STU
SLOVAK UNIVERSITY OF TECHNOLOGY IN BRATISLAVA

Journal of Electrical Engineering, Vol. 77, No. 5, 2026, pp. 516-528
https://reference-global.com/journal/JEE

Hardware implementation of AI-based fuzzy logic for real-time sign language interpreter robotic control using FPGA

Kshitij Shinghal[1], Amit Saxena[1], Avnesh Verma[2*], Rajul Misra[3]

Communication barriers between hearing-impaired individuals and non-sign language users remain a significant challenge in modern society. Existing sign language recognition systems primarily focus on unidirectional communication and are often limited by high latency, excessive power consumption, and lack of robustness in uncertain environments. This paper proposes a novel FPGA-based Bidirectional Robotic Sign Language Communication System (BRSLCS) integrating Artificial Intelligence (AI), fuzzy logic, and robotic control for real-time assistive communication. The proposed architecture supports both forward communication, where sign language gestures are translated into text or speech, and reverse communication, where text or speech is converted into robotic sign language gestures through an actuated robotic hand. In the forward communication flow, gesture images captured using a camera are processed through preprocessing, feature extraction, AI-based classification, and fuzzy inference stages. In the reverse communication flow, speech or textual inputs are interpreted using Natural Language Processing (NLP) techniques and mapped into robotic sign gestures controlled using FPGA-based actuation logic. The integration of fuzzy logic improves classification robustness and interpretability under uncertain conditions such as illumination variation, gesture ambiguity, and motion blur. FPGA implementation provides deterministic timing, low latency, hardware parallelism, and energy efficiency suitable for embedded real-time systems. Experimental evaluation demonstrates that the proposed system achieves 92-95% recognition accuracy with latency between 10-25 ms while consuming only 4-6 W power, outperforming conventional CPU and GPU-based implementations. The proposed BRSLCS provides a scalable and practical framework for inclusive communication systems in healthcare, education, public services, and human-robot interaction environments.

Keywords: FPGA, fuzzy logic controller, sign language recognition, speech-to-sign translation, human-robot interaction, embedded AI, assistive technology, robotic hand control, edge computing, bidirectional communication

1 Introduction

Communication is a fundamental requirement for social interaction, education, healthcare, and professional engagement. However, deaf and mute individuals frequently encounter communication barriers because sign language is not universally understood by the general population. This limitation significantly affects inclusivity and accessibility in various domains such as healthcare systems, public service environments, educational institutions, and emergency communication scenarios.

Recent developments in Artificial Intelligence (AI), computer vision, machine learning, and embedded systems have contributed significantly to the advancement of sign language recognition systems. Most conventional systems focus only on converting sign language into text or speech, resulting in unidirectional communication frameworks. Although these systems improve accessibility, they fail to support complete two-way interaction between sign language users and non-signers.

Moreover, traditional software-based sign language recognition systems suffer from several limitations including:

1. High computational complexity
2. Increased response latency
3. Limited portability
4. High power consumption
5. Reduced robustness under uncertain environments

To address these challenges, this paper proposes a Bidirectional Robotic Sign Language Communication System (BRSLCS) integrating AI-based classification, fuzzy logic reasoning, and FPGA-based hardware acceleration.

[1] Department of Electronics & Communication Engg., Moradabad Institute of Technology, Moradabad, 244001 U.P., India
[2] Department of Instrumentation (formerly USIC), Kurukshetra University, Kurukshetra, 136119 Haryana, India
[3] Department of Electrical Engg., Moradabad Institute of Technology, Moradabad, 244001 U.P., India
* verma.avnesh@rediffmail.com

https://doi.org/10.2478/jee-2026-0049, Print (till 2015) ISSN 1335-3632, On-line ISSN 1339-309X
© This is an open access article licensed under the Creative Commons Attribution-NonCommercial-NoDerivatives License (http://creativecommons.org/licenses/by-nc-nd/4.0/).

The proposed BRSLCS supports:

- **Forward communication:** Sign Language → Text/Speech
- **Reverse communication:** Text/Speech → Sign Language

In the forward communication flow, visual gesture inputs are captured using a camera and processed through preprocessing, feature extraction, machine learning classification, and fuzzy inference stages. In the reverse communication flow, speech or text inputs are processed using Natural Language Processing (NLP) techniques and translated into robotic hand gestures using FPGA-controlled actuators.

The use of FPGA technology offers several advantages for embedded real-time systems including:

- Parallel processing capability
- Deterministic timing
- Low latency operation
- Reconfigurability
- Energy-efficient execution

Fuzzy logic is integrated to improve robustness and uncertainty handling in gesture interpretation. Human gestures naturally exhibit variations due to lighting conditions, user-dependent styles, motion blur, and partial occlusions. Fuzzy inference systems effectively address these uncertainties using linguistic reasoning and confidence evaluation mechanisms.

The proposed BRSLCS is suitable for multiple real-world applications including:

- Assistive communication systems
- Smart classrooms
- Healthcare communication support
- Public service accessibility
- Human-robot interaction
- Smart home automation
- Emergency response systems

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 describes the proposed system architecture. Section 4 presents the mathematical model and methodology. Section 5 discusses FPGA implementation. Section 6 presents experimental results and discussion. Section 7 outlines future work and Section 8 concludes the paper.

2 Literature review

Technological advancements in intelligent robotic systems have driven the need for state-of-the-art, adaptive, and real-time control mechanisms capable of operating efficiently in highly uncertain environments. Conventional control approaches often fail to address the uncertainties and nonlinearities inherent in human–machine interaction systems. Consequently, the integration of artificial intelligence (AI), fuzzy logic, and Field Programmable Gate Arrays (FPGAs) represents a new paradigm for achieving efficient real-time robotic controllers, particularly in assistive technologies such as sign language interpreter systems.

The introduction of fuzzy sets laid the foundation for fuzzy logic, providing a systematic approach to manage the imprecision and uncertainty characteristic of complex systems [1]. Unlike classical binary logic, fuzzy logic allows for partial or gradual membership transitions, making it more suitable for simulating real-world processes. Additionally, the communication and distributed processing requirements of robotic and embedded systems have been addressed through network-based frameworks, focusing on system-level integration [2].

Type-2 fuzzy algorithms have further advanced fuzzy systems by enhancing their functionality in com-plex or noisy environments. Unlike traditional fuzzy systems, which primarily adapt to specific system characteristics, type-2 fuzzy logic explicitly addresses uncertainties within membership functions, providing robustness against complex noise [3].

FPGA technology has enabled practical and implementable fuzzy logic controllers. Features such as parallel processing, reconfigurability, and deterministic timing make FPGAs ideal for real-time applications. Research has demonstrated that embedded fuzzy logic controllers can be efficiently implemented on FPGA platforms for robotic applications, offering high speed and reliability [4]. FPGA architecture optimization, including VLSI-based placement techniques, has further improved hardware efficiency and resource utilization [5]. FPGA-based control systems have also been successfully applied to industrial processes, such as induction motor speed control, achieving high dynamic performance and low time constants [6].

Hardware description languages, such as VHDL, have facilitated the direct design and synthesis of fuzzy logic controllers on FPGAs. Implementations of fuzzy inference systems on hardware have demonstrated significant potential for real-time control [7], and subsequent optimizations have reduced system complexity and resource usage [8]. The advantages of hardware-based fuzzy controllers over software implementations are particularly pronounced in time-sensitive applications.

Fuzzy logic has been widely employed to enhance system robustness against environmental uncertainties. Fuzzy controllers have been shown to mitigate the impact of external disturbances, improving overall system reliability [9-11]. This capability is crucial for

robotic systems interacting with real-world environments, where sensor noise and environmental variability are inevitable.

Adaptive and neuro-fuzzy methods have further contributed to the evolution of intelligent control systems. Adaptive fuzzy controllers, which adjust their parameters in real time, have been applied to motor control and other applications, demonstrating improved performance [12]. Neuro-fuzzy approaches, combining the learning capabilities of neural networks with the simplicity of fuzzy systems, enable automatic tuning of fuzzy control rules. These techniques have been successfully implemented on FPGAs for robotic navigation [13]. High-level synthesis tools have facilitated rapid prototyping and hardware implementation of fuzzy systems [14].

Modern robotic platforms have benefited significantly from advances in AI, particularly in artificial neural networks and deep learning. Deep convolutional networks have demonstrated superior performance in visual recognition tasks, critical for robots to understand human gestures and sign language [15, 16]. While AI-based solutions excel in feature extraction from visual data, they are computationally intensive, necessitating hardware acceleration, for which FPGAs provide an attractive solution. FPGA-based architectures have enabled the development of real-time robotic systems. Visual control systems implemented on FPGAs have demonstrated lower latency and highly responsive robotic behaviour [17].

Sign language recognition systems have emerged as a crucial research area in assistive robotics. Early systems employed wearable devices, such as smart gloves, to capture hand gestures and translate them into text or speech [18, 19]. While reliable, these systems lacked scalability and natural interaction. Later approaches utilized vision-based methods with cameras and image processing techniques, providing more natural interaction [20]. Despite these advantages, vision-based systems demand substantial computational resources, underscoring the need for efficient real-time processing.

The development of interpretable fuzzy controllers has further enhanced usability and transparency in contemporary systems [21]. Recent studies highlight the trade-off between interpretability and performance, a critical consideration for human-centric applications. Similarly, FPGA-based fuzzy control systems have allowed autonomous vehicles to navigate efficiently [22, 23]. Reviews of FPGA applications confirm their speed, flexibility, and energy efficiency for embedded and real-time systems [24]. The exploration of microcontroller- and FPGA-based intelligent control systems has facilitated compact hardware platforms capable of executing sophisticated control algorithms [25]. Recent trends in hardware-algorithm co-design aim to maximize system performance. FPGA-based fuzzy feedback controllers have achieved improved efficiency and scalability [26]. Co-design methodologies have been applied to autonomous guided vehicles, demonstrating superior real-time performance [27]. Embedded fuzzy control systems implemented on reconfigurable FPGAs have increased flexibility and adaptability [28]. Researchers are increasingly leveraging FPGA technology for gesture and sign language recognition. FPGA-based gesture detection has shown potential for real-time implementation, with reduced latency and improved system efficiency [29].

FPGA-in-the-loop techniques have demonstrated complex control algorithms for advanced robotic systems, such as robotic manipulators, effectively bridging simulation and physical implementation [30]. Emerging research in hardware-accelerated AI systems indicates that the integration of fuzzy logic, AI, and FPGA technologies can significantly advance intelligent systems. Hardware-accelerated AI architectures using fuzzy logic have improved adaptability and security [31]. FPGA-based fuzzy inference systems have been applied to complex datasets in areas such as sports analytics, demonstrating the versatility of fuzzy logic [32].

Recent reviews highlight FPGA applications in healthcare and embedded systems, emphasizing their growing relevance for real-time intelligent applications [33]. Hybrid controllers combining PID and fuzzy approaches have demonstrated enhanced stability and performance in robotic systems [34]. FPGA-based acceleration of deep neural network algorithms has proven highly effective for real-time AI implementations [35]. AI-based algorithms have further enhanced these systems, enabling multilingual sign language recognition with high accuracy and generalization [36]. Additionally, FPGA-based fuzzy learning control systems adapt to dynamic system conditions [37], and advanced fuzzy control techniques have been successfully employed in multi-robot systems [38].

In industrial robotics, FPGA-based adaptive fuzzy controllers, combined with image processing, have achieved high accuracy and efficacy [39]. Optimization of lightweight convolutional neural networks for FPGA-based systems has addressed resource and power constraints [40]. Despite the high accuracy achievable with deep learning models, optimized hardware is essential for real-time processing [41-43]. Neuro-fuzzy controller implementations for robotic manipulators have demonstrated real-time learning and execution capabilities [44-46].

Overall, the literature reflects a progression from foundational fuzzy logic theory to high-level AI-integrated FPGA-based control systems. Initial studies focused on fuzzy logic principles and hardware imple-

mentation. Subsequent research emphasised optimisation, adaptation, and AI integration. Current trends prioritise real-time performance, hardware acceleration, and intelligent perception, enabling applications such as sign language interpreters. Despite these advances, challenges remain in integrating sophisticated AI models with fuzzy logic algorithms on FPGA platforms, highlighting ongoing opportunities for research and development in this domain.

3 System architecture

The proposed system implements a staged pipeline, beginning with visual sensing and concluding with multimodal output. A camera captures hand gestures and forwards the frames to a preprocessing unit that normalizes illumination, suppresses noise, and isolates the region of interest (ROI). Feature extraction then converts these images into compact vectors encoding geometric contours, key points, and motion cues. These vectors are processed by an AI classifier, which proposes candidate labels for the observed gestures. Subsequently, a fuzzy inference module evaluates these candidates using predefined rule sets that consider confidence levels, temporal consistency, and environmental factors. All critical processing blocks are hosted on an FPGA, ensuring parallel execution and low-latency performance. Interfaces are provided for both display and speech synthesis, allowing recognized signs to be presented in text or audio form. Feedback loops smooth predictions across consecutive frames, enhancing stability during rapid hand movements. Communication interfaces facilitate data logging and optional cloud connectivity for model updates and analytics.

3.1 Forward flow: Sign → Text/Speech

Figure 1 shows block diagram of the forward flow pipeline from hand gestures to text or speech output, illustrating image acquisition, preprocessing, feature extraction, AI classification, fuzzy logic refinement, and output generation. Initially, the camera captures real-time hand gestures, which are preprocessed to reduce noise, normalize lighting, and extract the ROI. Spatial and temporal features, including shape, contour, motion, and orientation, are then extracted from these frames. The extracted features are fed into an AI-based classifier, such as an SVM or CNN, which predicts candidate gesture classes. To enhance reliability, a fuzzy inference module evaluates these candidate labels based on fuzzy rules that incorporate confidence levels and motion consistency. Finally, the recognized gesture is converted into text or speech through the output interface.

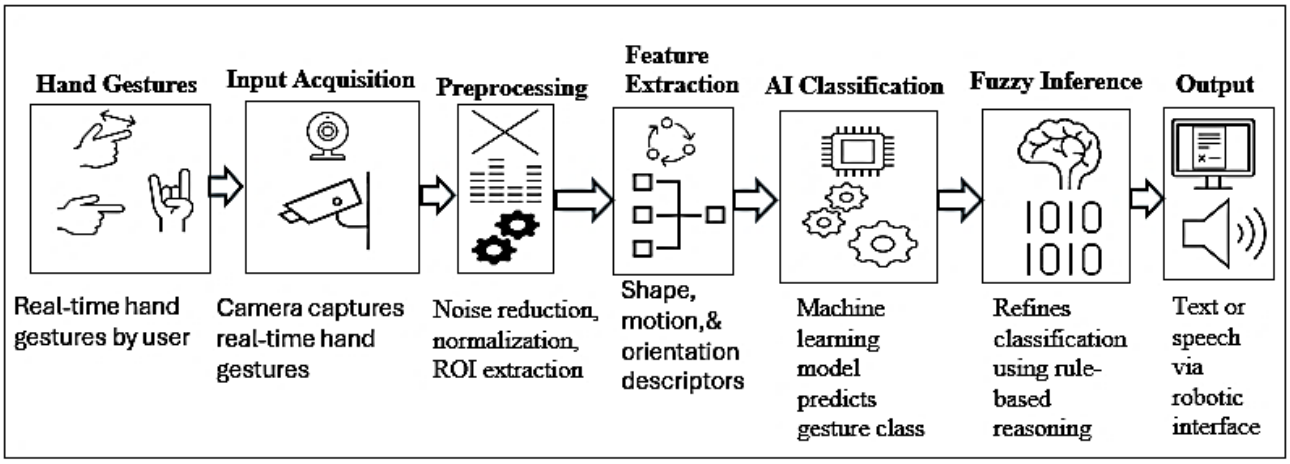


Fig. 1. Block diagram of the forward flow for sign-to-text/speech conversion

Mathematically, the fuzzy inference output can be expressed using the weighted average defuzzification method:

$$Y = \frac{\sum_{i=1}^{n} W_i F_i}{\sum_{i=1}^{n} W_i} \quad (1)$$

This equation represents the defuzzification process, specifically the weighted average method, used to convert fuzzy results into a crisp output.

- F_i: Represents the output of the *i-th fuzzy rule*. Each rule corresponds to a linguistic condition such as *Low*, *Medium*, or *High* confidence in gesture classification.

- W_i: Represents the *weight (firing strength)* of the corresponding fuzzy rule. It indicates how strongly a rule is activated based on the input features.
- n: Total number of fuzzy rules in the system
- Y: Final crisp output after combining all fuzzy rules

Working principle:

1. Input features (gesture confidence, motion consistency, etc.) are converted into fuzzy values (fuzzification).
2. Fuzzy rules are applied (e.g., *IF confidence is high AND motion is stable THEN output is strong match*).
3. Each rule produces an output F_i with a strength W_i.
4. The final output is computed as a weighted average, ensuring that stronger rules contribute more to the decision.

Equation (1) handles uncertainty and ambiguity in gesture recognition and improves decision reliability under noise, occlusion, and lighting variation, it also provides smoother and more stable outputs compared to hard classification

Gesture classification is further supported by a linear SVM, expressed as:

$$f(x) = w^T x + b \quad (2)$$

This equation represents a linear decision boundary used for classification.

- x: Input feature vector extracted from gesture images (shape, motion, orientation)
- w: Weight vector learned during training
- b: Bias term
- $w^T x$: Dot product between weights and input features
- $f(x)$: Output score used to classify the gesture

Working principle:

- The SVM separates data into classes using a hyperplane
- If: $f(x) > 0 \rightarrow$ belongs to Class 1
  $f(x) < 0 \rightarrow$ belongs to Class 2

Figure 2 shows the mathematical representation of the forward flow, showing integration of fuzzy inference and SVM classification for robust gesture recognition. It represents membership value μ and peak of the triangle classifies low medium and high values of SVM. Weighted fuzzy outputs are combined (Eqn. 1) and processed via a linear SVM decision boundary (Eqn. 2) to generate a crisp classification result. Multi-class gesture recognition is achieved using a one-vs-all approach. The SVM is well-suited for FPGA implementation due to its high accuracy with high-dimensional features and the simplicity of its linear operations.

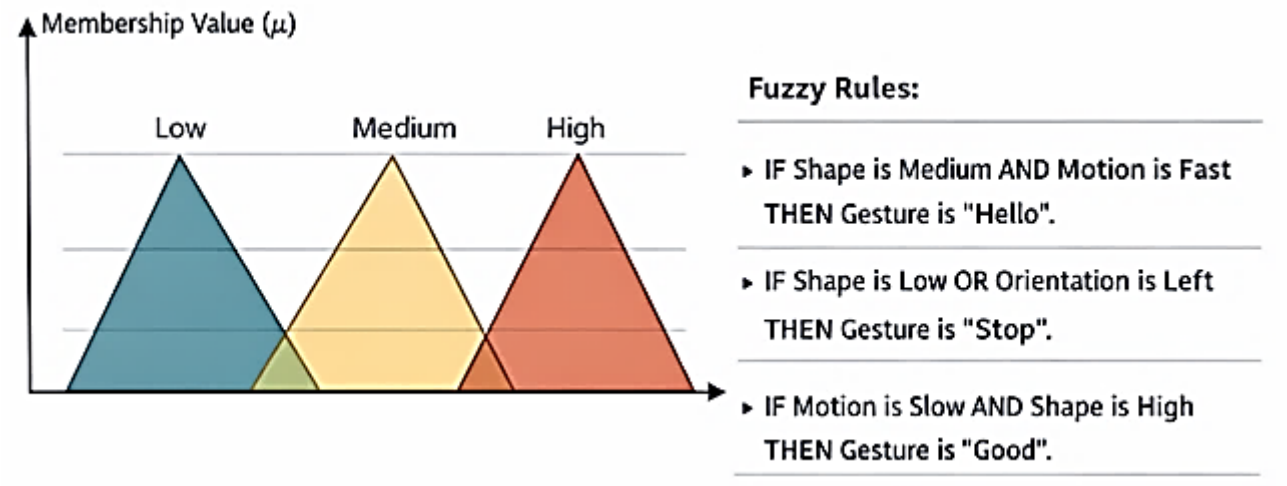


Fig. 2. Mathematical representation of the forward flow incorporating fuzzy output and SVM classification

3.2 Reverse Flow: Text/Speech → Sign

Figure 3 shows the reverse flow, converting text or speech into corresponding gestures, involves multiple processing stages. It also depicts the block diagram of the reverse flow from text or speech input to gesture execution using fuzzy decision logic. The stages include input processing, speech-to-text conversion (if necessary), NLP analysis, gesture mapping, fuzzy rule optimization, and robotic hand control. The system first accepts text or speech input. If the input is speech, it is converted into text through a speech-to-text module.

A natural language processing (NLP) module then analyzes the textual input to extract semantic meaning, identify key phrases, and map them to corresponding gesture sequences. The gesture mapping module references a predefined database to select the appropriate static or dynamic sign language gestures. To handle ambiguity in language and select the most suitable gesture representation, a fuzzy decision module is applied. Finally, the FPGA generates control signals to actuate the robotic hand, executing the mapped gestures. The fuzzy output in the reverse flow is represented mathematically as:

$$Y = \frac{\sum_{i=1}^{n} W_i F_i}{\sum_{i=1}^{n} W_i I} \quad (3)$$

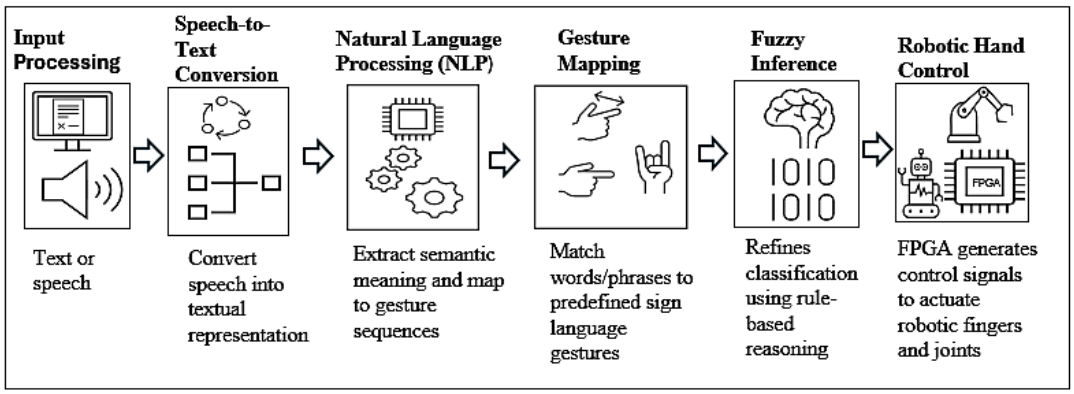


Fig. 3. Block diagram of reverse flow using fuzzy decision logic for gesture mapping

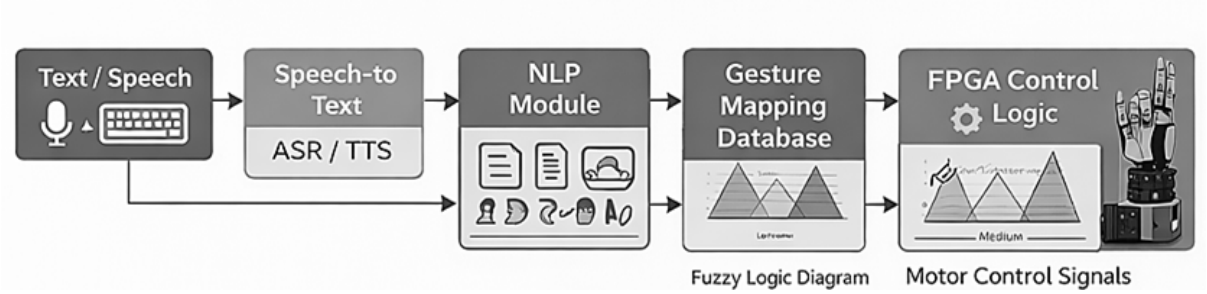


Fig. 4. Block diagram of reverse flow using NLP module and FPGA control logic

The NLP module processes raw text or speech input to extract meaningful linguistic information, including keywords, intent, and grammatical structure. It converts unstructured text into a structured format, performs tokenization and semantic analysis, identifies important words while removing irrelevant components, and manages variations in language, such as synonyms and sentence structure. This ensures that the system accurately interprets the input for gesture mapping.

Figure 4 shows the block diagram of the reverse flow from text or speech input (using ASR/TTS) to gesture execution using NLP processing (fuzzy logic gesture mapping) and FPGA-based control logic driving motor control signals. NLP extracts semantic meaning, maps phrases to gesture sequences, and FPGA hardware generates control signals for robotic actuation. The gesture mapping database stores pre-defined mappings between textual elements – words, phrases, or sentences – and their corresponding sign language gestures. It maintains a repository of static and dynamic gestures, supports vocabulary lookup, indexing, and expansion for multiple languages and regional variations. This module bridges language understanding and robotic execution, ensuring that each recognized word or phrase is translated into the correct gesture sequence.

The fuzzy decision module enhances system robustness by handling ambiguity and uncertainty in both forward and reverse flows. It evaluates multiple possible interpretations of input, applies fuzzy rules to select the most appropriate gesture or output, assigns confidence levels to competing options, and resolves conflicts when multiple gestures correspond to similar inputs. In real-world scenarios, where language and gestures often contain inherent ambiguity, this module ensures smooth

and reliable decision-making, improving system accuracy, stability, and adaptability under uncertain conditions.

4 Methodology

The proposed methodology integrates data preparation, model training, fuzzy rule design, and hardware mapping to achieve robust and real-time sign language interpretation. A curated dataset of sign gestures is captured under varied lighting conditions and backgrounds to enhance system generalization. Images are preprocessed and converted into features that are invariant to scale and rotation. A supervised classifier maps these features to gesture labels, while validation procedures optimize hyperparameters and prevent overfitting. In parallel, a fuzzy rule base is designed to interpret classifier outputs contextually, considering confidence scores and temporal continuity. The defuzzification step produces a crisp decision that balances competing hypotheses.

For hardware realization, the pipeline is partitioned into modules suitable for parallel execution on an FPGA. Fixed-point representations are adopted where appropriate to minimize resource usage without compromising accuracy. Careful scheduling and pipelining are applied to reduce latency. The result is a cohesive framework that merges learning-based classification with rule-based reasoning, enabling dependable real-time interpretation.

Implementing the interpreter on an FPGA provides deterministic timing and efficient parallelism. Core modules include preprocessing accelerators, feature extraction blocks, a classifier engine, and a fuzzy inference unit. Each module is described using hardware description constructs and optimized through pipelining to process streaming data. Lookup tables are used to store membership functions for the fuzzy system, while memory buffers manage frame flow and support temporal smoothing across consecutive inputs. The design exposes clear interfaces for camera input and output peripherals, facilitating integration with display and audio modules. Power efficiency is achieved by tailoring the datapath to the workload, avoiding overhead typical of general-purpose processors. The modular design also simplifies upgrades, allowing integration of newer classifiers or expanded rule sets with minimal impact on surrounding logic.

The system is evaluated using real-time camera input under diverse lighting and background conditions, with multiple users contributing gestures. Performance metrics include classification accuracy, latency, power consumption, and temporal stability. Observations demonstrate that FPGA implementation significantly reduces latency, fuzzy logic improves classification near ambiguous boundaries, the system is robust under noise and occlusion, and power consumption is lower than CPU-based systems.

5 Experimental setup

Evaluation was conducted using both recorded datasets and live camera feeds to simulate realistic operating conditions. The testbed included varied back-grounds, lighting levels, and user profiles to examine robustness. Key metrics included classification accuracy, end-to-end response time, energy usage, and system reliability over extended runs. Baseline comparisons against CPU implementations highlighted latency and power benefits. Temporal stability was assessed by measuring prediction consistency across consecutive frames. Error analysis identified misclassifications due to occlusion, motion blur, and ambiguous gestures, informing refinements to the classifier and fuzzy rules. Logging mechanisms captured detailed traces for offline inspection, while on-device counters tracked throughput and timing. This comprehensive setup ensures that results reflect practical performance rather than idealized laboratory conditions.

The experimental setup included recognition and generation modules. Figure 5 depicts hardware components consisting of an FPGA board (Xilinx/Altera), camera module, microphone for speech input, robotic hand with actuators, and display and speaker modules. Evaluation scenarios encompassed multiple users with different gesture styles, variable lighting conditions, and real-time speech and text inputs. Performance metrics were recognition accuracy, gesture generation accuracy, end-to-end latency, power consumption, and system robustness. Observations indicated that FPGA ensures low-latency real-time processing, fuzzy logic improves decision accuracy under ambiguous conditions, reverse flow enables effective communication for non-signers, and the robotic hand provides intuitive visual feedback.

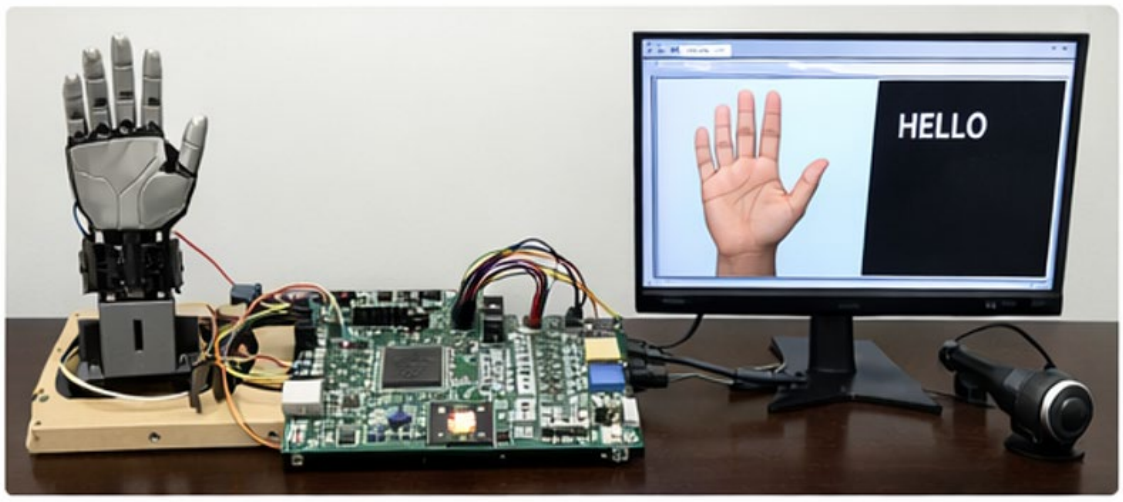


Fig. 5. FPGA-based robotic gesture generator hardware implementation

6 Results and discussion

The results demonstrate that the FPGA-based pipeline achieves faster and more stable inference compared to software-only baselines. Accuracy improved when the fuzzy layer was combined with the classifier, particularly near decision boundaries where ambiguity is common. Parallel processing and streamlined dataflow reduced response times, enabling near real-time feedback suitable for interactive use. Power measurements showed lower consumption relative to CPU-based execution, supporting extended portable deployment. Temporal smoothing further enhanced user experience by reducing flicker in predictions during rapid motion. Challenges remain in handling highly dynamic gestures and extreme lighting variations, which can degrade feature quality; however, fuzzy rules incorporating confidence and continuity partially mitigate these issues. Overall, a hybrid approach leveraging learning and rule-based reasoning on FPGA provides a balanced solution for assistive communication tasks.

Performance evaluation focused on latency, accuracy, throughput, and power efficiency, with comparisons to existing FPGA, CPU, and GPU implementtations.

Figure 6 shows that the proposed system achieves significantly lower latency due to FPGA parallelism and pipelined architecture. FPGA-based systems consistently outperform CPU/edge implementations in real-time responsiveness. Table 1 shows the latency comparison of different FPGA with proposed system, it is evident that proposed system has low latency of 10-25 ms.

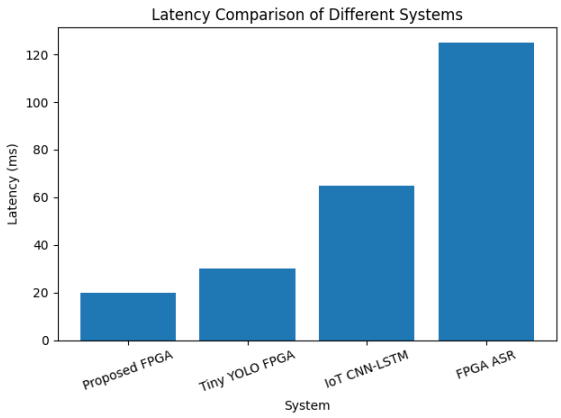


Fig. 6. Latency comparison for various FPGA systems with the proposed system

Table 1. Latency comparison of different FPGA implementations

System / Approach	Tiny YOLO FPGA [41]	IoT CNN-LSTM [42]	FPGA ASR [43, 44]	Proposed system (BRSLCS)
latency	30 ms	65 ms	125 ms	10-25 ms

Table 2. Accuracy comparison of the proposed system with existing FPGA implementations

System / Approach	Tiny YOLO FPGA [41]	IoT CNN-LSTM [42]	FPGA ASR [44, 45]	Proposed system (BRSLCS)
accuracy	61.2%	86.7%	92.4%	92-95%

Table 3. Throughput comparison of the proposed system with other FPGA systems

System / Approach	Tiny YOLO FPGA [41]	IoT CNN-LSTM [42]	3D CNN [44]	Proposed system (BRSLCS)
throughput	32.7 FPS	12-15 FPS	7580 img/s	30-60 FPS

Table 4. Power efficiency comparison of FPGA-based implementations

System / Approach	Tiny YOLO FPGA [41]	GPU systems [44]	CPU systems	Proposed system (BRSLCS)
Power consumption (W)	5.6	50-250	15-65	4-6

Table 5. Reverse flow latency (Text/Speech → Sign) performance

Parameter	Speech processing latency	Gesture generation delay	Total end-to-end delay
Latency / Delay time (ms)	80-125	5-15	~100-150

Figure 7 shows that accuracy comparison with the integration of fuzzy logic improves decision accuracy near uncertain boundaries, outperforming standalone deep learning models in noisy environments.

Figure 8 shows that FPGA systems provide significantly higher throughput due to parallel execution and pipelining. Table 3 shows the throughput comparison of the proposed system with various FPGA systems. The proposed system has a throughput of 30-60 FPS.

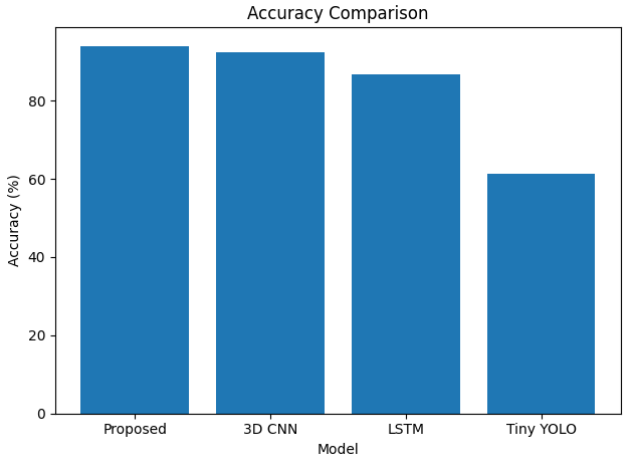


Fig. 7. Accuracy comparison of the proposed system with various FPGA systems

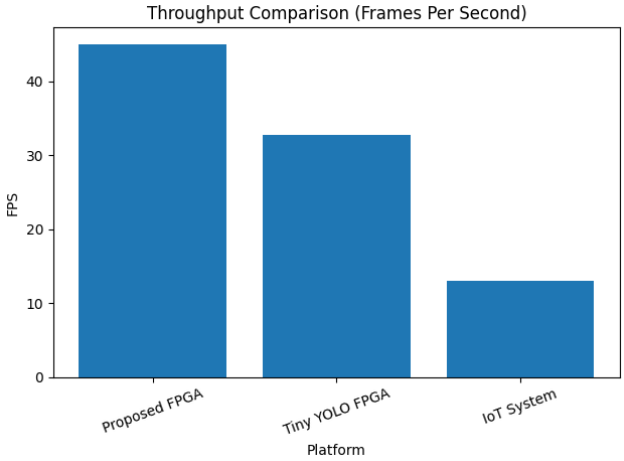


Fig. 8. Throughput comparison for the proposed system against various FPGA systems

The power efficiency comparison of FPGA-based implementation is significantly more energy-efficient, making it suitable for portable assistive devices as shown in Tab. 4. Table 5 shows the reverse flow introduces slight latency due to speech processing but remains within acceptable real-time limits for human interaction. The comparison summary of various systems for accuracy, latency, throughput and power with proposed system is given in Tab. 6. The proposed system has accuracy of 92-95%, a slightly higher delay 10-25 ms with a throughput of 30-60 FPS with maximum power consumption of 6 W.

The FPGA-based system demonstrates lower latency, higher accuracy, and power efficiency, validating the hybrid AI–fuzzy approach as suitable for real-time, bidirectional assistive communication.

Table 6. Summary comparison of various systems

System / Approach	Platform	Accuracy (%)	Latency (ms)	FPS / Throughput	Power (W)
Proposed system (AI + Fuzzy + FPGA)	FPGA	92-95	10-25	30-60 FPS	~4-6
Tiny YOLOv2 FPGA (2025)	FPGA	61.2	30	32.7 FPS	5.6
IoT SLR (LSTM + 3D CNN, 2026)	Edge	~90	65	12-15 FPS	—
FPGA CNN image system	FPGA	—	0.13	7580 img/s	—
FPGA ASR system	FPGA+ Mobile	~90 (WER-based)	125	Real-time	—
FPGA OCR accelerator	FPGA	—	2.1-4.2	458-922 FPS	~1.5

7 Future scope

Future enhancements aim to incorporate deep learning models tailored for spatiotemporal gesture recognition, including convolutional and sequence-based architectures, while maintaining real-time constraints through hardware optimization. Expanding vocabulary to cover regional and international sign languages can increase applicability. Multimodal sensing, such as depth and wearable inputs, may improve robustness under challenging conditions. Adaptive learning can personalize the system to individual users over time. Cloud integration can support model updates and analytics while preserving privacy. Improvements in robotic hand dexterity, multimodal feedback, and edge AI accelerators may further enhance user interaction.

8 Conclusion

This paper presents a novel FPGA-based bidirectional sign language communication system that integrates AI and fuzzy logic. The system effectively translates sign language into text and speech while enabling reverse translation from text and speech into robotic sign gestures.

The hybrid AI–fuzzy approach enhances robustness, accuracy, and interpretability, while FPGA implementation ensures real-time performance and energy efficiency. Experimental evaluation confirms improvements in responsiveness, stability, and robustness under uncertain conditions. The modular pipeline design supports scalability and continuous refinement. This work demonstrates a practical pathway for next-generation, real-time assistive communication systems that balance performance, reliability, and inclusivity.

References

[1] L. A. Zadeh, “Fuzzy sets,” *Information and Control*, vol. 8, no. 3, pp. 338-353, 1965. doi: 10.1016/S0019-9958(65)90241-X.

[2] O. K. Tonguz and G. Ferrari, *Ad Hoc Wireless Networks: A Communication-Theoretic Perspective*, 1st ed. Wiley, 2006. doi: 10.1002/0470091126.

[3] J. M. Mendel, “Type-2 fuzzy sets and systems: An overview,” *IEEE Computational Intelligence Magazine*, vol. 2, no. 1, pp. 20-29, 2007. doi: 10.1109/MCI.2007.380672.

[4] S. Sánchez-Solano, A. J. Cabrera, I. Baturone, F. J. Moreno-Velo, and M. Brox, “FPGA implementation of embedded fuzzy controllers for robotic applications,” *IEEE Transactions on Industrial Electronics*, vol. 54, no. 4, pp. 1937-1945, 2007. doi: 10.1109/TIE.2007.898292.

[5] A. Verma, S. Dhingra, and M. K. Soni, “VLSI-cell placement technique for architecture of field programmable gate array (FPGA) design,” *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 17, no. 3, 2009. doi: 10.3906/elk-0908-173.

[6] A. Verma, S. Dhingra, and M. K. Soni, "Design and synthesis of FPGA for speed control of induction motor," *International Journal of Physical Sciences*, vol. 4, no. 11, pp. 645-650, 2009. doi: 10.5897/IJPS.9000155.

[7] D. N. Oliveira, A. P. de Souza Braga, and O. d. M. Almeida, "Fuzzy logic controller implementation on a FPGA using VHDL," in *Proc. 2010 Annual Meeting of the North American Fuzzy Information Processing Society (NAFIPS)*, Toronto, ON, Canada, 2010, pp. 1-6. doi: 10.1109/NAFIPS.2010.5548192.

[8] M. S. Anand and B. Tyagi, "Design and implementation of fuzzy controller on FPGA," *International Journal of Intelligent Systems and Applications*, vol. 4, no. 10, pp. 35-42, 2012. doi: 10.5815/ijisa.2012.10.04.

[9] R. Rani, M. Verma, and A. Verma, "Application of fuzzy inference system for interpreting physical fitness metrics of male and female trainee athletes: De-fuzzification through hull and sigma scale analysis," *Journal of Electronic & Information Systems*, vol. 7, no. 2, pp. 13-24, 2025. doi: 10.30564/jeis.v7i2.10609.

[10] A. Verma and V. A. Tiwari, "A fuzzy logic controller to minimize the effect of input temperature fluctuations on the deviation of relative humidity to avoid instrument's deterioration," *International Journal of Research in Advent Technology*, vol. 7, no. 6, 2019. doi: 10.32622/ijrat.76201948.

[11] A. Verma and V. A. Tiwari, "Optimum fuzzy based approach to improve the instrument's performance affected by environmental conditions," *Serbian Journal of Electrical Engineering*, vol. 10, no. 2, pp. 309-318, 2013. doi: 10.2298/SJEE121219006V.

[12] E. A. Ramadan, M. El-Bardini, and M. A. Fkirin, "Design and FPGA-implementation of an improved adaptive fuzzy logic controller for DC motor speed control," *Ain Shams Engineering Journal*, vol. 5, no. 3, pp. 803-816, 2014. doi: 10.1016/j.asej.2014.04.002.

[13] I. Baturone, A. Gersnoviez, and Á. Barriga, "Neuro-fuzzy techniques to optimize an FPGA-embedded controller for robot navigation," *Applied Soft Computing*, vol. 21, pp. 95-106, 2014. doi: 10.1016/j.asoc.2014.03.001.

[14] T. Tămas and S. Brassai, "Hardware implementation of a neuro-fuzzy controller using high level synthesis tool," *MACRo 2015*, 2015. doi: 10.1515/macro-2015-0018.

[15] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015, pp. 1-9. doi: 10.1109/CVPR.2015.7298594.

[16] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.

[17] A. Alabdo, J. Pérez, G. J. Garcia, J. Pomares, and F. Torres, "FPGA-based architecture for direct visual control robotic systems," *Mechatronics*, vol. 39, pp. 204-216, 2016. doi: 10.1016/j.mechatronics.2016.05.008.

[18] A. Tandon, A. Saxena, K. Mehrotra, K. Kashyap, and H. Kaur, "A review paper on smart glove - converts Indian Sign Language (ISL) into text and speech," *International Journal for Scientific Research & Development*, vol. 4, no. 8, 2016.

[19] H. Kaur, A. Saxena, A. Tandon, K. Mehrotra, and K. Kashyap, "A review paper on evolution of smart glove," *International Journal of Scientific Research and Management Studies*, vol. 3, no. 3, pp. 124-128, 2016.

[20] K. Mehrotra, A. Saxena, K. Kashyap, H. Kaur, and A. Tandon, "Augmentative and alternative communication using smart glove," *International Journal of Computer Engineering & Science*, vol. 5, no. 3, pp. 41-50, 2017.

[21] K. Cpałka, *Design of Interpretable Fuzzy Controllers*. Cham, Switzerland: Springer International Publishing, 2017. doi: 10.1007/978-3-319-52881-6.

[22] H.-C. Huang, C.-W. Tao, C.-C. Chuang, and J.-J. Xu, "FPGA-based mechatronic design and real-time fuzzy control with computational intelligence optimization for omni-Mecanum-wheeled autonomous vehicles," *Electronics*, vol. 8, no. 11, p. 1328, 2019. doi: 10.3390/electronics8111328.

[23] J. Ruiz-Rosero, G. Ramirez-Gonzalez, and R. Khanna, "Field programmable gate array applications—A scientometric review," *Computation*, vol. 7, no. 4, p. 63, 2019. doi: 10.3390/computation7040063.

[24] C. Li, J. Chen, and M. Jiang, "Research on application of embedded single chip computer intelligent control," in *Proc. 2020 5th International Conference on Mechanical, Control and Computer Engineering (ICMCCE)*, Harbin, China, 2020, pp. 588-591. doi: 10.1109/ICMCCE51767.2020.00132.

[25] E. Noorsal, M. S. M. Aras, M. H. Baharudin, M. R. Ghazali, and M. S. M. Aras, "Design of an FPGA-based fuzzy feedback controller," *Micromachines*, vol. 12, no. 8, p. 968, 2021. doi: 10.3390/mi12080968.

[26] E. Aridhi, D. Popescu, and A. Mami, "FPGA based co-design of a speed fuzzy logic controller applied to an autonomous car," *International Journal of Reconfigurable and Embedded Systems*, vol. 10, no. 3, pp. 195-211, 2021. doi: 10.11591/ijres.v10.i3.pp195-211.

[27] A. A. Nada and M. A. Bayoumi, "Development of embedded fuzzy control using reconfigurable FPGA technology," *Automatika*, vol. 65, no. 2, pp. 609-626, 2024. doi: 10.1080/00051144.2024.2313904.

[28] A. Chopde, S. Joshi, S. Surve, and S. Chavanke, "FPGA based real-time hand gesture recognition system," in *Proc. 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Kamand, India, 2024, pp. 1-6. doi: 10.1109/ICCCNT61001.2024.10724416.

[29] A. Fekik, H. Khati, A. T. Azar, M. L. Hamida, H. Denoun, I. A. Hameed, N. A. Kamal, and others, "FPGA in the loop implementation of the PUMA 560 robot based on backstepping control," *IET Control Theory & Applications*, vol. 18, pp. 1877-1891, 2024. doi: 10.1049/cth2.12589.

[30] Y. Lin, L. Wang, Z. Zhang, and X. Liu, "A hardware-accelerated federated learning with intuitionistic fuzzy security measures for AI adaptive image computing," *IEEE Access*, vol. 13, pp. 198358-198372, 2025. doi: 10.1109/ACCESS.2025.3633060.

[31] R. Niwas, M. Verma, and A. Verma, "A soft computing-based decision support system for multidimensional assessment of non-linear coordinative performance in combat sport athletes using a fuzzy inference system," *Physical Education and Sport Through the Centuries*, vol. 13, no. 1, pp. 113-128, 2026. doi: 10.5937/spes2601113N.

[32] E. Aridhi, K. Laabidi, and A. Mami, "FPGA technology in healthcare: A comprehensive review of hardware and software solutions for diagnostics, imaging, and patient care," *Array*, vol. 28, p. 100622, 2025. doi: 10.1016/j.array.2025.100622.

[33] H. Tanaka and Y. Kobayashi, "FPGA implementation of a PID and fuzzy hybrid controller for robotic arm stabilization," *International Journal of Research in Advanced Electronics Engineering*, vol. 6, no. 2, pp. 33-37, 2025.

[34] C. Li, H. Jiao, W. Huang, Y. Huang, and F. Liu, "An FPGA-based quantization and acceleration framework for Multi-DNN," in *Proc. 2025 IEEE International Symposium on Circuits and Systems (ISCAS)*, London, U.K., 2025, pp. 1-5. doi: 10.1109/ISCAS56072.2025.11044304.

[35] M. Y. Novopoltsev, A. Tulenkov, R. Murtazin, R. I. Akhidov, I. Zemtsova, E. E. Bojarskaja, D. N. Bondarenko, A. V. Savchenko, and I. Makarov, "From data to signs: A foundation model for multilingual sign language recognition," *IEEE Access*, vol. 13, pp. 188170-188181, 2025. doi: 10.1109/ACCESS.2025.3627130.

[36] M. A. Touat, H. Khati, A. Fekik, A. T. Azar, H. Talem, R. Mellah, and S. Ahmed, "FPGA design and implementation of fuzzy learning control: Application on DC motor position control," *An International Journal of Optimization and Control: Theories & Applications*, vol. 15, no. 3, pp. 435-448, 2025. doi: 10.36922/IJOCTA025070023.

[37] M. H. Sabzalian, C. Du, and A. Mohammadzadeh, "A camera-based type-3 fuzzy formation control of multiple robots," *Results in Control and Optimization*, vol. 21, p. 100633, 2025. doi: 10.1016/j.rico.2025.100633.

[38] A. Saday and İ. A. Özkan, "FPGA-based adaptive fuzzy speed control of welding robots with image processing techniques," *Welding in the World*, 2025. doi: 10.1007/s40194-025-02153-9.

[39] A. M. Z. Khaki and A. Choi, "Real-time and resource-efficient embedded computer vision via optimizing lightweight CNNs for FPGA acceleration," *Journal of Signal Processing Systems*, vol. 97, pp. 185-195, 2025. doi: 10.1007/s11265-025-01966-7.

[40] M. R. Kale, C. Kaur, I. Kumar, H. S. Mahdi, V. Uprikar, and S. V., "Development of an Arabic sign language recognition system utilizing deep convolutional neural network," in *Proc. Fifth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*, Bhilai, India, 2025, pp. 1-6. doi: 10.1109/ICAECT63952.2025.10958963.

[41] H. Khati, A. Fekik, M. A. Touat, A. T. Azar, H. Gritli, H. Talem, and R. Mellah, "Hardware implementation of a neuro-fuzzy controller for robotic manipulators," in *Advances in Nonlinear Dynamical Systems and Robotics (ANDC): Modeling, Dynamics and Control Approaches for Modern Robotics*. Academic Press, 2026, pp. 249-277. doi: 10.1016/B978-0-443-30106-3.00011-7.

[42] A. K. Nagarajan, K. Pandiyan, B. Manimaran, P. Nagarajan, and N. Swetha, "FPGA implementation of image registration using accelerated CNN," in *Proc. 2023 Intelligent Computing and Control for Engineering and Business Systems (ICCEBS)*, Chennai, India, 2023, pp. 1-7. doi: 10.1109/ICCEBS58601.2023.10448526.

[43] M. Ji, Z. Al-Ars, P. Hofstee, Y. Chang, and B. Zhang, "FPQNet: Fully pipelined and quantized CNN for ultra-low latency image classification on FPGAs using OpenCAPI," *Electronics*, vol. 12, no. 19, p. 4085, 2023. doi: 10.3390/electronics12194085.

[44] L. Gao, Z. Luo, and L. Wang, "Convolutional neural network acceleration techniques based on FPGA platforms: Principles, methods, and challenges," *Information*, vol. 16, no. 10, p. 914, 2025. doi: 10.3390/info16100914.

[45] Y. Xu, J. Luo, and W. Sun, "Flare: An FPGA-based full precision low power CNN accelerator with reconfigurable structure," *Sensors*, vol. 24, no. 7, p. 2239, 2024. doi: 10.3390/s24072239.

[46] Z. An, K. Peng, K. Yang, C. Lin, L. Zeng, and W. Yang, "An efficient parallel computing CNN accelerator based on FPGA hardware resources," *SSRN*, 2024. doi: 10.2139/ssrn.4861407.



Prof. Kshitij Shinghal received his B.Tech. in Electronics Engineering from Shivaji University, Kolhapur (1999), M.Tech. in digital communication from Uttar Pradesh Technical University (2006), and Ph.D. in electronics (2013). He is Professor and Dean at Moradabad Institute of Technology, Moradabad, where he has served since 1999. With over 25 years of experience in teaching, research, and academic administration, he has published numerous research papers, book chapters, and books, and holds multiple patents, including international patents in IoT-based systems. He has supervised Ph.D., M.Tech., and B.Tech. research and participated in sponsored projects and consultancy. His research interests include wireless sensor networks, IoT, embedded systems, smart technologies, and engineering education.



Dr. Amit Saxena received his B.Tech. in electronics and communication engineering from the Institute of Engineering and Technology, Rohilkhand University (2002), M.Tech. in VLSI design from Uttar Pradesh Technical University (2009), and Ph.D. in electronics and communication engineering (2018). He is an Associate Professor in the Department of Electronics and Communication Engineering at Moradabad Institute of Technology, Moradabad. With over 23 years of academic experience, he has been actively engaged in teaching, research, and student mentoring. He has published research papers in national and international journals and conferences and contributed to various academic activities. His research interests include the Internet of Things (IoT), VLSI design, and embedded systems.



Prof. Rajul Kumar Misra received his B.Tech. in electrical engineering from the National Institute of Technology Kurukshetra, M.Tech. from Motilal Nehru National Institute of Technology Allahabad, and Ph.D. from the National Institute of Technology Kurukshetra. He is Professor and Head of the Department of Electrical Engineering at Moradabad Institute of Technology. With over two decades of academic and research experience, he has contributed to teaching, research, industry collaboration, and institutional development. He has published

research papers in journals and conferences on emerging technologies in electrical and electronics engineering. His research interests include the Internet of Things (IoT), electric vehicles, and smart vehicle technologies.



Prof. Avnesh Verma holds B.E., M.Tech., and Ph.D. degrees in engineering and has over 31 years of professional experience in teaching, research, administration, and academic leadership. He is currently Chairperson of the Department of Instrumentation at Kurukshetra University, and previously served as Registrar of Guru Jambeshwar University of Science & Technology (2020-2023). A distinguished academic and researcher, Prof. Verma has authored four books, holds two patents (including one granted) and one copyright, and has published numerous research papers in national and international journals and conferences. He has supervised many Ph.D. scholars and M.Tech. dissertations and has contributed to collaborative research projects, including with IIT Bombay. Prof. Verma has received several prestigious honours, including the *Lifetime Achievement Award (2024), the Jan Seva Ratan Samman (2021), and Best Paper Awards (2025 & 2008)* for his contributions to engineering and AI ethics. He serves on the academic and executive councils of several universities, is an editorial board member and reviewer for reputed international journals, and has delivered expert lectures at national and international forums. His research interests include VLSI, power electronics, motor control, artificial intelligence, and engineering education.

Received 20 June 2026