

Deep_Learning_Chat_Bot_(2)

October 16, 2023

0.1 Deep Learning ChatBot

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0.1.1 Importing Libraries

```
[1]: import json
import numpy as np
import pandas as pd
import pickle
import random
import matplotlib.pyplot as plt
import nltk
nltk.download('punkt')
nltk.download('wordnet')
from nltk.stem import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Embedding, GlobalAveragePooling1D , GlobalMaxPooling1D, Flatten , Conv1D, Dropout , Activation
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.preprocessing import LabelEncoder
```

```
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.optimizers import SGD
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data] Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
```

0.1.2 Loading Intents Files

```
[3]: with open('intents.json') as file:
      data = json.load(file)
```

0.1.3 Splitting the data into sentences , labels , responses

```
[4]: training_sentences = []
      training_labels = []
      labels = []
      responses = []

      for intent in data['intents']:
          for pattern in intent['patterns']:
              training_sentences.append(pattern)
              training_labels.append(intent['tag'])
              responses.append(intent['responses'])

          if intent['tag'] not in labels:
              labels.append(intent['tag'])

      num_classes = len(labels)
```

```
[5]: len(set(training_labels))
```

```
[5]: 46
```

```
[6]: training_sentences
```

```
[6]: ['What to do if Cuts?',
      'How to cure Cuts?',
      'Which medicine to apply for Cuts?',
      'what to apply on cuts?',
      'Cuts',
      'Hi',
      'How are you',
      'Is anyone there?',
      'Hello',
      'Whats up',
```

'cya',
'See you later',
'Goodbye',
'I am Leaving',
'Have a Good day',
'bye',
'how do you treat abrasions?',
'Do Abrasions cause scars?',
'Abrasions',
'what to do if abrasions?',
'Which medicine to apply for abrasions?',
'How to cure abrasions?',
'How do you treat Sting?',
'Stings',
'What to do if you get a sting?',
'Which medicine to apply if sting?',
'How to remove Splinters',
'How to cure Splinters?',
'What to do if I have splinters?',
'How do you bring a splinter to the surface?',
'How do you treat a sprain?',
'what to do if i get a sprain?',
'Which cream to apply if i get a sprain?',
'Which medicine to apply if I get a sprain?',
'How do you treat a strain?',
'what to do if i get a strain?',
'Which cream to apply if i get a strain?',
'Which medicine to apply if I get a strain?',
'How do you diagnose a strain?',
'Is heat or ice better for a pulled muscle?',
'How do you treat a mild Fever?',
'what to do if i get a mild fever?',
'Which medicine to take if I get a mild fever?',
'fever',
'How do you treat nasal Congestion?',
'what to do if i get a nasal congestion?',
'Which medicine to take if I have a nasal congestion?',
'what to do if i have a blocked nose?',
'How do you treat a blocked nose?',
'How long does nasal congestion last?',
'How to cure cough?',
'How do you treat cough?',
'what to do if i get a cough?',
'Which medicine to take if I get cough?',
'How do you get rid of cough?',
'How do you treat sore throat?',
'what to do if i get a sore throat?',

'Which medicine to take if I get a sore throat?',
'How to cure sore throat?',
'How do you treat gas problems?',
'what to do if i have Gastrointestinal problems?',
'Which medicine to take if I get gas problem?',
'How to cure Gas problems?',
'How do you treat Skin problems?',
'what to do if i get a skin allergy?',
'Which medicine to take if I get a skin allergy?',
'How to cure skin allergy?',
'How do you treat Abdominal Pain?',
'what to do if i get a Abdominal Pain?',
'Which medicine to take if I get a Abdominal Pain?',
'How to cure Abdominal Pain?',
'How do you treat Bruises?',
'what to do if i get a Bruise?',
'Which medicine to take if I get a Bruise?',
'How to cure Bruises?',
'How do you treat a Broken Toe?',
'what to do if i get a Broken Toe?',
'Which medicine to take if I get a Broken Toe?',
'How to cure Broken Toe?',
'How do you treat Choking?',
'what to do if i get a Choke?',
'Which medicine to take if I get Choked?',
'How to cure Choking?',
'How do you treat a wound?',
'what to do if i get a Wound?',
'Which medicine to take if I get wounded?',
'How to cure a wound?',
'How do you treat Diarrhea?',
'what to do if i get Diarrhea?',
'Which medicine to take if I get Diarrhea?',
'How to cure Diarrhea?',
'How do you treat a Frost bite?',
'what to do if i get a Frost bite?',
'Which medicine to take if I get a Frost bite?',
'How to cure Frost bite?',
'How do you treat Heat Exhaustion?',
'what to do if i feel Exhausted due to heat?',
'Which medicine to take if I get Exhausted?',
'How to cure Heat Exhaustion?',
'How do you treat Heat Stroke?',
'what to do if i get a Heat Stroke?',
'Which medicine to take if I get Stroke?',
'How to cure a Heat Stroke?',
'How do you treat a Insect Bite?',

'what to do if a insect bites me?',
 'Which medicine to take if I get bitten by a insect?',
 'How to cure insect bite?',
 'How do you treat a bleeding nose?',
 'what to do if i my nose is bleeding?',
 'Which medicine to take if I get nose bleed?',
 'How to cure nose bleeding?',
 'How do you treat a Pulled Muscle?',
 'what to do if my muscle is pulled?',
 'Which medicine to take if I got pulled muscle?',
 'How to cure a pulled muscle?',
 'How do you treat Rectal Bleeding?',
 'what to do if i get a Rectal Bleeding?',
 'Which medicine to take if I get Rectal Bleeding?',
 'How to cure Rectal Bleeding?',
 'How do you treat Sun Burn?',
 'what to do if i get a Sun Burn?',
 'Which medicine to take if I get Sun Burn?',
 'How to cure a Sun Burn?',
 'How do you treat Testicle Pain?',
 'what to do if i get a Testicle Pain?',
 'Which medicine to take if I get a Testicle Pain?',
 'How to cure Testicle Pain?',
 'How do you treat a Vertigo?',
 'what to do if i get a Vertigo?',
 'Which medicine to take if I get Vertigo?',
 'How to cure a Vertigo?',
 'How do you treat bleeding?',
 'what to do if i get a Bleeding?',
 'Which medicine to take if I get bleeding?',
 'How to cure Bleeding?',
 'How do you treat an eye Injury?',
 'what to do if i get a eye Injury?',
 'Which medicine to take if I injured my eye?',
 'How to cure injured eye?',
 'How do you treat a chemical burn?',
 'what to do if i get a Chemical Burn?',
 'Which medicine to take if I get burn due to chemicals?',
 'How to cure Chemical Burn?',
 'How do you treat a Poison?',
 'what to do if i get Poison?',
 'Which medicine to take if I am poisoned?',
 'How to cure Poisoning?',
 'How do you treat broken Teeth ?',
 'what to do if my Teeth got broken?',
 'Which medicine to take if I get broken teeth?',
 'cure broken teeth?',

'How do you treat a seizure?',
 'what to do if i get a seizure?',
 'Which medicine to take if I get seizure?',
 'How to cure seizure?',
 'How do you treat a head Injury?',
 'what to do if i get a Head Injury?',
 'Which medicine to take if I get injured in the head?',
 'How to cure Head Injury?',
 'How do you treat Faint?',
 'what to do if i feel like Fainting?',
 'Which medicine to take if I get a Faint?',
 'How to cure Fainting?',
 'How do you treat a mild Headache?',
 'what to do if i get a mild Headache?',
 'Which medicine to take if I have a mild headache?',
 'How to cure a mild headache?',
 'How do you treat a Cold?',
 'what to do if i get a mild Cold?',
 'Which medicine to take if I have a Cold?',
 'How to cure Cold?',
 'How do you treat Rashes?',
 'what to do if i get a Rash?',
 'Which medicine to take if I have a Rash?',
 'How to cure Rash?',
 'How do you treat a snake bite?',
 'what to do if i get a snake bite?',
 'Which medicine to take if I get a snake bite?',
 'How to cure snake bite?',
 'i got bit by a snake',
 'How do you treat a animal bite?',
 'How do you treat a monkey bite?',
 'How do you treat a dog bite?',
 'what to do if i get a animal bite?',
 'Which medicine to take if I get a monekey bite?',
 'How to cure dog bite?',
 'i got bit by a dog',
 'What to do if someone is Drowning?',
 'what to do if someone drowned?',
 'What steps to take if i see a drowning person?',
 'How to help a drowning person?',
 'How to give CPR??',
 'what to do in a CPR?',
 'What steps to take in a CPR??',
 'How to help a drowning person in CPR?',
 'How do you treat a Fracture?',
 'what to do if i get a Fracture?',
 'Which medicine to take if I have a Fracture?',

```
'How to cure a Fracture?']
```

```
[7]: training_labels
```

```
[7]: ['Cuts',  
      'Cuts',  
      'Cuts',  
      'Cuts',  
      'Cuts',  
      'greeting',  
      'greeting',  
      'greeting',  
      'greeting',  
      'greeting',  
      'goodbye',  
      'goodbye',  
      'goodbye',  
      'goodbye',  
      'goodbye',  
      'Abrasions',  
      'Abrasions',  
      'Abrasions',  
      'Abrasions',  
      'Abrasions',  
      'Abrasions',  
      'stings',  
      'stings',  
      'stings',  
      'stings',  
      'Splinter',  
      'Splinter',  
      'Splinter',  
      'Splinter',  
      'Sprains',  
      'Sprains',  
      'Sprains',  
      'Sprains',  
      'Strains',  
      'Strains',  
      'Strains',  
      'Strains',  
      'Strains',  
      'Strains',  
      'Fever',  
      'Fever',  
      'Fever',
```

'Fever',
'Nasal Congestion',
'Nasal Congestion',
'Nasal Congestion',
'Nasal Congestion',
'Nasal Congestion',
'Nasal Congestion',
'Cough',
'Cough',
'Cough',
'Cough',
'Cough',
'Sore Throat',
'Sore Throat',
'Sore Throat',
'Sore Throat',
'Gastrointestinal problems',
'Gastrointestinal problems',
'Gastrointestinal problems',
'Gastrointestinal problems',
'Skin problems',
'Skin problems',
'Skin problems',
'Skin problems',
'Abdominal Pain',
'Abdominal Pain',
'Abdominal Pain',
'Abdominal Pain',
'Bruises',
'Bruises',
'Bruises',
'Bruises',
'Broken Toe',
'Broken Toe',
'Broken Toe',
'Broken Toe',
'Choking',
'Choking',
'Choking',
'Choking',
'Wound',
'Wound',
'Wound',
'Wound',
'Diarrhea',
'Diarrhea',
'Diarrhea',

'Diarrhea',
'Frost bite',
'Frost bite',
'Frost bite',
'Frost bite',
'Heat Exhaustion',
'Heat Exhaustion',
'Heat Exhaustion',
'Heat Exhaustion',
'Heat Stroke',
'Heat Stroke',
'Heat Stroke',
'Heat Stroke',
'Insect Bites',
'Insect Bites',
'Insect Bites',
'Insect Bites',
'nose bleed',
'nose bleed',
'nose bleed',
'nose bleed',
'Pulled Muscle',
'Pulled Muscle',
'Pulled Muscle',
'Pulled Muscle',
'Rectal bleeding',
'Rectal bleeding',
'Rectal bleeding',
'Rectal bleeding',
'Sun Burn',
'Sun Burn',
'Sun Burn',
'Sun Burn',
'Testicle Pain',
'Testicle Pain',
'Testicle Pain',
'Testicle Pain',
'Vertigo',
'Vertigo',
'Vertigo',
'Vertigo',
'Normal Bleeding',
'Normal Bleeding',
'Normal Bleeding',
'Normal Bleeding',
'Eye Injury',
'Eye Injury',

'Eye Injury',
'Eye Injury',
'Chemical Burn',
'Chemical Burn',
'Chemical Burn',
'Chemical Burn',
'Poison',
'Poison',
'Poison',
'Poison',
'Teeth',
'Teeth',
'Teeth',
'Teeth',
'seizure',
'seizure',
'seizure',
'seizure',
'Head Injury',
'Head Injury',
'Head Injury',
'Head Injury',
'Fainting',
'Fainting',
'Fainting',
'Fainting',
'Headache',
'Headache',
'Headache',
'Headache',
'Cold',
'Cold',
'Cold',
'Cold',
'Rash',
'Rash',
'Rash',
'Rash',
'snake bite',
'snake bite',
'snake bite',
'snake bite',
'snake bite',
'animal bite',
'animal bite',
'animal bite',
'animal bite',

```
'animal bite',
'animal bite',
'animal bite',
'Drowning',
'Drowning',
'Drowning',
'Drowning',
'CPR',
'CPR',
'CPR',
'CPR',
'Fracture',
'Fracture',
'Fracture',
'Fracture']
```

0.1.4 Simple Baseline Using Logistic Regression

```
[8]: sentences_train, sentences_test, label_train, label_test = train_test_split(
      training_sentences, training_labels, test_size=0.20, random_state=1000)
```

```
[9]: from sklearn.feature_extraction.text import CountVectorizer

sentences_vectorizer = CountVectorizer()
sentences_vectorizer.fit(sentences_train)
Xlr_train = sentences_vectorizer.transform(sentences_train)
Xlr_test = sentences_vectorizer.transform(sentences_test)
Xlr_train
```

```
[9]: <159x129 sparse matrix of type '<class 'numpy.int64'>'
      with 900 stored elements in Compressed Sparse Row format>
```

```
[10]: from sklearn.linear_model import LogisticRegression
LRmodel = LogisticRegression()
LRmodel.fit(Xlr_train, label_train)

score_train = LRmodel.score(Xlr_train, label_train)

score_test = LRmodel.score(Xlr_test, label_test)

print("Accuracy Train :", score_train)
print("Accuracy Test :", score_test)
```

```
Accuracy Train : 0.9874213836477987
Accuracy Test : 0.575
```

0.1.5 Encoding The Data Labels

```
[11]: lbl_encoder = LabelEncoder()
      lbl_encoder.fit(training_labels)
      training_labels = lbl_encoder.transform(training_labels)
      training_labels

[11]: array([ 9,  9,  9,  9,  9, 41, 41, 41, 41, 41, 40, 40, 40, 40, 40, 40,  1,
          1,  1,  1,  1, 45, 45, 45, 45, 31, 31, 31, 31, 32, 32, 32, 32,
        33, 33, 33, 33, 33, 33, 14, 14, 14, 14, 23, 23, 23, 23, 23, 23,  8,
          8,  8,  8, 30, 30, 30, 30, 17, 17, 17, 17, 29, 29, 29, 29,  0,
          0,  0,  3,  3,  3,  3,  2,  2,  2,  2,  6,  6,  6,  6, 38, 38,
        38, 38, 10, 10, 10, 10, 16, 16, 16, 16, 20, 20, 20, 20, 21, 21, 21,
        21, 22, 22, 22, 22, 42, 42, 42, 42, 26, 26, 26, 26, 28, 28, 28, 28,
        34, 34, 34, 34, 36, 36, 36, 36, 37, 37, 37, 37, 24, 24, 24, 24, 12,
        12, 12, 12,  5,  5,  5,  5, 25, 25, 25, 25, 35, 35, 35, 35, 43, 43,
        43, 43, 18, 18, 18, 18, 13, 13, 13, 13, 19, 19, 19, 19,  7,  7,  7,
          7, 27, 27, 27, 27, 44, 44, 44, 44, 44, 39, 39, 39, 39, 39, 39, 39,
        11, 11, 11, 11,  4,  4,  4,  4, 15, 15, 15, 15])
```

0.1.6 NLP Text Tokannize , clean

```
[12]: vocab_size = 1000
      embedding_dim = 16
      max_len = 20
      oov_token = "<OOV>"

      tokenizer = Tokenizer(num_words=vocab_size, oov_token=oov_token) # adding out_
        ↳of vocabulary token
      tokenizer.fit_on_texts(training_sentences)
      word_index = tokenizer.word_index
      sequences = tokenizer.texts_to_sequences(training_sentences)
      padded_sequences = pad_sequences(sequences, truncating='post', maxlen=max_len)
```

0.1.7 Neural Network Baseline

```
[13]: baseline = Sequential()
      baseline.add(Dense(128, activation='relu'))
      baseline.add(Dense(128, activation='relu'))
      baseline.add(Dense(num_classes, activation='softmax'))

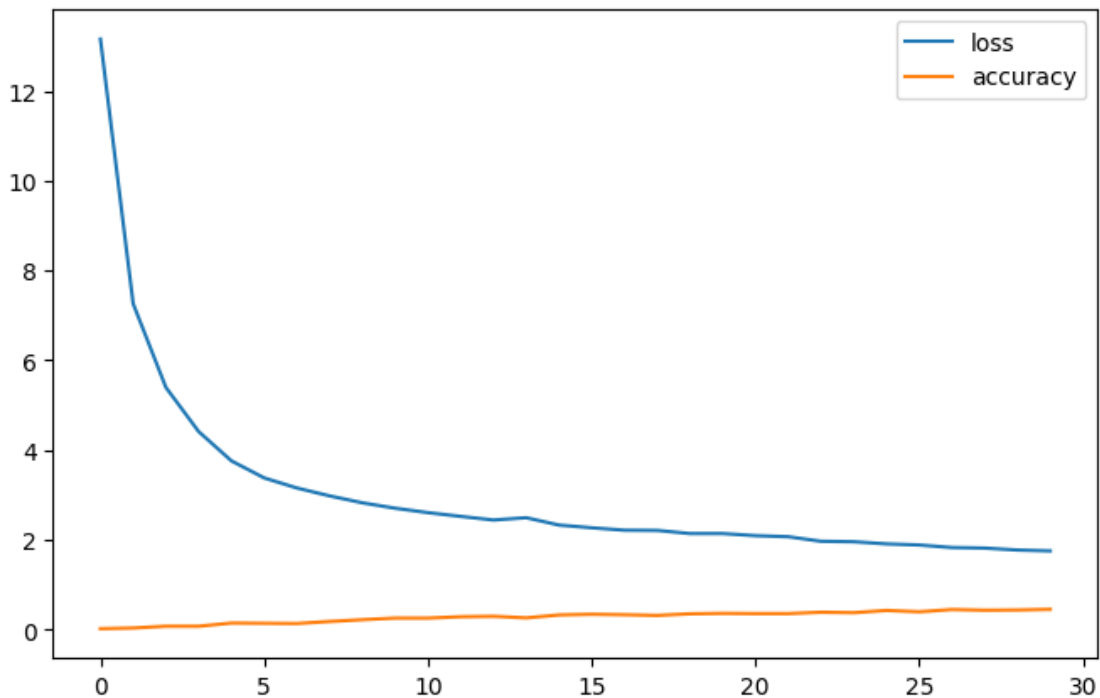
      baseline.compile(loss='sparse_categorical_crossentropy', optimizer='adam',
        ↳metrics=['accuracy'])
```

```
baseline_nn = baseline.fit(padded_sequences,np.array(training_labels),  
↪epochs=30)
```

```
Epoch 1/30  
7/7 [=====] - 3s 9ms/step - loss: 13.1581 - accuracy:  
0.0201  
Epoch 2/30  
7/7 [=====] - 0s 11ms/step - loss: 7.2616 - accuracy:  
0.0352  
Epoch 3/30  
7/7 [=====] - 0s 7ms/step - loss: 5.3961 - accuracy:  
0.0754  
Epoch 4/30  
7/7 [=====] - 0s 13ms/step - loss: 4.4126 - accuracy:  
0.0754  
Epoch 5/30  
7/7 [=====] - 0s 8ms/step - loss: 3.7602 - accuracy:  
0.1457  
Epoch 6/30  
7/7 [=====] - 0s 7ms/step - loss: 3.3799 - accuracy:  
0.1407  
Epoch 7/30  
7/7 [=====] - 0s 10ms/step - loss: 3.1552 - accuracy:  
0.1357  
Epoch 8/30  
7/7 [=====] - 0s 12ms/step - loss: 2.9791 - accuracy:  
0.1809  
Epoch 9/30  
7/7 [=====] - 0s 7ms/step - loss: 2.8248 - accuracy:  
0.2211  
Epoch 10/30  
7/7 [=====] - 0s 7ms/step - loss: 2.7045 - accuracy:  
0.2563  
Epoch 11/30  
7/7 [=====] - 0s 6ms/step - loss: 2.6063 - accuracy:  
0.2563  
Epoch 12/30  
7/7 [=====] - 0s 6ms/step - loss: 2.5226 - accuracy:  
0.2864  
Epoch 13/30  
7/7 [=====] - 0s 11ms/step - loss: 2.4422 - accuracy:  
0.2965  
Epoch 14/30  
7/7 [=====] - 0s 6ms/step - loss: 2.4933 - accuracy:  
0.2613  
Epoch 15/30  
7/7 [=====] - 0s 9ms/step - loss: 2.3298 - accuracy:
```

0.3266
 Epoch 16/30
 7/7 [=====] - 0s 13ms/step - loss: 2.2688 - accuracy:
 0.3417
 Epoch 17/30
 7/7 [=====] - 0s 17ms/step - loss: 2.2154 - accuracy:
 0.3317
 Epoch 18/30
 7/7 [=====] - 0s 10ms/step - loss: 2.2102 - accuracy:
 0.3166
 Epoch 19/30
 7/7 [=====] - 0s 6ms/step - loss: 2.1407 - accuracy:
 0.3518
 Epoch 20/30
 7/7 [=====] - 0s 7ms/step - loss: 2.1407 - accuracy:
 0.3618
 Epoch 21/30
 7/7 [=====] - 0s 13ms/step - loss: 2.0932 - accuracy:
 0.3568
 Epoch 22/30
 7/7 [=====] - 0s 9ms/step - loss: 2.0697 - accuracy:
 0.3568
 Epoch 23/30
 7/7 [=====] - 0s 7ms/step - loss: 1.9683 - accuracy:
 0.3869
 Epoch 24/30
 7/7 [=====] - 0s 7ms/step - loss: 1.9579 - accuracy:
 0.3769
 Epoch 25/30
 7/7 [=====] - 0s 7ms/step - loss: 1.9103 - accuracy:
 0.4271
 Epoch 26/30
 7/7 [=====] - 0s 7ms/step - loss: 1.8856 - accuracy:
 0.3970
 Epoch 27/30
 7/7 [=====] - 0s 7ms/step - loss: 1.8286 - accuracy:
 0.4472
 Epoch 28/30
 7/7 [=====] - 0s 12ms/step - loss: 1.8164 - accuracy:
 0.4322
 Epoch 29/30
 7/7 [=====] - 0s 9ms/step - loss: 1.7732 - accuracy:
 0.4372
 Epoch 30/30
 7/7 [=====] - 0s 11ms/step - loss: 1.7540 - accuracy:
 0.4523

```
[14]: pd.DataFrame(baseline_nn.history).plot(figsize=(8,5))
plt.show()
```



0.1.8 Buidling The Neural Model Using Embedding Layer

```
[15]: model = Sequential()
model.add(Embedding(vocab_size, embedding_dim, input_length=max_len))
model.add(GlobalAveragePooling1D())
model.add(Dense(16, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))

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

```
[16]: model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 20, 16)	16000
global_average_pooling1d ((None, 16)	0

GlobalAveragePooling1D)

dense_3 (Dense)	(None, 16)	272
dense_4 (Dense)	(None, 16)	272
dense_5 (Dense)	(None, 46)	782

```
=====
Total params: 17326 (67.68 KB)
Trainable params: 17326 (67.68 KB)
Non-trainable params: 0 (0.00 Byte)
-----
```

0.1.9 Train The Model On Our Data

- adding the early stop to know the proper epoch count , starting after 200

```
[17]: epochs = 400
      es = EarlyStopping(monitor='loss', mode='min', verbose=1, patience=200)
      history = model.fit(padded_sequences, np.array(training_labels), epochs=epochs,
                          ↪, callbacks=[es])
```

```
Epoch 1/400
7/7 [=====] - 2s 8ms/step - loss: 3.8292 - accuracy:
0.0201
Epoch 2/400
7/7 [=====] - 0s 5ms/step - loss: 3.8280 - accuracy:
0.0452
Epoch 3/400
7/7 [=====] - 0s 5ms/step - loss: 3.8272 - accuracy:
0.0452
Epoch 4/400
7/7 [=====] - 0s 11ms/step - loss: 3.8265 - accuracy:
0.0402
Epoch 5/400
7/7 [=====] - 0s 7ms/step - loss: 3.8258 - accuracy:
0.0352
Epoch 6/400
7/7 [=====] - 0s 6ms/step - loss: 3.8250 - accuracy:
0.0352
Epoch 7/400
7/7 [=====] - 0s 6ms/step - loss: 3.8242 - accuracy:
0.0352
Epoch 8/400
7/7 [=====] - 0s 8ms/step - loss: 3.8232 - accuracy:
0.0352
Epoch 9/400
```


7/7 [=====] - 0s 6ms/step - loss: 3.8222 - accuracy:
0.0352
Epoch 10/400
7/7 [=====] - 0s 6ms/step - loss: 3.8210 - accuracy:
0.0402
Epoch 11/400
7/7 [=====] - 0s 6ms/step - loss: 3.8196 - accuracy:
0.0402
Epoch 12/400
7/7 [=====] - 0s 6ms/step - loss: 3.8181 - accuracy:
0.0402
Epoch 13/400
7/7 [=====] - 0s 5ms/step - loss: 3.8165 - accuracy:
0.0503
Epoch 14/400
7/7 [=====] - 0s 4ms/step - loss: 3.8146 - accuracy:
0.0603
Epoch 15/400
7/7 [=====] - 0s 4ms/step - loss: 3.8124 - accuracy:
0.0603
Epoch 16/400
7/7 [=====] - 0s 4ms/step - loss: 3.8099 - accuracy:
0.0503
Epoch 17/400
7/7 [=====] - 0s 4ms/step - loss: 3.8067 - accuracy:
0.0653
Epoch 18/400
7/7 [=====] - 0s 4ms/step - loss: 3.8039 - accuracy:
0.0754
Epoch 19/400
7/7 [=====] - 0s 4ms/step - loss: 3.7999 - accuracy:
0.0704
Epoch 20/400
7/7 [=====] - 0s 4ms/step - loss: 3.7957 - accuracy:
0.0653
Epoch 21/400
7/7 [=====] - 0s 4ms/step - loss: 3.7912 - accuracy:
0.0653
Epoch 22/400
7/7 [=====] - 0s 4ms/step - loss: 3.7854 - accuracy:
0.0804
Epoch 23/400
7/7 [=====] - 0s 4ms/step - loss: 3.7783 - accuracy:
0.0754
Epoch 24/400
7/7 [=====] - 0s 3ms/step - loss: 3.7709 - accuracy:
0.0704
Epoch 25/400

7/7 [=====] - 0s 4ms/step - loss: 3.7630 - accuracy:
0.0704
Epoch 26/400
7/7 [=====] - 0s 4ms/step - loss: 3.7537 - accuracy:
0.0754
Epoch 27/400
7/7 [=====] - 0s 4ms/step - loss: 3.7423 - accuracy:
0.0704
Epoch 28/400
7/7 [=====] - 0s 4ms/step - loss: 3.7305 - accuracy:
0.0804
Epoch 29/400
7/7 [=====] - 0s 4ms/step - loss: 3.7161 - accuracy:
0.0804
Epoch 30/400
7/7 [=====] - 0s 4ms/step - loss: 3.7017 - accuracy:
0.0754
Epoch 31/400
7/7 [=====] - 0s 5ms/step - loss: 3.6838 - accuracy:
0.0804
Epoch 32/400
7/7 [=====] - 0s 4ms/step - loss: 3.6656 - accuracy:
0.0905
Epoch 33/400
7/7 [=====] - 0s 4ms/step - loss: 3.6477 - accuracy:
0.0754
Epoch 34/400
7/7 [=====] - 0s 4ms/step - loss: 3.6246 - accuracy:
0.0804
Epoch 35/400
7/7 [=====] - 0s 5ms/step - loss: 3.6002 - accuracy:
0.0955
Epoch 36/400
7/7 [=====] - 0s 4ms/step - loss: 3.5756 - accuracy:
0.1005
Epoch 37/400
7/7 [=====] - 0s 4ms/step - loss: 3.5471 - accuracy:
0.1106
Epoch 38/400
7/7 [=====] - 0s 5ms/step - loss: 3.5203 - accuracy:
0.1106
Epoch 39/400
7/7 [=====] - 0s 4ms/step - loss: 3.4871 - accuracy:
0.1156
Epoch 40/400
7/7 [=====] - 0s 4ms/step - loss: 3.4540 - accuracy:
0.1156
Epoch 41/400

7/7 [=====] - 0s 4ms/step - loss: 3.4237 - accuracy:
0.1156
Epoch 42/400
7/7 [=====] - 0s 4ms/step - loss: 3.3862 - accuracy:
0.1156
Epoch 43/400
7/7 [=====] - 0s 4ms/step - loss: 3.3510 - accuracy:
0.1206
Epoch 44/400
7/7 [=====] - 0s 4ms/step - loss: 3.3150 - accuracy:
0.1156
Epoch 45/400
7/7 [=====] - 0s 4ms/step - loss: 3.2757 - accuracy:
0.1206
Epoch 46/400
7/7 [=====] - 0s 5ms/step - loss: 3.2402 - accuracy:
0.1307
Epoch 47/400
7/7 [=====] - 0s 4ms/step - loss: 3.1999 - accuracy:
0.1357
Epoch 48/400
7/7 [=====] - 0s 4ms/step - loss: 3.1599 - accuracy:
0.1457
Epoch 49/400
7/7 [=====] - 0s 4ms/step - loss: 3.1228 - accuracy:
0.1608
Epoch 50/400
7/7 [=====] - 0s 5ms/step - loss: 3.0831 - accuracy:
0.1608
Epoch 51/400
7/7 [=====] - 0s 6ms/step - loss: 3.0443 - accuracy:
0.1608
Epoch 52/400
7/7 [=====] - 0s 4ms/step - loss: 3.0041 - accuracy:
0.1558
Epoch 53/400
7/7 [=====] - 0s 4ms/step - loss: 2.9650 - accuracy:
0.1558
Epoch 54/400
7/7 [=====] - 0s 4ms/step - loss: 2.9290 - accuracy:
0.1558
Epoch 55/400
7/7 [=====] - 0s 5ms/step - loss: 2.8914 - accuracy:
0.1407
Epoch 56/400
7/7 [=====] - 0s 4ms/step - loss: 2.8513 - accuracy:
0.1508
Epoch 57/400

7/7 [=====] - 0s 4ms/step - loss: 2.8162 - accuracy: 0.1608
Epoch 58/400
7/7 [=====] - 0s 4ms/step - loss: 2.7824 - accuracy: 0.1658
Epoch 59/400
7/7 [=====] - 0s 4ms/step - loss: 2.7421 - accuracy: 0.1759
Epoch 60/400
7/7 [=====] - 0s 4ms/step - loss: 2.7092 - accuracy: 0.1809
Epoch 61/400
7/7 [=====] - 0s 6ms/step - loss: 2.6756 - accuracy: 0.1759
Epoch 62/400
7/7 [=====] - 0s 4ms/step - loss: 2.6408 - accuracy: 0.2010
Epoch 63/400
7/7 [=====] - 0s 4ms/step - loss: 2.6065 - accuracy: 0.2261
Epoch 64/400
7/7 [=====] - 0s 5ms/step - loss: 2.5721 - accuracy: 0.2362
Epoch 65/400
7/7 [=====] - 0s 4ms/step - loss: 2.5399 - accuracy: 0.2211
Epoch 66/400
7/7 [=====] - 0s 4ms/step - loss: 2.5073 - accuracy: 0.2362
Epoch 67/400
7/7 [=====] - 0s 4ms/step - loss: 2.4745 - accuracy: 0.2362
Epoch 68/400
7/7 [=====] - 0s 4ms/step - loss: 2.4481 - accuracy: 0.2714
Epoch 69/400
7/7 [=====] - 0s 4ms/step - loss: 2.4158 - accuracy: 0.2462
Epoch 70/400
7/7 [=====] - 0s 4ms/step - loss: 2.3848 - accuracy: 0.2764
Epoch 71/400
7/7 [=====] - 0s 4ms/step - loss: 2.3574 - accuracy: 0.2714
Epoch 72/400
7/7 [=====] - 0s 4ms/step - loss: 2.3272 - accuracy: 0.3317
Epoch 73/400

7/7 [=====] - 0s 4ms/step - loss: 2.3017 - accuracy:
0.3467
Epoch 74/400
7/7 [=====] - 0s 6ms/step - loss: 2.2704 - accuracy:
0.3467
Epoch 75/400
7/7 [=====] - 0s 4ms/step - loss: 2.2465 - accuracy:
0.3719
Epoch 76/400
7/7 [=====] - 0s 4ms/step - loss: 2.2213 - accuracy:
0.3869
Epoch 77/400
7/7 [=====] - 0s 4ms/step - loss: 2.1914 - accuracy:
0.4271
Epoch 78/400
7/7 [=====] - 0s 4ms/step - loss: 2.1665 - accuracy:
0.4070
Epoch 79/400
7/7 [=====] - 0s 4ms/step - loss: 2.1420 - accuracy:
0.4472
Epoch 80/400
7/7 [=====] - 0s 5ms/step - loss: 2.1183 - accuracy:
0.4221
Epoch 81/400
7/7 [=====] - 0s 4ms/step - loss: 2.0925 - accuracy:
0.3920
Epoch 82/400
7/7 [=====] - 0s 5ms/step - loss: 2.0725 - accuracy:
0.3970
Epoch 83/400
7/7 [=====] - 0s 4ms/step - loss: 2.0499 - accuracy:
0.4271
Epoch 84/400
7/7 [=====] - 0s 4ms/step - loss: 2.0245 - accuracy:
0.4372
Epoch 85/400
7/7 [=====] - 0s 4ms/step - loss: 2.0041 - accuracy:
0.4673
Epoch 86/400
7/7 [=====] - 0s 4ms/step - loss: 1.9804 - accuracy:
0.4874
Epoch 87/400
7/7 [=====] - 0s 4ms/step - loss: 1.9605 - accuracy:
0.5276
Epoch 88/400
7/7 [=====] - 0s 5ms/step - loss: 1.9387 - accuracy:
0.5377
Epoch 89/400

7/7 [=====] - 0s 4ms/step - loss: 1.9171 - accuracy:
0.5528
Epoch 90/400
7/7 [=====] - 0s 4ms/step - loss: 1.8959 - accuracy:
0.5477
Epoch 91/400
7/7 [=====] - 0s 4ms/step - loss: 1.8783 - accuracy:
0.5628
Epoch 92/400
7/7 [=====] - 0s 4ms/step - loss: 1.8573 - accuracy:
0.5729
Epoch 93/400
7/7 [=====] - 0s 4ms/step - loss: 1.8397 - accuracy:
0.5628
Epoch 94/400
7/7 [=====] - 0s 4ms/step - loss: 1.8184 - accuracy:
0.5528
Epoch 95/400
7/7 [=====] - 0s 5ms/step - loss: 1.7974 - accuracy:
0.5578
Epoch 96/400
7/7 [=====] - 0s 4ms/step - loss: 1.7799 - accuracy:
0.5578
Epoch 97/400
7/7 [=====] - 0s 4ms/step - loss: 1.7624 - accuracy:
0.5980
Epoch 98/400
7/7 [=====] - 0s 4ms/step - loss: 1.7401 - accuracy:
0.6080
Epoch 99/400
7/7 [=====] - 0s 4ms/step - loss: 1.7232 - accuracy:
0.5980
Epoch 100/400
7/7 [=====] - 0s 4ms/step - loss: 1.7077 - accuracy:
0.6231
Epoch 101/400
7/7 [=====] - 0s 4ms/step - loss: 1.6900 - accuracy:
0.6432
Epoch 102/400
7/7 [=====] - 0s 4ms/step - loss: 1.6678 - accuracy:
0.6633
Epoch 103/400
7/7 [=====] - 0s 5ms/step - loss: 1.6516 - accuracy:
0.6633
Epoch 104/400
7/7 [=====] - 0s 4ms/step - loss: 1.6375 - accuracy:
0.6683
Epoch 105/400

7/7 [=====] - 0s 4ms/step - loss: 1.6207 - accuracy:
 0.6884
 Epoch 106/400
 7/7 [=====] - 0s 4ms/step - loss: 1.6013 - accuracy:
 0.6985
 Epoch 107/400
 7/7 [=====] - 0s 4ms/step - loss: 1.5862 - accuracy:
 0.6985
 Epoch 108/400
 7/7 [=====] - 0s 4ms/step - loss: 1.5668 - accuracy:
 0.7236
 Epoch 109/400
 7/7 [=====] - 0s 4ms/step - loss: 1.5488 - accuracy:
 0.7387
 Epoch 110/400
 7/7 [=====] - 0s 4ms/step - loss: 1.5324 - accuracy:
 0.7437
 Epoch 111/400
 7/7 [=====] - 0s 5ms/step - loss: 1.5161 - accuracy:
 0.7085
 Epoch 112/400
 7/7 [=====] - 0s 4ms/step - loss: 1.5026 - accuracy:
 0.6633
 Epoch 113/400
 7/7 [=====] - 0s 4ms/step - loss: 1.4861 - accuracy:
 0.6734
 Epoch 114/400
 7/7 [=====] - 0s 4ms/step - loss: 1.4715 - accuracy:
 0.7035
 Epoch 115/400
 7/7 [=====] - 0s 4ms/step - loss: 1.4591 - accuracy:
 0.7136
 Epoch 116/400
 7/7 [=====] - 0s 5ms/step - loss: 1.4439 - accuracy:
 0.7588
 Epoch 117/400
 7/7 [=====] - 0s 4ms/step - loss: 1.4285 - accuracy:
 0.7789
 Epoch 118/400
 7/7 [=====] - 0s 4ms/step - loss: 1.4096 - accuracy:
 0.8141
 Epoch 119/400
 7/7 [=====] - 0s 4ms/step - loss: 1.3951 - accuracy:
 0.7889
 Epoch 120/400
 7/7 [=====] - 0s 4ms/step - loss: 1.3784 - accuracy:
 0.7487
 Epoch 121/400

7/7 [=====] - 0s 4ms/step - loss: 1.3672 - accuracy:
0.7437
Epoch 122/400
7/7 [=====] - 0s 3ms/step - loss: 1.3508 - accuracy:
0.7638
Epoch 123/400
7/7 [=====] - 0s 3ms/step - loss: 1.3367 - accuracy:
0.7286
Epoch 124/400
7/7 [=====] - 0s 4ms/step - loss: 1.3243 - accuracy:
0.7186
Epoch 125/400
7/7 [=====] - 0s 4ms/step - loss: 1.3086 - accuracy:
0.7487
Epoch 126/400
7/7 [=====] - 0s 4ms/step - loss: 1.2962 - accuracy:
0.7487
Epoch 127/400
7/7 [=====] - 0s 4ms/step - loss: 1.2819 - accuracy:
0.7839
Epoch 128/400
7/7 [=====] - 0s 5ms/step - loss: 1.2703 - accuracy:
0.7789
Epoch 129/400
7/7 [=====] - 0s 4ms/step - loss: 1.2593 - accuracy:
0.7638
Epoch 130/400
7/7 [=====] - 0s 3ms/step - loss: 1.2411 - accuracy:
0.7538
Epoch 131/400
7/7 [=====] - 0s 4ms/step - loss: 1.2300 - accuracy:
0.7889
Epoch 132/400
7/7 [=====] - 0s 4ms/step - loss: 1.2141 - accuracy:
0.8191
Epoch 133/400
7/7 [=====] - 0s 4ms/step - loss: 1.2004 - accuracy:
0.8342
Epoch 134/400
7/7 [=====] - 0s 4ms/step - loss: 1.1895 - accuracy:
0.8191
Epoch 135/400
7/7 [=====] - 0s 5ms/step - loss: 1.1751 - accuracy:
0.7990
Epoch 136/400
7/7 [=====] - 0s 5ms/step - loss: 1.1638 - accuracy:
0.8191
Epoch 137/400

7/7 [=====] - 0s 4ms/step - loss: 1.1485 - accuracy:
0.8342
Epoch 138/400
7/7 [=====] - 0s 4ms/step - loss: 1.1389 - accuracy:
0.8492
Epoch 139/400
7/7 [=====] - 0s 4ms/step - loss: 1.1301 - accuracy:
0.8894
Epoch 140/400
7/7 [=====] - 0s 4ms/step - loss: 1.1155 - accuracy:
0.8794
Epoch 141/400
7/7 [=====] - 0s 4ms/step - loss: 1.1039 - accuracy:
0.8844
Epoch 142/400
7/7 [=====] - 0s 4ms/step - loss: 1.0909 - accuracy:
0.8995
Epoch 143/400
7/7 [=====] - 0s 5ms/step - loss: 1.0790 - accuracy:
0.8744
Epoch 144/400
7/7 [=====] - 0s 4ms/step - loss: 1.0686 - accuracy:
0.8844
Epoch 145/400
7/7 [=====] - 0s 4ms/step - loss: 1.0584 - accuracy:
0.8643
Epoch 146/400
7/7 [=====] - 0s 4ms/step - loss: 1.0452 - accuracy:
0.8643
Epoch 147/400
7/7 [=====] - 0s 4ms/step - loss: 1.0372 - accuracy:
0.8894
Epoch 148/400
7/7 [=====] - 0s 5ms/step - loss: 1.0209 - accuracy:
0.9146
Epoch 149/400
7/7 [=====] - 0s 4ms/step - loss: 1.0084 - accuracy:
0.8945
Epoch 150/400
7/7 [=====] - 0s 4ms/step - loss: 0.9966 - accuracy:
0.8844
Epoch 151/400
7/7 [=====] - 0s 5ms/step - loss: 0.9912 - accuracy:
0.8794
Epoch 152/400
7/7 [=====] - 0s 4ms/step - loss: 0.9768 - accuracy:
0.8894
Epoch 153/400

7/7 [=====] - 0s 5ms/step - loss: 0.9646 - accuracy:
0.9246
Epoch 154/400
7/7 [=====] - 0s 6ms/step - loss: 0.9544 - accuracy:
0.9045
Epoch 155/400
7/7 [=====] - 0s 6ms/step - loss: 0.9427 - accuracy:
0.9397
Epoch 156/400
7/7 [=====] - 0s 6ms/step - loss: 0.9375 - accuracy:
0.9095
Epoch 157/400
7/7 [=====] - 0s 5ms/step - loss: 0.9271 - accuracy:
0.9045
Epoch 158/400
7/7 [=====] - 0s 5ms/step - loss: 0.9114 - accuracy:
0.9246
Epoch 159/400
7/7 [=====] - 0s 6ms/step - loss: 0.9039 - accuracy:
0.9045
Epoch 160/400
7/7 [=====] - 0s 7ms/step - loss: 0.8940 - accuracy:
0.9146
Epoch 161/400
7/7 [=====] - 0s 5ms/step - loss: 0.8825 - accuracy:
0.9196
Epoch 162/400
7/7 [=====] - 0s 5ms/step - loss: 0.8713 - accuracy:
0.9246
Epoch 163/400
7/7 [=====] - 0s 5ms/step - loss: 0.8616 - accuracy:
0.9146
Epoch 164/400
7/7 [=====] - 0s 5ms/step - loss: 0.8523 - accuracy:
0.8945
Epoch 165/400
7/7 [=====] - 0s 4ms/step - loss: 0.8449 - accuracy:
0.8945
Epoch 166/400
7/7 [=====] - 0s 5ms/step - loss: 0.8320 - accuracy:
0.8995
Epoch 167/400
7/7 [=====] - 0s 5ms/step - loss: 0.8222 - accuracy:
0.9095
Epoch 168/400
7/7 [=====] - 0s 5ms/step - loss: 0.8168 - accuracy:
0.9095
Epoch 169/400

7/7 [=====] - 0s 6ms/step - loss: 0.8071 - accuracy:
0.9196
Epoch 170/400
7/7 [=====] - 0s 5ms/step - loss: 0.7974 - accuracy:
0.9196
Epoch 171/400
7/7 [=====] - 0s 5ms/step - loss: 0.7865 - accuracy:
0.9296
Epoch 172/400
7/7 [=====] - 0s 5ms/step - loss: 0.7792 - accuracy:
0.9397
Epoch 173/400
7/7 [=====] - 0s 4ms/step - loss: 0.7708 - accuracy:
0.9397
Epoch 174/400
7/7 [=====] - 0s 4ms/step - loss: 0.7613 - accuracy:
0.9246
Epoch 175/400
7/7 [=====] - 0s 4ms/step - loss: 0.7577 - accuracy:
0.9347
Epoch 176/400
7/7 [=====] - 0s 4ms/step - loss: 0.7446 - accuracy:
0.9447
Epoch 177/400
7/7 [=====] - 0s 5ms/step - loss: 0.7333 - accuracy:
0.9447
Epoch 178/400
7/7 [=====] - 0s 5ms/step - loss: 0.7242 - accuracy:
0.9497
Epoch 179/400
7/7 [=====] - 0s 4ms/step - loss: 0.7171 - accuracy:
0.9447
Epoch 180/400
7/7 [=====] - 0s 5ms/step - loss: 0.7064 - accuracy:
0.9397
Epoch 181/400
7/7 [=====] - 0s 5ms/step - loss: 0.7006 - accuracy:
0.9497
Epoch 182/400
7/7 [=====] - 0s 5ms/step - loss: 0.6951 - accuracy:
0.9397
Epoch 183/400
7/7 [=====] - 0s 6ms/step - loss: 0.6867 - accuracy:
0.9397
Epoch 184/400
7/7 [=====] - 0s 6ms/step - loss: 0.6793 - accuracy:
0.9095
Epoch 185/400

7/7 [=====] - 0s 5ms/step - loss: 0.6698 - accuracy:
 0.9296
 Epoch 186/400
 7/7 [=====] - 0s 5ms/step - loss: 0.6648 - accuracy:
 0.9497
 Epoch 187/400
 7/7 [=====] - 0s 4ms/step - loss: 0.6546 - accuracy:
 0.9397
 Epoch 188/400
 7/7 [=====] - 0s 4ms/step - loss: 0.6454 - accuracy:
 0.9497
 Epoch 189/400
 7/7 [=====] - 0s 4ms/step - loss: 0.6399 - accuracy:
 0.9497
 Epoch 190/400
 7/7 [=====] - 0s 6ms/step - loss: 0.6366 - accuracy:
 0.9548
 Epoch 191/400
 7/7 [=====] - 0s 4ms/step - loss: 0.6309 - accuracy:
 0.9548
 Epoch 192/400
 7/7 [=====] - 0s 4ms/step - loss: 0.6242 - accuracy:
 0.9698
 Epoch 193/400
 7/7 [=====] - 0s 5ms/step - loss: 0.6134 - accuracy:
 0.9548
 Epoch 194/400
 7/7 [=====] - 0s 7ms/step - loss: 0.6082 - accuracy:
 0.9447
 Epoch 195/400
 7/7 [=====] - 0s 6ms/step - loss: 0.5993 - accuracy:
 0.9497
 Epoch 196/400
 7/7 [=====] - 0s 4ms/step - loss: 0.5941 - accuracy:
 0.9548
 Epoch 197/400
 7/7 [=====] - 0s 5ms/step - loss: 0.5854 - accuracy:
 0.9548
 Epoch 198/400
 7/7 [=====] - 0s 4ms/step - loss: 0.5812 - accuracy:
 0.9497
 Epoch 199/400
 7/7 [=====] - 0s 4ms/step - loss: 0.5719 - accuracy:
 0.9347
 Epoch 200/400
 7/7 [=====] - 0s 4ms/step - loss: 0.5691 - accuracy:
 0.9397
 Epoch 201/400

7/7 [=====] - 0s 4ms/step - loss: 0.5608 - accuracy: 0.9347
Epoch 202/400
7/7 [=====] - 0s 6ms/step - loss: 0.5521 - accuracy: 0.9497
Epoch 203/400
7/7 [=====] - 0s 6ms/step - loss: 0.5440 - accuracy: 0.9648
Epoch 204/400
7/7 [=====] - 0s 8ms/step - loss: 0.5423 - accuracy: 0.9648
Epoch 205/400
7/7 [=====] - 0s 6ms/step - loss: 0.5386 - accuracy: 0.9698
Epoch 206/400
7/7 [=====] - 0s 5ms/step - loss: 0.5271 - accuracy: 0.9749
Epoch 207/400
7/7 [=====] - 0s 5ms/step - loss: 0.5201 - accuracy: 0.9749
Epoch 208/400
7/7 [=====] - 0s 7ms/step - loss: 0.5155 - accuracy: 0.9648
Epoch 209/400
7/7 [=====] - 0s 6ms/step - loss: 0.5094 - accuracy: 0.9648
Epoch 210/400
7/7 [=====] - 0s 7ms/step - loss: 0.5041 - accuracy: 0.9698
Epoch 211/400
7/7 [=====] - 0s 4ms/step - loss: 0.4978 - accuracy: 0.9698
Epoch 212/400
7/7 [=====] - 0s 5ms/step - loss: 0.4934 - accuracy: 0.9749
Epoch 213/400
7/7 [=====] - 0s 5ms/step - loss: 0.4902 - accuracy: 0.9749
Epoch 214/400
7/7 [=====] - 0s 6ms/step - loss: 0.4855 - accuracy: 0.9698
Epoch 215/400
7/7 [=====] - 0s 5ms/step - loss: 0.4795 - accuracy: 0.9497
Epoch 216/400
7/7 [=====] - 0s 6ms/step - loss: 0.4724 - accuracy: 0.9698
Epoch 217/400

7/7 [=====] - 0s 5ms/step - loss: 0.4707 - accuracy: 0.9548
Epoch 218/400
7/7 [=====] - 0s 6ms/step - loss: 0.4635 - accuracy: 0.9548
Epoch 219/400
7/7 [=====] - 0s 5ms/step - loss: 0.4569 - accuracy: 0.9598
Epoch 220/400
7/7 [=====] - 0s 5ms/step - loss: 0.4521 - accuracy: 0.9698
Epoch 221/400
7/7 [=====] - 0s 5ms/step - loss: 0.4461 - accuracy: 0.9849
Epoch 222/400
7/7 [=====] - 0s 6ms/step - loss: 0.4414 - accuracy: 0.9799
Epoch 223/400
7/7 [=====] - 0s 5ms/step - loss: 0.4375 - accuracy: 0.9799
Epoch 224/400
7/7 [=====] - 0s 6ms/step - loss: 0.4342 - accuracy: 0.9799
Epoch 225/400
7/7 [=====] - 0s 5ms/step - loss: 0.4274 - accuracy: 0.9849
Epoch 226/400
7/7 [=====] - 0s 6ms/step - loss: 0.4223 - accuracy: 0.9749
Epoch 227/400
7/7 [=====] - 0s 6ms/step - loss: 0.4182 - accuracy: 0.9698
Epoch 228/400
7/7 [=====] - 0s 5ms/step - loss: 0.4165 - accuracy: 0.9749
Epoch 229/400
7/7 [=====] - 0s 6ms/step - loss: 0.4095 - accuracy: 0.9849
Epoch 230/400
7/7 [=====] - 0s 5ms/step - loss: 0.4064 - accuracy: 0.9799
Epoch 231/400
7/7 [=====] - 0s 5ms/step - loss: 0.4022 - accuracy: 0.9799
Epoch 232/400
7/7 [=====] - 0s 6ms/step - loss: 0.3966 - accuracy: 0.9799
Epoch 233/400

7/7 [=====] - 0s 7ms/step - loss: 0.3935 - accuracy: 0.9799
Epoch 234/400
7/7 [=====] - 0s 5ms/step - loss: 0.3877 - accuracy: 0.9849
Epoch 235/400
7/7 [=====] - 0s 4ms/step - loss: 0.3874 - accuracy: 0.9799
Epoch 236/400
7/7 [=====] - 0s 5ms/step - loss: 0.3882 - accuracy: 0.9698
Epoch 237/400
7/7 [=====] - 0s 4ms/step - loss: 0.3782 - accuracy: 0.9849
Epoch 238/400
7/7 [=====] - 0s 4ms/step - loss: 0.3744 - accuracy: 0.9849
Epoch 239/400
7/7 [=====] - 0s 5ms/step - loss: 0.3705 - accuracy: 0.9899
Epoch 240/400
7/7 [=====] - 0s 4ms/step - loss: 0.3645 - accuracy: 0.9849
Epoch 241/400
7/7 [=====] - 0s 6ms/step - loss: 0.3614 - accuracy: 0.9899
Epoch 242/400
7/7 [=====] - 0s 7ms/step - loss: 0.3572 - accuracy: 0.9749
Epoch 243/400
7/7 [=====] - 0s 7ms/step - loss: 0.3514 - accuracy: 0.9799
Epoch 244/400
7/7 [=====] - 0s 6ms/step - loss: 0.3507 - accuracy: 0.9849
Epoch 245/400
7/7 [=====] - 0s 5ms/step - loss: 0.3440 - accuracy: 0.9849
Epoch 246/400
7/7 [=====] - 0s 5ms/step - loss: 0.3439 - accuracy: 0.9799
Epoch 247/400
7/7 [=====] - 0s 6ms/step - loss: 0.3396 - accuracy: 0.9899
Epoch 248/400
7/7 [=====] - 0s 6ms/step - loss: 0.3354 - accuracy: 0.9849
Epoch 249/400

7/7 [=====] - 0s 5ms/step - loss: 0.3318 - accuracy:
 0.9799
 Epoch 250/400
 7/7 [=====] - 0s 6ms/step - loss: 0.3294 - accuracy:
 0.9799
 Epoch 251/400
 7/7 [=====] - 0s 7ms/step - loss: 0.3255 - accuracy:
 0.9799
 Epoch 252/400
 7/7 [=====] - 0s 4ms/step - loss: 0.3205 - accuracy:
 0.9849
 Epoch 253/400
 7/7 [=====] - 0s 4ms/step - loss: 0.3164 - accuracy:
 0.9849
 Epoch 254/400
 7/7 [=====] - 0s 4ms/step - loss: 0.3172 - accuracy:
 0.9849
 Epoch 255/400
 7/7 [=====] - 0s 3ms/step - loss: 0.3123 - accuracy:
 0.9849
 Epoch 256/400
 7/7 [=====] - 0s 4ms/step - loss: 0.3066 - accuracy:
 0.9799
 Epoch 257/400
 7/7 [=====] - 0s 4ms/step - loss: 0.3046 - accuracy:
 0.9799
 Epoch 258/400
 7/7 [=====] - 0s 3ms/step - loss: 0.2991 - accuracy:
 0.9899
 Epoch 259/400
 7/7 [=====] - 0s 3ms/step - loss: 0.2948 - accuracy:
 0.9899
 Epoch 260/400
 7/7 [=====] - 0s 4ms/step - loss: 0.2925 - accuracy:
 0.9849
 Epoch 261/400
 7/7 [=====] - 0s 4ms/step - loss: 0.2917 - accuracy:
 0.9899
 Epoch 262/400
 7/7 [=====] - 0s 5ms/step - loss: 0.2899 - accuracy:
 0.9899
 Epoch 263/400
 7/7 [=====] - 0s 4ms/step - loss: 0.2847 - accuracy:
 0.9899
 Epoch 264/400
 7/7 [=====] - 0s 4ms/step - loss: 0.2822 - accuracy:
 0.9950
 Epoch 265/400


```

7/7 [=====] - 0s 4ms/step - loss: 0.2758 - accuracy:
1.0000
Epoch 266/400
7/7 [=====] - 0s 5ms/step - loss: 0.2753 - accuracy:
1.0000
Epoch 267/400
7/7 [=====] - 0s 5ms/step - loss: 0.2713 - accuracy:
0.9899
Epoch 268/400
7/7 [=====] - 0s 4ms/step - loss: 0.2703 - accuracy:
0.9899
Epoch 269/400
7/7 [=====] - 0s 5ms/step - loss: 0.2684 - accuracy:
0.9899
Epoch 270/400
7/7 [=====] - 0s 4ms/step - loss: 0.2636 - accuracy:
0.9849
Epoch 271/400
7/7 [=====] - 0s 4ms/step - loss: 0.2607 - accuracy:
0.9899
Epoch 272/400
7/7 [=====] - 0s 4ms/step - loss: 0.2570 - accuracy:
0.9899
Epoch 273/400
7/7 [=====] - 0s 5ms/step - loss: 0.2536 - accuracy:
0.9899
Epoch 274/400
7/7 [=====] - 0s 5ms/step - loss: 0.2495 - accuracy:
0.9899
Epoch 275/400
7/7 [=====] - 0s 5ms/step - loss: 0.2469 - accuracy:
0.9849
Epoch 276/400
7/7 [=====] - 0s 4ms/step - loss: 0.2445 - accuracy:
0.9849
Epoch 277/400
7/7 [=====] - 0s 3ms/step - loss: 0.2432 - accuracy:
0.9799
Epoch 278/400
7/7 [=====] - 0s 5ms/step - loss: 0.2406 - accuracy:
0.9849
Epoch 279/400
7/7 [=====] - 0s 5ms/step - loss: 0.2363 - accuracy:
0.9950
Epoch 280/400
7/7 [=====] - 0s 4ms/step - loss: 0.2348 - accuracy:
1.0000
Epoch 281/400

```

7/7 [=====] - 0s 4ms/step - loss: 0.2319 - accuracy:
0.9950
Epoch 282/400
7/7 [=====] - 0s 3ms/step - loss: 0.2286 - accuracy:
0.9899
Epoch 283/400
7/7 [=====] - 0s 3ms/step - loss: 0.2273 - accuracy:
0.9849
Epoch 284/400
7/7 [=====] - 0s 3ms/step - loss: 0.2251 - accuracy:
0.9950
Epoch 285/400
7/7 [=====] - 0s 3ms/step - loss: 0.2221 - accuracy:
0.9899
Epoch 286/400
7/7 [=====] - 0s 3ms/step - loss: 0.2176 - accuracy:
0.9950
Epoch 287/400
7/7 [=====] - 0s 3ms/step - loss: 0.2170 - accuracy:
0.9950
Epoch 288/400
7/7 [=====] - 0s 3ms/step - loss: 0.2170 - accuracy:
0.9950
Epoch 289/400
7/7 [=====] - 0s 5ms/step - loss: 0.2139 - accuracy:
0.9950
Epoch 290/400
7/7 [=====] - 0s 4ms/step - loss: 0.2092 - accuracy:
0.9950
Epoch 291/400
7/7 [=====] - 0s 3ms/step - loss: 0.2081 - accuracy:
0.9950
Epoch 292/400
7/7 [=====] - 0s 3ms/step - loss: 0.2040 - accuracy:
0.9950
Epoch 293/400
7/7 [=====] - 0s 4ms/step - loss: 0.2032 - accuracy:
0.9950
Epoch 294/400
7/7 [=====] - 0s 3ms/step - loss: 0.2010 - accuracy:
0.9950
Epoch 295/400
7/7 [=====] - 0s 3ms/step - loss: 0.1982 - accuracy:
0.9950
Epoch 296/400
7/7 [=====] - 0s 3ms/step - loss: 0.1951 - accuracy:
0.9950
Epoch 297/400

7/7 [=====] - 0s 3ms/step - loss: 0.1936 - accuracy: 0.9899
Epoch 298/400
7/7 [=====] - 0s 5ms/step - loss: 0.1928 - accuracy: 1.0000
Epoch 299/400
7/7 [=====] - 0s 4ms/step - loss: 0.1914 - accuracy: 0.9950
Epoch 300/400
7/7 [=====] - 0s 5ms/step - loss: 0.1899 - accuracy: 0.9950
Epoch 301/400
7/7 [=====] - 0s 4ms/step - loss: 0.1861 - accuracy: 0.9950
Epoch 302/400
7/7 [=====] - 0s 4ms/step - loss: 0.1849 - accuracy: 0.9950
Epoch 303/400
7/7 [=====] - 0s 4ms/step - loss: 0.1826 - accuracy: 0.9950
Epoch 304/400
7/7 [=====] - 0s 3ms/step - loss: 0.1789 - accuracy: 1.0000
Epoch 305/400
7/7 [=====] - 0s 3ms/step - loss: 0.1779 - accuracy: 1.0000
Epoch 306/400
7/7 [=====] - 0s 4ms/step - loss: 0.1750 - accuracy: 1.0000
Epoch 307/400
7/7 [=====] - 0s 4ms/step - loss: 0.1745 - accuracy: 1.0000
Epoch 308/400
7/7 [=====] - 0s 4ms/step - loss: 0.1703 - accuracy: 0.9950
Epoch 309/400
7/7 [=====] - 0s 4ms/step - loss: 0.1701 - accuracy: 1.0000
Epoch 310/400
7/7 [=====] - 0s 4ms/step - loss: 0.1679 - accuracy: 0.9950
Epoch 311/400
7/7 [=====] - 0s 4ms/step - loss: 0.1645 - accuracy: 0.9950
Epoch 312/400
7/7 [=====] - 0s 4ms/step - loss: 0.1637 - accuracy: 1.0000
Epoch 313/400

7/7 [=====] - 0s 4ms/step - loss: 0.1608 - accuracy:
1.0000
Epoch 314/400
7/7 [=====] - 0s 5ms/step - loss: 0.1602 - accuracy:
1.0000
Epoch 315/400
7/7 [=====] - 0s 4ms/step - loss: 0.1572 - accuracy:
1.0000
Epoch 316/400
7/7 [=====] - 0s 4ms/step - loss: 0.1560 - accuracy:
1.0000
Epoch 317/400
7/7 [=====] - 0s 4ms/step - loss: 0.1545 - accuracy:
1.0000
Epoch 318/400
7/7 [=====] - 0s 4ms/step - loss: 0.1521 - accuracy:
1.0000
Epoch 319/400
7/7 [=====] - 0s 3ms/step - loss: 0.1501 - accuracy:
1.0000
Epoch 320/400
7/7 [=====] - 0s 5ms/step - loss: 0.1487 - accuracy:
1.0000
Epoch 321/400
7/7 [=====] - 0s 4ms/step - loss: 0.1473 - accuracy:
1.0000
Epoch 322/400
7/7 [=====] - 0s 4ms/step - loss: 0.1452 - accuracy:
1.0000
Epoch 323/400
7/7 [=====] - 0s 4ms/step - loss: 0.1437 - accuracy:
1.0000
Epoch 324/400
7/7 [=====] - 0s 4ms/step - loss: 0.1422 - accuracy:
1.0000
Epoch 325/400
7/7 [=====] - 0s 5ms/step - loss: 0.1408 - accuracy:
1.0000
Epoch 326/400
7/7 [=====] - 0s 4ms/step - loss: 0.1379 - accuracy:
1.0000
Epoch 327/400
7/7 [=====] - 0s 6ms/step - loss: 0.1375 - accuracy:
1.0000
Epoch 328/400
7/7 [=====] - 0s 5ms/step - loss: 0.1360 - accuracy:
1.0000
Epoch 329/400

7/7 [=====] - 0s 5ms/step - loss: 0.1344 - accuracy:
1.0000
Epoch 330/400
7/7 [=====] - 0s 5ms/step - loss: 0.1327 - accuracy:
1.0000
Epoch 331/400
7/7 [=====] - 0s 4ms/step - loss: 0.1306 - accuracy:
1.0000
Epoch 332/400
7/7 [=====] - 0s 4ms/step - loss: 0.1297 - accuracy:
1.0000
Epoch 333/400
7/7 [=====] - 0s 4ms/step - loss: 0.1279 - accuracy:
1.0000
Epoch 334/400
7/7 [=====] - 0s 4ms/step - loss: 0.1272 - accuracy:
1.0000
Epoch 335/400
7/7 [=====] - 0s 5ms/step - loss: 0.1256 - accuracy:
1.0000
Epoch 336/400
7/7 [=====] - 0s 4ms/step - loss: 0.1247 - accuracy:
1.0000
Epoch 337/400
7/7 [=====] - 0s 5ms/step - loss: 0.1227 - accuracy:
1.0000
Epoch 338/400
7/7 [=====] - 0s 4ms/step - loss: 0.1217 - accuracy:
1.0000
Epoch 339/400
7/7 [=====] - 0s 5ms/step - loss: 0.1194 - accuracy:
1.0000
Epoch 340/400
7/7 [=====] - 0s 5ms/step - loss: 0.1203 - accuracy:
1.0000
Epoch 341/400
7/7 [=====] - 0s 4ms/step - loss: 0.1185 - accuracy:
1.0000
Epoch 342/400
7/7 [=====] - 0s 5ms/step - loss: 0.1186 - accuracy:
1.0000
Epoch 343/400
7/7 [=====] - 0s 12ms/step - loss: 0.1152 - accuracy:
1.0000
Epoch 344/400
7/7 [=====] - 0s 12ms/step - loss: 0.1128 - accuracy:
1.0000
Epoch 345/400

7/7 [=====] - 0s 12ms/step - loss: 0.1132 - accuracy:
1.0000
Epoch 346/400
7/7 [=====] - 0s 23ms/step - loss: 0.1124 - accuracy:
1.0000
Epoch 347/400
7/7 [=====] - 0s 8ms/step - loss: 0.1101 - accuracy:
1.0000
Epoch 348/400
7/7 [=====] - 0s 6ms/step - loss: 0.1087 - accuracy:
1.0000
Epoch 349/400
7/7 [=====] - 0s 7ms/step - loss: 0.1075 - accuracy:
1.0000
Epoch 350/400
7/7 [=====] - 0s 8ms/step - loss: 0.1060 - accuracy:
1.0000
Epoch 351/400
7/7 [=====] - 0s 12ms/step - loss: 0.1042 - accuracy:
1.0000
Epoch 352/400
7/7 [=====] - 0s 13ms/step - loss: 0.1039 - accuracy:
1.0000
Epoch 353/400
7/7 [=====] - 0s 11ms/step - loss: 0.1023 - accuracy:
1.0000
Epoch 354/400
7/7 [=====] - 0s 7ms/step - loss: 0.1011 - accuracy:
1.0000
Epoch 355/400
7/7 [=====] - 0s 7ms/step - loss: 0.1000 - accuracy:
1.0000
Epoch 356/400
7/7 [=====] - 0s 9ms/step - loss: 0.0982 - accuracy:
1.0000
Epoch 357/400
7/7 [=====] - 0s 7ms/step - loss: 0.0969 - accuracy:
1.0000
Epoch 358/400
7/7 [=====] - 0s 6ms/step - loss: 0.0963 - accuracy:
1.0000
Epoch 359/400
7/7 [=====] - 0s 11ms/step - loss: 0.0953 - accuracy:
1.0000
Epoch 360/400
7/7 [=====] - 0s 10ms/step - loss: 0.0954 - accuracy:
1.0000
Epoch 361/400

7/7 [=====] - 0s 17ms/step - loss: 0.0938 - accuracy:
 1.0000
 Epoch 362/400
 7/7 [=====] - 0s 5ms/step - loss: 0.0923 - accuracy:
 1.0000
 Epoch 363/400
 7/7 [=====] - 0s 15ms/step - loss: 0.0919 - accuracy:
 1.0000
 Epoch 364/400
 7/7 [=====] - 0s 16ms/step - loss: 0.0902 - accuracy:
 1.0000
 Epoch 365/400
 7/7 [=====] - 0s 13ms/step - loss: 0.0896 - accuracy:
 1.0000
 Epoch 366/400
 7/7 [=====] - 0s 25ms/step - loss: 0.0887 - accuracy:
 1.0000
 Epoch 367/400
 7/7 [=====] - 0s 13ms/step - loss: 0.0883 - accuracy:
 1.0000
 Epoch 368/400
 7/7 [=====] - 0s 12ms/step - loss: 0.0872 - accuracy:
 1.0000
 Epoch 369/400
 7/7 [=====] - 0s 16ms/step - loss: 0.0879 - accuracy:
 1.0000
 Epoch 370/400
 7/7 [=====] - 0s 7ms/step - loss: 0.0855 - accuracy:
 1.0000
 Epoch 371/400
 7/7 [=====] - 0s 7ms/step - loss: 0.0846 - accuracy:
 1.0000
 Epoch 372/400
 7/7 [=====] - 0s 12ms/step - loss: 0.0829 - accuracy:
 1.0000
 Epoch 373/400
 7/7 [=====] - 0s 6ms/step - loss: 0.0820 - accuracy:
 1.0000
 Epoch 374/400
 7/7 [=====] - 0s 9ms/step - loss: 0.0809 - accuracy:
 1.0000
 Epoch 375/400
 7/7 [=====] - 0s 6ms/step - loss: 0.0797 - accuracy:
 1.0000
 Epoch 376/400
 7/7 [=====] - 0s 10ms/step - loss: 0.0783 - accuracy:
 1.0000
 Epoch 377/400

```

7/7 [=====] - 0s 6ms/step - loss: 0.0784 - accuracy:
1.0000
Epoch 378/400
7/7 [=====] - 0s 6ms/step - loss: 0.0775 - accuracy:
1.0000
Epoch 379/400
7/7 [=====] - 0s 6ms/step - loss: 0.0769 - accuracy:
1.0000
Epoch 380/400
7/7 [=====] - 0s 10ms/step - loss: 0.0769 - accuracy:
1.0000
Epoch 381/400
7/7 [=====] - 0s 8ms/step - loss: 0.0750 - accuracy:
1.0000
Epoch 382/400
7/7 [=====] - 0s 10ms/step - loss: 0.0736 - accuracy:
1.0000
Epoch 383/400
7/7 [=====] - 0s 13ms/step - loss: 0.0732 - accuracy:
1.0000
Epoch 384/400
7/7 [=====] - 0s 9ms/step - loss: 0.0726 - accuracy:
1.0000
Epoch 385/400
7/7 [=====] - 0s 12ms/step - loss: 0.0717 - accuracy:
1.0000
Epoch 386/400
7/7 [=====] - 0s 8ms/step - loss: 0.0715 - accuracy:
1.0000
Epoch 387/400
7/7 [=====] - 0s 8ms/step - loss: 0.0704 - accuracy:
1.0000
Epoch 388/400
7/7 [=====] - 0s 8ms/step - loss: 0.0696 - accuracy:
1.0000
Epoch 389/400
7/7 [=====] - 0s 8ms/step - loss: 0.0691 - accuracy:
1.0000
Epoch 390/400
7/7 [=====] - 0s 4ms/step - loss: 0.0679 - accuracy:
1.0000
Epoch 391/400
7/7 [=====] - 0s 9ms/step - loss: 0.0671 - accuracy:
1.0000
Epoch 392/400
7/7 [=====] - 0s 16ms/step - loss: 0.0665 - accuracy:
1.0000
Epoch 393/400

```



```

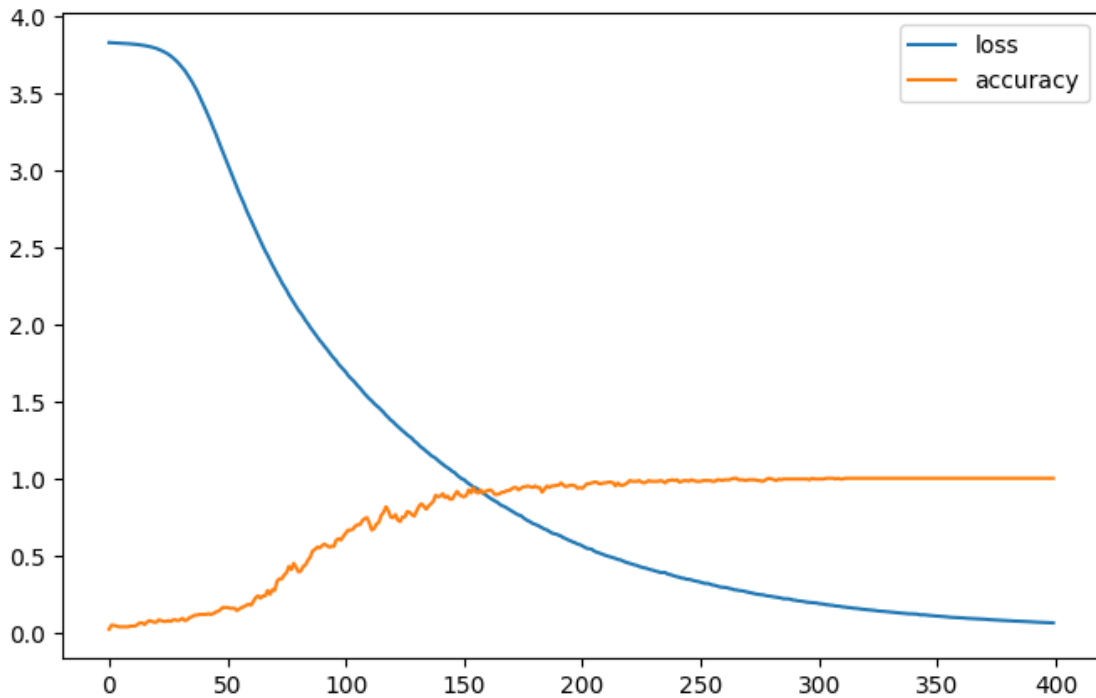
7/7 [=====] - 0s 6ms/step - loss: 0.0656 - accuracy:
1.0000
Epoch 394/400
7/7 [=====] - 0s 6ms/step - loss: 0.0647 - accuracy:
1.0000
Epoch 395/400
7/7 [=====] - 0s 8ms/step - loss: 0.0643 - accuracy:
1.0000
Epoch 396/400
7/7 [=====] - 0s 8ms/step - loss: 0.0631 - accuracy:
1.0000
Epoch 397/400
7/7 [=====] - 0s 6ms/step - loss: 0.0628 - accuracy:
1.0000
Epoch 398/400
7/7 [=====] - 0s 8ms/step - loss: 0.0624 - accuracy:
1.0000
Epoch 399/400
7/7 [=====] - 0s 6ms/step - loss: 0.0617 - accuracy:
1.0000
Epoch 400/400
7/7 [=====] - 0s 4ms/step - loss: 0.0609 - accuracy:
1.0000

```

```

[18]: pd.DataFrame(history.history).plot(figsize=(8,5))
      plt.show()

```



0.1.10 Saving The Model , Tokenizer , Encoded Labels

```
[19]: import pickle

model.save("chat_model")

with open('tokenizer.pickle', 'wb') as handle:
    pickle.dump(tokenizer, handle, protocol=pickle.HIGHEST_PROTOCOL)

with open('label_encoder.pickle', 'wb') as ecn_file:
    pickle.dump(lbl_encoder, ecn_file, protocol=pickle.HIGHEST_PROTOCOL)
```

0.1.11 Build The Model With Deep Neural Network

```
[20]: words=[]
classes = []
documents = []
ignore_words = ['?', '!']
data_file = open('intents.json', encoding='utf-8').read()

for intent in data['intents']:
    for pattern in intent['patterns']:

        w = nltk.word_tokenize(pattern)
        words.extend(w)

        documents.append((w, intent['tag']))

        if intent['tag'] not in classes:
            classes.append(intent['tag'])

words = [lemmatizer.lemmatize(w.lower()) for w in words if w not in ignore_words]
words = sorted(list(set(words)))

classes = sorted(list(set(classes)))

print (len(documents), "documents")
print (len(classes), "classes", classes)

print (len(words), "unique words", words)
```

```
pickle.dump(words,open('words.pkl','wb'))
pickle.dump(classes,open('classes.pkl','wb'))
```

199 documents

46 classes ['Abdominal Pain', 'Abrasions', 'Broken Toe', 'Bruises', 'CPR', 'Chemical Burn', 'Choking', 'Cold', 'Cough', 'Cuts', 'Diarrhea', 'Drowning', 'Eye Injury', 'Fainting', 'Fever', 'Fracture', 'Frost bite', 'Gastrointestinal problems', 'Head Injury', 'Headache', 'Heat Exhaustion', 'Heat Stroke', 'Insect Bites', 'Nasal Congestion', 'Normal Bleeding', 'Poison', 'Pulled Muscle', 'Rash', 'Rectal bleeding', 'Skin problems', 'Sore Throat', 'Splinter', 'Sprains', 'Strains', 'Sun Burn', 'Teeth', 'Testicle Pain', 'Vertigo', 'Wound', 'animal bite', 'goodbye', 'greeting', 'nose bleed', 'seizure', 'snake bite', 'stings']

138 unique words ['a', 'abdominal', 'abrasion', 'allergy', 'am', 'an', 'animal', 'anyone', 'apply', 'are', 'better', 'bit', 'bite', 'bitten', 'bleed', 'bleeding', 'blocked', 'bring', 'broken', 'bruise', 'burn', 'by', 'bye', 'cause', 'chemical', 'choke', 'choked', 'choking', 'cold', 'congestion', 'cough', 'cpr', 'cream', 'cure', 'cut', 'cya', 'day', 'diagnose', 'diarrhea', 'do', 'doe', 'dog', 'drowned', 'drowning', 'due', 'exhausted', 'exhaustion', 'eye', 'faint', 'fainting', 'feel', 'fever', 'for', 'fracture', 'frost', 'gas', 'gastrointestinal', 'get', 'give', 'good', 'goodbye', 'got', 'have', 'head', 'headache', 'heat', 'hello', 'help', 'hi', 'how', 'i', 'ice', 'if', 'in', 'injured', 'injury', 'insect', 'is', 'last', 'later', 'leaving', 'like', 'long', 'me', 'medicine', 'mild', 'monekey', 'monkey', 'muscle', 'my', 'nasal', 'nose', 'of', 'on', 'or', 'pain', 'person', 'poison', 'poisoned', 'poisoning', 'problem', 'pulled', 'rash', 'rectal', 'remove', 'rid', 'scar', 'see', 'seizure', 'skin', 'snake', 'someone', 'sore', 'splinter', 'sprain', 'step', 'sting', 'strain', 'stroke', 'sun', 'surface', 'take', 'teeth', 'testicle', 'the', 'there', 'throat', 'to', 'toe', 'treat', 'up', 'vertigo', 'what', 'whats', 'which', 'wound', 'wounded', 'you']

```
[21]: # initializing training data
training = []
output_empty = [0] * len(classes)
for doc in documents:

    bag = []

    pattern_words = doc[0]
    pattern_words = [lemmatizer.lemmatize(word.lower()) for word in
↳pattern_words]

    for w in words:
        bag.append(1) if w in pattern_words else bag.append(0)

    output_row = list(output_empty)
```

```

        output_row[classes.index(doc[1])] = 1

        training.append([bag, output_row])

random.shuffle(training)
training = np.array(training)
training

```

```
<ipython-input-21-267d94db582c>:21: VisibleDeprecationWarning: Creating an
ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-
tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant
to do this, you must specify 'dtype=object' when creating the ndarray.
  training = np.array(training)
```

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]


```

        [list([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, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 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, 1, 1, 0, 0, 0, 0, 1, 0, 0,
0, 0, 0, 0, 1, 0, 0, 0]),
        list([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]),
        dtype=object)

```

```

[22]: train_x = list(training[:,0])
train_y = list(training[:,1])
sentences_train, sentences_test, label_train, label_test = train_test_split(
    training_sentences, training_labels, test_size=0.20, random_state=1000)

```

```

[29]: from keras.optimizers import SGD
from keras.optimizers import legacy as legacy_optimizer

```

```

[30]: model = Sequential()
model.add(Dense(128, input_shape=(len(train_x[0]),), activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(len(train_y[0]), activation='softmax'))

# Compile model. Stochastic gradient descent with Nesterov accelerated gradient,
↳ gives good results for this model
# sgd = SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True)
sgd = legacy_optimizer.SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True)
model.compile(loss='categorical_crossentropy', optimizer=sgd,
↳ metrics=['accuracy'])

# fitting and saving the model
hist = model.fit(np.array(train_x), np.array(train_y), epochs=150,
↳ batch_size=5, verbose=1)
model.save('chatbot_model.h5', hist)

```

Epoch 1/150

/usr/local/lib/python3.10/dist-

packages/keras/src/optimizers/legacy/gradient_descent.py:114: UserWarning: The
`lr` argument is deprecated, use `learning_rate` instead.

super().__init__(name, **kwargs)

40/40 [=====] - 1s 2ms/step - loss: 3.8598 - accuracy:
0.0151

Epoch 2/150

40/40 [=====] - 0s 2ms/step - loss: 3.7974 - accuracy:

```

0.0653
Epoch 3/150
40/40 [=====] - 0s 2ms/step - loss: 3.7404 - accuracy:
0.0854
Epoch 4/150
40/40 [=====] - 0s 2ms/step - loss: 3.6879 - accuracy:
0.0854
Epoch 5/150
40/40 [=====] - 0s 2ms/step - loss: 3.5793 - accuracy:
0.1508
Epoch 6/150
40/40 [=====] - 0s 2ms/step - loss: 3.4354 - accuracy:
0.2462
Epoch 7/150
40/40 [=====] - 0s 2ms/step - loss: 3.2061 - accuracy:
0.2814
Epoch 8/150
40/40 [=====] - 0s 2ms/step - loss: 2.9780 - accuracy:
0.3568
Epoch 9/150
40/40 [=====] - 0s 2ms/step - loss: 2.6694 - accuracy:
0.4171
Epoch 10/150
40/40 [=====] - 0s 3ms/step - loss: 2.2102 - accuracy:
0.6131
Epoch 11/150
40/40 [=====] - 0s 2ms/step - loss: 1.9016 - accuracy:
0.5578
Epoch 12/150
40/40 [=====] - 0s 2ms/step - loss: 1.5734 - accuracy:
0.6985
Epoch 13/150
40/40 [=====] - 0s 2ms/step - loss: 1.2811 - accuracy:
0.7538
Epoch 14/150
40/40 [=====] - 0s 2ms/step - loss: 1.1059 - accuracy:
0.7538
Epoch 15/150
40/40 [=====] - 0s 2ms/step - loss: 0.8479 - accuracy:
0.8392
Epoch 16/150
40/40 [=====] - 0s 2ms/step - loss: 0.6715 - accuracy:
0.8693
Epoch 17/150
40/40 [=====] - 0s 2ms/step - loss: 0.6294 - accuracy:
0.8894
Epoch 18/150
40/40 [=====] - 0s 3ms/step - loss: 0.5246 - accuracy:

```

```

0.8894
Epoch 19/150
40/40 [=====] - 0s 2ms/step - loss: 0.5237 - accuracy:
0.8744
Epoch 20/150
40/40 [=====] - 0s 2ms/step - loss: 0.4152 - accuracy:
0.9246
Epoch 21/150
40/40 [=====] - 0s 2ms/step - loss: 0.3168 - accuracy:
0.9447
Epoch 22/150
40/40 [=====] - 0s 3ms/step - loss: 0.3156 - accuracy:
0.9447
Epoch 23/150
40/40 [=====] - 0s 2ms/step - loss: 0.2536 - accuracy:
0.9497
Epoch 24/150
40/40 [=====] - 0s 2ms/step - loss: 0.2338 - accuracy:
0.9548
Epoch 25/150
40/40 [=====] - 0s 3ms/step - loss: 0.2046 - accuracy:
0.9799
Epoch 26/150
40/40 [=====] - 0s 2ms/step - loss: 0.2448 - accuracy:
0.9648
Epoch 27/150
40/40 [=====] - 0s 2ms/step - loss: 0.1974 - accuracy:
0.9698
Epoch 28/150
40/40 [=====] - 0s 2ms/step - loss: 0.1618 - accuracy:
0.9698
Epoch 29/150
40/40 [=====] - 0s 2ms/step - loss: 0.1911 - accuracy:
0.9648
Epoch 30/150
40/40 [=====] - 0s 2ms/step - loss: 0.1054 - accuracy:
0.9950
Epoch 31/150
40/40 [=====] - 0s 2ms/step - loss: 0.1119 - accuracy:
0.9799
Epoch 32/150
40/40 [=====] - 0s 2ms/step - loss: 0.1295 - accuracy:
0.9950
Epoch 33/150
40/40 [=====] - 0s 2ms/step - loss: 0.0992 - accuracy:
0.9849
Epoch 34/150
40/40 [=====] - 0s 2ms/step - loss: 0.1040 - accuracy:

```



```

0.9799
Epoch 35/150
40/40 [=====] - 0s 2ms/step - loss: 0.1222 - accuracy:
0.9799
Epoch 36/150
40/40 [=====] - 0s 3ms/step - loss: 0.0930 - accuracy:
0.9849
Epoch 37/150
40/40 [=====] - 0s 2ms/step - loss: 0.0757 - accuracy:
0.9950
Epoch 38/150
40/40 [=====] - 0s 2ms/step - loss: 0.0958 - accuracy:
0.9799
Epoch 39/150
40/40 [=====] - 0s 2ms/step - loss: 0.1042 - accuracy:
0.9799
Epoch 40/150
40/40 [=====] - 0s 3ms/step - loss: 0.0939 - accuracy:
0.9799
Epoch 41/150
40/40 [=====] - 0s 2ms/step - loss: 0.0727 - accuracy:
0.9899
Epoch 42/150
40/40 [=====] - 0s 2ms/step - loss: 0.0673 - accuracy:
1.0000
Epoch 43/150
40/40 [=====] - 0s 3ms/step - loss: 0.0611 - accuracy:
1.0000
Epoch 44/150
40/40 [=====] - 0s 2ms/step - loss: 0.0868 - accuracy:
0.9799
Epoch 45/150
40/40 [=====] - 0s 2ms/step - loss: 0.0824 - accuracy:
0.9799
Epoch 46/150
40/40 [=====] - 0s 2ms/step - loss: 0.0783 - accuracy:
0.9950
Epoch 47/150
40/40 [=====] - 0s 2ms/step - loss: 0.0568 - accuracy:
0.9899
Epoch 48/150
40/40 [=====] - 0s 2ms/step - loss: 0.0666 - accuracy:
0.9849
Epoch 49/150
40/40 [=====] - 0s 2ms/step - loss: 0.0843 - accuracy:
0.9899
Epoch 50/150
40/40 [=====] - 0s 2ms/step - loss: 0.0679 - accuracy:

```

```

0.9799
Epoch 51/150
40/40 [=====] - 0s 2ms/step - loss: 0.0401 - accuracy:
1.0000
Epoch 52/150
40/40 [=====] - 0s 2ms/step - loss: 0.0545 - accuracy:
0.9950
Epoch 53/150
40/40 [=====] - 0s 2ms/step - loss: 0.0690 - accuracy:
0.9849
Epoch 54/150
40/40 [=====] - 0s 2ms/step - loss: 0.0646 - accuracy:
0.9899
Epoch 55/150
40/40 [=====] - 0s 2ms/step - loss: 0.0348 - accuracy:
1.0000
Epoch 56/150
40/40 [=====] - 0s 2ms/step - loss: 0.0420 - accuracy:
0.9950
Epoch 57/150
40/40 [=====] - 0s 2ms/step - loss: 0.0298 - accuracy:
1.0000
Epoch 58/150
40/40 [=====] - 0s 2ms/step - loss: 0.0373 - accuracy:
1.0000
Epoch 59/150
40/40 [=====] - 0s 3ms/step - loss: 0.0413 - accuracy:
0.9950
Epoch 60/150
40/40 [=====] - 0s 3ms/step - loss: 0.0442 - accuracy:
0.9950
Epoch 61/150
40/40 [=====] - 0s 2ms/step - loss: 0.0343 - accuracy:
0.9950
Epoch 62/150
40/40 [=====] - 0s 3ms/step - loss: 0.0425 - accuracy:
1.0000
Epoch 63/150
40/40 [=====] - 0s 2ms/step - loss: 0.0473 - accuracy:
0.9899
Epoch 64/150
40/40 [=====] - 0s 3ms/step - loss: 0.0510 - accuracy:
0.9899
Epoch 65/150
40/40 [=====] - 0s 2ms/step - loss: 0.0514 - accuracy:
0.9899
Epoch 66/150
40/40 [=====] - 0s 2ms/step - loss: 0.0463 - accuracy:

```

```

0.9950
Epoch 67/150
40/40 [=====] - 0s 2ms/step - loss: 0.0353 - accuracy:
1.0000
Epoch 68/150
40/40 [=====] - 0s 2ms/step - loss: 0.0281 - accuracy:
0.9950
Epoch 69/150
40/40 [=====] - 0s 2ms/step - loss: 0.0391 - accuracy:
0.9950
Epoch 70/150
40/40 [=====] - 0s 2ms/step - loss: 0.0185 - accuracy:
1.0000
Epoch 71/150
40/40 [=====] - 0s 2ms/step - loss: 0.0320 - accuracy:
0.9950
Epoch 72/150
40/40 [=====] - 0s 2ms/step - loss: 0.0339 - accuracy:
0.9950
Epoch 73/150
40/40 [=====] - 0s 2ms/step - loss: 0.0313 - accuracy:
0.9950
Epoch 74/150
40/40 [=====] - 0s 3ms/step - loss: 0.0228 - accuracy:
1.0000
Epoch 75/150
40/40 [=====] - 0s 2ms/step - loss: 0.0252 - accuracy:
1.0000
Epoch 76/150
40/40 [=====] - 0s 2ms/step - loss: 0.0362 - accuracy:
0.9950
Epoch 77/150
40/40 [=====] - 0s 2ms/step - loss: 0.0628 - accuracy:
0.9799
Epoch 78/150
40/40 [=====] - 0s 2ms/step - loss: 0.0360 - accuracy:
0.9950
Epoch 79/150
40/40 [=====] - 0s 2ms/step - loss: 0.0284 - accuracy:
1.0000
Epoch 80/150
40/40 [=====] - 0s 2ms/step - loss: 0.0310 - accuracy:
1.0000
Epoch 81/150
40/40 [=====] - 0s 2ms/step - loss: 0.0193 - accuracy:
1.0000
Epoch 82/150
40/40 [=====] - 0s 2ms/step - loss: 0.0204 - accuracy:

```

```

1.0000
Epoch 83/150
40/40 [=====] - 0s 3ms/step - loss: 0.0456 - accuracy:
0.9899
Epoch 84/150
40/40 [=====] - 0s 3ms/step - loss: 0.0310 - accuracy:
0.9950
Epoch 85/150
40/40 [=====] - 0s 3ms/step - loss: 0.0348 - accuracy:
1.0000
Epoch 86/150
40/40 [=====] - 0s 3ms/step - loss: 0.0238 - accuracy:
0.9950
Epoch 87/150
40/40 [=====] - 0s 4ms/step - loss: 0.0262 - accuracy:
1.0000
Epoch 88/150
40/40 [=====] - 0s 4ms/step - loss: 0.0339 - accuracy:
0.9950
Epoch 89/150
40/40 [=====] - 0s 4ms/step - loss: 0.0607 - accuracy:
0.9849
Epoch 90/150
40/40 [=====] - 0s 4ms/step - loss: 0.0307 - accuracy:
0.9899
Epoch 91/150
40/40 [=====] - 0s 4ms/step - loss: 0.0327 - accuracy:
0.9899
Epoch 92/150
40/40 [=====] - 0s 4ms/step - loss: 0.0129 - accuracy:
1.0000
Epoch 93/150
40/40 [=====] - 0s 3ms/step - loss: 0.0251 - accuracy:
0.9950
Epoch 94/150
40/40 [=====] - 0s 4ms/step - loss: 0.0189 - accuracy:
1.0000
Epoch 95/150
40/40 [=====] - 0s 4ms/step - loss: 0.0223 - accuracy:
0.9950
Epoch 96/150
40/40 [=====] - 0s 3ms/step - loss: 0.0149 - accuracy:
1.0000
Epoch 97/150
40/40 [=====] - 0s 3ms/step - loss: 0.0306 - accuracy:
0.9899
Epoch 98/150
40/40 [=====] - 0s 4ms/step - loss: 0.0347 - accuracy:

```

```

0.9899
Epoch 99/150
40/40 [=====] - 0s 4ms/step - loss: 0.0260 - accuracy:
1.0000
Epoch 100/150
40/40 [=====] - 0s 4ms/step - loss: 0.0251 - accuracy:
1.0000
Epoch 101/150
40/40 [=====] - 0s 4ms/step - loss: 0.0214 - accuracy:
0.9950
Epoch 102/150
40/40 [=====] - 0s 4ms/step - loss: 0.0187 - accuracy:
1.0000
Epoch 103/150
40/40 [=====] - 0s 3ms/step - loss: 0.0177 - accuracy:
1.0000
Epoch 104/150
40/40 [=====] - 0s 2ms/step - loss: 0.0102 - accuracy:
1.0000
Epoch 105/150
40/40 [=====] - 0s 2ms/step - loss: 0.0198 - accuracy:
0.9950
Epoch 106/150
40/40 [=====] - 0s 2ms/step - loss: 0.0183 - accuracy:
1.0000
Epoch 107/150
40/40 [=====] - 0s 2ms/step - loss: 0.0134 - accuracy:
1.0000
Epoch 108/150
40/40 [=====] - 0s 2ms/step - loss: 0.0272 - accuracy:
0.9899
Epoch 109/150
40/40 [=====] - 0s 2ms/step - loss: 0.0178 - accuracy:
0.9950
Epoch 110/150
40/40 [=====] - 0s 2ms/step - loss: 0.0159 - accuracy:
1.0000
Epoch 111/150
40/40 [=====] - 0s 3ms/step - loss: 0.0282 - accuracy:
0.9950
Epoch 112/150
40/40 [=====] - 0s 2ms/step - loss: 0.0100 - accuracy:
1.0000
Epoch 113/150
40/40 [=====] - 0s 2ms/step - loss: 0.0075 - accuracy:
1.0000
Epoch 114/150
40/40 [=====] - 0s 2ms/step - loss: 0.0124 - accuracy:

```

```

1.0000
Epoch 115/150
40/40 [=====] - 0s 2ms/step - loss: 0.0166 - accuracy:
0.9950
Epoch 116/150
40/40 [=====] - 0s 2ms/step - loss: 0.0149 - accuracy:
1.0000
Epoch 117/150
40/40 [=====] - 0s 3ms/step - loss: 0.0138 - accuracy:
1.0000
Epoch 118/150
40/40 [=====] - 0s 3ms/step - loss: 0.0142 - accuracy:
1.0000
Epoch 119/150
40/40 [=====] - 0s 2ms/step - loss: 0.0083 - accuracy:
1.0000
Epoch 120/150
40/40 [=====] - 0s 2ms/step - loss: 0.0146 - accuracy:
1.0000
Epoch 121/150
40/40 [=====] - 0s 3ms/step - loss: 0.0133 - accuracy:
1.0000
Epoch 122/150
40/40 [=====] - 0s 3ms/step - loss: 0.0169 - accuracy:
1.0000
Epoch 123/150
40/40 [=====] - 0s 3ms/step - loss: 0.0141 - accuracy:
0.9950
Epoch 124/150
40/40 [=====] - 0s 3ms/step - loss: 0.0208 - accuracy:
0.9950
Epoch 125/150
40/40 [=====] - 0s 3ms/step - loss: 0.0137 - accuracy:
1.0000
Epoch 126/150
40/40 [=====] - 0s 2ms/step - loss: 0.0483 - accuracy:
0.9849
Epoch 127/150
40/40 [=====] - 0s 3ms/step - loss: 0.0158 - accuracy:
0.9950
Epoch 128/150
40/40 [=====] - 0s 2ms/step - loss: 0.0172 - accuracy:
1.0000
Epoch 129/150
40/40 [=====] - 0s 2ms/step - loss: 0.0101 - accuracy:
1.0000
Epoch 130/150
40/40 [=====] - 0s 3ms/step - loss: 0.0104 - accuracy:

```

```

1.0000
Epoch 131/150
40/40 [=====] - 0s 3ms/step - loss: 0.0120 - accuracy:
1.0000
Epoch 132/150
40/40 [=====] - 0s 3ms/step - loss: 0.0114 - accuracy:
1.0000
Epoch 133/150
40/40 [=====] - 0s 3ms/step - loss: 0.0052 - accuracy:
1.0000
Epoch 134/150
40/40 [=====] - 0s 3ms/step - loss: 0.0075 - accuracy:
1.0000
Epoch 135/150
40/40 [=====] - 0s 3ms/step - loss: 0.0126 - accuracy:
1.0000
Epoch 136/150
40/40 [=====] - 0s 2ms/step - loss: 0.0100 - accuracy:
1.0000
Epoch 137/150
40/40 [=====] - 0s 2ms/step - loss: 0.0119 - accuracy:
1.0000
Epoch 138/150
40/40 [=====] - 0s 2ms/step - loss: 0.0172 - accuracy:
0.9950
Epoch 139/150
40/40 [=====] - 0s 3ms/step - loss: 0.0154 - accuracy:
1.0000
Epoch 140/150
40/40 [=====] - 0s 2ms/step - loss: 0.0132 - accuracy:
0.9950
Epoch 141/150
40/40 [=====] - 0s 2ms/step - loss: 0.0137 - accuracy:
1.0000
Epoch 142/150
40/40 [=====] - 0s 12ms/step - loss: 0.0207 - accuracy:
0.9950
Epoch 143/150
40/40 [=====] - 0s 6ms/step - loss: 0.0329 - accuracy:
0.9950
Epoch 144/150
40/40 [=====] - 0s 5ms/step - loss: 0.0266 - accuracy:
0.9950
Epoch 145/150
40/40 [=====] - 0s 2ms/step - loss: 0.0143 - accuracy:
1.0000
Epoch 146/150
40/40 [=====] - 0s 2ms/step - loss: 0.0054 - accuracy:

```

```

1.0000
Epoch 147/150
40/40 [=====] - 0s 2ms/step - loss: 0.0088 - accuracy:
1.0000
Epoch 148/150
40/40 [=====] - 0s 2ms/step - loss: 0.0162 - accuracy:
1.0000
Epoch 149/150
40/40 [=====] - 0s 2ms/step - loss: 0.0103 - accuracy:
0.9950
Epoch 150/150
40/40 [=====] - 0s 2ms/step - loss: 0.0056 - accuracy:
1.0000

```

```

/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3000:
UserWarning: You are saving your model as an HDF5 file via `model.save()`. This
file format is considered legacy. We recommend using instead the native Keras
format, e.g. `model.save('my_model.keras')`.

```

```

saving_api.save_model(

```

```

[34]: loss, accuracy = model.evaluate(np.array(train_x), np.array(train_y),
    ↪ verbose=False)
    print("Training Accuracy: {:.4f}".format(accuracy))

```

```

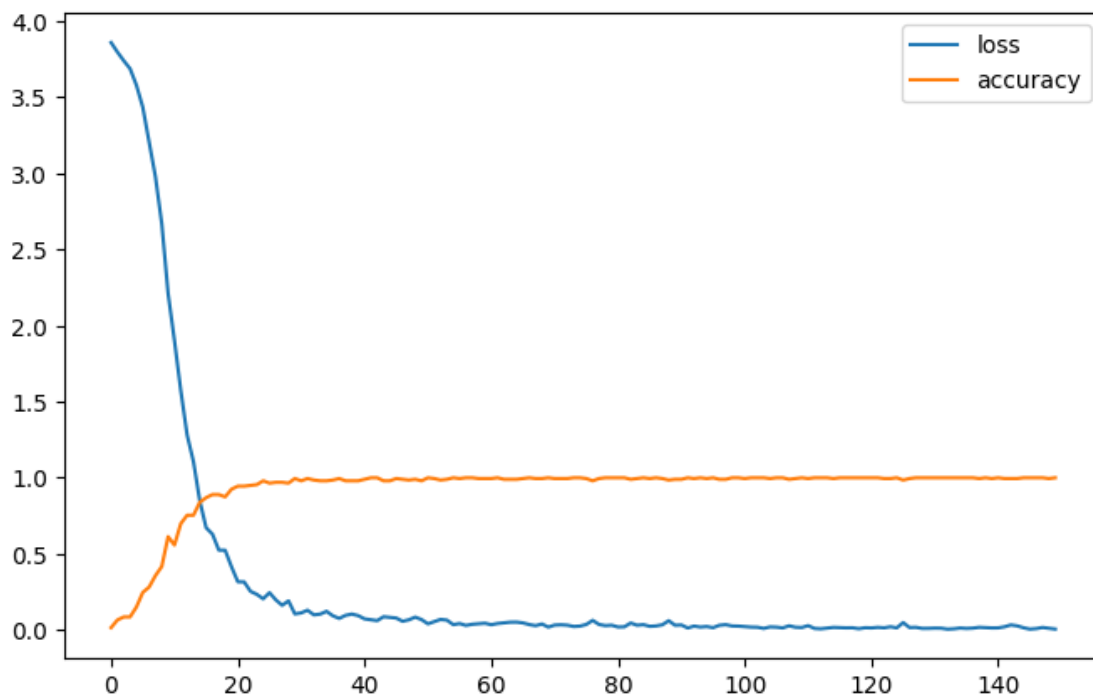
Training Accuracy: 1.0000

```

```

[35]: pd.DataFrame(hist.history).plot(figsize=(8,5))
    plt.show()

```

0.2 Build The Model With Conv

```
[36]: from keras.preprocessing.text import Tokenizer

sentences_train, sentences_test, label_train, label_test = train_test_split(
    training_sentences, training_labels, test_size=0.20, random_state=1000)

tokenizer = Tokenizer(num_words=5000)
tokenizer.fit_on_texts(sentences_train)
Xcnn_train = tokenizer.texts_to_sequences(sentences_train)
Xcnn_test = tokenizer.texts_to_sequences(sentences_test)
vocab_size = len(tokenizer.word_index) + 1
print(sentences_train[1])
print(Xcnn_train[1])
```

What to do if you get a sting?

[9, 1, 2, 5, 8, 7, 3, 42]

```
[37]: from keras.preprocessing.sequence import pad_sequences

maxlen = 100
Xcnn_train = pad_sequences(Xcnn_train, padding='post', maxlen=maxlen)
Xcnn_test = pad_sequences(Xcnn_test, padding='post', maxlen=maxlen)
```

```
print(Xcnn_train[0, :])
```

```
[ 4  1 14 65  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  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  0  0  0  0  0  0  0
  0  0  0  0]
```

```
[38]: embedding_dim = 200
textcnnmodel = Sequential()
textcnnmodel.add(Embedding(vocab_size, embedding_dim, input_length=maxlen))
textcnnmodel.add(Conv1D(128, 5, activation='relu'))
textcnnmodel.add(GlobalMaxPooling1D())
textcnnmodel.add(Dense(10, activation='relu'))
textcnnmodel.add(Dense(1, activation='sigmoid'))

textcnnmodel.
    ↪ compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
textcnnmodel.summary()
```

Model: "sequential_8"

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 100, 200)	26400
conv1d (Conv1D)	(None, 96, 128)	128128
global_max_pooling1d (GlobalMaxPooling1D)	(None, 128)	0
dense_24 (Dense)	(None, 10)	1290
dense_25 (Dense)	(None, 1)	11
Total params: 155829 (608.71 KB)		
Trainable params: 155829 (608.71 KB)		
Non-trainable params: 0 (0.00 Byte)		

```
[39]: textmodel = textcnnmodel.fit(Xcnn_train, np.
    ↪ array(label_train), epochs=50, verbose=1, validation_data=(Xcnn_test,
    ↪ label_test), batch_size=10)

loss, accuracy = textcnnmodel.evaluate(Xcnn_train, label_train, verbose=False)
print("Training Accuracy: {:.4f}".format(accuracy))
```

```
loss, accuracy = textcnmodel.evaluate(Xcnn_test, label_test, verbose=False)
print("Testing Accuracy: {:.4f}".format(accuracy))
```

```
Epoch 1/50
16/16 [=====] - 2s 71ms/step - loss: -15.6988 -
accuracy: 0.0314 - val_loss: -52.1992 - val_accuracy: 0.0250
Epoch 2/50
16/16 [=====] - 1s 47ms/step - loss: -112.4492 -
accuracy: 0.0314 - val_loss: -246.3446 - val_accuracy: 0.0250
Epoch 3/50
16/16 [=====] - 1s 69ms/step - loss: -449.3540 -
accuracy: 0.0314 - val_loss: -833.4328 - val_accuracy: 0.0250
Epoch 4/50
16/16 [=====] - 1s 64ms/step - loss: -1315.4128 -
accuracy: 0.0314 - val_loss: -2295.4248 - val_accuracy: 0.0250
Epoch 5/50
16/16 [=====] - 1s 89ms/step - loss: -3304.3079 -
accuracy: 0.0314 - val_loss: -5338.0288 - val_accuracy: 0.0250
Epoch 6/50
16/16 [=====] - 0s 30ms/step - loss: -7195.4897 -
accuracy: 0.0314 - val_loss: -11059.2344 - val_accuracy: 0.0250
Epoch 7/50
16/16 [=====] - 0s 27ms/step - loss: -14127.6367 -
accuracy: 0.0314 - val_loss: -20842.9707 - val_accuracy: 0.0250
Epoch 8/50
16/16 [=====] - 0s 27ms/step - loss: -25651.4512 -
accuracy: 0.0314 - val_loss: -36312.6992 - val_accuracy: 0.0250
Epoch 9/50
16/16 [=====] - 0s 28ms/step - loss: -43710.9297 -
accuracy: 0.0314 - val_loss: -59367.7812 - val_accuracy: 0.0250
Epoch 10/50
16/16 [=====] - 0s 27ms/step - loss: -69578.5703 -
accuracy: 0.0314 - val_loss: -93116.6953 - val_accuracy: 0.0250
Epoch 11/50
16/16 [=====] - 0s 30ms/step - loss: -106008.5547 -
accuracy: 0.0314 - val_loss: -139658.4062 - val_accuracy: 0.0250
Epoch 12/50
16/16 [=====] - 0s 28ms/step - loss: -155535.7344 -
accuracy: 0.0314 - val_loss: -202421.2500 - val_accuracy: 0.0250
Epoch 13/50
16/16 [=====] - 0s 31ms/step - loss: -222959.2969 -
accuracy: 0.0314 - val_loss: -283779.3438 - val_accuracy: 0.0250
Epoch 14/50
16/16 [=====] - 0s 27ms/step - loss: -309046.1250 -
accuracy: 0.0314 - val_loss: -388926.3750 - val_accuracy: 0.0250
Epoch 15/50
```

16/16 [=====] - 0s 24ms/step - loss: -418116.5625 - accuracy: 0.0314 - val_loss: -520589.4062 - val_accuracy: 0.0250
Epoch 16/50
16/16 [=====] - 0s 28ms/step - loss: -554635.5000 - accuracy: 0.0314 - val_loss: -682579.2500 - val_accuracy: 0.0250
Epoch 17/50
16/16 [=====] - 0s 29ms/step - loss: -722312.6250 - accuracy: 0.0314 - val_loss: -879208.8125 - val_accuracy: 0.0250
Epoch 18/50
16/16 [=====] - 0s 31ms/step - loss: -919740.5000 - accuracy: 0.0314 - val_loss: -1121194.0000 - val_accuracy: 0.0250
Epoch 19/50
16/16 [=====] - 0s 30ms/step - loss: -1165788.6250 - accuracy: 0.0314 - val_loss: -1402191.2500 - val_accuracy: 0.0250
Epoch 20/50
16/16 [=====] - 0s 28ms/step - loss: -1445839.1250 - accuracy: 0.0314 - val_loss: -1741473.3750 - val_accuracy: 0.0250
Epoch 21/50
16/16 [=====] - 0s 30ms/step - loss: -1789945.1250 - accuracy: 0.0314 - val_loss: -2125620.7500 - val_accuracy: 0.0250
Epoch 22/50
16/16 [=====] - 0s 29ms/step - loss: -2175619.5000 - accuracy: 0.0314 - val_loss: -2583095.2500 - val_accuracy: 0.0250
Epoch 23/50
16/16 [=====] - 0s 29ms/step - loss: -2630064.7500 - accuracy: 0.0314 - val_loss: -3100560.0000 - val_accuracy: 0.0250
Epoch 24/50
16/16 [=====] - 0s 28ms/step - loss: -3141595.2500 - accuracy: 0.0314 - val_loss: -3701546.5000 - val_accuracy: 0.0250
Epoch 25/50
16/16 [=====] - 0s 30ms/step - loss: -3743646.5000 - accuracy: 0.0314 - val_loss: -4364124.0000 - val_accuracy: 0.0250
Epoch 26/50
16/16 [=====] - 0s 27ms/step - loss: -4400942.0000 - accuracy: 0.0314 - val_loss: -5134994.5000 - val_accuracy: 0.0250
Epoch 27/50
16/16 [=====] - 1s 43ms/step - loss: -5146895.0000 - accuracy: 0.0314 - val_loss: -6006127.0000 - val_accuracy: 0.0250
Epoch 28/50
16/16 [=====] - 1s 44ms/step - loss: -5996760.0000 - accuracy: 0.0314 - val_loss: -6961702.5000 - val_accuracy: 0.0250
Epoch 29/50
16/16 [=====] - 1s 45ms/step - loss: -6950655.0000 - accuracy: 0.0314 - val_loss: -8008933.0000 - val_accuracy: 0.0250
Epoch 30/50
16/16 [=====] - 1s 45ms/step - loss: -7968929.0000 - accuracy: 0.0314 - val_loss: -9214248.0000 - val_accuracy: 0.0250
Epoch 31/50

16/16 [=====] - 1s 32ms/step - loss: -9141060.0000 - accuracy: 0.0314 - val_loss: -10512577.0000 - val_accuracy: 0.0250
Epoch 32/50
16/16 [=====] - 0s 29ms/step - loss: -10451823.0000 - accuracy: 0.0314 - val_loss: -11900190.0000 - val_accuracy: 0.0250
Epoch 33/50
16/16 [=====] - 0s 29ms/step - loss: -11804379.0000 - accuracy: 0.0314 - val_loss: -13512938.0000 - val_accuracy: 0.0250
Epoch 34/50
16/16 [=====] - 0s 28ms/step - loss: -13342624.0000 - accuracy: 0.0314 - val_loss: -15252854.0000 - val_accuracy: 0.0250
Epoch 35/50
16/16 [=====] - 0s 26ms/step - loss: -15046733.0000 - accuracy: 0.0314 - val_loss: -17089350.0000 - val_accuracy: 0.0250
Epoch 36/50
16/16 [=====] - 0s 27ms/step - loss: -16848546.0000 - accuracy: 0.0314 - val_loss: -19127014.0000 - val_accuracy: 0.0250
Epoch 37/50
16/16 [=====] - 0s 30ms/step - loss: -18807028.0000 - accuracy: 0.0314 - val_loss: -21357298.0000 - val_accuracy: 0.0250
Epoch 38/50
16/16 [=====] - 0s 31ms/step - loss: -20944024.0000 - accuracy: 0.0314 - val_loss: -23760262.0000 - val_accuracy: 0.0250
Epoch 39/50
16/16 [=====] - 0s 29ms/step - loss: -23301280.0000 - accuracy: 0.0314 - val_loss: -26270634.0000 - val_accuracy: 0.0250
Epoch 40/50
16/16 [=====] - 0s 27ms/step - loss: -25706922.0000 - accuracy: 0.0314 - val_loss: -29113940.0000 - val_accuracy: 0.0250
Epoch 41/50
16/16 [=====] - 0s 27ms/step - loss: -28453022.0000 - accuracy: 0.0314 - val_loss: -32030758.0000 - val_accuracy: 0.0250
Epoch 42/50
16/16 [=====] - 0s 26ms/step - loss: -31266780.0000 - accuracy: 0.0314 - val_loss: -35251976.0000 - val_accuracy: 0.0250
Epoch 43/50
16/16 [=====] - 0s 23ms/step - loss: -34390552.0000 - accuracy: 0.0314 - val_loss: -38632596.0000 - val_accuracy: 0.0250
Epoch 44/50
16/16 [=====] - 0s 23ms/step - loss: -37667668.0000 - accuracy: 0.0314 - val_loss: -42274584.0000 - val_accuracy: 0.0250
Epoch 45/50
16/16 [=====] - 0s 25ms/step - loss: -41192688.0000 - accuracy: 0.0314 - val_loss: -46145880.0000 - val_accuracy: 0.0250
Epoch 46/50
16/16 [=====] - 0s 29ms/step - loss: -44895560.0000 - accuracy: 0.0314 - val_loss: -50331892.0000 - val_accuracy: 0.0250
Epoch 47/50

```

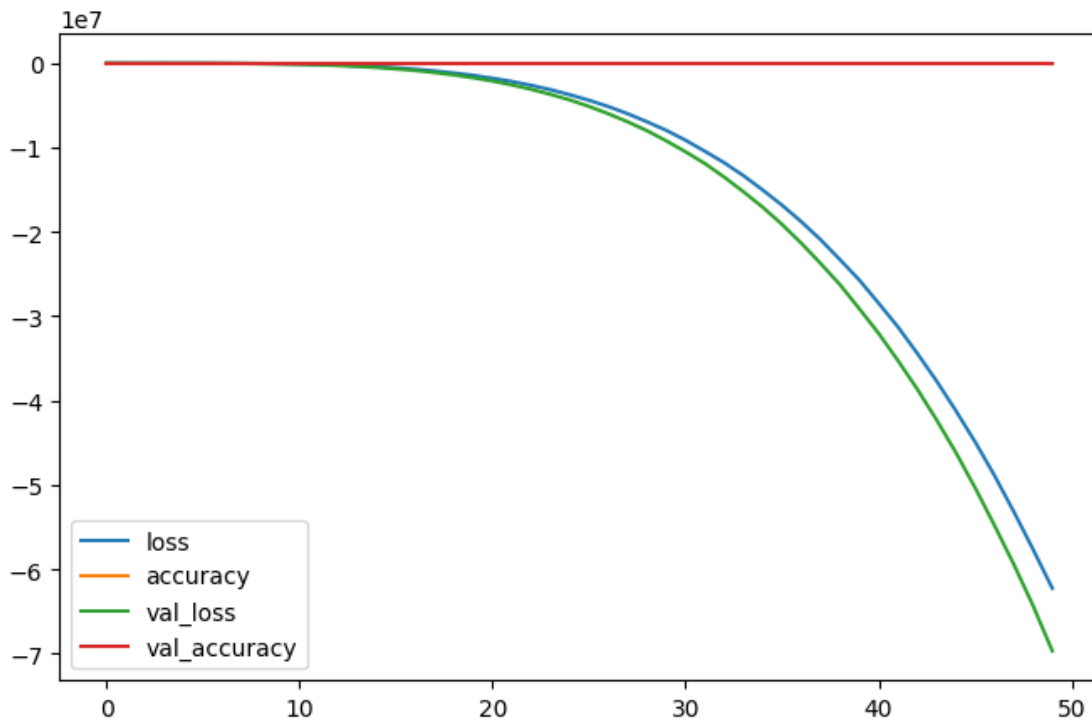
16/16 [=====] - 0s 28ms/step - loss: -48859212.0000 -
accuracy: 0.0314 - val_loss: -54782388.0000 - val_accuracy: 0.0250
Epoch 48/50
16/16 [=====] - 0s 30ms/step - loss: -53147340.0000 -
accuracy: 0.0314 - val_loss: -59390708.0000 - val_accuracy: 0.0250
Epoch 49/50
16/16 [=====] - 0s 27ms/step - loss: -57627268.0000 -
accuracy: 0.0314 - val_loss: -64298580.0000 - val_accuracy: 0.0250
Epoch 50/50
16/16 [=====] - 0s 29ms/step - loss: -62254220.0000 -
accuracy: 0.0314 - val_loss: -69681888.0000 - val_accuracy: 0.0250
Training Accuracy: 0.0314
Testing Accuracy: 0.0250

```

```

[40]: pd.DataFrame(textmodel.history).plot(figsize=(8,5))
      plt.show()

```



0.2.1 Sentiment Analysis

```

[52]: df = pd.read_excel('classify.xlsx')

```

```

[53]: df.head(15)

```

```
[53]:
```

	Tags	isdanger	\
0	"Cuts	1	
1	Abrasions	0	
2	"stings	1	
3	"Splinter	1	
4	Sprains	0	
5	Sore Throat	0	
6	Abdonominal Pain	0	
7	Fever	1	


```

                                Text
0  ["What to do if Cuts?", "How to cure Cuts?", "...
1  "how do you treat abrasions?", "Do Abrasions c...
2  "How do you treat Sting?", "Stings", "What to ...
3  "How to remove Splinters", "How to cure Splint...
4  How do you treat a sprain?", "what to do if i ...
5  "How do you treat sore throat?", "what to do i...
6  minal Pain",\n          "patterns": ["How do y...
7  How do you treat a mild Fever?", "what to do i...
```

```
[54]: !pip3 install neattext
```

```
Requirement already satisfied: neattext in /usr/local/lib/python3.10/dist-packages (0.1.3)
```

```
[55]: import neattext.functions as nf

df['Text'] = df['Text'].apply(nf.clean_text)
```

```
[56]: cleaned_data = [sentence for sentence in df['Text']]
cleaned_data
```

```
[56]: ['["what cuts?", "how cure cuts?", "which medicine apply cuts?", "what apply cuts?", "cuts"], ["wash cut properly prevent infection stop bleeding applying pressure 1-2minutes bleeding stops. apply petroleum jelly sure wound moist quick healing. finally cover cut sterile bandage. pain relievers acetaminophen applied.",
  "how treat abrasions?", "do abrasions cause scars?", "abrasions", "what abrasions?", "which medicine apply abrasions?", "how cure abrasions?"]',
  "responses": ["begin washed hands.gently clean area cool lukewarm water mild soap. remove dirt particles wound sterilized tweezers.for mild scrape that's bleeding, leave wound uncovered.if wound bleeding, use clean cloth bandage, apply gentle pressure area stop bleeding.cover wound bled thin layer topical antibiotic ointment, like bacitracin, sterile moisture barrier ointment, like aquaphor. cover clean bandage gauze. gently clean wound change ointment bandage day.watch area signs infection, like pain redness swelling. doctor suspect infection."],
```

'how treat sting?", "stings", "what sting?", "which medicine apply sting?"]
 "responses": ["remove stingers immediately. experts recommend scraping stinger
 credit card. applying ice site provide mild relief. apply ice 20 minutes hour
 needed. wrap ice towel cloth ice skin freezing skin. taking antihistamine
 diphenhydramine (benadryl) nonsedating loratadine (claritin) help itching
 swelling. acetaminophen (tylenol) ibuprofen (motrin)for pain relief needed. wash
 sting site soap water. placing hydrocortisone cream sting help relieve redness,
 itching, swelling.',

'how remove splinters", "how cure splinters?", "what splinters?", "how bring
 splinter surface?"]
 "responses": ["1. soak epsom salts. dissolve cup salts warm
 bath soak body splinter. failing that, salts bandage pad leave covered day;
 eventually help bring splinter surface. 2. vinegar oil. simple way draw stubborn
 splinter soak affected area oil (olive corn) white vinegar. pour bowl soak area
 20 30 minutes',

'treat sprain?", "what sprain?", "which cream apply sprain?", "which medicine
 apply sprain?"]
 "responses": ["use ice pack ice slush bath immediately 15 20
 minutes repeat hours awake. help stop swelling, compress ankle elastic bandage
 swelling stops. cases, pain relievers - ibuprofen (advil, motrin ib, others)
 naproxen sodium (aleve, others) acetaminophen (tylenol, others) manage pain
 sprained ankle.',

'how treat sore throat?", "what sore throat?", "which medicine sore throat?",
 "how cure sore throat?"]
 "responses": ["1) sure plenty rest drink lot fluids.
 2)inhale steam,run hot water sink.drape towel trap steam, person lean sink water
 running. tell breathe deeply mouth nose 5 10 minutes. repeat times day. 3)have
 sip chicken broth warm tea honey. don't honey child 12 months age',

'minal pain", "patterns": ["how treat abdonominal pain?", "what abdonominal
 pain?", "which medicine abdonominal pain?", "how cure abdonominal pain?"]
 "responses": ["1)provide clear fluids sip, water, broth, fruit juice diluted
 water. 2)serve bland foods, saltine crackers, plain bread, dry toast, rice,
 gelatin, applesauce. 3)avoid spicy greasy foods caffeinated carbonated drinks 48
 hours symptoms gone away',

'treat mild fever?", "what mild fever?", "which medicine mild fever?",
 "fever"]
 "responses": ["to treat fever home: 1)drink plenty fluids stay
 hydrated. 2)dress lightweight clothing. 3)use light blanket feel chilled, chills
 end. 4)take acetaminophen (tylenol, others) ibuprofen (advil, motrin ib,
 others). 5) medical help fever lasts days row']

```
[57]: ## Data Transformation
from sklearn.feature_extraction.text import CountVectorizer

cv = CountVectorizer(max_features=1400)
x = cv.fit_transform(cleaned_data).toarray()
y = df.iloc[:, -2].values
```

```
[58]: ## Data split
from sklearn.model_selection import train_test_split
```



```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.20,  
↪random_state=42)
```

```
[59]: # Naive Bayes  
from sklearn.naive_bayes import GaussianNB  
  
nb_model = GaussianNB()  
nb_model.fit(X_train,y_train)
```

[59]: GaussianNB()

```
[60]: # Test  
y_pred = nb_model.predict(X_test)  
print(y_pred[:10])  
print(y_test[:10])
```

```
[1 1]  
[0 0]
```

```
[61]: # Evaluate  
from sklearn.metrics import accuracy_score  
  
y_pred = nb_model.predict(X_test)  
  
accuracy_score(y_test,y_pred)
```

[61]: 0.0

```
[62]: ## Random Forest  
from sklearn.ensemble import RandomForestClassifier  
  
rf_model = RandomForestClassifier()  
rf_model.fit(X_train,y_train)  
  
# Test  
y_pred = rf_model.predict(X_test)  
print(y_pred[:10])  
print(y_test[:10])
```

```
[1 1]  
[0 0]
```

```
[63]: accuracy_score(y_test,y_pred)
```

[63]: 0.0

0.3 Demo

```
[ ]: import json
import numpy as np
from tensorflow import keras
from sklearn.preprocessing import LabelEncoder
import random
import pickle

with open("intents.json") as file:
    data = json.load(file)

def chat():
    # load trained model
    model = keras.models.load_model('chat_model')

    # load tokenizer object
    with open('tokenizer.pickle', 'rb') as handle:
        tokenizer = pickle.load(handle)

    # load label encoder object
    with open('label_encoder.pickle', 'rb') as enc:
        lbl_encoder = pickle.load(enc)

    # parameters
    max_len = 20

    while True:
        print("User: " ,end="")
        inp = input()
        if inp.lower() == "quit":
            break

        result = model.predict(keras.preprocessing.sequence.
        ↪pad_sequences(tokenizer.texts_to_sequences([inp]),
                                truncating='post', maxlen=max_len))
        tag = lbl_encoder.inverse_transform([np.argmax(result)])

        for i in data['intents']:
            if i['tag'] == tag:
                print("Mosif ChatBot:" , np.random.choice(i['responses']))

print("Start messaging with the Mosif bot (type quit to stop)!")
chat()
```