Real-time Sign Language Recognition Using OpenCV

Bridging the Communication Gap

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Abstract

Abstract Conversing with a person with a hearing disability is always a major challenge. Sign language has indelibly become the ultimate panacea and is a very powerful tool for individuals with hearing and speech disabilities to communicate their feelings and opinions to the world. It makes the integration process between them and others smooth and less complex. However, the invention of sign language alone is not enough. There are many strings attached to this boon. The sign gestures often get mixed and confused for someone who has never learned it or knows it in a different language. However, this communication gap which has existed for years can now be narrowed with the introduction of various techniques to automate the detection of sign gestures. In this project, we introduce Sign Language recognition using American Sign Language. American Sign Language (ASL) is a complete, natural language that has the same linguistic properties as spoken languages, with
grammar that differs from English.

Introduction

As well stipulated by Nelson Mandela, “Talk to a man in a language he understands, that goes to his head. Talk to him in his own language, that goes to his heart”, language is undoubtedly essential to human interaction and has existed since human civilization began. It is a medium humans use to communicate to express themselves and understand notions of the real world. Sadly, in the fast-changing society we live in, people with hearing impairment are usually forgotten and left out. They have to struggle to bring up their ideas, voice their opinions and express themselves to people who are different to them. Sign language, although being a medium of communication to deaf people, still has no meaning when conveyed to a non-sign language user. Hence, broadening the communication gap to prevent this from happening, we are putting forward a Sign Language Recognition (SLR) system. It will be an ultimate tool for people with hearing disability to communicate their thoughts as well as a very good interpretation for non-sign language user to understand what the latter is saying.

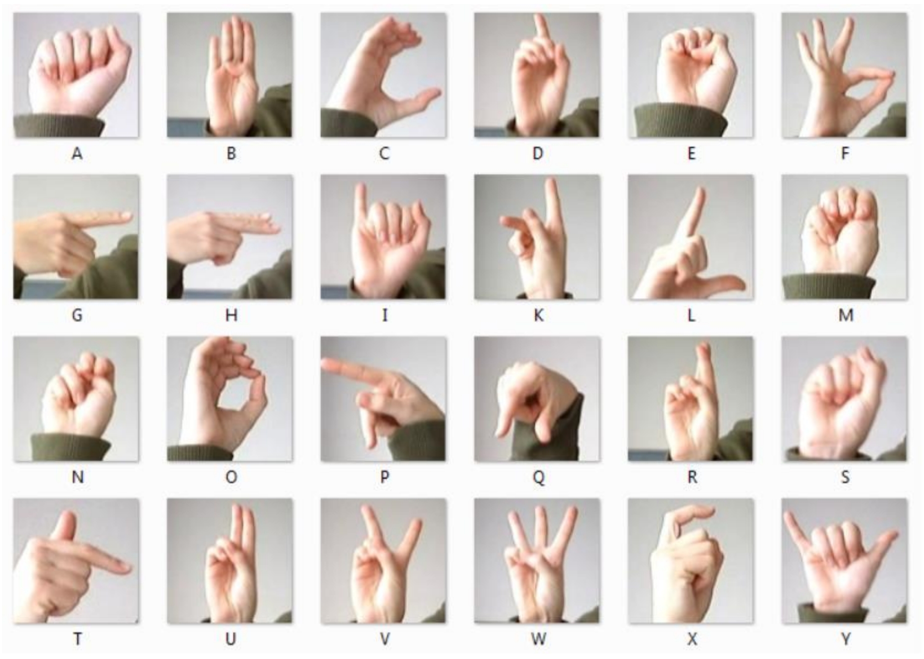
Deep learning is a kind of machine learning that focuses on teaching artificial neural networks to recognize patterns in complex data and learn how to anticipate or act on them. Convolutional neural networks (CNNs), one deep learning technique, have recently demonstrated encouraging results in the recognition of sign language. CNN uses perceptron learning rules along with supervised learning, to analyze the data. CNN is applied to process the image, natural language processing and other kinds of cognitive tasks.

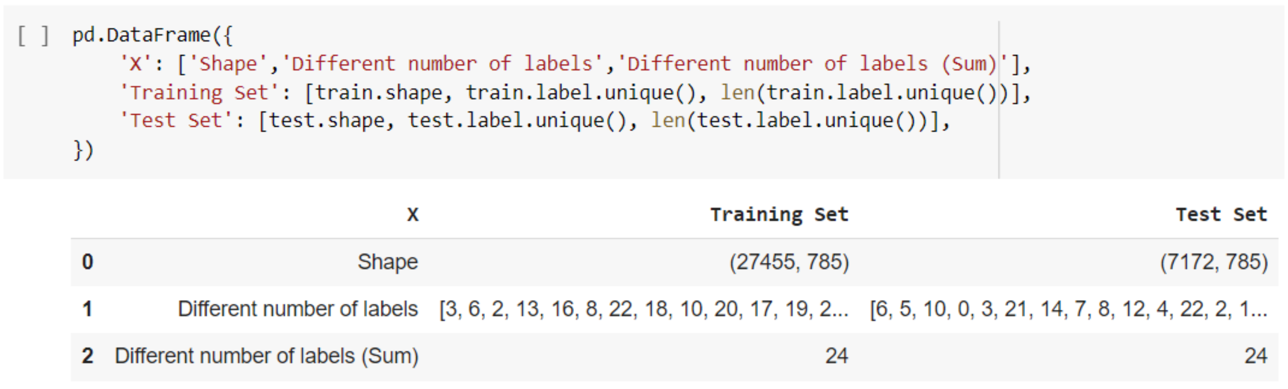
In this project, we explore the use of OpenCV, a popular computer vision library, to implement a real time sign language recognition system. The system uses the webcam to capture the real time input of user’s hand signs and processes the frames using computer vision techniques to recognize the corresponding static sign language gesture. We have decided to go with the static recognition of hand gestures because it increases accuracy as compared to when including dynamic hand gestures like for the alphabets J and Z. We have built and compared different models of CNNs for SLR and use the model with the best accuracy to recognize and predict the correct alphabet for the real time input.

Data Exploration

For this project, the primary source of data was the Sign Language MNIST from Kaggle. The American Sign Language letter database of hand gestures represent a multi-class problem with 24 classes of letters (excluding J and Z which require motion).

The dataset format is patterned to match closely with the classic MNIST. Each training and test case represents a label (0-25) as a one-to-one map for each alphabetic letter A-Z (and no cases for 9=J or 25=Z because of gesture motions). The training data (27,455 cases) and test data (7172 cases) are approximately half the size of the standard MNIST but otherwise similar with a header row of label, pixel1, pixel2…. pixel784 which represents a single 28x28 pixel image with grayscale values between 0-255. The original hand gesture image data represented multiple users repeating the gesture against different backgrounds. The Sign Language MNIST data came from greatly extending the small number (1704) of the color images included as not cropped around the hand region of interest.





```
[ ]  pd.DataFrame({
         'X': ['Shape','Different number of labels','Different number of labels (Sum)'],
         'Training Set': [train.shape, train.label.unique(), len(train.label.unique())],
         'Test Set': [test.shape, test.label.unique(), len(test.label.unique())],
     })
```

	X	Training Set	Test Set
0	Shape	(27455, 785)	(7172, 785)
1	Different number of labels	[3, 6, 2, 13, 16, 8, 22, 18, 10, 20, 17, 19, 2...	[6, 5, 10, 0, 3, 21, 14, 7, 8, 12, 4, 22, 2, 1...
2	Different number of labels (Sum)	24	24

Proposed Methodology

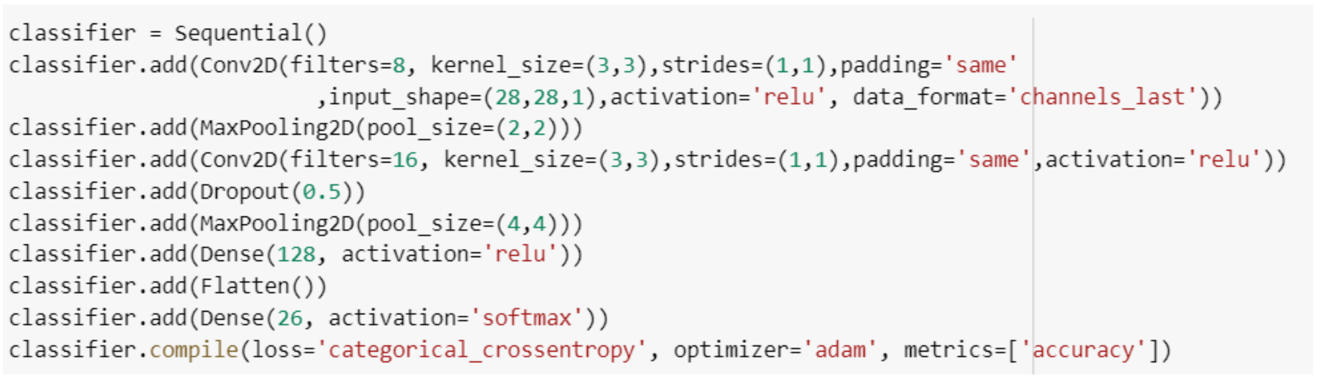
System implementation turns models into functional systems or new applications using newly developed designs. This project involves reshaping the dataset, data preprocessing, testing, and training the system. These steps are necessary to ensure that the system functions correctly and accurately recognize the alphabet from the hand sign given as input.

A. System Architecture

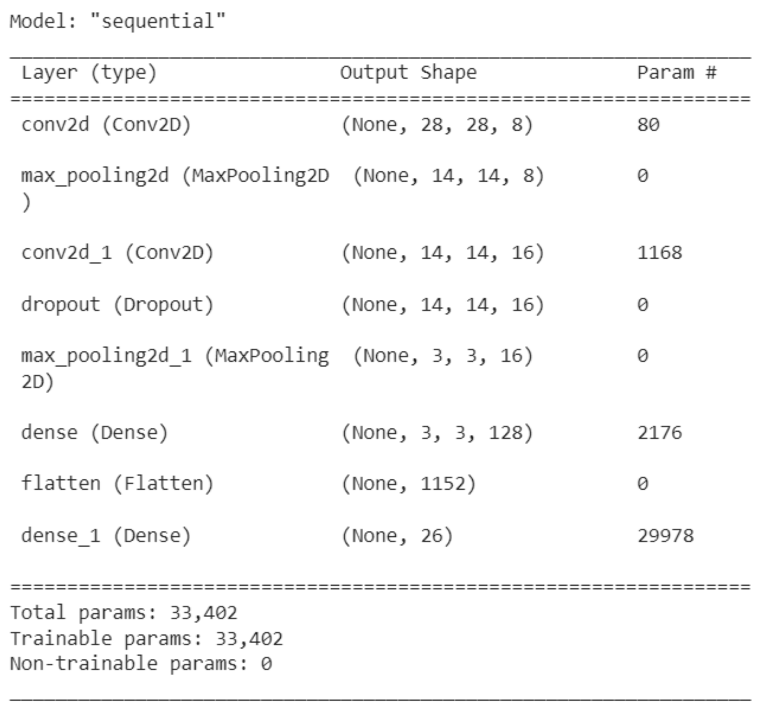
Convolutional neural network

Convolutional neural networks (CNN) is one of the most commonly used deep learning methods to analyze visual imagery. CNN involves less preprocessing compared to other image classification algorithms. The network learns the filters that are normally hand-engineered in other systems. The use of a CNN reduces the images into a format that is easier to process while preserving features that are essential for making accurate predictions.

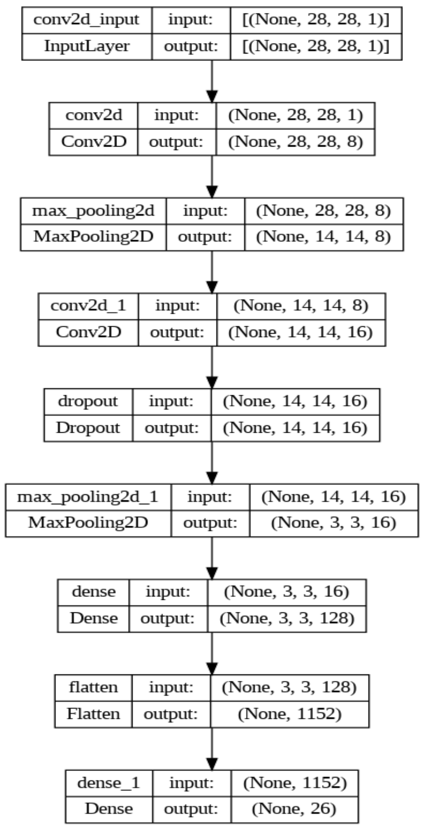
Model 1:



```
classifier = Sequential()
classifier.add(Conv2D(filters=8, kernel_size=(3,3),strides=(1,1),padding='same'
                          ,input_shape=(28,28,1),activation='relu', data_format='channels_last'))
classifier.add(MaxPooling2D(pool_size=(2,2)))
classifier.add(Conv2D(filters=16, kernel_size=(3,3),strides=(1,1),padding='same',activation='relu'))
classifier.add(Dropout(0.5))
classifier.add(MaxPooling2D(pool_size=(4,4)))
classifier.add(Dense(128, activation='relu'))
classifier.add(Flatten())
classifier.add(Dense(26, activation='softmax'))
classifier.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

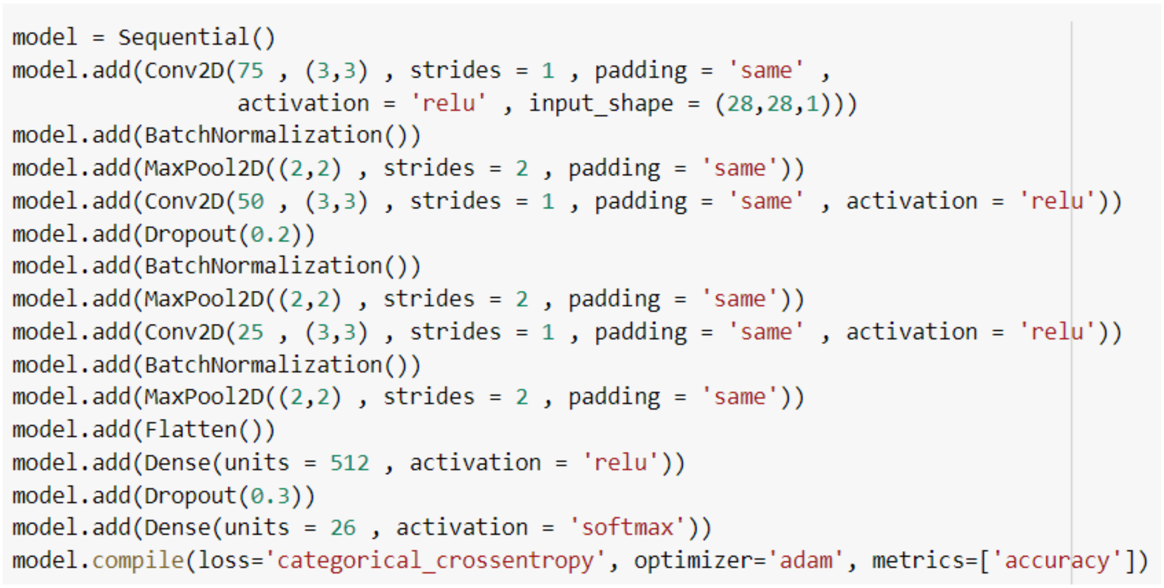


```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 28, 28, 8)         80

 max_pooling2d (MaxPooling2D  (None, 14, 14, 8)        0
 )

 conv2d_1 (Conv2D)           (None, 14, 14, 16)        1168

 dropout (Dropout)           (None, 14, 14, 16)        0

 max_pooling2d_1 (MaxPooling  (None, 3, 3, 16)         0
 2D)

 dense (Dense)               (None, 3, 3, 128)         2176

 flatten (Flatten)           (None, 1152)              0

 dense_1 (Dense)             (None, 26)                29978

=================================================================
Total params: 33,402
Trainable params: 33,402
Non-trainable params: 0
_________________________________________________________________
```

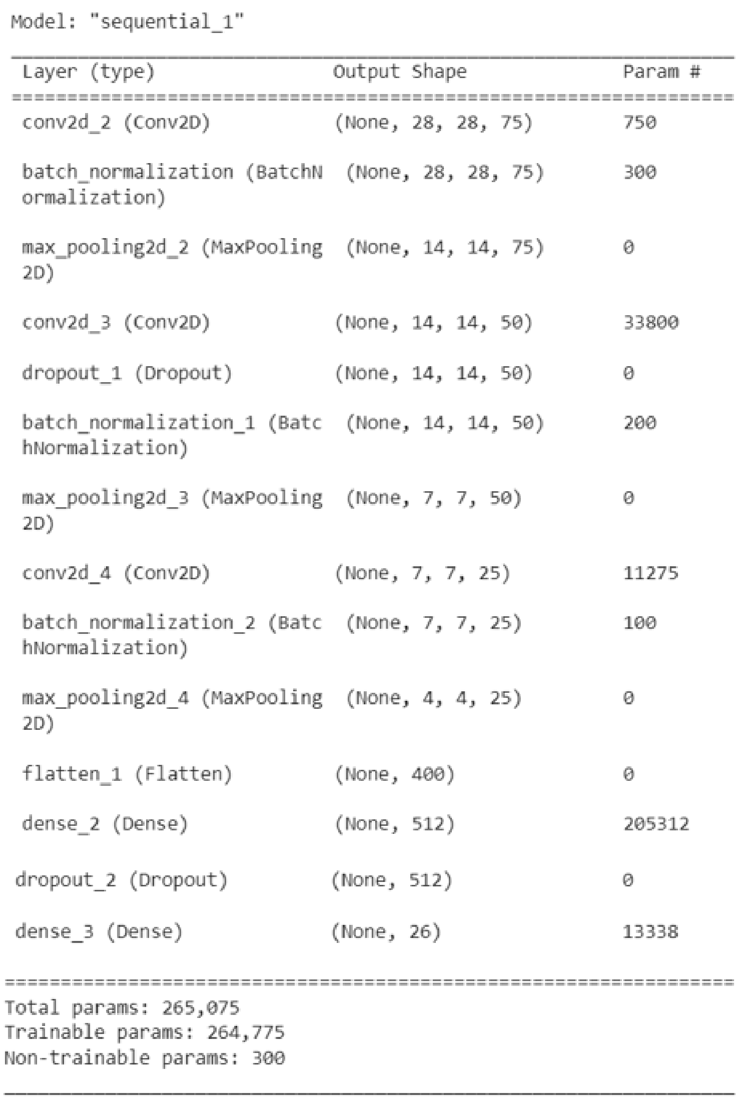

conv2d_input | InputLayer | input: [(None, 28, 28, 1)] | output: [(None, 28, 28, 1)]
conv2d | Conv2D | input: (None, 28, 28, 1) | output: (None, 28, 28, 8)
max_pooling2d | MaxPooling2D | input: (None, 28, 28, 8) | output: (None, 14, 14, 8)
conv2d_1 | Conv2D | input: (None, 14, 14, 8) | output: (None, 14, 14, 16)
dropout | Dropout | input: (None, 14, 14, 16) | output: (None, 14, 14, 16)
max_pooling2d_1 | MaxPooling2D | input: (None, 14, 14, 16) | output: (None, 3, 3, 16)
dense | Dense | input: (None, 3, 3, 16) | output: (None, 3, 3, 128)
flatten | Flatten | input: (None, 3, 3, 128) | output: (None, 1152)
dense_1 | Dense | input: (None, 1152) | output: (None, 26)

Summary of Model 1

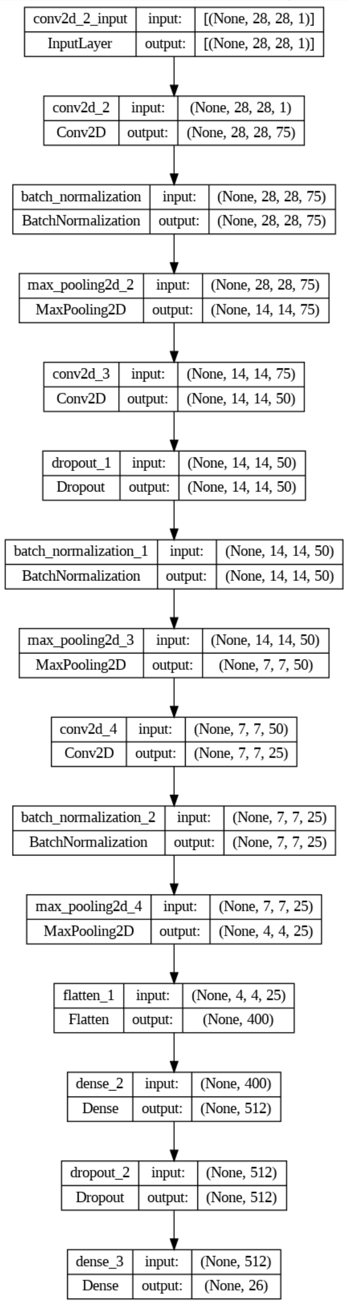
Model 2:



```
model = Sequential()
model.add(Conv2D(75 , (3,3) , strides = 1 , padding = 'same' ,
                 activation = 'relu' , input_shape = (28,28,1)))
model.add(BatchNormalization())
model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model.add(Conv2D(50 , (3,3) , strides = 1 , padding = 'same' , activation = 'relu'))
model.add(Dropout(0.2))
model.add(BatchNormalization())
model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model.add(Conv2D(25 , (3,3) , strides = 1 , padding = 'same' , activation = 'relu'))
model.add(BatchNormalization())
model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model.add(Flatten())
model.add(Dense(units = 512 , activation = 'relu'))
model.add(Dropout(0.3))
model.add(Dense(units = 26 , activation = 'softmax'))
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```



```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 28, 28, 75)        750

 batch_normalization (BatchN  (None, 28, 28, 75)       300
 ormalization)

 max_pooling2d_2 (MaxPooling  (None, 14, 14, 75)       0
 2D)

 conv2d_3 (Conv2D)           (None, 14, 14, 50)        33800

 dropout_1 (Dropout)         (None, 14, 14, 50)        0

 batch_normalization_1 (Batc  (None, 14, 14, 50)       200
 hNormalization)

 max_pooling2d_3 (MaxPooling  (None, 7, 7, 50)         0
 2D)

 conv2d_4 (Conv2D)           (None, 7, 7, 25)          11275

 batch_normalization_2 (Batc  (None, 7, 7, 25)         100
 hNormalization)

 max_pooling2d_4 (MaxPooling  (None, 4, 4, 25)         0
 2D)

 flatten_1 (Flatten)         (None, 400)               0

 dense_2 (Dense)             (None, 512)               205312

 dropout_2 (Dropout)         (None, 512)               0

 dense_3 (Dense)             (None, 26)                13338

=================================================================
Total params: 265,075
Trainable params: 264,775
Non-trainable params: 300
_________________________________________________________________
```



conv2d_2_input | input: | [(None, 28, 28, 1)]
InputLayer | output: | [(None, 28, 28, 1)]
conv2d_2 | input: | (None, 28, 28, 1)
Conv2D | output: | (None, 28, 28, 75)
batch_normalization | input: | (None, 28, 28, 75)
BatchNormalization | output: | (None, 28, 28, 75)
max_pooling2d_2 | input: | (None, 28, 28, 75)
MaxPooling2D | output: | (None, 14, 14, 75)
conv2d_3 | input: | (None, 14, 14, 75)
Conv2D | output: | (None, 14, 14, 50)
dropout_1 | input: | (None, 14, 14, 50)
Dropout | output: | (None, 14, 14, 50)
batch_normalization_1 | input: | (None, 14, 14, 50)
BatchNormalization | output: | (None, 14, 14, 50)
max_pooling2d_3 | input: | (None, 14, 14, 50)
MaxPooling2D | output: | (None, 7, 7, 50)
conv2d_4 | input: | (None, 7, 7, 50)
Conv2D | output: | (None, 7, 7, 25)
batch_normalization_2 | input: | (None, 7, 7, 25)
BatchNormalization | output: | (None, 7, 7, 25)
max_pooling2d_4 | input: | (None, 7, 7, 25)
MaxPooling2D | output: | (None, 4, 4, 25)
flatten_1 | input: | (None, 4, 4, 25)
Flatten | output: | (None, 400)
dense_2 | input: | (None, 400)
Dense | output: | (None, 512)
dropout_2 | input: | (None, 512)
Dropout | output: | (None, 512)
dense_3 | input: | (None, 512)
Dense | output: | (None, 26)

Summary of Model 2

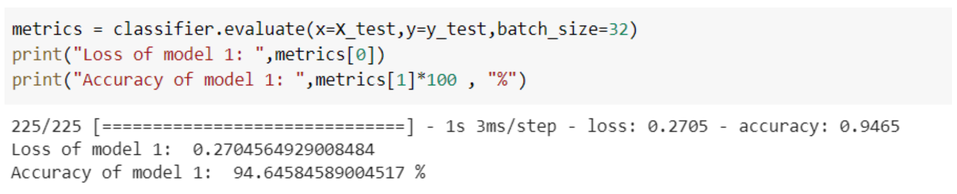
The first model has two convolutional layers with 8 and 16 filters, respectively, followed by max pooling, dropout regularization, two fully connected layers, and a softmax activation function for the output layer. The first convolutional layer uses a (3,3) kernel size and the input shape is (28,28,1). The second convolutional layer uses a (3,3) kernel size with a dropout regularization rate of 0.5. The model uses the softmax cross-entropy loss function and the Adam optimizer.

The second model has three convolutional layers with 75, 50, and 25 filters, respectively, followed by batch normalization, max pooling, dropout regularization, and two fully connected layers. The first convolutional layer uses a (3,3) kernel size and the input shape is (28,28,1). The 'same' padding ensures that the output feature maps have the same spatial dimensions as the input image. The ReLU activation function introduces non-linearity into the model, allowing it to learn complex patterns and features. Batch Normalization layer normalizes the activations of the previous layer to ensure that they have zero mean and unit variance, improving the stability and performance of the model. Then, MaxPool2D layer with a pool size of (2,2), 'same' padding, and stride of 2 performs downsampling on the output feature maps of the previous layer, reducing their spatial dimensions by half. The second convolutional layer uses a (3,3) kernel size with dropout regularization of 0.2, while the third convolutional layer uses a (3,3) kernel size. Followed by a Flatten layer which flattens the output feature maps of the previous layer into a one-dimensional vector, which is then fed into the fully connected layers of the model. Dense layer with 24 units and softmax activation: This layer is the output layer of the model, with 24 units representing the 24 classes of hand signs to be recognized. The softmax activation function normalizes the output of the layer to a probability distribution over the 24 classes.
The model uses the categorical cross-entropy loss function and the Adam optimizer.

Some differences between these models include:

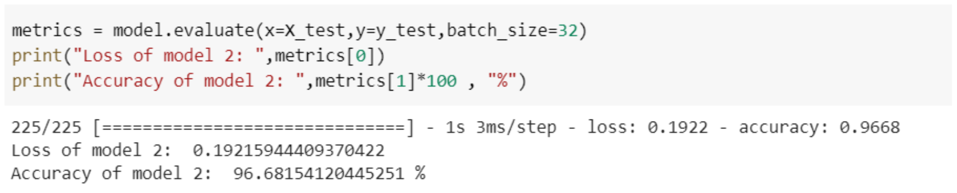
1. Number and size of convolutional filters: The second model has more convolutional filters and larger kernel sizes than the first model, which may allow it to extract more complex and high-level features from the input images.
2. Regularization techniques: The second model uses batch normalization in addition to dropout regularization, while the first model only uses dropout. Batch normalization can help to reduce overfitting and improve the generalization performance of the model.
3. Size of fully connected layers: The second model has larger fully connected layers with 512 units, while the first model has a smaller fully connected layer with 128 units. This may affect the capacity of the model to learn and represent complex patterns in the data.

Evaluation of the above two models:



```
metrics = classifier.evaluate(x=X_test,y=y_test,batch_size=32)
print("Loss of model 1: ",metrics[0])
print("Accuracy of model 1: ",metrics[1]*100 , "%")
```

```
225/225 [==============================] - 1s 3ms/step - loss: 0.2705 - accuracy: 0.9465
Loss of model 1:  0.2704564929008484
Accuracy of model 1:  94.64584589004517 %
```



```
metrics = model.evaluate(x=X_test,y=y_test,batch_size=32)
print("Loss of model 2: ",metrics[0])
print("Accuracy of model 2: ",metrics[1]*100 , "%")
```

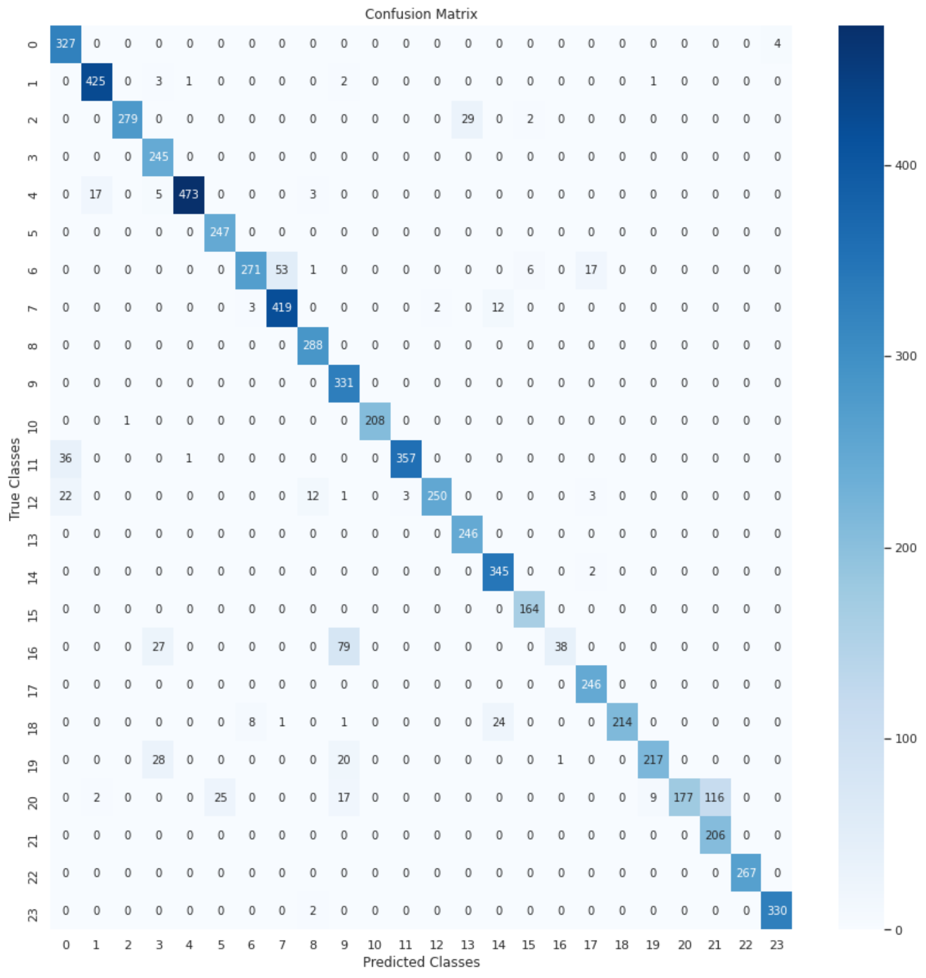
```
225/225 [==============================] - 1s 3ms/step - loss: 0.1922 - accuracy: 0.9668
Loss of model 2:  0.19215944409370422
Accuracy of model 2:  96.68154120445251 %
```

The outputs above show the evaluation metrics of the two models on a test set. The first model has a loss of 0.2705 and an accuracy of 94.65%, while the second model has a lower loss of 0.1922 and a higher accuracy of 96.68%. The evaluation metrics indicate that the second model performs better than the first model on the test set, as it has a lower loss and a higher accuracy.

Overall we can say that, the CNN model 2 with its multiple convolutional layers, batch normalization, max pooling, dropout regularization, and dense layers, is designed to learn and extract hierarchical features from the input images, making it a powerful architecture for hand sign recognition tasks. Hence we use the second model in further implementation of OpenCV.

Testing the model with test dataset:

We generated a confusion matrix to evaluate the performance of a classification model. It uses the predicted classes and true classes of the test set data to create a matrix that shows the number of true positives, true negatives, false positives, and false negatives for each class. The matrix is displayed as a heatmap using the Seaborn library, with the predicted classes on the x-axis and the true classes on the y-axis. The diagonal elements represent correct predictions, while the off-diagonal elements represent incorrect predictions. This allows us to identify which classes are being misclassified and to adjust the model accordingly.



B. Implementation of OpenCV

We developed a Python script that uses OpenCV and Keras to implement a real-time sign language recognition system. It loads a pre-trained model using the Keras API, captures frames from the webcam using OpenCV, crops the image to isolate the region of interest (ROI), applies Gaussian blur to the ROI, resizes the image to 28x28 pixels, converts the image to grayscale, and feeds it to the pre-trained model for prediction. The predicted output is then displayed in real-time on the captured frame. The script runs indefinitely until the user presses the 'q' key to quit.

Conclusion

The hand sign recognition project using deep learning and OpenCV has demonstrated the ability to accurately recognize American Sign Language (ASL) hand signs in real-time. With the use of convolutional neural networks (CNNs), the model was trained on a large dataset of ASL images and achieved a high level of accuracy of 96.86% in classifying hand signs. Additionally, the integration of OpenCV provided a real-time image processing solution that enhanced the model's ability to recognize hand signs in a variety of lighting conditions and backgrounds.

This project has important practical applications, particularly for individuals who are deaf or hard of hearing. By providing a reliable and efficient method for recognizing ASL hand signs, this project has the potential to improve communication and accessibility for this population**.**

Future Work

Deep learning-based sign language recognition has made tremendous strides in recent years. Future research has a ton of potential to enhance the precision and utility of these systems, though.

Creating systems that can recognize continuous sign language phrases rather than single signs or words is one potential direction for future research. This calls for more complex models that can manage changes in signature cadence and pace as well as temporal information processing. The creation of such technologies would make it possible for hearing and deaf people to communicate more naturally and effectively.

Enhancing the resilience of sign language recognition algorithms to environmental elements including illumination, camera angles, and occlusions is another area that needs further research. This can be accomplished by creating datasets with more complex scenarios and more robust deep learning models that can manage noisy and imperfect data.

Future research might also concentrate on creating sign language recognition systems that can adjust to the signing preferences and styles of different users. This can be done by using customized models that take into account the unique signing habits of every user and adjust to match them.

The use of multimodal techniques, which combine detection of sign language with other modalities like speech recognition or haptic input, may also be explored in future research. Deaf and hearing-impaired people can communicate more effectively overall thanks to these solutions, which also make communication more inclusive.

In conclusion, future research in deep learning for sign language recognition should concentrate on creating more complex models that can recognize continuous sign language sentences, enhancing models' robustness to environmental factors, creating customized models, and investigating multimodal communication methods.

References

- Sign Language Recognition System
- A CNN based human computer interface for American Sign Language
- Kaggle Sign Language MNIST
- Sign Language Recognition for Computer Vision Enthusiasts