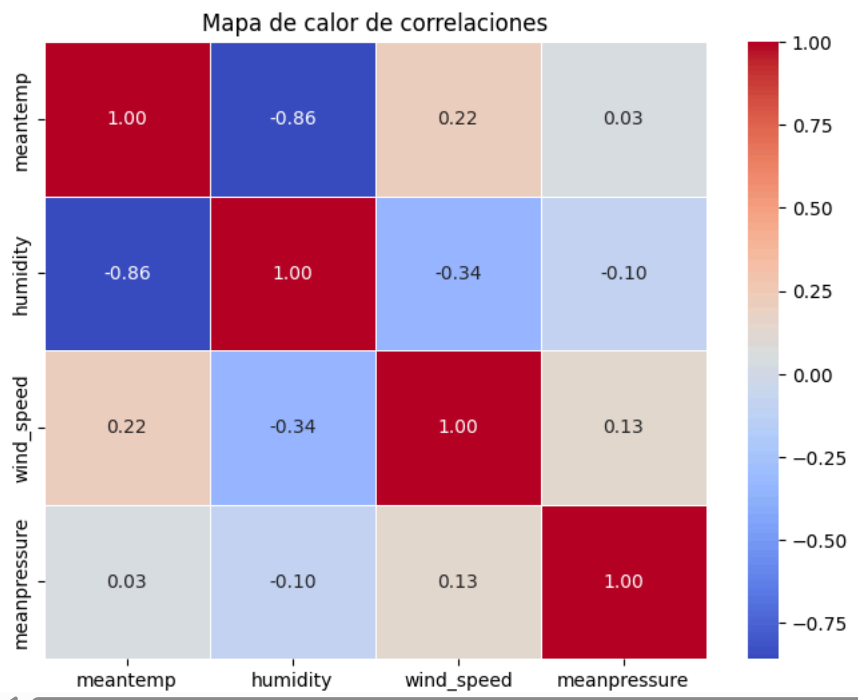
```
# Cargamos librerías
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.impute import SimpleImputer
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
import matplotlib.pyplot as plt


# Cargamos base de datos
df = pd.read_csv('DailyDelhiClimateTest.csv', parse_dates=['date'])
df.set_index('date', inplace=True)


# Seleccionar las columnas que vamos a usar
variables = ['meantemp', 'humidity', 'wind_speed', 'meanpressure']
df = df[variables]


# Mapa de correlación
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

# Calcular la matriz de correlación
corr_matrix = df.corr()

# Crear el heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)

# Título del gráfico
plt.title("Mapa de calor de correlaciones")

# Mostrar el gráfico
plt.show()
```



```
# Limpiar los datos
df.replace(['---', '', ' ', 'NaN'], np.nan, inplace=True)
imputer = SimpleImputer(strategy='mean')
df_imputed = pd.DataFrame(imputer.fit_transform(df), columns=variables, index=df.index)


# Escalar los datos entre 0 y 1
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(df_imputed)
```

```python
# Crear secuencias de tiempo
def create_dataset(dataset, look_back=60):
    X, Y = [], []
    for i in range(len(dataset) - look_back):
        X.append(dataset[i:(i + look_back), :])
        Y.append(dataset[i + look_back, 0])  # Predecimos meantemp
    return np.array(X), np.array(Y)


# División 80% entrenamiento, 20% test
train_size = int(len(scaled_data) * 0.8)  # 91
train_data = scaled_data[:train_size]
test_data = scaled_data[train_size - 60:]


# Crear datasets de entrenamiento y prueba
look_back = 60
X_train, y_train = create_dataset(train_data, look_back)
X_test, y_test = create_dataset(test_data, look_back)


# Modelo LSTM
model = Sequential([
    LSTM(100, input_shape=(X_train.shape[1], X_train.shape[2]), return_sequences=True),
    Dropout(0.2),
    LSTM(100, return_sequences=False),
    Dense(1)
])
model.compile(optimizer='adam', loss='mean_squared_error')
model.summary()
```

```
/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)
Model: "sequential"
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape                ┃         Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━┩
│ lstm (LSTM)                          │ (None, 60, 100)             │          42,000 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ dropout (Dropout)                    │ (None, 60, 100)             │               0 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ lstm_1 (LSTM)                        │ (None, 100)                 │          80,400 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ dense (Dense)                        │ (None, 1)                   │             101 │
└──────────────────────────────────────┴─────────────────────────────┴─────────────────┘
 Total params: 122,501 (478.52 KB)
 Trainable params: 122,501 (478.52 KB)
 Non-trainable params: 0 (0.00 B)
```

```python
# Entrenamiento
model.fit(X_train, y_train, epochs=50, batch_size=16, verbose=1)
```

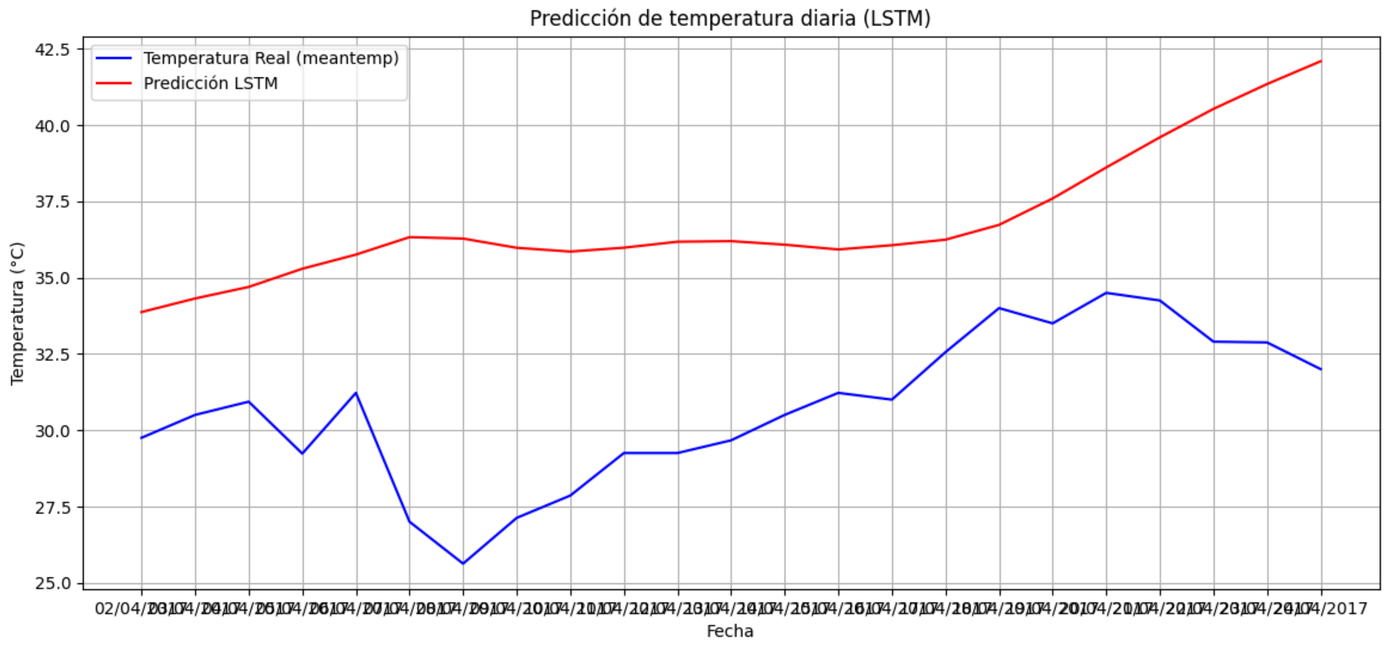
```
2/2                         0s 24ms/step - loss: 0.0130
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 84ms/step - loss: 0.0139
Epoch 37/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 82ms/step - loss: 0.0144
Epoch 38/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 80ms/step - loss: 0.0119
Epoch 39/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 87ms/step - loss: 0.0141
Epoch 40/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 85ms/step - loss: 0.0115
Epoch 41/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 84ms/step - loss: 0.0136
Epoch 42/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 80ms/step - loss: 0.0125
Epoch 43/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 85ms/step - loss: 0.0107
Epoch 44/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 83ms/step - loss: 0.0110
Epoch 45/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 81ms/step - loss: 0.0121
Epoch 46/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 82ms/step - loss: 0.0102
Epoch 47/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 85ms/step - loss: 0.0098
Epoch 48/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 87ms/step - loss: 0.0084
Epoch 49/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 83ms/step - loss: 0.0104
Epoch 50/50
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 81ms/step - loss: 0.0087
<keras.src.callbacks.history.History at 0x7e50dbff3550>
```

```
# Predicciones
predictions_scaled = model.predict(X_test)
```

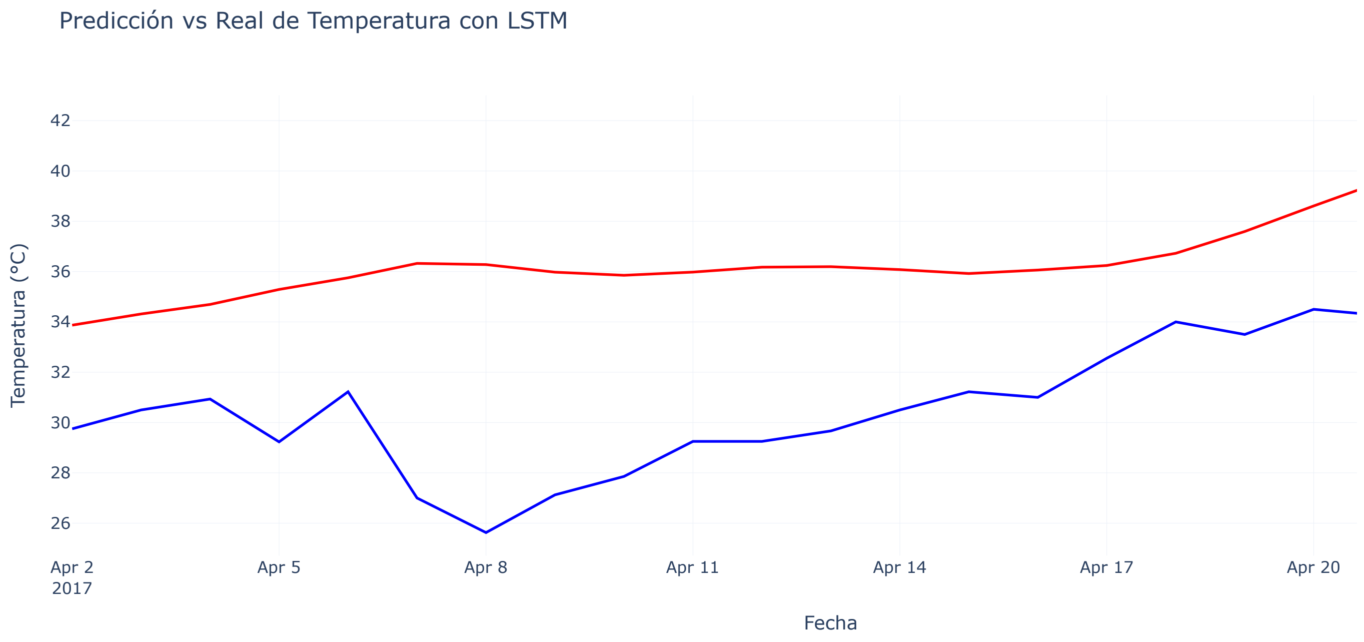
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 349ms/step
```

```
# Invertir escalado para comparar con valores reales
# Rellenamos con ceros las otras columnas para usar inverse_transform correctamente
predicted_full = np.concatenate([predictions_scaled, np.zeros((len(predictions_scaled), 3))], axis=1)
y_test_full = np.concatenate([y_test.reshape(-1, 1), np.zeros((len(y_test), 3))], axis=1)
predictions = scaler.inverse_transform(predicted_full)[:, 0]
real = scaler.inverse_transform(y_test_full)[:, 0]


# Fechas correspondientes a los datos reales
prediction_dates = df_imputed.index[train_size:]


# Gráfico
plt.figure(figsize=(14, 6))
plt.plot(prediction_dates, real, label='Temperatura Real (meantemp)', color='blue')
plt.plot(prediction_dates, predictions, label='Predicción LSTM', color='red')
plt.title('Predicción de temperatura diaria (LSTM)')
plt.xlabel('Fecha')
plt.ylabel('Temperatura (°C)')
plt.legend()
plt.grid(True)
plt.show()
```



```
# Evaluación mensual con R2 y gráfico interactivo con Plotly

import plotly.graph_objects as go
from sklearn.metrics import r2_score

# Asegurar que los índices estén en formato datetime
real_demand.index = pd.to_datetime(real_demand.index, dayfirst=True)
predictions_series.index = pd.to_datetime(predictions_series.index, dayfirst=True)

# Calcular R² mensual
r_squared_monthly = []
for month, group in real_demand.groupby(real_demand.index.month):
    pred_for_month = predictions_series[group.index]
    r_squared = r2_score(group, pred_for_month)
    r_squared_monthly.append((month, r_squared))
    print(f'R² para el mes {month}: {r_squared:.4f}')

# 📍 Gráfico interactivo con Plotly
fig = go.Figure()

fig.add_trace(go.Scatter(x=real_demand.index, y=real_demand,
                         mode='lines', name='Temperatura Real',
                         line=dict(color='blue')))

fig.add_trace(go.Scatter(x=predictions_series.index, y=predictions_series,
                         mode='lines', name='Predicción LSTM',
                         line=dict(color='red')))

fig.update_layout(
    title='Predicción vs Real de Temperatura con LSTM',
    xaxis_title='Fecha',
    yaxis_title='Temperatura (°C)',
    legend_title='Leyenda',
    template='plotly_white'
)

fig.show()

# 🔢 Mostrar los R² mensuales
for month, r_squared in r_squared_monthly:
    print(f"R² para el mes {month}: {r_squared:.4f}")
```

```
R² para el mes 4: -6.5098
```



```
R² para el mes 4: -6.5098
```

El modelo LSTM utilizado para predecir la temperatura no logró ajustarse adecuadamente a los datos reales, como se observa en la discrepancia entre las curvas de predicción y los valores reales, especialmente durante la segunda mitad del mes. La línea de predicción presenta una tendencia creciente más suave y continua, mientras que la temperatura real muestra mayor variabilidad. Esta diferencia sugiere que el modelo no está capturando correctamente los patrones y fluctuaciones de la serie temporal.