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An Effective E-Learning System For The Deaf & Mute Primary School Students

Kawsikan K.[1*], Jayakody E.D.D.L.[2], Kothalawala K.L.T.D.[3], Wijesekara M.P.[4], Hansi De Silva[5]

[1,2,3,4,5]Dept. of Computer Science and Software Engineering, Sri Lanka Institute of Information Technology, Colombo, Sri Lanka

[*]*Corresponding Author: kawsinote@gmail.com, Tel.: +94 77 174 6609*

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***Abstract*—** Sign language is a communication tool for people with deaf and mute conditions. It is a set of hand gestures used by deaf and mute people to communicate. Deaf and mute people face a lot of difficulties when communicating with ordinary people and struggle to learn new skills from others. Many researchers have carried out various approaches to solve the problems faced by deaf and mute people. Researchers have also focused on problems faced by deaf and mute children while learning. Most of the researchers have focused on teaching sign language. Providing a feedback mechanism is not well explored. Recognizing static and dynamic sign languages and providing feedback is a challenging problem. Sign language is not the same in every country. Therefore, a solution designed for one sign language can't be used to solve problems faced by another sign language. In this research, a web application called Esign Guru is developed to teach Sri Lankan static and dynamic sign language while also proving practice and feedback mechanisms for each sign language. The proposed system uses machine learning techniques to recognize sign language performed by the user. The system has a text-to-sign language summary module, which helps the students to learn the sign language summary for the given text. Esign Guru is a web application, which can be accessed via any browser without any special devices which makes it a cost-effective solution.

***Keywords*—**Static sign, dynamic sign, sign recognition, sign language practice, text-to-sign

I. INTRODUCTION

Speaking and hearing are two of the most important human capabilities which help us to communicate and become more connected to the community. Communication is an important tool for anyone who wants to gather knowledge. But not everyone has the same kind of abilities for communication. There are about 70 million deaf-mutes in the world and 63% of them are said to be born deaf. In Sri Lanka, about 300,000 people are deaf-mute. Moreover, the world health organization has revealed that approximately 9% of the population in Sri Lanka has a loss of hearing. There are so many obstacles faced by people with hearing disabilities. They find it very difficult to communicate with normal people. As a solution, sign language is used by people with hearing disabilities. But most ordinary people cannot understand sign language. Due to this communication obstacle, deaf-mute people struggle to convey their emotions and fail to understand the emotions of ordinary people. They face similar problems when learning as well. This makes deaf-mute people isolated from the rest of society. This not only becomes an obstacle for them in communication but also learning and teaching. Especially primary school children face more difficulty while learning new things. There are so many children suffering from hearing and speaking disabilities, who could do well with proper education. These children are at a disadvantage when compared to ordinary children. Therefore, it is important to assist them in their learning, making their life more meaningful. Many researchers have proposed various approaches to solve these kinds of problems. Mainly they have proposed two kinds of approaches to solving these problems. One is vision-based and the second is sensor-based. Sensor-based solutions have used special devices to capture the motions of differently-abled people and use many techniques to process and convert them to human-readable formats. Vision-based approaches on the other hand have mostly used convolutional neural networks to train images of static sign language and each frame of dynamic sign language. Further, most of the above research has been focused on American sign language and British sign language. Since there is no universal sign language existing solutions cannot be adopted for Sri Lankan sign language. As a solution, this research focuses on Sri Lankan sign language. Also, existing systems for Sri Lankan sign language are focused on a sensor-based approach which is a high-cost solution. Vision-based approaches carried for Sri Lankan sign language focus on static sign language. Recognizing dynamic sign language is not well explored.

To address the above problems, in this paper, an effective e-learning system for deaf-mute primary school children is introduced. Esign Guru is an e-learning platform for deaf-mute primary school students specially designed for Sri Lankan sign language. This application mainly focuses on teaching static and dynamic sign language with an opportunity to practice. This solution comes as a web application that can be accessed using any web browser without any special devices, which makes it a cost-effective solution. The student can learn static and dynamic sign language and then practice those sign language with the webcam turned on. The sign language recognition module extracts key points from hand gestures and classifies them into respective sign language meanings. This helps to provide scores to the student's profile based on their performance.

Since the publicly available datasets are mostly American and British sign language, it is difficult to gather datasets for Sri Lankan sign language. Therefore, the dataset for training the model is collected and trained using selected algorithms to predict correct sign language.

The structure of the paper is organized into the following sections. Section II discusses related work and literature review. Section III describes the methodology of all three subcomponents. Section IV discusses the research work results in detail and section V concludes the research work with future directions.

II. RELATED WORK

There are many pieces of research carried out by the research community regarding sign language, and the problems related to it. Some of the most researched sign languages are American sign language, British sign language, and Chinese sign language. Most researched areas are related to the application of computer vision to solve problems faced by deaf-mute people. Mainly there are two approaches followed in this research. One is sensor-based and the second is vision-based.

Considering the device or sensor-based sign language identification, a system is implemented by the authors for Indian sign language with the leap motion controller [1]. The implemented system uses long short-term memory (LSTM) for sequences of continuous gestures that recognize the connected gestures in sequence. It splits a sequence of signs into sub-units and models them with the neural network. The proposed system has an average accuracy of 72.3% and 89.5% on sign sentences and isolated sign words respectively. Similarly, the authors of another research proposed an approach to translate dynamic and static Indian sign language to speech [2]. It makes use of sensor gloves with flex sensors to track how each finger bends and an inertial measurement unit to read the hand’s orientation and gather information about the motions. 26 gestures could be classified by this model with a 98% accuracy.

The solution proposed by the authors for Chinese sign language [3] uses a Kinect sensor device to translate sign language into speech or text. This is an end-to-end solution for sign language recognition based on long short-term memory. The system takes the moving trajectories of 4 skeleton joints as inputs. Another solution proposed by the authors for Mexican sign language provides a real-time Mexican sign language translation system for the speech-impaired community [4]. Here the authors have considered translating 20 signs of meaningful words into text. The signs are collected using a Microsoft Kinect sensor with the help of 35 Mexican sign language signers. To store depth, skeleton tracking information, and color RGB-D camera is used by the recognition system for hand gestures. To interpret the hand gestures dynamic time-warping algorithm is used. For testing stages, the K-Fold Cross Validation method is used, and the results of the solution have achieved a mean accuracy of 99.1%.

Vision-based approaches have been implemented using machine learning and deep learning techniques. The solution proposed by the authors for American sign language is a vision-based application, that provides sign language to text translation to aid communication between ordinary people and speaking-impaired people [5]. The proposed model captures video sequences, and then spatial and temporal features are extracted from them. Thereafter convolutional neural network is used for spatial feature recognition and recurrent neural networks are used to train on temporal features. Utalk is a mobile application that has been developed to translate the two dynamic and static signs into Sri Lankan sign language [6]. This system uses image processing and machine learning techniques to implement the solution. In another research, the authors proposed a system utilizing deep learning to recognize static sign language based on skin color modeling [7]. This has been developed for number recognition and static word recognition in American sign language. It has an average accuracy of 93.67%, and it has 93.44% and 97.52% accuracy for number recognition and static word recognition respectively.

EasyTalk [8] is a sign language translation system that translates Sri Lankan sign language gestures into audio and text. It uses machine learning techniques for model training and TensorFlow for object detection. In another research, the system uses deep learning techniques to perform image classification for sign language for alphabets [9]. The proposed system has an accuracy of 90.3%. In another research, K. Amrutha and P. Prabu presented a machine learning-based sign language recognition system [10]. The developed model is a vision-based recognition and hand gesture detection, and the machine learning model assessment was carried out with the help of four volunteers in a monitored environment. For the classification, the k-nearest neighbor algorithm is used, and the model yielded an accuracy of 65%.

In another research framework for continuous recognition, sign language recognition is developed using a deep neural network, which translates videos of sign language to the sequence of text labels [11]. The proposed method outperformed the state-of-the-art by a relative improvement of more than 15% on both databases when tested against two demanding sign language recognition benchmarks.

An e-learning platform is proposed by N. Krishnamoorthy et al, to help the hearing-impaired community with effective learning [12]. The proposed platform offers sign language learning resources, practice opportunities, and question & answer sessions while also facilitating contact between students and teachers. The system features a low light enhancement module to improve the tutor's submitted videos, a module to change those videos to American sign language, and to translate sign language questions into text.

Considering the text-to-sign language translation, a system proposed for the educational environment produces still images of Arabic sign language for selected text input with 96% accuracy [13]. M. El-Gayyar, A. Ibrahim, and M.E. Wahed have utilized the power of cloud computing to achieve 79.8% acceptance with the text-to-sign conversion system [14]. A system developed by A. Luqman and S. Mahmoud has an 82% success rate [15]. A desktop application developed by S. M. Halawani, and A. B. Zaiton uses a representation of Arabic text to translate to sign language [16]. Another research done by N. Aouiti and M. Jemni has presented an online web-based Arabic sign language interpreter based on selected signs and words [17].

When we consider the above work, there are many research gaps that need to be addressed. This paper introduces a solution for addressing the above research gaps, and problems faced by Sri Lankan sign language-based e-learning system users. Since most of the research gaps are addressed in this solution, this will be a useful e-learning solution for deaf-mute children

III. METHODOLOGY

The proposed model consists of mainly three subcomponents. The system comprises a text-to-sign component, a component for practicing static signs, and a component for practicing dynamic signs. Each of the components is researched well and implemented according to the necessity and to fill any research gaps existing in Sri Lankan sign language-related solutions. The overall system diagram for this system is shown below in Figure.1

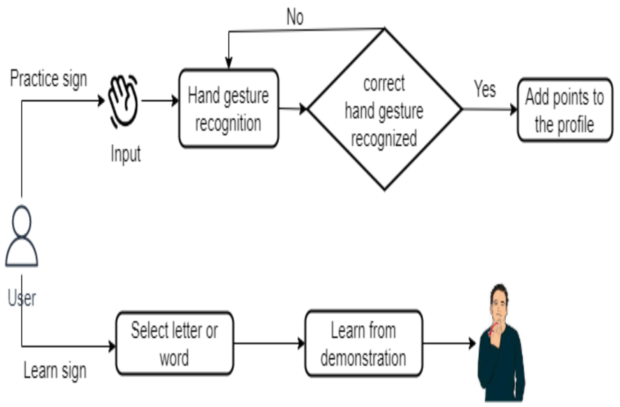


Figure 1. Overall system architecture

A. Text to sign language

Text-to-sign language module is introduced in this research to encourage deaf-mute children to learn sign language for the given text. The objective of this module is to provide a sign language summary for any given text. Through this component, the student can upload a text document, and then get the summary in Sri Lankan sign language. This module will be helpful for students who want to learn the summary quickly, without spending time reading the entire text. It is also proved that people with deaf and mute conditions understand sign language more compared to text. The dataset for this module is collected from a local school for the deaf and mute. The Sri Lankan sign language videos and images are collected and added to the database with proper labeling. Here the sign gestures are collected for 20 different words and stored in proper folders.

This module has 5 sub-modules that are processed to deliver the final output. These are the preprocessing techniques used in natural language processing.

1) *Tokenization*
2) *Removing punctuation and special characters*
3) *Removing stop words*
4) *Stemming*
5) *Produce final output*

The process of tokenization involves splitting the original text into discrete tokens for further study. The punctuation and special character removal module is responsible for removing punctuation marks and hyperlinks. The module that removes stop words is responsible for removing articles, prepositions, conjunctions, linking verbs, and helping verbs. These verbs are removed because there are no explicit sign language meanings for these words. The module that is responsible for stemming is developed to bring down a word to its base word. That means the words that are provided in various tenses or as an adverb are brought down to their base word.

At last, sign language videos for selected words from the given text are retrieved from the database using the labels. Then the retrieved signs are combined to produce the final output video in Sri Lankan sign language.

B. Static sign practice module

In this section practicing module for the static sign is discussed. Static signs are gestures with a single pose. Mostly static signs are used for letters and numbers in the Sri Lankan sign language system. For this research work, the sign language of English alphabets in Sri Lankan sign language is considered. English is taught as the main language in Sri Lankan deaf-mute schools. But for each word and letter, Sri Lankan sign language is used. The static sign dataset selected for the research uses one hand. The system overview diagram for the static sign practice module is shown in below Figure. 2. As demonstrated in the image, initially static signs are taught with the help of images of gestures and respective meanings. Thereafter in the practice module, the user is prompted to perform a sign language with the camera turned on. Through the webcam, the sign language performed by the user is detected and the key points are extracted.

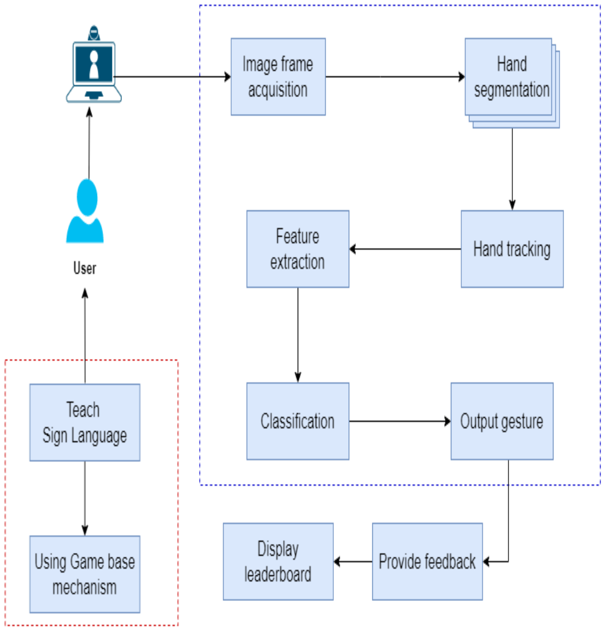
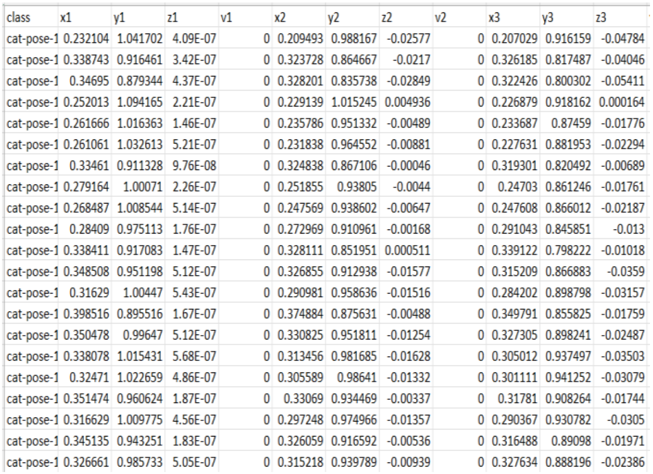


Figure 2. Overview diagram for static sign practice module

The dataset for static sign language is collected from the school for the deaf and mute. For the collection of hand landmark values of each gesture, the Media Pipe library is used. It concludes with twenty-one 3-dimensional landmarks of a single hand in just a single frame. Thereafter using panda's library landmarks values are stored in CSV file format. This enables us to use the data efficiently for model building. For each pose, 261 sets of landmarks values are captured. The static sign of Sri Lankan sign language is shown below in Figure 3.

Figure 3. Static sign demonstrated by volunteer

The Media Pipe is a high-fidelity finger and hand tracking solution. The landmark values captured using the Media Pipe are shown in below Figure. 4. The 3D key point values for each landmark are stored as x, y, and z features. This approach is followed for all 21 landmarks.



class	x1	y1	z1	v1	x2	y2	z2	v2	x3	y3	z3
cat-pose-1	0.232104	1.041702	4.09E-07	0	0.209493	0.988167	-0.02577	0	0.207029	0.916159	-0.04784
cat-pose-1	0.338743	0.916461	3.42E-07	0	0.323728	0.864667	-0.0217	0	0.326185	0.817487	-0.04046
cat-pose-1	0.34695	0.879344	4.37E-07	0	0.328201	0.835738	-0.02849	0	0.322426	0.800302	-0.05411
cat-pose-1	0.252013	1.094165	2.21E-07	0	0.229139	1.015245	0.004936	0	0.226879	0.918162	0.000164
cat-pose-1	0.261666	1.016363	1.46E-07	0	0.235786	0.951332	-0.00489	0	0.233687	0.87459	-0.01776
cat-pose-1	0.261061	1.032613	5.21E-07	0	0.231838	0.964552	-0.00881	0	0.227631	0.881953	-0.02294
cat-pose-1	0.33461	0.911328	9.76E-08	0	0.324838	0.867106	-0.00046	0	0.319301	0.820492	-0.00689
cat-pose-1	0.279164	1.00071	2.26E-07	0	0.251855	0.93805	-0.0044	0	0.24703	0.861246	-0.01761
cat-pose-1	0.268487	1.008544	5.14E-07	0	0.247569	0.938602	-0.00647	0	0.247608	0.866012	-0.02187
cat-pose-1	0.28409	0.975113	1.76E-07	0	0.272969	0.910961	-0.00168	0	0.291043	0.845851	-0.013
cat-pose-1	0.338411	0.917083	1.47E-07	0	0.328111	0.851951	0.000511	0	0.339122	0.798222	-0.01018
cat-pose-1	0.348508	0.951198	5.12E-07	0	0.326855	0.912938	-0.01577	0	0.315209	0.866883	-0.0359
cat-pose-1	0.31629	1.00447	5.43E-07	0	0.290981	0.958636	-0.01516	0	0.284202	0.898798	-0.03157
cat-pose-1	0.398516	0.895516	1.67E-07	0	0.374884	0.875631	-0.00488	0	0.349791	0.855825	-0.01759
cat-pose-1	0.350478	0.99647	5.12E-07	0	0.330825	0.951811	-0.01254	0	0.327305	0.898241	-0.02487
cat-pose-1	0.338078	1.015431	5.68E-07	0	0.313456	0.981685	-0.01628	0	0.305012	0.937497	-0.03503
cat-pose-1	0.32471	1.022659	4.86E-07	0	0.305589	0.98641	-0.01332	0	0.301111	0.941252	-0.03079
cat-pose-1	0.351474	0.960624	1.87E-07	0	0.33069	0.934469	-0.00337	0	0.31781	0.908264	-0.01744
cat-pose-1	0.316629	1.009775	4.56E-07	0	0.297248	0.974966	-0.01357	0	0.290367	0.930782	-0.0305
cat-pose-1	0.345135	0.943251	1.83E-07	0	0.326059	0.916592	-0.00536	0	0.316488	0.89098	-0.01971
cat-pose-1	0.326661	0.985733	5.05E-07	0	0.315218	0.939789	-0.00939	0	0.327634	0.888196	-0.02386

Figure 4. Landmark values captured

The model is trained using multiple machine learning algorithms and the best algorithm is selected. The tested machine learning algorithm includes gradient boosting classifier, logistic regression, random forest, and ridge classifier algorithm. The random forest algorithm is selected due to its highest accuracy. Table. 1 represents the accuracy obtained for each algorithm. Based on the accuracy of different algorithms, the random forest algorithm provided the highest accuracy.

Table 1. Comparison of different algorithms

Algorithm	Accuracy
Logistic regression	0.983
Ridge classifier	0.976
Random forest	0.992
Gradient boosting classifier	0.986

The main goal of this component is to provide a practicing environment for selected static sign language from Sri Lankan sign language. Primary school children can learn static sign language by looking at hand poses that are shown on the screen and their respective meanings in the parallel window. Learning without practice is not a good practice. Therefore, this module focuses on solving this problem.

In static sign language recognition, a webcam is used to capture the hand gesture and extract key points. To predict the hand gesture the machine learning model is used, which is saved as a pickle file and deployed for recognition.

After the model implementation, through the webcam, the system detects key points and predicts the correct static sign language performed by the user.

C. Dynamic sign practice module

In this section practicing module for the dynamic sign is discussed. Dynamic signs are gestures with multiple poses. Dynamic signs are used for words and sentences. For this research, the sign language of animals in the Sri Lankan sign language is considered. The dynamic sign dataset selected uses both hands.

This component focuses on providing a practicing environment for dynamic sign languages from the Sri Lankan sign language. Selected dynamic sign language includes sign language related to the animal such as dogs, cats, lions, elephants, and cows. The system overview diagram of the dynamic sign practice module is shown in Figure. 5.

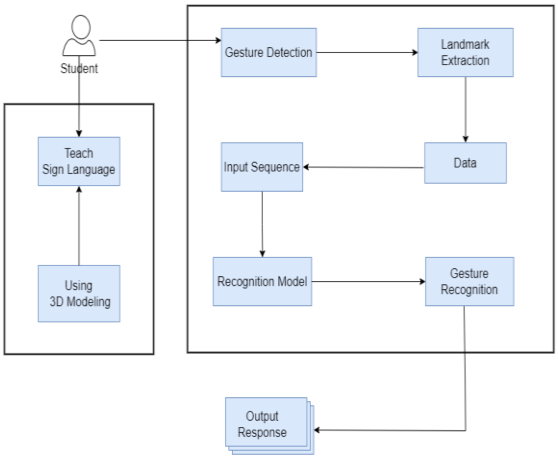


Figure 5. Overview diagram of dynamic sign module

The dataset for dynamic sign language is also collected from the school for the deaf and mute. For the collection of hand landmark values of each gesture, the Media Pipe library is used. It concludes with 21 3D landmarks of a single hand from just a single frame. Since the selected dynamic signs use 2 hands, a total of 42 landmarks are present in dynamic signs. The dynamic signs consist of hand movement which consists of 2 to 3 hand poses. For each pose, 261 sets of landmark values are captured. The dynamic sign that consists of 2 hand poses for a cat in Sri Lankan sign language is shown below in Figure. 6.


Figure 6. Two gestures of a dynamic sign

As an initial step students will be provided an opportunity to learn these sign languages. For each selected sign language, a video demonstration will show the respective meaning. Then in the next window student can demonstrate what he or she learned in front of the webcam and get scored for the performance.

For recognizing the dynamic signs, the Media Pipe library is used. It is used to extract the key points while the student performs any sign gesture. For dynamic sign language mostly, there are two or three gestures for each sign language. So, for each pose of a dynamic sign, key point values are extracted. Then it is stored in a comma-separated file for training the model.

When training the model with the dataset, it is tested with different algorithms to find the best algorithm. Table. 2 represents the accuracy of each algorithm used.

Table 2. Comparison of different algorithms

Algorithm	Accuracy
Logistic regression	0.982
Ridge classifier	0.971
Random forest	0.990
Gradient boosting classifier	0.983

The random forest algorithm is selected due to its high accuracy. After the model training is complete, the model is used for the recognition of each dynamic sign.

IV. RESULTS AND DISCUSSION

This section discusses the results of the implemented solution. Solving the problem faced by Sri Lankan deaf-mute students while learning from anywhere is the main target of this research work. Since the Sri Lankan sign language dataset is not available, the dataset is collected with the help of the local deaf-mute school.

A. Text to sign language

In this section, the results and discussion related to the text-to-sign module are discussed. To provide a summary in the form of sign language for each given text, the first step is the removal of stop words. Table. 3 shows the process of how the stop words are identified and removed.

Table 3. Removal of stop words

Input sentence	Words segment	Selected words segment
This is a new car	This is a new car	This new car
This is a black car	This is a black car	This black car
The car is red.	Car is red	Car red
Follow this https:	Follow this https:	Follow

After removing the stop words stemming is done to reduce the word to its base word. Table. 4 shows how stemming is implemented.

Table 4. Stemming procedure

Input word	After stemming
Flying	Fly
Going	Go

After the above process as mentioned in the methodology in detail, sign language for each selected word is gathered and combined. At last, the summary is provided in the form of a video.

B. Static sign practice module

In this section, the results and discussion related to static sign is discussed.

The static sign language recognition model is evaluated using different metrics and the one with the highest accuracy is selected. The application performed well for static sign language. Table. 5 represents the different metrics of the model created using the random forest algorithm and logistic regression.

Table 5. Performance of the model

Model	Precision	Recall	F1-Score
Random forest	0.99	0.99	0.99
Logistic regression	0.983	0.983	0.982

Static sign languages are taught using images of respective sign languages. The system provides a list of static signs to choose from. The student will be able to practice those signs thereafter. The implemented system is tested with 2 volunteers and received positive feedback. Figure. 7 displays the recognition of static signs. The sign language performed by the user gives an accuracy of 91%.

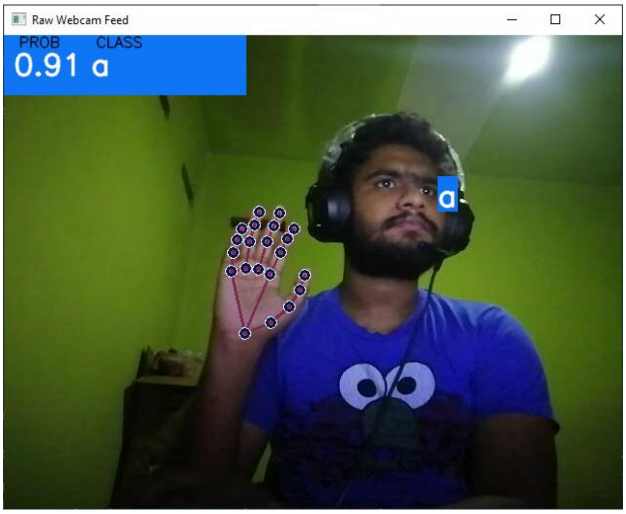


Figure 7. Static sign recognition

The static sign language practice module provided positive results for the solution. Real-time sign language recognition greatly improved the performance of the users.

C. Dynamic sign practice module

In this section, the results and discussion related to the dynamic sign will be discussed.

The dynamic sign language recognition model is evaluated using various algorithms, and the random forest algorithm is selected due to its highest accuracy. Figure. 8 displays the Cohen kappa score of 0.98% for prediction accuracy.

```
from sklearn.metrics import cohen_kappa_score
cohen_kappa_score(y_test, y_pred)
```

```
0.9877837603831272
```

Figure 8. Model accuracy

Dynamic sign language is taught with the help of videos and demonstration of hand gesture movements. This helps the students to get depth understanding of each sign gesture before starting the practice section. This also makes each sign more understandable and meaningful. Figure.9 displays the dynamic sign language learning environment. The sign language performed by the user gives an accuracy of 97%.

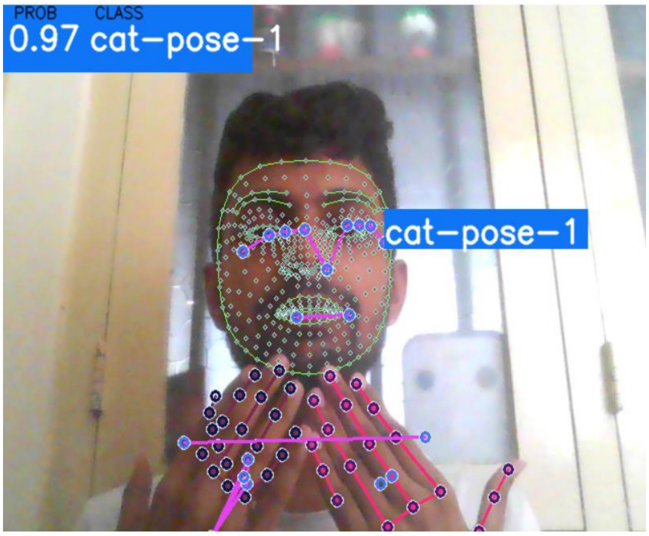


Figure 9. Practice dynamic sign

The results of the solution have received positive feedback from volunteer users. This product will be a great solution to the problems faced by the deaf-mute student community of Sri Lanka.

V. CONCLUSION AND FUTURE SCOPE

This paper presents a solution to the existing problem faced by deaf-mute school children in Sri Lanka. In Sri Lanka, there are not enough solutions that solve problems faced by deaf-mute children while learning. It is strongly believed that teaching sign language does not improve the communication skills of students, but an opportunity to practice those signs while getting some feedback will do. This will improve these skills and helps to retain them for a long period. For text-to-sign language summary natural language processing techniques are used and for gesture recognition, machine learning techniques are used. In recognition, only landmarks from hand gestures were considered since sign languages that use only hand gestures are targeted in this research. In future work, improving the teaching approach and supporting more sign languages will be focused.

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AUTHORS PROFILE

Mr. Kawsikan K. is a final year undergraduate pursuing his bachelor of science in Information Technology Specializing in Software Engineering at the Sri Lanka Institute of Information Technology. His main research work focuses on Cloud Security, Machine learning, Deep learning, and Human-Computer Interaction. He has 4 years of experience in software development and 2 years of experience in research development.

Mr. Jayakody E. D D. L. is a final year undergraduate pursuing his bachelor of science in Information Technology Specializing in Software Engineering at the Sri Lanka Institute of Information Technology. His main research work focuses on natural language processing, machine learning, deep learning, and cloud computing. He has 4 years of experience in software development and 2 years of experience in research development.

Mr. Kothalawala K. L. T. D. is a final year undergraduate pursuing his bachelor of science in Information Technology Specializing in Software Engineering at the Sri Lanka Institute of Information Technology. His main research work focuses on Web security, Machine learning, cloud security, and networking. He has 4 years of experience in software development and 2 years of experience in research development.

Mr. Wijesekara M. P. is a final year undergraduate pursuing his bachelor of science in Information Technology Specializing in Information Systems Engineering at the Sri Lanka Institute of Information Technology. His main research work focuses on Cloud Security, Machine learning, Deep learning, and human-computer interaction. He has 4 years of experience in software development and 2 years of experience in research development.

Miss Hansi De Silva pursued a Bachelor of Science in Information Technology specializing in Software Engineering at the Sri Lanka Institute of Information Technology, Sri Lanka in the year 2017. She also has a master's degree in Computer science from the University of Colombo School of Computing. She has published research papers in reputed international journals and conferences including IEEE and it’s also available online. Her main research work focuses on machine learning, natural language processing, and cloud computing. She has 5 years of teaching experience and 6 years of Research Experience.

