### CLASSIFIER FOR SINHALA FINGERSPELLING SIGN LANGUAGE

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### DECLARATION

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#### Abstract

Computer vision based sign language translation is usually based on using thousands of images or video sequences for model training. This is not an issue in the case of widely used languages such as American Sign Language. However, in case of languages with low resources such as Sinhala Sign Language, it's challenging to use similar methods for developing translators since there are no known data sets available for such studies.

In this study a sign language translation method is developed using a small data set for static signs of Sinhala Fingerspelling Alphabet. The classification model is simpler in comparison to Neural Networks based models which are used in most other sign language translation systems.

The methodology presented in this study decouples the classification step from hand pose estimation and uses postural synergies to reduce dimensionality of features. This enables the model to be successfully trained on a data set as small as 122 images. As evidenced by the experiments this method can achieve an average accuracy of over 87%. The size of the data set used is less than 12% of the size of data sets used in methods which have comparable accuracies.

Code and datasets are available at: https://github.com/aawgit/signs Keywords: Vision, Sign language, Sinhala, fingerspelling

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# Acronyms and Abbreviations

## Abbreviation Description

ASL	American Sign Language
ANN	Artificial Neural Networks
CNN	Convolutional Neural Networks
СРМ	Convolutional Pose Machine
DIP	Distal interphalangeal
DNN	Deep Neural Networks
DoF	Degree of freedom
DTW	Dynamic Time Warping
ELM	Extreme Learning Machine
FASSL	Fingerspelling Alphabet of Sinhala Sign Language
FPS	Frames per second
FV	Fisher Vector
HPT	Hyper Parameter Tuning
IP	Interphalangeal
KLT	Kanade–Lucas–Tomasi
KNN	K-Nearest Neighbour
LR	Logistic Regression
LSTM	Long Short Term Memory
MCP	Metacarpophalangeal
PCA	Principal Component Analysis
PIP	Proximal interphalangeal
RF	Random Forest
SORT	Simple Online and Realtime Tracking
SSD	Single Shot Detector
SSL	Sinhala Sign Language
ST-LSTM	Spatio-Temporal LSTM
TMC	Trapeziometacarpal