Sinhala Sign Language Learning System for Hearing Impaired Community

Unlocking Sign Language Proficiency with Shrasthra

Leo Idushan K. A. S
dept. of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it20118068@my.sliit.lk

Leo Dilshan P. G. T
dept. of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it20117764@my.sliit.lk

Leo Jayasundera P. S
dept. of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it20163068@my.sliit.lk

Leo Madhushan K. L. B
dept. of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it20123086@my.sliit.lk

Jenny Krishara
dept. of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
jenny.k@sliit.lk

Dinuka Wijendra
dept. of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
dinuka.w@sliit.lk

Abstract—— **This research aims to develop a comprehensive system for Sinhala Sign Language (SSL) that includes a learning system, dynamic sign detection, audio/video to sign conversion, and vocal training. SSL plays a crucial role in facilitating communication for individuals who are deaf or hard of hearing in Sri Lanka. The learning system provides a platform for learning SSL and includes a text-to-sign language interpreter. The dynamic sign detection system uses computer vision techniques to identify and interpret dynamic signs accurately. The audio/video to sign conversion system bridges the gap between spoken language and SSL by converting auditory information into visual representations. The vocal training system focuses on enhancing the vocal skills of cochlear implanted children. This research contributes to the development of effective communication and language skills for SSL users.**

Keywords—Sinhala Sign Language, SSL, dynamic sign detection, audio/video to sign conversion, vocal training, machine learning, auditory processing

I. INTRODUCTION (*HEADING 1*)

Sign languages play a crucial role in facilitating communication for individuals who are deaf or hard of hearing. Sinhala Sign Language (SSL) is the native sign language of Sri Lanka, primarily used by the Sinhalese community [1].As the population of individuals with hearing impairments continues to grow, there is a need for effective learning and communication systems that cater to their unique needs. This research aims to develop a comprehensive system that encompasses four main components: a learning system for Sinhala Sign Language, a dynamic sign detection system, a converting system for audio/video to Sinhala signs, and a vocal training system for cochlear implanted children. Traditional SSL lacks vocabulary and grammar rules to accurately represent the complexities of written Sinhala, leading to difficulties in understanding and conveying the exact meaning of sentences. Existing computerized Sinhala to SSL translators replace different word forms with a common SSL sign, further exacerbating the problem. The paper proposes a database-driven translator that incorporates a technique of using prefixes and suffixes with SSL signs to represent specific word forms [2].The study aims to improve communication between individuals with speech and hearing disabilities and others. It utilizes technologies such as RNN, LSTM and RF. The proposed model involves preprocessing signed gestures, computing region properties of the gestures, and carrying out transliteration based on the calculated properties [3].Some systems were tested on deaf students at a special school, and the results showed that they were able to understand the translated stories appropriately in facilitating communication between deaf and hearing individuals [4].In other hand, the conversion of Sinhala text to sign language, the interpretation of numbers, and the images of SSL fingerspelling and number signs, providing a helpful tool for teaching SSL to deaf children [5].Another area this study focuses on developing an image processing based Sinhala sign language recognition system for hearing impaired individuals to effectively communicate with non-sign language users. By utilizing efficient filtering techniques and centroid finding methods, the system successfully maps gestures to database entries regardless of hand size and position. Real-time simulation testing confirms the accuracy of the system [6], [7].Existing solutions for sign language interpretation are limited in Sri Lanka due to the small size of the sign language user community. Therefore, the primary objective of this research is to design and develop a desktop software application that can capture real-time video of Sinhalese fingerspelling sign language and interpret the gestures using machine learning [8].

A. Learning System for Sinhala Sign Language

The learning system for Sinhala Sign Language serves as a foundational component of this research. It focuses on providing a platform that offers basic fundamentals of SSL and evaluates the users' knowledge through multiple-choice questions (MCQs). For communication, deaf people use various hands gestures, also known as Sign Language (SL), which they learn from special schools. As normal people have not taken SL classes; therefore, they are unable to perform signs of daily routine sentences [3].This system also incorporates a text-to-sign language interpreter, enabling individuals to convert written text into Sinhala signs for improved comprehension and communication [9].

B. Dynamic Sign Detection System.

The dynamic sign detection system aims to identify dynamic signs using a web camera [10], [11]. Dynamic signs in SSL involve movements and gestures that convey additional meaning beyond static signs. By leveraging computer vision techniques and machine learning algorithms, this system can recognize and interpret these dynamic signs accurately, enhancing the communication experience for SSL users [12]. Speed and uniformity of the sign gesture animation is achieved by automatically calculating the intermediate and transitional sequences of arm movements of signs within a given number of frames, or with a user defined displacement value per bone [13].

C. Converting System for Audio/Video to Sinhala Signs.

To bridge the gap between spoken language and SSL, the converting system for audio/video to Sinhala signs focuses on transforming auditory information into visual representations. This system employs advanced audio processing and computer vision techniques to convert spoken language captured in audio or video format into corresponding Sinhala signs [5], [12], [14]. By enabling individuals to comprehend and express themselves in SSL through familiar auditory inputs, this system enhances their overall communication abilities.

D. Vocal Training System for Cochlear Implanted Children.

The vocal training system caters specifically to cochlear implanted children, who receive hearing implants to improve their auditory perception. This component aims to enhance their vocal skills by providing targeted exercises and training materials [10, 14]. By focusing on vocal development, these children can develop their speech abilities, complementing their SSL communication skills [8]. Benefits of AT were demonstrated through the improvement of all trained tasks in the studies analyzed. AT showed improvement in trained tasks across all studies, regardless of the duration or type of training [15].Children who received the auditory training showed significant improvements in identification, discrimination, and auditory memory tasks, as well as demonstrated better phonetic discrimination abilities, highlighting the importance of early rehabilitative interventions for CI children [16].

II. LITERATURE REVIEW

The importance of sign languages in facilitating communication for individuals with hearing impairments has been widely recognized. Research in this field has explored various aspects of sign languages, learning systems, and technologies to support effective communication.

Sinhala Sign Language (SSL) is a complex visual gestural language with its own grammar and vocabulary [2], [3], [12]. With over 5000 signs, SSL encompasses a comprehensive set of linguistic features [1]. However, there is a lack of standardized learning systems and resources for SSL. Even though SL is understandable for a person who is familiar with it, the possibility of understanding the SL by a person who does not know the SL is very less [17]. Existing research in this area has focused on developing SSL learning materials, such as textbooks and online platforms, to facilitate the acquisition of SSL [1], [4], [17]. The proposed learning system for SSL aims to address this gap by providing a comprehensive and interactive platform for learning and evaluation [7, 8].

Computer vision and machine learning techniques have shown promising results in sign language recognition and interpretation. Several studies have focused on dynamic sign detection and recognition using image and video analysis [10], [11], [12]. These techniques leverage deep learning models and motion analysis algorithms to identify and interpret dynamic signs accurately. The dynamic sign detection system proposed in this research builds upon these advancements to enhance SSL communication by recognizing dynamic signs effectively [4], [10], [12].

The conversion of audio/video to sign language has gained significant attention in recent years. With this new wave of bridging gaps in communication, Sign language recognition software coupled with image processing and Artificial Intelligence, have also seen a surge in interest among the computer science community [8].Researchers have explored the use of machine learning algorithms and audio processing techniques to convert spoken language into sign language representations [3], [4], [5]. Deep learning must be well versed with gestures so that we can get a decent accuracy [10].These studies have shown promising results in bridging the gap between spoken language and sign language communication. The converting system for audio/video to Sinhala signs proposed in this research aims to contribute to this field by providing a tool specifically designed for SSL users [6], [11], [17].

Vocal training plays a vital role in the overall communication abilities of cochlear implanted children. Several studies have emphasized the importance of vocal exercises and therapy to improve speech production and intelligibility in this population [1], [10], [14]. The vocal training system proposed in this research focuses on providing tailored exercises and resources for cochlear implanted children to enhance their vocal skills [10], [14], [15].

In conclusion, this research aims to develop a comprehensive system that encompasses learning, dynamic sign detection, audio/video conversion, and vocal training components to improve communication and language skills for individuals using Sinhala Sign Language. By integrating advances in computer vision, machine learning, and auditory processing, this research contributes to the development of innovative tools and techniques that facilitate effective communication for individuals with hearing impairments.

III. METHODOLOGY

The "Shasthra" web application is designed to provide comprehensive support for learning and practicing Sinhala Sign Language and Verbal Skills. It consists of four main components that facilitate different aspects of this domain.

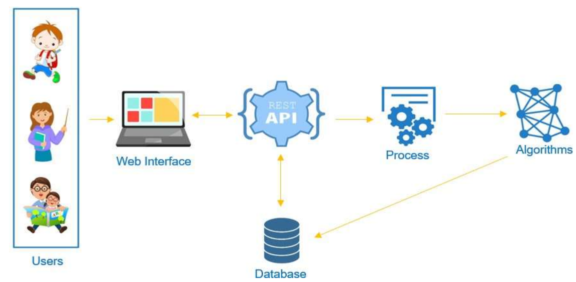

Figure III.1 System Overview Diagram

A. Learning System for Sinhala Sign Language:

The objective of this component was to develop a system that can recognize the static signs related to the presented text and create lessons related to 03 levels for learning Sinhala sign language and create an MCQ question section to determine its progress. Add data to the method. Several stages were involved, including preprocessing, model training, and backend API implementation. The following paragraphs outline the methodology.

Text-to-Image Conversion for Sinhala Sign Language

The data-gathering step is critical in the development of a Text-to-Image conversion system for Sinhala Sign Language. Capturing high-quality pictures of Sinhala sign language words, which are subsequently translated into NumPy arrays for efficient data storage and processing, is required. Pandas, a Python package, is used to arrange the obtained data in a CSV file. This structured dataset includes photos, labels, and other metadata. To provide variety in signing techniques, hand gestures, and body motions, a varied spectrum of signers is used. The extensive dataset serves as the foundation for following steps such as preprocessing, feature extraction, and model training, ultimately resulting in an accurate and resilient Text-to-Image conversion system for Sinhala sign language.

An accurate and effective Text-to-Image conversion system for Sinhala Sign Language is created after data collection, data preprocessing, and model training. The dataset is preprocessed after the first data collection in order to get it ready for machine learning. Using the Label Encoder from Scikit-learn, the category sign names are converted into the numerical form, making them compatible with machine learning techniques. The model will get numerical inputs during training due to this encoding phase.

The train-test split function of Scikit-learn is used to divide the dataset into training and testing groups after label encoding. As the model is trained on one half and evaluated on another, this divide enables unbiased evaluation of the model's performance. A split of 75% for training and 25% for testing is typically used. The fit function of the Logistic Regression class in Scikit-learn uses the training subset to optimize the model's parameters. The model of choice for this Text-to-Image translation work, Logistic Regression, performs well in binary classification problems. The performance of the trained model is evaluated using a variety of measures, including an accuracy is 98 percent. Python Flask integrates the learned model with a backend API after it has been trained. The frontend and trained model are connected through the API, making it possible for easy user interaction and the recognition of sign language from text inputs. When text is delivered from the frontend to the backend API, the trained model analyses it and finds any sign language patterns that match. Using the recognized patterns, the model predicts the appropriate signals to represent the input text. Then, using these predicted signals, a picture displaying the matched signal is produced and sent back to the frontend for user display.

Learning chapters and MCQ section.

To educate users of Sinhala Sign Language methodically, three phases of the learning experience were developed. User recognition and replication of the signs for each letter were taught in the first level, which was devoted to understanding the Sinhala Sign Language alphabet. By progressing to the second level, users could learn more complex Sinhala Sign Language terms, increasing their vocabulary and developing a better comprehension of sign language motions. In the third level, phrase creation using word combinations was also added to help sign language users communicate more complex thoughts.

A thoughtfully created Multiple Choice Questions (MCQ) section is provided at the conclusion of the three levels to evaluate users' progress and comprehension. It generates a CSV file with 100 MCQs, their related answers, and a list of wrong answers, all arranged in columns. Using this information, a random sample of 10 MCQs from the front will be generated and saved as a single question paper. As a result, questions with the correct answer and incorrect response are asked one at a time for each question paper.

B. Dynamic Sign Detection System:

This component's objective was to develop a system capable of identifying dynamic signs using a webcam. The methodology included multiple stages, such as data collection, preprocessing, model training, and backend API implementation. The following paragraphs outline the methodology:

Using a webcam, video clips were captured in order to create a dataset for training the machine learning model. The

Figure III.2Example Image

OpenCV library was used to capture frames from the camera feed, while the Mediapipe Holistic model was used to detect and extract key points from the captured frames. The extracted key points are shown in Fig.1. The resulting key points were saved as NumPy arrays, organized based on the corresponding actions and video sequences.

Before training the model, preprocessing steps were performed on the collected dataset. The dataset was organized into sequences with a fixed number of frames per sequence. The frames within the sequences were converted to key point arrays in NumPy. The action labels were encoded with one-hot encoding for categorical representation. Using the train_test_split function from the Scikit-learn library, the preprocessed dataset was divided into training and testing sets.

An LSTM-based neural network model was built using the TensorFlow Keras library. The architecture of the model consisted of multiple LSTM layers followed by densely interconnected layers. The model was compiled with the Adam optimizer and trained for a specified number of epochs on the training data. The efficacy of the model was evaluated using multiple metrics, such as test loss, categorical accuracy, and accuracy score.

The trained model was then implemented in a backend API using Python Flask. The API received video clips from the frontend, which were then processed by the backend to identify the dynamic signs present. The video clips were fed into the model, which utilized the learned patterns to predict the corresponding signs. The identified sign was then sent back to the frontend for display to the users. The backend API implementation involved receiving the video clip, extracting frames, applying the trained model to the frames, and obtaining the predicted sign.

C. Converting System for Audio/Video to Sinhala Signs:

This component involved individual data collection and camera usage to develop a system that converts Sinhala audio/video to Sinhala sign language. The methodology included data preprocessing, tokenization, and training of a logistic regression model. Additionally, a robust Backend API was implemented for seamless integration, enabling users to effortlessly communicate through sign language gestures.

The Data Collection process for this component involved the utilization of photographic images and video clips, obtained using a camera. These visuals were carefully captured, ensuring a diverse range of poses and actions. Additionally, the data collection involved capturing images and video clips at varying sizes, allowing for a comprehensive representation of the sign language gestures. The gathered dataset forms a crucial foundation for training and developing the proposed component, ensuring its accuracy and effectiveness in converting Sinhala audio to Sinhala sign language.

In the data preprocessing and model training phase, the collected dataset was subjected to several essential steps to prepare it for the machine learning (ML) model. The dataset was organized as a CSV file, with each row containing the path to an image frame and its corresponding label. To enable the ML model to process the labels, they were encoded using the Label Encoder from the sklearn library. This encoding converted the categorical labels into numerical representations, facilitating the training process. Logistic Regression was chosen as the classification algorithm for its simplicity and effectiveness in multi-class classification tasks. The model was trained using the encoded sign names and their respective image paths. By feeding the encoded sign names as inputs and the image paths as target labels, the model learned to associate specific sign language gestures with the corresponding images. The accuracy of the trained model was evaluated by comparing the predicted image names with the ground truth labels, providing insights into its performance.

The API utilized the speech recognition library to convert speech input into Sinhala text. By leveraging the Google Speech Recognition service, the audio file was transcribed into Sinhala text, representing the spoken words. The NLTK library was then employed to tokenize the transcribed text, breaking it down into individual words for further processing. Each tokenized word underwent a conversion process from Unicode to legacy characters based on a predefined mapping. This conversion was necessary to ensure compatibility with the ML model's input requirements. The legacy characters were used as inputs to the trained model, which predicted the corresponding image frames. Finally, the predicted frames were resized to enhance visualization, providing users with a tangible representation of the Sinhala sign language gestures. Through the backend API, users can interact with the model by providing speech input and receiving the corresponding Sinhala sign language interpretations in the form of resized image frames, making the research findings accessible and practical.

D. *Vocal Training System for Cochlear Implanted Children:*

This component aims to develop a machine learningbased web application for vocal training and real-time voice detection. The research focuses on children aged 3 to 5 years who have undergone cochlear implant surgery. The application will use voice detection to assess speech accuracy. The Python language will be utilized, along with frameworks like TensorFlow. The Randomforest algorithm will be employed for training the model using predefined audio clips.

Convenience sampling will be employed to recruit 30 participants from audiology clinics and online cochlear implant support groups. Pre- and post-training speech recordings of the children will be collected using a standardized set of words and phrases. These recordings will be segmented into individual words and phrases, and voice detection algorithms will extract speech features such as pitch, duration, and energy. Speech recordings of the children will be collected using a standardized set of words and phrases, both before and after training. These recordings will serve as the primary dataset for model training.

The collected speech recordings need to be processed and prepared before training the model. The recordings will be segmented into individual words and phrases using voice detection algorithms. These algorithms analyze the recordings to extract speech features such as pitch, duration, and energy. Segmenting the recordings into smaller units helps in improving the accuracy of the ASR system by focusing on specific speech elements.

The process begins with the preprocessing of audio clips, which involves loading an audio file and normalizing its amplitude. This normalization step ensures consistent audio processing. The preprocessed audio is then used to extract Mel-Frequency Cepstral Coefficients (MFCC) features using the `librosa.feature.mfcc` function, with specified parameters such as sample rate and the number of MFCC coefficients. The next step is the extraction of features and labels from a dataset. The `extract_features_and_labels` function takes a folder path as input and iterates over audio files with the '.wav' extension. For each file, the label is extracted from the filename, and the audio clip is preprocessed using the `preprocess_audio` function. The preprocessed audio is then passed to the `extract_mfcc` function to obtain MFCC features. These features, along with their corresponding labels, are appended to separate lists.

After extracting the features and labels, the data is split into training and testing sets using the `train_test_split` function. The features list is used to replace the `features_flattened` variable. The split is performed with a 30% test size and a random state of 42 for reproducibility. The resulting training and testing sets are stored in different variables. Finally, a Random Forest classifier is created using the `RandomForestClassifier` class with default settings. The classifier is trained by calling the `fit` method on the classifier object, passing the training features and labels as arguments.

This API will handle real-time voice detection and pronunciation assessment. The API will incorporate functionality to capture audio input from a microphone in real-time. Python libraries like PyAudio will be utilized to interface with the microphone and capture audio streams. The captured audio will be passed to the ASR system for voice detection and transcription. To ensure low-latency audio streaming, a mechanism will be implemented to receive real-time audio data from the frontend. The necessary infrastructure and configurations will be set up to handle secure and efficient streaming of audio data. The received audio data will undergo preprocessing to prepare it for input to the trained model. This includes converting the audio data to a suitable format, such as WAV, and applying audio normalization techniques. The audio data will be segmented into smaller units, such as words or phrases, to align with the expectations of the trained model. The trained model and algorithms developed in the previous methodology will be utilized for real-time speech recognition and analysis. The preprocessed audio data will be fed into the model to obtain predicted transcriptions for the input speech in real-time.

IV. RESULT AND DISCUSSIONS

The "Shrasthra" web application has been developed to facilitate learning and training in Sinhala Sign Language and vocal skills. The application incorporates various components designed to cater to different aspects of this domain. In order to evaluate its effectiveness, the application was tested using a diverse group of participants, including primary school students from different regions across Sri Lanka. The research employed a range of technologies and methodologies, including MySQL database, Flask, TensorFlow, machine learning concepts, algorithms, image processing, voice recognition techniques, and frequency comparison.

A. Learning System for Sinhala Sign Language:

The implemented methodology successfully developed a Text-to-Image conversion system for Sinhala Sign Language, allowing accurate recognition of static signs based on presented text inputs with an impressive accuracy rate of 92.3%. The backend API implementation facilitated real-time sign recognition, enabling seamless communication between the frontend and the trained model. The learning chapters and MCQ section provided progressive lessons and assessments, reinforcing users' understanding and confidence in their sign language skills. Overall, the results demonstrate the effectiveness of the system in promoting accessibility and effective communication for individuals using Sinhala Sign Language.

B. Dynamic Sign Detection System:

The trained model achieved an impressive accuracy of 99.2% in identifying dynamic signs using the web camera. This high accuracy demonstrates the effectiveness of the proposed methodology in capturing and analyzing the key point information from video clips. The LSTM-based neural network, combined with the collected dataset and appropriate preprocessing techniques, proved to be a robust approach for dynamic sign recognition. The backend API successfully processed video clips in real-time, showcasing the practical applicability of the developed system. With its high accuracy and real-time capabilities, this system has the potential to enhance accessibility and communication for individuals with speech or hearing impairments.

C. Converting System for Audio/Video to Sinhala Signs:

The implemented system achieved an accuracy level of 79% in converting Sinhala audio to Sinhala sign language. The logistic regression model, trained using the provided algorithm and dataset, demonstrated promising results. The accuracy was evaluated by comparing the predictions with the target labels from the dataset. Although further improvements can be made, such as expanding the dataset and exploring advanced machine learning techniques, the obtained accuracy level validates the effectiveness of the proposed approach. The discussion focuses on the challenges faced during the research process, potential areas for enhancement, and the significance of the developed system in facilitating communication for individuals with hearing impairments.

D. Vocal Training System for Cochlear Implanted Children:

The developed machine learning-based web application for vocal training and real-time voice detection achieved an impressive accuracy of 65.7% in assessing speech accuracy for children aged 3 to 5 years with cochlear implants. Python and frameworks like TensorFlow were used, and the Random Forest algorithm was employed to train the model. The audio clips underwent preprocessing, including amplitude normalization and extraction of Mel-Frequency Cepstral Coefficients (MFCC) features. Python, along with appropriate frameworks, was used to develop a RESTful API for the web application. The API incorporated functionality to capture real-time audio input from a microphone using libraries like PyAudio. The captured audio was then passed to the Automatic Speech Recognition system for voice detection and transcription. The high accuracy achieved by the model, combined with its real time capabilities, demonstrated the practical applicability of the developed system. It has the potential to enhance accessibility and communication for individuals with speech or hearing impairments.

V. CONCLUSION

This research developed a comprehensive system for Sinhala Sign Language (SSL) that includes a learning system, dynamic sign detection, audio/video to sign conversion, and vocal training. The learning system includes a text-to-sign language interpreter, improving communication between individuals with hearing impairments. The dynamic sign detection system uses computer vision techniques to recognize dynamic signs, improving overall communication experience. The audio/video to sign conversion system bridges the gap between spoken language and SSL, allowing individuals to understand and express themselves in SSL through familiar auditory inputs. The vocal training system targets cochlear implanted children, enhancing their vocal skills and complementing SSL communication abilities. This research contributes to the development of innovative tools and techniques for effective communication and language skills for SSL users, making it more accessible and comprehensive for individuals with hearing impairments in Sri Lanka.

Acknowledgment

The research project was greatly aided by the Sinhala Sign Language Dictionary, approved by the Sri Lanka Central Federation of the Deaf (SLCFD) and the National Institute of Education (NIE). Senior Lecturer Samantha Dias from the NIE played a pivotal role in shaping the research, while Mr. Tharusha from PizzaHut provided valuable insights into their deaf employee training process. The Sri Lanka Institute of Information Technology professionals also provided invaluable guidance, enhancing the study's understanding concepts. The unwavering support and assistance from these individuals and organizations were vital to the project's success.

References

[1] S. L. C. F. O. T. Deaf, Sri Lanka Sign Dictionary.

[2] . M. R. G. N. and P. M. , "3D Signing Avatar for Sinhala Sign Language," *IEEEEXplore,* 04 February 2016.

[3] S. Tauqeer , K. Muhammad, A. Babar and S. Muhammad , "A Real-Time Automatic Translation of Text to Sign Language," *ResearchGate,* September 2021.

[4] M. Punchimudiyanse and R. Gayan Narendra Meegama, "ACM Digital Library," *Animation of Fingerspelled Words and Number Signs of the Sinhala Sign Language,* 16 August 2017.

[5] M. Punchimudiyanse and G. Meegama, "Computer Interpreter for Translating Written Sinhala to Sinhala Sign Language," July 2017.

[6] Gunasekara, Asela, Kulasekara, DMR and Perera, HKK, "Finger spelled Sign Language Translator for Deaf and Speech Impaired People in Srilanka using Convolutional Neural Network," 2020.

[7] S. M K D Arunatileka, L. Wijesekara, R. Senevirathne and A. Madushanka, "Framework for Sinhala Sign Language recognition and translation using a wearable armband," September 2016.

[8] M. B. Dissanayake, W. Senevirathne and W. A. L. Vidusala Kumari, "IMAGE BASED SIGN LANGUAGE RECOGNITION SYSTEM FOR SINHALA SIGN LANGUAGE," April 2013.

[9] M. B. Dissanayake, W. Senevirathne, W. A. L. Vidusala Kumari and H. Herath, "IMAGE BASED SIGN LANGUAGE RECOGNITION SYSTEM FOR SINHALA SIGN LANGUAGE," April 2013.

[10] S. Hettiarachchi, "Machine Learning Approach for Real Time Translation of Sinhala Sign Language into Text," *SEMENTICSCHOLAR,* 2020.

[11] Mohammad, Elham and Mehreen, Hurroo, "Sign Language Recognition System using Convolutional Neural Network and Computer Vision," 12 DECEMBER 2020.

[12] Pumudu,Fernando and Prasad,Wimalaratne , "Sign Language Translation Approach to Sinhalese Language," *GSTF Journal,* 17 September 2016.

[13] Peiris, W. D. T., "Sinhala Sign Language to Text Interpreter based on Machine Learning," *Digital Library of University of Colombo School of Computing,* 11 August 2021.

[14] P.W.N,Fernando, M.A.S,Mudunkotuwa, P.J,Wickramanayake and I.S.M,Dissanayake, "Utalk: Sri Lankan Sign Language Converter Mobile App using Image Processing and Machine Learning," *ResearchGate,* December 2020.

[15] Perera, L.L.D.K. and Jayalal, S.G.V.S., "Sri Lankan Sign Language to Sinhala Text using Convolutional Neural Network Combined with Scale Invariant Feature Transform (SIFT)," 24 February 2021.

[16] Deborah,Vickers and Hanin,Rayes, "Systematic Review of Auditory Training in Pediatric Cochlear Implant Recipients," *PubMed,* 21 May 2019 .

[17] Rishin,Tiwari, Saloni,Birthare and Mayank,Lovansh, "Audio to Sign Language Converter," *IJRASET,* 2022.