The dataset I am using is a spam text message classification dataset. The model should be able to predict if a given text is real or spam.

Ham is real text messages, while spam is fake messages

```
import io
import pandas as pd
import tensorflow as tf
import pickle
import numpy as np
from google.colab import files
from tensorflow import keras
from keras.preprocessing.text import Tokenizer
from keras import layers, models
from sklearn.preprocessing import LabelEncoder
from tensorflow.python import metrics
from keras import preprocessing
```

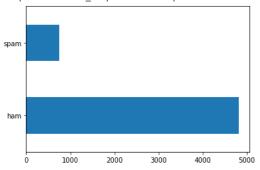
```
data = pd.read_csv('spamtextdata.csv', header=0, usecols=[0,1])
display(data)
```

| Г⇒ |      | C-4      | W  |
|----|------|----------|--|
| L, |      | Category | Message  |
|    | 0    | ham      | Go until jurong point, crazy Available only    |
|    | 1    | ham      | Ok lar Joking wif u oni                        |
|    | 2    | spam     | Free entry in 2 a wkly comp to win FA Cup fina |
|    | 3    | ham      | U dun say so early hor U c already then say    |
|    | 4    | ham      | Nah I don't think he goes to usf, he lives aro |
|    |      |          |  |
|    | 5567 | spam     | This is the 2nd time we have tried 2 contact u |
|    | 5568 | ham      | Will ü b going to esplanade fr home?           |
|    | 5569 | ham      | Pity, * was in mood for that. Soany other s    |
|    | 5570 | ham      | The guy did some bitching but I acted like i'd |
|    | 5571 | ham      | Rofl. Its true to its name                     |
|    | 5570 |          |  |

5572 rows × 2 columns

data['Category'].value\_counts().plot(kind='barh')

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f8091b63bb0>



```
np.random.seed(80085)
i = np.random.rand(len(data)) < 0.8
train = data[i]
test = data[~i]
print('Train shape: ', train.shape)
print('Test shape: ', test.shape)</pre>
```

Train shape: (4441, 2) Test shape: (1131, 2)

```
tokenizer = Tokenizer()
tokenizer.fit_on_texts(train.Message)
```

```
x_train = tokenizer.texts_to_matrix(train.Message, mode='tfidf')
x_test = tokenizer.texts_to_matrix(test.Message, mode='tfidf')
encode = LabelEncoder()
encode.fit(train.Category)
y_train = tf.keras.utils.to_categorical(encode.transform(train.Category), 2)
y_test = tf.keras.utils.to_categorical(encode.transform(test.Category), 2)
print("train shape: ", x_train.shape, y_train.shape)
print("test shape: ", x test.shape, y test.shape)
print("first five test labels: ", y_test[:5])
     train shape: (4441, 7951) (4441, 2)
     test shape: (1131, 7951) (1131, 2)
     first five test labels: [[1. 0.]
      [1. 0.]
      [1. 0.]
      [0. 1.]
      [0. 1.]]
```

## Sequential

Epoch 2/30

```
sequential = models.Sequential()
sequential.add(layers.Dense(32, input_dim=7951, kernel_initializer='normal', activation='relu'))
sequential.add(layers.Dense(32, input_dim=7951, kernel_initializer='normal', activation='relu'))
sequential.add(layers.Dense(2, kernel_initializer='normal', activation='softmax'))
sequential.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
history = sequential.fit(x_train, y_train, epochs=30, batch_size=128)
```

```
35/35 [====
    Epoch 3/30
Epoch 4/30
Epoch 5/30
35/35 [==========] - 0s 9ms/step - loss: 0.0101 - accuracy: 0.9980
Epoch 6/30
35/35 [============ ] - 0s 9ms/step - loss: 0.0053 - accuracy: 0.9998
Epoch 7/30
35/35 [====
   Epoch 8/30
35/35 [============ ] - 0s 9ms/step - loss: 0.0023 - accuracy: 0.9998
Epoch 9/30
Epoch 10/30
35/35 [============= ] - 0s 9ms/step - loss: 0.0013 - accuracy: 1.0000
Epoch 11/30
35/35 [============ ] - 0s 9ms/step - loss: 0.0010 - accuracy: 1.0000
Epoch 12/30
Epoch 13/30
35/35 [======
    Epoch 14/30
Epoch 15/30
Epoch 16/30
Epoch 17/30
35/35 [============= ] - 0s 9ms/step - loss: 3.7568e-04 - accuracy: 1.0000
Epoch 18/30
Epoch 19/30
Epoch 20/30
Epoch 21/30
Epoch 22/30
Epoch 23/30
Epoch 24/30
Epoch 25/30
```

```
Epoch 27/30
 35/35 [=====
       Epoch 28/30
 35/35 [============= - 0s 9ms/step - loss: 1.2428e-04 - accuracy: 1.0000
 Epoch 29/30
 Epoch 30/30
 score = sequential.evaluate(x_test, y_test, batch_size=100, verbose=1)
print('Accuracy: ', score[1])
 Accuracy: 0.9902740716934204
CNN
cnn = models.Sequential()
cnn.add(layers.Embedding(10000, 128, input_length=7951))
cnn.add(layers.Conv1D(32, 7, activation='relu'))
cnn.add(layers.MaxPooling1D(5))
cnn.add(layers.Conv1D(32, 7, activation='relu'))
cnn.add(layers.GlobalMaxPooling1D())
cnn.add(layers.Dense(2))
cnn.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = cnn.fit(x_train, y_train, epochs=5, batch_size=64)
 Epoch 1/5
 Epoch 2/5
       70/70 [===
 Epoch 3/5
 Epoch 4/5
 70/70 [====
      Epoch 5/5
 score = cnn.evaluate(x_test, y_test, batch_size=100, verbose=1)
print('Accuracy: ', score[1])
 Accuracy: 0.11671087890863419
Embedding
embed = models.Sequential()
embed.add(layers.Embedding(10000, 8, input_length=7951))
embed.add(layers.Flatten())
embed.add(layers.Dense(32, activation='relu'))
embed.add(layers.Dense(2, activation='relu'))
embed.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = embed.fit(x_train, y_train, epochs=10, batch_size=32, validation_split=.2)
 Epoch 1/10
 Epoch 2/10
 Epoch 3/10
 Epoch 4/10
 111/111 [===
       Epoch 5/10
 Epoch 6/10
 111/111 [==:
          Epoch 7/10
 Epoch 8/10
 Epoch 9/10
```

## **Analysis**

Accuracy: 0.883289098739624

The highest accuracy that I achieved was with the sequential model, followed by the embedding, with CNN having the lowest accuracy by far. My sequential model achieved an accuracy of 99%, while the embedding only achieved 88%. The CNN was very low, at only 11.6% accuracy.

My final project for my Machine Learning class was to analyze the performance of various machine learning models when trained on different datasets. My findings were the CNNs really relied on a large dataset and a decent number of epochs to achieve great performance. Their benefits are also much more apparent with more complex datasets. I believe this is a large part of why it was the worst performer here. The dataset that I used for this assignment was pretty small, under 8000 entries. It was also a very simple dataset, with only two classifications.

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