```
import pandas as pd
import numpy as np
import tensorflow as tf
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.layers import Bidirectional
import matplotlib.pyplot as plt
import seaborn as sns
import sqlite3
import sklearn
from sklearn.model_selection import train_test_split
import warnings
import os
warnings.filterwarnings("ignore")
```

```
conn = sqlite3.connect("password_data.sqlite")
df = pd.read_sql_query("SELECT * FROM Users", conn)
conn.close()
```

```
#Dataset Overview
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 3 columns):
 #   Column    Non-Null Count   Dtype
---  ------    --------------   -----
 0   index     100000 non-null  int64
 1   password  100000 non-null  object
 2   strength  100000 non-null  int64
dtypes: int64(2), object(1)
memory usage: 2.3+ MB
```

```
#Column Names
df.columns
```

```
Index(['index', 'password', 'strength'], dtype='object')
```

```
#Missing Values Per Column
df.isnull().sum()
```

	0
index	0
password	0
strength	0

```
#Duplicate Rows Count
df.duplicated().sum()
```

```
0
```

```
#Basic Statistics
df.describe(include='all')
```

	index	password	strength
count	100000.000000	100000	100000.000000
unique	NaN	100000	NaN
top	NaN	zxe870819	NaN
freq	NaN	1	NaN
mean	49999.500000	NaN	0.988730
std	28867.657797	NaN	0.510926
min	0.000000	NaN	0.000000
25%	24999.750000	NaN	1.000000
50%	49999.500000	NaN	1.000000
75%	74999.250000	NaN	1.000000
max	99999.000000	NaN	2.000000

```
#Class Distribution
df['strength'].value_counts()
```

strength	count
1	73883
0	13622
2	12495

```
#Most Common Characters in Weak Passwords
weak_chars = ''.join(df[df['strength'] == 0]['password'])
pd.Series(list(weak_chars)).value_counts().head(10)
```

	count
a	6975
1	5420
e	4767
o	4332
i	4002
s	3257
n	3235
r	3211
2	3178
0	2907

```
#Most Common Characters in Strong Passwords
strong_chars = ''.join(df[df['strength'] == 2]['password'])
pd.Series(list(strong_chars)).value_counts().head(10)
```

	count
M	5703
A	5621
a	5590
1	5349
N	4892
Q	4765
g	4704
0	4695
2	4652
e	4425

```
#Outlier Detection, i.e, passwords which are too long
Outliers = df[pd.Series(df['password'].apply(len)) > pd.Series(df['password'].apply(len)).quantile(0.99)]['password']
```

```
Outliers
```

	password
3	accounts6000webhost.com
180	karolina.susnina0U
192	<html>13476590nosD
242	Therockrockbottom72
306	twDLi4Sd2l5ZRJZ8UEvL
...	...
99091	griboedova.natalja1X
99187	QWERKaelani04032014
99255	345e9ret_TR4eyxsPv54E_i
99661	kristina-novokshonova1S
99963	FvGoE3H3Xg3M4DOouE9k

762 rows × 1 columns

```
Outliers.count()
```

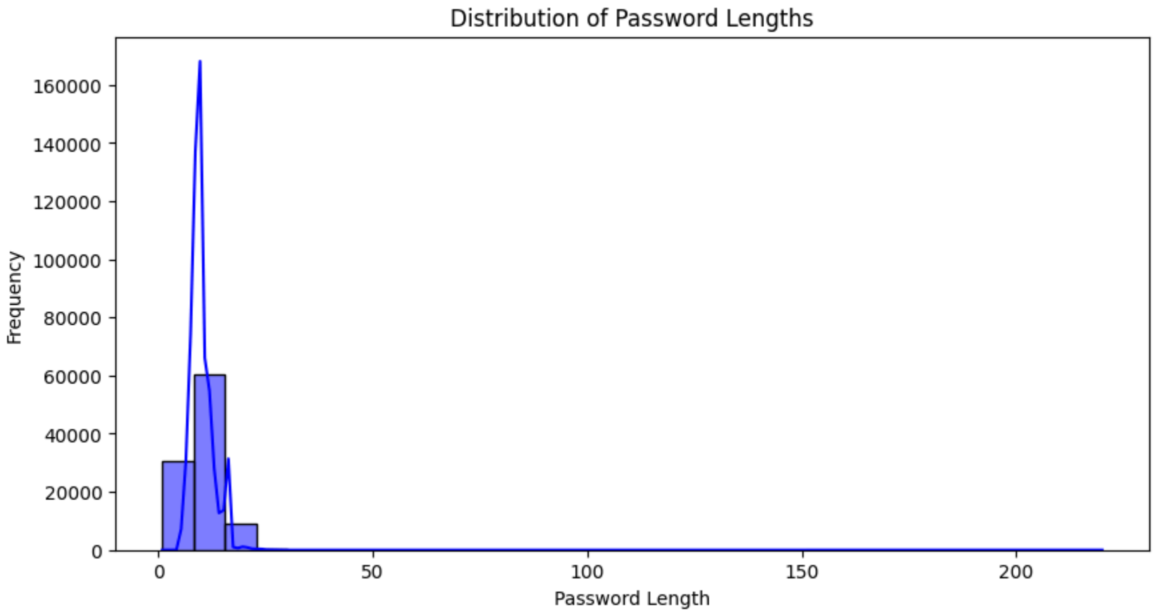
```
762
```

```
# Drop unnecessary columns like index (if present)
df.drop(columns=['index'], errors='ignore', inplace=True)

# Check for missing values
print("Missing values:\n", df.isnull().sum())

# Drop rows with missing passwords
df.dropna(inplace=True)
```

```
Missing values:
 password    0
strength    0
dtype: int64
```

```
# Plot password length distribution
df['length'] = df['password'].apply(len)

plt.figure(figsize=(10, 5))
sns.histplot(df['length'], bins=30, kde=True, color='blue')
plt.xlabel("Password Length")
plt.ylabel("Frequency")
plt.title("Distribution of Password Lengths")
plt.show()
```

```
# Print basic stats
print(df['length'].describe())
```




```
count    100000.000000
mean          9.986700
std           2.887813
min           1.000000
25%           8.000000
50%           9.000000
75%          11.000000
max         220.000000
```

```
# Find the optimal sequence length (excluding extreme outliers)
optimal_length = int(np.percentile(df['length'], 95))

print(f"Optimal Sequence Length: {optimal_length}")
```

```
Optimal Sequence Length: 16
```

```
# Tokenize passwords at character level
tokenizer = Tokenizer(char_level=True, filters="", oov_token="<OOV>")
tokenizer.fit_on_texts(df['password'])

# Convert passwords into sequences of numbers
password_sequences = tokenizer.texts_to_sequences(df['password'])

# Apply padding using the optimal length
X_padded = pad_sequences(password_sequences, maxlen=optimal_length, padding='pre', truncating='pre')

# Extract labels
y = df['strength'].values  # 0 = Weak, 1 = Medium, 2 = Strong


#splitting of ds
X_train, X_test, y_train, y_test = train_test_split(X_padded, y, test_size=0.2, random_state=42, stratify=y)


# Define the LSTM model
model = Sequential()

# Embedding Layer
model.add(Embedding(input_dim=len(tokenizer.word_index) + 1,
                    output_dim=64,
                    input_length=optimal_length))

# BiLSTM Layer
model.add(Bidirectional(LSTM(units=128, return_sequences=False, dropout=0.3)))

# Fully Connected Layer
model.add(Dense(units=3, activation='softmax'))

# Compile the Model
model.compile(loss='sparse_categorical_crossentropy',
              optimizer=Adam(learning_rate=0.001),
              metrics=['accuracy'])

# **Fix: Build the model before summary**
```

```
model.build(input_shape=(None, optimal_length))
model.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
embedding_4 (Embedding)	(None, 16, 64)	6,464
bidirectional_1 (Bidirectional)	(None, 256)	197,632
dense_3 (Dense)	(None, 3)	771

Total params: 204,867 (800.26 KB)
Trainable params: 204,867 (800.26 KB)

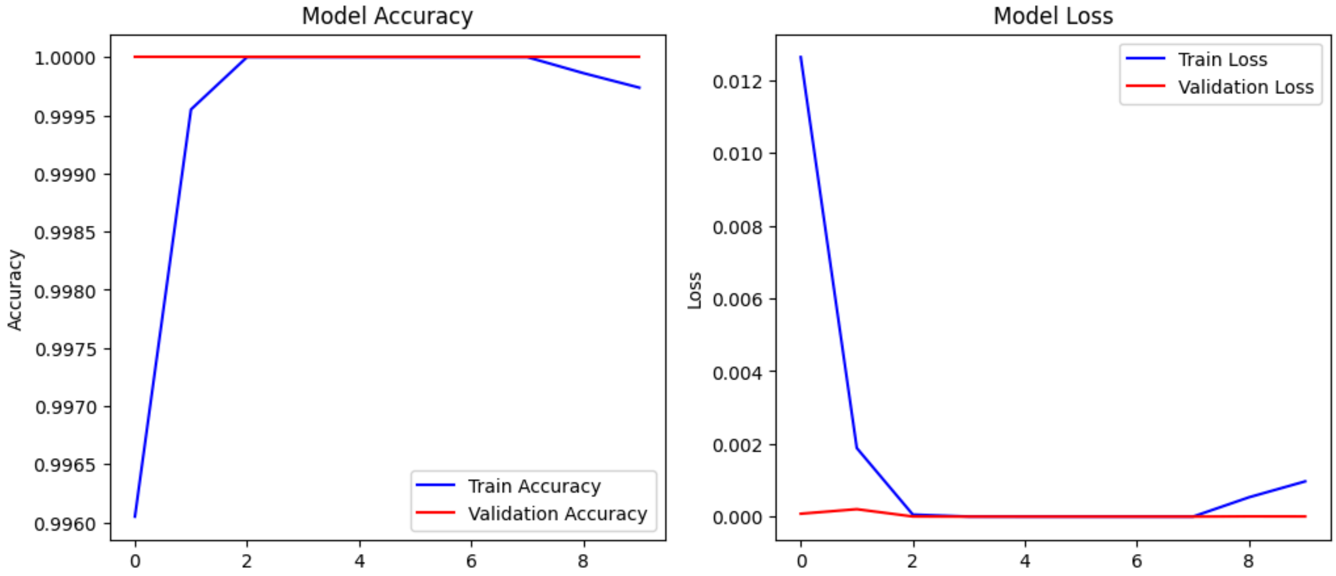
```
history = model.fit(X_train, y_train,
                    epochs=10,
                    batch_size=16,
                    validation_data=(X_test, y_test))
```

```
Epoch 1/10
5000/5000 ━━━━━━━━━━━━━━━━━━━━ 131s 25ms/step - accuracy: 0.9843 - loss: 0.0474 - val_accuracy: 1.0000 - val_loss: 7.9261e-05
Epoch 2/10
5000/5000 ━━━━━━━━━━━━━━━━━━━━ 142s 25ms/step - accuracy: 0.9998 - loss: 7.4653e-04 - val_accuracy: 1.0000 - val_loss: 2.0355e-04
Epoch 3/10
5000/5000 ━━━━━━━━━━━━━━━━━━━━ 142s 26ms/step - accuracy: 1.0000 - loss: 1.1828e-04 - val_accuracy: 1.0000 - val_loss: 3.2898e-06
Epoch 4/10
5000/5000 ━━━━━━━━━━━━━━━━━━━━ 141s 25ms/step - accuracy: 1.0000 - loss: 2.0319e-06 - val_accuracy: 1.0000 - val_loss: 6.8146e-08
Epoch 5/10
5000/5000 ━━━━━━━━━━━━━━━━━━━━ 123s 25ms/step - accuracy: 1.0000 - loss: 7.8058e-08 - val_accuracy: 1.0000 - val_loss: 4.6790e-09
Epoch 6/10
5000/5000 ━━━━━━━━━━━━━━━━━━━━ 144s 25ms/step - accuracy: 1.0000 - loss: 5.0402e-09 - val_accuracy: 1.0000 - val_loss: 6.5565e-11
Epoch 7/10
5000/5000 ━━━━━━━━━━━━━━━━━━━━ 143s 25ms/step - accuracy: 1.0000 - loss: 4.9026e-10 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 8/10
5000/5000 ━━━━━━━━━━━━━━━━━━━━ 142s 25ms/step - accuracy: 1.0000 - loss: 1.0462e-10 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 9/10
5000/5000 ━━━━━━━━━━━━━━━━━━━━ 142s 25ms/step - accuracy: 0.9999 - loss: 2.2718e-04 - val_accuracy: 1.0000 - val_loss: 5.5314e-06
Epoch 10/10
5000/5000 ━━━━━━━━━━━━━━━━━━━━ 146s 26ms/step - accuracy: 0.9998 - loss: 7.0281e-04 - val_accuracy: 1.0000 - val_loss: 4.0782e-06
```

```
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {accuracy:.4f}")
```

```
625/625 ━━━━━━━━━━━━━━━━━━━━ 10s 14ms/step - accuracy: 1.0000 - loss: 4.1339e-06
Test Accuracy: 1.0000
```

```
#plotting accuracy and loss
plt.figure(figsize=(12, 5))

# Plot Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='red')
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.title("Model Accuracy")
plt.legend()

# Plot Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='red')
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("Model Loss")
plt.legend()

plt.show()
```


Model Accuracy
Accuracy
1.0000
0.9995
0.9990
0.9985
0.9980
0.9975
0.9970
0.9965
0.9960
0
2
4
6
8
Train Accuracy
Validation Accuracy
Model Loss
Loss
0.012
0.010
0.008
0.006
0.004
0.002
0.000
Train Loss
Validation Loss