki. Table 6 summarizes the recognition accuracy for the numerical, alphabetical, and word gesture groups. The accuracy of each gesture was calculated using the following equation (2):

$$\% \text{ Accuracy} = \frac{N-F}{N} \times 100 \quad (2)$$

where F is the number of misidentified attempts, and N is the total number of repetitions for a given gesture. In this study, N=10 for each repeated trial. This repeated-test design provides a more reliable assessment of the proposed system under user-based experimental conditions.

The system achieved an overall accuracy of 91.2%, with mode-specific accuracies of 98% for numerals, 80% for alphabets, and 100% for words. The word gestures achieved perfect accuracy because of their simpler and more distinct hand configurations, whereas the lower accuracy for the alphabet suggests that more complex finger positions and orientations remain challenging. This variation indicates that further refinement may be achieved by improving sensor sensitivity or optimizing the recognition rules for more intricate signs.

Table 6. Designed system accuracy from 10-times repetition tests for 10 Numericals, 10 Alphabetical letters, and 5 Words

Modes	Letters/Words	N of correct attempts in 10	Accuracy in %	Accuracy of each mode in %	Accuracy of the overall system in %
Numerical	০ (0)	10/10	100%	98%	91.2%
	১ (1)	10/10	100%		
	২ (2)	10/10	100%		
	৩ (3)	10/10	100%		
	৪ (4)	10/10	100%		
	৫ (5)	10/10	100%		
	৬ (6)	10/10	100%		
	৭ (7)	10/10	100%		
	৮ (8)	10/10	100%		
	৯ (9)	8/10	80%		
Alphabetical	অ (a)	10/10	100%	80%	
	আ (ā)	8/10	80%		
	ক (ka)	7/10	70%		
	গ (ga)	8/10	80%		
	দ (da)	8/10	80%		
	ব (ba)	7/10	70%		
	ম (ma)	9/10	90%		
	য় (ya)	7/10	70%		
	ং (ma)	8/10	80%		
	ঃ (ha)	8/10	80%		
Words	আমি (Me)	10/10	100%	100%	
	তুমি (You)	10/10	100%		
	খাচ্ছি (Eating)	10/10	100%		
	ভালো হয়নি (Not Good)	10/10	100%		
	ঠিক আছে (Okay)	10/10	100%		

3.3 Confusion Matrix

The confusion matrix provides key performance metrics for the classification tasks. Accuracy measures the proportion of correct predictions, while the misclassification rate reflects the percentage of incorrect ones. Confusion Matrix for the 10 Bengali Numericals and selected 10 Bengali Alphabet letters were shown in Fig.21 and Fig. 22, respectively. The macro-F1 score averages F1 scores across all classes equally, and the weighted-F1 score considers the class distribution. The following equations (3), (4), (5), (6), (7), (8), (9), (10), (11) were used to calculate the confusion matrix's statistical measures.

$$\text{Precision} = \frac{TP}{(TP+FP)} \quad (3)$$

$$\text{Recall} = \frac{TP}{(TP+FN)} \quad (4)$$

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

$$\text{MacroF1} = \text{avg of F1 Scores} \quad (6)$$

$$\text{WeightedF1} = \text{weighted averaged of F1 Scores} \quad (7)$$

$$\text{Misclassification Rate} = \frac{\# \text{ incorrect predictions}}{\# \text{ total predictions}} \quad (8)$$

$$\text{True Negative Rate (TNR)} = \frac{TN}{(TN+FP)} \quad (9)$$

$$\text{False Positive Rate (FPR)} = 1 - \text{TNR} \quad (10)$$

$$\text{False Negative Rate (FNR)} = 1 - \text{Recall} \quad (11)$$

(a) Confusion Matrix for the 10 Bengali Numericals												
Target Output	০ (0)	১ (1)	২ (2)	৩ (3)	৪ (4)	৫ (5)	৬ (6)	৭ (7)	৮ (8)	৯ (9)	SUM	
০ (0)	10	0	0	0	0	0	0	0	0	0	10	100.00%
১ (1)	0	10	0	0	0	0	0	0	0	0	10	100.00%
২ (2)	0	0	10	0	0	0	0	0	0	0	10	100.00%
৩ (3)	0	0	0	10	0	0	0	0	0	0	10	100.00%
৪ (4)	0	0	0	0	10	0	0	0	0	0	10	100.00%
৫ (5)	0	0	0	0	0	10	0	0	0	0	10	100.00%
৬ (6)	0	0	0	0	0	0	10	0	0	0	10	100.00%
৭ (7)	0	0	0	0	0	0	0	10	0	0	10	100.00%
৮ (8)	0	0	0	0	0	0	0	0	10	0	10	100.00%
৯ (9)	0	0	0	0	0	0	0	0	0	10	10	100.00%
SUM	10	10	10	10	10	10	10	10	10	10	100	100.00%

(b) Confusion Matrix for the selected 10 Bengali Alphabet letters												
Target Output	অ (a)	আ (ā)	ক (ka)	গ (ga)	ঘ (da)	ব (ba)	ম (ma)	য (ya)	র (ra)	ল (la)	SUM	
অ (a)	10	0	0	0	0	0	0	0	0	0	10	100.00%
আ (ā)	0	10	0	0	0	0	0	0	0	0	10	100.00%
ক (ka)	0	0	10	0	0	0	0	0	0	0	10	100.00%
গ (ga)	0	0	0	10	0	0	0	0	0	0	10	100.00%
ঘ (da)	0	0	0	0	10	0	0	0	0	0	10	100.00%
ব (ba)	0	0	0	0	0	10	0	0	0	0	10	100.00%
ম (ma)	0	0	0	0	0	0	10	0	0	0	10	100.00%
য (ya)	0	0	0	0	0	0	0	10	0	0	10	100.00%
র (ra)	0	0	0	0	0	0	0	0	10	0	10	100.00%
ল (la)	0	0	0	0	0	0	0	0	0	10	10	100.00%
SUM	10	10	10	10	10	10	10	10	10	10	100	100.00%

Figure 21. (a) Confusion matrix for the 10 Bengali numericals and (b) Confusion Matrix for the selected 10 Bengali alphabet letters

(a) Statistical Measures of Confusion Matrix for the 10 Bengali Numericals							
Class Name	Precision	1-Precision	Recall	False Negative Rate	F1 score	Specificity (TNR)	False Positive Rate (FPR)
০ (0)	1.0000	0.0000	1.0000	0.0000	1.0000	1.0000	0.0000
১ (1)	1.0000	0.0000	1.0000	0.0000	1.0000	1.0000	0.0000
২ (2)	1.0000	0.0000	1.0000	0.0000	1.0000	1.0000	0.0000
৩ (3)	1.0000	0.0000	1.0000	0.0000	1.0000	1.0000	0.0000
৪ (4)	1.0000	0.0000	1.0000	0.0000	1.0000	1.0000	0.0000
৫ (5)	1.0000	0.0000	1.0000	0.0000	1.0000	1.0000	0.0000
৬ (6)	0.8333	0.1667	1.0000	0.0000	0.9091	0.9778	0.0222
৭ (7)	1.0000	0.0000	1.0000	0.0000	1.0000	1.0000	0.0000
৮ (8)	1.0000	0.0000	1.0000	0.0000	1.0000	1.0000	0.0000
৯ (9)	1.0000	0.0000	0.8000	0.2000	0.8889	1.0000	0.0000

(b) Statistical Measures of Confusion Matrix for Selected 10 Bengali Alphabets							
Class Name	Precision	1-Precision	Recall	False Negative Rate (FNR)	F1 score	Specificity (TNR)	False Positive Rate (FPR)
অ (a)	1.0000	0.0000	0.8333	0.1667	0.9091	1.0000	0.0000
আ (ā)	0.8000	0.2000	1.0000	0.0000	0.8889	0.9783	0.0217
ক (ka)	0.7000	0.3000	0.7778	0.2222	0.7368	0.9670	0.0330
গ (ga)	0.8000	0.2000	0.7273	0.2727	0.7619	0.9775	0.0225
ঘ (da)	0.8000	0.2000	0.7273	0.2727	0.7619	0.9775	0.0225
ব (ba)	0.7000	0.3000	0.7778	0.2222	0.7368	0.9670	0.0330
ম (ma)	0.9000	0.1000	0.7500	0.2500	0.8182	0.9886	0.0114
য (ya)	0.7000	0.3000	0.8750	0.1250	0.7778	0.9674	0.0326
র (ra)	0.8000	0.2000	0.8000	0.2000	0.8000	0.9778	0.0222
ল (la)	0.8000	0.2000	0.8000	0.2000	0.8000	0.9778	0.0222

Figure 22. (a) Statistical measures of the confusion matrix for the 10 Bengali numericals and (b) Statistical Measures of the confusion matrix for the selected 10 Bengali alphabet letters

For the ten Bengali numerical signs, the system achieved high performance: accuracy = 0.9800, misclassification rate = 0.0200, and both macro-F1 and weighted-F1 = 0.9798. In contrast, for the ten Bengali alphabetical signs, results were lower: accuracy = 0.8000, misclassification rate = 0.2000, and both macro-F1 and weighted-F1 = 0.7991. Here, macro-F1 and weighted-F1 are the same because we ran an equal number of test samples per class (10 of each); thus, the weighted average collapses to the simple (macro) average. These metrics show that the system recognized numerical gestures more accurately than alphabetical ones. These results are also shown in Table 7 below.

Table 7. Confusion matrix statistical measures for Bengali numerals and alphabet letters

	For 10 Bengali numerals	For 10 Bengali alphabet letters
Accuracy	0.9800	0.8000
Misclassification Rate	0.0200	0.200
Macro-F1	0.9798	0.7991
Weighted-F1	0.9798	0.7991

3.4 Cost analysis

The cost analysis of the Flex Sensor Glove-Based BdSL Interpreter System demonstrates its financial feasibility by evaluating the expenses of the essential hardware components. The total estimated prototype cost is 12,155 BDT (101.29 USD), with the major expenses attributed to the flex sensors, Arduino Mega 2560, and speaker, while the remaining costs are associated with wiring, connectors, and other miscellaneous components, as detailed in Table 7. It should be noted that this cost reflects a research prototype assembled using commercially available modules and off-the-shelf components. A mass-produced version is expected to cost approximately 5,000-7,000 BDT (40-60 USD) through component integration, custom PCB implementation, and economies of scale. Such reductions would improve affordability and accessibility for individuals with disabilities in Bangladesh and other resource-constrained settings. Therefore, the proposed system represents a cost-effective approach to Bangla Sign Language interpretation while maintaining practical functionality and ease of deployment.

Table 7. Cost analysis of the designed BdSL interpreter prototype system

Serial No.	Item	Quantity	Unit Price (BDT)	Estimated Cost (BDT)	Estimated Cost (USD)
1	2.2-inch Flex Sensor	10	500	5000	41.67
2	MPU6050	2	200	360	3.00
3	Arduino Mega 2560	1	1800	1800	15.00
4	Gloves	1	150	100	0.83
5	Vero Board	2	80	150	1.25
6	SD Card	1	350	350	2.92
7	SD Card Module	1	180	180	1.50
8	16x2 LCD Display + I2C	1	350	240	2.00
9	Long Wire (25 Gauge)	-	15	300	2.50
10	Jumper Wire (3 sets)	-	70	180	1.50
11	USB Boost Converter	2	130	240	2.00
12	TP4056 Type C	1	35	35	0.29
13	Speaker	1	350	500	4.17
14	Battery (3.7V 2000mAh)	5	200	450	3.75
15	Battery Housing	5	30	70	0.58
16	Miscellaneous	-	-	2000	16.67
Total				12,155	101.29

3.5 Comparison with State-of-the-Art Systems

To underscore the novelty of the designed prototype, this research work is compared with recent BdSL recognition approaches, including both wearable and vision-based systems, as shown in Table 8.

Table 8. Comparison with recent BdSL recognition systems

System	Gestures Recognized	Input Method	Output	Accuracy	Additional Features/Limitations	Ref.
Proposed System	25 (two-handed)	Flex sensors, MPU6050	Text + Audio	91.2%	Portable, dual outputs	-
Rahman et al. (2024)	8 (single-handed)	Flex sensors, MPU6050	Audio	99%	GPS/GSM tracking	[36]
Sarker and Hoque (2018)	Not specified	Flex sensors, accelerometer, gyroscope	Audio	99.5%	Bluetooth transmission	[34]
Islam et al. (2022)	Multiclass static words	Image-based (transfer learning)	Text	84.95%-99.92%	High accuracy for static signs	[27]
Siddique et al. (2023)	49 categories	Image-based (deep learning)	Text	Not specified	Limited by lighting	[8]
Begum et al. (2024)	Recognizes 41 Bengali word-level signs	5 flex sensor-based gloves, MPU6050, CNN-LSTM	Audio	90.34%-94.73%	Single-hand wearable glove design	[29]

Compared with Tanim Rahman et al. [36], the proposed system extends BdSL coverage by recognizing 25 two-handed gestures, including 10 numerals, 10 alphabet letters, and 5 commonly used words, whereas their system considered 8 single-handed gestures and reported 99% accuracy. Although the proposed system achieved an overall recognition accuracy of 91.2%, the two studies address different gesture scopes and task complexities; therefore, the comparison should be interpreted in terms of coverage, output modality, and deployment context rather than accuracy alone. Begum et al. [29] reported recognition accuracies of 90.34% and 94.73% for their two CNN and CNN-LSTM-based sensory glove models, respectively. Those approaches rely on deep learning and greater computational support, whereas the proposed TRC-based system is designed for real-time implementation on a low-cost Arduino platform for resource-limited settings. Likewise, image-based systems such as Islam et al. [27] and Siddique et al. [8] achieve strong recognition performance, but they depend on camera input and are more sensitive to lighting and environmental conditions. In contrast, the proposed wearable approach operates independently of ambient illumination and provides both text and speech outputs, improving accessibility for both hearing- and visually impaired users. Accordingly, the main contribution of this work is a practical and portable BdSL interface that balances recognition performance, gesture coverage, interpretability, and affordability for low-resource environments.

4. CONCLUSION

This work set out to build a low-cost, wearable interpreter for Bangla Sign Language (BdSL) using flex sensors and inertial sensing, and the results support sensor-glove technology as a genuinely accessible communication aid for deaf and speech-impaired users. Ten flex sensors, two MPU6050 modules, and a Threshold-Based Rule Classifier (TRC) work together to recognize Bengali numerals, alphabet letters, and common words in real time, without relying on cameras or computationally intensive machine-learning models. The system reached an overall recognition accuracy of 91.2%, which suggests rule-based sensor fusion can be a genuinely practical option for resource-constrained settings, since it is cheap to build and unaffected by the lighting, background, or camera-placement problems that vision-based systems run into. Pairing text output with speech further lowers the barrier to communication between sign-language users and the wider public. More broadly, this kind of assistive technology has a role to play in social participation, communication, and education for people with hearing impairments, particularly in developing countries, where cost is often the deciding factor in whether a technology gets adopted at all. Lowering that cost and technical barrier is what ties this work most directly to Sustainable Development Goal 10 (Reduced Inequalities), through affordable, inclusive communication tools for the deaf community, and it also speaks, more indirectly, to Sustainable Development Goal 4 (Quality Education), by making learning environments more inclusive for hearing-impaired students. The system isn't without limitations, though. Alphabet recognition lags behind numerals and words, since many Bengali letter signs share similar, closely-spaced finger configurations that are harder for a threshold-based classifier to tell apart, pointing to a need for more sophisticated discrimination methods down the line. The current implementation also covers only a subset of Bengali signs, and it recognizes static gestures only, without modeling the temporal transitions and dynamic movement that continuous sign language

actually depends on. The next steps are to extend the gesture database to all fifty Bengali letters, bring in lightweight machine-learning models to sharpen recognition of the more intricate signs, and shrink the hardware down with a custom PCB and Bluetooth connectivity. Overall, this work represents a significant advancement in wearable BdSL recognition by combining comprehensive gesture coverage, dual output modes, environmental robustness, and affordability, thereby laying a strong foundation for future developments toward a widely adopted communication aid in resource-limited settings, particularly in Bangladesh and other Bengali-speaking deaf communities.

ACKNOWLEDGMENTS

The authors greatly acknowledge the American International University-Bangladesh for providing all technical and financial support for this research.

REFERENCES

- [1] S. Goyal, I. Sharma, and S. Sharma, "Sign Language Recognition System For Deaf And Dumb People," *Int. J. Eng. Res. Technol.*, vol. 2, no. 4, Apr. 2013, doi: 10.17577/IJERTV2IS4261.
- [2] R. Rastogi, S. Mittal, and S. Agarwal, "A novel approach for communication among Blind, Deaf and Dumb people," in *2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom)*, Mar. 2015, pp. 605–610. Accessed: Dec. 05, 2024. [Online]. Available: <https://ieeexplore.ieee.org/abstract/document/7100321>
- [3] M. Alauddin and A. H. Joarder, "Deafness in Bangladesh," in *Hearing Impairment: An Invisible Disability How You Can Live With a Hearing Impairment*, J.-I. Suzuki, T. Kobayashi, and K. Koga, Eds., Tokyo: Springer Japan, 2004, pp. 64–69. doi: 10.1007/978-4-431-68397-1_13.
- [4] "Bangladesh Bureau of Statistics (BBS), Population and Housing Census 2022, National Report (Volume-I). Dhaka, Bangladesh." Accessed: Jul. 07, 2025. [Online]. Available: https://bbs.portal.gov.bd/sites/default/files/files/bbs.portal.gov.bd/page/b343a8b4_956b_45ca_872f_4cf9b2f1a6e0/2024-01-31-15-51-b53c55dd692233ac401ba013060b9cbb.pdf
- [5] "Bangladesh Bureau of Statistics (BBS), National Survey on Persons with Disabilities (NSPD) 2021. Dhaka, Bangladesh." Accessed: Jul. 07, 2025. [Online]. Available: https://bbs.portal.gov.bd/sites/default/files/files/bbs.portal.gov.bd/page/b343a8b4_956b_45ca_872f_4cf9b2f1a6e0/2022-06-13-15-24-ca6f018ab83c88a4db8ff51386439794.pdf
- [6] Department of Social Services, "Allowance Program for Persons with Disabilities," Department of Social Services. Accessed: Jun. 25, 2026. [Online]. Available: <http://dss.gov.bd/pages/static-pages/6922e03c933eb65569e261fc>
- [7] X. Yang, X. Chen, X. Cao, S. Wei, and X. Zhang, "Chinese Sign Language Recognition Based on an Optimized Tree-Structure Framework," *IEEE J. Biomed. Health Inform.*, vol. 21, no. 4, pp. 994–1004, Jul. 2017, doi: 10.1109/JBHI.2016.2560907.
- [8] S. Siddique, S. Islam, E. E. Neon, T. Sabbir, I. T. Naheen, and R. Khan, "Deep Learning-based Bangla Sign Language Detection with an Edge Device," *Intell. Syst. Appl.*, vol. 18, p. 200224, May 2023, doi: 10.1016/j.iswa.2023.200224.
- [9] Y. Liu *et al.*, "A wearable system for sign language recognition enabled by a convolutional neural network," *Nano Energy*, vol. 116, p. 108767, Nov. 2023, doi: 10.1016/j.nanoen.2023.108767.
- [10] Md. S. Alam, M. Tanvir, D. K. Saha, and S. K. Das, "Two Dimensional Convolutional Neural Network Approach for Real-Time Bangla Sign Language Characters Recognition and Translation," *SN Comput. Sci.*, vol. 2, no. 5, p. 387, Jul. 2021, doi: 10.1007/s42979-021-00783-6.
- [11] A. A. Zare and S. H. Zahiri, "Recognition of a real-time signer-independent static Farsi sign language based on fourier coefficients amplitude," *Int. J. Mach. Learn. Cybern.*, vol. 9, no. 5, pp. 727–741, May 2018, doi: 10.1007/s13042-016-0602-3.
- [12] Z. R. Saeed, Z. B. Zainol, B. B. Zaidan, and A. H. Alamoodi, "A Systematic Review on Systems-Based Sensory Gloves for Sign Language Pattern Recognition: An Update From 2017 to 2022," *IEEE Access*, vol. 10, pp. 123358–123377, 2022, doi: 10.1109/ACCESS.2022.3219430.
- [13] R. J. Johnson and J. E. Johnson, "Distinction between West Bengal Sign Language and Indian Sign Language Based on Statistical Assessment," *Sign Lang. Stud.*, vol. 16, no. 4, pp. 473–499, 2016, Accessed: Dec. 15, 2024. [Online]. Available: <https://muse.jhu.edu/pub/18/article/627362>
- [14] "The Silent Conversation," The Daily Star. Accessed: Dec. 15, 2024. [Online]. Available: <https://www.thedailystar.net/the-silent-conversation-37929>
- [15] "ISO 15919:2001," ISO. Accessed: Jul. 11, 2025. [Online]. Available: <https://www.iso.org/standard/28333.html>
- [16] A. Sengupta, T. Mallick, and A. Das, "A Cost Effective Design and Implementation of Arduino Based Sign Language Interpreter," in *2019 Devices for Integrated Circuit (DevIC)*, Mar. 2019, pp. 12–15. doi: 10.1109/DEVIC.2019.8783574.
- [17] D. Jadhav and A. Tripathy, "Gesture Aided Speech for Deaf and Mute," in *2018 3rd International Conference for Convergence in Technology (I2CT)*, Apr. 2018, pp. 1–6. doi: 10.1109/I2CT.2018.8529411.
- [18] H. Shaheen and T. Mehmood, "Talking Gloves: Low-Cost Gesture Recognition System for Sign Language Translation," in *2018 IEEE Region Ten Symposium (Tensymp)*, Jul. 2018, pp. 219–224. doi: 10.1109/TENCONSpring.2018.8692069.
- [19] B. Shubankar, M. Chowdhary, and M. Priyaadharshini, "IoT Device for Disabled People," *Procedia Comput. Sci.*, vol. 165, pp. 189–195, Jan. 2019, doi: 10.1016/j.procs.2020.01.092.

- [20] Y. Mori and M. Toyonaga, "Data-Glove for Japanese Sign Language Training System with Gyro-Sensor," in *2018 Joint 10th International Conference on Soft Computing and Intelligent Systems (SCIS) and 19th International Symposium on Advanced Intelligent Systems (ISIS)*, Dec. 2018, pp. 1354–1357. doi: 10.1109/SCIS-ISIS.2018.00211.
- [21] H. Rewari, V. Dixit, D. Batra, and N. Hema, "Automated Sign Language Interpreter," in *2018 Eleventh International Conference on Contemporary Computing (IC3)*, Aug. 2018, pp. 1–5. doi: 10.1109/IC3.2018.8530658.
- [22] N. Diliberti, C. Peng, C. Kaufman, Y. Dong, and J. T. Hansberger, "Real-Time Gesture Recognition Using 3D Sensory Data and a Light Convolutional Neural Network," in *Proceedings of the 27th ACM International Conference on Multimedia*, in MM '19. New York, NY, USA: Association for Computing Machinery, Oct. 2019, pp. 401–410. doi: 10.1145/3343031.3350958.
- [23] S. B. Rizwan, M. S. Z. Khan, and M. Imran, "American Sign Language Translation via Smart Wearable Glove Technology," in *2019 International Symposium on Recent Advances in Electrical Engineering (RAEE)*, Aug. 2019, pp. 1–6. doi: 10.1109/RAEE.2019.8886931.
- [24] E. B. Villagomez, R. A. King, M. J. Ordinario, J. Lazaro, and J. F. Villaverde, "Hand Gesture Recognition for Deaf-Mute using Fuzzy-Neural Network," in *2019 IEEE International Conference on Consumer Electronics - Asia (ICCE-Asia)*, Jun. 2019, pp. 30–33. doi: 10.1109/ICCE-Asia46551.2019.8942220.
- [25] P. Meier, K. Rohrmann, M. Sandner, and M. Prochaska, "Application of magnetic field sensors for hand gesture recognition with neural networks," in *2019 IEEE 1st Global Conference on Life Sciences and Technologies (LifeTech)*, Mar. 2019, pp. 200–203. doi: 10.1109/LifeTech.2019.8884006.
- [26] M. R. Cassim, J. Parry, A. Pantanowitz, and D. M. Rubin, "Design and construction of a cost-effective, portable sign language to speech translator," *Inform. Med. Unlocked*, vol. 30, p. 100927, Jan. 2022, doi: 10.1016/j.imu.2022.100927.
- [27] Md. M. Islam, Md. R. Uddin, Md. N. AKhtar, and K. M. R. Alam, "Recognizing multiclass Static Sign Language words for deaf and dumb people of Bangladesh based on transfer learning techniques," *Inform. Med. Unlocked*, vol. 33, p. 101077, Jan. 2022, doi: 10.1016/j.imu.2022.101077.
- [28] X. Huang *et al.*, "Tracing the Motion of Finger Joints for Gesture Recognition via Sewing RGO-Coated Fibers Onto a Textile Glove," *IEEE Sens. J.*, vol. 19, no. 20, pp. 9504–9511, Oct. 2019, doi: 10.1109/JSEN.2019.2924797.
- [29] H. Begum, O. Chowdhury, Md. S. R. Hridoy, and M. M. Islam, "AI-Based Sensory Glove System to Recognize Bengali Sign Language (BaSL)," *IEEE Access*, vol. 12, pp. 145003–145017, 2024, doi: 10.1109/ACCESS.2024.3472469.
- [30] N. Saleh, M. Farghaly, E. Elshaer, and A. Mousa, "Smart glove-based gestures recognition system for Arabic sign language," in *2020 International Conference on Innovative Trends in Communication and Computer Engineering (ITCE)*, Feb. 2020, pp. 303–307. doi: 10.1109/ITCE48509.2020.9047820.
- [31] D. N. Tze How, W. Z. Fahmi Bin Wan Ibrahim, and K. S. Mohamed Sahari, "A Dataglove Hardware Design and Real-Time Sign Gesture Interpretation," in *2018 Joint 10th International Conference on Soft Computing and Intelligent Systems (SCIS) and 19th International Symposium on Advanced Intelligent Systems (ISIS)*, Dec. 2018, pp. 946–949. doi: 10.1109/SCIS-ISIS.2018.00157.
- [32] J. C. S. McCaw, M. C. Yuen, and R. Kramer-Bottiglio, "Sensory Glove for Dynamic Hand Proprioception and Tactile Sensing," presented at the ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, American Society of Mechanical Engineers Digital Collection, Nov. 2018. doi: 10.1115/DETC2018-85703.
- [33] V. Mehra, A. Choudhury, and R. R. Choubey, "Gesture To Speech Conversion using Flex sensors, MPU6050 and Python," *Int. J. Eng. Adv. Technol. IJEAT*, doi: 10.35940/ijeat.F9167.088619.
- [34] S. Sarker and M. M. Hoque, "An Intelligent System for Conversion of Bangla Sign Language into Speech," in *2018 International Conference on Innovations in Science, Engineering and Technology (ICISSET)*, Oct. 2018, pp. 513–518. doi: 10.1109/ICISSET.2018.8745608.
- [35] Md. Yeasin *et al.*, "Design and Implementation of Bangla Sign Language Translator," in *2019 5th International Conference on Advances in Electrical Engineering (ICAEE)*, Sep. 2019, pp. 815–820. doi: 10.1109/ICAEE48663.2019.8975458.
- [36] T. Rahman, T. Chowdhury, and J. Sultana, "Bengali sign language translator with location tracking system," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 33, no. 3, Art. no. 3, Mar. 2024, doi: 10.11591/ijeecs.v33.i3.pp1760-1767.
- [37] M. Hadiuzzaman, M. Ali, A. S. Miah, A. Raj Shafi, and J. Shin, "BAUST Lipi: A BdSL Dataset with Deep Learning Based Bangla Sign Language Recognition," in *Proceedings of the 3rd International Conference on Computing Advancements*, in ICCA '24. New York, NY, USA: Association for Computing Machinery, Jun. 2025, pp. 280–285. doi: 10.1145/3723178.3723215.
- [38] R. H. Pranto and S. Siddique, "Real-time Bangla Sign Language Translator," Dec. 21, 2024, *arXiv:arXiv:2412.16497*. doi: 10.48550/arXiv.2412.16497.
- [39] World Medical Association, "World Medical Association Declaration of Helsinki: Ethical Principles for Medical Research Involving Human Subjects," *JAMA*, vol. 310, no. 20, pp. 2191–2194, Nov. 2013, doi: 10.1001/jama.2013.281053.
- [40] G. Saggio and G. Orenco, "Flex sensor characterization against shape and curvature changes," *Sens. Actuators Phys.*, vol. 273, pp. 221–231, Apr. 2018, doi: 10.1016/j.sna.2018.02.035.

BIOGRAPHY OF AUTHORS

Md. Sayzar Rahman Akash    received his B.Sc. and M.Sc. degrees in Electrical and Electronic Engineering from the American International University-Bangladesh (AIUB) in 2022 and 2024, respectively. He served as a Research Assistant at the Center for Biomedical Research (CBR), D2A2I, AIUB, starting in 2023. He was awarded the prestigious National Science and Technology (NST) Fellowship by the Ministry of Science and Technology, Government of Bangladesh. His research interests include biomedical signal processing and analysis, healthcare systems, RF signal and antenna design, nanotechnology, robotics, automation and IoT, and UAV applications.



Rethwan Faiz  received the M.B.A. and M.Sc. degrees in electrical and electronic engineering from American International University-Bangladesh (AIUB) in 2014 and 2021, respectively. He is currently an Associate Professor at AIUB. His research interests include wireless sensor networks, biomedical engineering, and nanoelectronics.



Mohammad Hasan Imam  completed his PhD in 2015 from the University of Melbourne, Australia, in Bio-signal Processing and Modeling. He is currently working as an Associate Professor in the Department of Electrical and Electronic Engineering at the American International University-Bangladesh (AIUB). His main research interests include Bioinformation processing, Model-based system dynamics analysis, Machine learning in healthcare, Biomedical signal processing, and Biomedical electronics.



G.M. Tanvirul Islam received a B.Sc. degree in Electrical and Electronic Engineering (EEE) from American International University-Bangladesh (AIUB), Dhaka, Bangladesh, in 2024. His research interests include biomedical signal processing, healthcare systems, renewable energy technology, robotics, and automation.



Sheikh Tanvir Alam received a B.Sc. degree in Electrical and Electronic Engineering (EEE) from American International University-Bangladesh (AIUB) in 2024. His research interests include semiconductor technology, IC design, AI applications, and programming. He has actively collaborated with researchers in the field of biomedical engineering, focusing on interdisciplinary approaches to technological innovation.



Jhon Dev received a B.Sc. degree in Electrical and Electronic Engineering (EEE) from American International University-Bangladesh (AIUB) in 2024. His research interests include PLC design, renewable energy technology, biomedical engineering, and robotics. He is passionate about leveraging technology to create innovative solutions in these fields.



Nuzat Nuary Alam  received the M.Sc. degree in bioengineering: digital body from the University of Nottingham, U.K., in 2013. She is currently an Assistant Professor at American International University-Bangladesh (AIUB). Her research interests include new-generation state-of-the-art electronics to develop medical devices and healthcare technologies.