

### **1. Deaf talk using 3D animated sign language: A sign language interpreter using Microsoft's Kinect v2**

This system relies on Microsoft's most up to date technology of "Kinect v2" which can track gestures, depth and motion. This project has been under development at Chinese Academy of Sciences for over two years. The system will store speech on user's request and send it to AT&T's Speech Recognition server. The server will then send the text from speech recognition as a string back. The system will then tokenize this string into words and search for their corresponding animations into the dictionary saved in database. These animations will then be played sequentially. This system is trustworthy enough given the accuracy rates 84% for sign language to speech and 87% for speech to sign language conversion.

### **2. Posterior-Based Analysis of Spatio-Temporal Features for Sign Language Assessment**

This paper suggests a technique by which the sign language is transmitted via manual(handshape, hand movement) and non-manual (facial expression, body posture, mouthing) channels. This technique is a combination of deep learning (3D model) and statistical techniques (KL-HMM framework). The suggested system The aim of this paper is to overcome these shortcomings by suggesting an approach that integrates the strengths of both deep learning techniques and statistical techniques to allow fine-grained evaluation of sign language videos.

### **3. An Approach for Minimizing the Time Taken by Video Processing for Translating Sign Language to Simple Sentence in English**

The paper explains a method to reduce the time taken for video processing module. There are three modules in the system architecture - Video Processing • Natural Language Processing • Text to Speech Conversion. It converts American Sign Language videos into a plain English sentence and then speech and then matches signs through the use of a video processing module, retrieves a corresponding Sign Writing Image File, and compares to a dictionary. The details of the matched sign are retrieved from an Excel document to populate an SSU frame, which will create a constructed English sentence. The system also converts sentence to speech.

### **4. Talking hands — An Indian sign language to speech translating gloves**

This paper suggests gesture recognition system which translates Indian Sign Language into speech using variety of sensors such as flex sensor, gyroscope and accelerometer in an effort to successfully identify the hand gesture's position and orientation. This system also targets to incorporate the output of the sensor into a smart phone that translate the sensor reading into a corresponding sign that is contained in a database. The output is in the form of speech that is easily understandable to others. This system is self-sustaining, user friendly and an entirely mobile system.

### **5. Sign language learning based on Android for deaf and speech impaired people**

The current paper proposes a mobile sign language translation system for people with speech and hearing impairments using the Sistem Isyarat Bahasa Indonesia (SIBI) on Android phones. The system employs Viola-Jones object detection for the recognition of hands and K-

Nearest Neighbors (KNN) for gesture classification. The application has components such as a gesture dictionary, translator, and sign language tutorials. Experimental findings reveal that the system is best when hand gestures are upright and in the range of 30 cm to 70 cm for optimal identification. The work contributes to enhanced communication between deaf and normal people through the availability of an affordable, mobile-based solution for real-time sign language interpretation.

## **6. Technical Approaches to Chinese Sign Language Processing: A Review**

This paper discusses different technical methods for Chinese Sign Language (CSL) processing, with an emphasis on recognition and translation methods. CSL processing assists in closing the communication barrier between the deaf and hearing communities by translating sign language movements to text or speech. The paper classifies CSL recognition systems under vision-based and sensor-based methods. Vision-based methods involve the use of cameras to record hand movement, while sensor-based methods employ wearable technology with motion and location sensors. The research identifies the difficulties of CSL recognition, such as signer dependency, continuous sign sentence recognition, and insufficient large-scale annotated datasets. It also discusses deep learning methods such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, which have enhanced recognition performance. However, incorporating non-manual features like facial expressions and body postures is still an open research field. In addition to this, the paper also explores current CSL datasets and calls for extensive, publicly accessible corpora for future research. It states that Neural Machine Translation (NMT) methods, traditionally applied to spoken languages, may be used in CSL for improved sign-to-text translation. This review is worth reading for researchers exploring how to enhance CSL recognition and improve accessibility for the deaf community.

## **7. Low-Frequency Entrainment to Visual Motion Underlies Sign Language Comprehension**

This paper explores how fluent sign language users process visual motion to understand sign language. Using EEG (electroencephalography), researchers measured brain activity while participants watched sign language videos and their time-reversed versions (which were not linguistically meaningful). The study found that signers rely primarily on low-frequency visual information (0.2–4 Hz) for comprehension. Machine learning models achieved 100% accuracy in distinguishing between brain responses to real sign language and reversed videos, confirming that signers use predictive processing strategies. This research provides insights into the neural mechanisms of sign language comprehension and suggests similarities between how the brain processes spoken and signed languages.

## **8. Enabling Two-Way Communication of Deaf Using Saudi Sign Language**

This paper presents a system for enabling two-way communication between deaf individuals and the hearing community using Saudi Sign Language (SSL). It introduces the Saudi Deaf Companion System (SDCS), which includes three main components: a Sign Recognition

Module (SRM) that converts sign language gestures into text, a Speech Recognition and Synthesis Module (SRSM) that converts spoken words into text, and an Avatar Module (AM) that translates the text into sign language using animated avatars.

The study also contributes by developing the King Saud University Saudi Sign Language (KSU-SSL) database, the largest SSL dataset, consisting of 293 signs across 10 domains. The system integrates artificial intelligence (AI), machine learning, and deep learning techniques to improve the accuracy of sign language recognition and translation. By facilitating communication, SDCS helps integrate the deaf community into mainstream society, improving accessibility in areas such as education, healthcare, and government services.

The paper highlights the challenges of communication for deaf individuals, the need for better technological solutions, and the advantages of avatar-based sign language interpretation.

Future work aims to expand the system to include all 3,000 signs in the Saudi Sign Dictionary and integrate it into portable devices and robots for broader accessibility.

## **9. A Comprehensive Review of Recent Advances in Deep Neural Networks for Lipreading With Sign Language Recognition**

The paper titled “A Comprehensive Review of Recent Advances In Deep Neural Networks For Lipreading With Sign Language Recognition”, studies advanced technologies of lipreading and sign language recognition using deep learning techniques. Lips movement is analyzed to interpret the spoken words, which is referred to as lipreading or visual speech recognition.

There are gestures and facial expressions involved within sign language recognition which is essential for a hearing impaired person. The review is concerned with a number of deep learning models from CNNs (Convolutional Neural Networks) to Long Short Term Memory (LSTM) and Transformers that improve the accuracy of lipreading. Additionally, it explains feature extraction, datasets, and other processes done in both domains. Unlike today, where deep learning is used for automatic feature extraction and sequence modeling, traditional lipreading relied on tools like Hidden Markov Models (HMMs) for feature extraction.

## **10. Word-Level Sign Language Recognition With Multi-Stream Neural Networks Focusing on Local Regions and Skeletal Information**

The paper “Word-Level Sign Language Recognition With Multi-Stream Neural Networks Focusing on Local Regions and Skeletal Information”

presents an innovative method on sign language word level recognition (WSLR) Improvement.

The authors argue that with the multitude of similarities in the sign gestures, WSLR requires finer distinctions than action recognition methods. This is why they have proposed a Multi-Stream Neural Network (MSNN) that includes three major parts: a base stream that captures the overall movements of the body, a local image stream intended to capture the handshapes and facial expressions, and a skeleton stream that delivers the relative positions of hands and body of the person. With the integration of these streams, the model increases the recognition rate by 10 to 15 percent compared to traditional systems. The experiments conducted on the WLASL and MS-ASL datasets show that this approach does help in recognizing distinguishing signs that are closely related to each other. Their work brings attention to the diverse viewpoints, background noise, and other difficulties that the systems face and how it can be improved upon with real-time systems and systems for different sign languages. Overall, this

work helps in addressing the communication barrier between the speech disabled persons and the normal hearing populace through enhancement in the automatic sign language recognition systems.

#### **11. MediSign: An Attention-Based CNN-BiLSTM Approach of Classifying Word Level Signs for Patient-Doctor Interaction in Hearing Impaired Community**

The article titled, “MediSign: An Attention-Based CNN-BiLSTM Approach of Classifying Word-Level Signs for Patient-Doctor Interaction in the Hearing Impaired Community” describes a system meant for sign language interpretation which is built using deep learning techniques to assist individuals with hearing disabilities in a medical environment. The research focuses on the difficulties that hearing-impaired patients experience when trying to interact with the doctors during their appointments, especially in developing countries with poor infrastructure with regard to accessibility. This problem is tackled by developing a dataset consisting of 30 medically relevant signs provided by twenty different individuals as the dataset. The MobileNetV2 (lightweight CNN) is used to extract word level signs features and is integrated with a Bidirectional Long Short Term Memory (BiLSTM) enhanced with an attention mechanism to classify the signs in the proposed model. The study achieved great results above the previous methods by 5%, with a validation accuracy of 95.83% and the F1-score of 93%. The study puts more focus on comparison of the model’s performance with available sign language recognition methods, taking into account the differences in background, illumination and skin color and the lack of need for sophisticated segmentation algorithms.

#### **12. Multi-Semantic Discriminative Feature Learning for Sign Gesture Recognition Using Hybrid Deep Neural Architecture**

This article describes a new method for Continuous Sign Language Recognition (CSLR), which integrates video and text by embedding them together in a joint latent space. It is not an easy process to do CSLR because it requires identifying sign language glosses and the related temporal segments from video shots. Old methods used to take advantage of visual features only, often missing the other information sources available such as text-based data and inter-gloss dependencies. The new approach proposed here consists of a multi-parameter cross-model framework for comprehension which combines text and video information from the learners in order to better the performance of the students in CSLR tasks. This approach contains two encoders, one for video and one for text. The video encoder uses CNN and RNN to capture spatial and temporal features. The text encoder utilizes gloss sequences by employing LSTMs to produce embeddings. These embeddings are transformed into the common latent space by means of a special LSTM based architecture, which enables to achieve alignment through a joint loss function. The accurate video representations are then classified through a jointly trained LSTM based decoder.

#### **13. Sign Language Recognition Based on CNN-BiLSTM Using RF Signals**

The authors introduce RF-SL, a system developed to use RFID signal based recognition for the contactless tagging of complex sign language gestures. The system incorporates an RFID reader, along with a multi-tag array designed to capture sign language movements while discarding environmental noise. The authors also introduced Varri+, a gesture signal

segmentation algorithm capable of reliably detecting the start and endpoints of each gesture. Furthermore, feature extraction is done with Convolutional Neural Network and Bi-Directional Long Short Term Memory networks are used for feature fusion, enabling more effective recognition. In controlled settings, the F-R, and E-SL performed realistic scenarios of signing with a new user and got an overall accuracy of 96.8% with 96.3% accuracy for new users RF-SL's strength proved to work effectively very strong in classrooms. As with any image based recognition software, sign language recognition systems built around cameras and computer vision algorithms suffer from low privacy. RF-SL does not indoor localization or require the use of Wi-Fi to work, which makes these devices unduly flexible and RF-SL promising for other countries. The next goal is to improve face recognition and tracking sign by cameras and add non-manual sign language features such as facial expressions.

#### **14. Continuous Sign Language Recognition Through Cross-Modal Alignment of Video and Text Embeddings in a Joint-Latent Space**

. The paper with the title, 'Multi-Semantic Discriminative Feature Learning for Sign Gesture Recognition Using Hybrid Deep Neural Architecture,' aims at providing a solution to a newly developed vision based sign language recognition system. Earlier sign language recognition systems (SLR) used to require extremely costly wearable sensors, or alternatively, they would not use sensors at all and would miss capturing multi spatial and temporal features. This work proposes a hybrid deep neural network (hDNN) framework to address these issues and automate the recognition of Indian and Russian sign language gestures. The framework captures both instrumental (hand actions) and non-instrumental (facial, body postures) features. Spatial features are captured by a 3D deep neural network with atrous convolutions, and temporal and sequential features are captured by attention based Bi-LSTM. Abstract features are captured by autoencoders, while hybrid attention is used to filter out counterproductive transitions and isolate useful sign gestures. The authors first propose the novel Indo-Russian sign language dataset, and what they find is that the model outperforms all other existing SLR methods. The system is superior to other approaches with regard to scaling up and improving recognition accuracy for multiple signers. This indicates the power of the system in aiding multilingual sign language recognition. Future work involves tackling segmentation ambiguities and model extension to permit continuous sign sentence recognition.

#### **15. Converting South African sign language to verbal**

This paper describes the development of a new attention sign language recognition network with keyframe sampling and skeletal features optimization accuracy. The authors explain the new method of key sign language video capture known as OptimKCC, or Optimized Keyframe Centered Clips, which captures key actions of sign language videos while exceeding to excess data filtering. They also introduce a new feature scope skeletal called multi-plane vector relation or MPVR that enhances feature representation by projecting the three dimensional skeletal data onto the three orthogonal planes. In order to enhance recognition accuracy of this model, the authors applied an attention-based bidirectional long short term memory BLSTM network. This method uses spatial and temporal features provided by the skeletal data. The model improves data accentuation vital spatial by providing weights to keyframes. The results from CSL and DEVISIGN datasets experiments show that the proposed method is more accurate at

recognizing signs than previous methods. Attention mechanisms will allow robust performance against signer variability and are beneficial to skeletal features and keyframe attention optimization for sign language recognition. This shows strong potential the proposed network has for practical application, in particular, for sign language encapsulation.

#### **16. A translator for American sign language to text and speech**

This paper presents an ASL translator using Haar-like classifiers and AdaBoost to recognize static hand signs with 98.7% accuracy. Trained on 28,000 positive and 11,100 negative samples, it processes live video to detect hand signs, convert them into text, and synthesize speech using SAPI 5.3. Special modifications were made for dynamic letters and additional SPACE and OK signs. Running at 15–20 FPS on an Intel Core i7, the system enables real-time communication for the hearing-impaired.

#### **17. A Real-Time Intelligent System Based on Machine-Learning Methods for Improving Communication in Sign Language**

This paper proposes a real-time intelligent system for recognizing Pakistan Sign Language (PSL) based on machine-learning approaches. It uses a customized glove with flex sensors and an MPU-6050 sensor to record finger motion and hand orientation. The system was trained with 5000 samples, utilizing decision trees, k-nearest neighbors (KNN), and support vector machines (SVM) with high accuracy (up to 97%). The research emphasizes the system's cost-effectiveness, portability, and compatibility with resource-poor settings, thus presenting it as a realistic tool for enhancing communication among hearing-impaired individuals.

#### **18. Technological Solutions for Sign Language Recognition**

The article titled “Technological Solutions for Sign Language Recognition” is centered on a scoping review regarding the evolution of sign language recognition, its visualization, and its synthesis. Newer technologies like computers, deep learning, and artificial intelligence are significantly improving the interpretation and translation of different sign languages. The work involved analysis from 2010 to 2021 focusing more than 2000 research papers through a systematic review methodology PRISMA. Major finds include the inclusion of Microsoft Kinect and Intel RealSense sensors together with deep learning methods, CNNs, and Transformers which improves the accuracy of recognition systems for sign languages considerably. The paper also discusses dataset problems and the need for real time translation. There is, however, an optimistic expectation of AI systems being able to provide real time translation Live making the deaf and hard of hearing able actively participate in communication.

#### **19. Boundary-Adaptive Encoder With Attention Method for Chinese Sign Language Recognition**

In the paper titled “Boundary-Adaptive Encoder With Attention Method for Chinese Sign Language Recognition”, some innovative solutions regarding problems of the hierarchical structure modeling of Chinese Sign Language Recognition (SLR) were proposed. The authors suggested a Boundary-Adaptive Encoder (BAE) which automatically detects and encodes sign language boundaries using bidirectional LSTMs. This enables both isolated and continuous SLR processing. Additionally, a window attention model was designed for more efficient decoding of

long sequences, while sign subword units were proposed to achieve more advanced granular recognition. From the experiments carried out, it was found that the efficiency of this method as compared to the already existing SLR techniques is much better in terms of the scope of adaption, accuracy, and especially for a large volume and complex sequence of signs.

## **20. Attention-Based Sign Language Recognition Network Utilizing Keyframe Sampling and Skeletal Features**

The multicasting system utilizes sensory gloves for BaSL interpretation in Bangladesh using deep neural networks and AI. The implementation of the project BaSL utilizes images and recordings of sign languages for its training and as a holistic approach uses vision-based and glove-based systems for recognition and translation. The usage of deep learning algorithms enhance the system's ability to interpret gestures significantly. The CNN-LSTM model outperformed the other algorithms that were implemented in the project achieving higher score of 94.73 %. The prototype was user independent and relatively inexpensive with reasonable latency. Through alteration of the sign words and phrases combined with the other vision-based techniques, the system can be improved greatly. This project sets a promising path towards integration of AI-based technologies in speech impaired communication. However, this new developed system has an extensive sign vocabulary recognition range while retaining low cost and high feasibility for the target audience.