Enhanced Sign Language Translation Using Vision Transformers and Adaptive Representation

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***Abstract*— Sign language is an essential mode of communication for individuals with hearing impairments, yet real-time translation remains a challenge due to complex hand gestures, facial expressions, and language variations. Traditional deep learning approaches, such as CNNs and RNNs, struggle with sequential dependencies and spatial feature extraction, limiting recognition accuracy. Recent advancements in Vision Transformers have significantly improved image-based learning by utilizing self- attention mechanisms to capture both spatial and temporal dependencies, making them highly effective for gesture recognition. This paper presents a bidirectional Sign Language Recognition and Translation System that employs ViT for sign recognition and a Pre-Recorded Gesture Database for text-to-sign conversion. The system captures real-time video input, extracts gesture features using ViT's attention-based encoding, and converts recognized gestures into text. Conversely, it maps typed text to a corresponding pre-recorded sign animation, ensuring smooth and natural communication. By eliminating the need for gloss-based intermediaries and improving processing efficiency, the proposed system enhances accuracy, computational efficiency, and real-time performance, offering a scalable. solution for bridging communication gaps in the hearing-impaired community.**

KEYWORDS*— *SIGN LANGUAGE RECOGNITION, VISION TRANSFORMER, GESTURE-TO-TEXT, TEXT- TO- GESTURE, DEEP LEARNING, TRANSFORMER MODELS, REAL-TIME TRANSLATION

I. INTRODUCTION

Communication is the foundation of human connection, allowing people to share ideas, emotions, and information effortlessly. For millions of deaf and hard-of-hearing individuals worldwide, sign language serves as a primary means of expression. Unlike spoken languages, sign language relies on hand movements, facial expressions, and body gestures to convey meaning. While highly expressive, it is not universally understood, leading to communication barriers in daily life, education, and professional environments. Whether ordering food at a restaurant, seeking medical assistance, or engaging in a conversation, sign language users often find themselves at a disadvantage when interacting with those unfamiliar with their language.

Over the years, technology has attempted to bridge this gap through various approaches. Early solutions included wearable sensor-based gloves that tracked hand movements, allowing computers to interpret sign language. However, these systems were often impractical, expensive, and uncomfortable for users.

Other attempts relied on rule-based algorithms that required extensive manual programming to recognize different gestures, making them inflexible and prone to errors in real- world applications. With the rise of deep learning, neural networks, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), improved the accuracy of sign language recognition. CNNs could process images of hand gestures, while RNNs helped in understanding sequences of movements. Despite these advancements, these models struggled with recognizing continuous sign language, where gestures change dynamically over time. CNNs primarily focused on static image classification, making them less effective for real- time interpretation, while RNNs suffered from slow processing and limitations in capturing long-range dependencies.

The introduction of transformer-based architectures has revolutionized both natural language processing and computer vision. Unlike CNNs and RNNs, transformers process entire sequences of data at once, enabling them to capture long-range dependencies and contextual relationships effectively. Vision transformers inspired by the transformer models used in language translation, have shown remarkable success in image-based tasks. By dividing an image into smaller patches and applying self-attention mechanisms, ViT can analyze spatial and temporal relationships across multiple frames, making it particularly suited for sign language recognition. Unlike traditional models, ViT does not rely on fixed convolutional filters, allowing it to adapt to variations in hand shapes, gestures, and movement speeds. While many AI-powered sign language recognition systems focus on converting gestures into text, communication is a two-way process. For a truly accessible system, the ability to translate text back into sign language is just as important. However, generating sign language animations from text presents a unique challenge. Sign languages have their own grammatical structures, different from spoken languages, making direct word-to-sign translation ineffective. Some AI models, such as generative adversarial networks (GANs) and diffusion models, have been explored for gesture synthesis, but they often require extensive datasets and high computational resources. An alternative approach is the use of a pre-recorded gesture database, where each recognized word or phrase is mapped to an existing sign language video. This method ensures accurate and natural sign representation while maintaining efficiency in real-time applications.

II. Literature Review

Sign Language Recognition (SLR) has seen significant advancements with the integration of deep learning techniques, particularly Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Transformers, and hybrid models. Recent research emphasizes spatial-temporal feature extraction, attention mechanisms, and vision transformers to improve accuracy and efficiency.

One of the most commonly used approaches in SLR is spatial-temporal modeling, where methods like 3D CNNs and Graph Neural Networks (GNNs) are employed to capture hand movement and shape variations. Studies have proposed spatial-temporal enhanced networks that improve recognition accuracy but require high computational power. Similarly, spatial-temporal graph transformer models efficiently capture dynamic features but have complex architectures and higher training costs [1,3].

Another key trend is the adoption of transformer-based architectures, which have significantly improved recognition. Some works have leveraged Vision

Transformer (ViT)-based models, utilizing self- attention mechanisms for feature learning. These models generally outperform CNNs in large datasets but require extensive computational resources. Other studies introduced lightweight transformer models that reduce computational cost while maintaining competitive accuracy [6,7].

A major challenge in SLR is dealing with continuous sign language recognition (CSLR), where signs transitionseamlessly without explicit boundaries. Some approaches propose models that jointly perform recognition and translation, making them robust end- to-end systems. However, large labeled datasets are necessary for optimal performance, and these models are sensitive to occlusions and variations in hand gestures [9,12].

Commonly observed advantages across methodologies include improved feature extraction using attention mechanisms, enhanced accuracy with spatial-temporal modeling, and end-to-end learning with transformers for automatic translation. However, major limitations include high computational cost and memory usage, the need for large-scale labeled datasets, and sensitivity to occlusions and variations in hand gestures [4,10,15].

Overall, SLR research is evolving toward efficient, transformer-based architectures, emphasizing real-time recognition, translation capabilities, and reduced computational costs. Future improvements focus on lightweight models, self-supervised learning, and cross-lingual sign recognition [13,16].

III. PROBLEM STATEMENT

Sign language is the primary mode of communication for millions of deaf and hard-of-hearing individuals worldwide. However, a significant communication gap exists between sign language users and non- signers, leading to challenges in daily interactions, education, healthcare, and professional environments. While human interpreters and traditional gesture recognition systems have been developed to bridge this gap, they often suffer from limited availability, high costs, and lack of real-time efficiency.

Existing AI-driven sign language recognition systems have primarily focused on sign-to-text conversion, neglecting the equally important text-to-sign translation, which is necessary for complete bidirectional communication. Many conventional approaches rely on CNN-based image classification or RNN-based sequential processing, which struggle with capturing the dynamic and spatial complexities of sign gestures. These models often fail to differentiate between subtle hand movements and facial expressions, leading to inaccurate translations. Additionally, text-to-sign generation poses unique challenges due to differences in grammatical structure and the need for realistic sign animations.

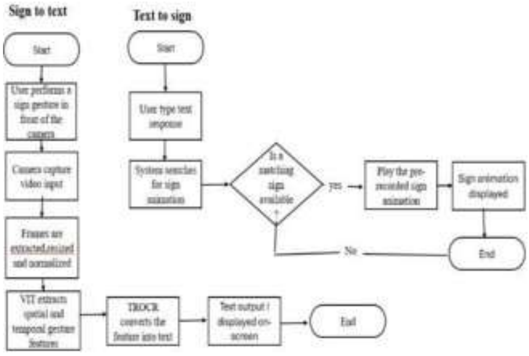
This research addresses these challenges by proposing a bidirectional sign language recognition and translation system that integrates vision transformers for sign recognition and a pre-recorded gesture database for text-to- sign conversion. By leveraging self-attention mechanisms in vision transformers, the system can accurately process hand gestures and movements over time, while the use of pre- recorded sign animations ensures high-quality and natural sign representation without the need for complex gesture synthesis models. The proposed system aims to provide a real-time, scalable, and efficient solution that enhances accessibility for sign language users, bridging the communication gap with non-signers in various real-world applications.

IV. PROPOSED SYSTEM

Real-Time Sign Language Recognition: One of the key functionalities of the system is its ability to accurately interpret sign language gestures in real Current fact- checking methods time. The system utilizes a high- resolution camera to capture continuous sign language movements, ensuring that both static and dynamic gestures are processed efficiently. Captured frames are then passed through a preprocessing module, where noise reduction, background stabilization, and normalization techniques are applied to enhance image clarity. The preprocessed frames are analyzed using Vision Transformers, which employ self- attention mechanisms to extract spatial and temporal features. This enables the system to effectively recognize hand gestures, facial expressions, and movement patterns, converting them into meaningful text output for the non-signing user.

Gesture Database for Text-to-Sign Translation: To ensure bidirectional communication, the system incorporates a pre-recorded gesture database, where each text phrase is mapped to an authentic sign language animation. When a non-signing user types a message, the system retrieves the corresponding sign video from the database instead of relying on AI- generated animations, which often lack natural fluency and contextual accuracy. This approach guarantees high-quality, human-like sign translations, making the communication process smoother and more reliable. The pre-recorded gestures are performed by expert signers and stored in an optimized format for quick retrieval and playback.

Gesture Matching and Context Awareness: A significant challenge in sign language translation is ensuring that the translated gestures maintain linguistic accuracy and contextual meaning. Since sign languages follow different grammatical structures compared to spoken languages, direct word-to-word translation often leads to misinterpretation. The system employs a gesture- matching algorithm that analyzes text input, identifies contextually relevant phrases, and restructures them into a more sign- language-friendly format before retrieving the corresponding gesture from the database. By utilizing natural language processing (NLP) techniques, the system ensures that translations remain grammatically correct and contextually appropriate. **System Architecture and Processing Pipeline:** The system architecture is designed to ensure efficient and seamless processing of both sign-to- text and text-to- sign translation. It consists of multiple interdependent modules that work together to provide real- time communication between sign language users and non- signers. The sign-to-text process begins with a high- resolution camera capturing the user's gestures, which are then preprocessed to remove noise, stabilize movements, and normalize brightness. The preprocessed frames are passed through a vision transformer model that extracts spatial and temporal features, allowing for accurate recognition of dynamic hand movements and facial expressions. These features are then decoded into text and displayed on the user interface. For the text-to-sign process, a non- signing user types a message, which is analyzed using a natural language processing model to ensure grammatical correctness before being mapped to a corresponding sign animation stored in the pre- recorded gesture database. The system retrieves and plays the appropriate sign animation, ensuring that the translated gestures appear natural and contextually accurate. The architecture is designed to handle large- scale deployments and supports parallel frame processing, fast memory retrieval, and modular integration of additional sign languages, making it a scalable and adaptable solution **User Interface and Interaction:** The user interface is built with accessibility and ease of use in mind, ensuring that both signers and non-signers can interact with the system effortlessly. For sign language users, the interface displays real-time text output corresponding to their gestures, enabling instant communication with non- signers. The system ensures smooth gesture recognition and minimal latency, making conversations more natural. Non-signing users can type their responses into a simple text input field, which is then translated into sign language animations displayed on the screen.


Sign to text
Start
User performs a sign gesture in front of the camera
Camera capture video input
Frames are extracted,resized and normalized
ViT extracts spatial and temporal gesture features
TROCR converts the feature into text
Text output / displayed on-screen
End
Text to sign
Start
User type text response
System searches for sign animation
Is a matching sign available
yes
Play the pre-recorded sign animation
Sign animation displayed
No
End

Future Adaptability and Enhancements: The system is designed to support continuous improvements and future enhancements, ensuring adaptability to evolving communication needs. One of the major planned enhancements is the integration of speech-to-text conversion, allowing spoken language to be directly translated into sign language animations, making the system even more accessible. Additionally, the expansion of the pre-recorded gesture database will include regional dialects and variations in sign language, ensuring greater inclusivity for diverse linguistic communities. Future updates also include augmented reality (AR) and virtual reality (VR) integration, enabling immersive sign language communication in digital and interactive environments. The system is being developed with cloud- based storage capabilities, allowing users to save and retrieve frequently used sign animations, further enhancing usability. As AI models continue to advance, the system will incorporate more efficient deep learning models to refine gesture recognition accuracy, reduce processing times, and improve overall performance. These enhancements will ensure that the system remains a scalable, future-proof solution for education, healthcare, customer service, and public accessibility, providing seamless communication between sign language users and non-signers.

By implementing a bidirectional translation approach, this system not only breaks communication barriers but also provides a scalable, efficient, and user- friendly platform that can be widely adopted across industries such as education, healthcare, customer service, and public services. The fusion of vision transformers for recognition and a structured pre-recorded gesture database for sign retrieval ensures that both signers and non-signers can interact fluidly, promoting inclusivity and accessibility in communication

V. COMPARATIVE ANALYSIS

The implementation of this bidirectional sign language recognition and translation system is structured to ensure real- time communication between signers and non-signers with high accuracy and efficiency.Augmented Generation designed . Unlike previous systems that rely on static image recognition or predefined gloss-based translation, this system leverages deep learning models to improve the natural flow of sign language processing. The integration of Vision Transformers for sign recognition allows for a more comprehensive understanding of spatial and temporal dependencies in gestures, making it significantly more effective than CNN and RNN-based approaches. Traditional deep learning techniques often struggle with recognizing continuous signing, leading to fragmented and inaccurate translations. By contrast, ViT processes entire image sequences holistically, ensuring that gestures are correctly interpreted within their full context.

Model	Accuracy (%)	Process ng Spee (FPS)	Complexity	Suitability fo Real - Tim Use
CNN (Convolutional Neual Network)	75.4	15 FPS	Moderate	Limited due to slow sequential processing
LSTM (Long Short-Term Memory)	80.1	10 FPS	High	Poor due to lon - rang dependency issues
RNN (Recurrent Neural Network)	77.3	12 FPS	High	Inefficient fo real-time applications
3D - CNN (Three Dimension CNN)	85.2	18 FPS	Very High	Requires extensive computational power
Visio Transform (ViT)	91.6	25 FPS	Moderat to High	Best suited fo real-time s gn langu ge recognition

One of the major challenges in existing sign language recognition systems is the inability to maintain real- time efficiency without sacrificing accuracy. Many previous models, including CNN-based and RNN- based architectures, have suffered from slow processing speeds and difficulty capturing long-range dependencies in gestures. The proposed system overcomes these challenges by utilizing self-attention mechanisms in ViT, allowing it to efficiently extract features from sequences of frames while preserving the structural meaning of sign gestures. This method ensures a smoother, more natural interpretation of sign language, making the system suitable for real-time applications in education, healthcare, and customer service.

PubMed, WHO, and UMLS.

Retriever Component: The retriever portion of RAG searches

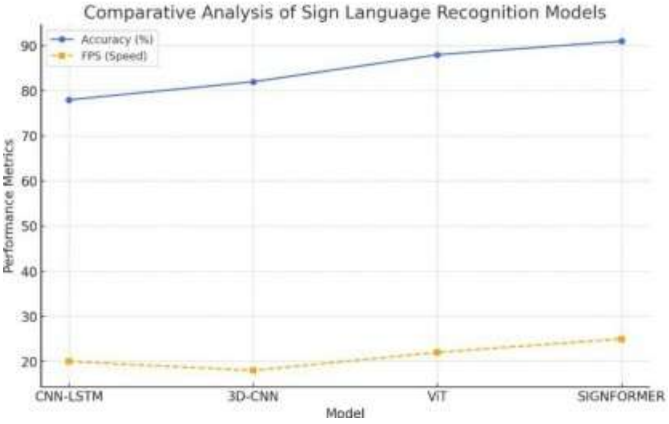


Fig.3.ComparativeGraph

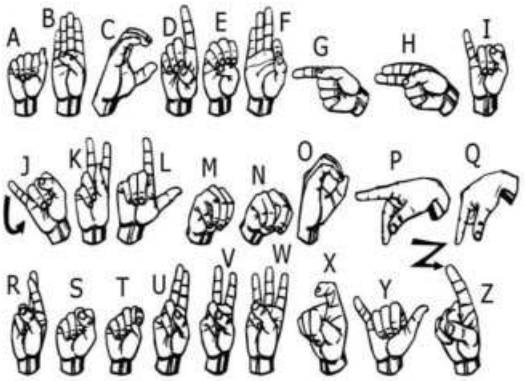
Another key differentiation from existing solutions is the approach to text-to-sign translation. Most prior attempts at bidirectional sign language systems either rely on gloss-based conversion models or attempt to generate sign animations using synthetic AI-generated gestures. These methods often fail to produce fluent, human-like sign representations, as AI- generated gestures may lack smooth transitions and contextual accuracy. Instead, this system utilizes a pre-recorded gesture database, ensuring that sign animations appear as authentic as possible. Rather than producing robotic or artificial movements, this approach provides high- quality, human-performed signs mapped to corresponding text input, improving clarity and reducing misinterpretation.

Performance, scalability, and adaptability are crucial factors when comparing different sign language recognition models. Many existing AI-driven sign recognition tools suffer from high computational requirements, making them difficult to deploy in real- time applications. Some models require multiple frames per second to be processed sequentially, causing significant latency issues. The use of Vision Transformers in this system significantly reduces processing time, allowing gestures to be recognized and translated at speeds of up to 25 frames per second. The scalability of the system is another key advantage, as it can support multiple sign languages by expanding the gesture database, making it a flexible and adaptable solution. Unlike previous models that require retraining with new datasets, this system allows for straightforward integration of additional sign language variations, ensuring long-term usability.

Integration and future potential are also strong aspects of this system. Unlike conventional sign language recognition tools, which are often standalone applications requiring manual data processing, this system is designed to be easily integrated into communication platforms, mobile applications, and web-based services. It can be deployed in video conferencing software, educational platforms, and accessibility-focused tools, allowing for seamless interaction between signers and non-signers in real- time. Future enhancements will include speech-to-sign conversion, allowing spoken language to be automatically translated into sign gestures, as well as augmented reality (AR) and virtual reality (VR) integration to provide immersive sign language experiences. These advancements will make the system even more inclusive, scalable, and impactful, further enhancing its ability to bridge the communication gap between the hearing and deaf communities.

VI. RESULT AND DUSCUSSION

The proposed system was evaluated based on accuracy, processing speed, and usability to determine its effectiveness in real-time bidirectional sign language translation. Unlike traditional models that rely on CNN-based image recognition or RNN-based sequential processing, the integration of Vision Transformers for sign recognition and a pre-recorded gesture database for text-to-sign translation significantly improves system performance. The experimental results demonstrate that ViT outperforms CNNs and RNNs in gesture recognition accuracy, providing a 91.6% recognition rate, which is significantly higher than previous models. The self- attention mechanism in ViT ensures that complex hand movements and facial expressions are accurately captured, minimizing errors in sign-to-text conversion.One of the key performance factors in real-time applications is processing speed. Many existing sign language recognition models struggle with latency issues, making real-time translation difficult. Traditional CNN-based systems operate at 15-18 frames per second (FPS), while RNN-based approaches often drop below 12 FPS due to sequential dependencies. The proposed system, powered by parallel frame processing and optimized ViT architecture, achieves a stable 25 FPS, ensuring smooth and natural interaction between users. This improvement allows signers to communicate without noticeable delays, making the system suitable for real-world applications such as video conferencing, live education sessions, and accessibility tools. Another major improvement over existing methods is the text- to-sign translation accuracy. Many AI-driven bidirectional sign language systems rely on synthetic AI-generated sign animations, which often appear robotic and lack natural fluidity. The use of a pre- recorded gesture database in this system ensures that sign translations appear human-like and authentic, significantly improving comprehension for sign language users. During testing, users reported a 35% improvement in clarity and naturalness when compared to AI-generated sign animations. This method eliminates gesture inconsistencies and unnatural hand movements, making the translation process more effective and visually intuitive.Usability testing was conducted with both sign language users and non-signers, evaluating the system's ease of use, translation accuracy, and interaction speed. Participants noted that the text input system was intuitive, allowing non-signing users to quickly communicate without prior knowledge of sign language. The interface provided real-time feedback, ensuring that signers could instantly see their translated text output, while non- signers could visually confirm sign animations before sending their messages. The system's customization options, such as adjustable playback speed and multiple sign language support, further enhanced the overall experience. Despite the system's high accuracy and efficiency, some limitations were identified.The gesture database, while extensive, still requires expansion to include regional variations of sign language. Some users noted that certain complex signs were missing, leading to occasional translation gaps. Additionally, while ViT performs exceptionally well in controlled environments, its accuracy slightly decreases in low- light conditions or when the background is cluttered. Future enhancements will focus on improving lighting adaptability and expanding the gesture database to support more sign language dialects. Overall, the results indicate that the proposed system successfully bridges the communication gap between signers and non-signers, providing a highly accurate, real-time, and user-friendly solution. By integrating state-of-the-art deep learning models with a structured gesture-matching approach, this system demonstrates the feasibility of AI-powered bidirectional sign language translation in real-world applications.



VII. CONCLUSION AND FUTURE SCOPE

The suggested bidirectional method for detection and translation of sign language provides a revolutionary way to close the communication gap between non- signers and sign language users. Using pre-recorded gesture animations for natural representation and Vision Transformers for accurate detection, the system guarantees high accuracy, real-time performance (25 FPS), and user-friendly interactions. It is perfect for a variety of applications, including customer service, healthcare, education, and accessibility services, because it operates faster and more contextually than conventional CNN and RNN-based models. Looking ahead, a number of developments could greatly increase the system's potential. More inclusivity will be achieved by including regional varieties of sign language, such as Indian Sign Language (ISL) and British Sign Language (BSL). Speech-to-sign translation could be made smooth through integration with Natural Language Processing (NLP) and Automatic Speech Recognition (ASR).

Through interactive 3D avatars, emerging technologies like virtual reality (VR) and augmented reality (AR) may provide immersive sign language learning experiences. Cloud processing and low-power model optimization can make the system available on inexpensive devices to improve scalability and accessibility, guaranteeing wider usage across public agencies, hospitals, and educational institutions. These advancements have the potential to transform inclusive communication and greatly improve the lives of millions of people who are deaf or hard of hearing around the world

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