```
In [1]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
        import glob
        from PIL import Image
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from sklearn.preprocessing import LabelBinarizer
        from sklearn.model selection import train test split
        from sklearn.metrics import accuracy score
        import warnings
        warnings.filterwarnings("ignore")
In [2]:
       #Intialised ImageDataGenerator from tensorflow module to preprocess the image
        datagen = ImageDataGenerator(
                rotation range=15,
                shear range=0.2,
                horizontal flip=True,
                featurewise center=True,
                width shift_range=0.05,
                height shift range=0.05,
                zoom range=0.1,
                fill mode='nearest')
In [3]: # Path to all images files of dataset - each folder - alphabet contains 100 images
        Patha="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/a/*.jpg"
        Pathb="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/b/*.jpg"
        Pathc="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/c/*.jpg"
        Pathd="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/d/*.jpg"
        Pathe="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/e/*.jpg"
        Pathf="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/f/*.jpg"
        Pathg="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/g/*.jpg"
        Pathh="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/h/*.jpg"
        Pathi="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/i/*.jpg"
        Pathj="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/j/*.jpg"
        Pathk="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/k/*.jpg"
        Pathl="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/l/*.jpg"
        Pathm="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/m/*.jpg"
        Pathn="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/n/*.jpg"
        Patho="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/o/*.jpg"
```

Pathp="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/p/\*.jpg"

```
slr
Pathq="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/q/*.jpg"
Pathr="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/r/*.jpg"
Paths="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/s/*.jpg"
Patht="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/t/*.jpg"
Pathu="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/u/*.jpg"
Pathv="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/v/*.jpg"
Pathw="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/w/*.jpg"
Pathx="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/x/*.jpg"
Pathy="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/y/*.jpg"
Pathz="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/dataset/z/*.jpg"
```

```
In [4]: # import the data from each alphabet folder and club into final dataframe
        def importing data(path):
            sample = []
            for filename in glob.glob(path):
                img = Image.open(filename, 'r')
                img = img.resize((128,128))
                sample.append(img)
            return sample
        data a = importing data(Patha)
        data b = importing data(Pathb)
        data c = importing data(Pathc)
        data d = importing data(Pathd)
        data e = importing data(Pathe)
        data f = importing data(Pathf)
        data g = importing data(Pathg)
        data h = importing data(Pathh)
        data i = importing data(Pathi)
        data j = importing data(Pathj)
        data k = importing data(Pathk)
        data 1 = importing data(Path1)
        data m = importing data(Pathm)
        data n = importing data(Pathn)
        data o = importing data(Patho)
        data p = importing data(Pathp)
        data q = importing data(Pathq)
        data r = importing data(Pathr)
        data s = importing data(Paths)
        data t = importing data(Patht)
        data u = importing data(Pathu)
        data v = importing data(Pathv)
```

```
data w = importing data(Pathw)
        data x = importing data(Pathx)
        data y = importing data(Pathy)
        data z = importing data(Pathz)
In [5]: def data import(a,b,c,d,e,f,g,h,i,j,k,l,m,n,o,p,q,r,s,t,u,v,w,x,y,z):
            df data a = pd.DataFrame({'image':a, 'label': 'a'})
            df_data_b = pd.DataFrame({'image':b, 'label': 'b'})
            df data c = pd.DataFrame({'image':c, 'label': 'c'})
            df data d = pd.DataFrame({'image':d, 'label': 'd'})
            df data e = pd.DataFrame({'image':e, 'label': 'e'})
            df data f = pd.DataFrame({'image':f, 'label': 'f'})
            df data g = pd.DataFrame({'image':g, 'label': 'g'})
            df data h = pd.DataFrame({'image':h, 'label': 'h'})
            df data i = pd.DataFrame({'image':i, 'label': 'i'})
            df data j = pd.DataFrame({'image':j, 'label': 'j'})
            df data k = pd.DataFrame({'image':k, 'label': 'k'})
            df data 1 = pd.DataFrame({'image':1, 'label': 'l'})
            df data m = pd.DataFrame({'image':m, 'label': 'm'})
            df data n = pd.DataFrame({'image':n, 'label': 'n'})
            df data o = pd.DataFrame({'image':o, 'label': 'o'})
            df data p = pd.DataFrame({'image':p, 'label': 'p'})
            df data q = pd.DataFrame({'image':q, 'label': 'q'})
            df_data_r = pd.DataFrame({'image':r, 'label': 'r'})
            df data s = pd.DataFrame({'image':s, 'label': 's'})
            df data t = pd.DataFrame({'image':t, 'label': 't'})
            df data u = pd.DataFrame({'image':u, 'label': 'u'})
            df data v = pd.DataFrame({'image':v, 'label': 'v'})
            df data w = pd.DataFrame({'image':w, 'label': 'w'})
            df data x = pd.DataFrame({'image':x, 'label': 'x'})
            df data y = pd.DataFrame({'image':y, 'label': 'y'})
            df data z = pd.DataFrame({'image':z, 'label': 'z'})
            final data = [df data a, df data b, df data c, df data d, df data e, df data f, df data g, df data h, df data i, df
            final data = pd.concat(final data)
            all data = final data['image']
            labels = final data['label']
            all data=np.stack(all data,axis=0)
            labels = LabelBinarizer().fit transform(labels)
            return all data,labels
```

```
= data_import(data_a,data_b,data_c,data_d,data_e,data_f,data_g,data_h,data_i,data_j,data_k,data_l,data_
        dataset, labels
In [6]: dataset.shape
Out[6]: (2600, 128, 128)
In [7]: dataset=dataset.reshape(2600,128,128,1)
        #augmentation method while preprocessing images
In [8]:
        def augmentation(dataset, labels, counts):
            augs=[]
            augs_data=[]
            augs_labels=[]
            i=0
            for batch in datagen.flow(dataset, labels,
                                   batch size=260):
                i += 1
                augs.append(batch)
                if i>counts:
                    break
            augs data=[]
            for i in range(counts):
                data=augs[i][0]
                augs_data.append(data)
            x = np.vstack(augs data)
            x = x/255.0
            for i in range(counts):
                label=augs[i][1]
                augs labels.append(label)
            y = np.vstack(augs labels)
            return x, y
In [9]: #augment all the images in dataset
        x,y = augmentation(dataset,labels,15)
        y = np.where(y==1)[1]
        from tensorflow.keras.utils import to_categorical
        y_onehot = to_categorical(y)
```

x train,x test,y train,y test = train test split(x,y onehot,test size=0.26,random state=2021)

```
#preprocess and train the data with cnn model layering
In [10]:
         import tensorflow as tf
         from tensorflow.keras.models import Model
         from tensorflow.keras.layers import Dense, Flatten, Input, MaxPooling2D, Conv2D, Dropout
         from tensorflow.keras import Sequential
         from tensorflow.keras.optimizers import Adam
         from tensorflow.keras.callbacks import EarlyStopping
         model = Sequential()
         model.add(Conv2D(12, (5, 5), activation='relu', padding='same', input shape=(128, 128, 1)))
         model.add(MaxPooling2D(2,2))
         model.add(Conv2D(24, (5, 5), activation='relu', padding='same',
                          kernel regularizer =tf.keras.regularizers.l1(l=0.01)))
         model.add(MaxPooling2D(2,2))
         model.add(Conv2D(36, (5, 5), activation='relu', padding='same',
                          kernel regularizer =tf.keras.regularizers.l2(l=0.01)))
         model.add(MaxPooling2D(2,2))
         model.add(Dropout(0.2))
         model.add(Conv2D(48, (5, 5), activation='relu',
                          kernel regularizer =tf.keras.regularizers.l2(l=0.01)))
         model.add(MaxPooling2D(2,2))
         model.add(Dropout(0.3))
         model.add(Flatten())
         m = model.output
         m = Dense(120, activation = "relu")(m)
         m = Dense(100, activation = "relu")(m)
         m = Dropout(0.2)(m)
         m = Dense(60, activation = "relu")(m)
         m = Dense(60, activation = "relu")(m)
         m = Dropout(0.2)(m)
         final layer = Dense(26, activation = "softmax")(m)
         cnn model = Model(inputs=model.input, outputs=final layer)
```

Model: "model"

Layer (type)	Output Shape	Param #
 conv2d_input (InputLayer)		
conv2d (Conv2D)	(None, 128, 128, 12)	312
<pre>max_pooling2d (MaxPooling2D )</pre>	(None, 64, 64, 12)	0
conv2d_1 (Conv2D)	(None, 64, 64, 24)	7224
<pre>max_pooling2d_1 (MaxPooling 2D)</pre>	(None, 32, 32, 24)	0
conv2d_2 (Conv2D)	(None, 32, 32, 36)	21636
<pre>max_pooling2d_2 (MaxPooling 2D)</pre>	(None, 16, 16, 36)	0
dropout (Dropout)	(None, 16, 16, 36)	0
conv2d_3 (Conv2D)	(None, 12, 12, 48)	43248
<pre>max_pooling2d_3 (MaxPooling 2D)</pre>	(None, 6, 6, 48)	0
dropout_1 (Dropout)	(None, 6, 6, 48)	0
flatten (Flatten)	(None, 1728)	0
dense (Dense)	(None, 120)	207480
dense_1 (Dense)	(None, 100)	12100
dropout_2 (Dropout)	(None, 100)	0
dense_2 (Dense)	(None, 60)	6060
dense_3 (Dense)	(None, 60)	3660
dropout_3 (Dropout)	(None, 60)	0

(None, 26)

dense 4 (Dense)

```
Total params: 303,306
Trainable params: 303,306
Non-trainable params: 0
Epoch 1/50
racy: 0.0363
Epoch 2/50
racy: 0.0398
Epoch 3/50
racy: 0.0398
Epoch 4/50
racy: 0.0363
Epoch 5/50
racy: 0.0363
Epoch 6/50
racy: 0.0363
Epoch 7/50
racy: 0.0363
Epoch 8/50
racy: 0.0363
Epoch 9/50
racy: 0.0363
Epoch 10/50
racy: 0.0363
Epoch 11/50
racy: 0.0363
Epoch 12/50
37/37 [===========] - 19s 509ms/step - loss: 0.9564 - accuracy: 0.0347 - val loss: 0.8506 - val accu
```

1586

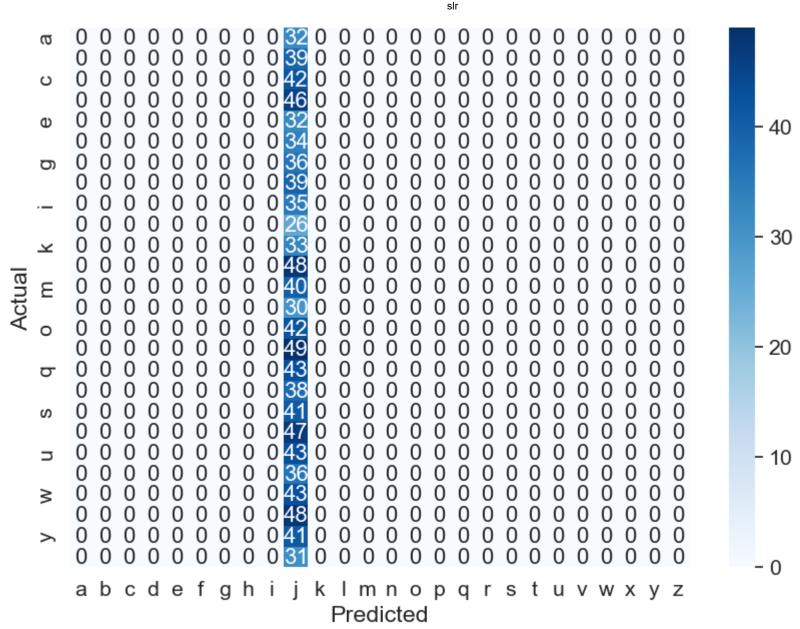
```
racy: 0.0381
Epoch 13/50
racy: 0.0398
Epoch 14/50
37/37 [===========] - 17s 450ms/step - loss: 0.6925 - accuracy: 0.0381 - val loss: 0.6102 - val accu
racy: 0.0398
Epoch 15/50
racy: 0.0398
Epoch 16/50
racy: 0.0398
Epoch 17/50
racy: 0.0398
Epoch 18/50
racy: 0.0398
Epoch 19/50
racy: 0.0398
Epoch 20/50
racy: 0.0398
Epoch 21/50
racy: 0.0398
Epoch 22/50
racy: 0.0398
Epoch 23/50
37/37 [============= ] - 17s 457ms/step - loss: 0.1910 - accuracy: 0.0373 - val loss: 0.1704 - val accu
racy: 0.0346
Epoch 24/50
racy: 0.0346
Epoch 25/50
racy: 0.0346
Epoch 26/50
racy: 0.0346
```

```
Epoch 27/50
racy: 0.0398
Epoch 28/50
racy: 0.0398
Epoch 29/50
racy: 0.0398
Epoch 30/50
racy: 0.0398
Epoch 31/50
racy: 0.0398
Epoch 32/50
racy: 0.0398
Epoch 33/50
37/37 [===========] - 18s 488ms/step - loss: 0.1790 - accuracy: 0.0468 - val loss: 0.1656 - val accu
racy: 0.0346
Epoch 34/50
37/37 [===========] - 19s 508ms/step - loss: 0.1793 - accuracy: 0.0390 - val loss: 0.1650 - val accu
racy: 0.0346
Epoch 35/50
racy: 0.0346
Epoch 36/50
racy: 0.0346
Epoch 37/50
racy: 0.0346
Epoch 38/50
37/37 [===========] - 19s 508ms/step - loss: 0.1782 - accuracy: 0.0338 - val loss: 0.1645 - val accu
racy: 0.0346
Epoch 39/50
racy: 0.0346
Epoch 40/50
racy: 0.0346
Epoch 41/50
```

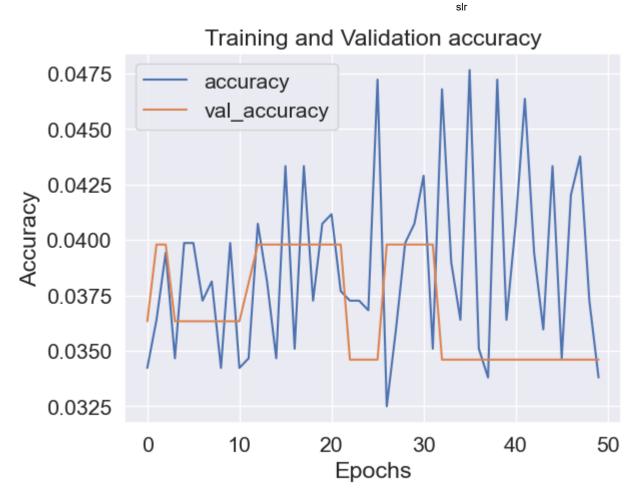
```
racy: 0.0346
   Epoch 42/50
   racy: 0.0346
   Epoch 43/50
   racy: 0.0346
   Epoch 44/50
   racy: 0.0346
   Epoch 45/50
   racy: 0.0346
   Epoch 46/50
   racy: 0.0346
   Epoch 47/50
   racy: 0.0346
   Epoch 48/50
   racy: 0.0346
   Epoch 49/50
   racy: 0.0346
   Epoch 50/50
   racy: 0.0346
In [11]: #get dataset and fit into algo and confusion matrix, classification report
   import seaborn as sn
   from sklearn.metrics import confusion matrix
   from sklearn.metrics import classification report
   predictions = cnn model.predict(x test)
   pred labels = np.argmax(predictions, axis = 1)
   tests=np.argmax(y test,axis=1)
   conf mx = confusion matrix(tests, pred labels)
   conf mx
   heat_cm = pd.DataFrame(conf_mx, columns=("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o","p","q","r","s","t
```

```
"w","x","y","z"), index =("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o"
                                                                       ,"p","q","r","s","t","u","v","w","x","y","z"))
heat cm.index.name = 'Actual'
heat cm.columns.name = 'Predicted'
plt.figure(figsize = (10,7))
sn.set(font scale=1.4)
sn.heatmap(heat cm, cmap="Blues", annot=True, annot kws={"size": 16},fmt='g')
plt.show()
print(classification report(tests, pred labels))
history df = pd.DataFrame(history.history)
plt.plot(history df.loc[:, ['accuracy']], label='accuracy')
plt.plot(history df.loc[:, ['val accuracy']], label='val accuracy')
plt.title('Training and Validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
plt.plot(history df.loc[:, ['loss']], label='loss')
plt.plot(history df.loc[:, ['val loss']], label='val loss')
plt.title('Training and Validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

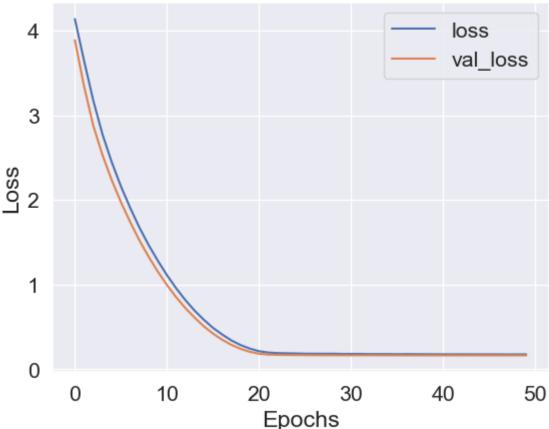
32/32 [======== ] - 2s 58ms/step



	precision	recall	f1-score	support
0	0.00	0.00	0.00	32
1	0.00	0.00	0.00	39
2	0.00	0.00	0.00	42
3	0.00	0.00	0.00	46
4	0.00	0.00	0.00	32
5	0.00	0.00	0.00	34
6	0.00	0.00	0.00	36
7	0.00	0.00	0.00	39
8	0.00	0.00	0.00	35
9	0.03	1.00	0.05	26
10	0.00	0.00	0.00	33
11	0.00	0.00	0.00	48
12	0.00	0.00	0.00	40
13	0.00	0.00	0.00	30
14	0.00	0.00	0.00	42
15	0.00	0.00	0.00	49
16	0.00	0.00	0.00	43
17	0.00	0.00	0.00	38
18	0.00	0.00	0.00	41
19	0.00	0.00	0.00	47
20	0.00	0.00	0.00	43
21	0.00	0.00	0.00	36
22	0.00	0.00	0.00	43
23	0.00	0.00	0.00	48
24	0.00	0.00	0.00	41
25	0.00	0.00	0.00	31
accuracy			0.03	1014
macro avg	0.00	0.04	0.00	1014
weighted avg	0.00	0.03	0.00	1014



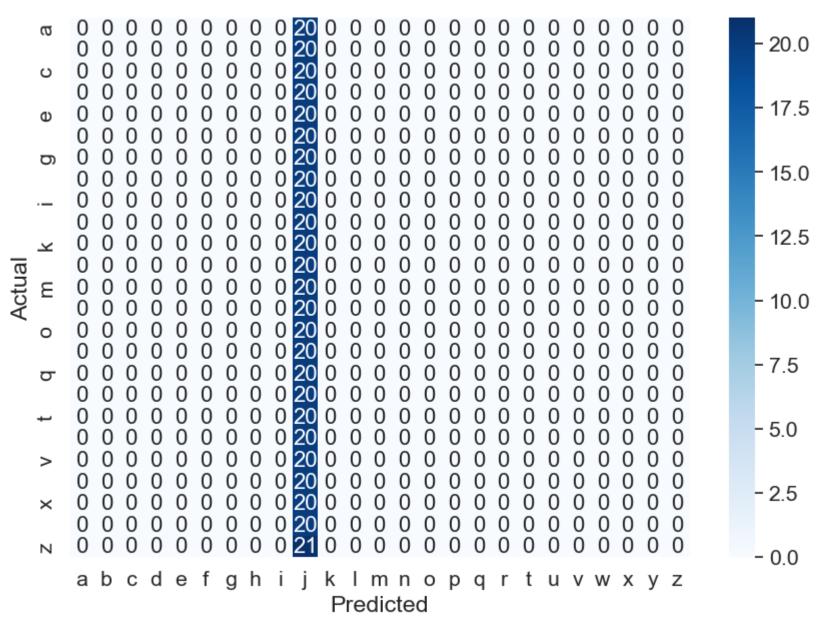




In [12]: # all the test data is loaded in test folder, were imported and clubbed into final df
 externala="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/a/\*.jpg"
 externalb="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/b/\*.jpg"
 externalc="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/c/\*.jpg"
 externald="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/d/\*.jpg"
 externale="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/e/\*.jpg"
 externalg="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/g/\*.jpg"
 externalh="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/h/\*.jpg"
 externali="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/i/\*.jpg"
 externalj="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/j/\*.jpg"
 externall="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/j/\*.jpg"
 externall="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/k/\*.jpg"
 externall="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/k/\*.jpg"
 externall="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/l/\*.jpg"
 externall="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/l/\*.jpg"
 externall="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/l/\*.jpg"
 externall="C:/Users/thipp/Fall2022/CS5710\_13469/Sign Language for Alphabets/test/l/\*.jpg"

```
externaln="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/test/n/*.jpg"
externalo="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/test/o/*.jpg"
externalp="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/test/p/*.jpg"
externalq="C:/Users/thipp/Fall2022/CS5710_13469/Sign Language for Alphabets/test/q/*.jpg"
externalr="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/test/r/*.jpg"
externals="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/test/s/*.jpg"
externalt="C:/Users/thipp/Fall2022/CS5710_13469/Sign Language for Alphabets/test/t/*.jpg"
externalu="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/test/u/*.jpg"
externalv="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/test/v/*.jpg"
externalw="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/test/w/*.jpg"
externalx="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/test/x/*.jpg"
externaly="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/test/y/*.jpg"
externalz="C:/Users/thipp/Fall2022/CS5710 13469/Sign Language for Alphabets/test/z/*.jpg"
external test a = importing_data(externala)
external test b = importing_data(externalb)
external test c = importing data(externalc)
external test d= importing data(externald)
external test e= importing data(externale)
external test f= importing data(externalf)
external test g= importing data(externalg)
external test h= importing data(externalh)
external test i= importing data(externali)
external test j= importing data(externalj)
external test k= importing data(externalk)
external test l= importing data(externall)
external test m= importing data(externalm)
external test n= importing data(externaln)
external test o= importing data(externalo)
external test p= importing data(externalp)
external test q= importing data(externalq)
external test r= importing data(externalr)
external test s= importing data(externals)
external test t= importing data(externalt)
external test u= importing data(externalu)
external test v= importing data(externalv)
external test w= importing data(externalw)
external test x= importing data(externalx)
external test y= importing data(externaly)
external test z= importing data(externalz)
external test data, external test label = data import(external test a, external test b, external test c, external test d,
```

```
external test e, external test f, external test g, external test h,
                                                      external test i, external test j, external test k, external test 1,
                                                      external test m, external test o, external test p,
                                                      external test q,external test r,external test s,external test t,
                                                      external test u, external test v, external test w, external test x,
                                                     external test y, external test z)
print(external test data.shape)
external test data=external test data.reshape(501,128,128,1)
external test data = external test data /255.0
external test pred = cnn model.predict(external test data)
external pred labels = np.argmax(external test pred, axis = 1)
external tests=np.argmax(external test label,axis=1)
external conf mx = confusion matrix(external tests, external pred labels)
heat cm = pd.DataFrame(external conf mx,
                      columns=("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o","p","q","r","t","u","v","w"
                      ,index =("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o","p","q","r","t","u","v","w"
heat cm.index.name = 'Actual'
heat cm.columns.name = 'Predicted'
plt.figure(figsize = (10,7))
sn.set(font scale=1.4)
sn.heatmap(heat cm, cmap="Blues", annot=True, annot kws={"size": 16},fmt='g')
plt.show()
(501, 128, 128)
16/16 [======== - - 1s 70ms/step
```



```
In [13]: x_for_ml = model.predict(x_train)
    x_test_ml = model.predict(x_test)
    y_train_ml = np.where(y_train==1)[1]
    y_test_ml = np.where(y_test==1)[1]
```

```
external data ml = model.predict(external test data)
         external label ml = np.where(external test label==1)[1]
         91/91 [======== ] - 6s 63ms/step
         32/32 [========= ] - 2s 62ms/step
         16/16 [======== ] - 1s 59ms/step
In [14]: #common method to execute various machine learning algorithms and their performances
         def machine learning(algorithm):
             algorithm.fit(x for ml, y train ml)
             prediction algo = algorithm.predict(x test ml)
             cm algo = confusion matrix(y test ml, prediction algo)
             heat cm = pd.DataFrame(cm algo, columns=("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o","p",
                                                     "q", "r", "s", "t", "u", "v", "w", "x", "y", "z"),
                                                     index=("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o","p"
                                                            ,"q","r","s","t","u","v","w","x","y","z"))
             heat cm.index.name = 'Actual'
             heat cm.columns.name = 'Predicted'
             plt.figure(figsize = (10,7))
             sn.set(font scale=1.4)
             sn.heatmap(heat cm, cmap="Blues", annot=True, annot kws={"size": 16},fmt='g')
             cm algo=plt.show()
             report = print(classification report(y test ml, prediction algo))
             algo accuracy = accuracy score(y test ml, prediction algo)
             prediction self algo = algorithm.predict(external data ml)
             cm self algo = confusion matrix(external label ml, prediction self algo)
             algo test accuracy = accuracy score(external label ml, prediction self algo)
             heat cm = pd.DataFrame(cm self algo, columns=("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o","p","q","
                                   index =("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o","p","q","r","s","t","u",
             heat cm.index.name = 'Actual'
             heat cm.columns.name = 'Predicted'
             plt.figure(figsize = (10,7))
             sn.set(font scale=1.4)
             sn.heatmap(heat cm, cmap="Blues", annot=True, annot kws={"size": 16},fmt='g')
             cm self algo=plt.show()
             return cm algo, report, cm self algo, algo accuracy, algo test accuracy
In [15]: def machine learning1(algorithm):
             #fit the training data into ML algorithm
```

slr

algorithm.fit(x for ml, y train ml)

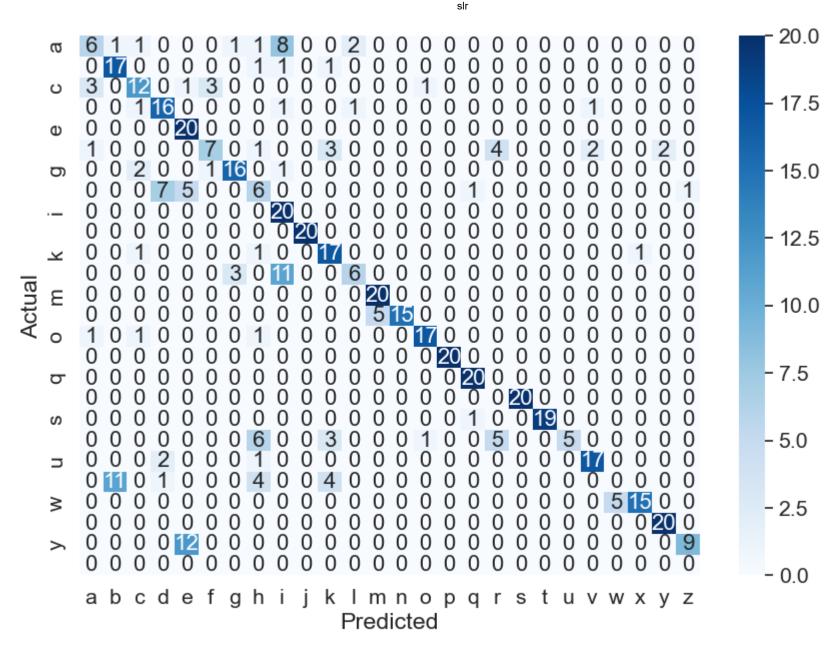
```
#Predict the data using test
prediction algo = algorithm.predict(x test ml)
#confustion matrix
cm algo = confusion matrix(y_test_ml, prediction_algo)
#plotting the confusion matrix
heat_cm = pd.DataFrame(cm_algo, columns=("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o","p",
                                         "q","r","s","t","u","v","w","x","y","z"),
                                         index=("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o","p"
                                                ,"q","r","s","t","u","v","w","x","y","z"))
heat cm.index.name = 'Actual'
heat cm.columns.name = 'Predicted'
plt.figure(figsize = (10,7))
sn.set(font scale=1.4)
sn.heatmap(heat cm, cmap="Blues", annot=True, annot kws={"size": 16},fmt='g')
cm algo=plt.show()
#classification report of training data
report = print(classification report(y test ml, prediction algo))
#accuracy of training data
algo accuracy = accuracy score(y test ml, prediction algo)
#predicting the external test dataset
prediction self algo = algorithm.predict(external data ml)
#test dataset confusion matrix
cm self algo = confusion matrix(external label ml, prediction self algo)
#test dataset accuracy
algo test accuracy = accuracy score(external label ml, prediction self algo)
heat cm = pd.DataFrame(cm self algo, columns=("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o","p","q",
                       index =("a","b","c","d","e","f","g","h","i","j","k","l","m","n","o","p","q","r","t","u","v",
heat cm.index.name = 'Actual'
heat cm.columns.name = 'Predicted'
plt.figure(figsize = (10,7))
sn.set(font scale=1.4)
sn.heatmap(heat cm, cmap="Blues", annot=True, annot kws={"size": 16},fmt='g')
cm self algo=plt.show()
return cm algo, report, cm self algo, algo accuracy, algo test accuracy
```

```
In [16]: #XgBoost Algorithm
    from xgboost import XGBClassifier
    from sklearn.model_selection import GridSearchCV
    xgb = XGBClassifier()

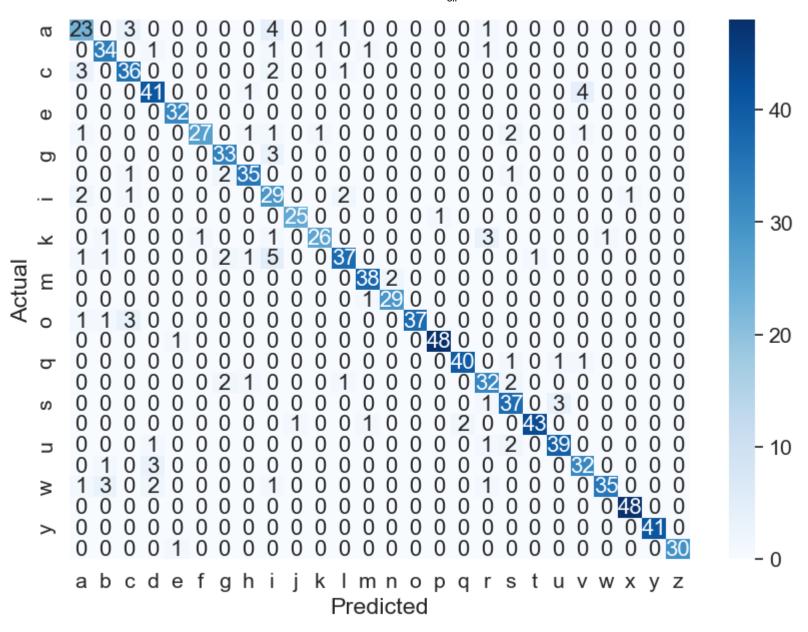
xgboost = XGBClassifier(n_estimators=50,learning_rate=0.1,
```

max depth=2,reg lambda=0.1) xgb\_cm, xgb\_report, xgb\_external\_cm, xgb\_acc, xgb\_ext\_acc = machine\_learning(xgboost) - 40 30 Actual - 20 - 10 - 0 abcdefghijklmnopqrstuvwxyz Predicted

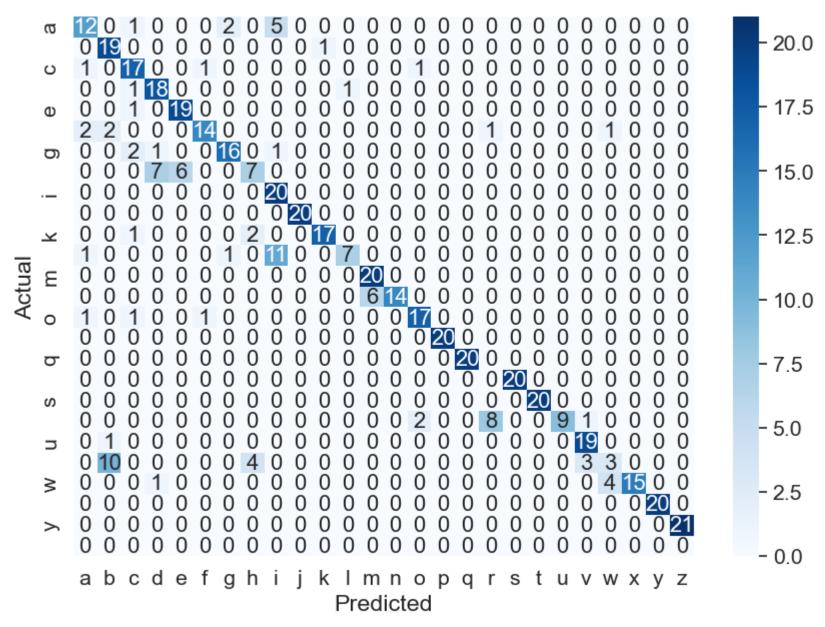
	precision	recall	f1-score	support
0	0.58	0.47	0.52	32
1	0.71	0.82	0.76	39
2	0.64	0.67	0.65	42
3	0.75	0.78	0.77	46
4	0.84	0.97	0.90	32
5	0.79	0.65	0.71	34
6	0.82	0.92	0.87	36
7	0.62	0.72	0.67	39
8	0.47	0.80	0.59	35
9	0.92	0.88	0.90	26
10	0.71	0.76	0.74	33
11	0.80	0.58	0.67	48
12	0.80	0.88	0.83	40
13	0.86	0.80	0.83	30
14	0.97	0.79	0.87	42
15	1.00	0.96	0.98	49
16	0.74	0.67	0.71	43
17	0.54	0.39	0.45	38
18	0.74	0.83	0.78	41
19	0.82	0.77	0.79	47
20	0.76	0.72	0.74	43
21	0.62	0.64	0.63	36
22	0.92	0.77	0.84	43
23	0.90	0.98	0.94	48
24	0.93	0.95	0.94	41
25	1.00	0.90	0.95	31
accuracy			0.77	1014
macro avg	0.78	0.77	0.77	1014
weighted avg	0.78	0.77	0.77	1014



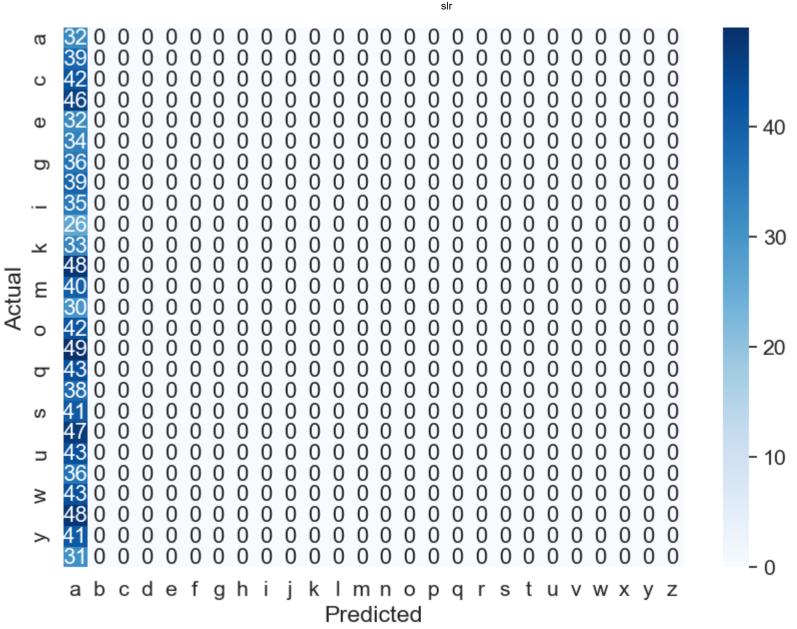
```
In [17]: #%% LGBM
         from lightgbm import LGBMClassifier
         lgbm = LGBMClassifier(n estimators=500,random state=2021)
         lgbm cm, lgbm report,lgbm cm external,lgb acc, lgb ext acc = machine learning(lgbm)
```



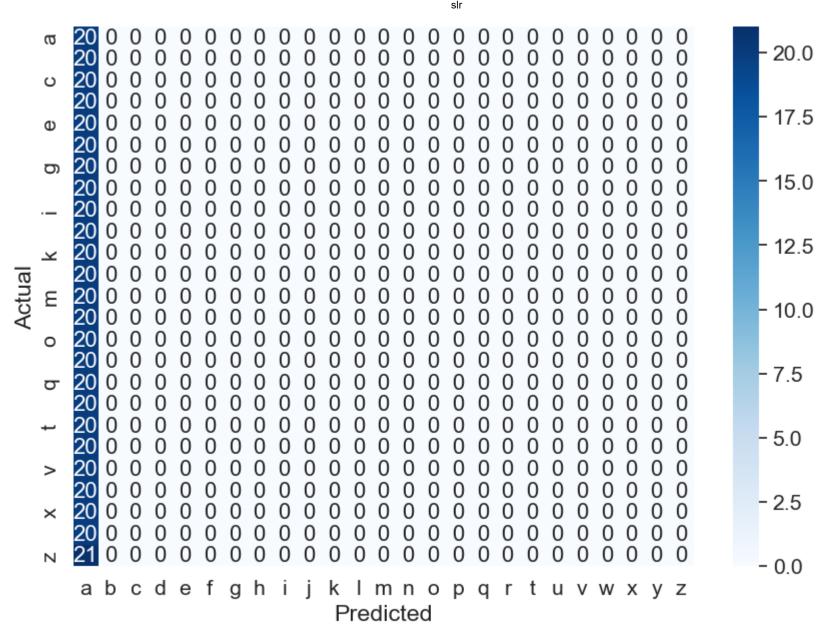
0       0.72       0.72       0.72       32         1       0.83       0.87       0.85       39         2       0.82       0.86       0.84       42         3       0.85       0.89       0.87       46         4       0.94       1.00       0.97       32         5       0.96       0.79       0.87       34         6       0.85       0.92       0.88       36         7       0.90       0.90       0.90       39         8       0.62       0.83       0.71       35         9       0.96       0.96       0.96       26         10       0.93       0.79       0.85       33         11       0.88       0.77       0.82       48         12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82		precision	recall	f1-score	support
2       0.82       0.86       0.84       42         3       0.85       0.89       0.87       46         4       0.94       1.00       0.97       32         5       0.96       0.79       0.87       34         6       0.85       0.92       0.88       36         7       0.90       0.90       0.90       39         8       0.62       0.83       0.71       35         9       0.96       0.96       0.96       26         10       0.93       0.79       0.85       33         11       0.88       0.77       0.82       48         12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95	0	0.72	0.72	0.72	32
3       0.85       0.89       0.87       46         4       0.94       1.00       0.97       32         5       0.96       0.79       0.87       34         6       0.85       0.92       0.88       36         7       0.90       0.90       0.90       39         8       0.62       0.83       0.71       35         9       0.96       0.96       0.96       26         10       0.93       0.79       0.85       33         11       0.88       0.77       0.82       48         12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91	1	0.83	0.87	0.85	39
4       0.94       1.00       0.97       32         5       0.96       0.79       0.87       34         6       0.85       0.92       0.88       36         7       0.90       0.90       0.90       39         8       0.62       0.83       0.71       35         9       0.96       0.96       0.96       26         10       0.93       0.79       0.85       33         11       0.88       0.77       0.82       48         12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       0.91       43         21       0.84       0.89 <td>2</td> <td>0.82</td> <td>0.86</td> <td>0.84</td> <td>42</td>	2	0.82	0.86	0.84	42
5       0.96       0.79       0.87       34         6       0.85       0.92       0.88       36         7       0.90       0.90       0.90       39         8       0.62       0.83       0.71       35         9       0.96       0.96       0.96       26         10       0.93       0.79       0.85       33         11       0.88       0.77       0.82       48         12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89 <td>3</td> <td>0.85</td> <td>0.89</td> <td>0.87</td> <td>46</td>	3	0.85	0.89	0.87	46
6       0.85       0.92       0.88       36         7       0.90       0.90       0.90       39         8       0.62       0.83       0.71       35         9       0.96       0.96       0.96       26         10       0.93       0.79       0.85       33         11       0.88       0.77       0.82       48         12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99 </td <td>4</td> <td>0.94</td> <td>1.00</td> <td>0.97</td> <td>32</td>	4	0.94	1.00	0.97	32
7       0.90       0.90       0.90       39         8       0.62       0.83       0.71       35         9       0.96       0.96       0.96       26         10       0.93       0.79       0.85       33         11       0.88       0.77       0.82       48         12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00<	5	0.96	0.79	0.87	34
8       0.62       0.83       0.71       35         9       0.96       0.96       0.96       26         10       0.93       0.79       0.85       33         11       0.88       0.77       0.82       48         12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	6	0.85	0.92	0.88	36
9       0.96       0.96       0.96       26         10       0.93       0.79       0.85       33         11       0.88       0.77       0.82       48         12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	7	0.90	0.90	0.90	39
10       0.93       0.79       0.85       33         11       0.88       0.77       0.82       48         12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	8	0.62	0.83	0.71	35
11       0.88       0.77       0.82       48         12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	9	0.96	0.96	0.96	26
12       0.93       0.95       0.94       40         13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	10	0.93	0.79	0.85	33
13       0.94       0.97       0.95       30         14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	11	0.88	0.77	0.82	48
14       1.00       0.88       0.94       42         15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	12	0.93	0.95	0.94	40
15       0.98       0.98       0.98       49         16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	13	0.94	0.97	0.95	30
16       0.95       0.93       0.94       43         17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	14	1.00	0.88	0.94	42
17       0.80       0.84       0.82       38         18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	15	0.98	0.98	0.98	49
18       0.82       0.90       0.86       41         19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	16	0.95	0.93	0.94	43
19       0.98       0.91       0.95       47         20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	17	0.80	0.84	0.82	38
20       0.91       0.91       0.91       43         21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	18	0.82	0.90	0.86	41
21       0.84       0.89       0.86       36         22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	19	0.98	0.91	0.95	47
22       0.97       0.81       0.89       43         23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	20	0.91	0.91	0.91	43
23       0.98       1.00       0.99       48         24       1.00       1.00       1.00       41	21	0.84	0.89	0.86	36
24 1.00 1.00 1.00 41	22	0.97	0.81	0.89	43
	23	0.98	1.00	0.99	48
25 1 00 0 07 0 00 31	24	1.00	1.00	1.00	41
25 1.00 0.57 0.58 51	25	1.00	0.97	0.98	31
accuracy 0.89 1014	accuracy			0.89	1014
macro avg 0.90 0.89 0.89 1014	macro avg	0.90	0.89	0.89	1014
weighted avg 0.90 0.89 0.90 1014	weighted avg	0.90	0.89	0.90	1014



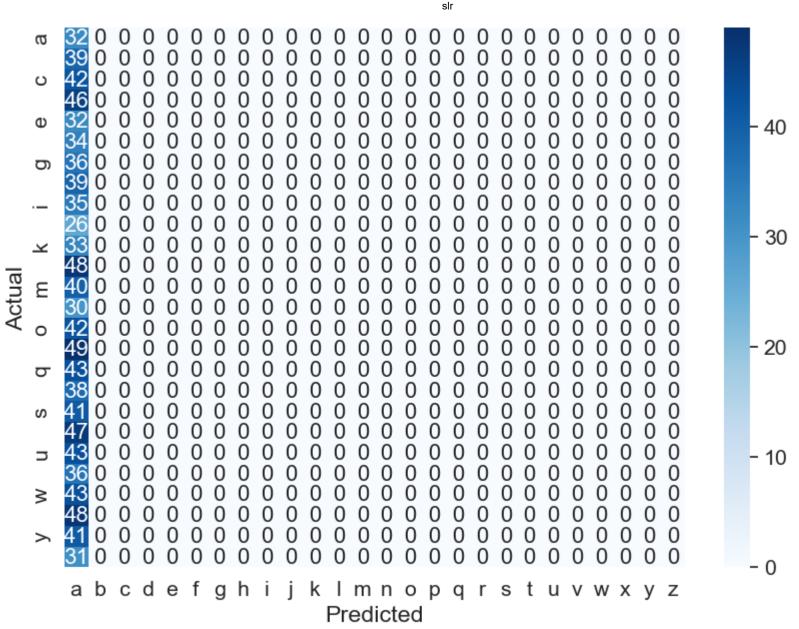
```
In [18]: #Support vector machine
    from sklearn.svm import SVC
    SVCClf = SVC(kernel = 'linear',gamma = 'scale', shrinking = False,)
    SVCClf_cm, SVCClf_report,SVCClf_cm_external, svc_acc, svc_ext_acc = machine_learning1(SVCClf)
```



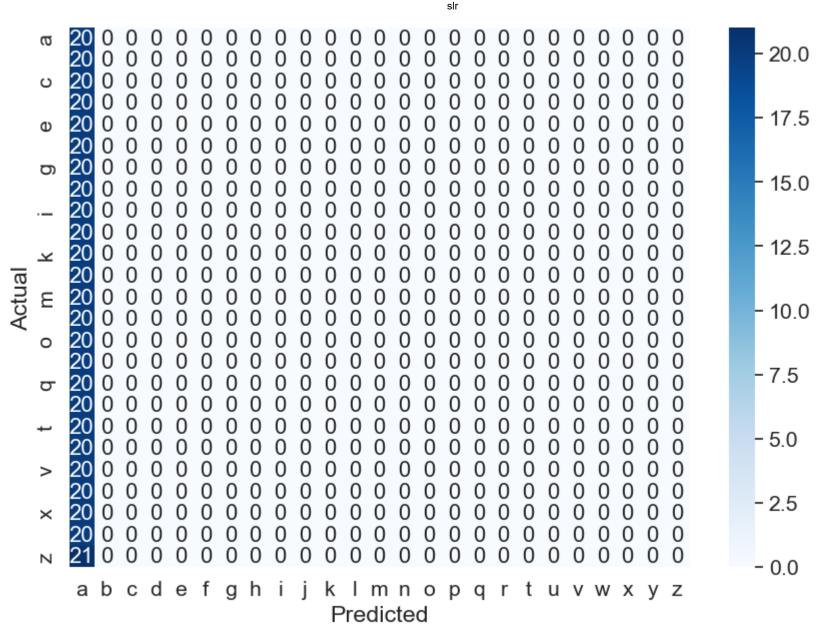
	precision	recall	f1-score	support
0	0.03	1.00	0.06	32
1	0.00	0.00	0.00	39
2	0.00	0.00	0.00	42
3	0.00	0.00	0.00	46
4	0.00	0.00	0.00	32
5	0.00	0.00	0.00	34
6	0.00	0.00	0.00	36
7	0.00	0.00	0.00	39
8	0.00	0.00	0.00	35
9	0.00	0.00	0.00	26
10	0.00	0.00	0.00	33
11	0.00	0.00	0.00	48
12	0.00	0.00	0.00	40
13	0.00	0.00	0.00	30
14	0.00	0.00	0.00	42
15	0.00	0.00	0.00	49
16	0.00	0.00	0.00	43
17	0.00	0.00	0.00	38
18	0.00	0.00	0.00	41
19	0.00	0.00	0.00	47
20	0.00	0.00	0.00	43
21	0.00	0.00	0.00	36
22	0.00	0.00	0.00	43
23	0.00	0.00	0.00	48
24	0.00	0.00	0.00	41
25	0.00	0.00	0.00	31
			0.00	4044
accuracy	0.00	0.01	0.03	1014
macro avg	0.00	0.04	0.00	1014
weighted avg	0.00	0.03	0.00	1014



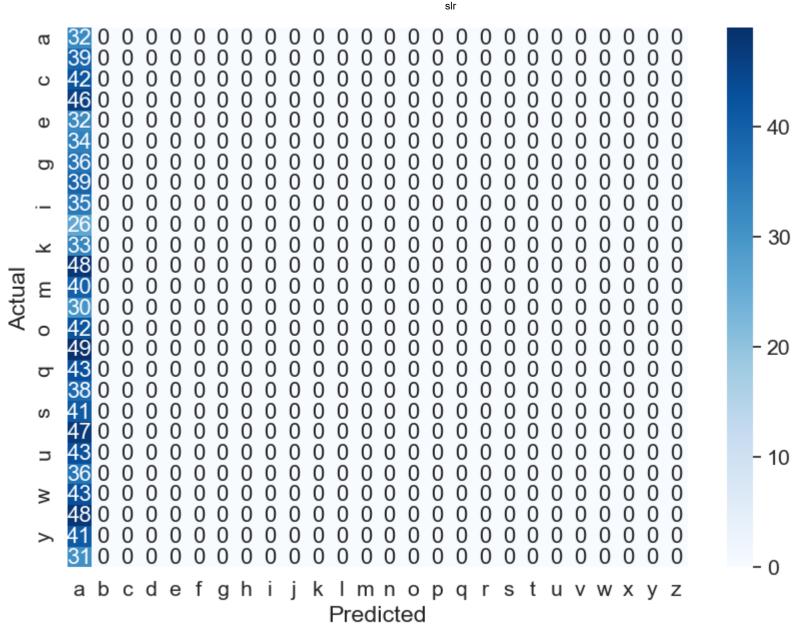
```
In [19]: #Decision Tree
         from sklearn.tree import DecisionTreeClassifier
         clf = DecisionTreeClassifier(criterion="gini", random_state=42,max_depth=3, min_samples_leaf=5)
         clf cm, clf report,clf cm external, clf acc, clf ext acc = machine learning1(clf)
```



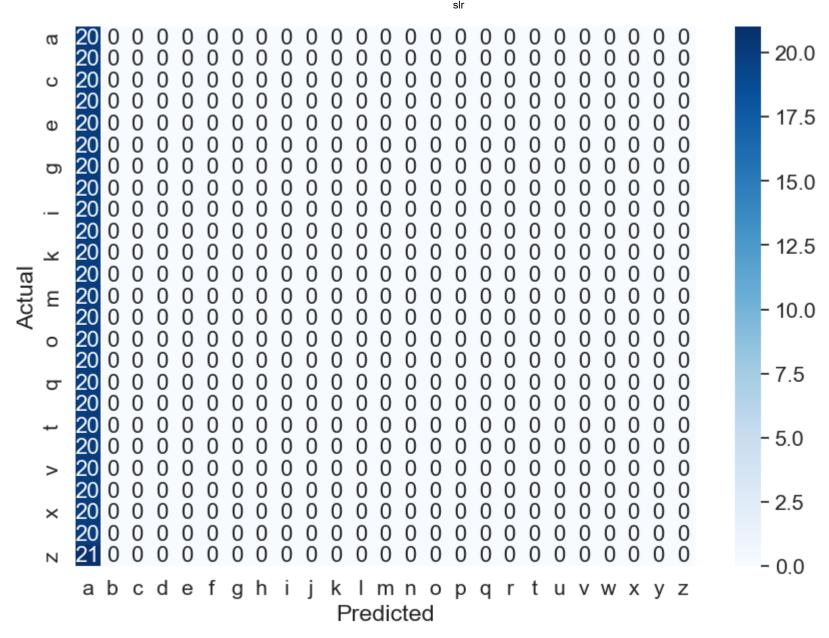
	precision	recall	f1-score	support
0	0.03	1.00	0.06	32
1	0.00	0.00	0.00	39
2	0.00	0.00	0.00	42
3	0.00	0.00	0.00	46
4	0.00	0.00	0.00	32
5	0.00	0.00	0.00	34
6	0.00	0.00	0.00	36
7	0.00	0.00	0.00	39
8	0.00	0.00	0.00	35
9	0.00	0.00	0.00	26
10	0.00	0.00	0.00	33
11	0.00	0.00	0.00	48
12	0.00	0.00	0.00	40
13	0.00	0.00	0.00	30
14	0.00	0.00	0.00	42
15	0.00	0.00	0.00	49
16	0.00	0.00	0.00	43
17	0.00	0.00	0.00	38
18	0.00	0.00	0.00	41
19	0.00	0.00	0.00	47
20	0.00	0.00	0.00	43
21	0.00	0.00	0.00	36
22	0.00	0.00	0.00	43
23	0.00	0.00	0.00	48
24	0.00	0.00	0.00	41
25	0.00	0.00	0.00	31
accuracy			0.03	1014
macro avg	0.00	0.04	0.00	1014
weighted avg	0.00	0.03	0.00	1014



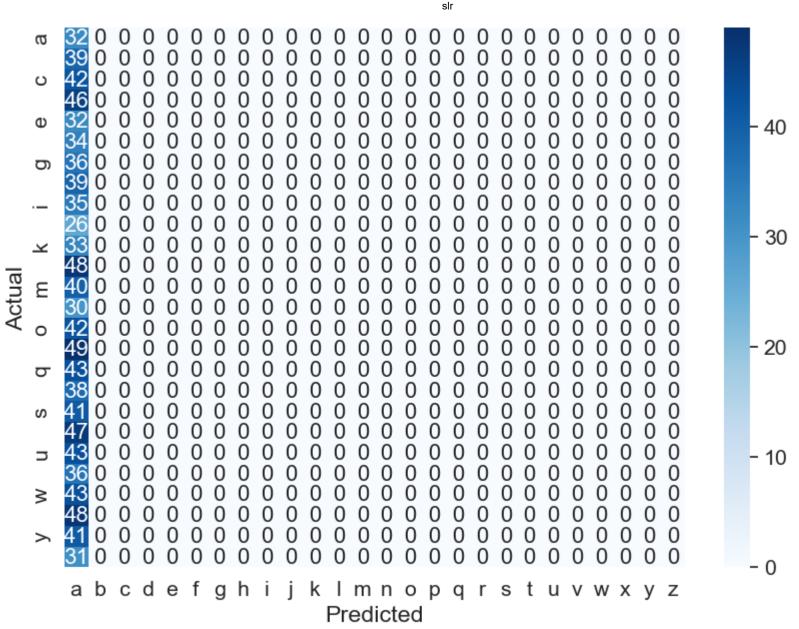
```
#LogisticRegression
In [20]:
         from sklearn.linear_model import LogisticRegression
         logreg = LogisticRegression(random_state = 0)
         logreg_cm, logreg_report,logreg_cm_external, logreg_acc, logreg_ext_acc = machine_learning1(logreg)
```



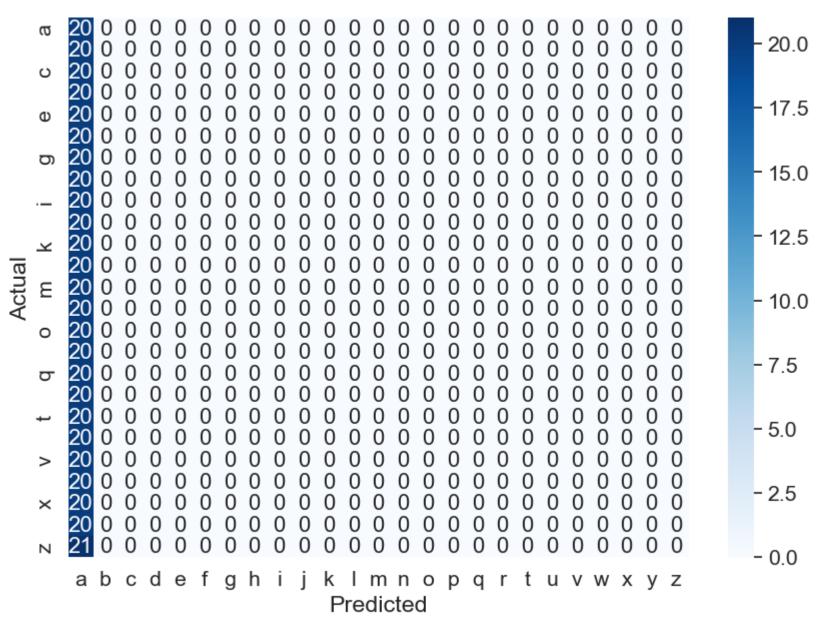
	precision	recall	f1-score	support
0	0.03	1.00	0.06	32
1	0.00	0.00	0.00	39
2	0.00	0.00	0.00	42
3	0.00	0.00	0.00	46
4	0.00	0.00	0.00	32
5	0.00	0.00	0.00	34
6	0.00	0.00	0.00	36
7	0.00	0.00	0.00	39
8	0.00	0.00	0.00	35
9	0.00	0.00	0.00	26
10	0.00	0.00	0.00	33
11	0.00	0.00	0.00	48
12	0.00	0.00	0.00	40
13	0.00	0.00	0.00	30
14	0.00	0.00	0.00	42
15	0.00	0.00	0.00	49
16	0.00	0.00	0.00	43
17	0.00	0.00	0.00	38
18	0.00	0.00	0.00	41
19	0.00	0.00	0.00	47
20	0.00	0.00	0.00	43
21	0.00	0.00	0.00	36
22	0.00	0.00	0.00	43
23	0.00	0.00	0.00	48
24	0.00	0.00	0.00	41
25	0.00	0.00	0.00	31
accuracy			0.03	1014
macro avg	0.00	0.04	0.00	1014
weighted avg	0.00	0.03	0.00	1014



```
In [21]: #RandomForestClassifier
         from sklearn.ensemble import RandomForestClassifier
         rf_clf = RandomForestClassifier(n_estimators = 100)
         rf_clf_cm, rf_clf_report,rf_clf_cm_external, rf_acc, rf_ext_acc = machine_learning1(rf_clf)
```



	precision	recall	f1-score	support
0	0.03	1.00	0.06	32
1	0.00	0.00	0.00	39
2	0.00	0.00	0.00	42
3	0.00	0.00	0.00	46
4	0.00	0.00	0.00	32
5	0.00	0.00	0.00	34
6	0.00	0.00	0.00	36
7	0.00	0.00	0.00	39
8	0.00	0.00	0.00	35
9	0.00	0.00	0.00	26
10	0.00	0.00	0.00	33
11	0.00	0.00	0.00	48
12	0.00	0.00	0.00	40
13	0.00	0.00	0.00	30
14	0.00	0.00	0.00	42
15	0.00	0.00	0.00	49
16	0.00	0.00	0.00	43
17	0.00	0.00	0.00	38
18	0.00	0.00	0.00	41
19	0.00	0.00	0.00	47
20	0.00	0.00	0.00	43
21	0.00	0.00	0.00	36
22	0.00	0.00	0.00	43
23	0.00	0.00	0.00	48
24	0.00	0.00	0.00	41
25	0.00	0.00	0.00	31
			0.00	4044
accuracy	0.00	0.01	0.03	1014
macro avg	0.00	0.04	0.00	1014
weighted avg	0.00	0.03	0.00	1014



```
In [22]: #Accuary of each alogirthm displaying as table
    res_table = pd.DataFrame({
        'Model': ['XGBoost','LGBM','SVC','Decision Tree','Logistic Regression','Random Forest'],
        'Train Score': [xgb_acc,lgb_acc,svc_acc,clf_acc,logreg_acc,rf_acc],
```

'Test Score' : [xgb\_ext\_acc,lgb\_ext\_acc,svc\_ext\_acc,clf\_ext\_acc,logreg\_ext\_acc,rf\_ext\_acc]})
res\_table.sort\_values(by='Train Score', ascending=False)

Out[22]:

,		Model	Train Score	<b>Test Score</b>
	1	LGBM	0.894477	0.566866
	0	XGBoost	0.772189	0.518962
	2	SVC	0.031558	0.039920
	3	Decision Tree	0.031558	0.039920
	4	Logistic Regression	0.031558	0.039920
	5	Random Forest	0.031558	0.039920