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Classification of Sign-language Using VGG16

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***Abstract**: Sign Language Recognition (SLR) aims to translate sign language into text or speech in order to improve communication between deaf-mute people and the general public. This task has a large social impact, but it is still difficult due to the complexity and wide range of hand actions. We present a novel 3D convolutional neural network (CNN) that extracts discriminative spatial-temporal features from photo datasets. This article is about classification of sign languages are not universal and are usually not mutually intelligible although there are also similarities among different sign languages. They are the foundation of local Deaf cultures and have evolved into effective means of communication. Although signing is primarily used by the deaf and hard of hearing, hearing people also use it when they are unable to speak, when they have difficulty speaking due to a health condition or disability (augmentative and alternative communication), or when they have deaf family members, such as children of deaf adults. In this article we use the 43500 image in the dataset in size 64*64 pixel by use CNN Architecture and achieved 100% accuracy.*

Keywords: *sign language Classification, Type of sign language, Deep Learning, Classification, Detection*

1. INTRODUCTION:

Sign language, as one of the most widely used communication methods for the deaf, is expressed through variations in hand shapes, body movement, and even facial expression. Because it is difficult to exploit information from hand shapes and body movement trajectory collaboratively, sign language recognition remains a difficult task. This paper proposes an effective recognition model for translating sign language into text or speech to assist hearing impaired people in communicating with normal people through sign language [3].

2. BACKGROUND:

2.1 DEEP LEARNING:

Deep learning is a particular branch of machine learning that focuses the learning of successive layers of always representations as it addresses the problem of learning representations from data [4-10].

The deep in deep learning refers to different layers of representations rather than any form of deeper understanding that can be attained through the approach [11-15]. The depth of the model means the number of layers that go into a data model. Layered representations learning and hierarchical representations learning could have been suitable titles for the topic. Today's deep learning techniques frequently comprise tens or even hundreds of representational layers that are learned automatically by exposure to training data [16-20].

Other machine learning techniques, known as shallow learning techniques, have a tendency to concentrate on learning just one or two layers of data representations [21-25]. These layered representations in deep learning are (nearly always) learned using neural network models, which are physically constructed as layers piled on top of one another. Although some of the basic ideas in deep learning were partly developed by taking inspiration from our understanding of the brain, deep-learning models are not models of the brain, even if the name "neural network" refers to biology [26-30]. There is no data that the brain uses learning methods similar to those found in modern deep-learning models. Pop-science articles may claim that deep learning is similar to the brain or that it was modeled after the brain, however this is incorrect. You don't need that shroud of "just like our minds" mystique and mystery, and you might as well forget anything you may have read about hypothetical links between deep learning and biology [31-35].

It would be confusing and counterproductive for beginners to the field to think of deep learning as being in any way related to neurobiology. Deep learning is, for our purposes, a mathematical framework for obtaining representations from data. What kind of representations have deep learning algorithms learned? Let's look at how a network with many layers functions. (See Figure 1) transforms a digit's image so that it may be classified as a number [36-40].

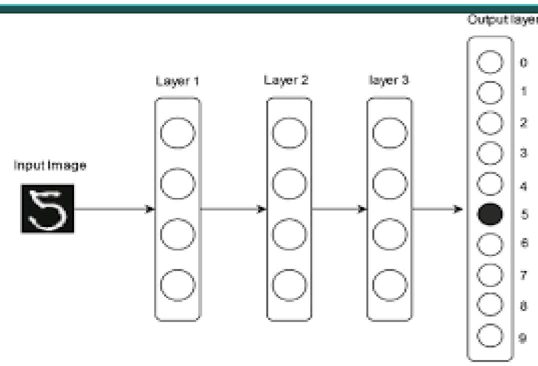


Figure 1:A deep neural netwok for digit classification

As you can see in Figure 2, the network alters the digit image into representations that range more from the original and give the more information about the result. Consider a deep network as a multistage information-distillation process, where information is passed through successively simpler filters until it is suitable for a given task[41].

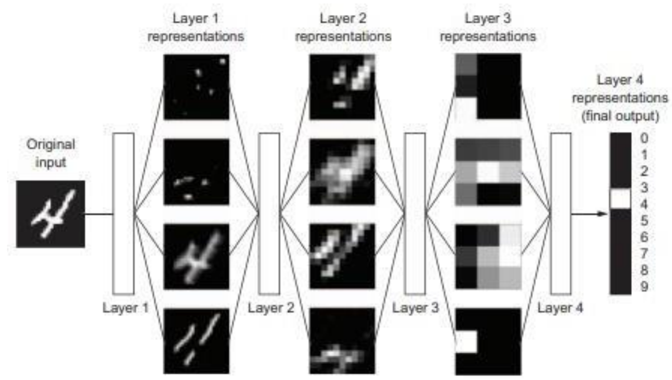


Figure 2: Deep representations learned by a digit-classification model

Technically speaking, a multistage method of learning data representations that is what deep learning is. It's a simple concept, yet it turns out that when enough scaled, even the most basic mechanics might appear to work like miracles [42]**.**

2.2 CNN:

A convolutional neural network, is a deep learning neural network made for handle structured sets of data like image arrays. The state-of-the-art for many visual applications, such as image classification, convolutional neural networks are widely used in computer vision. They have also found success in natural language processing for text classification[43-47].

The features in the input image, such as lines, colors, circles, or even eyes and faces, are very well detected by convolutional neural networks. Convolutional neural networks are extremely effective for computer vision because of this feature. Convolutional neural networks do not need any image processing, in contrast to older computer vision algorithms [48-52].

A feed-forward neural network with up to 20 or 30 layers is known as a convolutional neural network. A unique kind of whole such as the convolutional layer gives convolutional neural networks their power [53-55].

Each convolutional layer in a network can detect more complex shapes since they are stacked on top of one another. Written digits can be detected with three or four convolutional layers, while human faces can be identified with 25 layers[56-60].

A convolutional neural network uses convolutional layers to process input images and recognize progressively more complex features, simulating the structure of the human vision system[61-63].

2.2.1 Convolutional Neural Network Design

A convolutional neural network's architecture is a multi-layered feed-forward neural network created by successively stacking multiple hidden layers on top of each other. Convolutional neural networks can learn hierarchical features because of their successive structure [64-66].

Convolutional layers are frequently followed by activation layers, some of which are then followed by max - pooling, as the hidden layers [67]

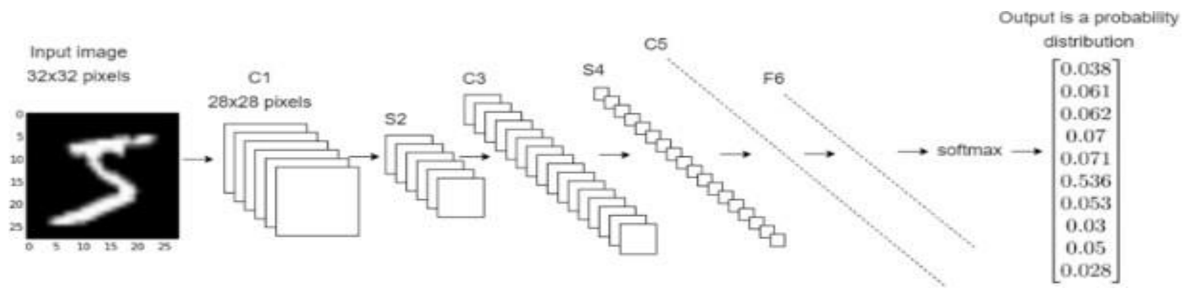


Figure 3:Convolutional Neural Network Design

VGG 16 Architecture:

The basic convolutional neural network VGG 16 is a simple convolutional neural network that helps knowledge of the basic design ideas. The top - performing model on the ImageNet dataset was found to be VGG16 out of all the setups. Let's analyze this configuration's fundamental architecture[68].

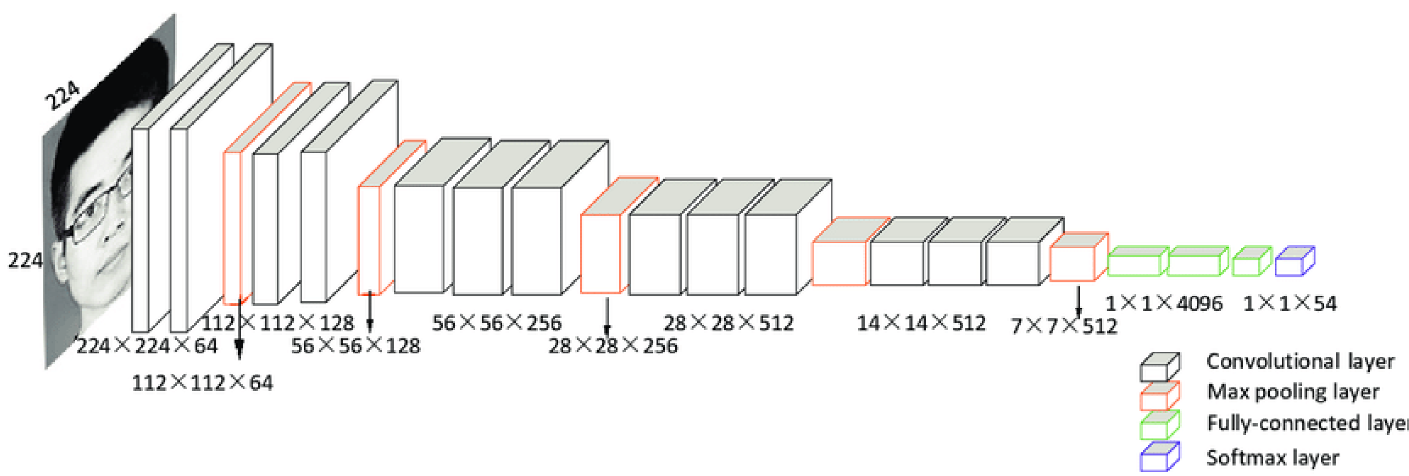


Figure 4: VGG 16 Architecture

Some of the types of networks is believed to possess as its input a fixed 224 by 224 image with three channels—R, G, and B. The only pre-processing being out is the normalization of each pixel's RGB values. The mean value is reduced from each pixel to achieve result[69].

After ReLU activations, the image is sent through the first stack of two convolution layers with a very small receptive area of 3 × 3. These two layers each include 64 filters. The padding is 1 pixel, and the convolution stride is fixed at 1 pixel. The spatial resolution is conserved in this setup, and the output activation map's dimensions equal those of the input image. The activation maps are then processed to spatial max pooling with a step of 2 pixels over a 2 x 2 pixel window. Thus, the size of the activation functions is halved.

The activations then flow through a second stack that is similar to the first but has 128 filters as opposed to 64 in the first stack. As a result, after the second layer, the size is 56 x 56 x 128. The third stack, which consists of a max pool layer and three convolutional layers, is then added. The output size of the stack is 28 x 28 x 256 due to the 256 filters that were applied in this case. Two stacks of three convolutional layers, each with 512 filters, are added after that. Both of these stacks' final outputs will be 7 × 7 x 512.

Three fully connected layers, with a smoothing layer in between, are placed after the stacks of convolutional layers. The last fully connected layer serves as the output layer and includes 1,000 neurons, which correspond to the 1,000 possible classes in the ImageNet dataset. The first two layers each have 4,096 neurons. The Softmax activation layer, which is designed for categorical classification, follows after the output layer [4].

2.3 TRANSFER LEARNING:

Data scientists can apply the knowledge gained from a machine learning model that was successfully involved for a similar task by using the transfer learning machine learning technique. This lesson uses humans' ability for information transfer as an illustration. Learning to use it will make the learning to operate other two-wheeled machines easier. Similar to how a model developed for autonomous automobile driving can be applied to driving trucks [8].

3. METHODOLOGY:

In this section, we evaluate the proposed solution as the selected VGG16 architecture, as well as the design choices, evaluation methods, and implementation details.

3.1 DATASET:

A total of 87000 images were collected for sign language classification, but only 43500 were used due to image size limitations. To build the CNN, images were downloaded from the Kaggle website. Each image was cropped to 64, 64 pixels. Image 29 class (A to Z, space, delete, and nothing) the type and number of sign language images used in this study. For each type of sign language use 70% from image for training and 15% from image for validation 15 % for testing. The generated model was trained based on the training set and evaluated using the test set.

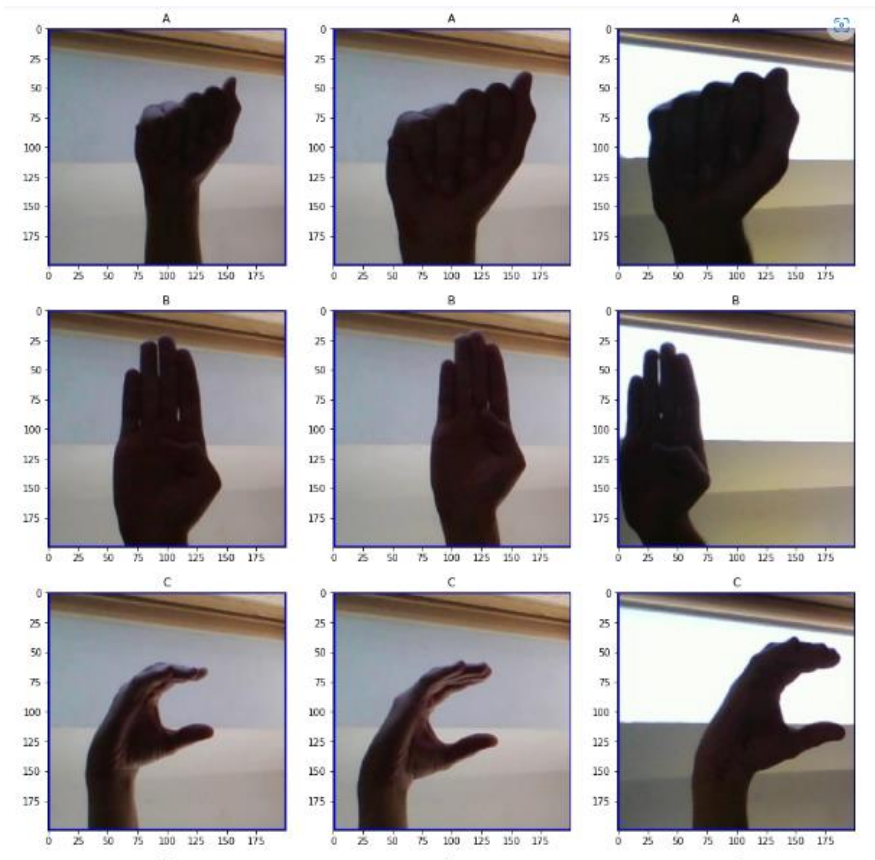
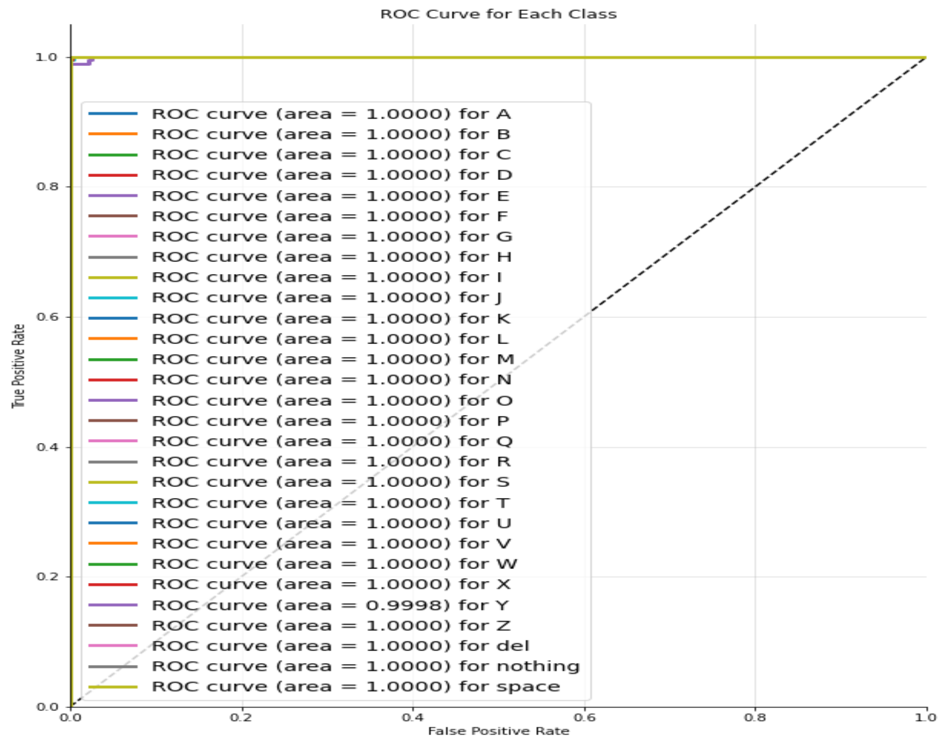


Figure 6: sample data set

3.2 EVALUATION:

Since we wanted our submissions to be as close to the actual probabilities as possible, we used the function with sigmoid as the last layer's activation function. The competition was a binary classification problem with area under the ROC (Average receiver operating characteristic) curve between the predicted probability and the observed target as an evaluation matrix.



3.3 VALIDATION METHOD:

In order to evaluate our model, We experimented to determine the best way to combine the available dataset into training and validation sets for sign language using basic hold-out validation and k-fold cross validation. In our experiment, we trained and tested our model 20 times using the standard hold-out validation method, using a different validation set each time. Since there was a lot of variation in the scores over the 20 times, as seen in Fig. 7, we came to the conclusion that the straightforward hold-out validation method was inappropriate for this dataset and chose to utilize the k-fold cross validation method instead.

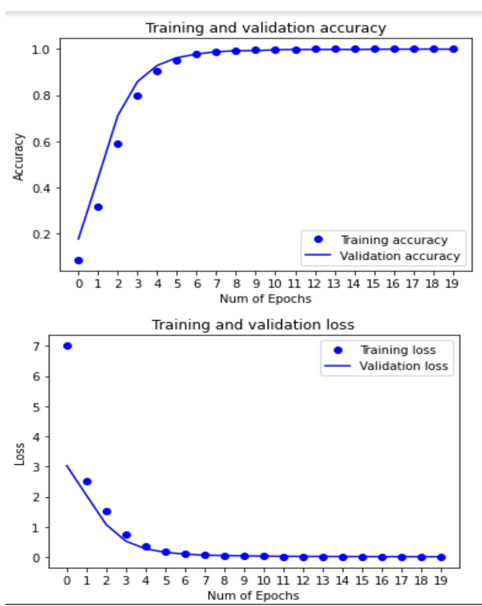


Figure 7: simple hold-out validation result

3.3 Loss and Accuracy rate:

The loss versus accuracy curve is a useful feature in terms of how much time and memory the model training process uses. The results of a convolution neural network's loss rate in the training and test sets after 20 repetitions are shown in Figure 8. Which suggests that the convolutional neural network successfully learned the input and can act as a good model for understanding sign language.

```
Epoch 1/20
61/61 [==============================] - 30s 233ms/step - loss: 7.0049 - accuracy: 0.0872 - val_loss: 3.0268 - val_accuracy: 0.1778
Epoch 2/20
61/61 [==============================] - 13s 210ms/step - loss: 2.5228 - accuracy: 0.3169 - val_loss: 2.0447 - val_accuracy: 0.4411
Epoch 3/20
61/61 [==============================] - 13s 211ms/step - loss: 1.5072 - accuracy: 0.5895 - val_loss: 1.0754 - val_accuracy: 0.7119
Epoch 4/20
61/61 [==============================] - 15s 248ms/step - loss: 0.7392 - accuracy: 0.7997 - val_loss: 0.5222 - val_accuracy: 0.8585
Epoch 5/20
61/61 [==============================] - 15s 243ms/step - loss: 0.3532 - accuracy: 0.9052 - val_loss: 0.2700 - val_accuracy: 0.9283
Epoch 6/20
61/61 [==============================] - 13s 214ms/step - loss: 0.1882 - accuracy: 0.9498 - val_loss: 0.1503 - val_accuracy: 0.9618
Epoch 7/20
61/61 [==============================] - 13s 217ms/step - loss: 0.0993 - accuracy: 0.9787 - val_loss: 0.0933 - val_accuracy: 0.9773
Epoch 8/20
61/61 [==============================] - 13s 215ms/step - loss: 0.0622 - accuracy: 0.9864 - val_loss: 0.0579 - val_accuracy: 0.9876
Epoch 9/20
61/61 [==============================] - 13s 211ms/step - loss: 0.0385 - accuracy: 0.9929 - val_loss: 0.0461 - val_accuracy: 0.9917
Epoch 10/20
61/61 [==============================] - 13s 215ms/step - loss: 0.0256 - accuracy: 0.9955 - val_loss: 0.0367 - val_accuracy: 0.9920
Epoch 11/20
61/61 [==============================] - 15s 245ms/step - loss: 0.0176 - accuracy: 0.9974 - val_loss: 0.0240 - val_accuracy: 0.9960
Epoch 12/20
61/61 [==============================] - 13s 212ms/step - loss: 0.0143 - accuracy: 0.9978 - val_loss: 0.0201 - val_accuracy: 0.9972
Epoch 13/20
61/61 [==============================] - 13s 214ms/step - loss: 0.0093 - accuracy: 0.9991 - val_loss: 0.0177 - val_accuracy: 0.9971
Epoch 14/20
61/61 [==============================] - 13s 214ms/step - loss: 0.0076 - accuracy: 0.9991 - val_loss: 0.0156 - val_accuracy: 0.9975
Epoch 15/20
61/61 [==============================] - 13s 214ms/step - loss: 0.0060 - accuracy: 0.9994 - val_loss: 0.0141 - val_accuracy: 0.9969
Epoch 16/20
61/61 [==============================] - 13s 213ms/step - loss: 0.0045 - accuracy: 0.9996 - val_loss: 0.0116 - val_accuracy: 0.9985
Epoch 17/20
61/61 [==============================] - 13s 214ms/step - loss: 0.0042 - accuracy: 0.9996 - val_loss: 0.0097 - val_accuracy: 0.9982
Epoch 18/20
61/61 [==============================] - 15s 243ms/step - loss: 0.0027 - accuracy: 1.0000 - val_loss: 0.0088 - val_accuracy: 0.9989
Epoch 19/20
61/61 [==============================] - 13s 215ms/step - loss: 0.0023 - accuracy: 0.9999 - val_loss: 0.0081 - val_accuracy: 0.9988
Epoch 20/20
61/61 [==============================] - 12s 203ms/step - loss: 0.0020 - accuracy: 1.0000 - val_loss: 0.0085 - val_accuracy: 0.9985
Time elapsed in seconds: 354.0117042064667
```

Figure 8: Loss and Accuracy rate

3.4 Confusion Matrix:

In this work, the proposed deep learning network CNN was trained on the sign language dataset. Afterwards, the model was evaluated on the test set, which showed good performance. Figure 9 presents the confusion matrix of the classification results, where each row represents the actual category, while each column stands for the predicted result.

```
[[182   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0 192   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0 187   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0 181   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0 181   0   0   0   1   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0 196   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0 185   1   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0 195   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0 187   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   1 180   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0 189   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0 211   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [ 0   0   0   0   0   0   0   0   0   0   0   0 188   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0 180   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0 212   0   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 215   0   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 194   0
    0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 195
    0   0   1   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0
  201   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0 181   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0 191   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0 169   1   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0 196   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0 202   0   0   0   0   1]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   2   0
    0   0   0   0   0   0 189   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0 181   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0 188   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
 [  0   0   0   0   0   0   0   0   0 191   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0 198]]
```

Figure 9: confusion matrix

3.5 Comparison of Classification Performance:

To evaluate the effectiveness of these models, the as-proposed method was compared with the existing methods for modern deep learning. The models were evaluated on the test set by the accuracy rate, and avg F1-score. In Figure 6, the model VGG16 achieved lower false positive and false negative rates, which demonstrates the effectiveness.

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	precision	recall	f1-score	support
A	1.0000	0.9945	0.9973	183
B	1.0000	1.0000	1.0000	192
C	1.0000	1.0000	1.0000	187
D	1.0000	1.0000	1.0000	181
E	0.9945	0.9945	0.9945	182
F	1.0000	1.0000	1.0000	196
G	0.9946	0.9946	0.9946	186
H	0.9949	1.0000	0.9974	195
I	0.9894	1.0000	0.9947	187
J	1.0000	0.9945	0.9972	181
K	1.0000	1.0000	1.0000	189
L	1.0000	1.0000	1.0000	211
M	1.0000	1.0000	1.0000	188
N	1.0000	1.0000	1.0000	180
O	1.0000	1.0000	1.0000	212
P	1.0000	1.0000	1.0000	215
Q	0.9898	1.0000	0.9949	194
R	1.0000	0.9949	0.9974	196
S	1.0000	0.9950	0.9975	202
T	1.0000	1.0000	1.0000	181
U	0.9948	1.0000	0.9974	191
V	1.0000	0.9941	0.9971	170
W	0.9949	1.0000	0.9975	196
X	1.0000	0.9951	0.9975	203
Y	1.0000	0.9895	0.9947	191
Z	1.0000	1.0000	1.0000	181
del	1.0000	1.0000	1.0000	188
nothing	1.0000	1.0000	1.0000	191
space	0.9950	1.0000	0.9975	198
accuracy			0.9982	5547
macro avg	0.9982	0.9982	0.9982	5547
weighted avg	0.9982	0.9982	0.9982	5547

Figure 10: Comparison of Classification Performance

3.6 Fully Connected and Dropout Layer:

Fully connected layer (FCL): is used for classification and inference. FCL includes numerous parameters to connect to every neurons in the previous layer, just like the conventional shallow neural network. However, FCL's large parameter set may contribute to the issue of over-fitting during training and dropout.

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Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 64, 64, 3)]	0
block1_conv1 (Conv2D)	(None, 64, 64, 64)	1792
block1_conv2 (Conv2D)	(None, 64, 64, 64)	36928
block1_pool (MaxPooling2D)	(None, 32, 32, 64)	0
block2_conv1 (Conv2D)	(None, 32, 32, 128)	73856
block2_conv2 (Conv2D)	(None, 32, 32, 128)	147584
block2_pool (MaxPooling2D)	(None, 16, 16, 128)	0
block3_conv1 (Conv2D)	(None, 16, 16, 256)	295168
block3_conv2 (Conv2D)	(None, 16, 16, 256)	590080
block3_conv3 (Conv2D)	(None, 16, 16, 256)	590080
block3_pool (MaxPooling2D)	(None, 8, 8, 256)	0
block4_conv1 (Conv2D)	(None, 8, 8, 512)	1180160
block4_conv2 (Conv2D)	(None, 8, 8, 512)	2359808
block4_conv3 (Conv2D)	(None, 8, 8, 512)	2359808
block4_pool (MaxPooling2D)	(None, 4, 4, 512)	0
block5_conv1 (Conv2D)	(None, 4, 4, 512)	2359808
block5_conv2 (Conv2D)	(None, 4, 4, 512)	2359808
block5_conv3 (Conv2D)	(None, 4, 4, 512)	2359808
block5_pool (MaxPooling2D)	(None, 2, 2, 512)	0
global_max_pooling2d_2 (GlobalMaxPooling2D)	(None, 512)	0
dense_2 (Dense)	(None, 29)	14877

Total params: 14,729,565
Trainable params: 14,729,565
Non-trainable params: 0

Figure 11: Fully Connected and Dropout Layer

4. CONCLUSION:

Sign language classification in a very important task in many field such as communication with deaf society. In this study, we proposed an approach that uses deep learning-based learning of images of a latter English (A to Z), space, delete and nothing from Kaggle website. We use a pre trained CNN Model VGG16 fine-tuned. In this paper, we trained and validated the proposed model and tested its performance with un-seen dataset for testing. The Accuracy rate we achieved was 100 % to 20 epoch. This indicates that our proposed model can effectively predicate and classify different sign language without error and with full performance.

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