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Advancements in Indian Sign Language Recognition Systems: Enhancing Communication and Accessibility for the Deaf and Hearing Impaired

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Abstract - **Sign language is an ocular-mobile language utilized by deaf or hearing-impaired individuals. It conveys a combination of handshapes, motions, facial expressions, and body postures. Sign language is an essential form of communication with its unique grammar and syntax. The communication barrier between those who use sign language and those who do not is substantial. India has approximately 63 million people in the deaf or hearing-impaired community (DHH). Therefore, research within the realm of sign language recognition (SLR) shows great potential in enhancing the quality of life for individuals facing hearing disabilities and promoting better communication and integration into society. In recent years, sign language recognition has attracted considerable attention due to its significant role in human-machine interaction, accessibility, real-time interpretation, educational tools, and communication aids. This study reviews the most current developments in Indian Sign Language Recognition Systems (ISLRS). It discusses the commonly used algorithms, standard datasets, and performance characteristics of these systems in detail. Lastly, it highlights the challenges and future perspectives of these emerging technologies.**
Keywords: **Indian Sign Language, Recognition, Dataset, Techniques**

I. INTRODUCTION

Sign language functions through visual cues and gestures used by the deaf community, relying on manual signs, facial expressions, and body movements. Research into sign language recognition systems has made significant progress in recent years in terms of both performance and accuracy. Global diversity exists, with distinct languages like American Sign Language (ASL), British Sign Language (BSL) and Indian Sign Language (ISL). In this research article, recent advancements in the realm of Indian Sign Language [1] have been noted. The hearing-impaired and speech-impaired individuals utilize Indian Sign Language, a visual language based on movements, to communicate with each other. This method of communication is highly intricate, incorporating body language, facial expressions, and hand gestures to convey messages. Its lexicon and grammatical features are distinct from those of any other spoken language in India [2].

Indian Sign Language was not officially recognised until relatively recently. The Rights of Persons with Disabilities Act, 2016, recognised ISL as the primary means of communication for the Deaf community. To advance and standardize ISL, the Department of Empowerment of Persons with Disabilities, Ministry of Social Justice and Empowerment, founded the Indian Sign Language Research and Training Centre (ISLRTC), an independent organization. The ISL system employs 33 distinct hand gestures, consisting of 10 numerical and 23 alphabetical representations. Specifically, the movements resembling the letters ‘h’ and ‘j’ are used, and the gesture for the letter ‘v’ bears resemblance to a digit. In 2001, Sibaji Panda, a deaf teacher, pioneered the first formal training course in Indian Sign Language (ISL) at the Ali Yavar Jung National Institute of Speech and Hearing Disabilities (AYJNISHD) [2].

A. Present Scenario of ISL

According to the June 2023 census, more than 1.5 million population around the world were impacted by loss in hearing in at least one ear and 63 million people in India have auditory impairment, which is about 6% of the Indian population. The deaf community in India primarily communicates using sign language. According to the National Association of Deaf People, there are approximately 18 million deaf individuals in the country. Research conducted in community settings revealed a prevalence of hearing loss ranging from 6% to 26.9% and a prevalence of severe hearing loss from 4.5% to 18.3%. Hearing impairment was more common among older people and in rural regions. Less than 300 licensed interpreters are available in India, despite the critical need for ISL interpreters in institutions and other settings where deaf and hearing people interact [3].

To enhance communication accessibility for individuals with hearing impairments, the Indian government has expanded the Indian Sign Language (ISL) vocabulary by incorporating 260 new signs related to financial subjects. With 10,000 words at the moment, the ISL dictionary hopes to have 30,000 terms in the future. It is anticipated that deaf people employed in the financial industry would gain from the addition of financial terminology to ISL. In addition, an online self-study ISL course was introduced to narrow the lack of effective communication between individuals who are hearing impaired and the general hearing population. The dictionary includes academic, legal, and medical terms. The first edition contains 3000 words, and the second edition contains 6000 words. The third edition contains 10,000 words, including the 6,000 words from the first and second editions [4].

On October 12, 2020, an app was launched, namely “Sign Learn,” which can convert the NCERT books from classes 1 to 12 into ISL to ensure that children with hearing impairments can easily access the books. The app is available for Android and Ios [4].

Sign language plays a vital role in facilitating communication within DHH communities. Interpreters play an important role in bridging the gap by facilitating interpretation, creating opportunities, and providing legal protections. They act as intermediaries, translating spoken language into sign language so that Deaf individuals can access information and services in various settings [1].

In accordance with the Indian Sign Language Research and Training Centre (ISLRTC), India currently has a total of 325 certified sign language interpreters. 304 Level-C/DISLI-certified interpreters are listed in India’s ISLRTC directory. North, South, East, West, Central, and North-East are the six zones into which the interpreters are separated. Therefore, vision-based SLR is required in order to convert sign language into the native tongue through text or voice. [5].

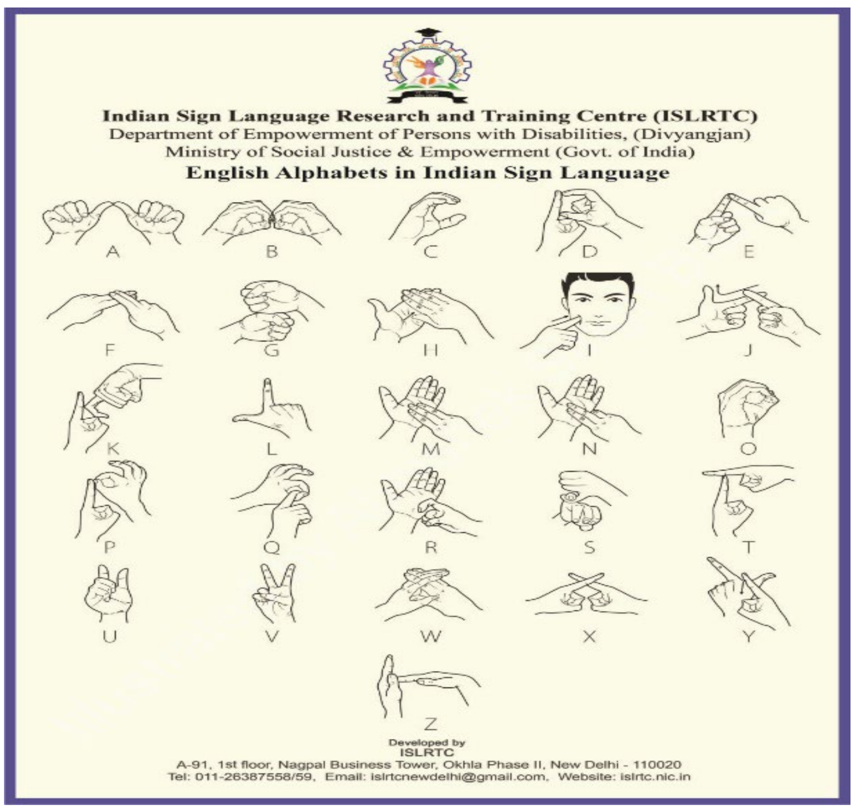

Fig. 1 ISL Alphabets

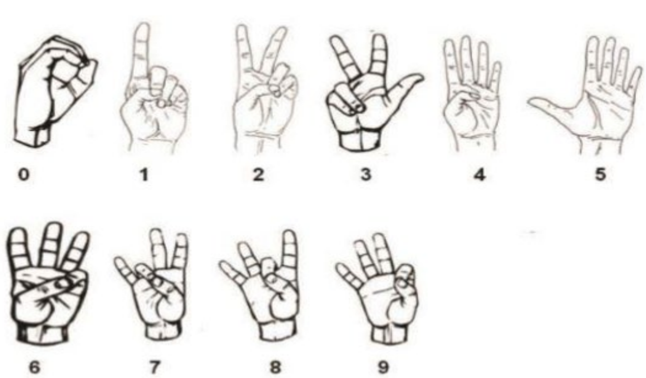

Fig. 2 ISL Digits

In this review manuscript, our focus will be directed towards the latest advancements in the field of sign language recognition, its feature matching techniques, and various types of classification methods. The process of machine learning and image processing technology involves splitting a dataset into a training set comprising 80% of the images and a testing set with the remaining 20% for assessment purposes.

II. LITERATURE REVIEW

The subject of SLR has been discussed extensively and is not brand-new. Different classifiers, such as neural networks, Bayesian networks, and linear classifiers, have been used to tackle this challenge during the past few years. Although linear models are simple to use, they need sophisticated feature extraction to achieve higher accuracy. Kakoty *et al.,* developed a system that translates the Indian and American Sign Language Alphabet and Numbers in real time, achieving an accuracy of 96.7%. Hand Kinematic Assessment was used to gather data on Finger and Wrist Joint Angles, utilizing a specially designed Data Glove. To facilitate recognition, a radial-based function Kernel Support Vector Machine (SVM) was employed with 10-X cross-validation [6].

Keskin *et al.,* used object identification using components to identify ASL numerals. Their dataset included 30,000 samples divided into ten (10) classes. Keskin et al. focused on using object identification based on components to recognize American Sign Language (ASL) numerals [7]. Sahoo used machine learning to learn Indian Sign Language (ISL). They used static hand motions that corresponded to the numbers 0 to 9 to train their model. A collection of 500 images was produced using a digital RGB sensor, one image for every digit. They used supervised learning techniques, such as Naive Bayes, to train their models. The average accuracy was 98.36%, and the slightly higher rate was 97.79% [8].

Jyotishman Bora *et al.,* 2023, designed an advanced machine learning model capable of comprehending Assamese Sign Language. This model was trained by combining two-dimensional and three-dimensional images and the Media Pipe hand tracking solution, which enabled it to accurately identify Assamese gestures with 99% accuracy. The Media Pipe system, which is lightweight and adaptable to a number of devices, offers an elevated level of precision in hand tracking and classification without sacrificing speed or accuracy [9].

Zhou Ren *et al.,* 2011, created a strong model for identifying sign language using a Kinect sensor. They applied a metric known as Finger Earth Mover's Distance (FEMD) to assess the dissimilarity in hand distances [10].

Sundar B. *et al.,* came up with a way to recognize ASL alphabets using Media Pipe. They were able to do it with 99% accuracy using (Long-short time memory network) LSTM, which is a way of recognizing hand gestures. It's really useful for human-computer Interaction (HCI) since it can turn gestures into text [11].

Kai Li *et al.,* 2018, presented an HCI interface which uses recognize depth-sensing camera to recognize sign language. It predicts the hand gesture using the Kalman filter in conjunction with the depth data obtained from the Kinect device, resulting in a smooth and reliable tracking system [12].

TABLE I RELATED RECENT LITERATURE ON SIGN LANGUAGE RECOGNITION TO TEXT CONVERSION

Sl. No.	Authors	Method Used	Sign Types
1	Kinjal, Devendra and Brijesh (2021)	TL	Sentence [13]
2	Akash, Jitendra and Rahul (2023)	LSTM, RNN	Sentence To Text [14]
3	Uma Bharathi, Ragavi and Karthika (2021)	CNN	Sentence To Text [15]
4	Tanya, Vasudha and Bindu (2023)	CNN	Text [16]
5	Aruna, Vinay and Vishesh (2022)	CNN	Text [17]
6	Victoria A. Adewale	KNN	Text And Speech [18]
7	Mahesh, Rajkumar and Lakshmi (2019)	SVM	Speech [19]
8	Sona, Akash and , Divyapriya (2021),	CNN, RNN, SVM	Text [20]

III. SIGN LANGUAGE RECOGNITION APPROACHES

The objective of sign language recognition technology is to interpret and comprehend gestures in sign language performed by individuals, primarily for the purpose of communication. Approximately 138 to 300 different varieties of sign language are in use worldwide at present. Computer vision, pattern recognition, machine learning, sensors, real-time processing, data collection, gesture variability, user interfaces, translation and synthesis, feedback mechanisms, human-robot interaction, and cultural and ethical considerations are all involved in the interdisciplinary realm of recognizing sign language. Researchers work to create reliable and real-time systems for effective communication with deaf or hearing-impaired individuals. They consider factors like regional dialects, individual signing styles, user interfaces, translation and synthesis, feedback mechanisms, human-robot interaction, and inclusivity. There are several approaches to sign language recognition, which can be broadly classified into the following types [1].

A. Vision-Based Approaches

1. *2D Image-Based Recognition:* This approach involves using cameras to recognize 2D images or recording video clips of sign language gestures. These images or video frames are then processed to recognise the signs using computer vision methods that include pattern recognition, feature extraction, and picture segmentation.
2. *3D Image-Based Recognition:* 3D cameras or depth sensors (e.g., Microsoft Kinect) capture depth information to recognise signs in three dimensions. This approach provides more information about the sign's position in space, which can improve accuracy [21].

B. Data-Based Approaches

Some sign language recognition systems use data gloves equipped with sensors to capture finger and hand movements. The data from the gloves was processed and analysed to recognise the sign language gestures.

C. Sensor-Based Approaches

1. *Accelerometers and Gyroscopes:* These sensors can be attached to different parts of the body to capture motion data. Then, machine learning techniques can be applied to recognise sign language gestures based on this data.
2. *Electromyography (EMG):* EMG sensors measure electrical activity in the muscles. They can be placed on the user's arm or hand to detect muscle movements associated with sign language gestures [21].

D. Computer Vision and Machine Learning

Many SLR systems utilise machine learning techniques, including deep learning, to analyse visual data or sensor data. For the processing of sequence and visual data, respectively, recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are widely used.

E. Data and Datasets

Building a robust SLR system often involves training and testing on extensive sign language datasets. These datasets contain examples of sign gestures that serve as training data for machine learning models. Prominent datasets include the American Sign Language (ASL) dataset, the Chinese Sign Language (CSL) dataset, and others specific to different sign languages.

F. Real-Time Recognition

Real-time recognition systems aim to recognise sign language gestures as they are made, allowing for natural and immediate communication between deaf and hearing individuals.

G. Gesture-to-Text or Gesture-to-Speech Translation

Some sign language recognition systems not only recognise signs but also translate them into text or speech, facilitating communication between non-signers and users of sign language. Sign Language Avatar and Animation: These systems can create avatars or animations that replicate the sign language gestures performed by a user, allowing for more dynamic and expressive communication. SiMAX is the first 3D animated sign language avatar system. It allows the deaf to access the digital world and translates texts into multiple sign languages. Pre trained Models with Transfer learning: Transfer learning, using pre trained models from computer vision or natural language processing tasks, has been applied to sign language recognition to leverage existing knowledge and improve recognition accuracy.

TABLE II SENSING APPROACH BASED SLR

Sensing Approach	Technologies	Authors
Sensor	Cyber Glove (x2) and 3D trackers	Kong and Raganath [22]
	Microsoft Kinect	HD Yang [23]
	Flex Sensor	Priyanka Lokhande, Riya Prajapati [24]
	Microsoft Kinect and Leap Motion sensor	Pradeep kr, Partha Pratim Roy [25]
	Firmly Stretchable Strain Sensor (Custom glove)	Li *et al.,* [26]
	Armband Module (8- channel EMG) Sensor	Kim *et al.,* [27]
	Surface EMG and inertial measurement unit	Gupta and Kumar [28]
	EMG sensor	Botros *et al.,* [29]
	Full-fibre auxetic-interlaced yarn sensor	Ronghui Wu [30]
Vision	Video Camera	Infantino *et al.,* [31]
	Kinect TM camera	Ong *et al.,* [32]
	Logitech c920 hd pro webcam	Sabyrov *et al.,* [33]
	Single camera video	Brock *et al.,* [34]
	Laptop camera	Hoang [35]
	Video Camera	Aly and aly [36]
	Microsoft Kinect V2	Sincan and Keles [37]

In real-time applications, the sensor-based technique is not the best option, even if it offers greater accuracy than the vision-based approach.

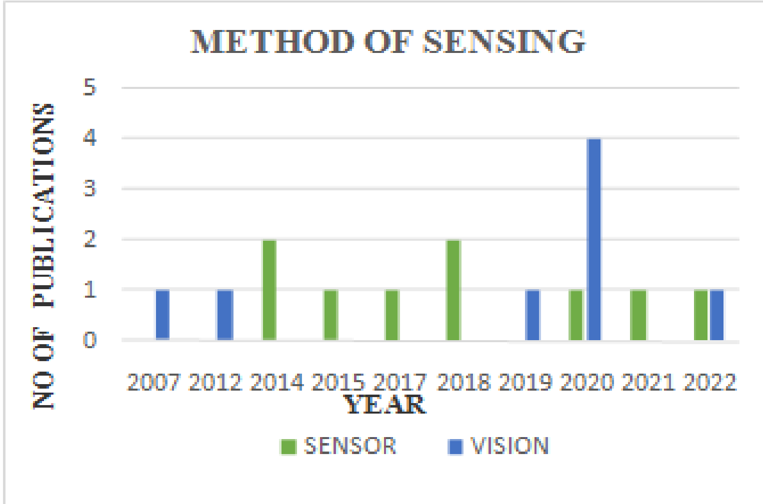

Fig. 3 No. of Publications [2007-2022]

IV. AVAILABLE DATASETS

A collection of video recordings or other data that depicts the motions and signs used in the visual-geometric language known as Indian Sign Language (ISL) is utilized by individuals who are deaf in India, is called an ISL dataset. These datasets are essential for research as well as the creation of tools for sign language interpretation and sign language recognition systems. ISL datasets may also be utilized in education to develop materials for solitary ISL study.

A first collection of Indian Sign Language data is called the "Indian Sign Language (ISL) Lexicon Dataset." The Indian Sign Language Research and Training Centre (ISLRTC), the Ministry of Social Justice Empowerment, and the Indian Institute of Technology (IIT) in Delhi worked together to create this dataset. To aid in the recognition and understanding of Indian Sign Language, the dataset was developed. [21]. Moreover, the first video dataset was published in 2021, i.e., "INSIGNVID: Indian Sign Language Video Dataset," which uses official ISL signs released by ISLRTC [38].

TABLE III AVAILABLE STANDARD ISL DATASETS

Dataset	Year	Sign Language
ISL Translate	2023	ISL [39]
Cislr	2022	ISL [40]
Insignvid	2021	ISL [38]
ISL-Cslrt	2021	ISL [41]
Thisl	2019	ISL [42]
Gesture Recognition System	2014	ISL [43]
Cmeri Lab Dataset	2011	ISL [44]
Iiita-Robita	2010	ISL [45]

V. MACHINE LEARNING ALGORITHMS

The idea of machine learning entails teaching computer programs to perform better on particular tasks. It demonstrates how it may be used in domains including data mining, pattern recognition, computer gaming, robotics, and virtual personal assistants. Three main learning types are involved in machine learning: clustering, regression, and classification. [46]. Some of the widely used machine learning techniques are discussed below.

A. Linear Regression

Linear regression is a supervised learning technique that is suitable for predicting continuous variables like real estate prices, sales forecasts, and exam scores. It is easy to understand and interpret, and it can be controlled for overfitting. Linear regression can also be incrementally learned, making it suitable for online learning. However, it has limitations such as linear assumptions, complex patterns, oversimplification, inappropriate covariates, and outliers' sensitivity. To address these issues, one can utilize sophisticated methods such as neural networks, decision trees, random forests, support vector machines, and polynomial regression. Depending on the type of data and the problem being solved, an algorithm might be chosen[47].

According to recent research, an approach that is frequently used is linear regression which is a statistical and machine learning technique used to illustrate the relationship between a dependent variable and one or more independent variables. Regularisation methods like Lasso and Ridge help prevent overfitting and improve model generalization. Robust linear regression methods like Huber regression and RANSAC reduce the influence of outliers. Bayesian linear regression incorporates Bayesian methods for modelling uncertainty in model parameters. Linear regression models are adapted for online learning scenarios where data arrives in a continuous stream, making them suitable for real-time applications. AutoML tools often include linear regression as an algorithm, making it easier for non-experts to use it effectively. Linear regression is sometimes used in conjunction with deep learning models to improve model performance and interpretability [48].

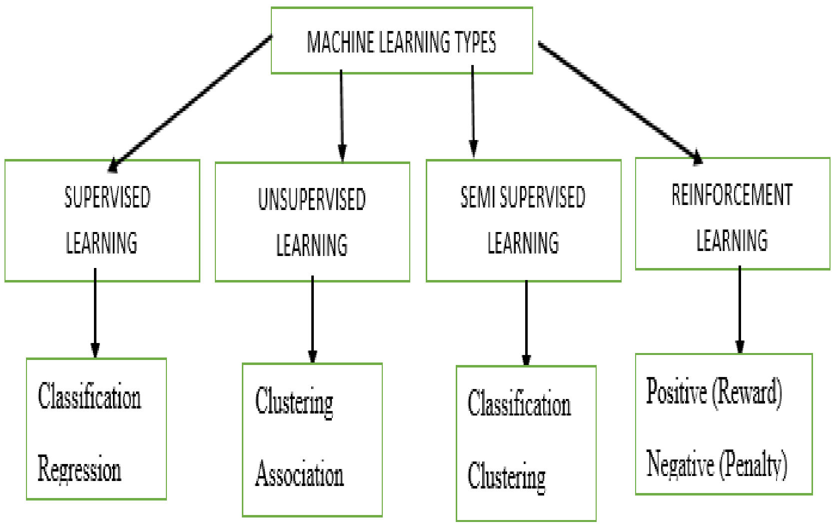

Fig. 4 Various Machine Learning Techniques

B. Logistic Regression

A machine learning technique called logistic regression is used to forecast the likelihood of binary or multi-class outcomes depending on input factors. It can handle a variety of results, including multinomial, ordinal, and spam detection. Its benefits include resistance to minor data noise, managing multi-collinearity, simplicity, computational efficiency, effective training, and ease of regularization. It also doesn't require scaling for input features. [47].

Disadvantages include linearity assumptions, overfitting, and identifying relevant independent variables. Logistic regression is used in various practical scenarios, such as disease risk prediction, cancer diagnosis, and engineering applications. It is widely used for binary and multi-class classification tasks [47].

It has undergone ongoing research and development, including regularisation techniques like Lasso and Ridge regularisation, elastic net regularisation, multinomial logistic regression, class imbalance handling, model interpretability, online learning, etc. These efforts aim to improve the performance, versatility, and interpretability of logistic regression, making it more suitable for a wide range of classification tasks. Researchers continue to explore innovative approaches and applications for this classic algorithm [48].

C. Decision Tree

Supervised machine learning techniques called decision trees are applied to regression and classification issues. They are categorised into classification and regression trees. Advantages include versatility, interpretability, handling mixed data types, handling missing values, and efficiency. However, they can be unstable due to small data changes, difficult to control tree size, prone to sampling error, and provide locally optimal solutions. Overfitting problems can be mitigated using ensemble methods like Random Forest [47].

Decision trees are applied in various fields such as library book prediction, tumour prognosis, fraud detection, credit risk assessment, customer churn prediction, and quality control in manufacturing. Researchers are working on improving ensemble methods, enhancing tree pruning and depth control, handling imbalanced datasets, extending decision trees to multi-label scenarios, handling missing data effectively, and enhancing interpretability and explainability. Additionally, researchers are exploring non-greedy splitting, scalable decision tree algorithms, and improving categorical variable handling, regression tree optimisation, adaptive learning, optimisation algorithms, and incorporating domain knowledge into decision tree construction [49].

D. Support Vector Machine

Encouragement In order to distinguish objects of various classes, Support Vector Machines (SVM) employ a hyperplane as the decision boundary in classification and regression issues. By applying kernel functions, they can manage both linear and non-linear separation. Benefits of SVM include adaptability, scalability for high-dimensional data, generalization, modeling of complicated functions, and convex optimization issues. However, it has disadvantages like training time, kernel selection, sensitivity to noise, a lack of probability estimates, and model interpretability. Many fields, including text categorization, fraud detection, handwriting recognition, face identification, and cancer diagnosis, use support vector machines (SVM) [47].

Researchers are exploring novel kernel functions, scalability, multi-class classification, cost-sensitive learning, online learning, deep learning integration, interpretability, optimisation algorithms, robustness to noise, kernel selection and tuning, explainability and trustworthiness, and hardware acceleration. In 2023, a brand-new technique called “Support Vector Machine Chains (SVMC)” was unveiled.

This technique decrements one feature at a time by combining many SVM classifiers into a structure. Additionally, the method introduces a novel voting procedure called tournament voting, in which classifiers compete in groups and the ultimate prediction is given to the class label that wins. SVMC surpassed SVM (88.11%) in experiments on 14 real-world datasets, while the tournament voting mechanism exceeded state-of-the-art approaches with a 6.88% improvement in average accuracy. [50].

E. Naïve Bayes

The Naïve Byes algorithm is a simple and probabilistic method based on conditional probability, assuming conditional independence between input features. Its advantages include ease of implementation, good performance, and scalability, handling continuous and discrete data, binary and multi-class classification, and providing probabilistic predictions. Disadvantages include simplicity, handling continuous variables, a lack of true online learning variants, limited scalability for high classes, and memory and computation issues. Despite these limitations, Naïve Bayes is valuable in machine learning for situations where its independence assumption is approximately true and simplicity, ease of implementation, and interpretability are essential [47].

Advanced variants like Averaged One-Dependence Estimators (AODE) and Tree Augmented Naïve Bayes have been developed, providing improved performance. Naïve Bayes has been adapted for online learning, feature engineering, text classification, imbalanced data handling, explainability, scalability, and integration with probabilistic graphical models. It has also been integrated into AutoML platforms for improved performance. Additionally, Naïve Bayes is being improved in spam detection, and benchmark datasets are being developed to assess its performance in real-world scenarios. Despite these advancements, Naïve Bayes remains a relevant and useful algorithm in various applications, and research is ongoing to adapt and enhance its capabilities [48].

F. K Nearest Neighbour

Data is categorized using the K-Nearest Neighbors (KNN) algorithm, a non-parametric classification method, according to how close it is to neighboring data points in a database. It is simple, easy to implement, low-cost, flexible, and competitive with complex models. However, it can be expensive for the classification of unknown records, computationally intensive, and can degrade accuracy due to noisy or irrelevant features. KNN is a lazy learner, not generalising on training data, and can suffer from the cause of dimensionality in higher-dimensional spaces. Its applications include recommendation systems, medical diagnosis, credit rating, handwriting detection, financial institution analysis, video recognition, political party vote forecasting, and image recognition [47].

Recent developments include efficiency improvements, distance metrics, parallel and distributed KNN, ensemble learning, class-imbalanced data handling, active learning, deep learning integration, transfer learning, visualization and explainability, benchmark datasets, healthcare applications, edge and IoT devices, and research on healthcare, predictive analytics, and diagnosis. Researchers are exploring novel distance metrics, parallel and distributed versions, and integrating KNN with deep learning models. KNN is also being explored in transfer learning scenarios, where knowledge gained from one domain can be leveraged to improve learning in a related domain. Tools for visualising KNN results and understanding its decisions are being developed [48].

G. K Means Clustering

The K-means clustering algorithm is an unsupervised learning method used for clustering data points based on their similarities. It offers computational efficiency, tight clusters, ease of implementation, and efficiency. However, it has disadvantages such as difficulty in determining the optimal value of K, sensitivity to cluster shape, initialization sensitivity, cluster size and density variation, spherical assumption, and no unique solution for K [47]. K Means is used in various applications such as document classification, customer segmentation, rideshare data analysis, IT alert clustering, call record details analysis, and insurance fraud detection.

It has ongoing developments and trends, including improved initialization methods, scalability, handling high-dimensional data, variants and extensions, hybrid clustering models, GPU acceleration, privacy-preserving K-Means, and its applications in healthcare. Researchers are working on strategies like K-Means++ and K-Means|| to improve convergence, addressing scalability concerns. K-Means is also being explored for its robustness to outliers, dynamic and online versions, interpretable clustering, and automated hyperparameter tuning. K-Means is also being integrated into deep learning models for tasks like unsupervised feature learning and high-dimensional space clustering [48].

H. Random Forest

Several decision trees are used in the Random Forest algorithm, a popular ensemble learning technique, to provide predictions or classifications. Each decision tree is trained using a random subset of training data, selected with replacement. The tree is grown to its fullest extent without pruning, allowing it to become deep. Each tree in the forest provides a classification, and the final prediction is the class with the most votes across all trees. Random Forest is known for its robustness, versatility, and effectiveness in machine learning tasks [48]. The Random Forest algorithm, a well-established ensemble learning method, has seen ongoing developments and trends. These include scalability and parallelization, handling imbalanced data, enhancing feature importance and interpretability, hyper parameter optimisation, imputation of missing data, privacy-preserving variants, and integration into deep learning frameworks, optimisation techniques, and applications in healthcare. Researchers are also exploring GPU acceleration and hybrid models that combine Random Forest with other machine learning algorithms. The algorithm remains popular and versatile in machine learning [48].

VI. DEEP LEARNING ALGORITHMS

A. Multilayer Perceptrons (MLPs)

Multilayer Perceptrons (MLPs) are basic multi-layer deep learning models in which every neuron is linked to every node in the layer below it. The weights for these connections are assigned random values, and activation functions are applied to the weighted inputs at each neuron. The model's output is determined by the combination of weights, inputs, and activation functions. If the predicted output does not match the expected output, the model calculates the loss and uses backpropagation to adjust the weights. MLPs are used in various applications, including image and speech recognition, data compression, classification problems, and social media sites for image data compression. However, they are limited to binary output and may get stuck in local minima during weight updates [51].

Multilayer perceptrons (MLPs) continue to be a fundamental building block in the field of deep learning. While the core principles of MLPs remain consistent, there have been some recent developments and trends in this field. The choice of activation functions in MLPs has evolved. While sigmoid and hyperbolic tangent (tanh) functions were commonly used, rectified linear unit (ReLU) and its variants have become the standard due to their effectiveness in mitigating the vanishing gradient problem. Batch normalisation is a technique that has been applied to improve training and convergence in MLPs [51].

There have been advancements in optimisation algorithms for training MLPs. Gradient descent variants like Adam and RMSprop have become popular for their ability to adapt learning rates during training. MLPs are used in various domains, including computer vision, natural language processing, healthcare, and finance, and are being improved through techniques like model pruning, quantization, and knowledge distillation.

B. Radial Basis Function Networks (RBFNs)

Radial Basis Function Networks (RBFNs) are a deep learning method that uses radial basis functions as activation functions. They are often faster than Multilayer Perceptrons (MLPs) in training and have applications in stock market analysis, speech recognition, image recognition, adaptive equalisation, and medical diagnosis. RBFNs have faster training times and better interpretability but may have slower classification and a higher computational load during classification [51].

Researchers are working on improving training algorithms, hybrid models, and applications in time series analysis, adaptive learning rates, regularisation techniques, kernel methods, real-time processing, interpretability and explainability, hardware acceleration, healthcare, and transfer learning. RBFNs are used in financial forecasting, stock market prediction, and other domains involving sequential data. They also benefit from regularisation techniques to prevent overfitting and improve generalization. RBFNs have also been applied to healthcare tasks, such as medical diagnosis and disease prediction. Staying updated with RBFNs can help practitioners leverage their capabilities effectively in various applications [51].

C. Convolutional Neural Networks (CNN)

Deep learning architectures called convolutional neural networks (CNNs) are employed in image and video processing applications. Convolutional, pooling, and fully linked layers make up their composition. Forecasting, picture identification, video analysis, face detection, and natural language processing are just a few of the many applications for CNNs. They offer high accuracy, hierarchical feature learning, and spatial invariance. However, they require computational power, large, labelled datasets, and complex architectures [52].

Convolutional neural networks (CNNs) have seen numerous advancements and applications since their inception. Recent trends include efficient architectures, self-supervised learning, transfer learning, attention mechanisms, object detection and localization, semantic segmentation, 3D CNNs, generative models, real-time applications, interpretability and explainability, edge and IoT devices, medical imaging, and hardware acceleration. CNNs have been designed for performance on edge devices and mobile platforms, with models like Mobile Net, Efficient Net, and Squeeze Net optimised for edge devices and mobile platforms.

Self-supervised learning techniques have gained popularity in training CNNs, leveraging large amounts of unlabeled data to pretrain models. CNNs have also made significant progress in semantic segmentation, enabling pixel-wise labelling of images [51]. They are now being deployed on edge and IoT devices for image and voice recognition and have shown exceptional performance in medical imaging tasks. The evolution of CNNs is expected to continue, driven by the need for more efficient and accurate visual data analysis solutions.

D. Recurrent Neural Networks (RNNs)

Recurrent neural networks (RNNs) are neural networks designed for tasks involving sequential data and temporal dependencies. They have a basic structure with cycles or loops, allowing them to maintain internal memory. Applications include natural language processing, speech recognition, time series prediction, handwriting recognition, and video analysis. RNNs have pros like sequential modelling, variable-length sequences, and memory. However, they have computational complexity and vanishing and exploding gradient problems [51].

Recurrent Neural Networks (RNNs) have seen significant advancements in recent years, including advanced architectures like Long Short-Term Memory (LSTM) networks and Gated Recurrent Unit (GRU) networks, bidirectional RNNs, attention mechanisms, hybrid models, efficient training techniques, transfer learning, generative models, natural language processing (NLP), time series forecasting, hardware acceleration, interpretability, and edge computing.

RNNs can now better capture long-term dependencies, analyze input sequences both forward and backward, and concentrate on certain segments of the input sequence thanks to these developments. RNNs have also become essential in generative models like recurrent autoencoders, which are used in various applications like text generation and music composition. Despite these advancements, RNNs remain a vital component in deep learning for tasks requiring sequential data modelling, and their adaptability and ongoing research make them valuable tools in various domains [51].

E. Long Short-Term Memory Networks (LSTMs)

One kind of recurrent neural network (RNN) intended to capture long-term dependencies in sequential data is the Long Short-Term Memory (LSTM) network. They overcome the vanishing gradient problem and are suitable for tasks requiring memory of past information. LSTMs work through three main gates: the forget gate, the input gate, and the output gate. They are used in tasks like anomaly detection, time-series forecasting, text and speech analysis, and video analysis [52].

Long Short-Term Memory (LSTM) networks are a key area of deep learning research, with recent developments in attention mechanisms, complex architectures, efficient variants, transfer learning, multimodal models, recurrent vision models, improved regularization, interpretability, reducing training time, edge computing, and biological inspiration.

Attention mechanisms enable LSTMs to focus on specific input sequences, making them useful for tasks like machine translation and text summarization. Complex architectures like stacked and bidirectional LSTMs capture longer-term dependencies, while efficient variants like Gated Recurrent Units (GRU) offer fewer parameters. LSTMs are also used in multimodal models, recurrent vision models, improved regularisation techniques, and edge computing for real-time processing of sequential data.

F. Restricted Boltzmann Machines (RBMs)

Restricted Boltzmann machines (RBMs) are a fundamental building block in deep learning, used in recommendation systems, feature extraction, and unsupervised learning tasks. These models consist of two layers: the visible input layer and the hidden layer. They are trained to learn underlying patterns in data and are suitable for unsupervised learning tasks. RBMs are used in recommendation systems, feature extraction, classification, and topic modeling. However, they face challenges in training and limited scalability [51].

Restricted Boltzmann machines (RBMs) are a classic neural network architecture used for unsupervised learning and feature extraction. They are often used in conjunction with other neural network architectures, such as deep belief networks and auto encoders, for improved performance. RBMs are also used for unsupervised pretraining in deep learning pipelines, helping initialise neural network weights.

RBMs are also used in energy-based models, particularly in collaborative filtering and recommendation systems. Variational autoencoders (VAEs) have gained popularity in unsupervised learning and generative modelling. RBMs face competition from other unsupervised methods like auto encoders and are still used for dimensionality reduction and feature extraction.

G. Generative Adversarial Networks (GANs)

GANs are a rapidly developing field in deep learning, with recent advancements in architecture, conditional GANs, StyleGAN, StyleGAN2, text-to-image synthesis, data augmentation, anomaly detection, medical imaging, bias and fairness, defence against adversarial attacks, privacy-preserving GANs, video generation, and energy-efficient GANs. These models are used in various fields, including computer vision, natural language processing, art, design, and healthcare, and are expected to continue advancing in the future [51].

Generative Adversarial Networks (GANs) are a rapidly evolving field in deep learning, with recent advancements in training techniques, self-attention mechanisms, consistency regularization, few-shot learning, conditional GANs for image translation, text-to-image synthesis, style transfer, data augmentation, privacy-preserving GANs, bias and fairness issues, anomaly detection, energy efficiency, video generation, content creation, and interdisciplinary applications. These models ensure the quality and diversity of created data in a variety of disciplines, such as healthcare, finance, and content development.

VII. TRANSFER LEARNING ALGORITHMS

A machine learning technique called transfer learning involves adapting a model created for one job to a related but distinct activity. It's particularly useful when you have a small dataset for the task at hand, but you can use a huge dataset and a pre-trained model for a similar job. Here are some transfer learning algorithms.

A. Feature Extraction

This involves using deep convolutional neural networks like VGG16 and VGG19 trained on the ImageNet dataset. They are often used to extract image features that can be used in other computer vision tasks. Residual networks (ResNet) can also be used for feature extraction [53]. Transfer learning has seen significant advancements in feature extraction, with pre-trained models, domain-specific pre-training, self-supervised learning, architectural innovations, efficiency and model compression, adversarial attacks, and defenses, few-shot and zero-shot learning, knowledge distillation, multi-modal feature extraction, and cross-lingual and multilingual learning. Researchers are exploring methods that are robust to attacks, enable few-shot and zero-shot learning, and develop lightweight models while maintaining performance. Staying updated on these developments is recommended through research publications, conferences, and deep learning frameworks [54].

B. Fine-Tuning

Fine-tuning is a process where the top layers of a pre-trained model, such as BERT, GPT, and ELMo, are trained for specific tasks after feature extraction. Fine-tuning in transfer learning has evolved significantly, with researchers exploring architectural variations, layer-specific fine-tuning, regularization techniques, loss function design, data augmentation, few-shot and zero-shot learning, multi-modal fine-tuning, adversarial training, quantization and model compression, transfer learning across domains, and online and incremental learning. These advancements aim to improve the performance, efficiency, and robustness of models [54].

C. Domain Adaption

Domain adaptation methods are used to align feature distributions between source and destination domains, such as Domain-Adversarial Neural Networks (DANN) and CycleGAN. Domain adaptation in transfer learning is a growing research area, aiming to improve model performance when applied to a target domain different from the source domain. Techniques include adversarial domain adaptation, self-training and pseudo-labeling, domain confusion loss, multimodal domain adaptation, few-shot domain adaptation, unsupervised domain adaptation, cross-domain sentiment analysis, domain adaptation benchmarks, zero-shot domain adaptation, and transfer learning with pre-trained models. Researchers are exploring how fine-tuning these models can enhance domain adaptation for tasks like text classification and question answering [55].

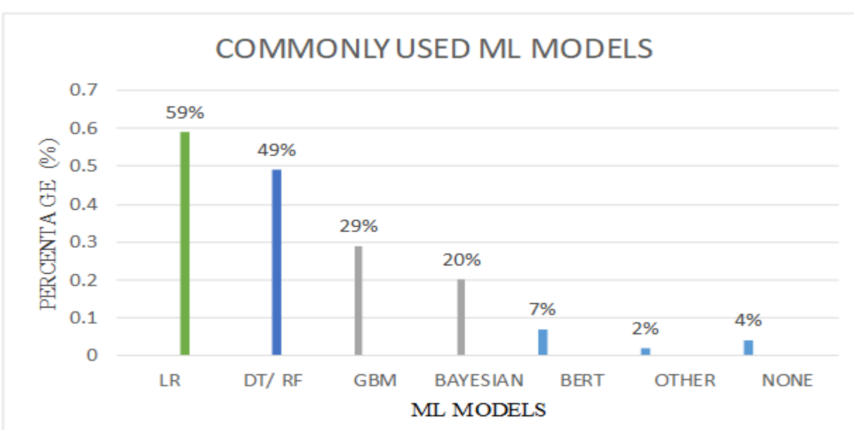

Fig. 5 Commonly used ML Models

D. Multi-Task Learning

Multi-task learning models, like Multi-Task CNN (MTCNN), are pre-trained for multiple tasks, such as face detection and face recognition. A machine learning approach called multi-task learning (MTL) trains models to do several tasks at once in an effort to increase performance and generalization. It has evolved to include multi-modal learning, meta-learning, transfer learning with pre-trained models, shared embeddings and parameters, architecture search and neural architecture optimisation, gradient task complexity, self-supervised learning, meta-transfer learning, multi-task reinforcement learning, domain adaptation, few-shot image classification, meta-learning for hyper parameter tuning, and transfer learning for medical imaging [54].

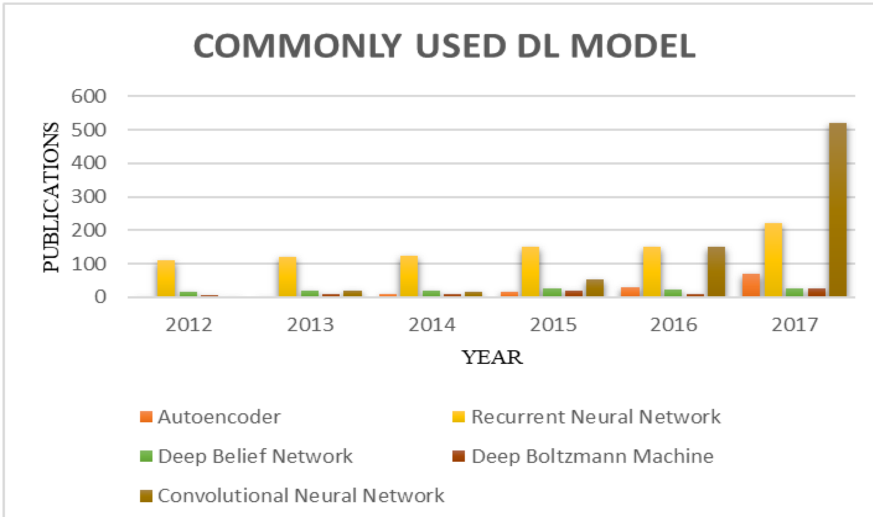

Fig 6: Commonly used DL Models

VIII. CONCLUSION

The paper discusses the recent updates of sign language recognition public datasets, its sensing approaches, and the various commonly used algorithms. It highlights the need for more interpreters to convert sign language motions into text or audio in order to help signers and non-signers communicate. It suggests that advanced technology can enable direct communication between signers and non-signers through various algorithms and methods. The paper also discusses potential future work in SLR, suggesting enhancing feature extraction and classification models to improve recognition results.

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