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Comparing Classification Algorithms on Sign Language Recognition

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Abstract

This work is proposed to shows the results various classifier techniques, For the most part of the Deep Learning and Machine Learning-based classifiers were used to distinctive the different gesture languages and this study is proposed to present the best classifier model to Characteristically sign language recognition (SLR), it is essentially utilized as a middle between normal individuals and individuals with inabilities We concentrate mainly on American sign language recognition techniques. Various classifiers like CNN, SVM, KNN, were development to the SLR system. Every classifier shows accuracy of recognition; we noticed the classifiers of deep learning executed the best recognition result as differentiated to different kinds of classifiers.

Keywords: CNN, SVM, KNN, Sign Language, Deep Learning, Machine Learning;

1. Introduction

Human existence without communication is exceptionally difficult to live. Various ways are utilized to impart and share their thoughts among sender and recipient. Discourse and Gesture are the most normal approaches to convey. Communication in audible method is called discourse and perceived through hearing. On the other hand, communication using body movement parts like hand and expressions of facial is called Gesture. Communication through signing is Gesture language that is gotten and perceived through the force of vision. Ordinary individuals have the alternative to utilize gesture-based communication yet hard of hearing individuals utilize communication through signing as the essential language. There are "7099" communicated in dialects on the planet and "142" sign dialects utilized by handicapped

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individuals (Ehnolgue, 2018). Table 1 show research in different gesture-based communication translation.

TABLE I. VARIOUS SIGN LANGUAGES AND THEIR COUNTRIES

Sign Language	**Country**
British Sign Language	United Kingdom (Elliott,2000)
Spanish Sign Language	Spain (. San-Segundo et al., 2008)
American Sign Language	United State of America (Vijayalakshmi and Aarthi, 2016)
Mexican Sign Language	Mexico (Caballero-Morales and TrujilloRomero, 2012)
Arabic Sign Language	Arab Middle East (Halawani et al., 2013)
Greek Sign Language	Greece (Karpouzis etal., 2007)
Indian Sign Language	India (Vij and Kumar, 2016)

In fact, sign language not a universal language, it different from country to country. Sign of same letter can be performed distinctively in different sign language. For example, letter ‘A’ its present with the single hand in American sign language while Hindi sign language used two hand for same letter. Gesture based communication is a significant tool to overcome any barrier between individuals who can't hear and the people who can hear. Gesture based communication isn't just utilized by hearing the disabled individual, be that as it may, it is additionally utilized by the parent(s) of a hard of hearing youngster, offspring of the hard of hearing individual, instructor of the hard of hearing understudy thus numerous another space of correspondence with hard of hearing (Dasgupta and Basu, 2008). The recognition of sign language is a collaborative research area includes computer vision, natural language processing, pattern matching and linguistics. Its objective is to develop various logarithms and techniques to identify the signs and retrieve the meaning. In sign language recognition systems, there are two main approaches: (a) sensor-based and (b) image-based. The main advantage of image-based systems the user does not need to wear any devices, but this approach needs many computations in the pre-processing the images, also need some set of constraints such background color, illumination, surrounding environment and skin color (Kausar and Javed, 2011). In fact, there are many methods and techniques used to recognize sign language. Machine learning has been used and it has given good results, such as the Support Vector Machine (SVM) and Key Nearest neighbour (KNN) algorithm, and then the deep learning method, which has very excellent results as it is characterized by many layers for feature extraction. Especially when the data set size is very large, examples of deep learning algorithms are Convolution Neural Network (CNN), and Recurrent Neural Network (RNN) and others. In this research paper, we made a comparison between several of the previously mentioned algorithms to recognize the American Sign Language. The results of the comparison will be analysed in the coming sections. The figure below shows the American Sign Language alphabet.

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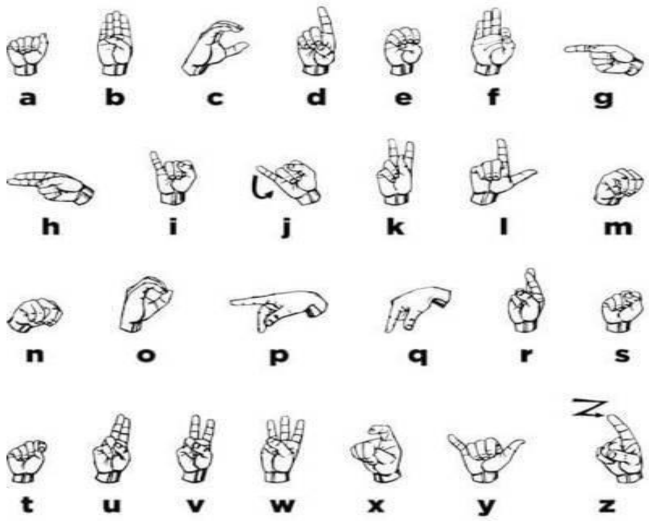

Fig. 1. American Sign Language alphabet

2. Machine Learning

Machine Learning (ML) is a part of Artificial Intelligent and is closely related to (and regularly covers with) computational statistics, which also interest on prediction making using PCs. It has robust ties to mathematical optimization, which conveys techniques, theory and application areas to the field. ML is relatively conflated with data mining (Louridas and **Ebert**, 2016), yet the last subfield interest more on data analysis exploratory and is known as unsupervised learning. ML can also be unsupervised and be used to learn and establish baseline pattern profiles for different afterward used to discover significant oddities (Jordan and Mitchell, 2015) . The pioneer of ML, Arthur Samuel, defined ML as a “field of study that gives computers the ability to learn without being explicitly programmed.” ML primarily centers on classification and regression based on known features previously teaches from the training data.

2.1 Support Vector Machine Classifier

Support Vector Machine (SVM) is one of the most strong and accurate techniques in all machine-learning algorithms. It principally incorporates Support Vector Classification (SVC) and Support Vector Regression (SVR). The SVC is depending on the idea of decision boundaries. A decision boundary separates a set of instances having different class values between two gatherings. The SVC upholds both double and multiclass classifications. The help vector is the nearest point the partition hyperplane which decides the ideal partition hyperplane. In the classification process, the mapping input vectors located on the separation hyperplane side of the feature space fall into one category, and the positions fall into the other class on the other side of the plane. In the instance of data points that are not linearly separable, the SVM utilizes proper kernel functions to map them into higher dimensional spaces so they become detachable in those spaces (Kotpalliwar and R. Wajgi, 2015).

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2.2 K-Nearest Neighbor Classifier

The kNN classifier is depends on a distance function that measures the distinction or closeness between two occasions. The standard Euclidean distance d (x, y) between two instances x and y defined as:

$$d(x,y)=\sqrt{\sum_{k=1}^{n}(x_k-y_k)^2} \qquad (1)$$

where, xk is the k th featured element of instance x, yk is the k th featured element of the instance y and n is the total number of features in the dataset.
Assume that the design set for kNN classifier is U. The total number of samples in the design set is S. Let C = {C1, C2 …CL} are the L independent class labels that are available in S. Let x be an input vector for which the class label must be predicted. Let yk denote the k th vector in the design set S. The kNN algorithm is to find the k nearest vectors in design set S to input vector x. Then the input vector x is classified to class Cj if the majority of the k closest vectors have their class as Cj (Sharifi et al., 2015).

3. Deep Learning

As of late, fundamental AI approaches have been generally supplanted with more profound models that utilize several layers and pass data in vector design between layers, continuously refining the assessment until a positive acknowledgment is accomplished. Such algorithms are normally portrayed as "deep learning" frameworks or deep neural networks, and they work on standards like the ML systems depicted above, even though with far more prominent intricacy. given of the construction of the network, two algorithms are generally utilized for various undertakings: Convolutional Neural Networks (CNNs) that incorporate at least one convolutional layer, and Recurrent Neural Networks (RNNs) that include at least one recurrent layer. Contingent upon the number, what's more, sort of layers, these networks can display various properties and are for the most part reasonable for various kinds of assignments, while the training stage definitively impacts the efficiency of the algorithm The general standard is that larger and more specific datasets consider more powerful network training, and in this way, the nature of the training set is a significant factor. Extra tweaking of a model can generally be accomplished by changing a portion of the relevant hyperparameters that characterize the training method (LeCun et al., 2015).

3.1 Convolution Neural Network Classifier

CNN architectures for classification and features extraction. In CNN models, the first set of layers includes low-level properties which include most of the essential information about edges. And second one deeper than first one, and so on. A fully connected layer neurons is added to the convolutional layers to collect the extracted features from the convolutional layers. different fully connected layer features for best recognition results. After extractions, all features for each image by CNN deep layers Classification stage is realized with dense/fully connected layers followed by functions of activation. Lastly, the SoftMax regression is employed to classify each category throughout the ultimate part of the model. that's a generalization of bringing regression in so far because it will be enforced to continuous data

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(rather than binary classification) which might represent multiple decision boundaries, it contracts with multinomial labelling.

4. Our Proposed Comparative and Evaluation the Result

In our proposed comparison, we compared the three most powerful algorithms in machine learning and deep learning, SVM and KNN from machine learning and CNN from deep learning. The three algorithms were applied to recognize American Sign Language, a dataset which consists of 25 classes of sign characters, The training data (30,357 image) and test data (8074 image) , the total of data set (38,431) image that equal approximately 1537 image for each class. the multiple users represented the data and repeating the sign against variety backgrounds. all the images of the dataset equal to 28 × 28× 1.After pre-processing procedures for data set, we have applied the three algorithms separately in order to recognize the American Sign Language, and the results were different When we used the SVM algorithm, the result was 100%, when using KN, the result was 99%, and when using CNN, the result was 100%.The following figures show the results obtained, But we noticed that when we increased the data set size , the CNN algorithm gave better results than the rest of the algorithms.

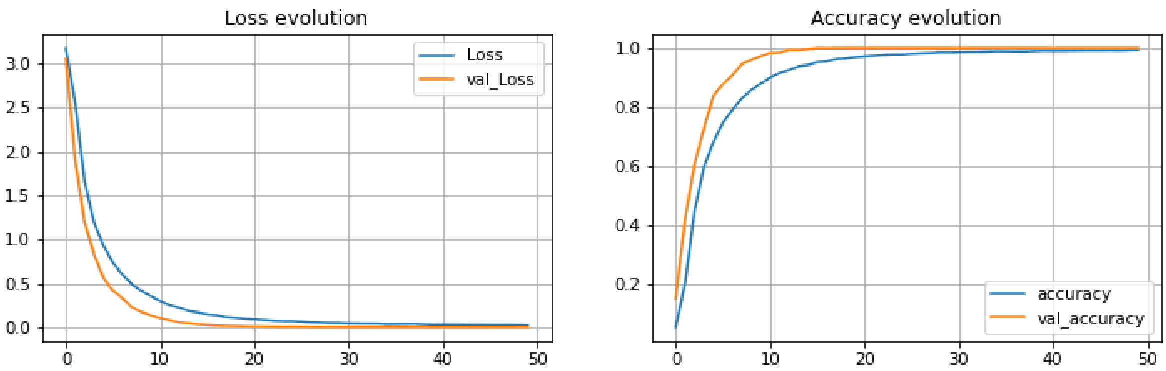

Fig. 2. Accuracy and loss evolution of CNN Classifier

14	1.00	1.00	1.00	280
15	1.00	1.00	1.00	253
16	1.00	1.00	1.00	266
17	1.00	1.00	1.00	282
18	1.00	1.00	1.00	264
19	1.00	1.00	1.00	252
20	1.00	1.00	1.00	255
21	1.00	1.00	1.00	228
22	1.00	1.00	1.00	256
23	1.00	1.00	1.00	257
24	1.00	1.00	1.00	250
accuracy			1.00	6072
macro avg	1.00	1.00	1.00	6072
weighted avg	1.00	1.00	1.00	6072

Fig. 3. Confusion Matrix of SVM Classifier

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[16]

0	1.00	1.00	1.00	254
1	0.99	1.00	1.00	212
2	1.00	1.00	1.00	257
3	1.00	1.00	1.00	277
4	1.00	1.00	1.00	202
5	1.00	1.00	1.00	254
6	1.00	1.00	1.00	255
7	1.00	1.00	1.00	221
8	1.00	1.00	1.00	268
10	1.00	1.00	1.00	240
11	1.00	1.00	1.00	281
12	0.99	1.00	0.99	234
13	1.00	0.99	0.99	274
14	1.00	1.00	1.00	280
15	1.00	1.00	1.00	253
16	1.00	1.00	1.00	266
17	0.99	0.99	0.99	282
18	1.00	1.00	1.00	264
19	1.00	1.00	1.00	252
20	0.98	0.99	0.99	255
21	1.00	0.98	0.99	228
22	1.00	0.99	0.99	256
23	1.00	1.00	1.00	257
24	1.00	1.00	1.00	250

Fig. 4. Confusion Matrix of KNN Classifier

5. Conclusion

In this study, we have compared the classification algorithms of machine learning and deep learning to classify American Sign Language. This proposed study is performed to represent the best classifier based on sign language recognition; The full operations and performances complete on sign language recognition are represented based on the classifiers of deep learning and machine learning. We got the results of the classifications on sign language: CNN 100%, SVM 100%, KNN 99%, we noticed a CNN classifier based on deep learning represents the most accurate results of our work. Also, we noticed that when we increased the data set size, the deep learning techniques gave better results than machine learning.

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