Lab Assignment-5 Time Series Forecasting using LSTM

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? Experiment 5.1: Time Series Forecasting using LSTM

Objective:

To forecast future values of a univariate time series using LSTM-based models.

Dataset: Airline Passengers

? Expected Outcome:

Prediction vs actual plot

RMSE/MAE values

```
import pandas as pd import
numpy as np import
matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler from keras.models
import Sequential from keras.layers import LSTM, Dense from
sklearn.metrics import mean_squared_error, mean_absolute_error

# Load dataset url =
'https://raw.githubusercontent.com/jbrownlee/Datasets/master/airline-passengers.csv' df
= pd.read_csv(url, usecols=[1]) df.columns = ['Passengers']

# Normalize the dataset scaler =
MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(df)

# Create sequences def create_dataset(data,
time_step=20):     X, Y = [], []     for i
in range(len(data) - time_step - 1):
        X.append(data[i:(i + time_step), 0])
Y.append(data[i + time_step, 0])     return
np.array(X), np.array(Y)

time_step = 20
X, y = create_dataset(scaled_data, time_step)
X = X.reshape(X.shape[0], X.shape[1], 1)

# Split into train/test
train_size = int(len(X) * 0.8)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]

# Build model model = Sequential() model.add(LSTM(64,
return_sequences=True, input_shape=(time_step, 1)))
model.add(LSTM(64)) model.add(Dense(1))
```

```
model.compile(loss='mean_squared_error', optimizer='adam') model.fit(X_train, y_train,
validation_data=(X_test, y_test), epochs=100, batch_size=16, verbose=1)

# Prediction train_predict =
model.predict(X_train) test_predict
= model.predict(X_test)

# Invert scaling train_predict_inv =
scaler.inverse_transform(train_predict.reshape(-1, 1)) test_predict_inv
= scaler.inverse_transform(test_predict.reshape(-1, 1)) y_test_inv =
scaler.inverse_transform(y_test.reshape(-1, 1))

# Plot prediction vs actual
plt.figure(figsize=(10, 6))
plt.plot(y_test_inv, label='Actual')
plt.plot(test_predict_inv, label='Predicted')
plt.title("Actual vs Predicted Passenger
Count") plt.xlabel("Time") plt.ylabel("Number
of Passengers") plt.legend() plt.grid(True)
plt.show()

# Evaluation rmse = np.sqrt(mean_squared_error(y_test_inv,
test_predict_inv)) mae = mean_absolute_error(y_test_inv,
test_predict_inv) print(f"RMSE: {rmse:.2f}, MAE: {mae:.2f}")
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim`
 argument   super().__init__(**kwargs)
Epoch 1/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 5s 93ms/step - loss: 0.0731 - val_loss: 0.0447
Epoch 2/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 0.0227 - val_loss: 0.0349
Epoch 3/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0129 - val_loss: 0.0645
Epoch 4/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - loss: 0.0116 - val_loss: 0.0285
```

```
Epoch 5/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - loss: 0.0075 - val_loss: 0.0228
Epoch 6/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - loss: 0.0073 - val_loss: 0.0286
Epoch 7/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - loss: 0.0079 - val_loss: 0.0227
Epoch 8/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 0.0070 - val_loss: 0.0237
Epoch 9/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - loss: 0.0080 - val_loss: 0.0235
Epoch 10/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 0.0068 - val_loss: 0.0227
Epoch 11/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 0.0069 - val_loss: 0.0227
Epoch 12/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 0.0076 - val_loss: 0.0226
Epoch 13/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0073 - val_loss: 0.0226
Epoch 14/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - loss: 0.0059 - val_loss: 0.0230
Epoch 15/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 0.0058 - val_loss: 0.0232
Epoch 16/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - loss: 0.0068 - val_loss: 0.0227
Epoch 17/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0068 - val_loss: 0.0236
Epoch 18/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - loss: 0.0066 - val_loss: 0.0225
Epoch 19/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0064 - val_loss: 0.0228
Epoch 20/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0071 - val_loss: 0.0255
Epoch 21/100
Epoch 21/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - loss: 0.0078 - val_loss: 0.0223
Epoch 22/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 0.0073 - val_loss: 0.0243
Epoch 23/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - loss: 0.0063 - val_loss: 0.0229
Epoch 24/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step - loss: 0.0098 - val_loss: 0.0222
Epoch 25/100
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7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0071 - val_loss: 0.0262
Epoch 26/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - loss: 0.0080 - val_loss: 0.0223
Epoch 27/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - loss: 0.0067 - val_loss: 0.0235
Epoch 28/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0058 - val_loss: 0.0224
Epoch 29/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0074 - val_loss: 0.0237
Epoch 30/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0081 - val_loss: 0.0238
Epoch 31/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0068 - val_loss: 0.0221
Epoch 32/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0060 - val_loss: 0.0226
Epoch 33/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0080 - val_loss: 0.0214
Epoch 34/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0054 - val_loss: 0.0211
Epoch 35/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0072 - val_loss: 0.0212
Epoch 36/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0059 - val_loss: 0.0212
Epoch 37/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0057 - val_loss: 0.0210
Epoch 38/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0065 - val_loss: 0.0224
Epoch 39/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0063 - val_loss: 0.0198
Epoch 40/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0073 - val_loss: 0.0193
Epoch 41/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0053 - val_loss: 0.0204
Epoch 42/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0062 - val loss: 0.0178 p
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Epoch 43/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0076 - val_loss: 0.0173
Epoch 44/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - loss: 0.0057 - val_loss: 0.0185
Epoch 45/100
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7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 0.0056 - val_loss: 0.0134
Epoch 46/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0058 - val_loss: 0.0122
Epoch 47/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0039 - val_loss: 0.0091
Epoch 48/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0049 - val_loss: 0.0159
Epoch 49/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0050 - val_loss: 0.0077
Epoch 50/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 0.0042 - val_loss: 0.0113
Epoch 51/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0041 - val_loss: 0.0057
Epoch 52/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0029 - val_loss: 0.0134
Epoch 53/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0029 - val_loss: 0.0081
Epoch 54/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0032 - val_loss: 0.0137
Epoch 55/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0020 - val_loss: 0.0082
Epoch 56/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0033 - val_loss: 0.0069
Epoch 57/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0028 - val_loss: 0.0108
Epoch 58/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0032 - val_loss: 0.0082
Epoch 59/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0026 - val_loss: 0.0138
Epoch 60/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0024 - val_loss: 0.0095
Epoch 61/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0027 - val_loss: 0.0107
Epoch 62/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0027 - val_loss: 0.0107
Epoch 63/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0022 - val_loss: 0.0084
Epoch 64/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0027 - val_loss: 0.0094
Epoch 65/100
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7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0023 - val_loss: 0.0062
Epoch 66/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0027 - val_loss: 0.0119
Epoch 67/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 0.0024 - val_loss: 0.0087
Epoch 68/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0031 - val_loss: 0.0088
Epoch 69/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0026 - val_loss: 0.0150
Epoch 70/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0026 - val_loss: 0.0095
Epoch 71/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0026 - val_loss: 0.0084
Epoch 72/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0020 - val_loss: 0.0118
Epoch 73/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.0031 - val_loss: 0.0151
Epoch 74/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0026 - val_loss: 0.0094
Epoch 75/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0030 - val_loss: 0.0080
Epoch 76/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0025 - val_loss: 0.0078
Epoch 77/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0027 - val_loss: 0.0147
Epoch 78/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0027 - val_loss: 0.0082
Epoch 79/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0024 - val_loss: 0.0151
Epoch 80/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0033 - val_loss: 0.0084
Epoch 81/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0027 - val_loss: 0.0111
Epoch 82/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0029 - val_loss: 0.0121
Epoch 83/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0024 - val_loss: 0.0106
Epoch 84/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0025 - val_loss: 0.0091
Epoch 85/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0027 - val_loss: 0.0090
Epoch 86/100
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7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0023 - val_loss: 0.0078
Epoch 87/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0027 - val_loss: 0.0124
Epoch 88/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0022 - val_loss: 0.0077
Epoch 89/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0031 - val_loss: 0.0094
Epoch 90/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0024 - val_loss: 0.0115
Epoch 91/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0024 - val_loss: 0.0095
Epoch 92/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0022 - val_loss: 0.0101
Epoch 93/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0022 - val_loss: 0.0055
Epoch 94/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 0.0033 - val_loss: 0.0090
Epoch 95/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0022 - val_loss: 0.0086
Epoch 96/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.0021 - val_loss: 0.0080
Epoch 97/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - loss: 0.0024 - val_loss: 0.0072
Epoch 98/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - loss: 0.0023 - val_loss: 0.0053
Epoch 99/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0028 - val_loss: 0.0076
Epoch 100/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0027 - val_loss: 0.0118
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 73ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
```
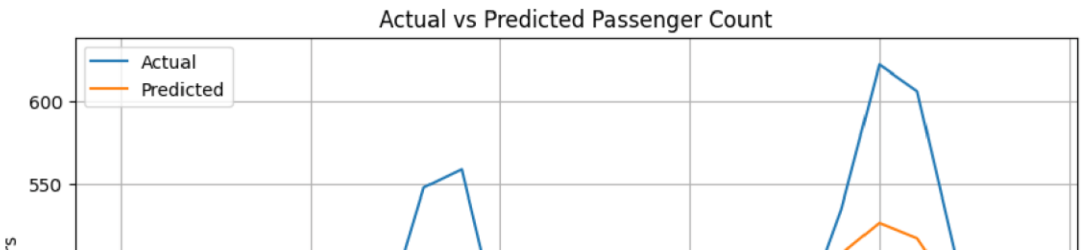
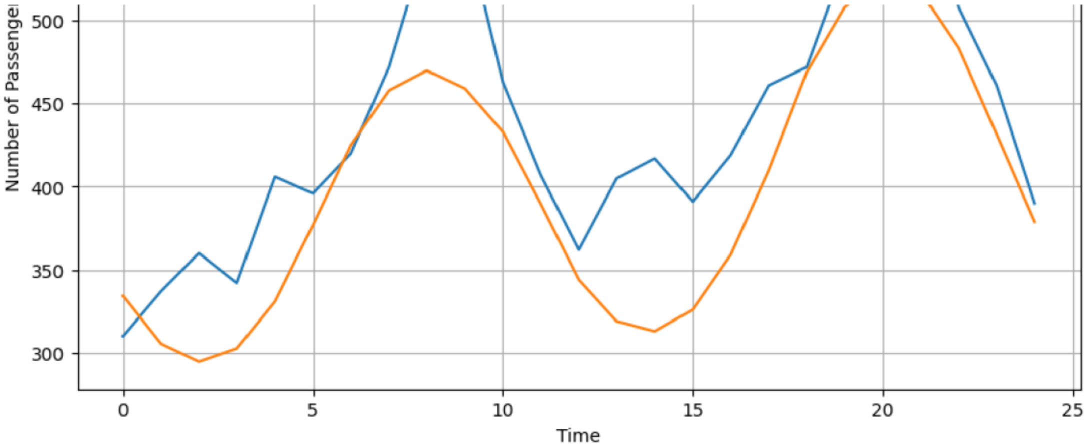






```
RMSE: 56.29, MAE: 46.50
```

? Experiment 5.2: Sequence Text Prediction using LSTM

Objective:

To generate next characters/words based on a given input sequence using LSTM.

Expected Outcome:

Auto-generated text samples

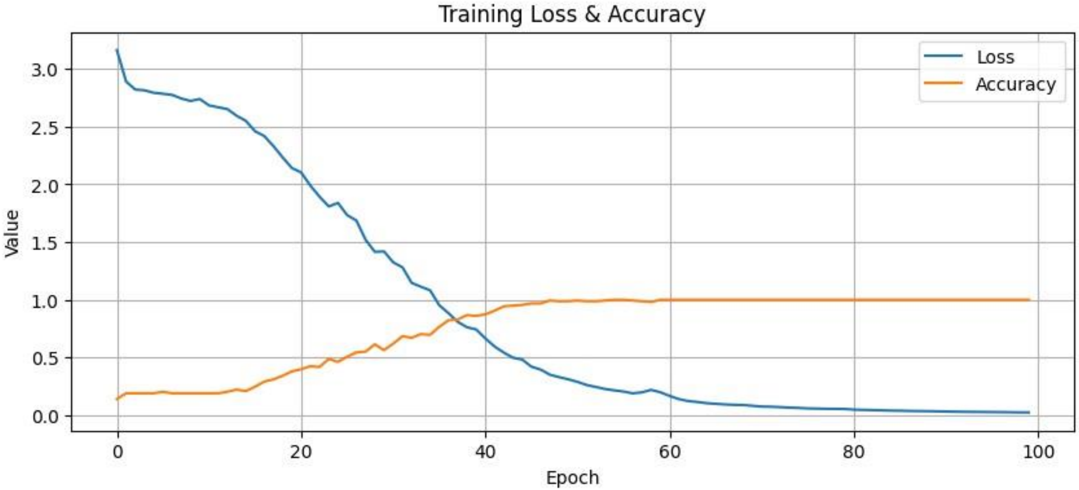
Training accuracy/loss plots

```
import numpy as np import
matplotlib.pyplot as plt from
keras.models import Sequential
from keras.layers import LSTM,
Dense import re

# 1. Load and clean Shakespeare sample text
text = """
To be, or not to be, that is the question:
Whether 'tis nobler in the mind to suffer
The slings and arrows of outrageous fortune,
Or to take arms against a sea of troubles And
by opposing end them. """ text = text.lower()
text = re.sub(r'[^a-zA-Z .,!?\'\"]+', ' ',
text)

# 2. Create character to integer mapping chars =
sorted(list(set(text))) char_to_int = {c: i for i,
c in enumerate(chars)} int_to_char = {i: c for c,
i in char_to_int.items()}

# 3. Create sequences
seq_length = 40
```

```
step = 1
sequences = []
next_chars = []

for i in range(0, len(text) - seq_length, step):
    sequences.append(text[i:i+seq_length])

next_chars.append(text[i + seq_length]) print("Total

sequences:", len(sequences))

# 4. Encode sequences
X = np.zeros((len(sequences), seq_length, len(chars)),
dtype=np.bool_) y = np.zeros((len(sequences), len(chars)),
dtype=np.bool_)

for i, seq in enumerate(sequences):
for t, char in enumerate(seq):
X[i, t, char_to_int[char]] = 1
y[i, char_to_int[next_chars[i]]] = 1

# 5. Build LSTM model model = Sequential() model.add(LSTM(128,

input_shape=(seq_length, len(chars)))) model.add(Dense(len(chars),

activation='softmax')) model.compile(loss='categorical_crossentropy',

optimizer='adam', metrics=['accuracy'])

# 6. Train
history = model.fit(X, y, batch_size=8, epochs=100, verbose=0)

# 7. Plot loss/accuracy plt.figure(figsize=(10, 4))
plt.plot(history.history['loss'], label='Loss')
plt.plot(history.history['accuracy'],
label='Accuracy') plt.title('Training Loss &
Accuracy') plt.xlabel('Epoch') plt.ylabel('Value')
plt.legend() plt.grid(True) plt.show()
```

```
# 8. Text Generation Function def
generate_text(seed_text, length=200):
    generated = seed_text.lower()
for _ in range(length):
        x_pred = np.zeros((1, seq_length, len(chars)), dtype=np.bool_)
for t, char in enumerate(seed_text):
            if char in char_to_int:
                x_pred[0, t, char_to_int[char]] =
1         pred = model.predict(x_pred,
verbose=0)[0]         next_index =
np.argmax(pred)         next_char =
int_to_char[next_index]

        generated += next_char
seed_text = seed_text[1:] + next_char
return generated

# 9. Example text generation seed_text = "to be,
or not to be, that is the que"
print("\nGenerated Text:\n")
print(generate_text(seed_text))
```

```
Total sequences: 158
```




```
Generated Text: to be, or not to be, that is the queon hetthr rioofeer hr   ii  oo ts  a  sss       noon  to uuer  rbbleeeeeeeee

f t t uussse   ss n
```

Experiment 5.3: Sequence Text Classification using LSTM

Objective:

To classify text sequences using LSTM-based models

Expected Outcome:

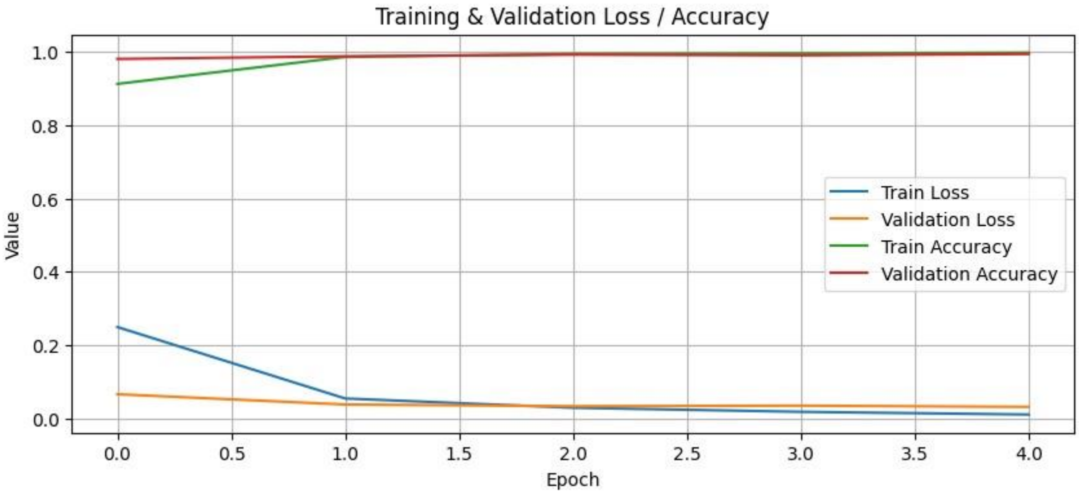
Classification metrics: accuracy, precision, F1-score

Confusion matrix visualization

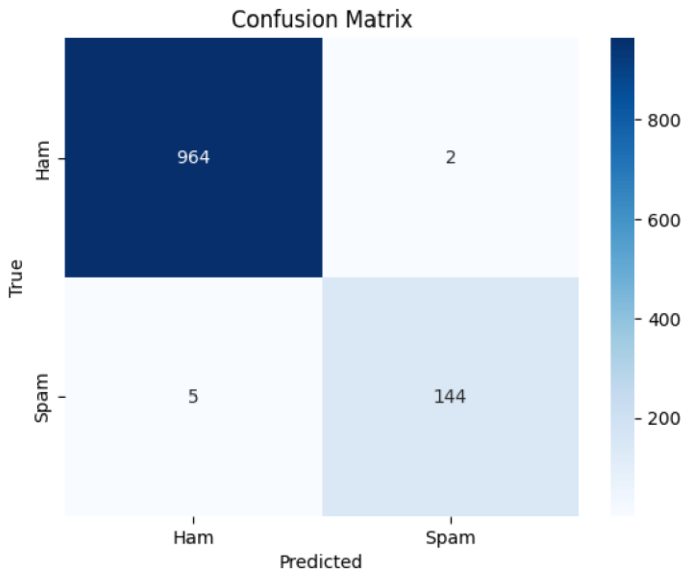
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from tensorflow.keras.models import Sequential from
tensorflow.keras.layers import Embedding, LSTM, Dense, SpatialDropout1D
from tensorflow.keras.preprocessing.text import Tokenizer from
tensorflow.keras.preprocessing.sequence import pad_sequences from
sklearn.model_selection import train_test_split from sklearn.metrics
import classification_report, confusion_matrix

# 1. Load Dataset url =
"https://raw.githubusercontent.com/justmarkham/DAT8/master/data/sms.tsv"

df = pd.read_csv(url, sep='\t', names=["label", "message"])
print("Sample Data:\n", df.head())

# 2. Encode Labels df['label'] =
df['label'].map({'ham': 0, 'spam': 1})

# 3. Text Tokenization and
Padding max_words = 5000 max_len
= 100

tokenizer = Tokenizer(num_words=max_words, lower=True)
tokenizer.fit_on_texts(df['message'].values)
X =

tokenizer.texts_to_sequences(df['message'].values) X

= pad_sequences(X, maxlen=max_len) y =

df['label'].values

# 4. Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# 5. Build LSTM Model model = Sequential() model.add(Embedding(max_words, 128,
input_length=max_len)) model.add(SpatialDropout1D(0.2)) model.add(LSTM(100,
dropout=0.2, recurrent_dropout=0.2)) model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam',
metrics=['accuracy'])

# 6. Train the Model history = model.fit(X_train, y_train, epochs=5, batch_size=64,
validation_data=(X_test, y_test), verbose=1)

# 7. Plot Accuracy and Loss plt.figure(figsize=(10, 4))
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation
Accuracy') plt.title('Training & Validation Loss / Accuracy')
plt.xlabel('Epoch') plt.ylabel('Value') plt.legend() plt.grid(True)
plt.show()

# 8. Evaluate the Model y_pred =
(model.predict(X_test) > 0.5).astype("int32")

# Classification Report print("\nClassification Report:\n")
print(classification_report(y_test, y_pred, target_names=['Ham',
'Spam']))

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred) sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['Ham', 'Spam'], yticklabels=['Ham', 'Spam']) plt.xlabel('Predicted') plt.ylabel('True')
plt.title('Confusion Matrix') plt.show()
```

```
Sample Data:
  label                                            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...
Epoch 1/5
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/embedding.py:90: UserWarning: Argument `input_length` is deprecated.
Just   warnings.warn(
70/70 ━━━━━━━━━━━━━━━━━━━━ 17s 186ms/step - accuracy: 0.8440 - loss: 0.3948 - val_accuracy: 0.9803 - val_loss: 0.0666
Epoch 2/5
70/70 ━━━━━━━━━━━━━━━━━━━━ 19s 164ms/step - accuracy: 0.9857 - loss: 0.0577 - val_accuracy: 0.9874 - val_loss: 0.0386
Epoch 3/5
70/70 ━━━━━━━━━━━━━━━━━━━━ 19s 138ms/step - accuracy: 0.9933 - loss: 0.0266 - val_accuracy: 0.9919 - val_loss: 0.0340
Epoch 4/5
70/70 ━━━━━━━━━━━━━━━━━━━━ 16s 216ms/step - accuracy: 0.9956 - loss: 0.0213 - val_accuracy: 0.9901 - val_loss: 0.0355
Epoch 5/5
70/70 ━━━━━━━━━━━━━━━━━━━━ 18s 182ms/step - accuracy: 0.9977 - loss: 0.0115 - val_accuracy: 0.9937 - val_loss: 0.0321
```




```
35/35 ━━━━━━━━━━━━━━━━━━━━ 1s 27ms/step
Classification Report:

              precision    recall  f1-score   support

         Ham       0.99      1.00      1.00       966
Spam       0.99      0.97      0.98       149

    accuracy                           0.99      1115
macro avg       0.99      0.98      0.99      1115
weighted avg       0.99      0.99      0.99      1115
```



Dataset

Experiment 5.1 - Airline Passengers

Experiment 5.2 - Shakespeare's Text

Experiment 5.3 - SMS Spam Collection Dataset

Declaration

I, Manavi Pawar, confirm that the work submitted in this assignment is my own and has been completed following academic integrity guidelines. The code is uploaded on my GitHub repository account, and the repository link is provided below: Github Link: https://github.com/Manavi05/Deep-Learning/blob/main/Assignment5_DL.ipynb

Signature: Manavi Pawar