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Sinhala Sign Language Recognition using Leap Motion and Deep Learning

Priyantha Kumarawadu[1], Mohamad Izzath[2]

[1,2]School of Computing, Asia Pacific Institute of Information Technology, Colombo, Sri Lanka

E-mail: [1]priyantha@apiit.lk, [2]izzath0@gmail.com

Abstract

A sign language recognition system for low-resource Sinhala Sign Language using Leap Motion (LM) and Deep Neural Networks (DNN) has been presented in this paper. The study extracts static and dynamic features of hand movements of Sinhala Sign Language (SSL) using a LM controller which acquires the position of the palm, radius of hand sphere and positions of five fingers, and the proposed system is tested with the selected 24 letters and 6 words. The experimental results prove that the proposed DNN model with an average testing accuracy of 89.2% outperforms a Naïve Bayes model with 73.3% testing accuracy and a Support Vector Machine (SVM) based model with 81.2% testing accuracy. Therefore, the proposed system which uses 3D non-contact LM Controller and machine learning model has a great potential to be an affordable solution for people with hearing impairment when they communicate with normal people in their day-to-day life in all service sectors.

Keywords: Sinhala Sign Language, Deep Neural Networks, Naïve Bayes, Support Vector Machine, Hand Gesture Recognition, Sign Language Classification, Leap Motion Controller

1. Introduction

Over 430 million adults and 30 million children of the world population experience profound hearing loss ranging from mild to hard [1]. As with Sri Lanka, there are over 300,000 hearing impaired people, however the World Health Organization has revealed that 9% of the Sri Lankan population has loss of hearing [2]. With the limitation of social acceptance, barriers in effective communication, lack of support in Sinhala sign language to Sinhala language interpretation have become a major constraint for a person with hearing impairment, to get required services efficiently including access to public education and public health services in the country. Especially during the spread of COVID-19,

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communication for many people who are deaf or hard hearing, has become even more difficult with protective masks which blocks the facial expressions and lip reading which are vital for their communication.

Research on Sign Language recognition has been carried out for many sign languages using different machine learning techniques. Hidden Markov Model (HMM) which was widely used for pattern recognition systems [3], [4] has been applied in sign language recognition systems. HMM has been used for recognition of vocabulary with 53 signs in American Sign Language using videos [5] and the study has recorded a 90% accuracy. A HMM based sign language recognition system has been developed to recognize 26 words in Chinese Sign Language [6]. Furthermore, HMM based model has been developed to recognize 20 isolated words from Standard Arabic Language [7]. A sign language interpreter with real-time gesture recognition has been presented using HMM for 51 fundamental postures, 6 orientations and 8 motion primitives in Taiwanese Sign Language [8]. With the advancement of artificial intelligence, various studies have been conducted on sign language recognition using machine learning techniques. An Artificial Neural Network (ANN) model has been constructed for recognition and classification of signs in Spanish Sign Language using a low-cost glove to capture the hand movements [9]. A sign recognition model based on Principal Component Analysis and ANN has been proposed using images captured with 3MP camera [10] where the data in the study included 15 images per sign, however results of the study was not impressive due to lack of data in the training of the ANN model. Kang et.al. [11] proposed a real time finger spelling system using Convolutional Neural Network (CNN) and depth maps with 1000 images. Authors in this study have analysed 31 various hand signs including fingerspelling of letters and numbers. Support Vector Machine (SVM) algorithm has also been widely used for both static and dynamic gesture classification. Other machine learning algorithms which have been used for hand gesture classification include k-nearest neighbour, random forest, Naive Bayes classifier and linear discriminant analysis.

A very limited number of previous studies were available for recognition and interpretation of Sinhala Sign Language (SSL) and therefore, real-time Sinhala Sign Language recognition still remains as an open problem. A real-time translation between SSL and Sinhala Language using dynamic time wrapping and nearest neighbour classification-based gesture identification algorithm [12]. Authors have further conducted an integrated 3D simulation with a chat module allowing users to exchange messages via words or sign based simulations. A real time SSL translator has been developed based on letter-based signs using image processing and machine learning [13] where a database of hand gestures representing 26 categories have been created and those digital images have been processed, recognized and classified by a CNN with 91% validation accuracy.

In this paper, a Sinhala Sign Language recognition system using Naive Bayes classifier has been proposed. A compact and low-cost leap motion sensor has been used to capture hand gesture data against the existing different data capturing methods like CyberGlove [14] or Microsoft Kinect [15] which used in sign language recognition systems. The sensory data obtained from the Application Programming Interface (API) of the leap sensor have been examined and calibrated, and the features of hand gestures of Sinhala signs have been derived. Proposed system has been trained, validated and tested with the collected data representing 30 hand signs of letters and words in Sinhala Language. The study records a convincing training and testing accuracy. Further a real-time experiment is also conducted with the proposed Sinhala Sign Language recognition system for selected signs and results are presented here.

2. Data Acquisition

2.1 Sinhala Sign Language

Conversational gestures in SSL were the preferred method in communication compared to fingerspelling gestures. This can be used to express a word or a phrase in comparison to the letter to letter translation in fingerspelling method. Compared to grammar rules in Sinhala Language, SSL has very limited number of rules to accommodate complete interpretation of a phrase or a sentence in Sinhala Language. Fingerspelling alphabet contains finger signs to represent 60 characters in Sinhala Language and this uses phonetic pronunciation of a word since one-to-one correspondence between more than 1000 potential Sinhala letters and finger spelt is hard to construct. The fingerspelling system in SSL breaks down the union of consonants, vowels, and phonemes of Sinhala letters and represents each element as a distinct handshape [16]. For an example, to create the word "Sri Lanka" in Sinhala language (ශ්රී ලංකා), finger spelt form needs to represent eight phonemes that leads to eight corresponding handshapes such as (ශ් + ∪ + ඊ) (ල් +අ) (ං) (ක් + ආ) [16]. Due to phonetic pronunciation nature of Sinhala Language and directional rotations in SSL, the sliding of hands in different directions, make SSL recognition more complicated. English fingerspelling which is based on British Sign Language is also used in Sinhala Sign Language [17]. SSL requires decoding of a given number into the place value system in hand spelling unless otherwise there is a sign representing the number.

2.2 Image-based Sign Recognition

A large number of sign language recognition researches were based on image processing and recognition. This mainly consists of two processes: detection of hand gesture images of signs using image processing algorithm and classification of signs into respective language using a classification algorithm. In image-based sign recognition systems, images of handshapes were captured by a camera pointed at a person [18], [19]. Although this method has a minimum user adaptation to the sign language recognition system, those systems have inherent limitation in capturing, pre-processing and feature extraction of images mainly due to computational limitations and added overheads during pre-processing of data when removing distracted noise from unwanted background objects. In order to avoid the overlapping between hand and head of signer when image is captured, the camera is generally mounted above the signer. To reduce the complexities in mathematical computational in determining convexities of images, the methods such as data glove devices and color markers have been used in data acquisition aiming at extracting accurate gesture features from handshapes [20]. These systems include a pair of gloves with optical sensors that run full length of each of the five fingers attached to it. The glove device then turns finger movements to electrical signals which determines the hand postures.

Image processing-based sign recognition in Sinhala Sign Language has been researched by few researchers. A prototype of an image-based Sinhala sign language recognition mechanism has been developed using HMM and this converts dynamic gestures into predefined words or phrases in Sinhala Language. A model for translation of hand signs of SSL has been presented using a convolutional neural network (CNN). The study has used a total of 1170 images of hand gestures for training and testing of the CNN model which has given 91% validation accuracy.

2.3 Sensor-based Data Acquisition

Hand tracking devices with arrays of sensors have been used recently in sign language recognition researches. After collecting hand gesture data through an array of sensors, machine learning models were used to classify those hand gestures. A depth sensor-based real-time hand pose estimation framework has been proposed to recognize first ten digits in American Sign Language (ASL) [21]. In this model, authors have used a hand model with a hierarchical skeleton for sign recognition and a model using artificial neural networks, support vector machine has been utilized as a pose classifier. Kinect sensors with high performance 3D image capturing have been used for a gesture recognition system focusing on fingertip positions [22]. Multiple low-cost Leap Motion sensors have been employed in HMM based ASL recognition System which was developed to recognize 10 different digits in ASL [23].

A glove-based data acquisition technique has also used as another approach wherein the position and orientation of hands were recognized using a special glove equipped with several sensors worn by a user. Instrumented glove specially designed for sign language detection use sensors like accelerometer and proximity sensor mounted on the glove for measuring hand movements. The complexity of glove-based sign language recognition system heavily depends on number of sensors embedded in the glove and the spacing between those sensors. The number of data channels increases according to the number of sensors embedded in those gloves. Using sensors for data acquisition facilitates direct access to data pre-processing and easy conversion of raw data into a required data format. This also eliminates the environmental and background noises which influence on data at the data capturing process.

Leap Motion Controller (LMC) which has been recently used for acquiring data of finger and palm position, orientation, movement and speed in a 3D space, transfers data into a 3D space with a skeletal representation [24]. LMC comes with an application Programming Interface (API). A machine learning based hand gesture recognition system has been developed using a Kinect sensor with a LMC to recognize 28 Arabic alphabet signs in the Arabic Sign Language A similar study was conducted to recognize 10-digit gestures using LMC and SVM classifier [25] and a better performance has been recorded with a histogram of oriented gradient features from LMC data. Alphabet detection in ASL for static hand signs has been presented using decision tree algorithm and genetic algorithm.

However, recognition of a hand gesture of sign language is challenging due to varying finger, hand movements, changes in speed of hand movement and hand position variations. In this research, LMC has been used in both static and dynamic handshapes recognition with a Naive Bayes classifier.

3. Proposed SSL Recognition System

The main objective of this research was to develop a Sinhala Sign Language interpreter which translates Sinhala hand signs into Sinhala language. Although there were very limited number of research on SSL recognition they were mostly on static Sinhala Signs. In this paper, the proposed SSL recognition system is capable of handling both static and dynamic Signs of SSL. The system captures hand gestures through LMC, and processes captured information, identifies corresponding words and phrases reference to the communication in SSL and displays them as a message in Sinhala Language enabling non-SSL speaker to understand and interact with a hearing-impaired person.

3.1 LMC and its API

In this study, a leap motion sensor was utilized to collect the hand signs of Sinhala Sign Language at an intimate proximity. A higher precision and a tracking rate was obtained here. LMC directly captured the skeletal data of hand signs including position of the hand, fingers, rotation and velocity of hands based on the coordinate system of the sensor. The data captured through LMC was pre-processed, organized in a vector form and stored as a reference data for recognition model. Each static sign or dynamic gesture sign has been represented as an object using a 3-dimensional vector considering its direction and position in the Euclidian space of the LMC display. API that came with the LMC was used to transmit data to a pre-processing module which was developed in this study. For effective use of LMC, hand movement were performed at about 2 feet above the sensor. A total of 23 features were extracted and were used as input to the classier.

3.2 Classifier Development

In this study, the proposed DNN model was compared with a Naïve Bays model and a multi-class SVM model for prediction of Sinhala Sign Language.

DNN model was implemented in Python using Keras and TensorFlow open source libraries. The proposed DNN consisted of one input layer with 23 input nodes, two hidden layers with each 128 nodes and an output layer with 30 nodes. Densely connected hidden layers used the rectified linear unit (ReLU) activation function as given in Equation (1)

$$R(z) = \max(0, z) \tag{1}$$

where the output is zero when z is less than zero and output is equal to z when z is above or equal to zero. In order to handle the multiclass classification problem, the output layer with 30 nodes were implemented with Softmax activation function which returns an array of 30 probability scores that sum to 1 as given in the Equation 2.

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \tag{2}$$

where $\vec{z}$ is the input vector from previous layer to the Softmax function and k is the number of classes in the multi-class classifier. In the proposed DNN model, k is equal to 30 classes. All four layers of proposed DNN model used Adam optimizer with a learning rate of 0.001, an exponential decay rate of 0.9 for the first moment and an exponential decay rate of 0.999 for the second moment. Since the classification classes are mutually exclusive, the sparse categorical cross-entropy loss function was used.

The Naive Bayes classifier was selected due to its implementation simplicity, faster computational speed and higher performance efficiency in small data sets without compromising its classification accuracy. Further the independence of each feature of a sign , the non-interaction between each other and the low sensitivity to noise were some of the other reasons for Naïve Bayes classifier to be selected in sign language recognition. The classier was based on the Bayes Probability rule which is given in the Equation 3.

$$P(Y/(X_1, \dots X_n) = \frac{P(X_1, \dots\dots X_n/Y)P(Y)}{P(X_1 \dots\dots X_n)} \tag{3}$$

For a given data matrix $X = x_1 + x_2 + \cdots . + x_n$ where x was a dependent feature vector with dimension n where n was a number of features in the sample, and the probability of observing, class y, is $P(y/X)$ assuming that all features of X were mutually independent

When creating the classifier model, the probability of a given set of inputs for all possible values of variable y was calculated and picked the output with maximum probability as in the Equation (4).

$$argmax_y P(y) \prod_{i=1}^{n} P(x_i/y) \tag{4}$$

The third classier that was tested in this research was a SVM based classier which obtains a hyperplane H_0 that maximises the separation of input data to their respective classes as given in the Equation (5).

$$H_0 = W^T x_i + b = 0 \quad (5)$$

where x_i is the input vector, W is the weight factor and b is the bias. Therefore, the linear classifier is defined as:

$$f(x) = sign(W^T x + b) \quad (6)$$

Since the classification problem under investigation in the paper belongs to multiclass classification with 30 classes, one vs All (OVA) techniques that formulated multiclass classification problem into sub binary classification was used while the final prediction was done through majority voting.

3.3 Proposed System Architecture

The architecture of the proposed system is shown in Figure 1. This comprises three major components: builder, interpreter and classifier. The system architecture was all managed and executed with the help of leap service of LMC which was connected with the Interpreter and the Builder through the API service of LMC. The gestures were recognized using the builder application and they were saved in a dataset.

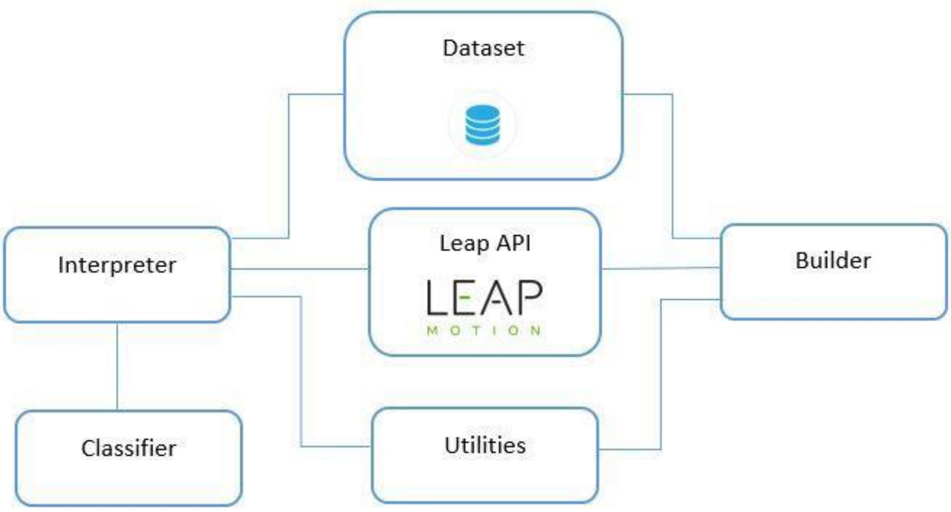

Figure 1. Architecture of the Proposed System

Figure 2. Sinhala Language Sign Alphabet

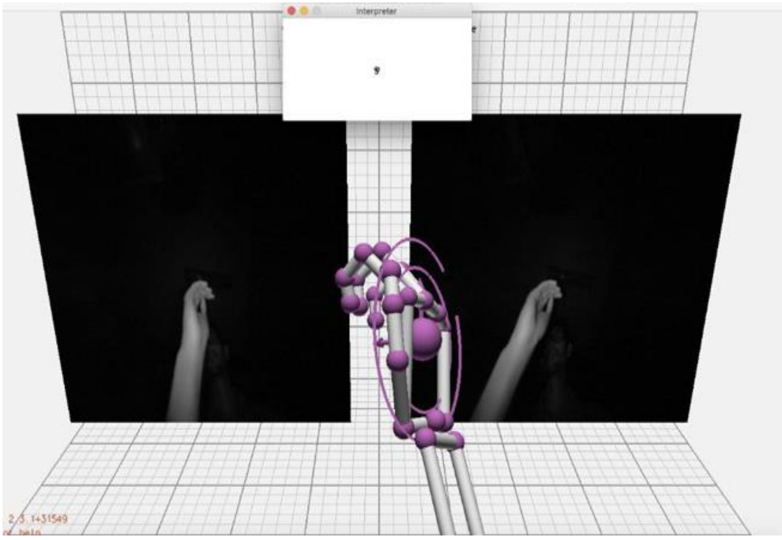

Figure 3. Test Case 4 (T4): Recognizing the letter "ඉ"

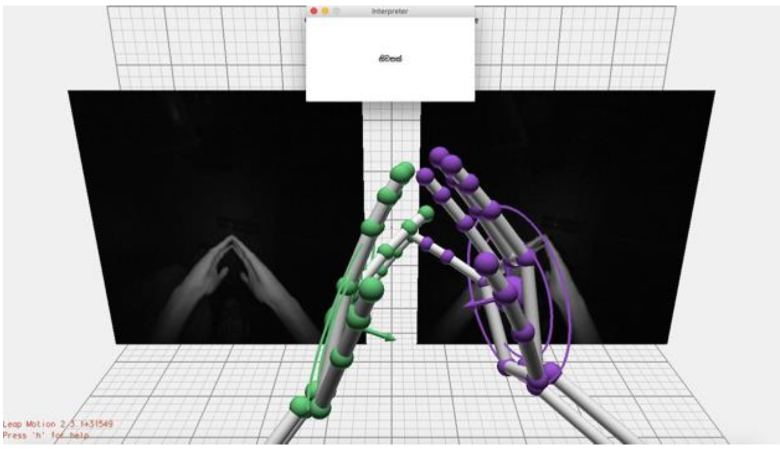

Figure 4. Test Case 25 (T25): Recognizing the word "නිවස"

Interpreter was responsible in recognizing a sign from the dataset and displaying the text output of the sign. Builder created the Sinhala hand signs, trained the data and saved the gestures in the dataset. Utilities application was used to help the classifier to extract features from hand gestures. Classifier was used to train the dataset value and to normalize hand gesture data received from leap motion controller using its leap service. Dataset was the storage and this was used to store the recognized values from the leap motion controller. This stored the raw data representing hand gesture values of palm and fingertips in a numeric way.

4. Experiment and Results

All machine learning experiments and the application in this study were built using Keras and TensorFlow Python libraries. The complete application consisted of three major system components: Interpreter, Builder and Classifier. Three classifiers which were experimented in study were DNN classifier, Naïve Bayes Classifier and SVM based classifier which were trained and tested to classify a number pre-identified Sinhala signs and words which have been pre-identified for feature extraction. A total of 1862 data sets representing hand signs of Sinhala alphabet and some words have been used in this study. Four signers who performed hand gestures were instructed to keep their hands 40 cm above the LMC. Data dictionary in this research represented data equivalent to Sinhala signs of only 24 selected letters in Sinhala alphabet and hand signs of 6 Sinhala words as shown in Figure 2. Each sign was performed about 60 times and data set which was built for classification included about 60 data samples per sign in the data dictionary. Training data set which was used for parameter setting of the classifier constituted to 70% of total data. Validation data set used for parameter tuning of the classifier was 10% of total data and remaining 20% of data was used for testing the classifier. Table 1 represents the data samples selected for the study, English sound or English meaning of Sinhala words and number of data samples of each sign. Pre-processing of cartesian space data which were obtained from Software Development Kit (SDK) of LMC controller via LMC's API was performed prior to start training and testing of machine learning model. After the recognition of the sign, classifier module sent the information to the display module to display the corresponding Sinhala alphabet character or Sinhala word which allows a non-sign language speaker to understand the hand sign expression of a hearing-impaired person.

DNN based Sinhala Sign Language classifier recorded an overall training accuracy and overall testing accuracy were 93.7% and 89.2% respectively for the preselected signs which were used for the experiment whereas the testing accuracy of DNN classifier of individual signs varied from 86.7% to 92.3% as in the Table 1. Furthermore, average training and testing accuracies of Naïve Bayes classifier were 77.8% and 73.3% respectively, and the training and testing accuracies of SVM based classifier were 87.1% and 81.2% respectively. A total of 372 signs were used as test cases. A similar number of data samples were used in training and testing for each sign as in Table 1. In addition, the real time testing was performed using new signers who were not used during the data collection process. When performing hand gestures, all signers were instructed to maintain the same distance from the LMC and the same hand movement speed was maintained as the signers who performed hand gestures in the data collection process. The results obtained during the real time experiment of the prototype model were shown in Figure 3 and Figure 4. This illustrates how the system has recognized the two signs of Sinhala character "ඉ" and Sinhala word "නිවස". The corresponding Sinhala meanings were displayed on the connected display screen as shown above.

As depicted in the Table 1, Deep Neural Network based SSL classifier reported the highest overall testing accuracy of 89.2% when compared to the Naïve Bayes classier and SVM classifier. Furthermore, it was noted that the proposed DNN based classifier resulted average SSL recognition accuracy, sensitivity and specificity for pre-selected letters and words were over 89%.

Table 1. Results for a selected number of Sinhala signs and words

Case #	**Sinhala Sign**	**English sound/word**	**Total Data Samples**	**Testing Accuracy (%)**		
				DNN	**Naïve Bayes**	**SVM**
T1	අ	A	60	92.3	74.3	83.2
T2	ආ	Ã	60	91.5	75.2	81.7
T3	ඇ	Æ	60	90.3	72.4	87.3
T4	ඉ	I	60	89.3	70.2	81.3
T5	උ	U	60	90.5	72.7	78.1
T6	එ	E	60	91.3	71.4	80.2
T7	ඔ	O	60	91.4	75.1	78.3
T8	ක	Ka	60	87.3	69.4	83.1

T9	ග	Ga	60	87	73.1	79.8
T10	ච	Ca	62	86.8	71.2	78.3
T11	ට	Ta	62	88.1	69.6	85.3
T12	ඩ	Da	60	91	74.2	80.3
T13	ත	Ta	60	90.3	72.9	84.1
T14	ද	Da	60	89.5	77.6	82.8
T15	න	Na	62	90.2	71.8	80.1
T16	ප	Pa	60	90.4	74.3	77.5
T17	බ	Ba	62	91	73.4	79.4
T18	ම	Ma	62	86.8	71.7	80.4
T19	ය	Ya	62	86.8	72.5	81.9
T20	ර	Ra	60	87.9	76.1	81.6
T21	ල	La	62	88.3	75.7	82.5
T22	ව	Va	60	89.3	73.4	82.1
T23	හ	Ha	60	90	77.3	80.5
T24	ස	Sa	60	90.3	69.7	80.9
T25	නිවස	House	68	86.7	74.1	77.9
T26	ඇඳ	Bed	68	88.1	73.5	81.5
T27	ස්තූතියි	Thank you	68	88.9	77.1	82.6
T28	දුරකතනය	Telephone	68	89.3	70.5	78.9
T29	බල්ලා	Dog	68	89.3	73.1	81.6
T30	අපි	We	68	87.9	74.5	82.1
Average Testing Accuracy (%)				89.2	73.3	81.2

5. Conclusion

The main objective of this study is to design and develop a Sinhala Sign Language recognition system using a machine learning algorithm and facilitate the communication between a person with hearing impairment and a person with normal hearing through a real time conversion of hand gestures and displaying the corresponding meaning in Sinhala text on a display screen. During the pre-research, it is found that there are very limited researches conducted on real time Sinhala Sign Language recognition and translation to Sinhala text. This was the main motivation behind this study. A low-cost Leap Motion Controller is used for feature extraction and handshape tracking. All hand gestures are performed at a constant height above the LMC in order to unify data capturing condition which was one of the limitations of the study. A Deep Neural Network based Sinhala Sign Language recognition system is developed and the results of DNN classifier are compared with two other classifiers: Naïve Bayes and SVM for benchmarking purposes. The DNN based classifier produces an impressive overall accuracy in Sinhala Sign Language recognition for a selected number of Sinhala alphabet and words.

As future works, a combination of general position of hands and speed at which the hand signs are performed could be investigated. This will enhance the flexibility of performing hand signs, the recognition of complex and dynamic sign expressions. Furthermore, computational complexity of the classification model and its efficiency will be investigated.

References

[1] World Health Organization, “World Report on Hearing”, Geneva; BY-NC-SA 3.0 IGO: Licensee: CC, (2021)

[2] M. Ranaweera Premasiri, H. A. D. K. N. Hettiarachchi, J. C. Delmar, P. H. S. Dias, G. S. Mallika, W. G. S. A. K. Rajapaksha, A. N. Jayasekara, S. M. W. Samarakoon et al. (Eds.). “Sri Lankan Sign Dictionary: Sinhala Language”. National Institute of Education, Maharagama, Sri Lanka (2015)

[3] B. H. Juang and L. R. Rabiner, “Hidden Markov models for speech recognition,” Technometrics, vol. 33, no. 3, pp. 251–272, (1991)

[4] H. Bunke, M. Roth, and E. G. Schukat-Talamazzini, “Off-line cursive handwriting recognition using hidden Markov models,” Pattern recognition, vol. 28, no. 9, pp. 1399–1413, (1995)

[5] K. Grobel and M. Assan, “Isolated sign language recognition using hidden Markov models,” in Proceedings of the IEEE International Conference on System, Man and Cybernetics, pp. 162-167, (1996)

[6] J. Wu, W. Gao, Y. Song, W. Liu, and B. Pang, “A simple sign language recognition system based on data glove,” in Proceedings of the 4th International Conference on Signal Processing, Vol. 2, pp. 1257-1260, (1998)

[7] A.A Aliaa, A Youssif, Amal Elsayed Aboutabl and Heba Hamdy Ali, “Arabic Sign Language (ArSL) Recognition System Using HMM” International Journal of Advanced Computer Science and Applications (IJACSA), Vol. 2(11), (2011)

[8] R-H. Liang and M. Ouhyoung, “A Sign Language Recognition System Using Hidden Markov Model and Context Sensitive Search” Proceedings of the ACM Symposium on Virtual Reality Software and Technology, Hong Kong, pp. 59-66, July (1996)

[9] Saldaña González, G., Cerezo Sánchez, J., Bustillo Díaz, M.M., Ata Pérez, A., 2018. “Recognition and Classification of Sign Language for Spanish” Computer Systems (2018)

[10] Zafar Ahmed Ansari and Gaurav Harit, “Nearest Neighbor Classification of Indian Sign

Language Gestures using Kinect Camera", in Sadhana, Vol. 41, No. 2, pp. 161-182, (2016)

[11] Kang, B., Tripathi, S., & Nguyen, T. Q. "Real-time sign language fingerspelling recognition using convolutional neural networks from depth map", 3rd IAPR Asian Conference on Pattern Recognition (ACPR) (pp. 136-140). IEEE, (2015)

[12] P. Fernando & P. Wimalaratne, "Sign Language Translation Approach to Sinhalese Language" GSTF Journal of Computing, Vol. 5 (1) pp. 52-59, (2016)

[13] S.D. Hettiarachchi & R.G.N. Meegama, "Machine Learning Approach for Real Time Translation of Sinhala Sign Language into Text", Proceedings of International Conference on Advances in Computing and Technology (ICACT-2020), pp 23-25 (2020)

[14] H. Wang, M. C. Leu, and C. Oz, "American sign language recognition using multi-dimensional hidden Markov models," Journal of Information Science and Engineering, vol. 22, no. 5, pp. 1109–1123, (2006)

[15] S. Lang, M. Block, and R. Rojas, "Sign language recognition using Kinect," Artificial Intelligence and Soft Computing, pp. 394–402, Springer Berline Heidelberg, (2012)

[16] A. Stone, "An introduction to Sri Lankan Sign Language." Matara, Sri Lanka : Karunaratne & Sons, Sri Lanka, (2007)

[17] H.C.M. Herath, W.A.L.V.Kumari, W.A.P.B Senevirathne and M.B Dissanayake, "Image based Sign Language Recognition System for Sinhala Sign Language", Proceedings of SAITM Research Symposium on Engineering Advancements, Colombo, Sri Lanka (2013)

[18] C. Vogler and D. Metaxas. "Adapting Hidden Markov Models for ASL recognition by using three-dimensional computer vision methods", In Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, pages 156–161, Orlando, FL, (1997)

[19] Y. Cui and J. Weng. "Learning-based hand sign recognition." In Proc. of the Intl. Workshop on Automatic Face- and Gesture-Recognition, Zurich, (1995)

[20] S. G. Wysoski, M. V. Lamar, S. Kuroyanagi and Akira Iwata, "A Rotation Invariant Approach On Static-Gesture Recognition Using Boundary Histograms Networks", IEEE Proceedings of the 9th International Conference on Neural Information Processing, (2002)

[21] C. Keskin, F. Kırac¸, Y. E. Kara, and L. Akarun, "Real time hand pose estimation using depth sensors," in Consumer Depth Cameras for Computer Vision. Springer, pp. 119–137 (2013)

[22] C. Zhang, X. Yang, and Y. Tian, "Histogram of 3d facets: A characteristic descriptor for hand gesture recognition," in Automatic Face and Gesture Recognition (FG), 2013 10th IEEE International Conference and Workshops on. IEEE, pp. 1–8 (2013)

[23] K. Fok, N. Ganganath, C. Cheng and C. K. Tse, "A Real-Time ASL Recognition System Using Leap Motion Sensors," International Conference on Cyber-Enabled Distributed, (2015)

[24] M.A. Almasre and H. Al-Nuaim, "Real-time Letter Recognition Model for Arabic Sign Language Using Kinect and Leap Motion Controller v2", International journal of Advanced

Engineering, Management and Science, Vol. 2(5) pp 514-522 (2016)

[25] Mohandes, M., Aliyu, S., & Deriche, M. "Arabic sign language recognition using the Leap Motion Controller". Paper presented at King Fahd University of Petroleum & Minerals Dhahran, 31261, Saudi Arabia., IEEE Xplore (2014)

Author's biography

Priyantha Kumarawadu is a professor and head of machine learning lab at Asia Pacific Institute of Information Technology, Sri Lanka. In addition, he currently serves as the Head of the School of Computing at Asia Pacific Institute of Information Technology. His research interests include IoT, machine learning and its applications.

Mohamad Izzath was an undergraduate student at Asia Pacific Institute of Information Technology, Sri Lanka and has received a BEng in Software degree from Staffordshire University, UK. Currently, he works as a software engineer at Calcey Technologies in Sri Lanka.