

Practice project for A-Z Handwritten Alphabet Recognition by Deep Learning

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Data Provider: SACHIN PATEL

Obtained From: Kaggle

URL: <https://www.kaggle.com/datasets/sachinpatel21/az-handwritten-alphabets-in-csv-format>

Q1: Main objective of the analysis that also specifies whether your model will be focused on a specific type of Deep Learning or Reinforcement Learning algorithm and the benefits that your analysis brings to the business or stakeholders of this data.

Answer:

This analysis will be focused on deep learning algorithms and their applications to in hand writing alphabet recognition and reconstruction
The process would investigate pros and cons of each algorithms for practical uses

```
In [2]: import warnings
warnings.simplefilter('ignore')
```

```
In [3]: #Import Data processing Libraries
import numpy as np
import pandas as pd
from random import sample
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

Q2: Brief description of the data set you chose, a summary of its attributes, and an outline of what you are trying to accomplish with this analysis.

Answer:

I am choosing a self-found hand written alphabet dataset.
The dataset contains 26 folders (A-Z) containing handwritten images in size 28x28 pixels, each alphabet in the image is centre fitted to 20x20 pixel box.
Each image is stored as Gray-level, at digital range from 0 to 255.
The data will be evaluated for the knowledge depth (number of samples) for each alphabet.

```
In [4]: #Load Data, data is preprocessed
rawData=pd.read_csv(r"C:\Users\kai-w\Desktop\05_Deep Learning and Reinforcement Learning\A_Z Handwritten Data.csv",header=0)
```

```
In [5]: rawData.head()
```

```
Out[5]:
```

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	...	0.639	0.640	0.641	0.642	0.643	0.644	0.645	0.646	0.647	0.648
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
2	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
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 785 columns

```
In [6]: rawData.describe()
```

```
Out[6]:
```

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	...	0.639	0.640	0.641	0.642	0.643	0.644	0.645	0.646	0.647	0.648
count	372450.000000	372450.0	372450.0	372450.0	372450.0	372450.0	372450.0	372450.0	372450.0	372450.0	...	372450.000000	372450.000000	372450.000000	372450.000000	372450.000000	372450.000000	372450.000000	372450.000000	372450.000000	372450.000000
mean	13.523490	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.001616	0.001592	0.001117	0.000929	0.000685	0.000596	0.000618	0.000690	0.000239	0.000011
std	6.740824	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.490788	0.517297	0.421332	0.419180	0.385566	0.319820	0.208942	0.335227	0.134852	0.006554
min	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	10.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	14.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	18.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
max	25.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	252.000000	226.000000	229.000000	228.000000	235.000000	194.000000	103.000000	198.000000	82.000000	4.000000

8 rows × 785 columns

```
In [7]: rawData.dtypes.value_counts()
```

```
Out[7]:
```

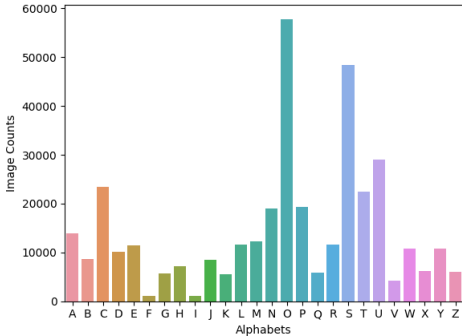
```
int64    785
Name: count, dtype: int64

785 columns, implying 28x28 pixel image, and a classifier column
First column indicate character
```

```
In [8]: #Distribution of alphabets
alphaDist = rawData.iloc[:,0].value_counts()[range(0,26)]
alphaDict = {chr(65+i) for i in range(0,26)}
fig=sns.barplot(x=alphaDict, y=alphaDist)
fig.set_xlabel('Alphabets')
fig.set_ylabel('Image Counts')
```

```
Out[8]:
```

Text(0, 0.5, 'Image Counts')



```
In [9]: #some basic features
alphaDist.describe()
```

```
Out[9]:
```

count	26.000000
mean	14325.000000
std	13353.826172
min	1120.000000
25%	6125.000000
50%	10821.500000
75%	17724.750000
max	57825.000000

Name: count, dtype: float64

```
In [98]: #replace column names to 1 to 784
targets=rawData.iloc[:,0]
data=rawData.iloc[:,1:]
data.columns=range(1,785)
data.head()
```

```
Out[98]:
```

	1	2	3	4	5	6	7	8	9	10	...	775	776	777	778	779	780	781	782	783	784
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

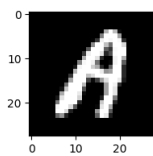
5 rows × 784 columns

```
In [99]: #Reshape data from 1x784 to 28x28
reshaped_data = data.values.reshape(data.shape[0], 28, 28, 1) #add additional column as filter id
data=reshaped_data

#validate data shape
data.shape
```

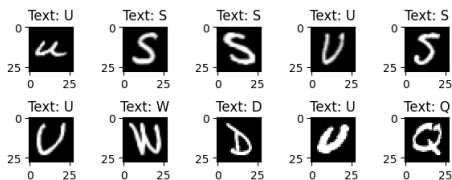
```
Out[99]: (372450, 28, 28, 1)
```

```
In [13]: fig = plt.figure
plt.figure(figsize=(2,2))
plt.imshow(data[0], cmap='gray')
plt.show()
```



```
In [14]: #Plot some of the Letters to test for data integrity
nFigRow=2
nFigCol=5
fig, axes = plt.subplots(nFigRow, nFigCol, figsize=(1.2*nFigCol,1.2*nFigRow))

for i in range(nFigRow*nFigCol):
    ax = axes[i%nFigRow, i//nFigCol]
    imgIdx = sample(range(0,data.shape[0]),1)[0]
    ax.imshow(data[imgIdx], cmap='gray')
    ax.set_title('Text: {}'.format(chr(targets[imgIdx]+65)))
plt.tight_layout()
plt.show()
```



Q3: Brief summary of data exploration and actions taken for data cleaning or feature engineering.

Answer:

Data Exploration:

- Column 0 denote the letter from 0 to 25, denoting alphabets A-Z, will apply `chr(65+<value>)` to convert
- Data values are at range 0 to 255
- The depth for each letter is different, most in "O" fewer in "I" and "F"
- Each letter has at least 1120 samples

Data Engineering:

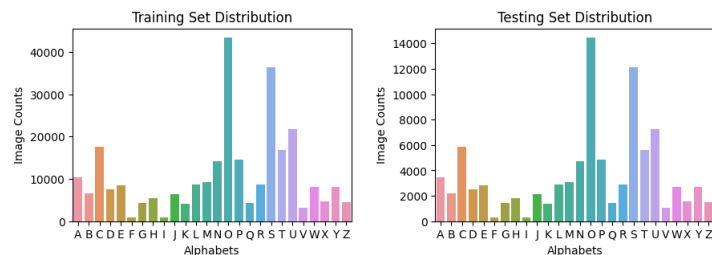
- Normalized the value to 0-1, by dividing 255
- Separated store letter identifier as "Targets", and image information as "Data"
- Reformated column to 1 to 784
- Reshaped each record to 28x28 format

Now going for Machine Learning ...

```
In [51]: #Loading sklearn dependents
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data, targets, stratify=targets, test_size=0.25)
```

```
In [16]: #Distribution of alphabets in train and test sets
alphaDistTrain = y_train.value_counts()[range(0,26)]
alphaDistTest = y_test.value_counts()[range(0,26)]
alphaDict = [chr(65+i) for i in range(0,26)]

####
fig, axes = plt.subplots(1, 2, figsize=(10,3))
plt.subplots_adjust(left=0.1,bottom=0.1, right=0.9, top=0.9,wspace=0.3, hspace=0.4)
sns.barplot(ax=axes[0], x=alphaDict, y=alphaDistTrain)
axes[0].set_title("Training Set Distribution")
axes[0].set_xlabel('Alphabets')
axes[0].set_ylabel('Image Counts')
sns.barplot(ax=axes[1], x=alphaDict, y=alphaDistTest)
axes[1].set_title("Testing Set Distribution")
axes[1].set_xlabel('Alphabets')
axes[1].set_ylabel('Image Counts')
fig.show()
```



```
In [44]: #Loading keras models
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation, Flatten
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras import backend as K
import gc
```

```
In [52]: # Convert targets to categorical
y_train = keras.utils.to_categorical(y_train, len(y_train.unique()))
y_test = keras.utils.to_categorical(y_test, len(y_test.unique()))
```

Deep Learning Model #1

CNN model of CNN DEMO's learning parameters

Only grey scale image, additional filter may not be applicable even they are considered in CNN

```
In [21]: #Clear failed models due to debug process
K.clear_session()

model = Sequential()

# 5x5 convolution with 2x2 stride and 32 filters; 28x28 > 14x14x32
model.add(Conv2D(filters=32, kernel_size=(5, 5), strides = (2,2), padding='same',
    input_shape=X_train.shape[1:]))
model.add(Activation('relu'))

# another convolution with 2x2 stride and 32 filters; 14x14x32 > 7x7x32
model.add(Conv2D(filters=32, kernel_size=(5, 5), strides = (2,2), padding='same'))
model.add(Activation('relu'))

# 2x2 max pooling to reduces image to 3 x 3 x 32
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

# Flatten turns 3x3x32 into 288x1
model.add(Flatten())

# Apply dense Layers
model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
# Output Layer
model.add(Dense( y_test.shape[1] ))
model.add(Activation('softmax'))

# Compile model with Loss function, optimizer, and evaluation parameters
model.compile(
    loss='categorical_crossentropy',
    optimizer=keras.optimizers.Adam(), #use Adam optimized with default setting
    metrics=['accuracy'] #evaluate model using accuracy
)

# Save model 1
model.save('DL_Project_CNN_1.h5')

model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 14, 14, 32)	832
activation (Activation)	(None, 14, 14, 32)	0
conv2d_1 (Conv2D)	(None, 7, 7, 32)	25632
activation_1 (Activation)	(None, 7, 7, 32)	0
max_pooling2d (MaxPooling2D)	(None, 3, 3, 32)	0
dropout (Dropout)	(None, 3, 3, 32)	0
flatten (Flatten)	(None, 288)	0
flatten_1 (Flatten)	(None, 288)	0
dense (Dense)	(None, 512)	147968
activation_2 (Activation)	(None, 512)	0
dropout_1 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 26)	13338
activation_3 (Activation)	(None, 26)	0
Total params: 187,770		
Trainable params: 187,770		
Non-trainable params: 0		

Deep Learning Model #2

CNN model with lower convolution (1 pass)
Attempt "tanh" for activation
because of grey scale in characters, assume 1 filter

```
In [87]: #Clear failed models due to debug process
K.clear_session()

#establish CNN model #2
model = Sequential()

# 5x5 convolution with 2x2 stride and 1 filter; 28x28x1 > 14x14x1
model.add(Conv2D(filters=1, kernel_size=(5, 5), strides = (2,2), padding='same',
    input_shape=X_train.shape[1:]))

# Attempt tanh for learning algorithm
model.add(Activation('relu'))

# 2x2 max pooling to reduces image to 7 x 7 x 1
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

# Flatten turns 7x7x1 into 49x1
model.add(Flatten())

# Apply dense Layer
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
# Output Layer
model.add(Dense( y_test.shape[1] ))
model.add(Activation('softmax'))

# Compile model with Loss function, optimizer, and evaluation parameters
model.compile(
    loss='categorical_crossentropy',
    optimizer=keras.optimizers.Adam(), #use Adam optimized with default setting
    metrics=['accuracy'] #evaluate model using accuracy
)

# Save model 2
model.save('DL_Project_CNN_2.h5')

model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 14, 14, 1)	26
activation (Activation)	(None, 14, 14, 1)	0
max_pooling2d (MaxPooling2D)	(None, 7, 7, 1)	0
dropout (Dropout)	(None, 7, 7, 1)	0
flatten (Flatten)	(None, 49)	0
dense (Dense)	(None, 512)	25600
activation_1 (Activation)	(None, 512)	0
dropout_1 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 26)	13338
activation_2 (Activation)	(None, 26)	0
Total params: 38,964		
Trainable params: 38,964		
Non-trainable params: 0		

Deep Learning Model #3

CNN model of alternative learning parameters, 1-layer of Convolution of larger strides
Attempt 8 filters for grey scale in characters
Also try 2 desnsse layer architecture

```
In [88]: #Clear failed models due to debug process
K.clear_session()

model = Sequential()

# 5x5 convolution with 5x5 stride and 1 filters; 28x28 > 6x6x8
model.add(Conv2D(filters=8, kernel_size=(5, 5), strides = (5,5), padding='same',
    input_shape=X_train.shape[1:]))
model.add(Activation('relu'))

# 2x2 max pooling to reduces image to 3 x 3 x 1
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

# Flatten turns 3x3x8 into 72x1
model.add(Flatten())

# Apply 2 sequential dense Layers of Lower number nodes
model.add(Flatten())
model.add(Dense(256))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(256))
model.add(Activation('relu'))
model.add(Dropout(0.5))
# Output Layer
model.add(Dense( y_test.shape[1] ))
model.add(Activation('softmax'))

# Compile model with loss function, optimizer, and evaluation parameters
model.compile(
    loss='categorical_crossentropy',
    optimizer=keras.optimizers.Adam(), #use Adam optimized with default setting
    metrics=['accuracy'] #evaluate model using accuracy
)

# Save model 3
model.save('DL_Project_CNN_3.h5')

model.summary()
```

Model: "sequential"		
Layer (type)	Output Shape	Param #

conv2d (Conv2D)	(None, 6, 6, 8)	208

activation (Activation)	(None, 6, 6, 8)	0

max_pooling2d (MaxPooling2D)	(None, 3, 3, 8)	0

dropout (Dropout)	(None, 3, 3, 8)	0

flatten (Flatten)	(None, 72)	0

flatten_1 (Flatten)	(None, 72)	0

dense (Dense)	(None, 256)	18688

activation_1 (Activation)	(None, 256)	0

dropout_1 (Dropout)	(None, 256)	0

dense_1 (Dense)	(None, 256)	65792

activation_2 (Activation)	(None, 256)	0

dropout_2 (Dropout)	(None, 256)	0

dense_2 (Dense)	(None, 26)	6682

activation_3 (Activation)	(None, 26)	0

Total params: 91,370		
Trainable params: 91,370		
Non-trainable params: 0		

Training Models

```
In [89]: #Set number of samples to be considered for calculating loss function and update the model parameters
batch_size=64 #Mini-Batch Gradient Descent
```

```
In [90]: # Train and fit model 1
model_1 = keras.models.load_model('DL_Project_CNN_1.h5')
model_1_rec=model_1.fit(X_train, y_train, batch_size=batch_size, epochs=15, validation_data=(X_test, y_test), shuffle=True)
K.clear_session()
gc.collect()
del model_1

Epoch 1/15
4365/4365 [=====] - 79s 18ms/step - loss: 0.2586 - accuracy: 0.9242 - val_loss: 0.0761 - val_accuracy: 0.9792
Epoch 2/15
4365/4365 [=====] - 47s 11ms/step - loss: 0.1206 - accuracy: 0.9649 - val_loss: 0.0622 - val_accuracy: 0.9824
Epoch 3/15
4365/4365 [=====] - 48s 11ms/step - loss: 0.0998 - accuracy: 0.9710 - val_loss: 0.0537 - val_accuracy: 0.9853
Epoch 4/15
4365/4365 [=====] - 47s 11ms/step - loss: 0.0887 - accuracy: 0.9739 - val_loss: 0.0459 - val_accuracy: 0.9875
Epoch 5/15
4365/4365 [=====] - 46s 11ms/step - loss: 0.0804 - accuracy: 0.9763 - val_loss: 0.0443 - val_accuracy: 0.9875
Epoch 6/15
4365/4365 [=====] - 46s 11ms/step - loss: 0.0756 - accuracy: 0.9775 - val_loss: 0.0426 - val_accuracy: 0.9886
Epoch 7/15
4365/4365 [=====] - 47s 11ms/step - loss: 0.0725 - accuracy: 0.9785 - val_loss: 0.0426 - val_accuracy: 0.9882
Epoch 8/15
4365/4365 [=====] - 49s 11ms/step - loss: 0.0688 - accuracy: 0.9796 - val_loss: 0.0403 - val_accuracy: 0.9891
Epoch 9/15
4365/4365 [=====] - 47s 11ms/step - loss: 0.0663 - accuracy: 0.9799 - val_loss: 0.0398 - val_accuracy: 0.9890
Epoch 10/15
4365/4365 [=====] - 46s 11ms/step - loss: 0.0644 - accuracy: 0.9809 - val_loss: 0.0388 - val_accuracy: 0.9895
Epoch 11/15
4365/4365 [=====] - 46s 11ms/step - loss: 0.0629 - accuracy: 0.9815 - val_loss: 0.0384 - val_accuracy: 0.9898
Epoch 12/15
4365/4365 [=====] - 45s 10ms/step - loss: 0.0607 - accuracy: 0.9818 - val_loss: 0.0372 - val_accuracy: 0.9901
Epoch 13/15
4365/4365 [=====] - 46s 11ms/step - loss: 0.0606 - accuracy: 0.9820 - val_loss: 0.0368 - val_accuracy: 0.9902
Epoch 14/15
4365/4365 [=====] - 47s 11ms/step - loss: 0.0589 - accuracy: 0.9823 - val_loss: 0.0388 - val_accuracy: 0.9898
Epoch 15/15
4365/4365 [=====] - 46s 11ms/step - loss: 0.0586 - accuracy: 0.9822 - val_loss: 0.0357 - val_accuracy: 0.9907
```

```
In [91]: # Train and fit model 2
model_2 = keras.models.load_model('DL_Project_CNN_2.h5')
model_2_rec=model_2.fit(X_train, y_train, batch_size=batch_size, epochs=15, validation_data=(X_test, y_test), shuffle=True)
K.clear_session()
gc.collect()
del model_2
```

```
Epoch 1/15
4365/4365 [=====] - 39s 9ms/step - loss: 1.1109 - accuracy: 0.6653 - val_loss: 0.5103 - val_accuracy: 0.8829
Epoch 2/15
4365/4365 [=====] - 37s 8ms/step - loss: 0.8190 - accuracy: 0.7524 - val_loss: 0.4877 - val_accuracy: 0.8906
Epoch 3/15
4365/4365 [=====] - 37s 8ms/step - loss: 0.7547 - accuracy: 0.7714 - val_loss: 0.4870 - val_accuracy: 0.8873
Epoch 4/15
4365/4365 [=====] - 37s 8ms/step - loss: 0.7222 - accuracy: 0.7818 - val_loss: 0.4808 - val_accuracy: 0.8864
Epoch 5/15
4365/4365 [=====] - 37s 8ms/step - loss: 0.6974 - accuracy: 0.7896 - val_loss: 0.5267 - val_accuracy: 0.8686
Epoch 6/15
4365/4365 [=====] - 37s 8ms/step - loss: 0.6846 - accuracy: 0.7940 - val_loss: 0.4846 - val_accuracy: 0.8857
Epoch 7/15
4365/4365 [=====] - 39s 9ms/step - loss: 0.6771 - accuracy: 0.7960 - val_loss: 0.4986 - val_accuracy: 0.8767
Epoch 8/15
4365/4365 [=====] - 37s 8ms/step - loss: 0.6663 - accuracy: 0.7986 - val_loss: 0.4909 - val_accuracy: 0.8773
Epoch 9/15
4365/4365 [=====] - 36s 8ms/step - loss: 0.6571 - accuracy: 0.8023 - val_loss: 0.5033 - val_accuracy: 0.8749
Epoch 10/15
4365/4365 [=====] - 42s 10ms/step - loss: 0.6527 - accuracy: 0.8022 - val_loss: 0.5151 - val_accuracy: 0.8682
Epoch 11/15
4365/4365 [=====] - 46s 10ms/step - loss: 0.6486 - accuracy: 0.8040 - val_loss: 0.5403 - val_accuracy: 0.8606
Epoch 12/15
4365/4365 [=====] - 42s 10ms/step - loss: 0.6450 - accuracy: 0.8054 - val_loss: 0.5248 - val_accuracy: 0.8635
Epoch 13/15
4365/4365 [=====] - 39s 9ms/step - loss: 0.6379 - accuracy: 0.8081 - val_loss: 0.5261 - val_accuracy: 0.8643
Epoch 14/15
4365/4365 [=====] - 36s 8ms/step - loss: 0.6362 - accuracy: 0.8087 - val_loss: 0.5405 - val_accuracy: 0.8598
Epoch 15/15
4365/4365 [=====] - 39s 9ms/step - loss: 0.6314 - accuracy: 0.8091 - val_loss: 0.5283 - val_accuracy: 0.8654
```

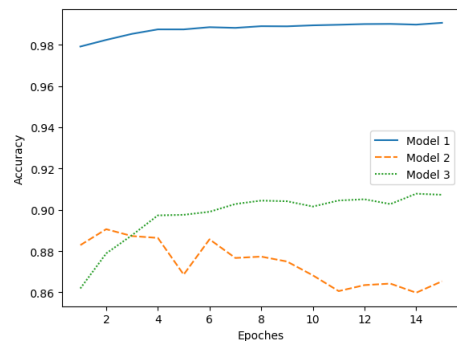
```
In [92]: # Train and fit model 3
model_3 = keras.models.load_model('DL_Project_CNN_3.h5')
model_3_rec=model_3.fit(X_train, y_train, batch_size=batch_size, epochs=15, validation_data=(X_test, y_test), shuffle=True)
K.clear_session()
gc.collect()
del model_3
```

```
Epoch 1/15
4365/4365 [=====] - 42s 9ms/step - loss: 1.1850 - accuracy: 0.6450 - val_loss: 0.4938 - val_accuracy: 0.8619
Epoch 2/15
4365/4365 [=====] - 41s 9ms/step - loss: 0.8681 - accuracy: 0.7376 - val_loss: 0.4176 - val_accuracy: 0.8789
Epoch 3/15
4365/4365 [=====] - 40s 9ms/step - loss: 0.8107 - accuracy: 0.7548 - val_loss: 0.3876 - val_accuracy: 0.8877
Epoch 4/15
4365/4365 [=====] - 40s 9ms/step - loss: 0.7823 - accuracy: 0.7629 - val_loss: 0.3658 - val_accuracy: 0.8973
Epoch 5/15
4365/4365 [=====] - 42s 10ms/step - loss: 0.7643 - accuracy: 0.7696 - val_loss: 0.3577 - val_accuracy: 0.8976
Epoch 6/15
4365/4365 [=====] - 40s 9ms/step - loss: 0.7527 - accuracy: 0.7720 - val_loss: 0.3581 - val_accuracy: 0.8991
Epoch 7/15
4365/4365 [=====] - 41s 9ms/step - loss: 0.7444 - accuracy: 0.7747 - val_loss: 0.3428 - val_accuracy: 0.9028
Epoch 8/15
4365/4365 [=====] - 42s 10ms/step - loss: 0.7375 - accuracy: 0.7771 - val_loss: 0.3332 - val_accuracy: 0.9045
Epoch 9/15
4365/4365 [=====] - 44s 10ms/step - loss: 0.7322 - accuracy: 0.7784 - val_loss: 0.3357 - val_accuracy: 0.9042
Epoch 10/15
4365/4365 [=====] - 41s 9ms/step - loss: 0.7281 - accuracy: 0.7804 - val_loss: 0.3365 - val_accuracy: 0.9016
Epoch 11/15
4365/4365 [=====] - 41s 9ms/step - loss: 0.7179 - accuracy: 0.7831 - val_loss: 0.3336 - val_accuracy: 0.9045
Epoch 12/15
4365/4365 [=====] - 41s 9ms/step - loss: 0.7214 - accuracy: 0.7817 - val_loss: 0.3310 - val_accuracy: 0.9051
Epoch 13/15
4365/4365 [=====] - 40s 9ms/step - loss: 0.7166 - accuracy: 0.7834 - val_loss: 0.3310 - val_accuracy: 0.9028
Epoch 14/15
4365/4365 [=====] - 44s 10ms/step - loss: 0.7151 - accuracy: 0.7843 - val_loss: 0.3286 - val_accuracy: 0.9078
Epoch 15/15
4365/4365 [=====] - 43s 10ms/step - loss: 0.7122 - accuracy: 0.7853 - val_loss: 0.3271 - val_accuracy: 0.9073
```

```
In [93]: val_acc=pd.DataFrame([model_1_rec.history['val_accuracy'],
                             model_2_rec.history['val_accuracy'],
                             model_3_rec.history['val_accuracy']]).T
val_acc.index=list(range(1,len(val_acc.index)+1))
val_acc.columns=["Model 1", "Model 2", "Model 3"]
```

```
In [94]: fig=sns.lineplot(val_acc)
fig.set_xlabel('Epochs')
fig.set_ylabel('Accuracy')
```

```
Out[94]: Text(0, 0.5, 'Accuracy')
```



Q4: Summary of training at least three variations of the Deep Learning model you selected. For example, you can use different clustering techniques or different hyperparameters.

Answer:

3 CNN models of different hyperparameters are tested:

Model 1: 2 convolution layers of 32 filters, 5x5 convolution, and 2x2 strides

rendering 288 inputs per picture, and 187,770 parameters to optimize

Model 2: 1 convolution layers of 1 filter, 5x5 convolution, and 2x2 strides, 512-node dense layer for NN

rendering 49 inputs per picture, and 38,964 parameters to optimize, 512-node dense layer for NN

Model 3: 1 convolution layers of 8 filters, 5x5 convolution, and 5x5 strides, 2x256-node dense layer for NN

rendering 72 inputs per picture, and 91,370 parameters to optimize

Summary:

In spite of grey-scale image, a 32 filter convolution seem work very well on hand-written alphabet recognition Comparatively, single convolution layer of 1 filter is able to approach to near 90% accuracy, with much less parameters to optimize. But this model requires more training Increase filter seem have better initial prediction, but less improvements observed. Larger stride seem not affect too much after some adequate amount of training. Nevertheless, 2-layered NN with same amount of nodes seem make some minor improvements long with each epoch. In spite of higher number of parameters for optimization, the final predictability seem only have small improvements.

Q5: A paragraph explaining which of your Deep Learning models you recommend as a final model that best fits your needs in terms of accuracy or explainability.

Answer:

For this data set of hand-written alphabetic letters, first model of 2-layered convolution with 32 filters achieved best accuracy, at 99.13%, at cost of higher number of inputs after convolution and more parameters to optimize

Q6: Summary Key Findings and Insights, which walks your reader through the main findings of your modeling exercise.

Answer:

1. Number of filters in convolution layer is important for initial parameter optimization
2. 2-layer convolution seem lead to better improvements in initial parameter optimization
3. ReLU may not be the best activation method for low filter convolution

Q7: Suggestions for next steps in analyzing this data, which may include suggesting revisiting this model or adding specific data features to achieve a better model.

Answer:

It is difficult to optimize CNN architecture as many parameters are to be evaluated. As for this gray-scale alphabetic dataset, hyperparameters such as kernel and strides may be of less impact to the final predictability. On the other hand, should the alphabetic become RGB color, the CNN may be adjusted with different kernel size and strides. On the other hand, the number of layers may also be investigated further.