Feature Based Myanmar Fingerspelling Image Classification Using SIFT, SURF and BRIEF

Ni Htwe Aung
Department of Computer Engineering and Information Technology, Yangon Technological University, Myanmar
nhadec@gmail.com

Ye Kyaw Thu
Language and Speech Science Research Lab, Waseda University, Japan
wasedakuma@gmail.com

Su Su Maung
Department of Computer Engineering and Information Technology, Yangon Technological University, Myanmar
susuela@gmail.com

Abstract

Deaf people use Sign Language and Fingerspelling as a fundamental communication method. Fingerspelling or manual spelling is a method of spelling words using hand movements, and most often used to spell out names of people, places, organizations, books and other words for which no sign exists. In this experiment, the images for 31 static fingerspelling characters of Myanmar consonant are used as the input images. Three feature vectors extraction methods (SIFT, SURF, and BRIEF) were done separately on our collected Myanmar Sign Language (MSL) fingerspelling images. MSL fingerspelling data are classified with seven different approaches; Multilayer Perceptron, Gaussian Naïve Bays, Decision Tree, Logistic Regression, Random Forest, Support Vector Machine and K-Nearest Neighbor. In this paper, we provide the performance results of different features on different classifiers and the highest classification rate is up to 97% with SURF feature and Random Forest classifier. Moreover, 10-fold cross validation was made in our experiment and we provide the classification results for each classifier.

1. Introduction

According to the 2014 Myanmar national census, about 1.3 percent of the total population of 51.48 million in Myanmar is Deaf and hearing impairment [1]. Myanmar Sign Language is mainly used as a communication language among Myanmar Deaf people. In communicating with hearing people, deaf people face many difficulties and so they feel isolated from their surroundings because there are limited resources of information written in their languages. Since Myanmar Language is the tonal language, and Myanmar Sign Language and Myanmar written Language have different grammar structure, most of the deaf people are difficult to read or write well the Myanmar written text. Moreover, MSL fingerspelling classification system has not gained a lot of attention by researchers in Myanmar and there are very little research works that have been done on it. Therefore, we start working the image classification experiment for 31 static fingerspelling characters of Myanmar alphabets by using different Machine Learning models. In this paper, we used the Myanmar fingerspelling characters that are currently using in Mary Chapman School for the deaf, Yangon. Features of fingerspelling images are extracted by using Scale Invariant Feature Transform (SIFT), Speeded Up Robust Feature (SURF), and Binary Robust Independent Elementary Features (BRIEF). The extracted features of Myanmar fingerspelling images are classified by using seven classifiers which are well-known in image classification; Multilayer Perceptron (MLP), Gaussian Naïve Bays, Decision Tree, Logistic Regression, Random Forest, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN).

2. Sign Language

A sign is a form of non-verbal communication done by using body parts, hand shapes, positions and movements of the hand, arms, facial expressions or movements of the lips and used instead of oral communication. A sign language is a type of language that uses signs or action to communicate instead of sounds [2]. Sign Language (SL) is a visual language because it is based on the vision as the most powerful tool that a deaf person has to communicate other. SL is not a universal language because different sign languages are used in different countries. Sign languages are genuine languages with their own grammar. The grammar of sign language is very different from the grammars of spoken languages [3].

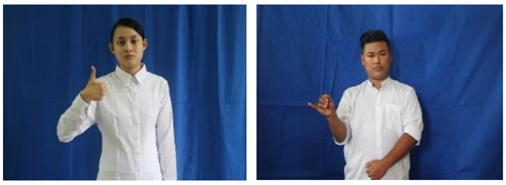
A sign language contains three major components [2]. The first major component is fingerspelling which means for each letter of the alphabet there is a corresponding sign. This type of communication is mainly used for spelling names of people, places, organizations, and other words for which no signs exist or for emphasizing or clarifying a particular word [4]. The second essential component of any sign language is word level sign vocabulary which means for each word of the vocabulary there is a corresponding associated sign in the sign language. The most commonly used type of communication between people with hearing disabilities in combination with the facial expression is this type. The third essential component in sign communication is non-manual-features. This type of communication involves facial expressions, tongue, mouth, eyebrows and body position.

2.1. Myanmar Sign Language

Myanmar Sign Language is mainly used by Myanmar Deaf people and it is a very important part in Myanmar deaf culture. MSL has different grammatical structure from Myanmar language. Like other sign languages, MSL is constructed with two structures of sign: manual sign (MS) and non-manual sign (NMS). The manual sign is a combination of hand shape, hand position and hand movement to represent meaning. The non-manual sign comprises movement of head, tension and slack, movement of upper part of body, eyebrows, eyelid and mouth gesture without including hands to give meaning and feeling [5]. There are four deaf schools in Myanmar: "Mary Chapman School for the Deaf in Yangon," "School for the Deaf, Mandalay," "Immanuel School for the Deaf in Kalay" and "School for the Deaf, Tamwe, Yangon". MSL used in each region are not the same. In 2010, a government project was set up to establish a national sign language with the aid of the Japanese Federation of the Deaf.

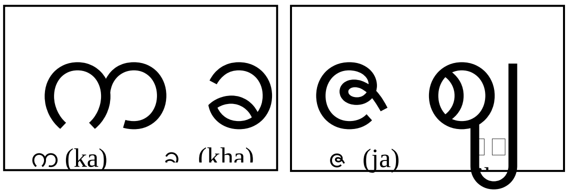
2.2. Myanmar Fingerspelling

Myanmar fingerspelling is the basic part of Myanmar Sign Language for the deaf people and it is used to represent Myanmar consonant, vowels and numbers with hands. Moreover, it is mainly used to spell out names of people, cities, places, organizations, and other words for which no sign exists in sign language. Sometimes, fingerspelling is used in combination with existing signs to clearly express the concept or meaning. There are two different fingerspelling character sets for Myanmar Sign Language: one is used in southern Myanmar (e.g. used at "Mary Chapman School for the Deaf", Yangon) and another is used in northern Myanmar (e.g. used at "Mandalay School for the Deaf", Mandalay). They are similar in consonant but mainly different in vowels, medial and symbol [6]. Only focuses on 33 Myanmar consonant fingerspelling characters, twelve of them are different between Mary Chapman School for the Deaf and Mandalay Deaf School. Figure 1 shows an example of Myanmar fingerspelling character difference between Mary Chapman School and Mandalay School. Signs used in Mary Chapman were invented by Dr. Maliwan Tammasaeng in collaboration with Myanmar Sign Language teachers and students in 1987 [7]. MSL fingerspelling also consists of two forms: static, which represents a single image and dynamic, which represents a series of images [8]. Figure 2 shows an example of static and dynamic MSL fingerspelling characters.



Mary Chapman Sign of ဋ (tta)   Mandalay Sign of ဋ (tta)

Figure 1. An example of MSL fingerspelling character difference between Mary Chapman School and Mandalay School



(a)   (b)

Figure 2. An example of (a) static and (b) dynamic MSL fingerspelling character (Used mmFingerspelling.ttf developed by Dr. Ye Kyaw Thu [9])

3. Related Work

The first Myanmar Fingerspelling Recognition System was developed by Wah Wah et al. [10]. This system only focused on 30 static and opened fingerspelling characters of Myanmar alphabets. The images used in this system are bare-handed images. The system used a data set of 2,700 hand gesture images. They used five different operations in the preprocessing step. They are image filtering, skin detection, grayscale conversion, image segmentation and image resizing. They contributed the modified Canny edge detection for feature extraction. They developed the system using Artificial Neural Network (ANN) for 1,500 training images and 1,200 testing images. The system gave the accuracy result of 96% recognition rate. They implemented the system by using MATLAB Programming Language.

4. Data Sets

In our experiment, we collect fingerspelling images that contain the upper part of the human body acted by 11 deaf signers in Mary Chapman School for the Deaf, Yangon. We use both male and female deaf signers who have age between 12 and 25. In this work, the fingerspelling images are captured without the aid of any data gloves or wearable tracking devices or special markers like other systems. The input images have been captured using a simple 2D digital camera; each one of them has a size of 1,920 x 1,080 pixels. All images capturing is done in in-door environments with two different backgrounds; white background and blue background under normal lighting conditions. The system has used the total of 24,713 fingerspelling images.

5. Experimental Setup

5.1. Preprocessing

Among 33 Myanmar Fingerspelling characters, 31 characters that are using in Mary Chapman School for the Deaf (Yangon) are used in this experiment. These 31 signs are static and other two signs (ဇ , ဈ) are dynamic. All collected videos are converted to multiple image frames and then resize these images to 128x128 dimensions. Then the resized images are converted into grayscale images.

5.2. Feature Extraction

Feature extraction plays an important role in the area of computer vision and image processing. The main step of feature extraction is to convert the raw data information into relevant representations (feature vectors) [11]. These feature vectors are used to train and test the classifiers in order to classify the input image data. In this paper, three feature extraction methods are done separately on the grayscale images. SIFT algorithm extracts 128 feature vectors from each grayscale image. SURF algorithm extracts 64 feature vectors and BRIEF algorithm extracts 2,048 feature vectors. We apply these extracted features to train and test the classifiers discussed in Section 6. The details of three feature extraction methods used in our experiment are discussed in the following subsections.

5.2.1. Scale Invariant Feature Transform (SIFT)

In 2004, David G. Lowe, University of British Columbia, developed a new algorithm, Scale Invariant Feature Transform (SIFT), which extract keypoints and compute its descriptors [12]. SIFT transforms image data into scale-invariant coordinates relevant to local features. It generates a large numbers of features that densely cover the image over the full range of scales and locations. SIFT takes basically 512 bytes because it uses 128 dim-vectors for descriptors and using floating point numbers.

There are four main steps involved in SIFT algorithm.

i. **Scale-space extrema detection:** Firstly, the algorithm searches over all scales and image locations. By using a difference-of-Gaussian (DoG) function, it can be efficiently identified the points of interest, which are termed keypoints, that are invariant to scale and orientation.

ii. **Keypoint localization:** At this stage, some keypoints are eliminated from the candidate list of keypoints which have low contrast or are poorly localized on an edge [12]. The algorithm performs a detailed model fit at each candidate location to determine accurate location and scale.

iii. **Orientation assignment:** It assigns one or more orientations to each keypoint to achieve invariance to rotation based on local image gradient directions. An orientation histogram is formed from the gradient orientations of sample points on the image data. Once the histogram is filled, the orientations corresponding to the highest peak and local peaks that are within 80% of the highest peaks are taken and an additional keypoints are created having same location and scale but difference in directions.

iv. **Keypoint descriptor:** It measures the local image gradients at the selected scale in the region around each keypoint. These keypoints are transformed into a representation that allows for significant levels of local shape distortion and change in illumination.

5.2.2. Speeded Up Robust Features (SURF)

In 2006, Bay, H., Tuytelaars, T. and Van Gool, L, published "SURF: Speeded Up Robust Features" which introduced a new algorithm called SURF [13]. SURF algorithm is based on the same principles and steps as SIFT, but SURF is faster than SIFT and details in each step are different. SURF is a framework, which is used to improve the performance of object recognition system. SURF uses an integer approximation of the determinant of Hessian matrix to detect interest points. SURF uses 64 dim-vectors for descriptors and therefore it takes minimum of 256 bytes. Using this algorithm, a set of feature pairs between the query image and each individual database image can be generated. SURF algorithm has powerful attributes, such as scaling, translation, lighting and rotation invariance [14]. Moreover, the algorithm used only 64 dimensions, so it can reduce the time for feature computation and matching, and can increase simultaneously the robustness. SURF is good for handling images with blurring and rotation, but not good for handling images with viewpoint change and illumination change.

5.2.3. Binary Robust Independent Elementary Features (BRIEF)

BRIEF is a compact and easy-computed method to find the binary strings directly without finding descriptors. It takes smoothened image patch and selects a set of n_d (**x,y**) location pairs and then compares some pixel intensity on these location pairs. It is faster than other descriptors in matching using Hamming distance [15]. BRIEF is a general-purpose feature descriptor which cannot detect the keypoints by itself, so it is needed to use in conjunction with any other feature detectors like SIFT, SURF etc. Moreover, BRIEF is more sensitive to image distortions and transformations because it is not designed to be rotationally invariant. In our experiment, 2,048 feature vectors are extracted from each image using BRIEF algorithm.

6. Classification

Classification is a supervised learning approach in which the classifier model learns from the input data and then uses this model to classify new data. There are many types of classification algorithms such as Linear Classifiers (e.g., Logistic Regression, Naïve Bayes Classifier), Support Vector Machines, Decision Trees, Random Forest, Nearest Neighbor, Neural Networks and so on. In our experiment, we use seven classifiers to classify each of the three features (discussed in Section 5) extracted from Myanmar fingerspelling images.

6.1. Multilayer Perceptron (MLP)

A multilayer perceptron is a class of feed-forward artificial neural network that generates a set of outputs from a set of inputs [16]. An MLP consists of three layers of nodes: an input layer to receive the signal, a hidden layer and an output layer that makes a decision or prediction about the input [17]. MLP is widely used for solving problems that require supervised learning as well as research into computational neuroscience and parallel distributed processing. Applications include speech recognition, image recognition and machine translation.

6.2. Gaussian Naive Bays

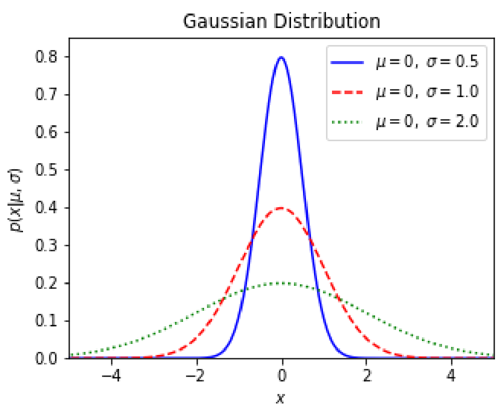


Figure 3. Gaussian Distribution for various σ

Gaussian classifier is based on a Bayesian methodology. It can be used to characterize a group of feature vectors of any number of dimensions with two values: a mean vector and a covariance matrix. The Gaussian model can be used to find the probability of any unknown vector and this unknown vector can be assigned to the model which provides the highest probability [18]. Figure 3 shows how various standard deviations determine the width of the distribution.

6.3. Decision Tree

Decision tree is one of the most popular machine learning algorithms and can be used for both classification and regression problems. It is also a frequency-based algorithm which is computationally faster. It is easily interpretable and can be converted to rules. The main idea of this algorithm is to solve the problems by using tree representation [19]. Each internal (non-leaf) node of the tree represents a feature, each branch represents a decision (rule) and each leaf (or terminal) node represents a class label (outcome) [20]. To estimate the information contained by each attribute, decision tree uses the information gain as a criterion. Deep decision trees may suffer from overfitting. This is due to the amount of specificity leading to smaller sample of events that meet the previous assumptions. This small sample could lead to unsound conclusions. However, decision tree does not require much of data preprocessing and any assumptions of distribution of data.

6.4. Logistic Regression

Logistic regression is a type of Linear Classifiers. It is also the most famous multivariable algorithm that analyzes the relationship between multiple independent variables (features) and multiple dependent variables (labels). It uses the logistic sigmoid function to predict the probability of occurrence of an event [21]. The sigmoid function is the S-shaped curve that takes the real-valued number between 0 and 1. Figure 4 shows the steps that the logistic regression works to get the desired output.

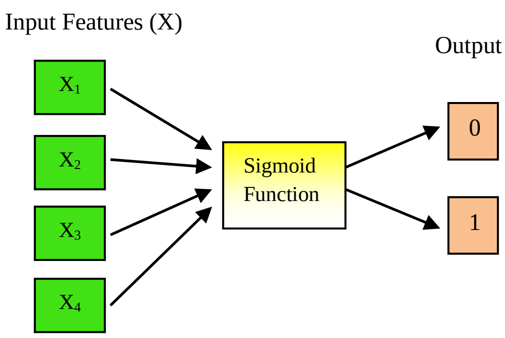


Figure 4. Logistic Regression Algorithm

6.5. Random Forest

Random forest is a flexible and easy to use algorithm which can be used for classification and regression. Random forest collects decision trees on randomly selected data samples and these trees work in parallel to get prediction [22]. Then the random forest works as an ensemble model to select the best final prediction result by means of voting. Figure 5 shows how the random forest classifier works to get the predicted value. Random forest can be considered as a highly accurate and robust method and it cannot suffer from the overfitting problem because it takes the average of all predictions. Random forest can also handle the missing values with two ways: using median values to replace continuous variables, and computing the proximity-weighted average of missing values.

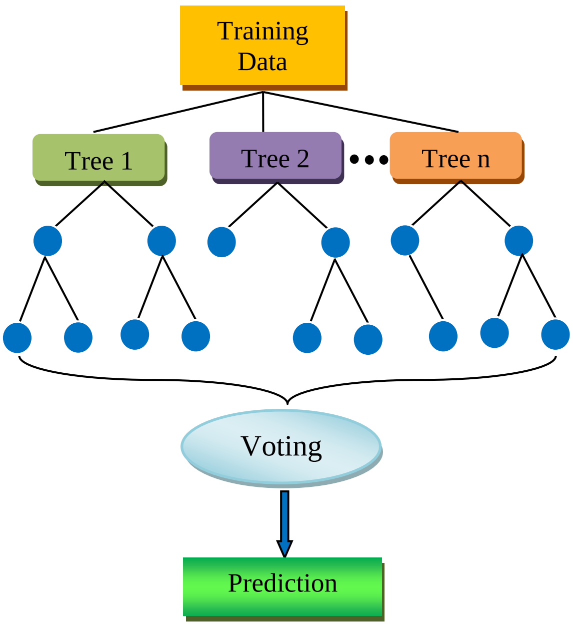


Figure 5. Example of Random Forest Classifier

6.6. Support Vector Machine (SVM)

SVM constructs a set of separating hyperplanes in a high dimensional space, which is use for classification, regression and outliers detection. The good separation can be achieved by the hyperplane as shown in figure 6. It uses non-parametric with binary classifier approach and handles more input data efficiently. SVM is effective in high dimensional spaces and also memory efficient because a subset of training points in the support vectors (also called decision function) is used. If the two label classes are needed to classify, SVM performs by finding a line/hyperplane that can fairly separate the two classes as shown in figure 6. To identify the right hyperplane, SVM maximizes the distance (also called margin) between nearest data points in each class. It separates the points on left of the line into red triangle class and points on the right into the blue square class. Accuracy depends on hyperplane selection. The structure of the SVM algorithm is more complicated than other methods. This gives the low result transparency [23].

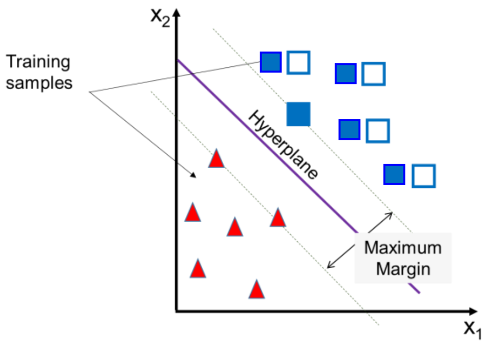


Figure 6. Optimal separating hyperplane *maximizes* the margin of the training data

6.7. K-Nearest Neighbor (KNN)

K nearest neighbors is a simple algorithm that stores all available cases and classifies the new cases based on the similarity measure (e.g., distance functions). In the beginning of 1970's, KNN has been used in statistical estimation and pattern recognition as a non-parametric technique [24]. It is useful for both classification and regression predictive problems. In classification, an object is classified by a majority poll of its neighbors, with the object being assigned to the class most common among its k nearest neighbors [25]. It is commonly used because of its easy of interpretation and low calculation time. In figure 7, the test sample (**green circle**) should be classified either to the first class of **dog** or to the second class of **cat**. If k = 3 (solid line circle) it is assigned as dog because there are 2 classes of dog and only 1 class of cat inside the inner circle. If $k = 5$ (dashed line circle) it is assigned as the cat (3 cats and 2 dogs inside the dashed line circle).

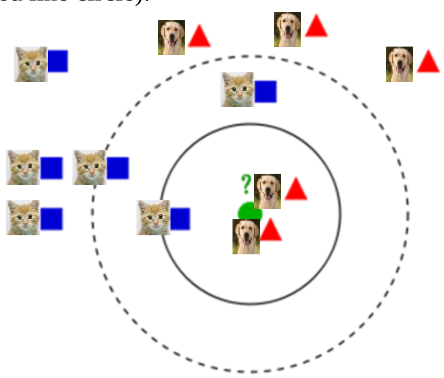


Figure 7. Example of KNN classifier

7. Results and Discussion

For 31 Myanmar Fingerspelling images, 16,557 images are used for training the model and the remaining 8,156 images are used for testing in classification phase. Accuracy is calculated as the ratio of successful recognition of sample images to the number of samples used for testing in classification. Accuracy of classification rate for each classifier with different features is shown in Table 1. Bold numbers in Table 1 indicate the highest accuracy percentage of each feature extraction method. According to Table 1, MLP and Gaussian Naïve Bayes classifiers can give the prediction accuracy lower than 50% for all feature extraction methods. Logistic regression and SVM models give the very low accuracy results for SURF features and up to 80% recognition rate for BRIEF features. For SIFT features, although SVM model get 90% accuracy, Logistic regression get 65% accuracy result. Through the experiments, SIFT algorithm works well for random forest and KNN classifiers. SURF features effectively work and give the high accuracy for random forest and KNN classifiers according to Table 1. Using BRIEF features, the comparable accuracy scores can be provided by using decision tree, random forest, SVM and KNN classifiers. Among all classifiers, random forest classifier model give the highest accuracy score of up to 97% for all feature extraction methods as shown in Table 1.

In our experiment, 10-fold cross validation for each classifier was made in order to train and test the model 10-times on different subsets of training data and build up an estimate of the model performance on unseen data. This is used to flag problems like overfitting and to derive a more accuracy of model prediction performance.

Table 1. Accuracy in percentages on different classifiers with different features

Classifiers	Feature Extraction Methods		
	SIFT	**SURF**	**BRIEF**
MLP	25%	24%	5%
Gaussian	26%	12%	48%
Decision Tree	89%	92%	78%
Logistic Regression	65%	15%	73%
Random Forest	**95%**	**97%**	**81%**
SVM	90%	14%	80%

KNN	94%	96%	**81%**

Accuracy of 10-fold results for each classifier with SIFT features is graphically represented in figure 8. According to figure 8, random forest classifier gives the highest accuracy score although the accuracy scores are very low in MLP and Gaussian Naïve Bayes models. Decision Tree, SVM and KNN classifiers give the comparable accuracy scores around 90% in 10-fold cross validation for SIFT features.

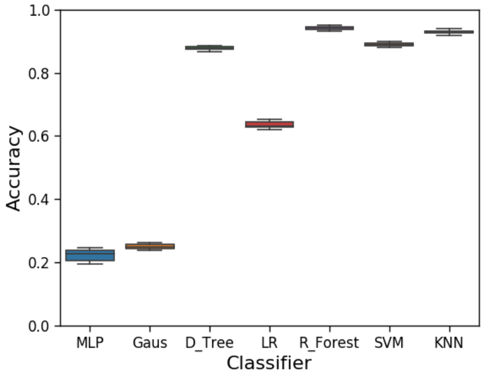


Figure 8. Accuracy of 10-fold cross validation on different classifiers using SIFT feature extraction method

Figure 9 illustrates the 10-fold cross validation result for each classifier using SURF features. Although the scores for MLP, Gaussian Naïve Bayes, logistic regression and SVM models are very low, the scores of decision tree, random forest and KNN classifiers achieved above 90% as shown in figure 9.

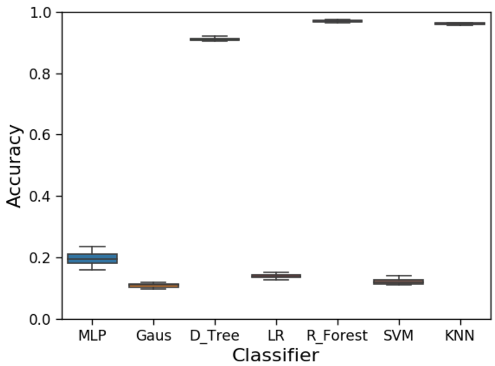


Figure 9. Accuracy of 10-fold cross validation on different classifiers using SURF feature extraction method

For BRIEF features, only MLP and Gaussian classifier get the low accuracy but Decision Tree, Random Forest, SVM and KNN classifiers give the comparable accuracy scores around 80% as shown in figure 10. Logistic Regression classifier gets the accuracy score of above 70% for BRIEF features.

According to figures 8, 9, and 10, it can be concluded that Random Forest classifier can give better results for all feature extraction methods that used in our experiment.

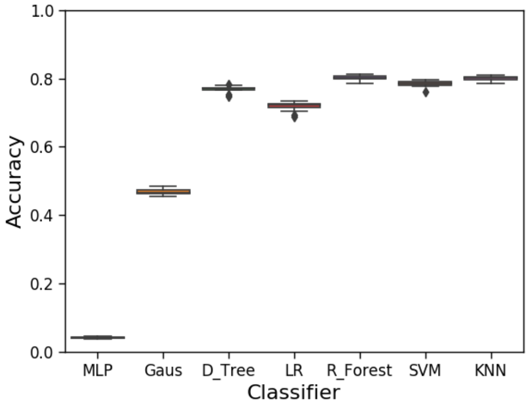


Figure 10. Accuracy of 10-fold cross validation on different classifiers using BRIEF feature extraction method

8. Conclusion & Future Works

Our experimental results show that the system is capable of classifying 31 Myanmar Fingerspelling characters effectively with very few image processing steps (only two stages are used) and no need for other image enhancement techniques. Moreover, any special expensive hardware such as gloves or sensors are not needed for our system and web camera can be used for real time processing. Feature extraction methods used in our experiment can effectively be classified with high accuracy scores in some classifiers (Decision Tree, Random Forest and KNN) used in our experiment. In Myanmar, fingerspelling recognition system is needed for deaf people to communicate with ordinary people. We plan to make a real time Myanmar fingerspelling recognition system for all Myanmar fingerspelling characters including (both static and dynamic) consonant, vowels, numbers and symbols by applying deep neural network.

Acknowledgement

We would like to thank the headmaster, teachers and students from Mary Chapman School for the Deaf, Yangon and all participants for their kind contributions to our research input experiments. We would like to thank JICA EEHE Project (Project for

Enhancement of Engineering Higher Education in Myanmar) for their supporting of research fund to our research.

References

[1] "The 2014 Myanmar Population and Housing Census", The Union Report, Census Report Volume 2, Page [26], Department of Population, Ministry of Immigration and Population, May 2015

[2] Ilan Steinberg, Tomer M. London, Dotan Di Castro, *"Hand Gesture Recognition in Images and Video"*, Technion-Israel Institute of Technology, 2003

[3] *https://en.m.wikipedia.org/wiki/Sign_language*; Nature of Sign Language

[4] Adithya V., Vinod P., Usha Gopalakrishnan, *"Artificial Neural Network Based Method for Indian Sign Language Recognition"*, IEEE Conference on Information and Communication Technologies (ICT 2013), JeJu Island, pp. 1080-1085, April 2013.

[5] Myanmar Sign Language Basic Conversation Book

[6] *"Text book of Speaking and Myanmar Sign Communication"*, Mary Chapman School for the Deaf, 1988

[7] *https://en.m.wikipedia.org/wiki/Burmese_Sign_language*; Nature of Myanmar Sign Language

[8] *https://en.m.wikipedia.org/wiki/Fingerspelling*; Structure of Fingerspelling

[9] Ye Kyaw Thu, S. A. W. M. and URANO, Y. *"Direct Keyboard Mapping (DKM) Layout for Myanmar Fingerspelling Text Input (study with Developed Fingerspelling Font)"*

[10] *"Myanmar Sign Language Recognition System Using Artificial Neural Network"*, Wah Wah, December, 2014

[11] *"A Detailed Review of Feature Extraction in Image Processing Systems"*, Gaurav Kumar, Panipat, Haryana, India, er.gkgupta@gmail.com, Pradeep Kumar Bhatia, Hisar, Haryana, India, pkbhatia.gju@gmail.com, Fourth International Conference on Advanced Computing and Communication Technologies, 2014

[12] *"Distinctive Image Features from Scale-Invariant Keypoints"*, David G. Lowe, Computer Science Department, University of British Columbia, Vancouver, B.C., Canada, lowe@cs.ubc.ca, January 5, 2004

[13] *"SURF: Speeded Up Robust Features"*, Herbert Bay, Tinne Tuytelaars, and Luc Van Gool, ETH Zurich, {bay, vangool} @vision.ee.ethz.ch, Katholieke Universiteit Leuven, {Tinne.Tuytelaars, Luc.Vangool}@esat.kuleuven.be

[14] Swapnali B.,Vijay K.,Varsha H., *"Feature based object detection scheme"*, Techno vision International Conf.,2014

[15] *"BRIEF: Binary Robust Independent Elementary Features"*, Michael Calonder, Vincent Lepetit, Christoph Strecha, and Pascal Fua, 11th European Conference on Computer Vision (ECCV), Heraklion, Crete. LNCS Springer, September 2010

[16] *"Multilayer Perceptron: Architecture Optimization and Training"*, Hassan Ramchoun, Mohammed Amine Janati Idrissi, Youssef Ghanou, Mohamed Ettaouil, Modeling and Scientific Computing Laboratory, Faculty of Science and Technology, University Sidi Mohammed Ben Abdellah, Fez, Morocco, International Journal of Interactive Multimedia and Artificial Intelligence, Vol.4, No 1, 2016

[17] *https://skymind.ai/wiki/multilayer-perceptron*; Multilayer perceptron

[18] *"A Survey on Image Classification Methods and Techniques for Improving Accuracy"*, R.R Darlin Nisha, V.Gowri, Department of Computer Science and Engineering, SNS College of Engineering, International Journal of Advanced Research in Computer Engineering & Technology (IJARCET) _ Volume 3, Issue 1, January 2014

[19] *"A Survey on Decision Tree Algorithms of Classification in Data Mining"*, Himani Sharma[1], Sunil Kumar[2], 1M.Tech Student, 2 Assistant Professor, Department of computer Science, SRM University, Chennai, India ; International Journal of Science and Research (IJSR) , ISSN (Online): 2319-7064, Index Copernicus Value (2013): 6.14 | Impact Factor (2015): 6.391

[20] *"Chapter 9: Decision Trees"*, Lior Rokach,Oded Maimon, liorr@eng.tau.ac.il, maimon@eng.tau.ac.il, Department of Industrial Engineering, Tel-Aviv University

[21] "*An Introduction to Logistic Regression: From Basic Concepts to Interpretation with Particular Attention to Nursing Domain"*, Park, Hyeoun-Ae, J Korean Acad Nurs, Vol.43, No.2, April-2013

[22] *"Random Forest"*, Leo Breiman, Statistic Department, University of California, Berkeley, CA 94720, January, 2001

[23] "*Survey On Image Classification Methods In Image Processing"*, Chaitali Dhaware, Mrs. K. H. Wanjale, International Journal of Computer Science Trends and Technology (IJCST) – Volume 4 Issue 3, May - Jun 216

[24]*https://www.saedsayad.com/k_nearest_neighbors.htm*; k Nearest Neighbor Classifier
[25] *https://medium.com/@adi.bronshtein/a-quick-introduction-to-k-nearest-neighbors-algorithm-62214cea29c7*, k Nearest Neighbor algorithm