SEUSL

Sri Lankan Journal of Technology
Research

SLJoT
2025 Issue 02 19-25
ISSN-2773-6970

Real-Time Sri Lankan Static Sign Language System using EfficientNet-B0

Y.M.W.T. Jayasekara[1], I.M. Kalith[1] and A.R.F. Shafana[1*]

[1] Department of Information and Communication Technology, South Eastern University of Sri Lanka, Oluvil, Sri Lanka

*Corresponding Author: arfshafana@seu.ac.lk || ORCID: 0000-0001-6926-9196

Received: 31-10-2025 * Accepted: 30-12-2025 * Published Online: 31-12-2025

Abstract – Sign Language serves as an important medium of communication for the deaf and hard of hearing community. However, there is a lack of understanding among the public regarding the various signs used. Although around 300,000 Sinhala-speaking individuals are either deaf or hard of hearing, dedicated applications for Sri Lankan Sign Language detection are quite limited. In contrast, various sign language detection systems for other popular sign languages, such as American Sign Language (ASL) and British Sign Language (BSL), exist in abundance. This study aims to design and develop a lightweight mobile application, backed by the Efficient-B0 model, for Sri Lankan Static Sign Language detection. This application can detect five popular words using nine static signs and can be scaled up in the future. The developed application was found to be lightweight, efficient, and usable among the target users, achieving an accuracy of over 90% for real-time sign detection.

Keywords- Android application, EfficentNet-B0, Hand tracking, Sri Lankan sign language

Recommended APA Citation

Jayasekara, Y. M. W. T., Kalith, I. M., & Shafana, A. R. F. (2025). Real-time Sri Lankan static sign language system using EfficientNet-B0. *Sri Lankan Journal of Technology, 6*(2), 19–25.

Introduction

Sign language is a unique form of communication that uses a combination of hand gestures, facial expressions, and body language to convey meaning (Seymour & Tseou, 2015). It is a visual language that is used by the deaf and hard-of-hearing communities around the world. One of the challenges faced by the deaf and hard-of-hearing community around the world is the lack of recognition and the support for sign languages. It could be seen that the general public are quite unaware of the different sign languages and its relevant interpretations (Punchimudiyanse & Meegama, 2017). In addition, many countries do not recognize sign language as an official language, and there is often limited access to sign language interpreters and other resources that are essential for effective communication. As a result, deaf and hard-of-hearing individuals often face significant barriers to education, employment, and social participation.

In addition to this, it is important to note that sign language is not a worldwide language. Instead, different countries have their own sign languages, often with different dialects and variations within the same country. For instance, American Sign Language (ASL) and British Sign Language (BSL) used in the United States and Canada, and the United Kingdom, respectively are two prominent sign languages (Wadawan & Kumar, 2020). Both possess distinct grammatical structures and are not derived from spoken languages. BSL employs a different set of signs and hand gestures compared to ASL and boasts around 70,000 users in the UK. Indian Sign Language (ISL) is prevalent in India and has over 1.8 million users, also having its unique grammar and vocabulary, distinct from spoken languages. Worldwide, various other sign languages, such as French Sign Language, Indonesian Sign Language, and Japanese Sign Language, exist, each characterized by its own distinct vocabulary, grammar, and syntax, with no mutual intelligibility among them (Yugopuspito et al., 2018). This problem is even more serious to Sri Lankan Sign Language (SLSL), that has a very limited number of users. Statistics report that around 300, 000 Sinhala-speaking individuals are either deaf or hard of hearing (DHH) (Udugama et al., 2024).

To address this problem, we propose a light-weight mobile application that leverages machine learning, image, and video processing to interpret SLSL. The application will allow deaf individuals to express themselves in their native language, i.e. Sinhala, which can then be converted into written or spoken language for ordinary people. Our proposed mobile application aims to facilitate effective communication between deaf and ordinary people, promote inclusivity, and reduce the language barrier through the use of technology.

Related Works

Primarily, many research works have been done for the American Sign Language (ASL), a prominent sign language system. For instance, Joglekar et al. (2020) developed a real-time intelligent translation system that detects the ASL through live video capture and translate to their relevant plain text using image processing and CNN model. The built model had an accuracy of 91.82%. Another study conducted by Dahanayaka et al. (2019) focused on the initial four letters of ASL. The developed application performed two primary tasks: the first task involved translating sign language into spoken language, while the second task involved translating spoken language into text, making it accessible to deaf and mute individuals. CNN and Mel-frequency Cepstral Coefficient were used respectively for sign language recognition and automatic speech recognition yielding an overall accuracy of 95%. Other works for ASL includes a CNN based system by Tolentino et al. (2021) with 93.67%, a detection system using AdaBoost and Haar-like classifiers with 98.7% precision (Truong et al., 2016) and a real-time detection utilizing CNN and convex hull algorithm producing an accuracy of 98.05% (Taskiran et al., 2018).

Besides the prominent ASL sign detection systems, numerous efforts have been pledged across various other local sign languages as well. For instance, Yugopuspito et al. (2018), developed a mobile application for Bahasa Indonesian Language using convolutional neural network. The built model had an accuracy of 95.13% that could recognize nearly 23 gestures. Seymour & Tsoeu (2015) developed an android based mobile application for African Sign Language that could recognize 24 static alphanumeric characters and 7 numeric unique digits with an accuracy of 99%. For Indian Sign Language System, the work of Wadhawan & Kumar (2020) is appreciated for producing a model with 99.72% and 99.90% on coloured and grayscale images by testing upon 50 different CNN models. This indicates that the localization of this system has a significant research interest across the world.

With special reference to Sri Lankan sign language systems, only few works have been conducted in this regard. Notably, Dissanayake & Wickramanayake (2018) developed a convertor for both static and dynamic Sri Lankan sign language called "Utalk" producing an accuracy of 0.97 and 0.95 respectively. The developed system was able to convert both static and dynamic signs from video inputs to text using machine learning and computer vision. Another notable initiative for Sri Lankan sign language system is an image-based tutor developed by Fernando & Wickramarathne (2020) for recognizing 8 static signs. The accuracy was also high for the above tutor.

As mentioned earlier, despite the existence of various approaches for reliable automatic recognition of sign language, there is a scarcity of research on a straightforward, hand-held and light-weight and efficient system for recognizing Sinhala Sign Language.

Methodology

The Methodology applied for this study is illustrated in Figure 1 below.

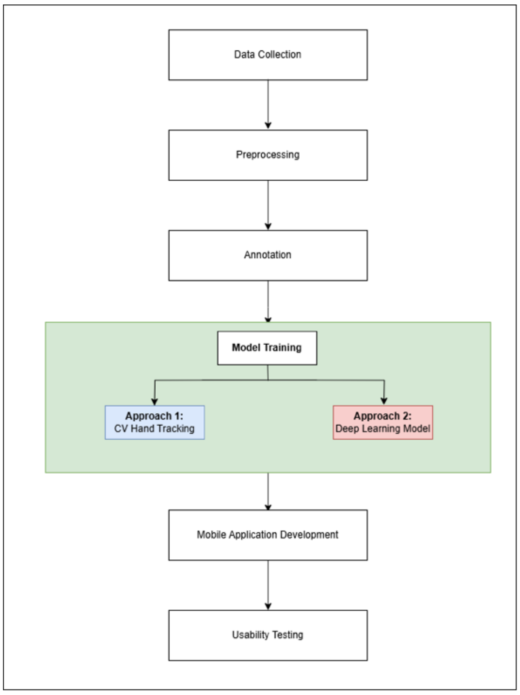

Figure 1. *Applied methodology*

Dataset

Among the various static signs in Sri Lankan sign language, nine distinct static signs (අ, ආ, ඉ, ඊ, ක්, ල්, ම්, ත්, ය්) that allows the representation of five frequently used Sinhala words such as අම්මා (mother), තාත්තා (father), අයියා (elder brother), අක්කා (elder sister) and මල්ලි (younger brother) were selected for this study. Prior to actual data collection, few authentic reference materials such as Sri Lanka Sign Dictionary, Sinhala Sign Language, and New Priorities in the Hearing-Impaired Education System were used to identify the particular static signs. For each of the selected static sign, a set of 500 images were captured using a high-quality camera generating a total of 4 500 image dataset.

Image Preprocessing

The captured images were pre-processed to have the image size of 96 x 96 as they were to be fed into a mobile application. The pre-processed dataset was split into training and test data as 85% and 15% respectively. In addition, due to the practical difficulty in handling Sinhala characters, the images were annotated with equivalent English characters as shown in Figure. 2.

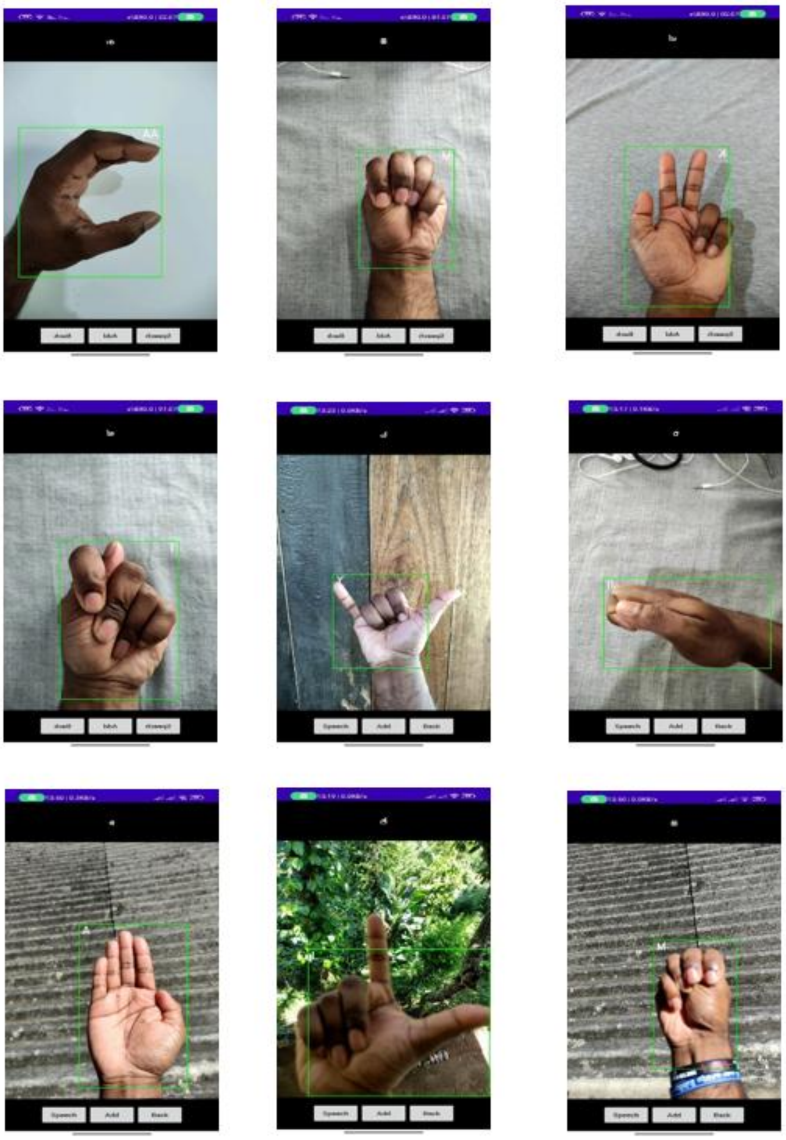

Figure 2. *Annotation of each letter with equivalent English characters*

Model Training

There were two approaches to the desired model training. One with the hand-tracking methodology and the other with the EfficientNet-B0 based gesture recognition. Despite the fact that these choices belong to two different approaches, the purpose was to ultimately identify the most feasible approach for the deployment in a light-weight mobile application.

Model 1

Model 1 was developed to recognize static signs in Sri Lankan Sign Language using CV zone hand-tracking module. This relies on detecting hand landmarks to recognize gestures using geometric and spatial relationships between hand joints. The computational complexity of this approach is significantly lower than any image-based approach (Molchanov et al., 2016).

Accordingly, this study used 21 key points on hand, which served as the basis for generating the required dataset. A dataset comprising 4500 images was created, with 500 images allocated to each of the nine static signs in Sri Lankan Sign Language. The process involved capturing images through the hand-tracking module by detecting the hand landmarks. This dataset was later augmented to provide a diverse and comprehensive representation of the nine signs for the model training. The model was subsequently trained using this dataset using theTensorFlow library.

Model 2

This model used a transfer learning approach, EfficientNet-B0 of the convolutional neural network architecture, for training the pre-processed image dataset. 28 convolutional layers were used for this training. The study at first place opts for transfer learning models since it could better suit for mobile applications and provide relatively a higher accuracy (Choe et al., 2020). Despite there are many different transfer learning models, EfficientNet-B0 was chosen due to its proven accuracy on image classification with limited computational resources (El Zein et al., 2021). In addition, it has proven computational efficiency, lower battery consumption and faster inference speeds even on smaller datasets (Hussain et al., 2023).

Model Evaluation and Mobile Application Development

The models were evaluated in terms of accuracy, efficiency and compatibility for integration into a light-weight mobile application. The model that was best suited for the mobile application was converted into a FlatBuffer file (.tflite) for integration. Android Studio was used to build the mobile application. Finally, an APK was developed, installed on a device, and tested on various lighting condition for its usability (See Figure 3).

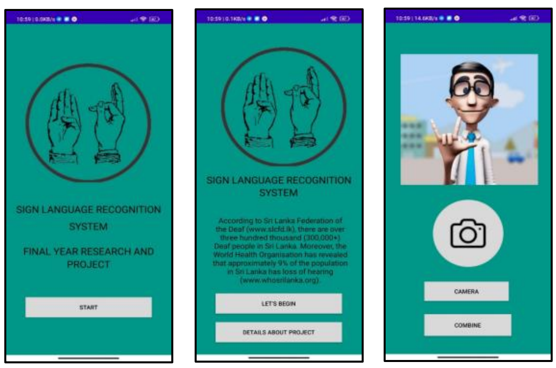

Figure 3. *Mobile Application Interface*

Results and Discussion

The developed system was tested under various lighting and background conditions, and the results are presented in Table 1.

Table 1
Model Performance Metrics (For application development)

Model	Technology	Accuracy	Mobile Application compatibility
Model 1	OpenCV TensorFlow	95%	No
Model 2	EfficientNet-B0	90%	Yes

Based on accuracy and the compatibility for mobile application, Model 2 was found to be the most suitable and integrated into the mobile application to create five words (අම්මා තාත්තා අයියා අක්කා and මල්ලි) using nine signs, initially.

The developed mobile application achieved an accuracy over 90% in recognizing the nine Sri Lankan static signs concerned in this particular study. However, under certain lighting conditions, the application produced incorrect outputs, which is a serious concern for deaf individuals who heavily rely on visual cues. Thus, in future work, it is recommended to add a module in the mobile application to preprocess the image captured to a neutral background, before interpreting the static signs. While this current study is limited to static signs, the future work would focus on dynamic sign detection based on spatiotemporal features.

Conclusion

At present, around 300,000 Sinhala-speaking individuals are either deaf or hard of hearing; However, dedicated applications for Sri Lankan Sign Language detection remains limited. This study aimed to design and develop a light-weight mobile application that can detect Sri Lankan static signs in real-time. The study employed two approaches using hand tracking and deep learning and the results indicate that the Efficient-B0 deep learning model based approach was the most suitable for the real-time sign detection due to its light-weight nature and computational efficiency. The developed mobile application has the capability of detecting five frequently used Sinhala words using nine static signs with substantial accuracy of above 90%. In addition, the study also contributes with a curated dataset of 4500 images for Sri Lankan sign language which is limited currently. Although the developed application has the limitations of poor performance in various lighting condition, the prototype can be improved to seamlessly work with more static Sinhala signs as a future work.

References

Choe, D., Choi, E., & Kim, D. K. (2020). The real-time mobile application for classifying endangered parrot species using the CNN models based on transfer learning. *Mobile Information Systems, 2020.*

Dahanayaka, D., Madhusanka, B., & Atthanayake, I. (2021). A multi-modular approach for sign language and speech recognition for deaf-mute people. *Engineer: Journal of the Institution of Engineers, Sri Lanka, 54*(9).

Dissanayake, I. S. M., Wickramanayake, P. J., Mudunkotuwa, M. A. S., & Fernando, P. W. N. (2020). Utalk: Sri Lankan sign language converter mobile app using image processing and machine learning. In *2nd International Conference on Advancements in Computing (ICAC*IEEE.

El Zein, O. M., Soliman, M. M., Elkholy, A. K., & Ghali, N. I. (2021). Transfer learning-based model for pneumonia detection in chest X-ray images. *International Journal of Intelligent Engineering & Systems, 14*(5).

Fernando, K. S. S., & Wickramarathne, H. (2018, August). Sri Lankan sign language tutor. in *1st International Conference on Business Innovation* (p. 70).

Hussain, A., Ul Amin, S., & Fayaz, M. (2023). An Efficient and Robust Hand Gesture Recognition System of Sign Language Employing Finetuned Inception-V3 and Efficientnet-B0 Network. *Computer Systems Science & Engineering*, *46*(3).

Joglekar, S., Sawant, H., Jain, A., Dhadda, P., & Sonawane, P. (2020). A multi-modular approach for gesture recognition and text formulation in American Sign Language. *International Journal of Computer Applications Technology and Research, 9*(7).

Molchanov, P., Yang, X., Gupta, S., Kim, K., Tyree, S., & Kautz, J. (2016). Online detection and classification of dynamic hand gestures with recurrent 3d convolutional neural network. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4207-4215).

Punchimudiyanse, M., & Meegama, R. G. N. (2017). Animation of fingerspelled words and number signs of the Sinhala Sign Language. *ACM Transactions on Asian and Low-Resource Language Information Processing, 16*(4).

Seymour, M., & Tšoeu, M. (2015, September). A mobile application for South African Sign Language (SASL) recognition. In *AFRICON 2015* (pp. 1-5). IEEE.

Taskiran, M., Killioglu, M., & Kahraman, N. (2018, July). A real-time system for recognition of American sign language by using deep learning. In *2018 41st international conference on telecommunications and signal processing (TSP)* (pp. 1-5). IEEE.

Tolentino, L. K. S., Juan, R. S., Thio-ac, A. C., Pamahoy, M. A. B., Forteza, J. R. R., & Garcia, X. J. O. (2019). Static sign language recognition using deep learning. *International Journal of Machine Learning and Computing*, *9*(6), 821-827.

Truong, V. N., Yang, C. K., & Tran, Q. V. (2016, October). A translator for American sign language to text and speech. In *2016 IEEE 5th Global Conference on Consumer Electronics* (pp. 1-2). IEEE.

Udugama, L. S., Nethsinghe, R., Southcott, J., Kularathna, S., Dhanapala, T. D. T., & Alwis, K. A. C. (2024). Sign language usage of deaf or hard of hearing Sri Lankans. *The Journal of Deaf Studies and Deaf Education*, *29*(2), 187-198.

Wadhawan, A., & Kumar, P. (2020). Deep learning-based sign language recognition system for static signs. *Neural computing and applications*, *32*(12), 7957-7968.

Yugopuspito, P., Murwantara, I. M., & Sean, J. (2018, November). Mobile sign language recognition for bahasa indonesia using convolutional neural network. In *Proceedings of the 16th International Conference on Advances in Mobile Computing and Multimedia* (pp. 84-91).