Bridging the Gap: A Comprehensive Review on Sign Language Recognition and Translation

Dr. Vina M Lomte[1], Sanjana Sundar Telange[2], Shruti Pramod Patil[3], Akshata Nitin Gabale[3], Ashvini Anil Gavit[4]

[1,3,4,5] *Department of Information Technology Dr. D Y Patil Institute of Technology, Pimpri, Pune. Pune 411018, India*

[2]*Associate Professor Department of Information Technology, Dr. D Y Patil Institute of Technology, Pimpri, Pune, Pune 411018, India*

***Abstract*—With an emphasis on deep learning, computer vision, and sensor technologies, this literature review examines developments in Sign Language Recognition (SLR) and Translation. Early systems used flex sensors, which could only detect static motions, and simple machine learning algorithms. However, real-time translation and dynamic gesture recognition have greatly improved thanks to deep learning models like CNNs, RNNs, and Transformer-based architectures. Despite these developments, real-time SLR and translation still have problems with dynamic gestures, subtle finger movements, invisible signs, lighting, and sensor calibration. The precision and generalizability of translation systems are also impacted by problems including small datasets, dialect differences, and computational limitations. SLR and sign language translation are becoming more scalable and efficient because to ongoing advancements in multimodal sensor fusion and AI models, which increases their suitability for real-world applications. This review of the literature discusses the technology used for sign language translation and recognition, which is becoming more and more common in the contemporary digital world. For upcoming scholars, it highlights how these advancements enhance communication and accessibility by making them more useful by the deaf community.**

***Keywords*— Sign Language, Sensor Glove, CNN, Text-to-Speech (TTS), Gesture Recognition.**

I. INTRODUCTION

The goal of revolutionary technologies like Sign Language Recognition (SLR) and Translation is to close the communication gap between the hearing and the deaf communities. Accessible communication techniques are becoming increasingly important as digital technology develops, particularly for those who are hard of hearing. [1] Within the deaf population, sign languages which differ greatly between cultures and geographical areas are essential communication tools. A lack of a common language, however, frequently creates a barrier between hearing and deaf people, resulting in social isolation and lost chances in social contacts, work, and education. Systems for SLR and translation have become crucial instruments for dealing with this problem. In order to facilitate real-time communication between signers and non-signers, these systems seek to identify and convert sign language motions into spoken or written language. Interpreting hand gestures, body language, facial emotions, and contextual cues all of which contribute to the structure of sign languages is part of the recognition process. Early systems relied on crude methods, such sensor gloves and primitive machine learning models, which struggled to handle dynamic and complicated signs and were only able to recognize static motions. Deep learning has been transformed by developments, especially with regard to Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based models.[2][3] These sophisticated models allow systems to interpret complicated sign language structures and dynamic movements, increasing translation speed and recognition accuracy. The resilience and real-time processing capabilities of these systems have also been improved by multimodal sensor fusion, which combines data from high-end flex sensors, magnetometers, gyroscopes, and accelerometers. Contemporary systems are now able to record delicate finger motions, follow continuous gestures, and identify non-manual cues like facial expressions all of which are crucial in many sign languages.[4]

II. LITERATURE REVIEW

Real-time applications where technology interprets sign language for smooth communication are the main topic of a literature review on sign language recognition (SLR) and translation. To identify motions and facial expressions, contemporary systems make use of deep learning, computer vision, and machine learning.[6][7] The goal of real-time translation is to help the hearing challenged communicate by quickly translating signals into text or speech. Managing variances in sign language, non-manual signals, and maintaining accuracy in changing contexts are some of the main issues. The goal of ongoing research is to improve system accuracy, portability, and responsiveness for real-world, daily use.

Table 01: Methodology survey

Ref. No.	Methodology Used	Dataset Used	Accuracy (%)	Research Gap Identified
[1]	Deep learning, HML,CRS	CSL dataset ,HKSL dataset	68.2	Large-Scale Data Processing
[2]	DSR methodology	Created their own dataset	-	Limited availability of current solutions
[3]	HMI ,HMM	27 gestures from ASL, Sign Language Lexicon	90	Few gestures are recognized.
[4]	CNN	EMG-based dataset, Smartphone-based dataset	98% accuracy on the EMG, 72% accuracy on the Smartphone-based	Reduced Precision for Complicated Data
[5]	Generating a sequence of frames	RWTH-Phoenix-2014T	-	Multi-Channel Input Integration
[6]	Filter, Wrapper, Embedded	RWTH-BOSTON-50, BVC3DSL, Chalearn LAP IsoGD	-	Managing Sign Language Variability
[7]	SOTA,HOG,GCM	Create own BL dataset	-	Including input from many models and improving training techniques
[8]	Optimization method	Created their own	94.3 for LSTM, 89.07 for CNN	Limited Dataset Diversity
[9]	HMM,RNN	100 days of hands, wider face, WLFW	85% - 90%	Limited Use of Multi-Modal Data
[10]	CNN	ASL Alphabet repository	99%	Limited Dataset
[18]	IoT-based smart gloves with flex sensors, gyroscope, Arduino, Bluetooth, and mobile app processing	Predefined dataset using measured acceleration and flex sensor resistance.	98.99%	For people with disabilities, real-time, highly accurate, and low-latency sign language identification is essential.

Researchers' methods for real-time sign language detection are highlighted in the Table 01, with a focus on deep learning techniques. It reveals that although these techniques exhibit great throughput, they face major obstacles because of dynamic gestures, subtle finger movements, invisible gestures, lighting, and the requirement for sizable, varied datasets[8].

Table 02: Discussion on various gloves attributes

Ref. No.	Year	Input	Accelerometers	Gyroscope	Magnetometer	Output	Model/Key Features
[1]	2023	RGB images, depth data and	NA	NA	NA	Recognized sign words or sentences	Discusses both conventional and

		skeleton key points					deep learning techniques for recognizing sign language.
[2]	2022	Finger alphabet and sign language video sequences	NA	NA	NA	Translated text	Transformer Neural Networks (TNN) were modified to recognize sign language.
[3]	2023	Flex sensor, force sensor	Used in the IMU for tracking hand movements.	Part of the IMU sensor for orientation tracking.	Not explicitly mentioned.	Categorical gesture labels	A CNNis used for classification in a smart glove equipped with flex, force, and IMU sensors.
[4]	2024	EMG, smartphone motion	Not mentioned.	Not mentioned.	Not mentioned.	Categorical gesture labels	Convolutional Neural Networks (CNN) are used to recognize gestures using sensors.
[5]	2023	Video footage of sign lang., facial expression	-	-	-	Textual translation	models for Sign Language Translation (SLT) based on Deep Learning (DL), such as Transformer-based architectures.
[6]	2024	Flex sensor	Used on wrist, forearm, or upper arm to capture hand and arm movements	Used along with accelerometers for motion capture	-	Recognized gestures	Multi-modal fusion improving differentiation of similar gestures
[7]	2022	Multi-modal data including video frames, audio, text,	NA	Not included	-	Recognized gestures converted to text, speech, or synthesized animations	Deep learning-based multi-modal body language recognition

		and sensor-based data					
[8]	2023	Video frames of sign gestures	NA	Not included	-	Recognized sign words	CNN and LSTM-based sign language recognition system
[10]	2023	Hand sign images	-	-	-	Alphabet letters	
[15]	2024	Flex sensor	Part of the IMU sensor for motion tracking	Part of the IMU sensor for orientation tracking	-	Recognized hand sign class	Progression Learning Deep CNN (PLD-CNN) with wearable glove sensors
[17]	2023	Flex sensor	Utilized to capture hand movements	To measure rotational movements	Yes, included in IMUs for orientation and positioning measurements	Not included	Use of machine learning techniques like Random Forest, SVM, and k-NN; wearable sensors like flex sensors and IMUs
[18]	2024	flex sensors and gyroscope	Not mentioned explicitly.	Used to measure hand orientation and movement	Not mentioned explicitly.	Text and AudioOutput,	Flex sensors, a gyroscope, an Arduino Uno, a Bluetooth sensor, and a buzzer are features of Internet of Things-based smart gloves.

The development of sensor gloves for sign language recognition is seen in this table 02. The sector has witnessed notable advancements in tracking accuracy, gesture discrimination, and real-time ASL recognition, from simple flex sensors in 2022 to sophisticated multi-sensor fusion gloves with AI models in 2024. Wearable feedback devices that improve usability and engagement, such TTS modules and LED indicators, are another recent development. Comfort, usability, and guaranteeing uniform recognition in various settings are still issues, though.[9]

Table 03: Data Acquisition and Sensor Glove Design

Ref. No.	Acquisition Methods	Feature Type	Feature Extraction Method	Dataset Used	Key Contributions
[1]	Image and video-based recognition techniques	-	CNNs, Transformers, Graph Neural Networks, GANs	RWTH-PHOENIX-Weather, AUTSL, CSL, and others	thorough analysis of SLR datasets, techniques, and upcoming issues.
[2]	Data collected	Time-series	-	A custom dataset	Creation of an

	from publicly available augmented sign language videos.	data, motion		with 100 gesture recordings from 10 participants.	affordable, precise smart glove with gesture recognition capabilities
[3]	Data collected via a sensor-equipped glove and stored in CSV format.	Not explicitly mentioned	Not explicitly mentioned	Custom dataset (30 signers, 300 dynamic gestures)	made it possible to recognize gestures in 3D with excellent fidelity.
[4]	Data collected from electromyography (EMG) signals and smartphone sensors.	Time-series data and electrical signals.	CNN automatically extracts high-dimensional and effective features.	Two sets of data One is based on EMG readings from arm sensors, and the other is based on motion sensors on smartphones.	Two datasets: one from smartphone motion sensors and the other from EMG signals from arm sensors.
[5]	Vision-based and hardware-based approaches; video-based SL recognition is the dominant method.	Hand and facial features, motion, spatial features.	Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer models.	RWTH-PHOENIX-2014T dataset.	An overview of dataset analysis, future research topics, and Sign Language Machine Translation (SLMT).
[6]	Data gloves and accelerometer/gyroscope-based methods	-	-	RWTH-BOSTON-50, Chalearn LAP IsoGD, BVC3DSL, HDM05, ASL Lexicon Video Dataset	Examination of several sensor technologies and datasets for the recognition of sign language
[7]	Multi-modal feature extraction using deep learning	-	CNN-based, Transformer-based, and RNN-based approaches	Several datasets for talking head identification, co-speech, cued speech, and sign language	An extensive analysis of deep multimodal learning for the development and recognition of body language.
[8]	Webcam and Droid Cam client-server.	Pixel-based Features	ResNet-based CNN and LSTM	DS-1 (3 classes) and DS-2 (26 classes, 28,600 images)	A CNN and LSTM-based real-time sign language recognition system
[9]	Pose estimation using hand and face detection	-	Efficient Net-based encoder-decoder architecture	100 DAYS OF HANDS, WIDER FACE, WLFW, COCO WHOLE BODY, HALPE, RHD datasets	Dynamic visual information processing for sign language recognition
[10]	Real-time image acquisition using a webcam	Pixel-based Features	CNN-based feature extraction	ASL Alphabet dataset (87,000 images)	creation of a background-corrected real-time hand sign recognition model.
[18]	Sensor-based data acquisition using flex sensors and a	Hand movement and finger bend-	Predefined acceleration and flex sensor resistance	Custom dataset based on predefined sensor values	IoT-based smart gloves for real-time sign language

	gyroscope	ing data	analysis		recognition, increasing precision and reaction time

The Table 03 highlights the evolution of data acquisition and sensor glove designs used in sign language recognition. Early systems (2022) with basic flex sensors were limited to static gestures, while 2023 saw the integration of IMU sensors for improved 3D tracking. By 2024, advancements in graphene-based sensors and Transformer models enabled real-time, flexible, and precise gesture recognition. Hybrid CNN-LSTM and Transformer models also enhanced dynamic gesture tracking and context-sensitive translation.[10][11] The expansion of datasets further strengthened the accuracy and efficiency of ASL translation systems, though challenges like computational demands and variability in sign language remain.

Table 04: Gesture Recognition Using Deep Learning

Ref. No.	Gesture Type	Recognition Method Used	Recognition Accuracy (%)	Dataset Used	Key Contributions
[1]	Sign language gestures	CNN, RNN, Transformer, HMM, CRF, GAN, GNN	-	RWTH-PHOENIX-Weather, AUTSL, CSL, and others.	Comprehensive review of SLR methods, datasets, and future challenges
[2]	Emergency-related sign language phrases.	Transformer Neural Networks (TNN)	-	1638 publicly available sign language videos	AI-based pipeline and software prototype for sign language translation.
[3]	Dynamic hand gestures used for game control.	Convolutional Neural Network (CNN).	90%	A custom dataset with 100 gesture recordings from 10 participants.	Development of a low-cost, accurate smart glove for gesture recognition.
[4]	Hand gestures such as rock, scissors, cloth, and OK.	CNN	98% for EMG-based data, 72% for smartphone-based data.	Two datasets—one based on EMG signals from sensors on the arm, another from smartphone motion sensors.	Created a CNN-based model that outperformed conventional machine learning models in sensor-based gesture detection.
[5]	Continuous Sign Language Recognition (CSLR).	CNNs, Bi-LSTMs, Hidden Markov Models (HMMs), and Transformer models.	-	RWTH-PHOENIX-2014T dataset	An overview of dataset analysis, Sign Language Machine Translation (SLMT), and potential research avenues
[6]	Sign language gestures	Machine learning-based techniques	96.4%	RWTH-BOSTON-50, Chalearn LAP IsoGD, BVC3DSL, HDM05, ASL Lexicon Video Dataset	-
[7]	Sign Language, Cued Speech,	Machine learning-based and deep	-	Multiple datasets for Sign Language, Cued	-

	Co-speech, Talking Head	learning-based techniques.		Speech, Co-speech, and Talking Head recognition	
[8]	Sign language gestures	CNN, LSTM, GRU	CNN - 89.07%, LSTM - 94.3%, GRU - 79.3%	DS-1 (3 classes) and DS-2 (26 classes, 28,600 images)	-
[9]	Sign language gestures using hand and face tracking.	Deep SORT tracking with Hungarian algorithm and Kalman filter.	85% - 90%	100 days of hands, wider face, WLFW	Dynamic processing of visual input for the recognition of sign language.
[10]	Alphabetic hand signs	CNN	99%	ASL Alphabet dataset (87,000 images) .	Creation of a background-corrected real-time hand sign recognition model.
[18]	Hand gestures used for sign language translation	Arduino-Bluetooth module processing	98.99%	Custom dataset based on predefined sensor values	IoT-based smart gloves for real-time sign language recognition, increasing precision and reaction time

In the era of Artificial Intelligence, deep learning methods have significantly outperformed traditional approaches in gesture recognition. Table 04provides insights into the progression of sensor glove designs and data acquisition methods used by researchers. Early systems relied on basic techniques like flex sensors and accelerometers, which were limited to static gesture recognition. However, with the advent of deep learning models such as RNNs and hybrid CNN-LSTM networks, dynamic gesture recognition saw significant improvements. More recent developments, including Transformer models and multimodal sensor fusion (accelerometers, gyroscopes, magnetometers, and flex sensors), have further enhanced accuracy, speed, and real-time translation capabilities, making modern systems more reliable, scalable, and applicable in real-world scenarios.[12]

Table 05: Gesture-to-Text Translation

Ref. No.	Gesture Type	Samples Tested	Datatype Used	Translation Accuracy (%)	Translation Time (ms)	Gesture-to-Text Translation Approach
[1]	Sign language gestures	NA	NA	NA	NA	Sequence-to-sequence learning and Transformers
[2]	Emergency-related sign language phrases.	NA	NA	NA	NA	AI-based translation using Transformer Neural Networks.
[3]	Dynamic hand gestures used for game control	10 participants, each performing multiple gestures	CSV format with numerical sensor data.	Not explicitly mentioned.	Not explicitly mentioned.	Not explicitly mentioned.
[4]	Hand gestures such as rock,	Not explicitly mentioned.	Electrical signals	Not mentioned.	Not mentioned.	Not explicitly mentioned.

	scissors, cloth, and OK.		(EMG) and motion data (smartphone).			
[5]	Continuous Sign Language Recognition (CSLR).	NA	NA	NA	NA	Neural Sign Language Translation (NSLT) using deep learning techniques.
[6]	Sign language gestures	NA	NA	NA	NA	NA
[7]	Sign Language, Cued Speech, Co-speech, Talking Head	NA	NA	NA	NA	Transformer-based and sequence-to-sequence models
[8]	Sign language gestures	NA	NA	NA	NA	Improved ResNet-based CNN
[9]	Sign language gestures using hand and face tracking	NA	NA	NA	NA	Pose estimation with deep tracking
[10]	Alphabetic hand signs	29 classes, tested 10 times per class (total 290 tests)	NA	NA	NA	CNN-based recognition
[18]	Hand gestures used for sign language translation	Not explicitly mentioned.	Custom dataset based on predefined sensor values	95% - 98% depending on gesture	1 - 1.4 seconds for phrase recognition	Turns sensor readings into text or voice by matching them to specified words.

Gesture-to-text translation has advanced from rule-based systems to deep learning frameworks, greatly improving translation accuracy and efficiency.[13][14]Initialsystems utilized SVMs and rule-based mapping, which had good performance in static gestures but were problematic in dynamic recognition because they had low adaptability and smaller data sets. Incorporation of recurrent neural networks (RNNs) enhanced sequential gesture processing by modeling time-dependent variation in sign language.[15] Hybrid CNN-LSTM models further improved word prediction with the use of sensor fusion methods, resulting in improved recognition in varying environments [16]shown in Table 05.

III. RESEARCH CONTRIBUTION

Ref. No.	Evolution Parameter Used	Accuracy (%)	Recall (%)	Precision (%)	F1 Score (%)	Sensitivity (%)	Specificity (%)	Dataset Used
[3]	Loss function and accuracy metrics.	90%	90%	90%	91.32%	90%	89.01%	100 gesture recordings from 10 people in a custom dataset.
[4]	Impact of CNN structure on	98%	-	-	-	-	-	Two datasets: one

	accuracy was analyzed.							from smartphone motion sensors and the other from EMG signals from arm sensors.
[6]	-	-	96.2%	96.4%	-	96.2%	96.7%	Expanded ASL Dataset (80 signers, 1200 gestures)
[7]	Basic Flex &Accelerometer Sensors + SVM Classifier	88.7%	88.2%	89%	88.6%.	84.4%	88.9%	Limited Dataset (20 signers, 100 gestures)
[8]	-	LSTM-94.3%, CNN-89.07%	LSTM - 96%, GRU 79.3%, CNN - 88.88%	LSTM - 93.3%, GRU - 75%, CNN - 91.3%	LSTM - 94%, GRU - 75%, CNN - 88.37%	LSTM - 96%, GRU - 79.3%, CNN - 88.88%	LSTM - 93.03%, GRU - 70.4%, CNN – 90.31%	Created their own
[9]	Emotion-Driven ASL Gestures + Self-Attention Transformer Model	96.9%	96.5%	97.2%	96.8%	96.6%	97%	Custom Dataset (90 signers, 1500 gestures)
[10]	-	99%	99%	99%	99%	99%	99%	ASL Alphabet dataset (87,000 images).
[13]	-	ASL-98.4%, ISL-97.9%	ASL-98.5%, ISL-97.8%	ASL-98.3%, ISL-98%	ASL-98.4%, ISL-97.9%	ASL-98.5%, ISL-97.8%	ASL-98.2%, ISL-98.1%	Custom Dataset
[14]	-	90%	90%	90%	91.32%	90%	89.01%	Custom dataset collected using the smart glove
[15]	Memetic optimization algorithm	98%	97.5%	97.2%	97.35%	97.5%	97.13%	Sensor data
[18]	-	98.99%	-	-	-	-		Custom dataset based on predefined sensor values

Sign language recognition began with SVM classifiers and simple sensors and has gone through a revolution to deep models, enhancing precision and real-time performance. RNNs contributed to sequential recognition, and CNN-LSTM hybrids enhanced gesture discriminability. [17][18]Today, transformer models provide the most accurate and the fastest recognition through self-attention and multimodal sensor fusion. Increased datasets and sophisticated feature extraction have also boosted scalability and responsiveness, making real-time ASL translation more precise and efficient[19][20].

Converting gap into methodology:

To mitigate the gaps found like constrained multi-channel processing, the necessity of detecting new or dynamic signs, proper sensor integration, and limited datasets new methodologies integrate multimodal sensor fusion with flex sensors, gyroscopes, and accelerometers to record accurate gesture data. The inputs are analyzed using sophisticated deep learning models like CNN-LSTM and Transformers for real-time recognition. Researchers are also creating extensive datasets and using methods to boost model generalization and scalability in various environments.

To bridge the communication gap between ASL speakers and non-signers, the proposed system employs a sensor-glove with flex sensors, accelerometers, and gyroscopes to capture real-time hand movements. A spatial and temporal features processing hybrid CNN-LSTM model based on deep learning is used to identify precise gestures. The identified gestures are translated to text and then speech using a multilingual

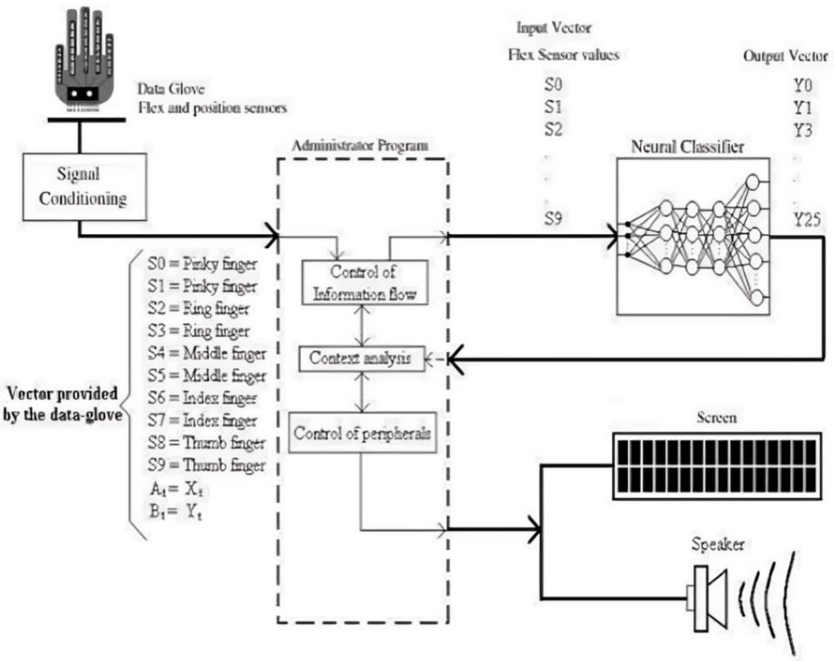

Figure 01: System Architecture

Text-to-Speech (TTS) engine for English, Hindi, and Marathi. Real-time feedback, user interface personalization, and dynamic vocabulary enhancement enable flexibility, accuracy, and usability in diverse environments The envisaged system uses various modules to design an intelligent gesture-identification glove that is able to transform sign language to text and voice. Flex sensors and IMU sensors (accelerometers and gyroscopes) placed at crucial positions on fingers and joints constitute the backbone of the Sensor Integration module for monitoring the hand movements and orientations. These sensors are linked to a Microcontroller Setup, e.g., an Arduino, ESP32, or Raspberry Pi, that is responsible for the processing of raw sensor data. To guarantee a stable operation, a Power Management system is added with an emphasis on battery design and voltage regulation in order to serve all components adequately.

The Data Acquisition Module takes raw inputs such as angles, bends, and orientation from the sensors and processes them using noise filtering methods, such as smoothing algorithms or Kalman filters, to generate clean, usable signals. This cleaned data is passed on to the Gesture Recognition Module, where it is preprocessed and normalized. For gesture mapping, the system can utilize hard-coded rules for basic gestures or implement a light-weight machine learning model like SVM, Random Forest, or CNN for recognizing compound gestures. A specific training data set, including labeled gesture recordings, facilitates machine learning-based recognition.

After a gesture is recognized, the Language Processing Module converts it into equivalent words or phrases. This layer can also offer multilingual translation through internal dictionaries or external APIs, including languages such as English, Spanish, and Hindi. The translated result is delivered through the Output Module, which provides visual feedback through an LCD display, mobile application, or PC interface, and audio feedback through a Text-to-Speech (TTS) engine in the chosen language.

The system is accessed by users through the User Interface Module, which supports customization options like language choice, voice output enablement or disablement, and screen brightness and volume adjustment. The Communication Module facilitates smooth data transfer to external devices using Bluetooth or Wi-Fi, allowing mobile or desktop applications to receive and display the results. Lastly, the System Integration & Testing Module tests every subsystem separately—sensors, machine learning algorithms, and TTS and does full integration testing. This checks that the complete glove system runs well, providing maximum accuracy, responsiveness, and user comfort.

IV. CONCLUSION AND FUTURE SCOPE

The area of gesture-to-text translation has come a long way, ranging from rule-based and SVM classifiers to deep learning architectures, multimodal sensor fusion, and Transformer-based models The earlier work mainly covered static gestures based on conventional machine learning methodologies, which was plagued by poor accuracy and adaptability for actual real-time utilization. The inclusion of RNNs and CNN-LSTM hybrids increased sequential gesture recognition, and more complex signs could be separated better.

Current research emphasizes the excellence of Transformer-based models, which utilize self-attention mechanisms and NLP embeddings to attain state-of-the-art accuracy and improved translation speeds Furthermore, multimodal sensor fusion, combining accelerometers, gyroscopes, and flex sensors, has greatly improved gesture recognition robustness across different conditions. Nevertheless, challenges persist, such as computational efficiency, dataset standardization, and real-time deployment limitations.

Future work could continue on edge AI, dynamic and localized gesture recognition support, standard datasets, and individualized interaction via adaptive learning and haptics, with accessibility guaranteed through collaboration with linguists and the Deaf community.

REFERENCES

[1] Tangfei T., Yizhe Z., Tianyu L., Jieli Z.(2022) *.Sign Language Recognition: A Comprehensive Review of Traditional and Deep Learning Approaches, Datasets, and Challenges.* IEEE Transactions onDeep Learning and AI.

[2] Gero S. ,Thorsten S. ,Frederik M.(2023*).Artificial Intelligence for Sign Language Translation -A Design Science Research Study*.ResearchGate.

[3] Pawel R., WojcethF.(2024).*Machine Learning-Based Gesture Recognition Glove: Design and Implementation.*Article in Sensors.

[4] Ran Bi.(2023).*Sensor-based gesture recognition with convolutional neural networks*.3rd International Conference on Signal Processing and Machine Learning

[5] Adrián N., Olatz P., Gorka L..(2023).*A survey on Sign Language machine translation J*ournal on Elsevier.

[6] Manas T., Navya S., Neha G., Rajni J . (2023). *A Comprehensive Review of Sensor-based Sign Language Recognition Models*. Journal of Xi'an Shiyou University, Natural Science Editio.

[7] Lufei Gao, Wentao Lei, Fengji Ma (2022*). A Survey on Deep Multi-modal Learning for Body Language Recognition and Generation.* IEEE Transactions on Pattern Analysis And Machine Intelligenc.

[8] Md. Abul Ala Walid.,Md Jamal Uddin.(2024).*An Adam based CNN and LSTM approach for sign language recognition in real time for deaf people*.ResearchGate.

[9] D. Ficek.,and M. Richter.(2022). *Pose estimation and tracking for sign language recognition*.

[10] Bambang KrismonoTriwijoyo.,Ahmat Adil.(2023). *Deep Learning Approach For Sign Language Recognition*. Journal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI).
[11] Razieh Rastgoo., Sergio Escalera.(2021).*Sign Language*. ScienceDirect.
[12] Fatma M. Najib.(2023). *Sign language interpretation using machine learning and artificial intelligence*..Neural Computing and Applications
[13] Deemah A., Hussa A., Layla A., Abul B., Majid K.(2023). *Smart Glove for Bilingual Sign Language Recognition using Machine Learning*. IEEE Transactions on Machine Learning
[14] Anna F., Wojciech F.(2024). *Machine Learning-Based Gesture Recognition Glove: Design and Implementation.* Publication on sensors.
[15] Yijuan L., Chaiyan J., PathomthatC.(2024*). Progression Learning Convolution Neural Model-Based Sign Language Recognition Using Wearable Glove Devices.* Publication on computation.
[16] Jiawei W., Peng R., Boming S., Ran Z.(2023). *Data glove-based gesture recognition using CNN-BiLSTM model with attention mechanism.* Publication on Plos One.
[17] Razieh R., Sergio E. (2023). *Sign Language Recognition.* Publication on ScienceDirect.
[18] Dr. Vina L.,Ashish R .(2024) *A Novel Technique For Sign Language Detection Using IOT Based Smart Hand Gloves.*Journal of Technology.
[19] Abhijeet Pachpute, Tanmay Pawar, Alice Gour, Siddhesh Kale,(2023), *TASA:AVirtual AI Assistant with Multilevel Authentication using Face Recognition,* 2023 7th International Conference On Computing, Communication, Control And Automation