

### Architecture used in the Paper

Each image is multiplied with a filter matrix, which is used to extract the feature from it. Initially the filter contains random values and it is a  $3 \times 3$  matrix. The result matrix will be  $32 \times 32$  and if we use more than one filter, the result will change. For example if we use 4 filters, the output will be  $32 \times 32 \times 4$ . The pooling process is to reduce the dimension of the image as well as the depth of image. This process is used to flattened the image, finally the array will be  $1 \times 1 \times 1024$ . This array and the label is feed in to the training process with set of some parameters. The training process will start with set of hyperparameters like no of epochs, number of images per epoch and the most important parameter, the training rate. The training rate must be very low so that the model can get the best fit. For each epochs, the loss value is calculated. Initially, the loss value will be larger, and in time it will comes to nearly zero. After the training is stopped, some value will be generated for the filters. We need to store those values. And we are using one-hot encoding, so if the detect object is correct, then there will be one in the object position in the label and other nine values will be zero.

## Dataset details

- Name of the dataset used: American Sign Language
- The link of dataset:  
<https://www.kaggle.com/datasets/kapillondhe/american-sign-language>
- The total number of samples in the dataset : 121,608 samples
- Dimension of images (150 , 150)
- Number of classes & their labels : 27 classes with labels (from a to z and space sign)
- The ratio used for training, and testing : Training (85.72% of the training dataset) = 84,000 images testing dataset (14.28 % of the testing dataset) = 14,000 images



## Implementation details

### -The hyperparameters used in the model

```
kerasModel=keras.models.Sequential([
    keras.layers.Conv2D(200,kernel_size=(3,3),activation='relu',input_shape=(size,size,3)),
    keras.layers.Conv2D(150,kernel_size=(3,3),activation='relu'),
    keras.layers.MaxPool2D(4,4),
    keras.layers.Conv2D(120,kernel_size=(3,3),activation='relu'),
    keras.layers.Conv2D(80,kernel_size=(3,3),activation='relu'),
    keras.layers.Conv2D(50,kernel_size=(3,3),activation='relu'),
    keras.layers.MaxPool2D(4,4),
    keras.layers.Flatten(),
    keras.layers.Dense(120,activation='relu'),
    keras.layers.Dense(100,activation='relu'),
    keras.layers.Dense(50,activation='relu'),
    keras.layers.Dropout(rate=0.5),
    keras.layers.Dense(28,activation='softmax'),
])
```

### - model summery

Model: "sequential\_5"

Layer (type)	Output Shape	Param #
conv2d_25 (Conv2D)	(None, 62, 62, 200)	5600
conv2d_26 (Conv2D)	(None, 60, 60, 150)	270150
max_pooling2d_10 (MaxPooling)	(None, 15, 15, 150)	0
conv2d_27 (Conv2D)	(None, 13, 13, 120)	162120
conv2d_28 (Conv2D)	(None, 11, 11, 80)	86480
conv2d_29 (Conv2D)	(None, 9, 9, 50)	36050
max_pooling2d_11 (MaxPooling)	(None, 2, 2, 50)	0
flatten_5 (Flatten)	(None, 200)	0
dense_20 (Dense)	(None, 120)	24120
dense_21 (Dense)	(None, 100)	12100
dense_22 (Dense)	(None, 50)	5050
dropout_3 (Dropout)	(None, 50)	0
dense_23 (Dense)	(None, 28)	1428
Total params: 603,098		
Trainable params: 603,098		
Non-trainable params: 0		
None		

```
Epoch 1/10
2532/2532 [=====] - 105s 41ms/step - loss: 0.8754 - accuracy: 0.7259
Epoch 2/10
2532/2532 [=====] - 104s 41ms/step - loss: 0.1166 - accuracy: 0.9638
Epoch 3/10
2532/2532 [=====] - 102s 40ms/step - loss: 0.0755 - accuracy: 0.9771
Epoch 4/10
2532/2532 [=====] - 104s 41ms/step - loss: 0.0783 - accuracy: 0.9791
Epoch 5/10
2532/2532 [=====] - 103s 41ms/step - loss: 0.0500 - accuracy: 0.9859
Epoch 6/10
2532/2532 [=====] - 103s 41ms/step - loss: 0.0575 - accuracy: 0.9850
Epoch 7/10
2532/2532 [=====] - 103s 41ms/step - loss: 0.0424 - accuracy: 0.9885
Epoch 8/10
2532/2532 [=====] - 104s 41ms/step - loss: 0.0422 - accuracy: 0.9894
Epoch 9/10
2532/2532 [=====] - 104s 41ms/step - loss: 0.0477 - accuracy: 0.9885
Epoch 10/10
2532/2532 [=====] - 104s 41ms/step - loss: 0.0366 - accuracy: 0.9900
```

- The Accuracy : 98.3%



Epoch	Train Loss
0	0.85
1	0.12
2	0.08
3	0.08
4	0.05
5	0.06
6	0.04
7	0.04
8	0.04
9	0.04
10	0.04

Figure 1 is a heatmap visualization of the 2019-2020 season COVID-19 data. The x-axis represents the date from March 1, 2020, to March 1, 2021. The y-axis represents the number of cases, ranging from 0 to 400. The color scale indicates the number of cases, with darker blue representing higher values. The heatmap shows a significant increase in cases starting around March 2020, peaking in late 2020, and then declining. The data is presented in a grid format with numerical values for each date.