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Abstract

Oralism is an ideology and practice that advocates communication that is based solely on speech. This practice is encouraged from a pretty early age in our country. As a consequence, the hearing impaired are constantly forced to negotiate with schools, colleges, organisations, workspaces, and families that don't acknowledge the need and preference for sign language over oral languages. This results in inconsideration of an entire community for admissions, jobs and general social position. We aim to close that communication gap a little and take a step towards fighting the stigma associated with Sign Language. The aim is to provide a system for efficient communication with the deaf.

Keywords: sign language, continuous sign language, vision based, computer vision, sign language recognition, scopus.

1. INTRODUCTION

Sign language is a gesture based language that acts as one of the primary means of communication for speech impared and hard hearing individuals. With the same levels of complexity as any spoken language, sign language has thousands of signs formed by different hand gestures and facial expressions. The objective is to translate Indian sign language to text/speech:

- Continuous Sign Language Recognition(CSLR) is a task where a sequence of glosses (gestures) needs to be identified in a continuous stream of video data. Additionally, glosses may only involve very detailed and fine-grained human movements. Above facts highlight the possible challenges in the CSLR field.

- The shortcomings of the publicly available sign language datasets narrow down the range of applications and limit the potential of the systems being trained on them. By training the model on a dictionary containing millions of words, there has been a victory in achieving speech recognition, which is similar to sign identification in many ways.

- Approaches to sign language identification involving a single discipline have limited value in the real world as the algorithms are usually trained on such datasets that don't reflect real world value.

- The system must precisely detect & model the variety which enhances the amount and heterogeneity of training data required.

- Similarly, signals which are non-manual are taken from complementary datasets.

2. RELATED WORKS

Nicholas Adaloglou[1]et. al. have conducted an experimental comparative study for sign language recognition in computer vision based methods. Scene text recognition and speech, two new sequence training criteria, were introduced for this task. Furthermore, a lot of pre training schemes were thoroughly discussed. For the Greek sign language a new RGB+D dataset is created. According to the authors, this is the first sign language dataset where gloss level annotations and sentences are provided for a video capture.
An in-depth analysis of the most characteristic Deep Neural Network based Sign Language Recognition model architectures has been conducted in the paper. After extensive experiments in three publicly available datasets, a comparative evaluation of the most representative sign language recognition architecture is presented. Along with this evaluation, a new publicly available large-scale RGB+D dataset is also introduced for the Greek Sign Language, suitable for SLR. Two Connectionist Temporal Classification(CTC) variations known from other application fields, Entropy Regularization CTC & Stimulated CTC, are evaluated for CSLR and it is noticed that the combination of these two tackle two important issues. Firstly, the ambiguous boundaries of adjacent glosses and secondly, intra-gloss dependencies. Also, a pre-training scheme has been provided, in which transfer learning from a proximal isolated dataset can be a good initialization for Continuous Sign Language Recognition training. The main finding of the work is that while 3D Convolutional Neural Network based architectures are more effective in isolated Sign Language Recognition, 2D Convolutional Neural Network based models with an intermediate per gloss representation achieve superior results in the majority of the Continuous Sign Language Recognition datasets.

Amit Moryossef[2] et. al propose a realtime light weight sign language detection model for video conferencing needs. Based on human pose estimation optical flow features are extracted. They have made use of a linear classifier to display that these attributes are significant with 80% precision, when checked on DGS Corpus. Improvements of up to 91 percent accuracy are observed when a repetitive model is used on the input directly. For video conferencing applications, a demo application is described in the browser for sign language detection. Unlike sign language recognition, the purpose of sign language detection is to detect if and when something is being signed. This paper proposes a *"simple human optical flow representation"*, which is given as an input to a neural network that is temporally sensitive to perform a frame wise binary classification, to determine if the user is making signs or not. This is for videos that are based on pose estimation.

The authors collate different possible inputs, like partial pose estimation, full body posture estimation, and bounding boxes, and collate their acquisition time considering the targeted real-time application. The baseline systems indicate that accuracy between 79.9% to 84.3% can be achieved on the test set when used as a linear classifier with a specified number of context frames. Nevertheless, all of the recurrent models perform better than the baselines, for which the accuracy achieved is between 87.7% to 91.5% on the test set. There are many restrictions to the perspective. The first being that it depends on the posture estimation system to run in real-time on the signer's device. This poses a challenge, as performing state-of-the-art posture estimation on a single frame on a GPU with OpenPose can take upto 300ms. Also, the model might not be able to differentiate between casual gesturing and signing. Another drawback is that high frequency audio can adversely affect pets with sensitive hearing.

Mohit Patil[3] et. al. introduce a system for grid based recognition of gestures and poses of Indian Sign Language. This system provides both: real time detection and precision. Techniques like object stabilization and skin color, Face detection, are used. Segmentation is also used for tracking and hand detection.

The paper describes a system to successfully classify all the 33 hand poses in Indian Sign Language. One hand gestures are only taken into consideration in this research. The system put forward in this paper is able to precisely detect a user's hand movements using methods such as Skin colour Extraction, Object Stabilisation, Hand extraction and Face elimination

The system classifies all 28 (8 digits and 20 letters) hand poses in Indian Sign Language with 96.4% accuracy. The system also classifies 10 gestures with 98.23% average accuracy. The approach used is a Hidden Markov Model chain for every sign and a kNN model which classifies each hand pose. It is concluded from the results that the system is able to detect hand postures and signs in Indian Sign Language with precision and in real-time. The presented method is common and can be further extended to other two-handed and single-handed signs. The procedure shown in this study can be used in other Languages, provided the dataset is fulfilling the current precondition of the system.

Yanqiu Liao[4] et. al. presented *"a multimodal dynamic sign language recognition technique based on adeep 3-dimensional residual ConvNet and bi-directional LSTM networks, which is named as BLSTM-3D residual network (B3D ResNet)"*. The approach consists of three main parts. Firstly, to reduce the space and time complexity of network calculation, the object is restricted to the video frames.The B3D ResNet, to establish an transitional score for each action in the sequence after feature examination, it extracts spatiotemporal features from the videos automatically. Finally, the dynamic sign language is precisely recognised by classifying the video sequences. The study is done on test datasets, including SLR_Dataset and *"DEVISIGN_D"* dataset. The outputs infer that the suggested technique can get precision (86.9% on SLR_Dataset and 89.8% on the DEVISIGN_D dataset). Additionally, the B3D ResNet is efficiently able to identify complex hand signs from big video sequence data, and get high identification precision for over 500 vocabularies from Chinese sign language. Following are the contributions of this research:

- An end-to-end new neural network (trainable) - BLSTM-3D Residual Network. Residual Network is suggested for recognition of dynamic sign language and is able to solve the complicated hand gestures identification with comparatively lesser error rates and differentiating between the identical sign gestures from different users by fine-tuning the BLSTM-3D RestNet model.
- Comparing this approach with the latest techniques, the given B3D ResNet has the ability of learning on a bigger dataset, consisting of over 500 daily vocabularies than Alphabets and simple number dataset.
- This technique can attain good results in dynamic hand gesture recognition, along with a preprocessing network that has been proved in the experiment.

Lean Karlo[5] et. al. developed the system as a source for people new in Sign Language that involves detection of hand signs based on modeling of skin colour. The Convolutional Neural Network (CNN) provides the pictures into the model for image classification. For image training Keras was used. The system acquired 93.67% of average testing precision, of which ASL alphabet recognition was 90.04%, for static word recognition 97.52% and 93.44% for number recognition, when provided with a uniform background and proper lighting condition, surpassing results of other related studies. The method was used for quick computation and is done in real time.

A system is developed in this study that recognizes static sign signals and converts them into correlating words. Using a web camera a vision-based approach is used to obtain the data from the user and can be used offline as well. The purpose of making this system is that it can be used as a learning tool for those who want to know more about the basics of sign language such as numbers, alphabets and some common static signs. The purview of the study includes numbers, basic static signs and American Sign Language alphabets(A–Z). One of the main characteristics of this study is the capability of the system to create words by fingerspelling without the use of any sensors or other external technologies. It is observed that the unique alphabets such as A, C and D got the highest precision with 100% rating, and the lowest is Z with 67.78%. The overall alphabet recognition precision of the system is the average of each alphabet's precision. The system attains 90.04% precision. It also reaches an average time of 4.31 seconds for alphabet recognition of hands that are not in the dataset. The static word recognition reaches 97.52% precision with an average of 2.9 seconds real-time number recognition of hands that are not in the dataset.

Out of the 3 systems tested, the identification for static word gesture has the highest precision and average time of 97.52% and 2.9 sec, respectively. The static words dataset gestures show that the gestures are more distinctive from each other compared to the ASL letters and alphabet gestures. The aim of the project is to come up with a system that translates static sign language into its respective word equivalent including numbers, letters and basic static signs to familiarize the user with the fundamentals of sign language. In spite of having an average precision, the system is still well-matched with the other previously existing systems, as it can perform identification at the given precision with larger vocabularies and without any gadgets such as gloves or hand markings.

The paper titled "Self-Attention-based Fully-Inception Networks for Continuous Sign Language Recognition", **Mingjie Zhou, Michael Ng, Zixin Cai, Ka Chun Cheung[6]**, uses a Self attention based model and compares it with the traditional RNN using a real-life dataset of "*German sign language : RWTH-PHOENIX-Weather 2014"*. In this paper, the authors present a method for continuous sign language identification. This method avails the advantage of *"fully inception, clip-level feature learning with Aggregation Cross Entropy and self-attention networks"* with Connectionist Temporal Classification. The inception modules that are stacked fully have the ability of extracting dynamic local temporal attributes and noisy information is filtered out. The Connectionist Temporal Classification with self-attention networks have the capability to extract global sequential attributes effectively. Also, the Aggregation Cross Entropy with clip-level feature learning improves the recognition performance. Experiments conducted on the biggest real life dataset *"RWTH-PHOENIX-Weather multi-signer 2014"* demonstrates the worthiness of the approach.

Danielle Bragg et. al.[7] discusses the need for deep interdisciplinary knowledge for conducting research on Sign Language recognition. This provides key to the background often ignored by computer scientists, thus urging for a new call of action from the research community.
An interdisciplinary approach is presented by the authors to process the sign language. Inclusion of deaf studies have been done to understand the community that will be benefited by the technology. The paper states that *"linguistics"* is important to identify the structures of sign languages that are supposed to be handled by the algorithms. Machine Translation(MT) and Natural Language Processing(NLP) provide some strong methods for analyzing, translating and modeling.

To detect signed content, Computer Vision is necessary and to generate signed content, graphics are necessary. An interdisciplinary workshop with 39 participants was also conducted by the authors. The workshop brings together concepts from various scenarios to incorporate the state of the art from different fields, to discuss the major problems faced in the processing of sign language and to put together a call to action for the research community. Authors synthesize the findings of the conducted workshop to provide an extensive associative foundation for future research in sign language recognition.
The major contributions in the work are:

- Insights and orientation for analyzers from any field, particularly for people who are stepping in this field.
- Emphasizing the opportunities and needs for associative collaboration.
- Prioritizing the main issues in the field for researchers to handle them accordingly.

For computer technologists and scientists, the paper gives a key background on sign language linguistics and Deaf culture that is often lacking in many works. It also contextualizes important domains they may be working within like Human Computer Interaction, computer vision, computer graphics, MT, NLP. For the viewers not having a background in computer science, it gives a general view of how sign language recognition works and helps in explaining the problems that the current methods have to face. To incorporate the state of the art from an associative view, this paper gives a direction for analyzers in any field, in particular to those stepping in the field. Instead of focusing on important works in a particular domain, it relates these fields to each other and shows that sign language recognition is dependent on all. This paper helps to orient readers irrespective of their fields and highlights collaboration opportunities. It helps the research community too, to regroup their problems.

The paper by **Jie Huang et. al.[8]** focuses on decomposing continuous Sign Language Recognition (SLR) into single isolated worlds and solving these problems using temporal segmentation. The problems encountered are diverse such as incorrect labeling of isolated fragments, incorrect detection of diverse movements. To solve this problem Hierarchical Attention Networks(HAN) are used which are extensions of Long Short Term Memory(LSTM).

The process adopted includes passing the entire video through the HAN’s and acquiring the output word by word. The biggest fear of temporal segmentation is that inaccurate recognition of transitional movements between hand gestures can lead to drastically different output results.

For video description generation a two layer LSTM coupled with a CNN provides promising results.

One of the most integral steps is video feature representation which comprises upper body movements mainly hand gestures. These are read by using Kinect style RGB-D sensors which provide a convenient 3D-model. For gesture recognition a combination of R-CNN is used and a video data is passed through it which is processed frame by frame for various gestures.

In this paper, the authors, **Shobhit Sinha et. al.[9]** are using Convolutional Neural Network to devise a robust model that is able to understand 29 American Sign Language characters consisting of 3 special characters and 26 alphabets. The authors further hosted the model over a instantaneous video interface which gives predictions instantaneously gives the corresponding English alphabets on the screen just like subtitles. This system is looked at as a translator from American Sign Language to English for alphabets. Authors have conceptualized this method in this paper and have explored few uses that can be executed.

In the paper, authors **Archana S. Ghotkar et. al.[10]** have focussed on the problems for vision based sign language recognition systems with an aim, which is to give an overview of Sign Language recognition. To the Indian hearing impaired, it is a great noble contribution.

Following are some of the observations from the paper:

Attribute	Alternatives	Comment

Capturing Devices	3D camera, web camera (2D)	To minimise price, a normal web camera (2D) is used for application of HCI but nowadays 3-D cameras like Microsoft kinect can be found in the market that gives the depth and skeleton information. Using the camera major preprocessing work of the picture decreases.
Use of Gesture Identification	Symbolic language: Sign languages, *“robotic interface and behavior [57], mobile application, virtual reality, home care and security[58], Multidirectional control-3D design, advertising, gaming, computer interface[56]”*	Research is going on, over many applications, that will take place of conventional hardware by hand but anticipated finite signs that are used in multidirectional control but speed & robustness are necessary working attributes. However, in sign language the vocabulary set is predefined and it is so big that it is a difficult work for analyzers.
Softwares for implementation	.NET, PYTHON, C#, VC++, JAVA, MATLAB	OpenCV is suggested for realtime use as of execution speed and free cost.

Table 1: Table of observations from papers

In this paper by **Dongxu Li et. al.[11]**, the authors introduced a new *“large-scale Word-Level American Sign Language video dataset”*, which has over 2000 words, demonstrated by 100 signers. To the community, the dataset was made available publicly. To the author's understanding, it is the biggest American Sign Language dataset to be public so far, to help study word-level sign identification. On the basis of this huge dataset, the authors were able to test with many deep learning techniques of word-level sign identification and assess the performance on huge scale scenarios.

To be specific, the authors implemented and compared two different models as follows
(i) 2D human pose based approach.
(ii) Holistic visual appearance based method
Both the approaches were significant baselines and benefited the group for method benchmarking. The authors have suggested a pose based, novel, temporal graph convolution network (Pose-TGCN) which models the temporal and spatial dependencies in human posture trajectories at the same time, which further improves the working of the posture based method. The performance shows that the appearance based and posture based models achieve comparable results upto 62.63% at top ten precision on over 2,000 glosses or words, emphasizing problems and validity of the dataset. Baseline deep models, along with the large-scale dataset, have been made available freely on github by the authors.

Muthu Mariappan et. al.[12]in this work, identify the Regions of Interest (ROI), for recognising the signs by the signer, and track them using OpenCV’s *“skin segmentation feature”*. The prediction and training of hand poses have been done by applying *“Fuzzy C-Means Clustering Machine Learning algorithm”*. There are many applications of gesture recognition like gesture human-computer interaction, automated homes, controlled robots, sign language interpretation and game control. This system is used to identify the real time signs.

The authors, **Vincent Hernandez et. al.[13]** have proposed to analyze sixty gestures from the American Sign Language, based upon the data given by the *“LeapMotion sensor”* by using distinct conventional deep learning and machine learning models consisting of a model called “*DeepConvLSTM''*.
DeepConvLSTM helps in combining the recurrent and convolutional layers with the Short-Long Term Memory cells. Kinematic model of hand, thumb, fingers, forearms is also put forward. Also the simple data enhancement method is used to augment the neural network generalization.
Convolutional Neural Network &DeepConvLSTM demonstrate the highest precision compared to other models with 89.3 % and 91.1 % respectively, in comparison to the multi-layer

perceptron or recurrent neural network, convolutional layers are integrated with deep learning model to get a suitable solution for sign language identification with depth sensors data.

A vision based system, after trying Convolutional Neural Network for the identification of hand gesture based letters in Arabic and converting these letters into Arabic speech is suggested in the paper by **M. M. Kamruzzaman[14]**. The system proposed automatically detects hand gesture letters and gives the output using a deep learning model in the Arabic language. The proposed system gives 90% precision in identifying the Arabic hand gesture-based characters ensuring that the system is highly dependable. This precision could further be improved by the use of advanced hand gestures identification devices like Xbox Kinect or Leap Motion. After identifying the Arabic hand gesture-based characters, the result is put into a 'text into the speech' engine thus giving Arabic language audio as the output.
Major aim of this study is proposing a system for the users having speech disorders to improve their Arabic sign language communication and thus minimizing connections of signed languages. Moreover, this system can effectively be used in hand sign identification for computer human interaction. This system is in the initial stages but is capable of correct recognition of the hand numbers and transfers it into speech with 90% precision. The authors suggest that to further increase the quality and precision of the system, devices such as Xbox Kinect or Leap Motion can be used and increasing the extent of the dataset can also be considered & published as future work. This system produces the Arabic audio as an output of identified Arabic hand gesture based characters respectively. This proposed tool appears successful by focusing on the very important and neglected social issue and gives an adequate answer for users with hearing impairment.

3. DATA COLLECTION

There are various platforms and websites containing many documents like Google Scholar, Scopus, Web of Science, ScienceDirect and many more. These platforms consist of the statistical information which can be used for the Bibliometric Analysis. These platforms contain the research papers as journals, articles, review papers and conference papers. These research papers are easily accessible because of their open access or using the institutional credentials. Here, in this paper for data collection, Web of Science is considered as it has an immense amount of data for Bibliometric analysis [16].

4. BIBLIOMETRIC ANALYSIS

4.1 Database Search Query

Web of Science	"indian sign language"
Scopus	"indian sign language"

Table 2: Database and Search query

4.2 Analysis by research areas

Figure 1 shows a breakup of different research areas in which articles related to Indian Sign Language were published. Most of them were published in the computer science field.

Figure 1: List of research areas

Source: http://www.http://apps.webofknowledge.com/ (Web of Science, Checked on 15th Feb'21)

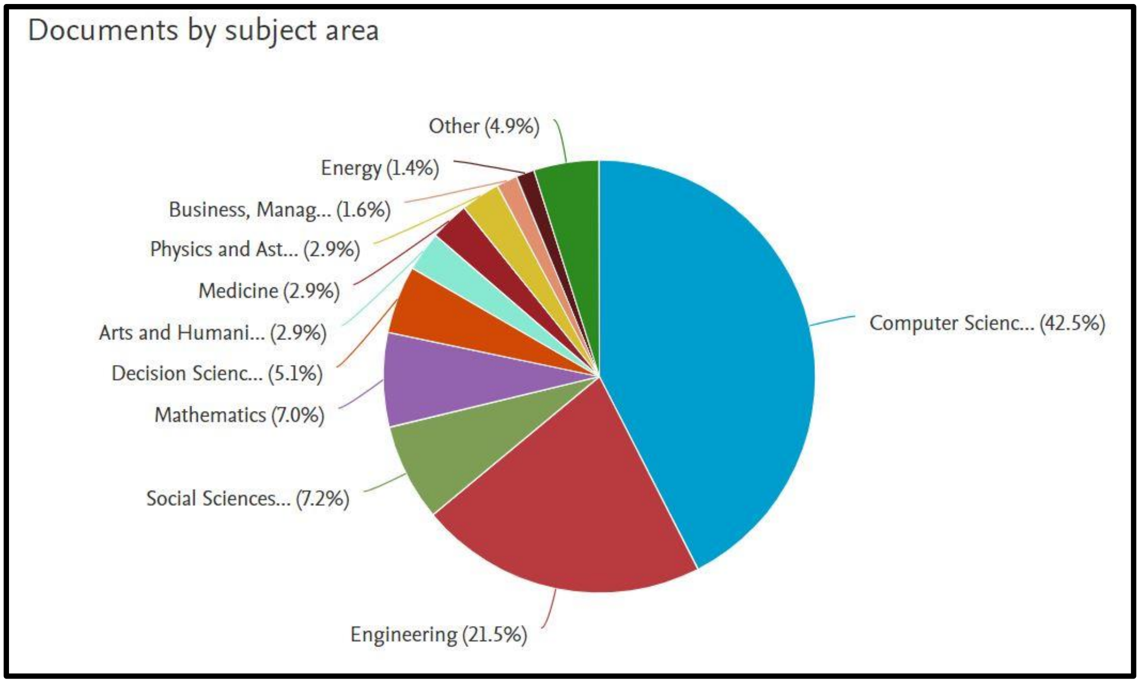

Figure 2: Top ten popular subject areas
Source: http://www.scopus.com (Checked on 15th Feb'21)

Figure 2 shows the work is done in the subject area for Indian Sign Language. From the pie chart, it is clear that the maximum work and research has been implemented in Computer Science, followed by Engineering and Social Sciences

4.3 Analysis by Year

Figure 3 & 4 shows the documents for Indian sign language shows an interval from 1994 to 2020. The bar graph represents the number of documents published in the last years in this specific area. On analyzing, the research work was carried out from 2017 to 2020. However, this finding shows that less work has been done in the span of 1994 to 2015.

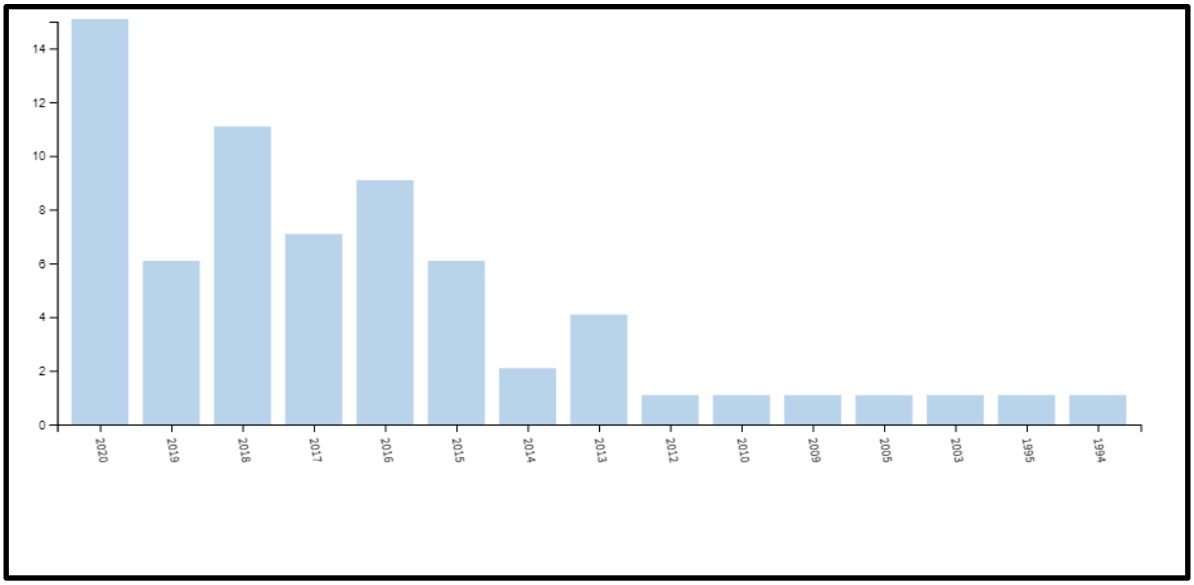

Figure 3: Year-wise publications

Source: http://www.http://apps.webofknowledge.com/ (Web of Science, Checked on 13th Feb'21)

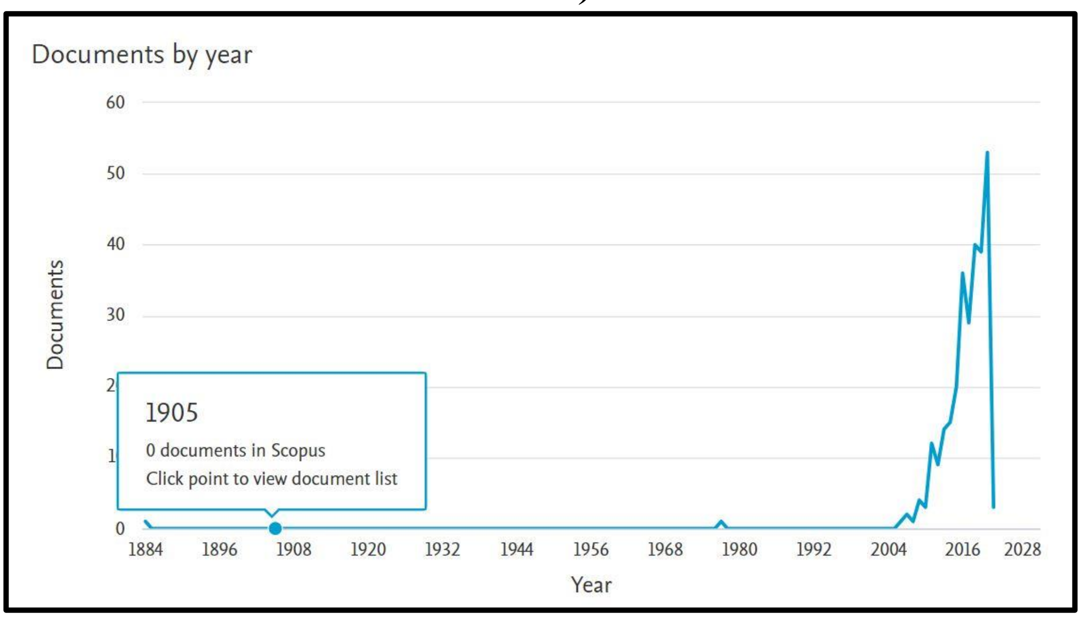

Figure 4: Year-wise publications

Source: http://www.scopus.com (Checked on 15th Feb'21)

4.4 Analysis By document type

Figure 5 & 6 shows the types of documents published on the topic "indian sign language". Most of the documents published were Conference papers which accounted for 55.1% of the total, followed by articles, and so on.

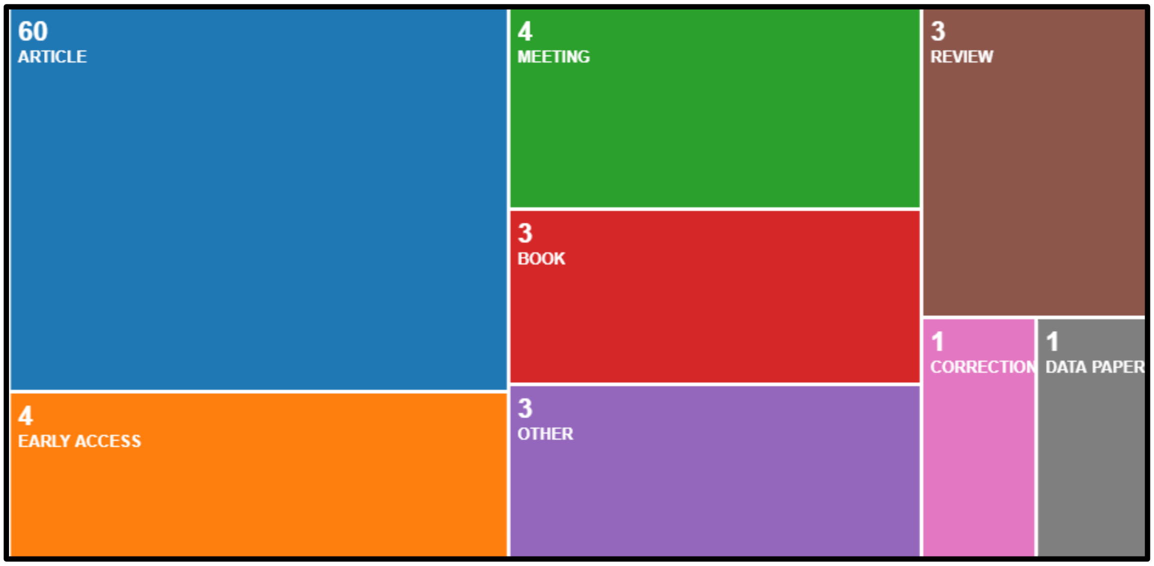

Figure 5: Types of documents published
Source: http://www.http://apps.webofknowledge.com/ (Web of Science, Checked on 13th Feb'21)

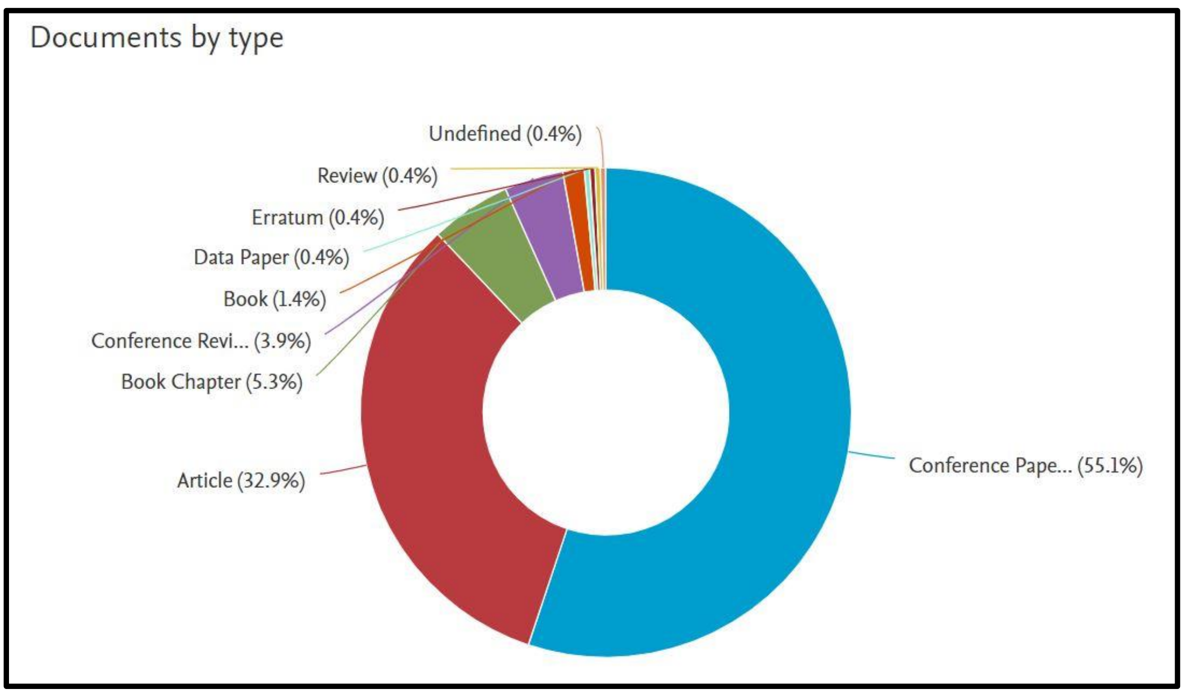

Figure 6: Types of documents published
Source: http://www.scopus.com (Checked on 15th Feb'21)

4.5 Analysis by country

Figure 7 & 8 shows the countries wise distribution of publication of the topic “indian sign language”. Most of the papers on the topic come from India account to almost 250 papers, followed by the United States of America (USA) for about 25 papers.

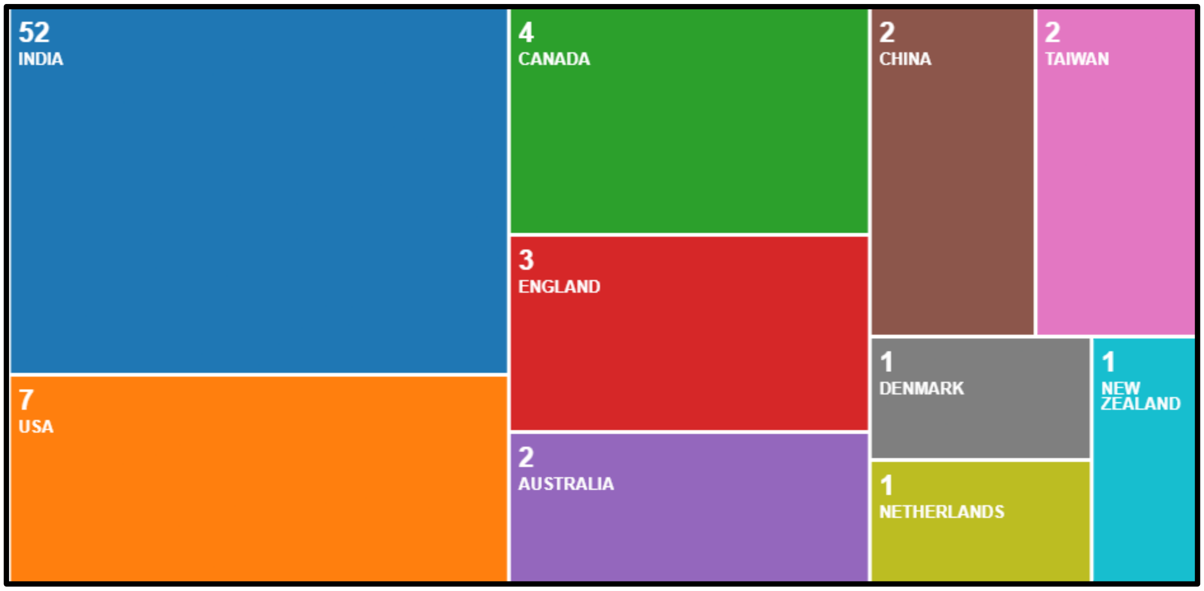

Figure 7: Country-wise publications

Source: http://www.http://apps.webofknowledge.com/ (Web of Science, Checked on 13th Feb’21)

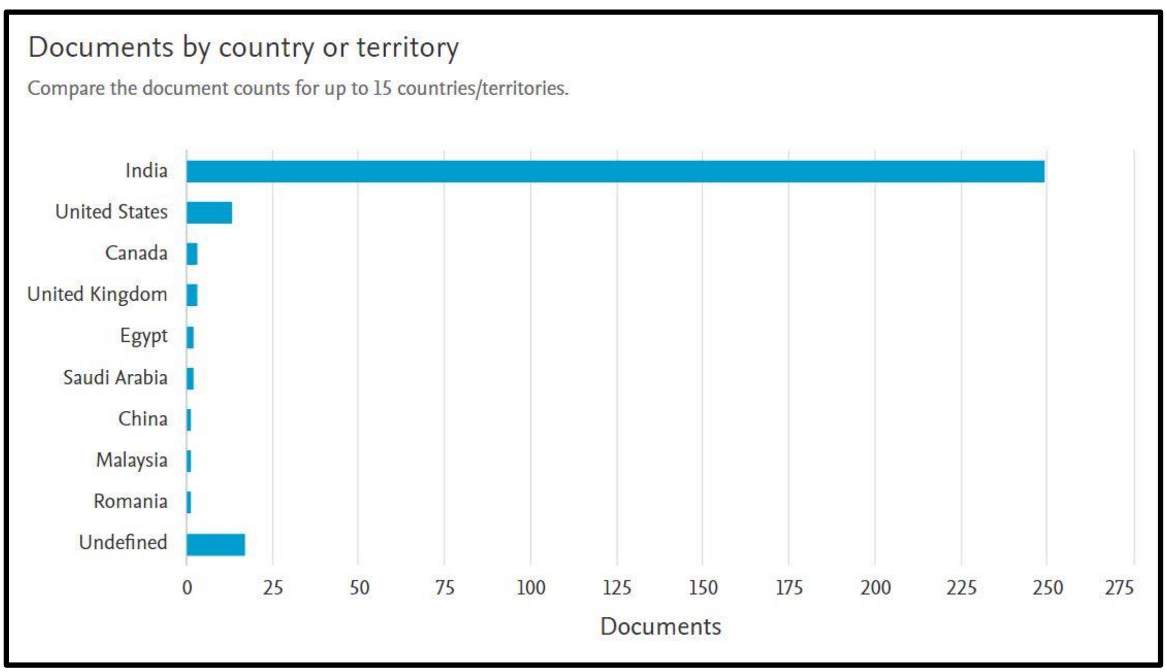

Figure 8: Country-wise publications

Source: http://www.scopus.com (Checked on 15th Feb’21)

4.6 Analysis by source titles

Figure 9 shows the titles under which papers related to the field of indian sign language are published. Most papers are published under the title of sign language studies, followed by rest stated below.

Figure 9: Title-wise publications

Source: http://www.http://apps.webofknowledge.com/ (Web of Science, Checked on 13th Feb'21)

4.7 Analysis by publications per year

Figure 10 shows the number of publications done per year from a time period from 2010-2021. The number of publications remained less from the period of 2010-2016. Majority of publications on the topic were done between 2018-2021.

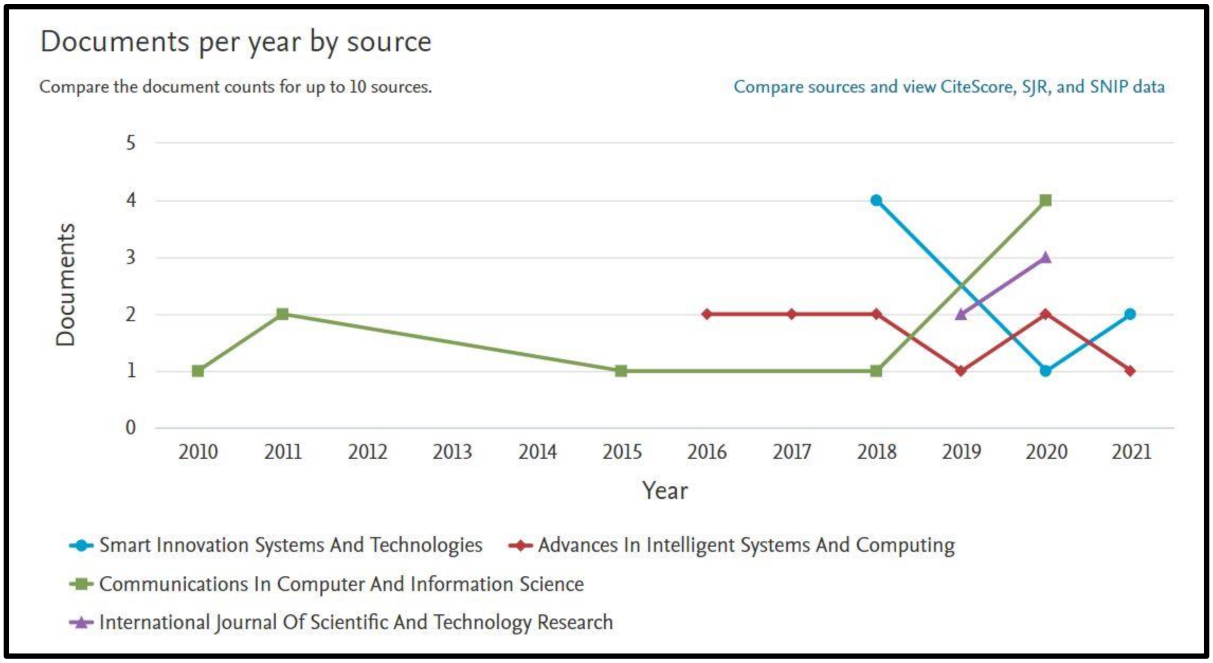

Figure 10: Publications per year

Source: http://www.scopus.com (Checked on 15th Feb'21)

4.8 Analysis by affiliations

Figure 11 & 12 show the institutions and affiliations under which the publications were done.

Figure 11: Institution-wise publications

Source: http://www.http://apps.webofknowledge.com/ (Web of Science, Checked on 13th Feb'21)

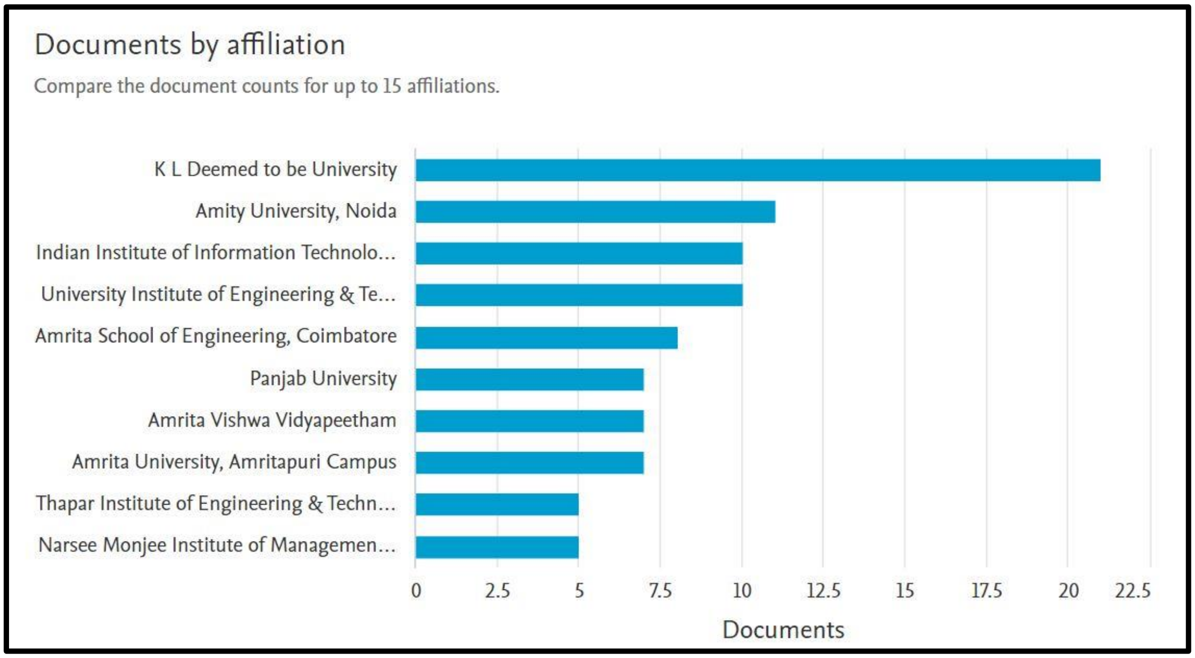

Figure 12: Institution-wise publications

Source: http://www.scopus.com (Checked on 15th Feb'21)

4.9 Network Analysis

Network analysis allows us to recognize the number of entities in the network, the strength of the relationship between them and the most relevant entities of the network, when it is put into the study of the social agents, responsible for scientific publications. The basic assumption in this study is that better answers of social phenomena are given by analysis of the relations among members.

The data was extracted from Scopus using the keywords mentioned in Table 2.

Data has been imported from Scopus. Figure 13,14 and 15 show the analysis based on the terms or keywords. In the figure 13, the relationship between various keywords related to Indian Sign Language is shown. The Minimum occurrence of a keyword is set to 1, out of 373 keywords.In this case, 373 keywords meet the threshold.

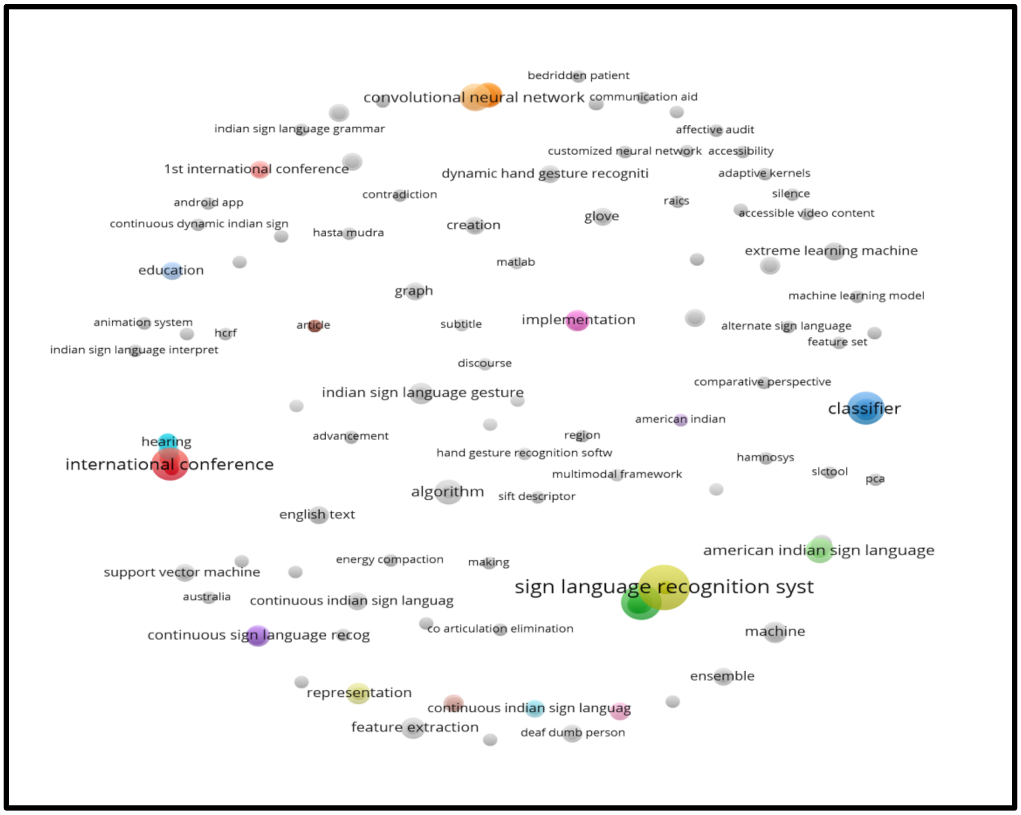

Figure 13: Network Visualization diagram based on the keywords (For 373 keywords)
Source: http://www.scopus.com (Checked on 17th Feb'21)

From these 373 keywords, the largest set or network has 27 keywords which is shown in Figure 14.

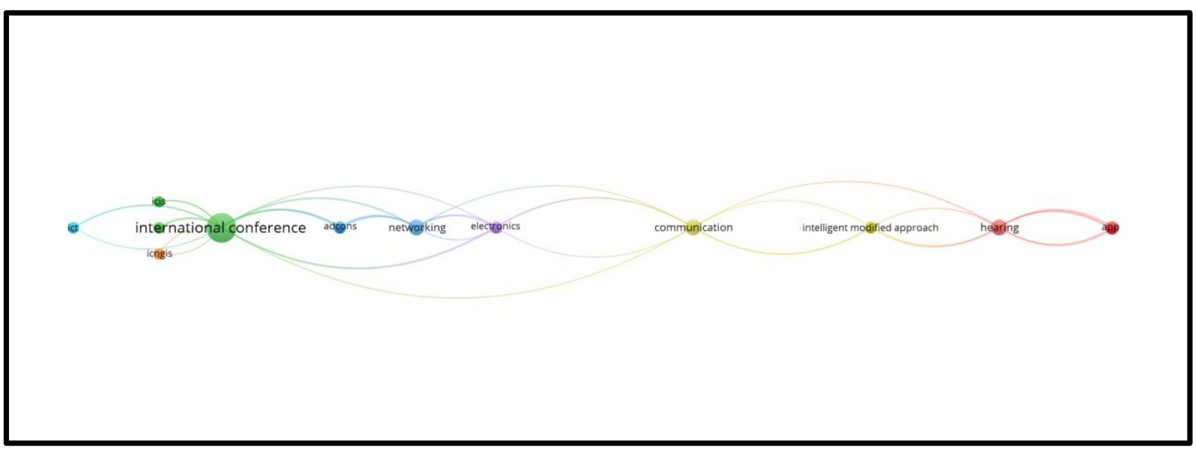

Figure 14: Network Visualization diagram based on the keywords (For 27 keywords)
Source: http://www.scopus.com (Checked on 17th Feb'21)

Figure 15 shows the network for which the minimum occurrence of a keyword is set to 5, out of 373 keywords. We get 13 keywords that meet the threshold as shown below.

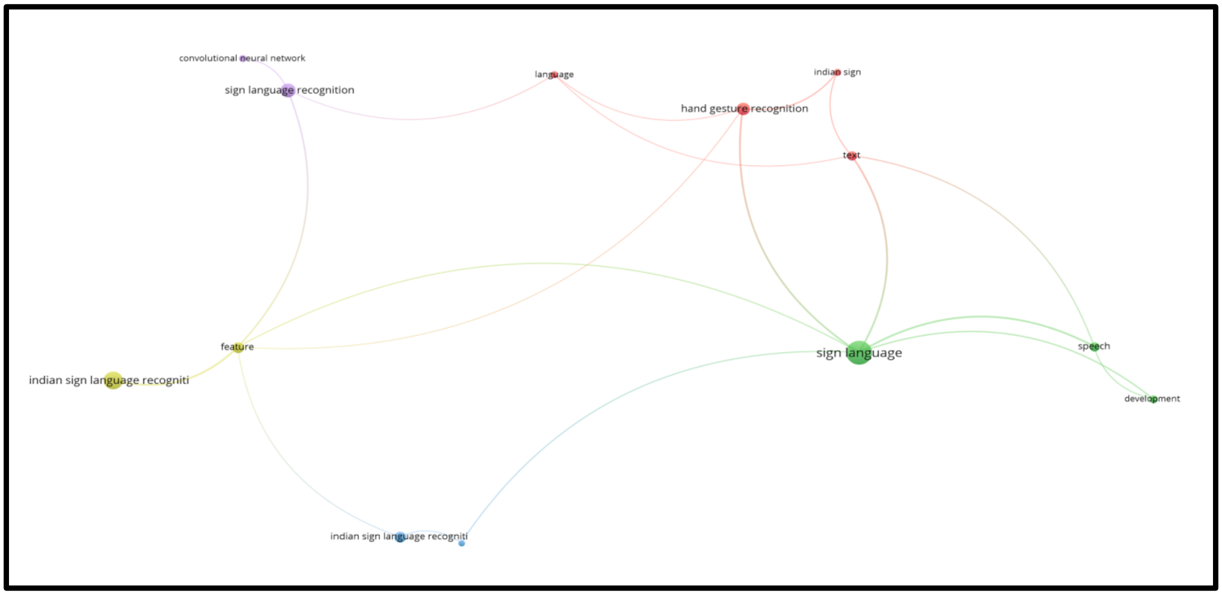

Figure 15: Network Visualization diagram based on the keywords (For 13 keywords)
Source: http://www.scopus.com (Checked on 17th Feb'21)

The analysis shown ahead is based on the authors.Figure 16 shows the network for which the minimum occurrence of the co-authors is set to 1. The authors selected or that meet the threshold are 570 with the largest network having 53 authors as shown in Figure 17.

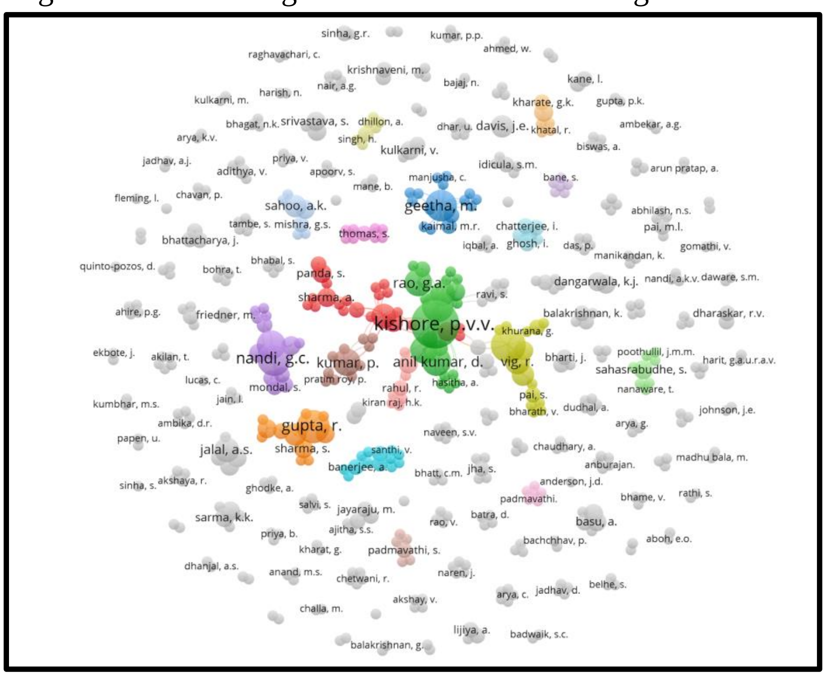

Figure 16: Network Visualization diagram based on the authors (For 570 authors)
Source: http://www.scopus.com (Checked on 17th Feb'21)

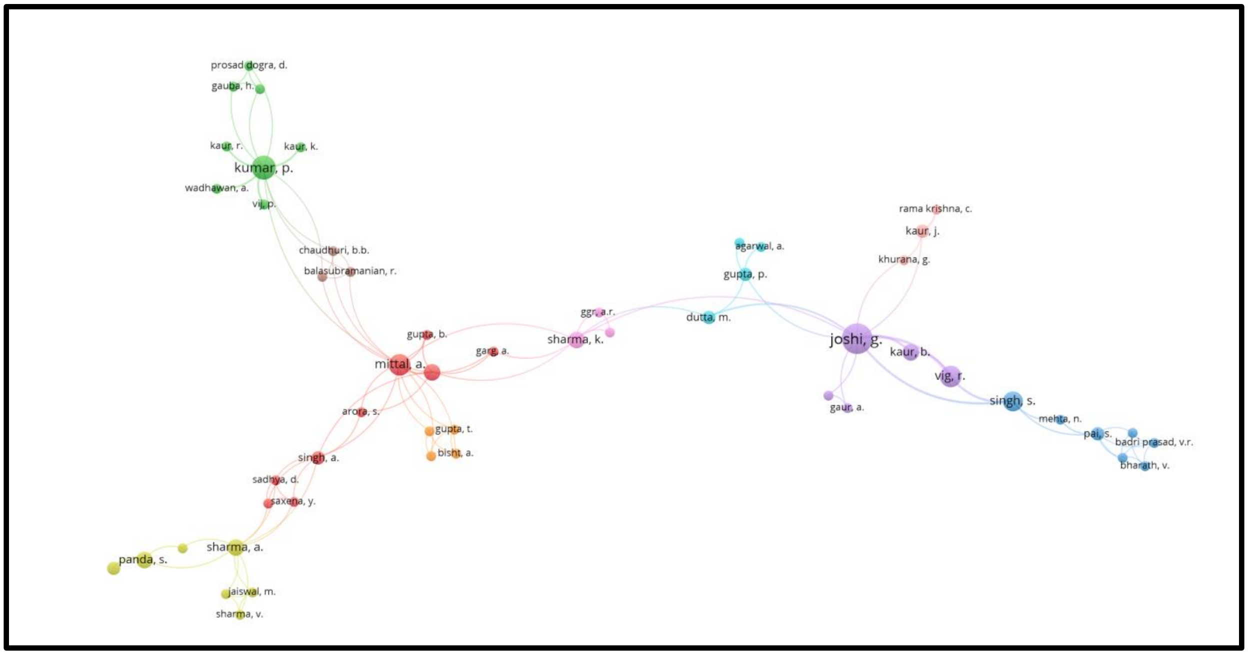

Figure 17: Network Visualization diagram based on the authors (For 53 authors)
Source: http://www.scopus.com (Checked on 17th Feb'21)

For figure 18, the minimum occurrence of a co-author is set to 3. The authors meeting the threshold are 45 with the largest network having 8 authors as shown in Figure 19.

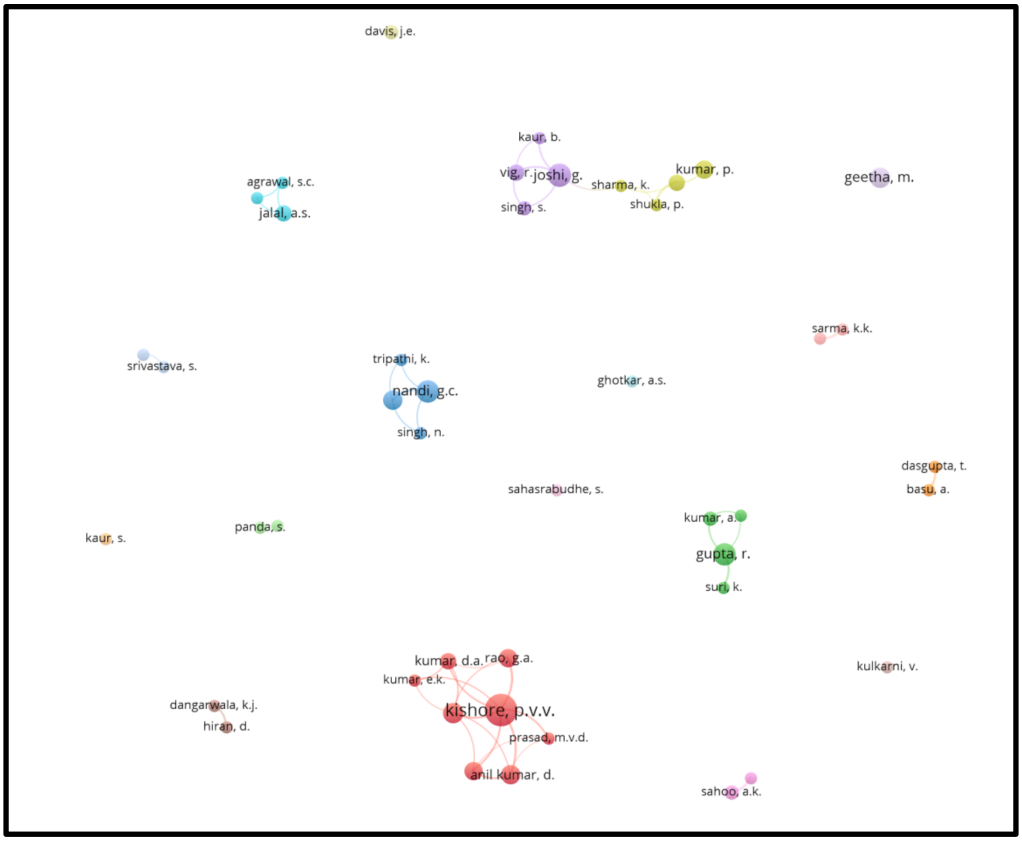

Figure 18: Network Visualization diagram based on the authors (For 45 authors)
Source: http://www.scopus.com (Checked on 17th Feb'21)

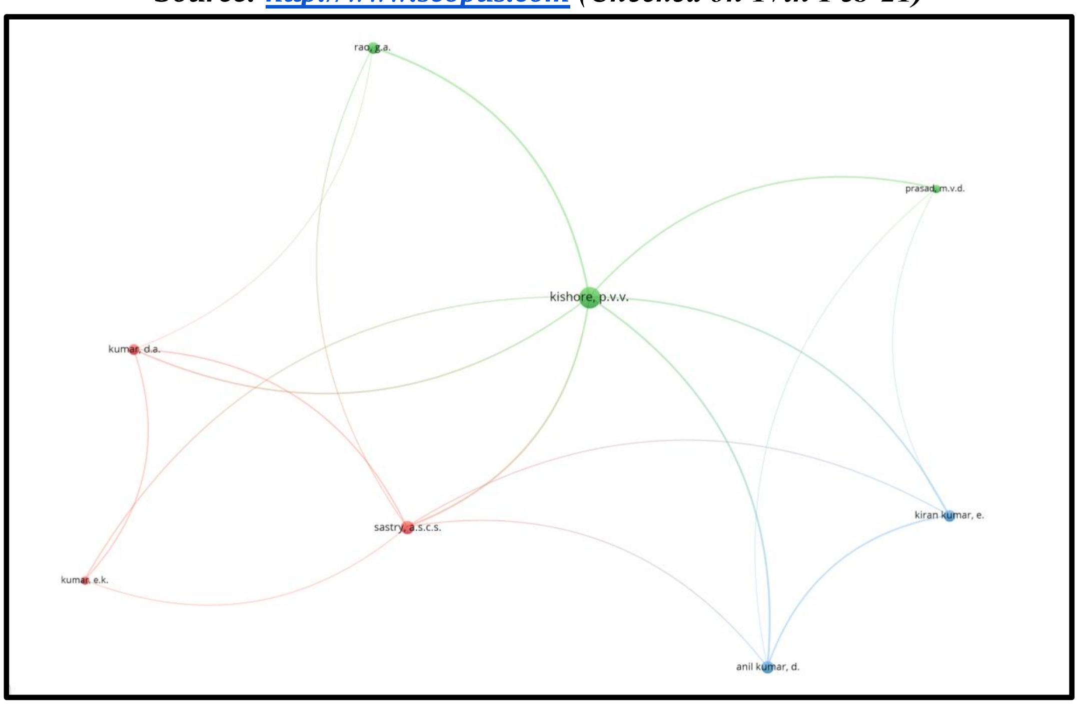

Figure 19: Network Visualization diagram based on the authors (For 8 authors)
Source: http://www.scopus.com (Checked on 17th Feb'21

5. CONCLUSION

The use of Artificial Intelligence has shown a significant rise in benefits to differently abled communities. Sign language recognition helps to bridge the communication gap with the Deaf community. The Deaf community is widespread throughout the world and helping them communicate with the rest of the world is an essential benign gesture towards the whole mankind and we wish to be a part of it. This bibliometric analysis will help the upcoming researchers to conviniently learn more about the topic and the works done in this field.

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