In [1]:

```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import random
import seaborn as sns
from keras.preprocessing.image import ImageDataGenerator
```

In [2]:

```
#importing the dataset
train=pd.read_csv('sign_mnist_train.csv')
test=pd.read_csv('sign_mnist_test.csv')
```

In [3]:

```
print(train.shape)
print(test.shape)
```

(27455, 785) (7172, 785)

In [4]:

train.head()

Out[4]:

																	•							
	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9		pixel775	pixel776	pixel777	pixel778	pixel779	pixel78	,						
0	3	107	118	127	134	139	143	146	150	153		207	207	207	207	206	20	ľ						
1	6	155	157	156	156	156	157	156	158	158		69	149	128	87	94	16	i						
2	2	187	188	188	187	187	186	187	188	187		202	201	200	199	198	19	1						
3	2	211	211	212	212	211	210	211	210	210		235	234	233	231	230	22							
4	13	164	167	170	172	176	179	180	184	185		92	105	105	108	133	16							
5 r	OWC Y	795 col	umne								5 rows x 795 columns													

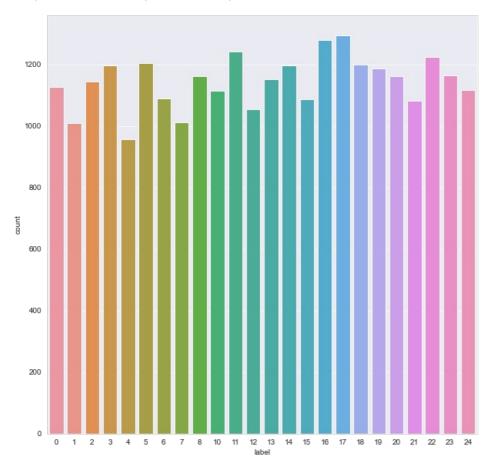
5 rows x 785 columns

In [5]:

```
plt.figure(figsize = (10,10)) # Label Count
sns.set_style("darkgrid")
sns.countplot(train['label'])
```

Out[5]:

<matplotlib.axes._subplots.AxesSubplot at 0x25e377c9ee0>



In [7]:

```
# Create training and testing arrays
train_set = np.array(train, dtype = 'float32')
test_set = np.array(test, dtype='float32')
```

In [8]:

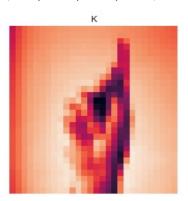
```
#Specifying class labels class_names = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K','L', 'M', 'N', 'O', 'P', 'Q', 'R', 'S', 'T', 'U', 'V', 'W', 'X', 'Y']
```

In [9]:

```
#See a random image for class label verification
i = random.randint(1,27455)
plt.imshow(train_set[i,1:].reshape((28,28)))
plt.imshow(train_set[i,1:].reshape((28,28)))
label_index = train["label"][i]
plt.title(f"{class_names[label_index]}")
plt.axis('off')
```

Out[9]:

(-0.5, 27.5, 27.5, -0.5)



In [10]:

```
# Define the dimensions of the plot grid
W_grid = 5
L_{grid} = 5
fig, axes = plt.subplots(L_grid, W_grid, figsize = (10,10))
axes = axes.ravel() # flatten the 15 x 15 matrix into 225 array
n_train = len(train_set) # get the length of the train dataset
# Select a random number from 0 to n_train
for i in np.arange(0, W_grid * L_grid): # create evenly spaces variables
# Select a random number
index = np.random.randint(0, n_train)
# read and display an image with the selected index
axes[i].imshow( train_set[index,1:].reshape((28,28)) )
label_index = int(train_set[index,0])
axes[i].set_title(class_names[label_index], fontsize = 8)
axes[i].axis('off')
plt.subplots_adjust(hspace=0.4)
```



In [11]:

```
# Prepare the training and testing dataset
X_train = train_set[:, 1:] / 255
y_train = train_set[:, 0]
X_test = test_set[:, 1:] / 255
y_test = test_set[:,0]
```

In [12]:

```
#Visualize train images
plt.figure(figsize=(10, 10))
for i in range(25):
  plt.subplot(5, 5, i + 1)
  plt.xticks([])
  plt.yticks([])
  plt.grid(False)
  plt.imshow(X_train[i].reshape((28,28)), cmap=plt.cm.binary)
  label_index = int(y_train[i])
  plt.title(class_names[label_index])
plt.show()
```



In [13]:

```
#Split the training and test sets
from sklearn.model_selection import train_test_split
X_train, X_validate, y_train, y_validate = train_test_split(X_train, y_train, test_size = 0.2, random_state = 123
45)
print(X_train.shape)
print(y_train.shape)

(21964, 784)
```

In [14]:

(21964,)

```
# Unpack the training and test tuple
X_train = X_train.reshape(X_train.shape[0], *(28, 28, 1))
X_test = X_test.reshape(X_test.shape[0], *(28, 28, 1))
X_validate = X_validate.reshape(X_validate.shape[0], *(28, 28, 1))
print(X_train.shape)
print(y_train.shape)
print(X_validate.shape)
```

```
(21964, 28, 28, 1)
(21964,)
(5491, 28, 28, 1)
```

In [15]:

```
# With data augmentation to prevent overfitting
datagen = ImageDataGenerator(
  featurewise_center=False, # set input mean to 0 over the dataset
  samplewise_center=False, # set each sample mean to 0
  featurewise_std_normalization=False, # divide inputs by std ofthe dataset
  samplewise_std_normalization=False, # divide each input by its std
  zca_whitening=False, # apply ZCA whitening
  rotation_range=10, # randomly rotate images in the range (degrees, 0 to 180)
  zoom_range = 0.1, # Randomly zoom image
  width_shift_range=0.1, # randomly shift images horizontally (fraction of total width)
  height_shift_range=0.1, # randomly shift images vertically (fraction of total height)
  horizontal_flip=False, # randomly flip images
  vertical_flip=False) # randomly flip images
datagen.fit(X_train)
```

In [16]:

```
#Library for CNN Model
import keras
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Dense, Flatten, Dropout,BatchNormalization
from keras.optimizers import Adam
from keras.callbacks import ReduceLROnPlateau
```

In [17]:

```
#Defining the Convolutional Neural Network
cnn_model = Sequential()
cnn_model.add(Conv2D(32, (3, 3), input_shape = (28,28,1), activation='relu'))
cnn_model.add(BatchNormalization())
cnn_model.add(MaxPooling2D(pool_size = (2, 2)))
cnn_model.add(Conv2D(64, (3, 3), input_shape = (28,28,1), activation='relu'))
cnn_model.add(Dropout(0.2))
cnn_model.add(BatchNormalization())
cnn_model.add(MaxPooling2D(pool_size = (2, 2)))
cnn_model.add(Conv2D(128, (3, 3), input_shape = (28,28,1), activation='relu'))
cnn_model.add(BatchNormalization())
cnn_model.add(MaxPooling2D(pool_size = (2, 2)))
cnn_model.add(Flatten())
cnn_model.add(Dense(units = 512, activation = 'relu'))
cnn_model.add(Dropout(0.25))
cnn_model.add(Dense(units = 25, activation = 'softmax'))
cnn_model.summary()
```

Model: "sequential"

Layer (type)	Output	Shape	Param #
conv2d (Conv2D)	(None,	26, 26, 32)	320
batch_normalization (BatchNo	(None,	26, 26, 32)	128
max_pooling2d (MaxPooling2D)	(None,	13, 13, 32)	0
conv2d_1 (Conv2D)	(None,	11, 11, 64)	18496
dropout (Dropout)	(None,	11, 11, 64)	0
batch_normalization_1 (Batch	(None,	11, 11, 64)	256
max_pooling2d_1 (MaxPooling2	(None,	5, 5, 64)	0
conv2d_2 (Conv2D)	(None,	3, 3, 128)	73856
batch_normalization_2 (Batch	(None,	3, 3, 128)	512
max_pooling2d_2 (MaxPooling2	(None,	1, 1, 128)	0
flatten (Flatten)	(None,	128)	0
dense (Dense)	(None,	512)	66048
dropout_1 (Dropout)	(None,	512)	0
dense_1 (Dense)	(None,	25)	12825
Total params: 172,441 Trainable params: 171,993 Non-trainable params: 448			

```
In [18]:
```

```
#Compiling
cnn_model.compile(loss ='sparse_categorical_crossentropy', optimizer='adam', metrics =['accuracy'])
```

In [19]:

learning_rate_reduction=ReduceLROnPlateau(monitor='val_accuracy',patience=2,verbose=1,factor=0.5,min_lr=0.00001)

In [20]:

#Training the CNN model

```
history = cnn_model.fit(datagen.flow(X_train, y_train, batch_size = 512), epochs = 20, verbose=1, validation_data
= (X_validate, y_validate),callbacks=[learning_rate_reduction])
Epoch 1/20
: 3.2344 - val_accuracy: 0.0459
Epoch 2/20
: 3.2623 - val_accuracy: 0.0459
Epoch 3/20
: 3.2628 - val_accuracy: 0.0563
Epoch 4/20
: 3.2407 - val_accuracy: 0.0829
Epoch 5/20
: 3.0212 - val_accuracy: 0.1776
Epoch 6/20
: 2.9480 - val_accuracy: 0.1945
Epoch 7/20
: 2.9165 - val_accuracy: 0.1601
Epoch 8/20
: 2.1802 - val_accuracy: 0.3779
Epoch 9/20
: 1.4570 - val_accuracy: 0.5305
Epoch 10/20
: 0.9138 - val_accuracy: 0.7130
Epoch 11/20
: 0.3053 - val_accuracy: 0.9051
Epoch 12/20
: 0.2977 - val_accuracy: 0.8986
Epoch 13/20
: 0.0701 - val_accuracy: 0.9783
Epoch 14/20
: 0.0479 - val_accuracy: 0.9869
Epoch 15/20
: 0.0188 - val_accuracy: 0.9931
Epoch 16/20
: 0.0184 - val_accuracy: 0.9953
Epoch 17/20
: 0.1633 - val_accuracy: 0.9443
Epoch 18/20
43/43 [============ ] - ETA: 0s - loss: 0.0218 - accuracy: 0.9920
Epoch 00018: ReduceLROnPlateau reducing learning rate to 0.00050000000237487257.
: 0.0313 - val_accuracy: 0.9867
Epoch 19/20
: 0.0022 - val_accuracy: 0.9995
Epoch 20/20
: 0.0018 - val_accuracy: 0.9995
```

In [21]:

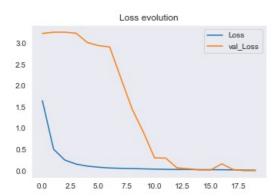
```
#Visualizing the training performance
plt.figure(figsize=(12, 8))

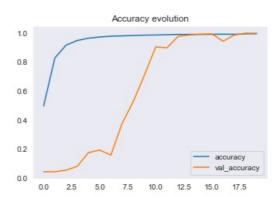
plt.subplot(2, 2, 1)
plt.plot(history.history['loss'], label='Loss')
plt.plot(history.history['val_loss'], label='val_Loss')
plt.legend()
plt.grid()
plt.title('Loss evolution')

plt.subplot(2, 2, 2)
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.legend()
plt.grid()
plt.title('Accuracy evolution')
```

Out[21]:

Text(0.5, 1.0, 'Accuracy evolution')





In [22]:

```
#Predictions for the test data
predicted_classes = cnn_model.predict_classes(X_test)
```

WARNING:tensorflow:From <ipython-input-22-2f08a57fd4c0>:2: Sequential.predict_classes (from tensorfl ow.python.keras.engine.sequential) is deprecated and will be removed after 2021-01-01. Instructions for updating:

Please use instead:* `np.argmax(model.predict(x), axis=-1)`, if your model does multi-class classi fication (e.g. if it uses a `softmax` last-layer activation).* `(model.predict(x) > 0.5).astype("int32")`, if your model does binary classification (e.g. if it uses a `sigmoid` last-layer activation).

In [23]:

```
L = 5
W = 5
fig, axes = plt.subplots(L, W, figsize = (12,12))
axes = axes.ravel()

for i in np.arange(0, L * W):
    axes[i].imshow(X_test[i].reshape(28,28))
    axes[i].set_title(f"Prediction Class = {predicted_classes[i]:0.1f}\n True Class = {y_test[i]:0.1f}\")
    axes[i].axis('off')
plt.subplots_adjust(wspace=0.5)
```



In [24]:

from sklearn.metrics import confusion_matrix
from sklearn import metrics
cm = metrics.confusion_matrix(y_test, predicted_classes)

In [25]:

```
#Defining function for confusion matrix plot
def plot_confusion_matrix(y_true, y_pred, classes,
                          normalize=False,
                          title=None,
                          cmap=plt.cm.Blues):
   if not title:
        if normalize:
           title = 'Normalized confusion matrix'
        else:
           title = 'Confusion matrix, without normalization'
   # Computing confusion matrix
   cm = confusion_matrix(y_true, y_pred)
   if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
        print('Confusion matrix, without normalization')
# Visualizing
   fig, ax = plt.subplots(figsize=(10, 10))
   im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
   ax.figure.colorbar(im, ax=ax)
   # We want to show all ticks...
   ax.set(xticks=np.arange(cm.shape[1]),
          yticks=np.arange(cm.shape[0]),
           xticklabels=classes, yticklabels=classes,
           title=title,
           ylabel='True label',
           xlabel='Predicted label')
  # Rotating the tick labels and setting their alignment.
   plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
            rotation_mode="anchor")
   # Looping over data dimensions and create text annotations.
   fmt = '.2f' if normalize else 'd'
   thresh = cm.max() / 2.
   for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, format(cm[i, j], fmt),
                    ha="center", va="center",
                    color="white" if cm[i, j] > thresh else "black")
   fig.tight_layout()
    return ax
np.set_printoptions(precision=2)
```

In [26]:

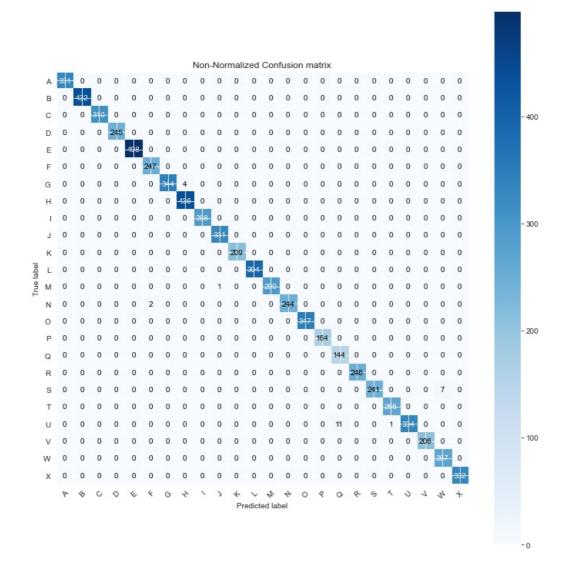
```
#Specifying class labels class_names = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M', 'N', 'O', 'P', 'Q', 'R', 'S', 'T', 'U', 'V', 'W', 'X', 'Y']
```

In [27]:

plt.figure(figsize=(20,20))
plot_confusion_matrix(y_test, predicted_classes, classes = class_names, title='Non-Normalized Confusion matrix')
plt.show()

Confusion matrix, without normalization

<Figure size 1440x1440 with 0 Axes>

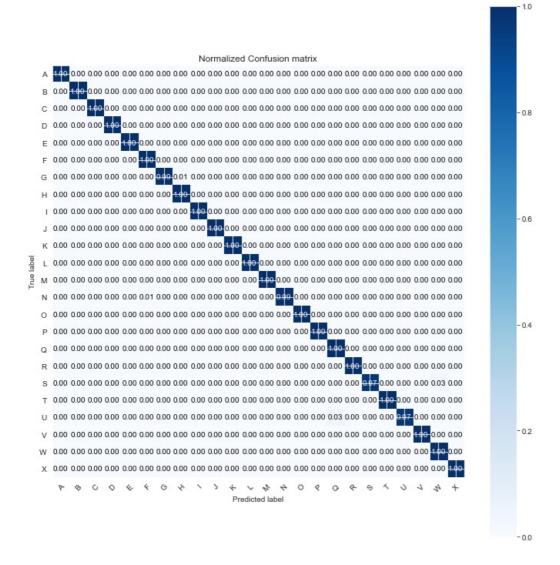


In [28]:

```
plt.figure(figsize=(35,35))
plot_confusion_matrix(y_test, predicted_classes, classes = class_names, normalize=True, title='Normalized Confusi
on matrix')
plt.show()
```

Normalized confusion matrix

<Figure size 2520x2520 with 0 Axes>



```
In [40]:
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score
print(classification_report(y_test, predicted_classes))
```

print("Accuracy:",accuracy_score(y_test, predicted_classes)*100)

```
precision
                           recall f1-score
                                              support
         0.0
                   1.00
                             1.00
                                       1.00
                                                  331
         1.0
                   1.00
                            1.00
                                       1.00
                   1.00
                             1.00
                                                  310
         2.0
                                       1.00
         3.0
                   1.00
                             1.00
                                       1.00
                                                  245
         4.0
                   1.00
                             1.00
                                       1.00
                                                  498
         5.0
                   0.99
                            1.00
                                       1.00
                                                  247
         6.0
                   1.00
                             0.99
                                       0.99
                                                  348
         7.0
                   0.99
                             1.00
                                       1.00
                                                  436
                  1.00
                            1.00
                                      1.00
                                                  288
        8.0
        10.0
                  1.00
                            1.00
                                      1.00
                   1.00
        11.0
                             1.00
                                       1.00
                                                  209
        12.0
                   1.00
                             1.00
                                       1.00
                                                  394
                   1.00
                             1.00
        13.0
                                       1.00
                                                  291
        14.0
                  1.00
                             0.99
                                       1.00
                                                  246
                   1.00
        15.0
                             1.00
                                       1.00
                                                  347
        16.0
                   1.00
                             1.00
                                       1.00
                                                  164
        17.0
                  0.93
                            1.00
                                       0.96
                                                  144
        18.0
                  1.00
                            1.00
                                      1.00
                                                  246
                   1.00
                             0.97
                                       0.99
        19.0
                                                  248
        20.0
                   1.00
                             1.00
                                       1.00
                                                  266
                  1.00
                            0.97
                                       0.98
        21.0
                                                  346
        22.0
                  1.00
                            1.00
                                       1.00
                                                  206
        23.0
                   0.97
                             1.00
                                       0.99
                                                  267
        24.0
                   1.00
                             1.00
                                       1.00
                                                  332
    accuracy
                                       1.00
                                                 7172
                   0.99
                             1.00
                                       1.00
                                                 7172
   macro avg
weighted avg
                   1.00
                             1.00
                                       1.00
                                                 7172
```

Accuracy: 99.63747908533185

```
In [30]:
```

```
predicted_classes.shape
```

Out[30]:

(7172,)

In [31]:

```
y_test.shape
```

Out[31]:

(7172,)

In [42]:

```
#Convert To One Hot encoded Vector
labels = np.zeros((y_test.shape[0],25))

temp = pd.DataFrame(labels)
temp.head()
```

Out[42]:

_		0	1	2	3	4	5	6	7	8	9	 15	16	17	18	19	20	21	22	23	24
-	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 25 columns

```
In [43]:
   for i in range(y_test.shape[0]):
                           index = int(y_test[i])
                           labels[i][index] = 1
 In [44]:
 print(labels.shape)
  (7172, 25)
  In [45]:
  temp = pd.DataFrame(y_test)
  temp.head()
Out[45]:
                               0
                       6.0
                    5.0
      2 10.0
                     0.0
                    3.0
  In [46]:
  temp = pd.DataFrame(labels)
  temp.head()
 Out[46]:
                                                                     2 3 4 5 6 7 8 9 ... 15 16 17 18 19 20 21 22 23 24
      1 \quad 0.0 \quad 0.0 \quad 0.0 \quad 0.0 \quad 0.0 \quad 1.0 \quad 0.0 \quad 0.0 \quad 0.0 \quad 0.0 \quad \dots \quad 0.0 \quad 0
       2 \quad 0.0 \quad
      \mathbf{3} \quad 1.0 \quad 0.0 \quad 0.0
      5 rows × 25 columns
 In [47]:
  def convert_to_one_hot_encoded(y):
                           output_classes = 25
                           labels = np.zeros((y.shape[0],output_classes))
                            for i in range(y.shape[0]):
                                                     index = int(y[i])
                                                     labels[i][index] = 1
                           return labels
  In [48]:
  from sklearn.metrics import roc_auc_score
  predictions = convert_to_one_hot_encoded(predicted_classes)
 y_actual = convert_to_one_hot_encoded(y_test)
   scores = []
  for i in range(y_actual.shape[0]):
                           scores.append(roc_auc_score(y_actual[i],predictions[i]))
  scores = np.array(scores)
  print(np.mean(scores)*100)
 99.81118702361034
```

In []: