Step 1: Data Import

https://www.kaggle.com/code/ryuodan/asl-detection-walkthrough
https://www.kaggle.com/code/razinw/asl-alphabet-classification-with-cnn

In [1]:
```
import os
from os import listdir
from os.path import isfile, join
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score
from sklearn.metrics import plot_roc_curve
import random
import matplotlib.image as mpimg
import matplotlib.pyplot as plt
import numpy as np
import cv2
import tensorflow as tf
from tensorflow.keras import utils
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPooling2D,
from tensorflow.keras import layers, models
from sklearn import preprocessing
from sklearn.metrics import confusion_matrix
from scikeras.wrappers import KerasClassifier
from sklearn.model_selection import cross_val_score
import keras
import keras_metrics
```

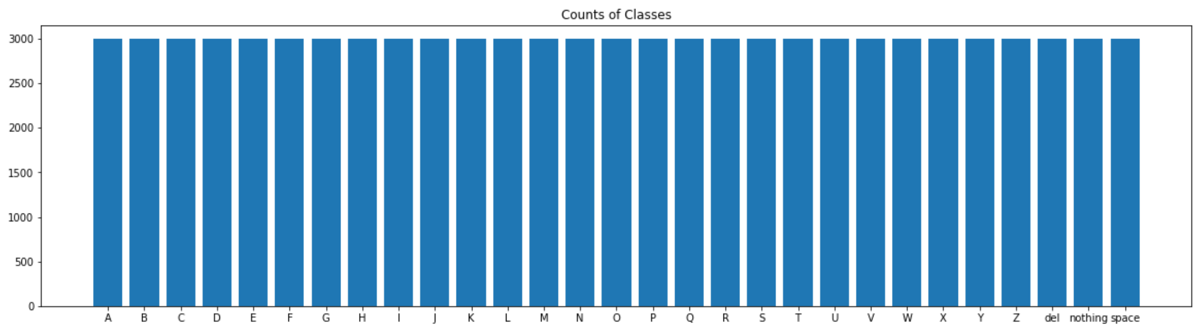
We iterate through each subfolder in the train folder, and for each subfolder, we add the paths of the image files to our list. Then we convert this to a dataframe.

In [2]:
```
all_data = []
train_folder = r'archive\asl_alphabet_train\asl_alphabet_train'

for folder in os.listdir(train_folder):
    label_folder = os.path.join(train_folder, folder)
    onlyfiles = [{'label':folder,'path':os.path.join(label_folder, f)} for f in os.
                 if os.path.isfile(os.path.join(label_folder, f))]
    all_data += onlyfiles

data_df = pd.DataFrame(all_data)
```

Step 2: Data Exploration

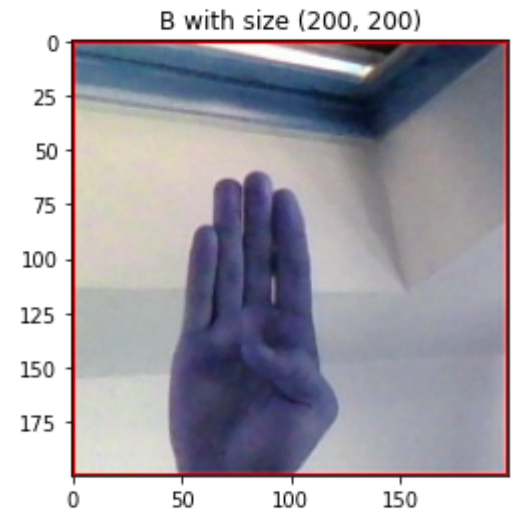
We perform exploratory analysis in order to view the distribution of our classes in our dataset. In addition, we provide previews of the original image and resized images to give a high-level overview of the types of inputs our models will be performing predictive analyses on.

In [3]:
```
counts = data_df.groupby(by='label').size().to_frame(name='vals')

plt.figure(figsize=(20, 5))
plt.bar(counts.index, counts.vals)
plt.title('Counts of Classes')
plt.show()
```

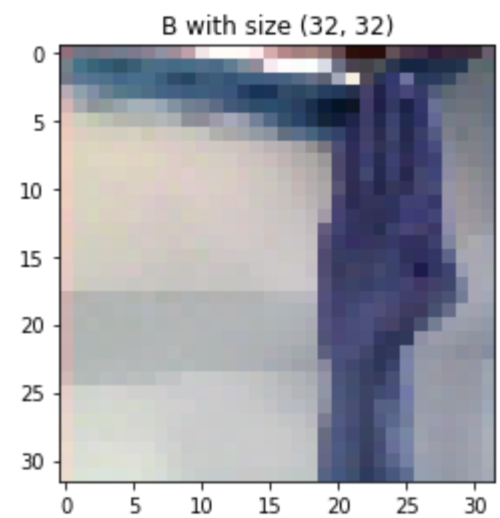


In [4]:
```
signs = data_df['label'].unique().tolist()

def show_image(label, signs, size):
    if label not in signs:
        print('Error: Unknown Label')
        return 0
    rows = data_df[data_df['label']==label]['path']
    rand_img = random.randint(a=0, b=len(rows))
    filepath = rows.iloc[rand_img]
    img = cv2.imread(filepath)
    img = cv2.resize(img, size)
    plt.figure()
    plt.title(label + " with size " + str(size))
    plt.imshow(img)
```

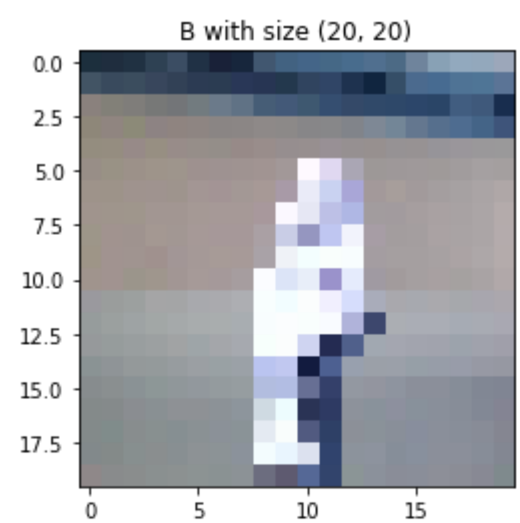
In [5]:
```
original_size = 200, 200
show_image('B', signs, original_size)
```



In [6]:
```
ideal_size = 32, 32
show_image('B', signs, ideal_size)
```



In [7]:
```
reduced_size = 20, 20
show_image('B', signs, reduced_size)
```



Step 3: Data Processing

We use the cv2 package to read an image from a filepath and resize it. We then convert the image to an numpy array of values between 0 and 255. This way, we can feed our data into our models.

In [8]:
```
def encode_imgs(paths, size):
    res = []
    for path in paths:
        img = cv2.imread(path)
        img = cv2.resize(img, size)
        res.append(img)
    res = np.array(res)
    res = res.astype('float32')/255.0
    return res
```

Step 4: Data Modeling

First, we establish a logistic regression model as a baseline, mainly to illustrate that this problem is solvable through machine learning. Logistic regression is relatively more simple than the neural networks we build, so we predict our neural networks will perform at least as well as this logistic regression model.

In [9]:
```
def run_logr(data_df, label1, label2, size):
    binary_df = data_df.loc[(data_df['label'] == label1) | (data_df['label'] == lab
    encoded = encode_imgs(binary_df['path'], size)
    print('Data Encoded!\n')
    X_train, X_test, y_train, y_test = train_test_split(encoded, binary_df['label']
    X_train = X_train.reshape(X_train.shape[0], X_train.shape[1] * X_train.shape[2]
    X_test = X_test.reshape(X_test.shape[0], X_test.shape[1] * X_test.shape[2] * X_

    lr = LogisticRegression()
    lr.fit(X_train, y_train)
    print('Model fitted!\n')

    y_pred_test = lr.predict(X_test)
    print('Predictions made!\n')
    print('Confusion Matrix: \n')
    print(confusion_matrix(y_test, y_pred_test))
    test_acc = accuracy_score(y_test, y_pred_test)
    test_f1 = f1_score(y_test, y_pred_test, pos_label=label1)
    test_rec = recall_score(y_test, y_pred_test, pos_label=label1)
    test_pre = precision_score(y_test, y_pred_test, pos_label=label1)
    plot_roc_curve(lr, X_test, y_test)
    plt.show()

    print('Logistic Regression Metrics: ' + label1 + ' and ' + label2)
    print('Testing Accuracy: ' + str(test_acc))
    print('Testing F1 Score: ' + str(test_f1))
    print('Testing Recall: ' + str(test_rec))
    print('Testing Precision: ' + str(test_pre))
```

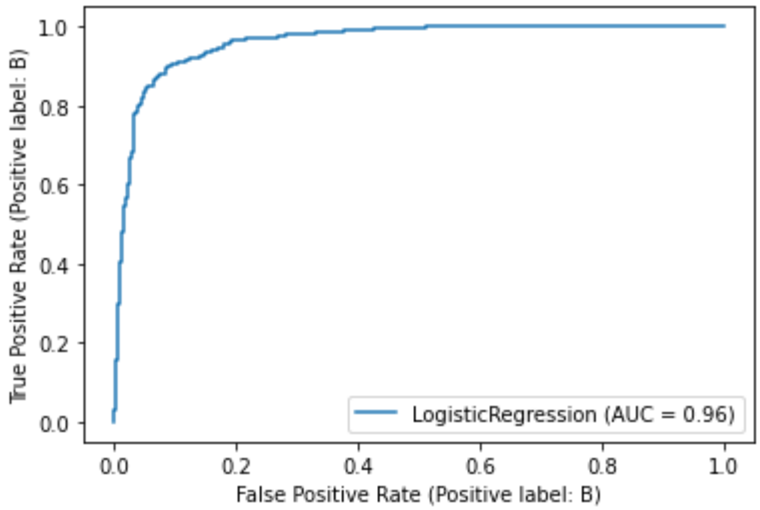
Logistic Regression: Two "Similar" Signs

The letter A and the letter B have similar signs, so let's see how our Logistic Regression model performs.

In [10]:
```
run_logr(data_df, 'A', 'B', ideal_size)
```

```
Data Encoded!

C:\Users\Justin\AppData\Local\Programs\Python\Python37\lib\site-packages\sklearn\li
near_model\_logistic.py:818: ConvergenceWarning: lbfgs failed to converge (status=
1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
C:\Users\Justin\AppData\Local\Programs\Python\Python37\lib\site-packages\sklearn\ut
ils\deprecation.py:87: FutureWarning: Function plot_roc_curve is deprecated; Functi
on :func:`plot_roc_curve` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: :meth:`sklearn.metric.RocCurveDisplay.from_predictions` or :m
eth:`sklearn.metric.RocCurveDisplay.from_estimator`.
  warnings.warn(msg, category=FutureWarning)
```

```
Model fitted!

Predictions made!

Confusion Matrix:

[[640  72]
 [ 76 712]]
```




```
Logistic Regression Metrics: A and B
Testing Accuracy: 0.9013333333333333
Testing F1 Score: 0.896358543417367
Testing Recall: 0.898876404494382
Testing Precision: 0.8938547486033519
```

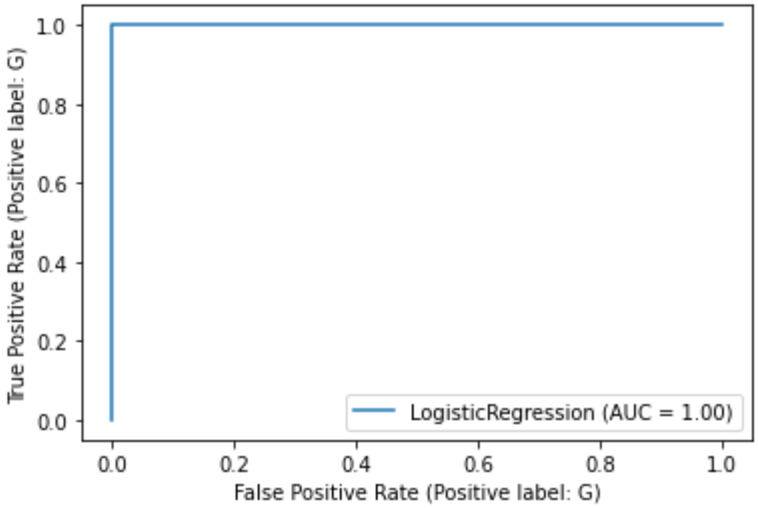
Logistic Regression: Two "Different" Signs

The letters C and G are vastly different signs, so let's see how our Logistic Regression model performs.

In [11]:
```
run_logr(data_df, 'C', 'G', ideal_size)
```

```
Data Encoded!

C:\Users\Justin\AppData\Local\Programs\Python\Python37\lib\site-packages\sklearn\li
near_model\_logistic.py:818: ConvergenceWarning: lbfgs failed to converge (status=
1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
C:\Users\Justin\AppData\Local\Programs\Python\Python37\lib\site-packages\sklearn\ut
ils\deprecation.py:87: FutureWarning: Function plot_roc_curve is deprecated; Functi
on :func:`plot_roc_curve` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: :meth:`sklearn.metric.RocCurveDisplay.from_predictions` or :m
eth:`sklearn.metric.RocCurveDisplay.from_estimator`.
  warnings.warn(msg, category=FutureWarning)
```

```
Model fitted!

Predictions made!

Confusion Matrix:

[[712   0]
 [  0 788]]
```




```
Logistic Regression Metrics: C and G
Testing Accuracy: 1.0
Testing F1 Score: 1.0
Testing Recall: 1.0
Testing Precision: 1.0
```

Building Neural Networks

First, we encode the data to ideal size (32, 32) and the reduced size (20, 20).

In [12]:
```
encoded_data = encode_imgs(data_df['path'], ideal_size)
reduced_data = encode_imgs(data_df['path'], reduced_size)
```

In [13]:
```
le = preprocessing.LabelEncoder()
le.fit(data_df.label)
data_df['categorical_label'] = le.transform(data_df.label)
```

NN 1

3 hidden layers (20, 40, 40 filters), input size (20, 20)

NN 2

3 hidden layers (32, 64, 64 filters), input size (32, 32)

NN 3

3 hidden layers (45, 90, 90 filters), input size (32, 32)

In [14]:
```
model1 = models.Sequential()
model1.add(layers.Conv2D(20, (3, 3), activation='relu', input_shape=(20, 20, 3)))
model1.add(layers.MaxPooling2D((2, 2)))
model1.add(layers.Conv2D(40, (3, 3), activation='relu'))
model1.add(layers.MaxPooling2D((2, 2)))
model1.add(layers.Conv2D(40, (3, 3), activation='relu'))
model1.add(layers.Flatten())
model1.add(layers.Dense(40, activation='relu'))
model1.add(layers.Dense(29))

model1.summary()

model2 = models.Sequential()
model2.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model2.add(layers.MaxPooling2D((2, 2)))
model2.add(layers.Conv2D(64, (3, 3), activation='relu'))
model2.add(layers.MaxPooling2D((2, 2)))
model2.add(layers.Conv2D(64, (3, 3), activation='relu'))
model2.add(layers.Flatten())
model2.add(layers.Dense(64, activation='relu'))
model2.add(layers.Dense(29))

model2.summary()

model3 = models.Sequential()
model3.add(layers.Conv2D(45, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model3.add(layers.MaxPooling2D((2, 2)))
model3.add(layers.Conv2D(90, (3, 3), activation='relu'))
model3.add(layers.MaxPooling2D((2, 2)))
model3.add(layers.Conv2D(90, (3, 3), activation='relu'))
model3.add(layers.Flatten())
model3.add(layers.Dense(90, activation='relu'))
model3.add(layers.Dense(29))

model3.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 18, 18, 20)        560       
                                                                 
 max_pooling2d (MaxPooling2D  (None, 9, 9, 20)         0         
 )                                                               
                                                                 
 conv2d_1 (Conv2D)           (None, 7, 7, 40)          7240      
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 3, 3, 40)         0         
 2D)                                                             
                                                                 
 conv2d_2 (Conv2D)           (None, 1, 1, 40)          14440     
                                                                 
 flatten (Flatten)           (None, 40)                0         
                                                                 
 dense (Dense)               (None, 40)                1640      
                                                                 
 dense_1 (Dense)             (None, 29)                1189      
                                                                 
=================================================================
Total params: 25,069
Trainable params: 25,069
Non-trainable params: 0
_________________________________________________________________
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_3 (Conv2D)           (None, 30, 30, 32)        896       
                                                                 
 max_pooling2d_2 (MaxPooling  (None, 15, 15, 32)       0         
 2D)                                                             
                                                                 
 conv2d_4 (Conv2D)           (None, 13, 13, 64)        18496     
                                                                 
 max_pooling2d_3 (MaxPooling  (None, 6, 6, 64)         0         
 2D)                                                             
                                                                 
 conv2d_5 (Conv2D)           (None, 4, 4, 64)          36928     
                                                                 
 flatten_1 (Flatten)         (None, 1024)              0         
                                                                 
 dense_2 (Dense)             (None, 64)                65600     
                                                                 
 dense_3 (Dense)             (None, 29)                1885      
                                                                 
=================================================================
Total params: 123,805
Trainable params: 123,805
Non-trainable params: 0
_________________________________________________________________
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_6 (Conv2D)           (None, 30, 30, 45)        1260      
```

```
 max_pooling2d_4 (MaxPooling  (None, 15, 15, 45)       0
 2D)

 conv2d_7 (Conv2D)           (None, 13, 13, 90)        36540

 max_pooling2d_5 (MaxPooling  (None, 6, 6, 90)         0
 2D)

 conv2d_8 (Conv2D)           (None, 4, 4, 90)          72990

 flatten_2 (Flatten)         (None, 1440)              0

 dense_4 (Dense)             (None, 90)                129690

 dense_5 (Dense)             (None, 29)                2639

=================================================================
Total params: 243,119
Trainable params: 243,119
Non-trainable params: 0
_________________________________________________________________
```

NN 4

1 hidden layer (32 filters), input size (32, 32)

In [15]:
```python
model4 = models.Sequential()
model4.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model4.add(layers.MaxPooling2D((2, 2)))
model4.add(layers.Flatten())
model4.add(layers.Dense(32, activation='relu'))
model4.add(layers.Dense(29))

model4.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_9 (Conv2D)           (None, 30, 30, 32)        896

 max_pooling2d_6 (MaxPooling  (None, 15, 15, 32)       0
 2D)

 flatten_3 (Flatten)         (None, 7200)              0

 dense_6 (Dense)             (None, 32)                230432

 dense_7 (Dense)             (None, 29)                957

=================================================================
Total params: 232,285
Trainable params: 232,285
Non-trainable params: 0
_________________________________________________________________
```

In [16]:
```
def run_nn(model, optimizer, epochs, batch_size, data_df, data):
    X_train, X_test, y_train, y_test = train_test_split(data, data_df['categorical_

    model.compile(optimizer=optimizer,
                  loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=Tru
                  metrics=['accuracy'])

    history = model.fit(X_train, y_train, epochs=5, batch_size = 64, shuffle=True,
    metrics = pd.DataFrame(history.history)

    print('\n----------------------\n')
    print(metrics)

    y_pred_test = model.predict(X_test)
    y_test_classes =np.argmax(y_pred_test,axis=1)

    confusion = confusion_matrix(y_test, y_test_classes)
    confusion_df = pd.DataFrame(confusion)
    confusion_df.index = sorted(list(set(data_df['label'])))

    acc_test = accuracy_score(y_test, y_test_classes)
    f1_test = f1_score(y_test, y_test_classes, average='weighted')
    prec_test = precision_score(y_test, y_test_classes, average='weighted')
    rec_test = recall_score(y_test, y_test_classes, average='weighted')

    print("\n----------------------\n")
    print("Accuracy on testing set: ", acc_test)
    print("F1 score on testing set: ", f1_test)
    print("Precision on testing set: ", prec_test)
    print("Recall on testing set: ", rec_test)

    return confusion_df
```

In [17]:
```
confusion_df1 = run_nn(model1, 'adam', 5, 64, data_df, reduced_data)
confusion_df1
```

```
Epoch 1/5
1020/1020 [==============================] - 21s 20ms/step - loss: 2.2994 - accurac
y: 0.3095 - val_loss: 1.6304 - val_accuracy: 0.4850
Epoch 2/5
1020/1020 [==============================] - 20s 19ms/step - loss: 1.3015 - accurac
y: 0.5826 - val_loss: 1.1617 - val_accuracy: 0.6150
Epoch 3/5
1020/1020 [==============================] - 20s 19ms/step - loss: 0.9439 - accurac
y: 0.6885 - val_loss: 0.8558 - val_accuracy: 0.7206
Epoch 4/5
1020/1020 [==============================] - 20s 19ms/step - loss: 0.7442 - accurac
y: 0.7521 - val_loss: 0.7209 - val_accuracy: 0.7572
Epoch 5/5
1020/1020 [==============================] - 20s 19ms/step - loss: 0.6109 - accurac
y: 0.7926 - val_loss: 0.5775 - val_accuracy: 0.8051

----------------------

       loss  accuracy  val_loss  val_accuracy
0  2.299420  0.309487  1.630377      0.485011
1  1.301513  0.582559  1.161728      0.615034
2  0.943867  0.688460  0.855777      0.720552
3  0.744210  0.752077  0.720926      0.757241
4  0.610949  0.792613  0.577513      0.805149

-----------------------

Accuracy on testing set:  0.8051494252873563
F1 score on testing set:  0.8051631258817623
Precision on testing set:  0.8176217205303256
Recall on testing set:  0.8051494252873563
```

Out[17]:

	0	1	2	3	4	5	6	7	8	9	...	19	20	21	22	23	24	2
A	555	30	0	4	57	5	0	0	3	0	...	4	0	0	0	0	3	
B	3	576	1	4	79	2	1	0	16	0	...	0	7	16	1	0	0	
C	5	2	689	8	1	4	0	0	0	0	...	0	1	0	0	0	0	
D	1	11	2	647	19	31	2	0	6	0	...	1	2	0	0	0	0	
E	24	40	0	4	607	25	7	0	11	0	...	1	0	0	0	0	0	
F	0	0	1	0	7	648	19	0	15	1	...	0	0	0	0	0	15	
G	0	0	0	0	0	9	639	44	7	19	...	0	0	0	0	0	0	
H	0	0	0	0	0	0	25	695	3	5	...	0	0	0	0	0	0	
I	0	0	0	2	5	4	19	0	664	20	...	0	0	9	1	1	1	
J	0	0	0	0	0	0	6	4	5	709	...	0	0	0	0	0	1	
K	0	3	0	1	0	0	0	0	49	0	...	0	3	24	13	0	0	
L	13	0	0	2	0	8	0	0	0	0	...	15	1	1	0	0	0	
M	10	0	0	0	2	1	0	0	7	8	...	1	0	1	8	4	5	
N	7	0	0	0	2	5	6	0	2	30	...	1	0	2	9	2	39	
O	4	0	10	5	2	17	3	0	1	0	...	5	1	8	9	14	24	1
P	0	0	0	0	0	2	5	5	0	4	...	0	0	0	0	0	0	
Q	0	0	3	0	0	0	1	0	0	0	...	0	0	0	0	0	5	
R	0	4	0	0	0	0	10	0	14	9	...	0	114	36	1	4	2	
S	4	1	1	0	1	15	0	0	0	0	...	34	2	4	3	3	26	
T	9	0	0	0	4	8	0	0	0	0	...	525	0	1	1	12	32	1
U	4	28	0	0	2	0	0	0	2	0	...	0	391	101	5	20	1	
V	1	2	0	2	0	5	3	0	19	0	...	1	22	518	71	8	7	
W	0	8	0	1	6	0	4	0	14	0	...	0	4	94	525	5	9	
X	0	0	0	0	0	15	0	0	14	4	...	12	21	31	2	501	52	1
Y	0	0	0	0	0	1	0	0	1	31	...	2	0	0	1	0	640	
Z	3	0	4	1	0	1	0	0	0	0	...	30	5	2	0	21	112	58
del	0	0	0	1	1	0	3	0	0	1	...	0	1	0	0	5	8	
nothing	0	0	0	0	0	0	1	0	0	0	...	0	0	0	0	0	0	
space	0	0	0	0	0	0	2	0	0	11	...	0	0	0	0	0	20	

29 rows × 29 columns

In [18]:

```
confusion_df2 = run_nn(model2, 'adam', 5, 64, data_df, encoded_data)
confusion_df2
```

```
Epoch 1/5
1020/1020 [==============================] - 78s 76ms/step - loss: 1.4665 - accurac
y: 0.5528 - val_loss: 0.5729 - val_accuracy: 0.8127
Epoch 2/5
1020/1020 [==============================] - 78s 76ms/step - loss: 0.3923 - accurac
y: 0.8691 - val_loss: 0.3030 - val_accuracy: 0.8900
Epoch 3/5
1020/1020 [==============================] - 77s 76ms/step - loss: 0.2001 - accurac
y: 0.9331 - val_loss: 0.1524 - val_accuracy: 0.9492
Epoch 4/5
1020/1020 [==============================] - 77s 76ms/step - loss: 0.1225 - accurac
y: 0.9596 - val_loss: 0.1301 - val_accuracy: 0.9551
Epoch 5/5
1020/1020 [==============================] - 78s 77ms/step - loss: 0.0859 - accurac
y: 0.9722 - val_loss: 0.0921 - val_accuracy: 0.9696

----------------------

       loss  accuracy  val_loss  val_accuracy
0  1.466454  0.552751  0.572889      0.812690
1  0.392285  0.869149  0.303043      0.889977
2  0.200150  0.933073  0.152425      0.949195
3  0.122524  0.959602  0.130149      0.955126
4  0.085860  0.972184  0.092085      0.969609

-----------------------

Accuracy on testing set:  0.9696091954022988
F1 score on testing set:  0.969329590654926
Precision on testing set:  0.9712433772171185
Recall on testing set:  0.9696091954022988
```

Out[18]:

	0	1	2	3	4	5	6	7	8	9	...	19	20	21	22	23	24	2
A	715	0	0	1	0	0	0	0	0	0	...	2	0	0	0	0	0	
B	0	714	0	7	5	0	0	0	1	0	...	0	0	0	0	0	0	
C	0	0	727	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
D	0	0	0	753	0	0	0	0	0	0	...	0	0	0	0	0	0	
E	8	2	0	7	734	6	0	0	0	0	...	0	0	0	1	0	0	
F	0	0	0	0	0	724	0	0	0	0	...	0	0	0	0	0	0	
G	0	0	0	0	0	7	711	0	1	0	...	0	0	0	0	0	4	
H	0	0	0	0	0	0	7	732	0	0	...	0	0	0	0	0	0	
I	0	0	0	0	0	3	0	0	744	0	...	0	0	0	0	0	1	
J	0	0	0	0	0	0	2	0	1	728	...	0	0	0	0	0	5	
K	0	0	0	1	0	0	0	0	0	0	...	0	0	5	4	0	0	
L	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
M	5	0	0	0	1	0	0	0	0	1	...	0	0	0	8	0	0	
N	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
O	0	0	0	2	0	0	0	0	0	0	...	0	0	0	0	0	0	
P	0	0	0	0	0	0	0	0	0	3	...	0	0	0	0	0	0	
Q	0	0	0	0	0	0	0	0	0	0	...	1	0	0	0	0	0	
R	0	0	0	0	0	0	0	0	0	0	...	0	13	3	2	2	0	
S	5	0	0	0	1	2	0	0	0	0	...	52	0	0	0	11	16	
T	0	0	0	0	0	2	0	0	0	0	...	718	0	0	0	2	1	1
U	0	0	0	1	0	0	0	0	0	0	...	0	696	2	4	7	0	
V	0	0	0	0	0	0	0	0	4	0	...	0	0	627	100	3	1	
W	0	0	0	0	0	0	0	0	0	0	...	0	0	3	748	1	0	
X	0	0	0	0	0	1	0	0	0	0	...	1	0	0	6	693	6	1
Y	0	0	0	0	0	1	0	0	0	0	...	0	0	0	0	2	706	
Z	0	0	0	0	0	0	0	0	0	0	...	0	2	0	0	0	0	80
del	0	0	0	0	1	0	1	0	0	0	...	0	0	0	0	0	0	
nothing	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
space	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	1	

29 rows × 29 columns

In [19]:

```
confusion_df3 = run_nn(model3, 'adam', 5, 64, data_df, encoded_data)
confusion_df3
```

```
Epoch 1/5
1020/1020 [==============================] - 118s 114ms/step - loss: 1.3295 - accur
acy: 0.5916 - val_loss: 0.4815 - val_accuracy: 0.8393
Epoch 2/5
1020/1020 [==============================] - 116s 114ms/step - loss: 0.3239 - accur
acy: 0.8930 - val_loss: 0.2108 - val_accuracy: 0.9303
Epoch 3/5
1020/1020 [==============================] - 115s 112ms/step - loss: 0.1550 - accur
acy: 0.9492 - val_loss: 0.0984 - val_accuracy: 0.9689
Epoch 4/5
1020/1020 [==============================] - 115s 113ms/step - loss: 0.1004 - accur
acy: 0.9671 - val_loss: 0.1049 - val_accuracy: 0.9626
Epoch 5/5
1020/1020 [==============================] - 119s 117ms/step - loss: 0.0701 - accur
acy: 0.9779 - val_loss: 0.0802 - val_accuracy: 0.9720

----------------------

       loss  accuracy  val_loss  val_accuracy
0  1.329503  0.591586  0.481489      0.839264
1  0.323881  0.892981  0.210805      0.930299
2  0.155001  0.949241  0.098398      0.968874
3  0.100413  0.967111  0.104922      0.962575
4  0.070145  0.977870  0.080207      0.971954

-----------------------

Accuracy on testing set:  0.9719540229885058
F1 score on testing set:  0.9719503401826124
Precision on testing set:  0.973931597908162
Recall on testing set:  0.9719540229885058
```

Out[19]:

	0	1	2	3	4	5	6	7	8	9	...	19	20	21	22	23	24	2
A	719	2	0	0	3	0	0	0	0	0	...	2	0	0	0	0	0	
B	0	736	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
C	0	0	727	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
D	0	0	1	738	0	0	0	0	0	0	...	0	0	0	0	0	0	
E	8	33	1	0	702	2	0	0	0	0	...	2	0	0	0	0	0	
F	0	0	0	0	0	723	0	0	0	0	...	0	0	0	0	0	0	
G	0	0	0	0	0	0	721	2	0	0	...	0	0	0	0	0	0	
H	0	0	0	0	0	0	0	739	0	0	...	0	0	0	0	0	0	
I	0	4	0	2	2	0	0	4	724	0	...	0	0	0	9	0	0	
J	0	0	0	0	0	0	0	0	0	723	...	0	0	0	0	0	13	
K	0	8	0	0	0	0	0	0	4	0	...	0	8	6	16	0	0	
L	0	0	0	0	0	0	0	0	0	0	...	1	0	0	0	0	0	
M	3	0	0	0	0	0	0	0	0	0	...	0	0	0	0	1	0	
N	0	0	0	0	0	0	0	0	0	0	...	0	0	0	1	0	0	
O	2	0	3	0	0	0	0	0	0	0	...	5	0	0	0	0	0	
P	0	0	0	0	0	0	0	1	0	0	...	1	0	0	0	0	2	
Q	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
R	0	3	0	0	0	0	0	0	0	0	...	0	108	3	1	0	0	
S	0	0	0	0	0	0	0	0	3	0	...	27	0	0	0	15	1	
T	0	0	0	0	0	0	0	0	0	0	...	729	0	0	0	1	9	
U	0	1	0	0	0	0	0	0	0	0	...	0	710	3	6	15	0	
V	0	5	0	0	0	0	0	0	0	0	...	0	24	619	94	10	0	
W	0	3	0	0	0	0	0	0	0	0	...	0	0	0	752	0	0	
X	2	0	0	0	0	0	0	0	0	0	...	0	6	0	0	715	1	
Y	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	710	
Z	0	0	1	0	0	0	0	0	0	0	...	1	0	0	0	0	0	80
del	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
nothing	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
space	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	

29 rows × 29 columns

In [20]:

```
confusion_df4 = run_nn(model4, 'adam', 5, 64, data_df, encoded_data)
confusion_df4
```

```
Epoch 1/5
1020/1020 [==============================] - 46s 44ms/step - loss: 2.7771 - accurac
y: 0.1560 - val_loss: 2.2759 - val_accuracy: 0.2635
Epoch 2/5
1020/1020 [==============================] - 45s 44ms/step - loss: 2.0881 - accurac
y: 0.3065 - val_loss: 1.9190 - val_accuracy: 0.3652
Epoch 3/5
1020/1020 [==============================] - 45s 44ms/step - loss: 1.8171 - accurac
y: 0.3849 - val_loss: 1.7247 - val_accuracy: 0.4143
Epoch 4/5
1020/1020 [==============================] - 45s 44ms/step - loss: 1.6346 - accurac
y: 0.4356 - val_loss: 1.5727 - val_accuracy: 0.4472
Epoch 5/5
1020/1020 [==============================] - 45s 44ms/step - loss: 1.5049 - accurac
y: 0.4741 - val_loss: 1.4423 - val_accuracy: 0.4953

----------------------

       loss  accuracy  val_loss  val_accuracy
0  2.777118  0.155954  2.275889      0.263494
1  2.088121  0.306529  1.918957      0.365195
2  1.817104  0.384889  1.724670      0.414253
3  1.634560  0.435556  1.572677      0.447172
4  1.504934  0.474100  1.442312      0.495264

-----------------------

Accuracy on testing set:  0.49526436781609195
F1 score on testing set:  0.48700689599581193
Precision on testing set:  0.49170432149624177
Recall on testing set:  0.49526436781609195
```

Out[20]:

	0	1	2	3	4	5	6	7	8	9	...	19	20	21	22	23	24	2
A	364	22	6	23	77	146	1	0	65	1	...	0	0	0	0	0	0	
B	52	265	0	49	3	256	0	0	19	5	...	0	0	0	2	0	0	
C	5	0	545	24	33	0	0	0	42	29	...	0	0	0	0	0	0	
D	29	68	20	370	20	114	0	0	97	0	...	2	0	0	0	0	0	
E	217	38	25	53	218	80	22	0	50	2	...	4	0	0	0	0	0	
F	71	87	16	24	70	359	0	0	53	0	...	0	0	0	0	0	0	
G	4	0	0	0	0	0	506	130	0	76	...	0	0	0	0	0	0	
H	0	0	0	0	0	0	257	376	0	68	...	0	0	0	0	0	0	
I	12	5	26	48	48	4	0	0	354	15	...	6	0	0	0	0	0	
J	0	0	11	0	0	0	21	103	6	435	...	0	0	0	0	0	0	
K	0	40	0	8	0	0	0	0	26	4	...	5	0	3	22	0	0	
L	2	4	25	1	1	0	0	0	96	0	...	1	0	0	0	0	0	
M	0	0	24	0	0	0	0	1	35	14	...	22	0	0	0	1	0	
N	0	0	13	0	0	0	7	23	10	55	...	12	0	0	0	0	1	
O	0	2	8	1	0	0	0	0	66	3	...	41	1	0	0	6	7	
P	0	0	0	0	0	0	0	32	0	23	...	0	0	0	0	0	0	
Q	0	0	1	0	0	0	0	0	0	3	...	3	0	0	0	0	0	
R	0	0	0	0	0	0	0	0	6	2	...	31	193	71	24	44	14	
S	0	1	0	0	0	0	0	0	5	21	...	33	10	1	4	39	104	6
T	1	0	0	0	0	0	0	0	37	0	...	239	11	0	0	48	12	15
U	0	0	0	0	0	0	0	0	3	7	...	23	291	66	65	66	38	
V	0	0	0	0	0	0	0	0	0	15	...	0	184	124	314	9	12	
W	0	0	0	0	0	0	0	0	0	0	...	1	109	110	438	7	5	
X	0	0	0	0	0	0	0	0	3	5	...	20	69	4	7	113	192	13
Y	0	0	0	0	0	0	0	1	1	18	...	20	31	1	10	42	323	3
Z	0	0	0	0	0	0	0	0	7	0	...	113	35	0	0	68	76	24
del	0	0	0	0	0	0	0	2	0	10	...	3	0	0	0	0	0	
nothing	0	0	0	0	0	0	0	0	0	5	...	0	0	0	0	0	0	
space	0	0	0	0	0	0	0	0	1	2	...	0	4	4	4	1	54	

29 rows × 29 columns

In [27]:
```
def run_kfold_nn(model, epochs, batch_size, encoded_data, data_df, cv):
    kc = KerasClassifier(model = model, epochs = epochs, batch_size = batch_size, v
    cvs = cross_val_score(kc, encoded_data, data_df['label'], cv = cv)
    return cvs
```

In [28]:
```
cvs1 = run_kfold_nn(model1, 1, 64, reduced_data, data_df, 3)
cvs2 = run_kfold_nn(model2, 1, 64, encoded_data, data_df, 3)
cvs3 = run_kfold_nn(model3, 1, 64, encoded_data, data_df, 3)
cvs4 = run_kfold_nn(model4, 1, 64, encoded_data, data_df, 3)
```

```
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmp4_n1kb_z\a
ssets
907/907 [==============================] - 18s 19ms/step - loss: 0.4690 - accuracy:
0.8403
454/454 [==============================] - 3s 7ms/step
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmpfh8i06jc\a
ssets
907/907 [==============================] - 18s 19ms/step - loss: 0.3891 - accuracy:
0.8679
454/454 [==============================] - 3s 7ms/step
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmp2pd19ms5\a
ssets
907/907 [==============================] - 18s 19ms/step - loss: 0.5554 - accuracy:
0.8116
454/454 [==============================] - 3s 7ms/step
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmpdwaohslq\a
ssets
907/907 [==============================] - 52s 57ms/step - loss: 0.0579 - accuracy:
0.9819
454/454 [==============================] - 7s 15ms/step
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmpjuvrd701\a
ssets
907/907 [==============================] - 46s 50ms/step - loss: 0.0619 - accuracy:
0.9798
454/454 [==============================] - 8s 18ms/step
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmp9lt4ik9l\a
ssets
907/907 [==============================] - 50s 54ms/step - loss: 0.0829 - accuracy:
0.9733
454/454 [==============================] - 7s 15ms/step
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmp4y2pw4qo\a
ssets
907/907 [==============================] - 75s 82ms/step - loss: 0.0458 - accuracy:
0.9860
454/454 [==============================] - 11s 23ms/step
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmp7996ugnq\a
ssets
907/907 [==============================] - 70s 77ms/step - loss: 0.0465 - accuracy:
0.9855
454/454 [==============================] - 11s 22ms/step
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmp9csomr7o\a
ssets
907/907 [==============================] - 72s 78ms/step - loss: 0.0666 - accuracy:
0.9797
454/454 [==============================] - 10s 23ms/step
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmp3254mn2u\a
ssets
907/907 [==============================] - 24s 26ms/step - loss: 1.3396 - accuracy:
0.5298
454/454 [==============================] - 4s 9ms/step
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmp_n3g1aqe\a
ssets
907/907 [==============================] - 24s 26ms/step - loss: 1.2352 - accuracy:
0.5649
454/454 [==============================] - 4s 10ms/step
INFO:tensorflow:Assets written to: C:\Users\Justin\AppData\Local\Temp\tmpbotsmpcw\a
ssets
907/907 [==============================] - 27s 29ms/step - loss: 1.5327 - accuracy:
0.4608
```

```
454/454 [==============================] - 5s 10ms/step
```

In [29]:

```
print(cvs1)
print(cvs2)
print(cvs3)
print(cvs4)
```

```
[0.74272414 0.64634483 0.80265517]
[0.94337931 0.84306897 0.96455172]
[0.88506897 0.92241379 0.95137931]
[0.42844828 0.32713793 0.52306897]
```