Experiment No. 9

Code:

```
[ ]
Start coding or generate with AI.
```

```
[1]
✓ 5s
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
```

```
[3]
✓ 0s
url = 'https://raw.githubusercontent.com/plotly/datasets/master/
monthly-milk-production-pounds.csv'
data = pd.read_csv(url)
# Convert 'Month' to datetime
data['Month'] = pd.to_datetime(data['Month'])
# Plot the data
plt.figure(figsize=(10, 6))
plt.plot(data['Month'], data['Monthly milk production (pounds per cow)'])
plt.title('Monthly Milk Production (1962-1975)')
plt.xlabel('Year')
plt.ylabel('Pounds per Cow')
plt.grid(True)
plt.show()
```

```
[5]
✓ 0s
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(data['Monthly milk production (pounds per
cow)'].values.reshape(-1, 1))

# Prepare Data for LSTM

def create_dataset(dataset, look_back=12):
    X, y = [], []
    for i in range(len(dataset) - look_back):
        X.append(dataset[i:i + look_back, 0])
        y.append(dataset[i + look_back, 0])
    return np.array(X), np.array(y)
look_back = 12
X, y = create_dataset(scaled_data, look_back)
X = X.reshape(X.shape[0], X.shape[1], 1)
```

```
[6]
✓ 0s
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:]
```

```
[7]
✓ 21s
model = Sequential()
model.add(LSTM(50, input_shape=(look_back, 1)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mean_squared_error')
history = model.fit(X_train, y_train, epochs=50, batch_size=1,
validation_data=(X_test, y_test))
```

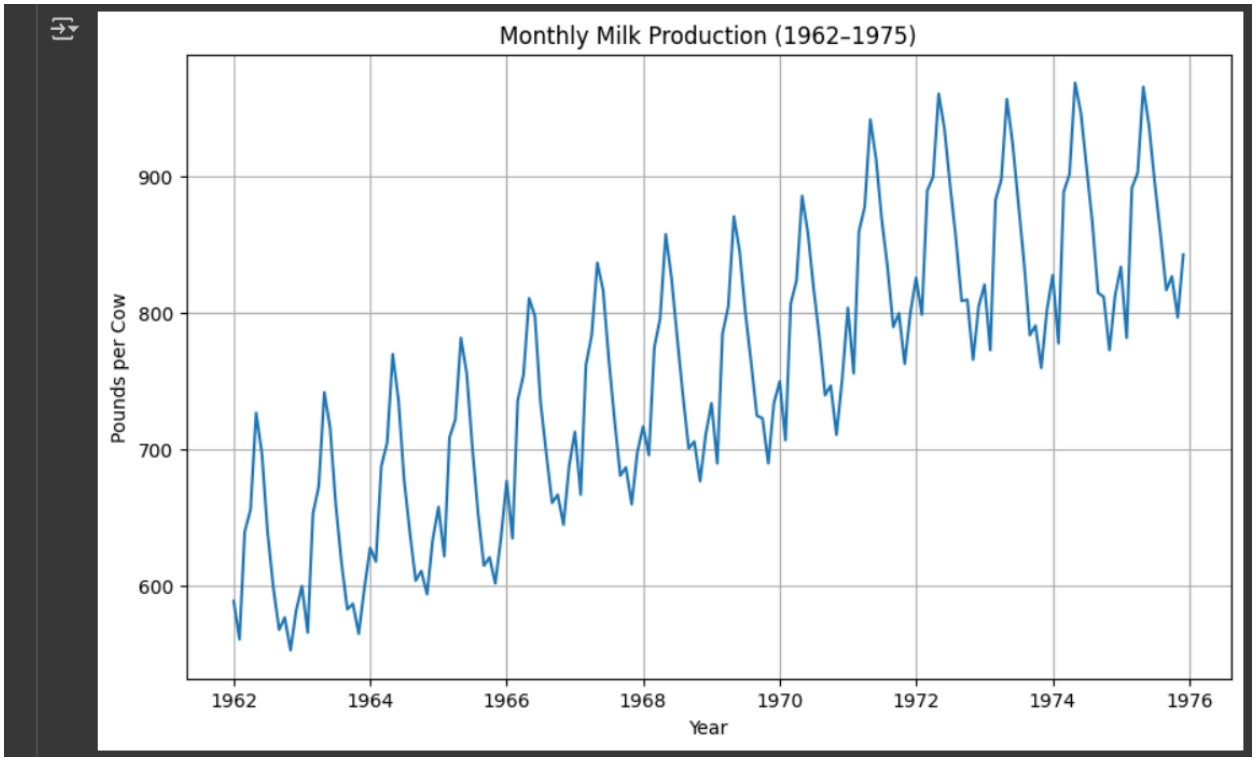
```
[8]
✓ 0s
    train_pred = model.predict(X_train)
    test_pred = model.predict(X_test)

    4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 66ms/step
    1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step

[9]
✓ 0s
    train_pred = scaler.inverse_transform(train_pred)
    y_train_inv = scaler.inverse_transform(y_train.reshape(-1, 1))
    test_pred = scaler.inverse_transform(test_pred)
    y_test_inv = scaler.inverse_transform(y_test.reshape(-1, 1))

[10]
✓ 0s
    plt.figure(figsize=(12, 6))
    plt.plot(data['Month'], data['Monthly milk production (pounds per cow)'],
    label='Original Data')
    plt.plot(data['Month'][look_back:look_back+len(train_pred)], train_pred,
    label='Train Prediction')
    plt.plot(data['Month'][look_back+len(train_pred):], test_pred, label='Test
    Prediction')
    plt.xlabel('Year')
    plt.ylabel('Pounds per Cow')
    plt.title('LSTM Time Series Forecasting')
    plt.legend()
    plt.grid(True)
    plt.show()
```

Output:



Epoch 1/50

/usr/local/lib/python3.12/dist-packages/keras/src/layers/rnn/rnn.py:199: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

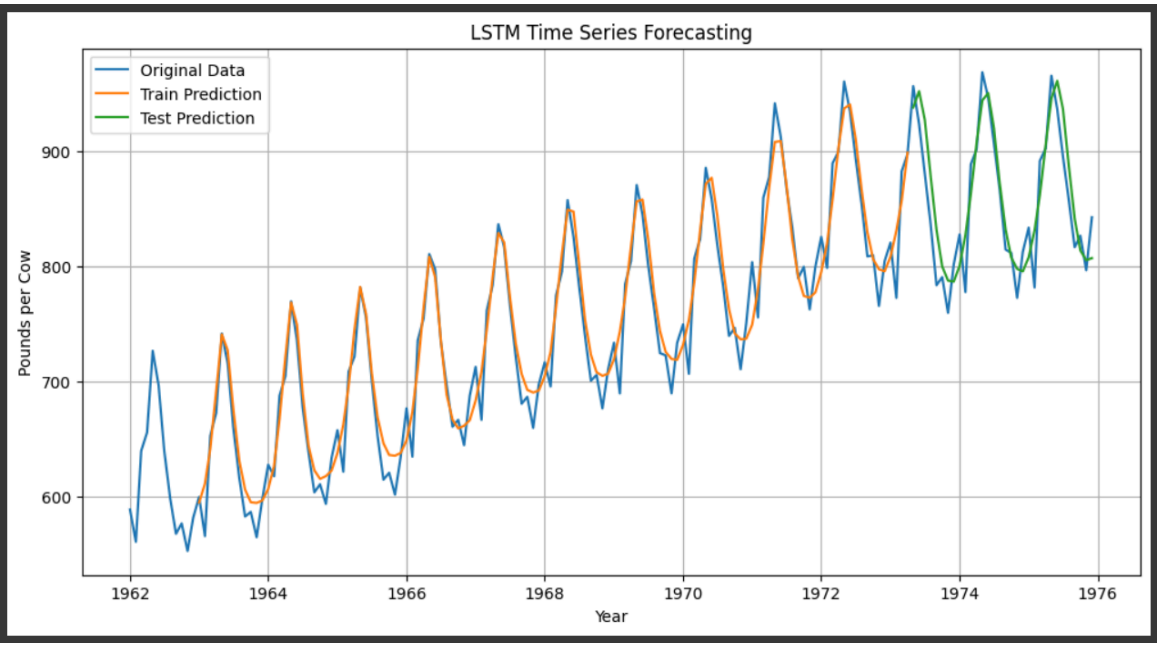
```
  super().__init__(**kwargs)

124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - loss: 0.0750 -
val_loss: 0.0294
Epoch 2/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0335 -
val_loss: 0.0220
Epoch 3/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0223 -
val_loss: 0.0189
Epoch 4/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0170 -
val_loss: 0.0171
Epoch 5/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0127 -
val_loss: 0.0054
Epoch 6/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0087 -
val_loss: 0.0134
Epoch 7/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0069 -
val_loss: 0.0091
Epoch 8/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0043 -
val_loss: 0.0091
Epoch 9/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0040 -
val_loss: 0.0043
Epoch 10/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0052 -
val_loss: 0.0061
Epoch 11/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0049 -
val_loss: 0.0067
Epoch 12/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0037 -
val_loss: 0.0058
Epoch 13/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0038 -
val_loss: 0.0048
```

Epoch 14/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0047 - val_loss: 0.0044
Epoch 15/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0040 - val_loss: 0.0045
Epoch 16/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0035 - val_loss: 0.0100
Epoch 17/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0039 - val_loss: 0.0087
Epoch 18/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0042 - val_loss: 0.0145
Epoch 19/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0045 - val_loss: 0.0056
Epoch 20/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0035 - val_loss: 0.0039
Epoch 21/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0044 - val_loss: 0.0038
Epoch 22/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0037 - val_loss: 0.0042
Epoch 23/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0034 - val_loss: 0.0048
Epoch 24/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0031 - val_loss: 0.0043
Epoch 25/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **1s** 5ms/step - loss: 0.0037 - val_loss: 0.0044
Epoch 26/50
124/124 ━━━━━━━━━━━━━━━━━━━━ **1s** 6ms/step - loss: 0.0030 - val_loss: 0.0058
Epoch 27/50

124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0028 - val_loss: 0.0036
Epoch 28/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0038 - val_loss: 0.0041
Epoch 29/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0030 - val_loss: 0.0036
Epoch 30/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0024 - val_loss: 0.0044
Epoch 31/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0028 - val_loss: 0.0044
Epoch 32/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0025 - val_loss: 0.0102
Epoch 33/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0040 - val_loss: 0.0126
Epoch 34/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0035 - val_loss: 0.0040
Epoch 35/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0031 - val_loss: 0.0050
Epoch 36/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0029 - val_loss: 0.0046
Epoch 37/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0035 - val_loss: 0.0043
Epoch 38/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0038 - val_loss: 0.0038
Epoch 39/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0026 - val_loss: 0.0053
Epoch 40/50

124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0035 - val_loss: 0.0038
Epoch 41/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0028 - val_loss: 0.0073
Epoch 42/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0026 - val_loss: 0.0089
Epoch 43/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0032 - val_loss: 0.0048
Epoch 44/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0031 - val_loss: 0.0042
Epoch 45/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0034 - val_loss: 0.0117
Epoch 46/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0046 - val_loss: 0.0037
Epoch 47/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0037 - val_loss: 0.0040
Epoch 48/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **1s** 3ms/step - loss: 0.0042 - val_loss: 0.0075
Epoch 49/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0026 - val_loss: 0.0048
Epoch 50/50
124/124 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 3ms/step - loss: 0.0035 - val_loss: 0.0044


LSTM Time Series Forecasting
Original Data
Train Prediction
Test Prediction
Pounds per Cow
900
800
700
600
1962
1964
1966
1968
1970
1972
1974
1976
Year