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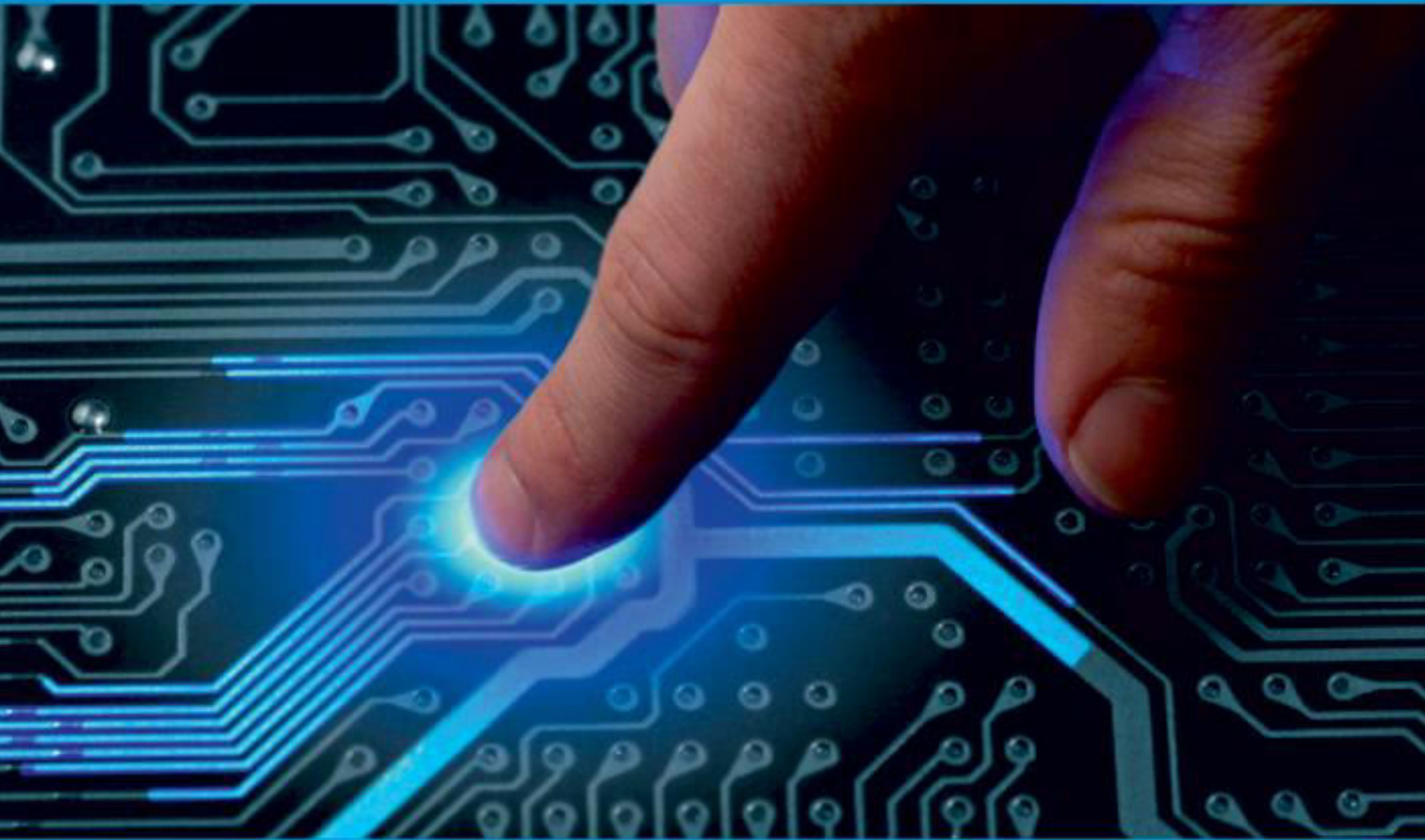

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Comparative Review of Sign Languages

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ABSTRACT: Sign languages have unique linguistic structures and grammar, distinct from spoken languages and are natural languages that rely on visual-gestural communication. They are used by various communities around the world as a means of interaction. The study and understanding of sign languages have been relatively limited compared to spoken languages. Considering the current tech-era we are in the need of sign languages recognition system mainly hand gestures. The paper aims to explore various sign languages, their characteristics existing models, and the advancements made in the field of sign language research. A comprehensive review of Indian and American Sign Languages in the context of mining and Artificial Intelligence (AI). The Paper presents an overview on challenges related to data collection, cultural sensitivity, technological limitations, and ethical considerations and also indicate various classification and models that can be applied to sign languages recognition.

KEYWORDS: Sign language, tech-era, hand gestures, Indian Sign Language, American Sign language, mining, AI, sign languages recognition.

I. INTRODUCTION

Sign languages, as unique linguistic systems, possess distinctive grammatical structures and rely on visual-gestural communication, setting them apart from spoken languages. They serve as natural languages utilized by diverse communities worldwide for effective interaction. However, despite their significance, the study and comprehension of sign languages have remained relatively limited in comparison to spoken languages. In the current era of technology, there arises a pressing need for the development of sign language recognition systems, particularly focusing on hand gestures. This paper aims to delve into the exploration of various sign languages, their characteristics, existing models, and the advancements achieved in the field of sign language research. Specifically, it presents a comprehensive review of Indian and American Sign Languages, within the context of mining and Artificial Intelligence (AI). Moreover, this paper addresses the challenges associated with data collection, cultural sensitivity, technological limitations, and ethical considerations inherent to sign language research. It further identifies various classification approaches and models that can be applied to enhance the recognition of sign languages. By bridging the gap between sign language and technology, this research contributes to the advancement of sign language recognition systems, thereby facilitating more inclusive and accessible communication for individuals who rely on sign languages.

II. ABOUT VARIOUS SIGN LANGUAGES

Various sign languages around the world exhibit unique characteristics and regional variations, reflecting the diversity of their respective cultures. We will compare these sign languages briefly.
1. American Sign Language (ASL):
- Origin: Developed in the United States and parts of Canada.
- Grammar: ASL follows a topic-comment structure, utilizing facial expressions, body movements, and handshapes to convey meaning.
- Manual Alphabet: Utilizes a one-handed fingerspelling system.

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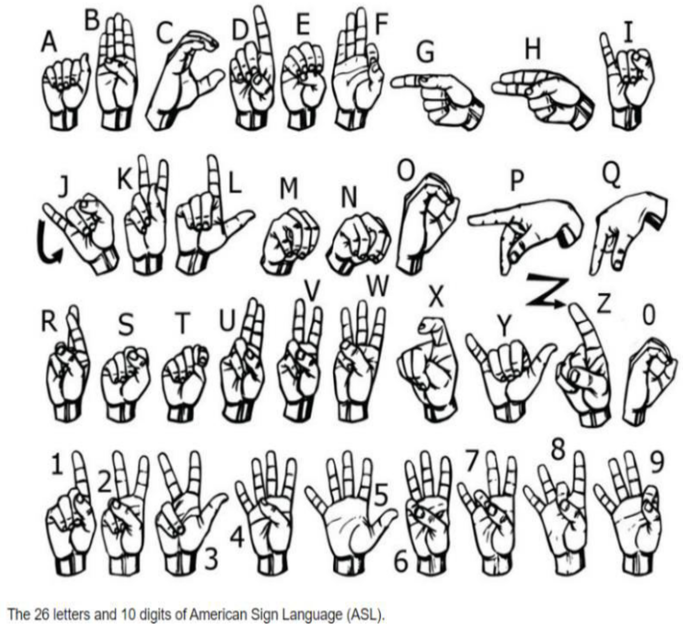

Fig.1. The 26 letters and 10 digits of American Sign Language (ASL)

2. British Sign Language (BSL):
   - Origin: Developed in the United Kingdom.
   - Grammar: BSL relies on a subject-object-verb word order and incorporates facial expressions and body movements.
   - Manual Alphabet: BSL uses a two-handed fingerspelling system.

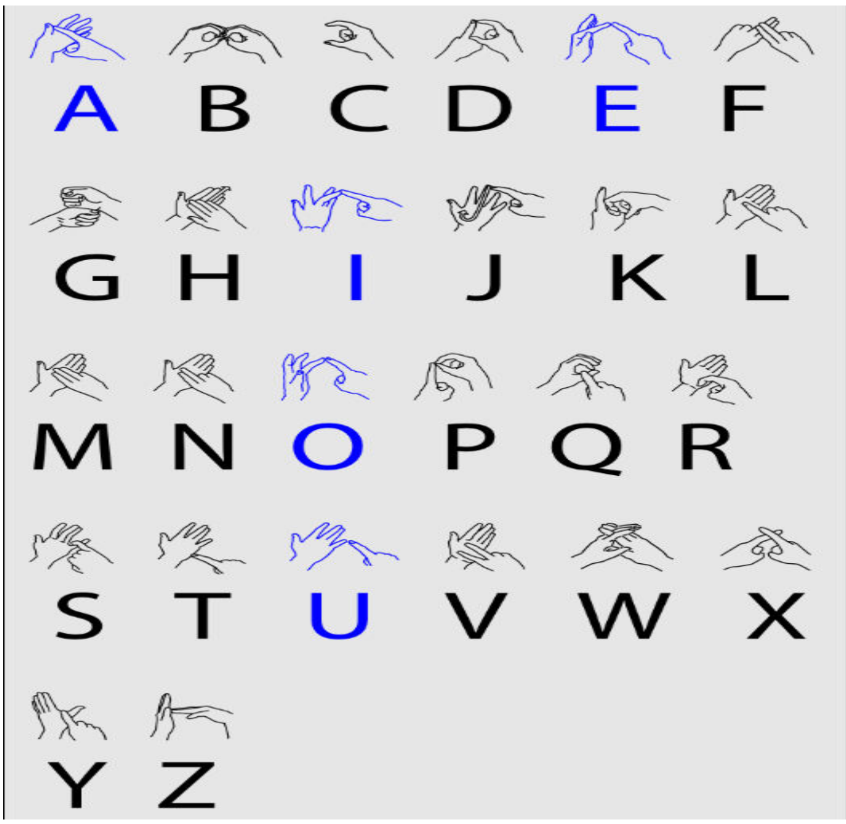

Fig.2. British Sign Language (BSL)

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3. Australian Sign Language (Auslan):
   - Origin: Developed in Australia.
   - Grammar: Auslan exhibits a mix of British Sign Language and Irish Sign Language influences, employing a subject-object-verb word order.
   - Manual Alphabet: Utilizes a two-handed fingerspelling system like BSL.

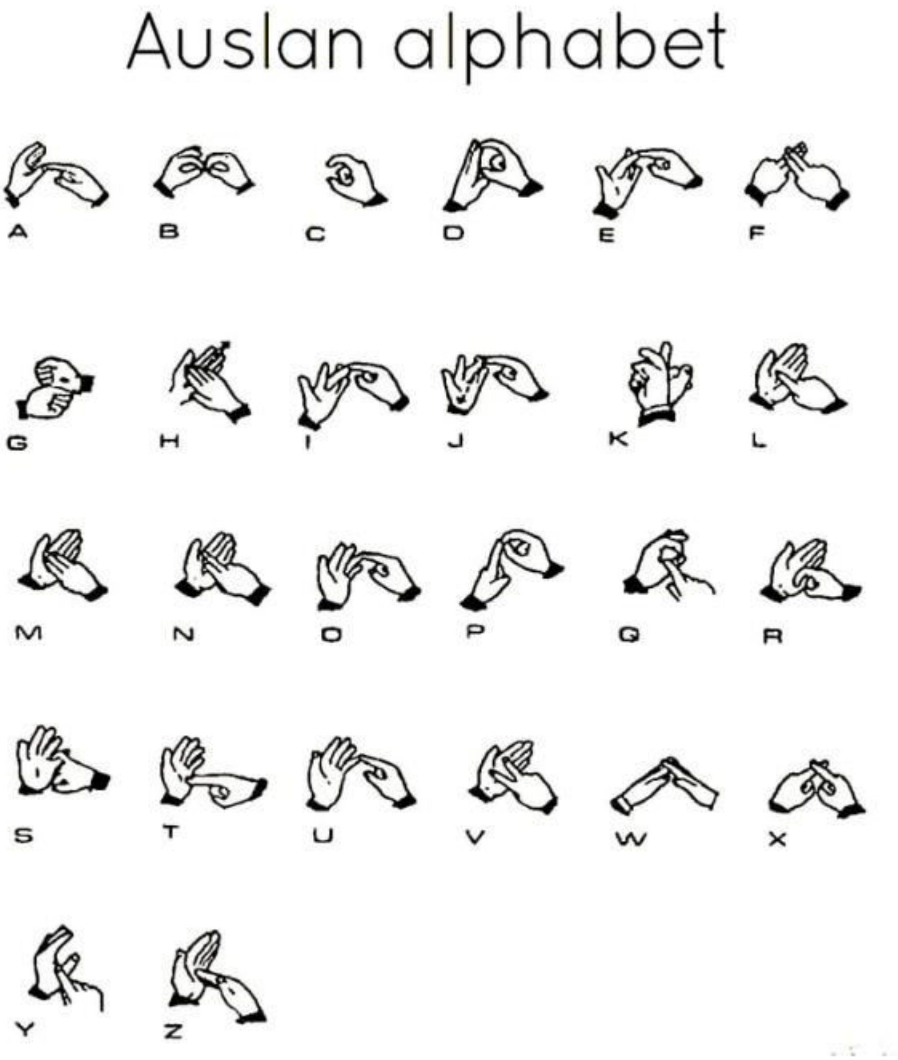

Fig.3. Australian Sign Language (Auslan)

4. Japanese Sign Language (JSL):
   - Origin: Developed in Japan.
   - Grammar: JSL uses a subject-object-verb word order and incorporates facial expressions, body movements, and space to convey meaning.
   - Manual Alphabet: JSL does not utilize a manual alphabet and relies primarily on ideographic signs.

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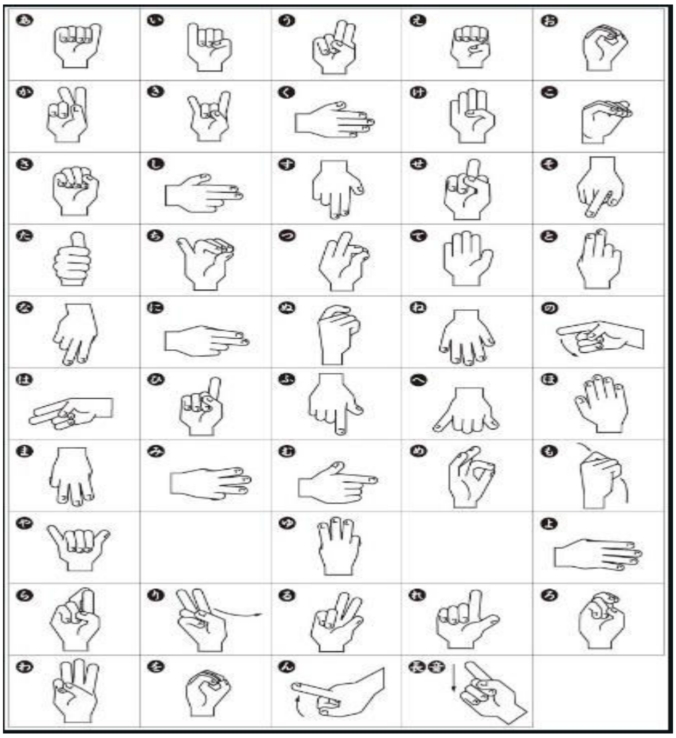

Fig.4. Japanese Sign Language (JSL)

5. Indian Sign Language (ISL):
   - Origin: Developed in India.
   - Grammar: ISL follows a subject-object-verb word order and incorporates facial expressions, body movements, and handshapes to convey meaning.
   - Manual Alphabet: ISL employs a one-handed fingerspelling system like ASL.

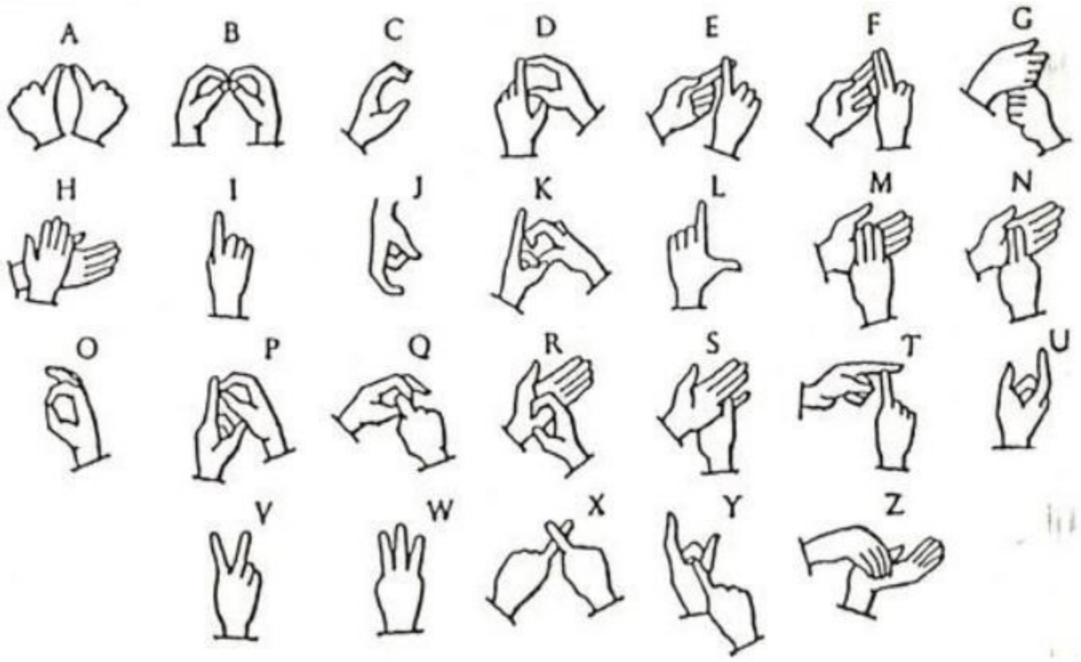

Fig.5. Indian Sign Language (ISL)

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III. LITERATURE REVIEW

At first, we summarize some of the attempts that has been made for ISL and ASL recognition and translation.
In [1], three CNN models were developed to recognize ASL and ISL alphabets. This model gave an accuracy of 98.34% with 50 epochs. A real time sign language to speech conversion and speech to sign language conversion was achieved using this model. In [2], It employed a vision-based approach which is simple, cheap, and reliable to convert an RGB image to binary and match it with information using a comparing algorithm. It converts sign language to text. In [3], the authors have proposed a real-time model for ISL gesture recognition, based on the incoming image data from the Kinect. They were able to achieve real-time implementation of 36 static based gestures. Reference [4] proposed a sensor-based system for deaf-mute people using glove technology, using components like flex sensor, Arduino and accelerometer. In this, the deaf-mute people wear the gloves to perform hand gesture. The system converts the gesture to corresponding text and then to speech.[5] presents the first comprehensive evaluation of a proposed three-layered CNN architecture, four popular pre-trained deep models, gradient-based optimizers and optimization hyperparameters for static ISL recognition. This comparative analysis can be used as a reference for researchers to select the suitable deep model, optimizer and hyperparameters for the static ISL recognition. [6] throws light on how the sign language recognition has come a long way from where it started. It discusses that current work rarely depends on using sensors or coloured gloves that were used by earlier techniques. The availability of multi-modal devices that help in detecting and tracking signer body parts motivated researchers to abandon sensor-based technique in favour of more software-oriented technique.

IV. EXISTING SYSTEMS FOR RECOGNITION AND TRANSLATION

Sign language recognition and translation techniques have made significant advancements in recent years, aiming to bridge the communication gap between sign language users and non-sign language users. Below, is an in-depth overview of various existing techniques for sign language recognition and translation:
1. Computer Vision-based Approaches:
- Hand Gesture Recognition: This approach focuses on recognizing and tracking hand gestures to interpret sign language. It involves techniques such as hand segmentation, feature extraction (e.g., shape, motion, or appearance-based features), and classification algorithms (e.g., Hidden Markov Models (HMMs), Support Vector Machines (SVMs), or Convolutional Neural Networks (CNNs)).
Pose Estimation: By estimating the 3D pose of the signer's hands and body, this technique provides a deeper understanding of sign language gestures. It can be achieved using depth sensors, RGB-D cameras, or marker-based motion capture systems.

2. Sensor-based Approaches:
- Glove-based Systems: These systems employ data gloves equipped with sensors to capture hand movements and gestures. The sensors can include accelerometers, gyroscopes, or flex sensors, which provide information about hand position, orientation, and finger movements. Machine learning algorithms are then used to interpret the captured data and recognize signs.
- Wearable Devices: Advances in wearable technology have led to the development of smart gloves, wristbands, or armbands that incorporate sensors for capturing hand and arm movements. These devices can wirelessly transmit the data to a computer for sign language recognition and translation.

3. Depth-based Approaches:
- Depth Cameras: Depth cameras, such as Microsoft Kinect or Intel RealSense, capture depth information along with RGB data, enabling accurate tracking of hand and body movements. Depth-based approaches leverage this information for sign language recognition using techniques like skeleton tracking, gesture recognition, or spatiotemporal analysis.
4. Deep Learning-based Approaches:
- Convolutional Neural Networks (CNNs):CNNs have shown success in extracting features from sign language images or video frames. They can learn spatial patterns, motion information, and perform classification or translation tasks. CNN architectures like ResNet, VGG, or Inception have been utilized for sign language recognition.
- Recurrent Neural Networks (RNNs): RNNs, particularly Long Short-Term Memory (LSTM) networks, are commonly used for sequence modelling and temporal dependencies in sign language translation. They can take input as sequential frames or hand trajectories and generate corresponding text or spoken language translations.
Transformer-based Models: Transformer models, such as the popular architecture known as the Transformer or its variants (e.g., BERT, GPT), have shown promising results in sign language translation tasks. These models capture

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long-range dependencies and perform well on sequential data, making them suitable for sign language recognition and translation.

5.Data-driven Approaches:
- Large-scale Sign Language Corpora: Building comprehensive datasets of sign language videos or motion capture data is crucial for training robust recognition and translation models. Collecting diverse data from various signers and linguistic variations enhances the system's performance and generalization.
- Crowdsourcing and User Feedback: Involving the sign language community through crowdsourcing platforms or user feedback helps improve the accuracy and usability of recognition and translation systems. Feedback from sign language users can be used for model fine-tuning, error correction, and user-centric improvements.

It is worth noting that the techniques mentioned above often complement each other, and hybrid approaches combining multiple techniques are commonly employed for more accurate and robust sign language recognition and translation systems. Continued research and advancements in these areas hold the potential to further enhance the accessibility and inclusivity of communication for sign.

V. CHALLENGES

While sign language recognition and translation systems have made significant progress, they still face certain drawbacks and challenges. Below, are the detailed drawbacks associated with the different types of systems mentioned earlier:

1. Computer Vision-based Approaches:
-Limited Viewpoints: Computer vision-based systems heavily rely on camera perspectives and may struggle to accurately recognize signs from different viewpoints or when the signer's hands are partially occluded.
-Lighting Conditions: Variations in lighting conditions, such as low light or harsh lighting, can affect the performance of computer vision algorithms, leading to decreased accuracy in hand gesture recognition.
- Complex Backgrounds: Cluttered or complex backgrounds may interfere with the hand segmentation process, resulting in inaccurate recognition or false positives/negatives.

2. Sensor-based Approaches:
- Limited Flexibility: Sensor-based systems typically require users to wear specialized devices such as gloves or armbands, which can be cumbersome and limit the naturalness of signing gestures. This restricts the freedom of signers and may not be practical for everyday use.
- Sensor Calibration: Proper calibration of sensors is crucial for accurate tracking, and calibration errors can lead to inaccurate recognition and translation. Maintaining calibration over time and adjusting for individual differences among users can be challenging.

3. Depth-based Approaches:
- Sensitivity to Noise and Occlusion: Depth cameras may be sensitive to noise, occlusions, or fast movements, resulting in incomplete or inaccurate tracking of hand and body movements. This can lead to errors in sign language recognition and translation.
- Limited Range and Field of View: Depth cameras have limitations in their range and field of view, which may restrict the ability to capture the full signing space accurately, especially for large and dynamic sign language movements.

4. Deep Learning-based Approaches:
-Data Requirements: Deep learning models, especially those with many parameters, require substantial amounts of annotated training data to achieve optimal performance. Collecting and annotating large-scale sign language datasets can be time-consuming, resource-intensive, and challenging due to the linguistic and cultural variations in sign languages.
- Generalization to New Signs or Variations: Deep learning models may struggle to generalize to unseen signs or variations that were not present in the training data. This limitation can affect the accuracy and robustness of the system when faced with novel or rare sign language gestures.

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5. Data-driven Approaches:
-Data Bias and Representation: The availability of diverse and representative sign language data can be a challenge, leading to biases in the training data. Insufficient representation of different sign language variations, regional dialects, or signer demographics can impact the system's performance and inclusiveness.
- Ethical Considerations: Collecting and utilizing sign language data require careful consideration of ethical aspects, such as informed consent, privacy, and ensuring the protection of personal information and cultural sensitivities.

Addressing these drawbacks requires ongoing research and development, including improvements in data collection methodologies, algorithmic robustness, user-centric design, and ethical considerations. Overcoming these challenges will contribute to more accurate, reliable, and accessible sign language recognition and translation systems.

VI. CONCLUSION

In conclusion, sign languages are unique and complex linguistic systems that rely on visual-gestural communication. Despite their importance as natural languages used by diverse communities worldwide, the study and understanding of sign languages have been relatively limited compared to spoken languages. However, in the current technological era, there is a growing need for sign language recognition systems, particularly focused on hand gestures. This paper has provided an in-depth exploration of Indian and American Sign Languages, within the context of mining and Artificial Intelligence (AI).

Through a comprehensive review of existing models and advancements in sign language research, this paper has shed light on the potential of technology to bridge the gap between sign language and the broader communication landscape. It has also addressed challenges related to data collection, cultural sensitivity, technological limitations, and ethical considerations inherent in sign language research.

By identifying various classification approaches and models for sign language recognition, this research contributes to the advancement of inclusive and accessible communication for individuals who rely on sign languages. The integration of technology and AI in sign language recognition systems holds promise for breaking down barriers and promoting effective communication between sign language users and non-sign language users.

As we move forward, it is crucial to continue research efforts in the field of sign language recognition, addressing the identified challenges and exploring novel solutions. By fostering collaboration between researchers, technologists, and the sign language community, we can strive towards more accurate, robust, and user-friendly sign language recognition and translation systems.

Ultimately, the goal is to create a future where sign language users can fully participate and communicate on equal terms, ensuring inclusivity, accessibility, and empowerment for all.

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