Advancing Weather Forecasting: A Comparative Analysis of Long Short-Term Memory and Support Vector Machines

Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import seaborn as sns
from geopy.distance import distance
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf, month_plot, quarter_
from statsmodels.tsa.stattools import adfuller
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.preprocessing import MinMaxScaler
import torch
import torch.nn as nn
import time
from joblib import dump, load
```

Loading the Dataset

In [2]:
```
# Load the dataset
data = pd.read_csv('aggregated_hourly_data.csv')
data = data.dropna()
```

Data Transformation

In [3]:
```
# Calculate decimal degrees for latitude and longitude - even though there are geog
### but for this analysis i have not used geographical points
###though i have calculated some geographical varaiables

data['st_lat'] = data['st_lat'].apply(lambda x: int(str(x)[-2:])/3600 + int(str(x)[
data['st_long'] = data['st_long'].apply(lambda x: (int(str(x)[-2:])/3600 + int(str(
datahead = data.head(5)
datahead
```

Out[3]:

	Unnamed: 0	date	ind	rain	ind.1	temp	ind.2	wetb	dewpt	vappr	...	sun	vis
370509	370509	2007-12-31 02:00:00	2	0.0	0	9.6	0	8.8	8.0	10.7	...	0.0	20000.0
370510	370510	2007-12-31 03:00:00	0	0.0	0	9.7	0	8.8	7.9	10.6	...	0.0	20000.0
370511	370511	2007-12-31 04:00:00	0	0.0	0	9.9	0	8.8	7.6	10.4	...	0.0	20000.0
370512	370512	2007-12-31 05:00:00	0	0.0	0	10.4	0	9.3	8.2	10.8	...	0.0	20000.0
370513	370513	2007-12-31 06:00:00	0	0.0	0	10.6	0	9.7	8.7	11.3	...	0.0	20000.0

5 rows × 28 columns

In [4]:

```
data.drop(columns=['Unnamed: 0'], inplace=True)
data.info()
datahead = data.head(100)
# rename columns
data.rename(columns = {'ind': 'i_rain', 'ind.1': 'i_temp', 'ind.2': 'i_wetb',
                                  'ind.3': 'i_wdsp', 'ind.4': 'i_wddir'}, inplace =
print('Column names: ', data.columns)
# Are all datetime values unique?
print('Unique timestamps: ', data.date.nunique())
print('All timestamps: ', data.shape[0])
# Set timestamp as an index
data.set_index('date', inplace = True)
data.head()
# Convert index to datetime objects
data.index = pd.to_datetime(data.index)
# Check for missing hours in index
print('Unique Timestamps in our data: ', data.index.nunique())
print('Total range: ', (data.index.max() - data.index.min()) / pd.Timedelta('1 hour
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 662345 entries, 370509 to 2962034
Data columns (total 27 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   date       662345 non-null  object 
 1   ind        662345 non-null  int64  
 2   rain       662345 non-null  float64
 3   ind.1      662345 non-null  int64  
 4   temp       662345 non-null  float64
 5   ind.2      662345 non-null  int64  
 6   wetb       662345 non-null  float64
 7   dewpt      662345 non-null  float64
 8   vappr      662345 non-null  float64
 9   rhum       662345 non-null  float64
 10  msl        662345 non-null  float64
 11  ind.3      662345 non-null  float64
 12  wdsp       662345 non-null  float64
 13  ind.4      662345 non-null  float64
 14  wddir      662345 non-null  float64
 15  ww         662345 non-null  float64
 16  w          662345 non-null  float64
 17  sun        662345 non-null  float64
 18  vis        662345 non-null  float64
 19  clht       662345 non-null  float64
 20  clamt      662345 non-null  float64
 21  county     662345 non-null  object 
 22  st_id      662345 non-null  int64  
 23  st_name    662345 non-null  object 
 24  st_height  662345 non-null  int64  
 25  st_lat     662345 non-null  float64
 26  st_long    662345 non-null  float64
dtypes: float64(19), int64(5), object(3)
memory usage: 141.5+ MB
Column names:  Index(['date', 'i_rain', 'rain', 'i_temp', 'temp', 'i_wetb', 'wet
b', 'dewpt',
       'vappr', 'rhum', 'msl', 'i_wdsp', 'wdsp', 'i_wddir', 'wddir', 'ww', 'w',
       'sun', 'vis', 'clht', 'clamt', 'county', 'st_id', 'st_name',
       'st_height', 'st_lat', 'st_long'],
      dtype='object')
Unique timestamps:  123503
All timestamps:  662345
Unique Timestamps in our data:  123503
Total range:  123502.0
```

Removing Nulls

In [5]:

```
# count NAs
data.isnull().sum()
# look at rows with NAs
data[data.isna().any(axis=1)]
# fill NAs by interpolating (default method = 'linear')
data.interpolate(inplace = True)
# make sure all NAs are filled
data.isnull().sum()
# drop indicators
data.drop(columns = ['i_rain', 'i_temp', 'i_wetb', 'i_wdsp', 'i_wddir'], inplace =
# count unique values in each column
data.nunique()
```

```
C:\Users\Syed Muhammad Mohsin\AppData\Local\Temp\ipykernel_25792\1707903422.py:6:
FutureWarning: DataFrame.interpolate with object dtype is deprecated and will rais
e in a future version. Call obj.infer_objects(copy=False) before interpolating ins
tead.
  data.interpolate(inplace = True)
```

Out[5]:

```
rain         153
temp         426
wetb         342
dewpt        327
vappr        210
rhum          80
msl          978
wdsp          53
wddir         37
ww            74
w             71
sun           11
vis           87
clht         157
clamt         10
county         6
st_id          8
st_name        8
st_height      8
st_lat         8
st_long        8
dtype: int64
```

EXPLORATORY DATA ANALYSIS

In [6]:

```
# look at statistics
Datadesc = data.describe().T
#Datadesc.to_excel('datadesc.xlsx')
Datadesc
```

Out[6]:

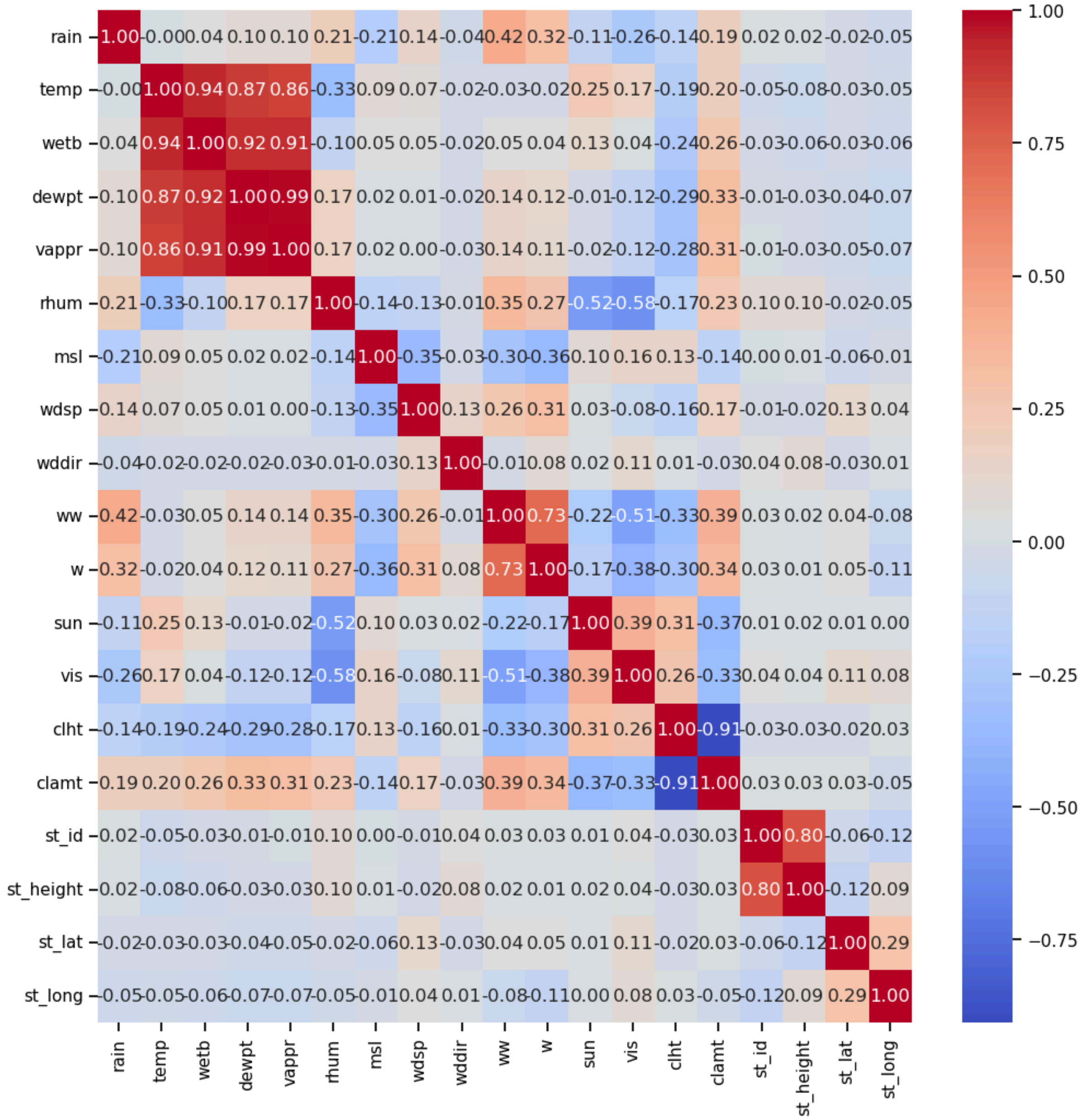
	count	mean	std	min	25%	50%	7
rain	662345.0	0.124380	0.497221	0.000000	0.000000	0.000000	0.000
temp	662345.0	9.922873	4.830016	-15.400000	6.600000	10.000000	13.400
wetb	662345.0	8.596542	4.525487	-49.900000	5.500000	8.900000	11.900
dewpt	662345.0	7.185166	4.513444	-16.400000	3.900000	7.400000	10.600
vappr	662345.0	10.570086	3.175379	1.700000	8.100000	10.300000	12.800
rhum	662345.0	84.142935	12.114841	20.000000	77.000000	87.000000	94.000
msl	662345.0	1013.246276	12.529400	948.200000	1005.500000	1014.400000	1021.900
wdsp	662345.0	9.918461	5.575393	0.000000	6.000000	9.000000	13.000
wddir	662345.0	200.974477	84.909557	0.000000	140.000000	220.000000	260.000
ww	662345.0	17.189089	23.643263	0.000000	2.000000	2.000000	25.000
w	662345.0	33.520283	28.703269	0.000000	11.000000	11.000000	62.000
sun	662345.0	0.167173	0.324983	0.000000	0.000000	0.000000	0.100
vis	662345.0	26918.633144	15137.275498	5.000000	17000.000000	25000.000000	40000.000
clht	662345.0	270.422165	401.669618	0.000000	20.000000	41.000000	250.000
clamt	662345.0	5.746390	2.323820	0.000000	4.000000	7.000000	7.000
st_id	662345.0	2477.993177	1668.160880	518.000000	532.000000	2375.000000	3904.000
st_height	662345.0	86.559600	63.482789	9.000000	20.000000	71.000000	155.000
st_lat	662345.0	53.042253	0.842819	51.847222	52.690278	53.305556	53.427
st_long	662345.0	-7.964170	1.358236	-10.240833	-8.918056	-8.486111	-6.438

Correlation Matrix

In [7]:

```
# Select only numeric columns for correlation analysis - excluding geographical dat
numeric_data = data.select_dtypes(include='number')
corr_matrix = numeric_data.corr()

# Look at correlations between weather variables recorded from Dublin Airport stati
sns.set_context('notebook', font_scale=1)
fig, ax = plt.subplots(figsize=(12, 12))
sns.heatmap(data=numeric_data.corr(), annot=True, fmt='.2f', cmap='coolwarm', ax=ax
plt.show()
```



Distribution of Variables - Transforming Data Weekly

In [8]:
```
# making the weekly aggregated data-
## creating aggregated weekly data to analyse the temporal trends and patterns
### making it more effective than using raw data as an input

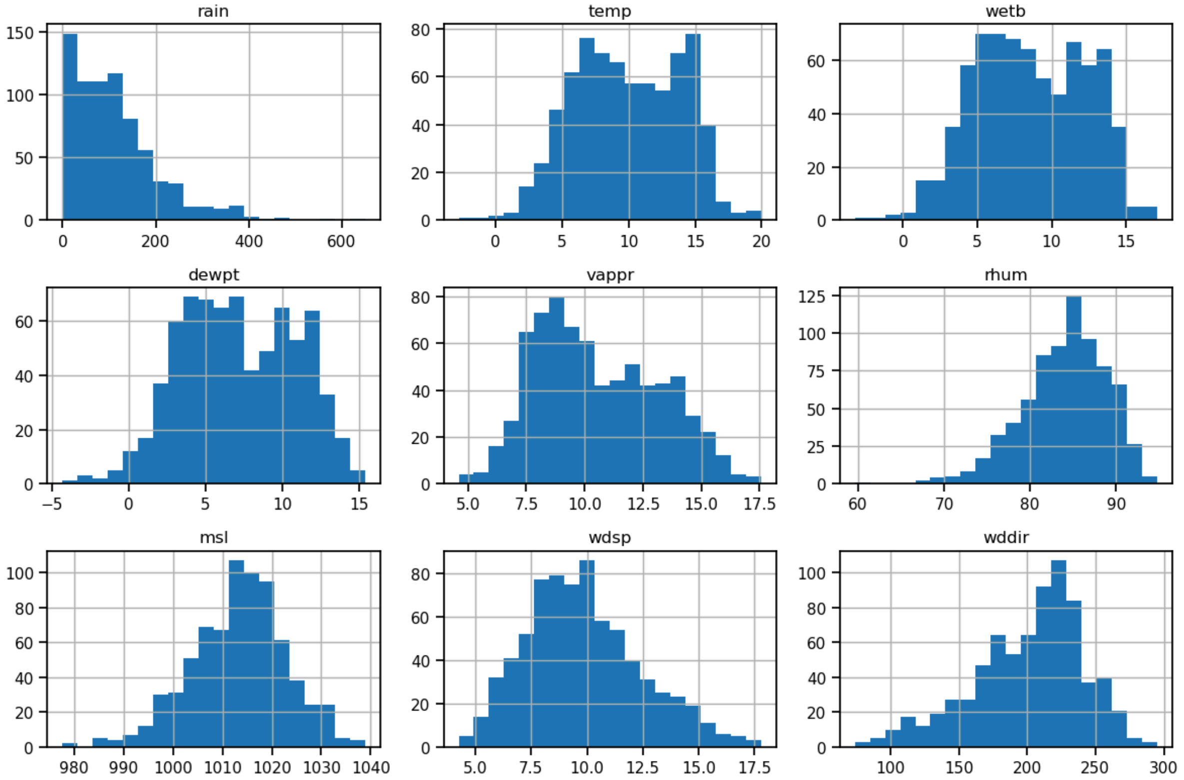
rainfall_weekly = data[['rain']].resample('W').sum()
all_weekly = data[['temp', 'wetb', 'dewpt', 'vappr',
                   'rhum', 'msl', 'wdsp', 'wddir']].resample('W').mean()
weekly_da = pd.concat([rainfall_weekly, all_weekly], axis = 1)
weekly_da.isna().sum()




# visualize distribution of values for each variable with histogram
fig, axList = plt.subplots(3, 3, sharex=False, sharey=False)
axList = axList.flatten()
fig.set_size_inches(12, 8)
for i,ax in enumerate(axList[0:len(weekly_da.columns)]):
    weekly_da.hist(column = weekly_da.columns[i], bins = 20, ax=ax)
```

```
fig.tight_layout()
fig.show()
```

```
C:\Users\Syed Muhammad Mohsin\AppData\Local\Temp\ipykernel_25792\2327037471.py:22:
UserWarning: Matplotlib is currently using module://matplotlib_inline.backend_inli
ne, which is a non-GUI backend, so cannot show the figure.
  fig.show()
```



MODELLING

LSTM VS SVM

LONG-SHORT TERM MEMORY - RAINFALL FORECASTING

In [9]:
```
# Extract rainfall data - from the weekly data aggregated data created earlier
rainfall_data = weekly_da['rain'].values.astype(float)
# Normalize data - min max scaler
scaler = MinMaxScaler(feature_range=(-1, 1))
rainfall_data_normalized = scaler.fit_transform(rainfall_data.reshape(-1, 1))
# Convert data to PyTorch tensors
rainfall_tensor = torch.FloatTensor(rainfall_data_normalized).view(-1)
def create_sequences(data, seq_length):
    xs = []
    ys = []
    for i in range(len(data) - seq_length):
        x = data[i:i+seq_length]
        y = data[i+seq_length:i+seq_length+1]
        xs.append(x)
        ys.append(y)
    return torch.stack(xs), torch.stack(ys)

# Define sequence length
seq_length = 5
# Create sequences
xs, ys = create_sequences(rainfall_tensor, seq_length)
```

```
# Split data into training and testing sets
train_size = int(len(xs) * 0.8)
test_size = len(xs) - train_size
train_X, test_X = xs[:train_size], xs[train_size:]
train_y, test_y = ys[:train_size], ys[train_size:]

# Define LSTM model
class LSTM(nn.Module):
    def __init__(self, input_size=1, hidden_layer_size=100, output_size=1):
        super().__init__()
        self.hidden_layer_size = hidden_layer_size
        self.lstm = nn.LSTM(input_size, hidden_layer_size)
        self.linear = nn.Linear(hidden_layer_size, output_size)
        self.hidden_cell = (torch.zeros(1,1,self.hidden_layer_size),
                            torch.zeros(1,1,self.hidden_layer_size))

    def forward(self, input_seq):
        lstm_out, self.hidden_cell = self.lstm(input_seq.view(len(input_seq) ,1, -1
        predictions = self.linear(lstm_out.view(len(input_seq), -1))
        return predictions[-1]

# Hyperparameters for tuning - could have used more hidden layers but computational
learning_rates = [0.001, 0.01]
hidden_layer_sizes = [10, 50]

# Record validation losses and MSEs and Record training times
validation_losses = []
mse_values = []
training_times_rain_lstm = []

# Train models with different hyperparameters
for lr in learning_rates:
    for hidden_size in hidden_layer_sizes:
        start_time = time.time() # started time for collecting training times
        # Instantiate the model, define loss function and optimizer
        model = LSTM(hidden_layer_size=hidden_size)
        loss_function = nn.MSELoss()
        optimizer = torch.optim.Adam(model.parameters(), lr=lr)

        # Train the model with epochs set to 50
        epochs = 50
        train_losses = []
        val_losses = []

        for i in range(epochs):
            model.train()
            epoch_train_loss = 0
            # Record start time
            start_time = time.time()
            for seq, labels in zip(train_X, train_y):
                optimizer.zero_grad()
                model.hidden_cell = (torch.zeros(1, 1, model.hidden_layer_size),
                                torch.zeros(1, 1, model.hidden_layer_size))

                y_pred = model(seq)

                single_loss = loss_function(y_pred, labels)
                epoch_train_loss += single_loss.item()
                single_loss.backward()
                optimizer.step()

            # Calculate epoch training time and appending epoch training time to th
            epoch_time = time.time() - start_time
```

```
            training_times_rain_lstm.append(epoch_time)
            train_losses.append(epoch_train_loss / len(train_X))

            model.eval()
            epoch_val_loss = 0
            with torch.no_grad():
                for seq, labels in zip(test_X, test_y):
                    model.hidden_cell = (torch.zeros(1, 1, model.hidden_layer_size)
                                        torch.zeros(1, 1, model.hidden_layer_size))

                    y_pred = model(seq)
                    val_loss = loss_function(y_pred, labels)
                    epoch_val_loss += val_loss.item()

                # Record validation loss
                val_losses.append(epoch_val_loss / len(test_X))

            if i % 10 == 1:
                print(f'lr: {lr}, hidden_size: {hidden_size}, epoch: {i:3} train_lo

        validation_losses.append(val_losses)

        # Make predictions using the trained model lstm-rainfall
        model.eval()
        test_predictions = []
        for seq in test_X:
            with torch.no_grad():
                model.hidden = (torch.zeros(1, 1, model.hidden_layer_size),
                                torch.zeros(1, 1, model.hidden_layer_size))
                test_predictions.append(model(seq).item())

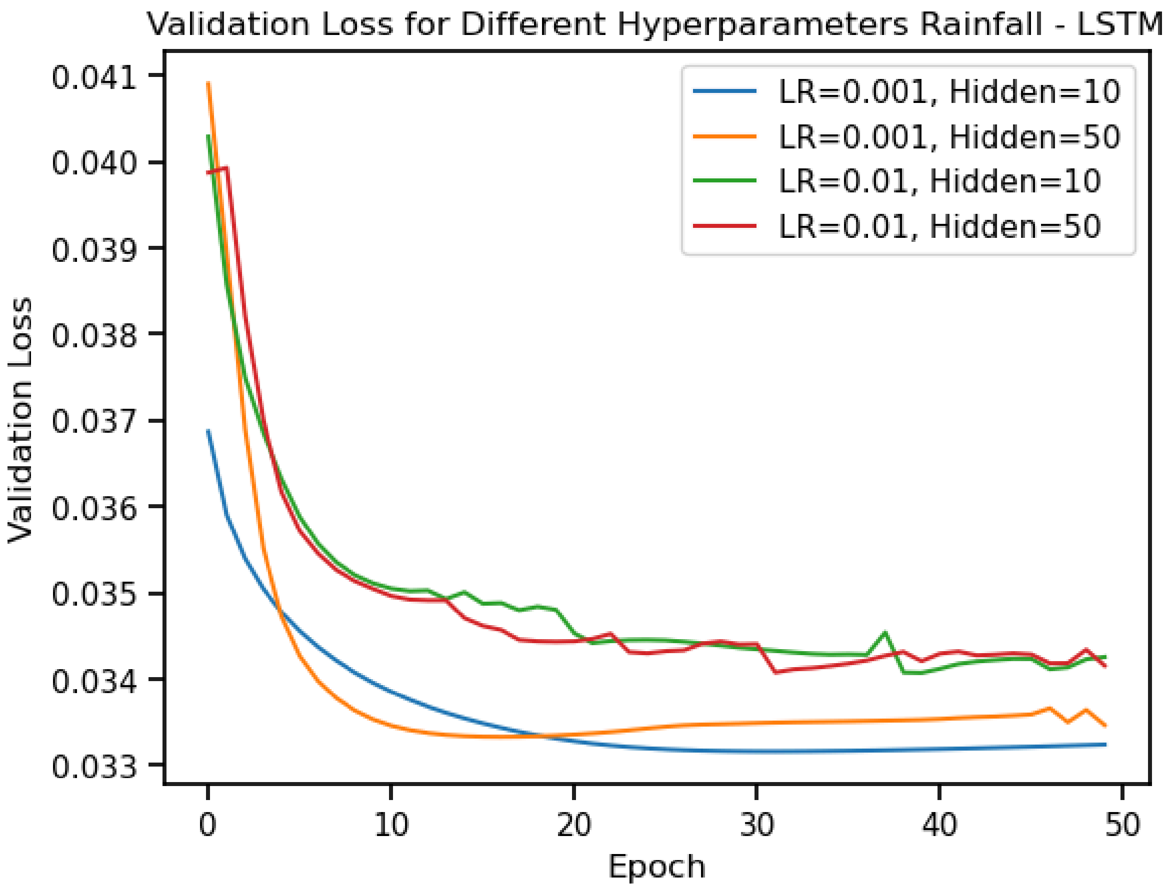
        # Inverse transform the predictions
        test_predictions = scaler.inverse_transform(np.array(test_predictions).resh
        # Calculate MSE for rainfall
        mse_rainfall = ((scaler.inverse_transform(test_y.reshape(-1, 1)) - test_pre
        mse_values.append({
            'lr': lr,
            'hidden_size': hidden_size,
            'mse_rainfall': mse_rainfall
        })

# Plot validation loss graphs for each set of hyperparameters
for idx, (lr, hidden_size) in enumerate([(lr, hidden_size) for lr in learning_rates
    plt.plot(validation_losses[idx], label=f'LR={lr}, Hidden={hidden_size}')

plt.xlabel('Epoch')
plt.ylabel('Validation Loss')
plt.title('Validation Loss for Different Hyperparameters Rainfall - LSTM')
plt.legend()
plt.show()

# Convert MSE values to DataFrame
mse_df_rain_lstm = pd.DataFrame(mse_values)
# Display the MSE values table
print("MSE Values Rainfall:")
print(mse_df_rain_lstm)
```

```
lr: 0.001, hidden_size: 10, epoch:   1 train_loss_rainfall: 0.07602387 val_loss_ra
infall: 0.03590120 epoch_time: 1.25 seconds
lr: 0.001, hidden_size: 10, epoch:  11 train_loss_rainfall: 0.07180347 val_loss_ra
infall: 0.03375670 epoch_time: 1.15 seconds
lr: 0.001, hidden_size: 10, epoch:  21 train_loss_rainfall: 0.07109370 val_loss_ra
infall: 0.03324873 epoch_time: 1.23 seconds
lr: 0.001, hidden_size: 10, epoch:  31 train_loss_rainfall: 0.07083794 val_loss_ra
infall: 0.03315763 epoch_time: 1.20 seconds
lr: 0.001, hidden_size: 10, epoch:  41 train_loss_rainfall: 0.07064841 val_loss_ra
infall: 0.03318968 epoch_time: 1.27 seconds
lr: 0.001, hidden_size: 50, epoch:   1 train_loss_rainfall: 0.07680452 val_loss_ra
infall: 0.03893052 epoch_time: 1.51 seconds
lr: 0.001, hidden_size: 50, epoch:  11 train_loss_rainfall: 0.07139355 val_loss_ra
infall: 0.03340363 epoch_time: 1.43 seconds
lr: 0.001, hidden_size: 50, epoch:  21 train_loss_rainfall: 0.07077269 val_loss_ra
infall: 0.03336529 epoch_time: 1.46 seconds
lr: 0.001, hidden_size: 50, epoch:  31 train_loss_rainfall: 0.06968960 val_loss_ra
infall: 0.03349022 epoch_time: 1.56 seconds
lr: 0.001, hidden_size: 50, epoch:  41 train_loss_rainfall: 0.06886658 val_loss_ra
infall: 0.03354351 epoch_time: 1.47 seconds
lr: 0.01, hidden_size: 10, epoch:   1 train_loss_rainfall: 0.07623863 val_loss_rai
nfall: 0.03857206 epoch_time: 1.15 seconds
lr: 0.01, hidden_size: 10, epoch:  11 train_loss_rainfall: 0.07295657 val_loss_rai
nfall: 0.03501853 epoch_time: 1.15 seconds
lr: 0.01, hidden_size: 10, epoch:  21 train_loss_rainfall: 0.07237298 val_loss_rai
nfall: 0.03441368 epoch_time: 1.14 seconds
lr: 0.01, hidden_size: 10, epoch:  31 train_loss_rainfall: 0.07149480 val_loss_rai
nfall: 0.03432428 epoch_time: 1.13 seconds
lr: 0.01, hidden_size: 10, epoch:  41 train_loss_rainfall: 0.07100196 val_loss_rai
nfall: 0.03417190 epoch_time: 1.11 seconds
lr: 0.01, hidden_size: 50, epoch:   1 train_loss_rainfall: 0.07754331 val_loss_rai
nfall: 0.03993025 epoch_time: 1.49 seconds
lr: 0.01, hidden_size: 50, epoch:  11 train_loss_rainfall: 0.07268040 val_loss_rai
nfall: 0.03492030 epoch_time: 1.41 seconds
lr: 0.01, hidden_size: 50, epoch:  21 train_loss_rainfall: 0.07207873 val_loss_rai
nfall: 0.03446159 epoch_time: 1.54 seconds
lr: 0.01, hidden_size: 50, epoch:  31 train_loss_rainfall: 0.07323821 val_loss_rai
nfall: 0.03407450 epoch_time: 1.48 seconds
lr: 0.01, hidden_size: 50, epoch:  41 train_loss_rainfall: 0.06852092 val_loss_rai
nfall: 0.03431610 epoch_time: 1.43 seconds
```




```
MSE Values Rainfall:
      lr  hidden_size  mse_rainfall
0  0.001           10   3550.368425
1  0.001           50   3533.907725
2  0.010           10   4174.129595
3  0.010           50   3958.486429
```

Creating a df to save model losses (train and validation) for comparison

In [10]:

```
# Create a DataFrame for hyperparameters, validation losses, and training times for
lstm_data = []
for lr in learning_rates:
    for hidden_size in hidden_layer_sizes:
        idx = learning_rates.index(lr) * len(hidden_layer_sizes) + hidden_layer_siz
        lstm_data.append({
            'Learning Rate': lr,
            'Hidden Size': hidden_size,
            'Validation Loss': validation_losses[idx][-1],  # Get the last validati
            'Training Time': training_times_rain_lstm[idx]  # Get the training time
        })

# Convert the LSTM data to a DataFrame
df_hyperparameters_lstm_rain = pd.DataFrame(lstm_data)

# Display the DataFrame
print(df_hyperparameters_lstm_rain)
```

```
   Learning Rate  Hidden Size  Validation Loss  Training Time
0          0.001           10         0.033237       1.090688
1          0.001           50         0.033461       1.254242
2          0.010           10         0.034252       1.224217
3          0.010           50         0.034153       1.120978
```

In [11]:
```
#This line of code is generated to draw the hyperparameter comparison (using a df t
#df_hyperparameters_lstm_rain.to_excel('df_hyperparameters_lstm_rain.xlsx')
```

Best LSTM Model Trained with best hyperparameters - Rainfall

In [12]:
```
# Find the index of the minimum validation loss
best_index = np.unravel_index(np.argmin(validation_losses), np.array(validation_los
best_lr_index = best_index[0] // len(hidden_layer_sizes)
best_hidden_size_index = best_index[0] % len(hidden_layer_sizes)
best_lr = learning_rates[best_lr_index]
best_hidden_size = hidden_layer_sizes[best_hidden_size_index]

# Instantiate the best model with the best hyperparameters
best_model_lstm_rainfall = LSTM(hidden_layer_size=best_hidden_size)
loss_function = nn.MSELoss()
optimizer = torch.optim.Adam(best_model_lstm_rainfall.parameters(), lr=best_lr)

# Train the best model
## Train the best model lstm rainfall over best set of hyperparameters deduced earl
epochs = 100
best_train_losses = []
best_val_losses = []

for i in range(epochs):
    best_model_lstm_rainfall.train()
    epoch_train_loss = 0
    for seq, labels in zip(train_X, train_y):
        optimizer.zero_grad()
        best_model_lstm_rainfall.hidden_cell = (torch.zeros(1, 1, best_model_lstm_r
                        torch.zeros(1, 1, best_model_lstm_rainfall.hidden_layer_siz

        y_pred = best_model_lstm_rainfall(seq)

        single_loss = loss_function(y_pred, labels)
        epoch_train_loss += single_loss.item()
        single_loss.backward()
        optimizer.step()

    best_train_losses.append(epoch_train_loss / len(train_X))

    best_model_lstm_rainfall.eval()
    epoch_val_loss = 0
    with torch.no_grad():
        for seq, labels in zip(test_X, test_y):
            best_model_lstm_rainfall.hidden_cell = (torch.zeros(1, 1, best_model_ls
                            torch.zeros(1, 1, best_model_lstm_rainfall.hidden_layer

            y_pred = best_model_lstm_rainfall(seq)
            val_loss = loss_function(y_pred, labels)
            epoch_val_loss += val_loss.item()

        # Record validation loss
        best_val_losses.append(epoch_val_loss / len(test_X))

    if i % 25 == 1:
        print(f'Best model: lr={best_lr}, hidden_size={best_hidden_size}, epoch: {i

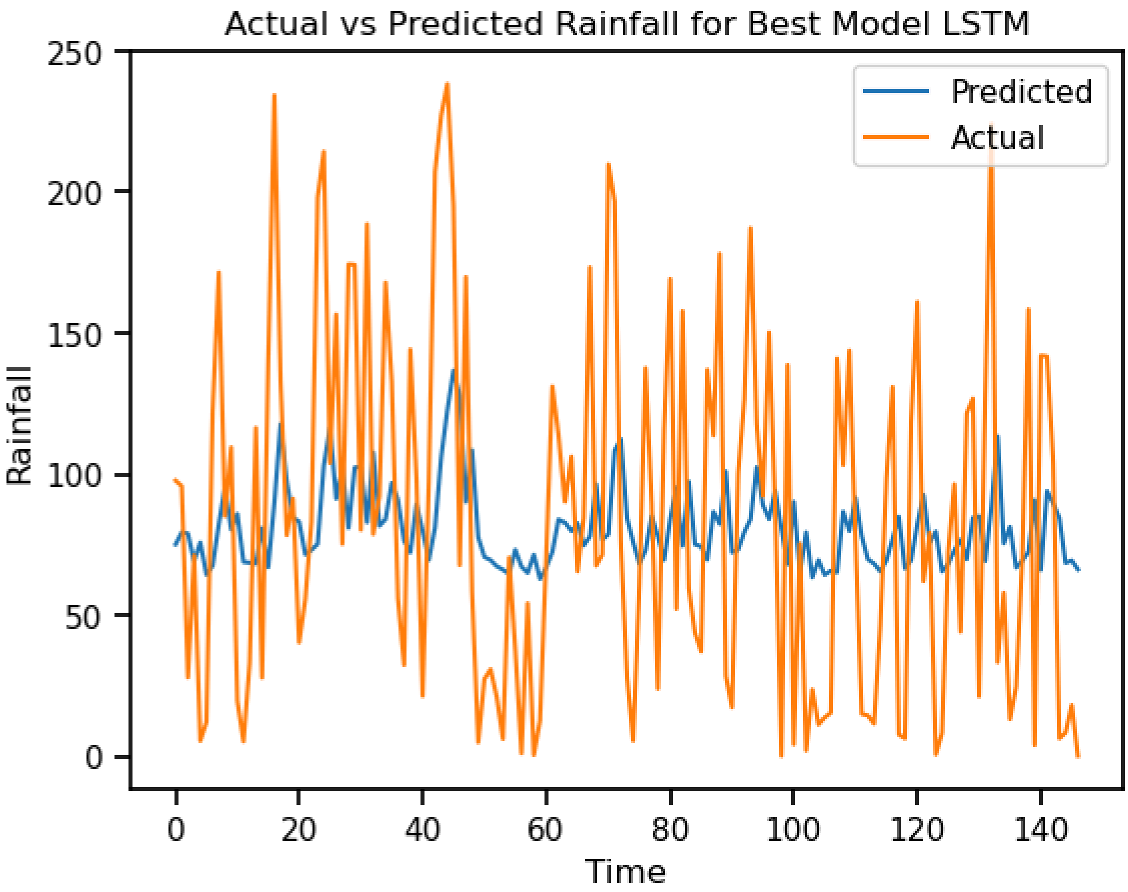
# Make predictions using the best model
best_model_lstm_rainfall.eval()
best_test_predictions_rain_lstm = []
for seq in test_X:
    with torch.no_grad():
```

```
        best_model_lstm_rainfall.hidden = (torch.zeros(1, 1, best_model_lstm_rainfa
                        torch.zeros(1, 1, best_model_lstm_rainfall.hidden_layer_siz
        best_test_predictions_rain_lstm.append(best_model_lstm_rainfall(seq).item()

# Inverse transform the predictions
best_test_predictions_rain_lstm = scaler.inverse_transform(np.array(best_test_predi

# Plot actual vs predicted for the best model
plt.plot(best_test_predictions_rain_lstm, label='Predicted')
plt.plot(scaler.inverse_transform(test_y.reshape(-1, 1)), label='Actual')
plt.xlabel('Time')
plt.ylabel('Rainfall')
plt.title('Actual vs Predicted Rainfall for Best Model LSTM')
plt.legend()
plt.show()
```

```
Best model: lr=0.001, hidden_size=10, epoch:   1 train_loss_rainfall: 0.07630340 v
al_loss_rainfall: 0.03624599
Best model: lr=0.001, hidden_size=10, epoch:  26 train_loss_rainfall: 0.07075860 v
al_loss_rainfall: 0.03347538
Best model: lr=0.001, hidden_size=10, epoch:  51 train_loss_rainfall: 0.06944639 v
al_loss_rainfall: 0.03419261
Best model: lr=0.001, hidden_size=10, epoch:  76 train_loss_rainfall: 0.06772627 v
al_loss_rainfall: 0.03409336
```



Saving the test file

In [13]:
```
# Save the test data as a NumPy file
np.save('test_X.npy', test_X)
```

Saving the Model-LSTM_Rainfall

In [14]:
```
### SAVING THE MODEL- LSTM
# Save the best model as a joblib file
dump(best_model_lstm_rainfall, 'best_model_lstm_rainfall.joblib')

# Load the best model from the joblib file ( if needed)
#loaded_model = load('best_model_lstm_rainfall.joblib')

# Load the test data from the NumPy file
#loaded_test_X = np.load('test_X.npy')



## to use this test text convert to the test to pytorch tensor to be utilized
```

Out[14]:
```
['best_model_lstm_rainfall.joblib']
```

LONG-SHORT TERM MEMORY - TEMPERATURE FORECASTING

In [15]:
```
# Extract temperature data
temperature_data = weekly_da['temp'].values.astype(float)

# Normalize data
scaler = MinMaxScaler(feature_range=(-1, 1))
temperature_data_normalized = scaler.fit_transform(temperature_data.reshape(-1, 1))

# Convert data to PyTorch tensors
temperature_tensor = torch.FloatTensor(temperature_data_normalized).view(-1)

def create_sequences(data, seq_length):
    xs = []
    ys = []
    for i in range(len(data) - seq_length):
        x = data[i:i+seq_length]
        y = data[i+seq_length:i+seq_length+1]
        xs.append(x)
        ys.append(y)
    return torch.stack(xs), torch.stack(ys)

# Define sequence length
seq_length = 5

# Create sequences
xs, ys = create_sequences(temperature_tensor, seq_length)

# Split data into training and testing sets
train_size = int(len(xs) * 0.8)
test_size = len(xs) - train_size
train_X, test_X = xs[:train_size], xs[train_size:]
train_y, test_y = ys[:train_size], ys[train_size:]

# Define LSTM model
class LSTM(nn.Module):
    def __init__(self, input_size=1, hidden_layer_size=100, output_size=1):
        super().__init__()
        self.hidden_layer_size = hidden_layer_size
        self.lstm = nn.LSTM(input_size, hidden_layer_size)
        self.linear = nn.Linear(hidden_layer_size, output_size)
        self.hidden_cell = (torch.zeros(1,1,self.hidden_layer_size),
                            torch.zeros(1,1,self.hidden_layer_size))
```

```
    def forward(self, input_seq):
        lstm_out, self.hidden_cell = self.lstm(input_seq.view(len(input_seq) ,1, -1
        predictions = self.linear(lstm_out.view(len(input_seq), -1))
        return predictions[-1]

# Hyperparameters for tuning
learning_rates = [0.001, 0.01]
hidden_layer_sizes = [10, 50]

# Record validation losses and MSEs
validation_losses = []
mse_values = []
# Record training times
training_times_temp_lstm = []

# Train models with different hyperparameters
for lr in learning_rates:
    for hidden_size in hidden_layer_sizes:
        # Instantiate the model, define loss function and optimizer
        model = LSTM(hidden_layer_size=hidden_size)
        loss_function = nn.MSELoss()
        optimizer = torch.optim.Adam(model.parameters(), lr=lr)

        # Train the model
        epochs = 50
        train_losses = []
        val_losses = []

        for i in range(epochs):
            model.train()
            epoch_train_loss = 0
            # Record start time
            start_time = time.time()
            for seq, labels in zip(train_X, train_y):
                optimizer.zero_grad()
                model.hidden_cell = (torch.zeros(1, 1, model.hidden_layer_size),
                                torch.zeros(1, 1, model.hidden_layer_size))

                y_pred = model(seq)

                single_loss = loss_function(y_pred, labels)
                epoch_train_loss += single_loss.item()
                single_loss.backward()
                optimizer.step()

                # Calculate epoch training time
            epoch_time = time.time() - start_time

           # Append epoch training time to the list
            training_times_temp_lstm.append(epoch_time)
            train_losses.append(epoch_train_loss / len(train_X))

            model.eval()
            epoch_val_loss = 0
            with torch.no_grad():
                for seq, labels in zip(test_X, test_y):
                    model.hidden_cell = (torch.zeros(1, 1, model.hidden_layer_size)
                                    torch.zeros(1, 1, model.hidden_layer_size))

                    y_pred = model(seq)
                    val_loss = loss_function(y_pred, labels)
                    epoch_val_loss += val_loss.item()

                # Record validation loss
```

```
                val_losses.append(epoch_val_loss / len(test_X))

            if i % 10 == 1:
                print(f'lr: {lr}, hidden_size: {hidden_size}, epoch: {i:3} train_lo


        validation_losses.append(val_losses)

        # Make predictions using the trained model
        model.eval()
        test_predictions = []
        for seq in test_X:
            with torch.no_grad():
                model.hidden = (torch.zeros(1, 1, model.hidden_layer_size),
                                torch.zeros(1, 1, model.hidden_layer_size))
                test_predictions.append(model(seq).item())

        # Inverse transform the predictions
        test_predictions = scaler.inverse_transform(np.array(test_predictions).resh

        # Calculate MSE for temperature
        mse_temperature = ((scaler.inverse_transform(test_y.reshape(-1, 1)) - test_


        mse_values.append({
            'lr': lr,
            'hidden_size': hidden_size,
            'mse_temperature': mse_temperature
        })

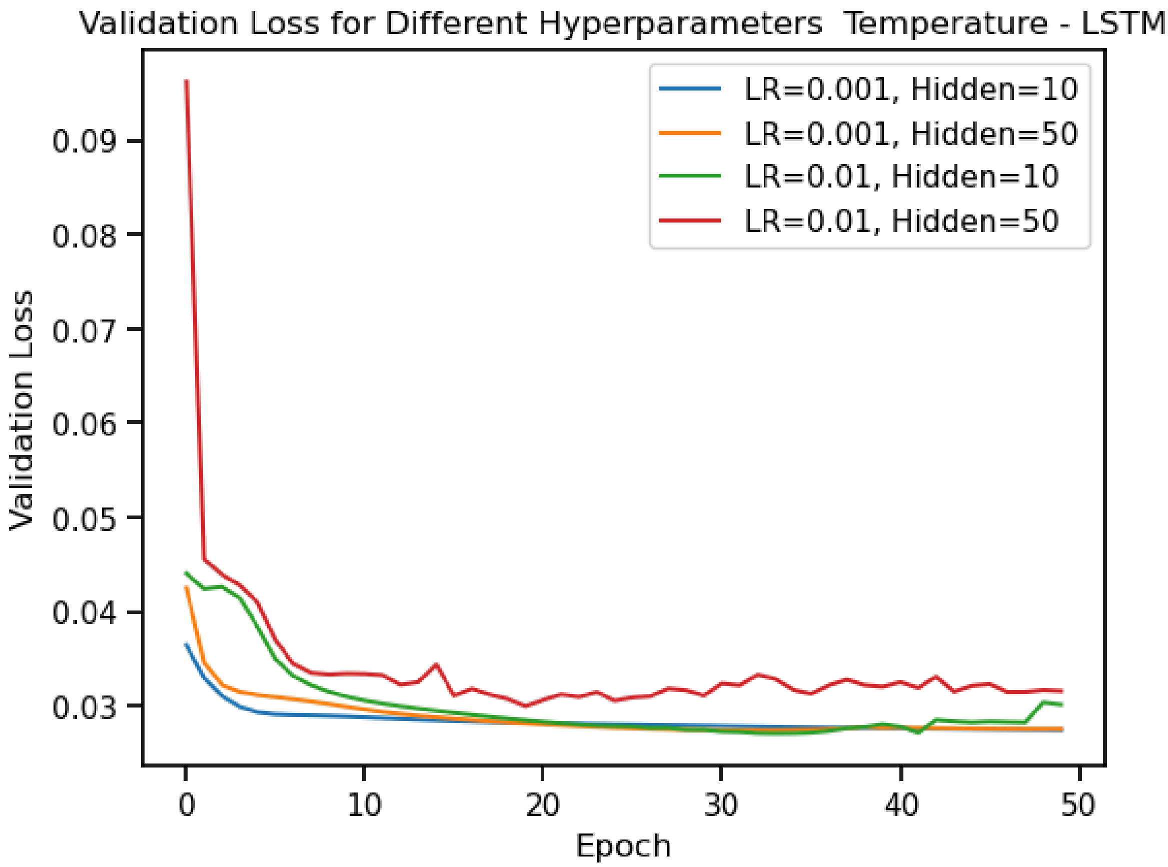
# Plot validation loss graphs for each set of hyperparameters
for idx, (lr, hidden_size) in enumerate([(lr, hidden_size) for lr in learning_rates
    plt.plot(validation_losses[idx], label=f'LR={lr}, Hidden={hidden_size}')

plt.xlabel('Epoch')
plt.ylabel('Validation Loss')
plt.title('Validation Loss for Different Hyperparameters  Temperature - LSTM')
plt.legend()
plt.show()

# Convert MSE values to DataFrame
mse_df_temp_lstm = pd.DataFrame(mse_values)

# Display the MSE values table
print("MSE Values:")
print(mse_df_temp_lstm)
```

```
lr: 0.001, hidden_size: 10, epoch:   1 train_loss_temperature: 0.03826221 val_loss
_temperature: 0.03296080  epoch_time: 1.16 seconds
lr: 0.001, hidden_size: 10, epoch:  11 train_loss_temperature: 0.02787560 val_loss
_temperature: 0.02870887  epoch_time: 1.15 seconds
lr: 0.001, hidden_size: 10, epoch:  21 train_loss_temperature: 0.02729108 val_loss
_temperature: 0.02813397  epoch_time: 1.13 seconds
lr: 0.001, hidden_size: 10, epoch:  31 train_loss_temperature: 0.02702738 val_loss
_temperature: 0.02783833  epoch_time: 1.14 seconds
lr: 0.001, hidden_size: 10, epoch:  41 train_loss_temperature: 0.02683518 val_loss
_temperature: 0.02758594  epoch_time: 1.16 seconds
lr: 0.001, hidden_size: 50, epoch:   1 train_loss_temperature: 0.03464158 val_loss
_temperature: 0.03459286  epoch_time: 1.41 seconds
lr: 0.001, hidden_size: 50, epoch:  11 train_loss_temperature: 0.02823700 val_loss
_temperature: 0.02934927  epoch_time: 1.39 seconds
lr: 0.001, hidden_size: 50, epoch:  21 train_loss_temperature: 0.02730909 val_loss
_temperature: 0.02792965  epoch_time: 1.43 seconds
lr: 0.001, hidden_size: 50, epoch:  31 train_loss_temperature: 0.02672229 val_loss
_temperature: 0.02739959  epoch_time: 1.40 seconds
lr: 0.001, hidden_size: 50, epoch:  41 train_loss_temperature: 0.02593279 val_loss
_temperature: 0.02765058  epoch_time: 1.39 seconds
lr: 0.01, hidden_size: 10, epoch:   1 train_loss_temperature: 0.03687944 val_loss_
temperature: 0.04240744  epoch_time: 1.14 seconds
lr: 0.01, hidden_size: 10, epoch:  11 train_loss_temperature: 0.03220438 val_loss_
temperature: 0.03023518  epoch_time: 1.29 seconds
lr: 0.01, hidden_size: 10, epoch:  21 train_loss_temperature: 0.03141422 val_loss_
temperature: 0.02815167  epoch_time: 1.16 seconds
lr: 0.01, hidden_size: 10, epoch:  31 train_loss_temperature: 0.03068597 val_loss_
temperature: 0.02721832  epoch_time: 1.14 seconds
lr: 0.01, hidden_size: 10, epoch:  41 train_loss_temperature: 0.03100885 val_loss_
temperature: 0.02713575  epoch_time: 1.16 seconds
lr: 0.01, hidden_size: 50, epoch:   1 train_loss_temperature: 0.04605461 val_loss_
temperature: 0.04556071  epoch_time: 1.36 seconds
lr: 0.01, hidden_size: 50, epoch:  11 train_loss_temperature: 0.03386287 val_loss_
temperature: 0.03324554  epoch_time: 1.36 seconds
lr: 0.01, hidden_size: 50, epoch:  21 train_loss_temperature: 0.03110022 val_loss_
temperature: 0.03121962  epoch_time: 1.37 seconds
lr: 0.01, hidden_size: 50, epoch:  31 train_loss_temperature: 0.02798713 val_loss_
temperature: 0.03217605  epoch_time: 1.41 seconds
lr: 0.01, hidden_size: 50, epoch:  41 train_loss_temperature: 0.02634635 val_loss_
temperature: 0.03190569  epoch_time: 1.42 seconds
```




```
MSE Values:
      lr  hidden_size  mse_temperature
0  0.001           10         3.741914
1  0.001           50         3.683452
2  0.010           10         4.937453
3  0.010           50         5.029695
```

Creating a df to save model losses (train and validation) for comparison

In [16]:

```
# Create a DataFrame for hyperparameters, validation losses, and training times for
lstm_data_temp = []
for lr in learning_rates:
    for hidden_size in hidden_layer_sizes:
        idx = learning_rates.index(lr) * len(hidden_layer_sizes) + hidden_layer_siz
        lstm_data_temp.append({
            'Learning Rate': lr,
            'Hidden Size': hidden_size,
            'Validation Loss': validation_losses[idx][-1],  # Get the last validati
            'Training Time': training_times_rain_lstm[idx]  # Get the training time
        })

# Convert the LSTM data to a DataFrame
df_hyperparameters_lstm_temp = pd.DataFrame(lstm_data_temp)

# Display the DataFrame
print(df_hyperparameters_lstm_temp)
```

```
   Learning Rate  Hidden Size  Validation Loss  Training Time
0          0.001           10         0.027431       1.090688
1          0.001           50         0.027529       1.254242
2          0.010           10         0.030135       1.224217
3          0.010           50         0.031584       1.120978
```

In [17]:
```
#This line of code is generated to draw the hyperparameter comparison (using a df t
#df_hyperparameters_lstm_temp.to_excel('df_hyperparameters_lstm_temp.xlsx')
```

Best LSTM Model Trained with best hyperparameters - Temperature

In [18]:
```
# Find the index of the minimum validation loss
best_index = np.unravel_index(np.argmin(validation_losses), np.array(validation_los
best_lr_index = best_index[0] // len(hidden_layer_sizes)
best_hidden_size_index = best_index[0] % len(hidden_layer_sizes)
best_lr = learning_rates[best_lr_index]
best_hidden_size = hidden_layer_sizes[best_hidden_size_index]

# Instantiate the best model with the best hyperparameters
best_model_lstm_temp = LSTM(hidden_layer_size=best_hidden_size)
loss_function = nn.MSELoss()
optimizer = torch.optim.Adam(best_model_lstm_temp.parameters(), lr=best_lr)

# Train the best model lstm temperature over best set of hyperparameters deduced ea
epochs = 100
best_train_losses = [] # calculating training losses and validation losses
best_val_losses = []

for i in range(epochs):
    best_model_lstm_temp.train()
    epoch_train_loss = 0
    for seq, labels in zip(train_X, train_y):
        optimizer.zero_grad()
        best_model_lstm_temp.hidden_cell = (torch.zeros(1, 1, best_model_lstm_temp.
                        torch.zeros(1, 1, best_model_lstm_temp.hidden_layer_size))

        y_pred = best_model_lstm_temp(seq)

        single_loss = loss_function(y_pred, labels)
        epoch_train_loss += single_loss.item()
        single_loss.backward()
        optimizer.step()

    best_train_losses.append(epoch_train_loss / len(train_X))

    best_model_lstm_temp.eval()
    epoch_val_loss = 0
    with torch.no_grad():
        for seq, labels in zip(test_X, test_y):
            best_model_lstm_temp.hidden_cell = (torch.zeros(1, 1, best_model_lstm_t
                            torch.zeros(1, 1, best_model_lstm_temp.hidden_layer_siz

            y_pred = best_model_lstm_temp(seq)
            val_loss = loss_function(y_pred, labels)
            epoch_val_loss += val_loss.item()

        # Record validation loss
        best_val_losses.append(epoch_val_loss / len(test_X))

    if i % 25 == 1:
        print(f'Best model: lr={best_lr}, hidden_size={best_hidden_size}, epoch: {i

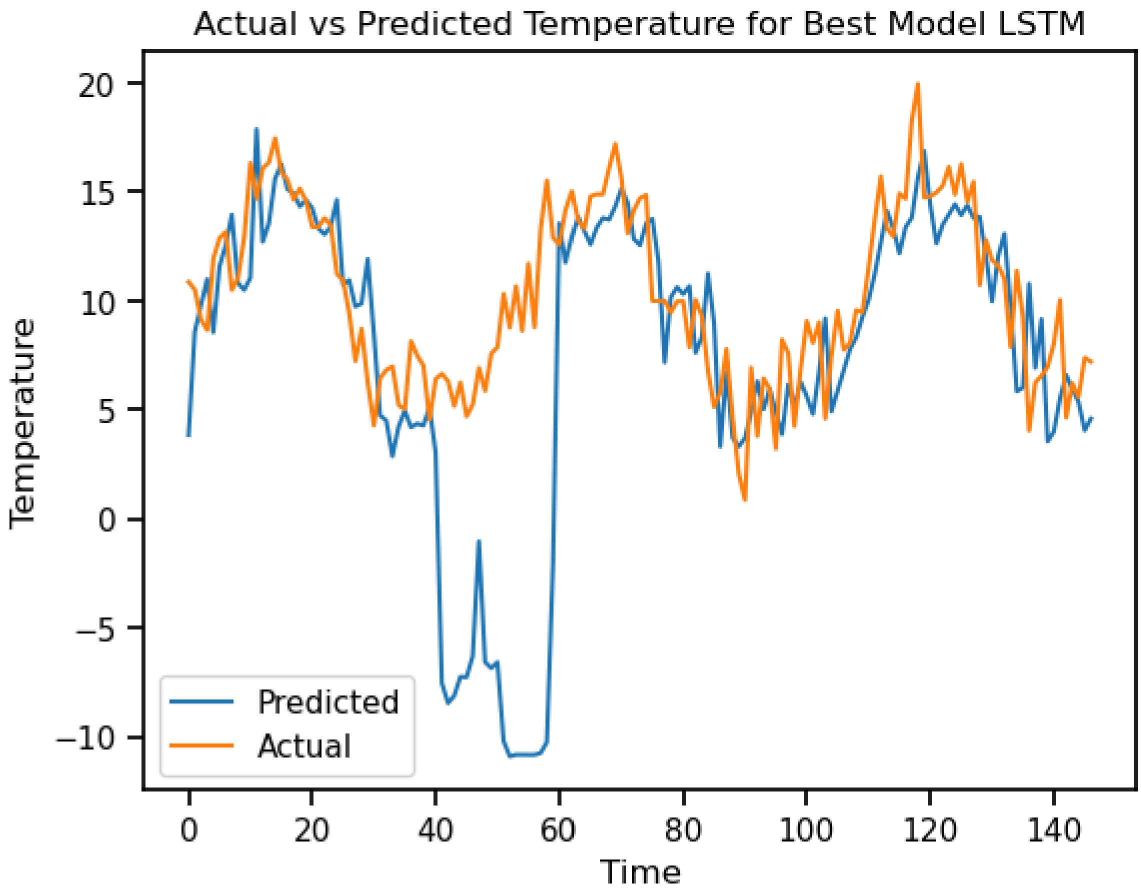
# Make predictions using the best model
best_model_lstm_temp.eval()
best_test_predictions_lstm_temp = []
for seq in test_X:
    with torch.no_grad():
```

```
        best_model_lstm_temp.hidden = (torch.zeros(1, 1, best_model_lstm_temp.hidde
                        torch.zeros(1, 1, best_model_lstm_temp.hidden_layer_size))
        best_test_predictions_lstm_temp.append(best_model_lstm_temp(seq).item())

# Inverse transform the predictions
best_test_predictions_lstm_temp = scaler.inverse_transform(np.array(best_test_predi

# Plot actual vs predicted for the best model
plt.plot(best_test_predictions_lstm_temp, label='Predicted')
plt.plot(scaler.inverse_transform(test_y.reshape(-1, 1)), label='Actual')
plt.xlabel('Time')
plt.ylabel('Temperature')
plt.title('Actual vs Predicted Temperature for Best Model LSTM')
plt.legend()
plt.show()
```

```
Best model: lr=0.01, hidden_size=10, epoch:   1 train_loss_temperature: 0.03693691
val_loss_temperature: 0.04347377
Best model: lr=0.01, hidden_size=10, epoch:  26 train_loss_temperature: 0.03041685
val_loss_temperature: 0.02793481
Best model: lr=0.01, hidden_size=10, epoch:  51 train_loss_temperature: 0.02838734
val_loss_temperature: 0.02899118
Best model: lr=0.01, hidden_size=10, epoch:  76 train_loss_temperature: 0.02470626
val_loss_temperature: 0.02907690
```



Saving the Model file - LSTM-Temperature

In [19]:
```
#Saving the model
# Save the best model as a joblib file
dump(best_model_lstm_temp, 'best_model_lstm_temp.joblib')

# Load the best model from the joblib file ( if you need loading of the model - con
#loaded_model_lstm_temp = load('best_model_lstm_temp.joblib')
```

Out[19]:
```
['best_model_lstm_temp.joblib']
```

SVM

SVM - Rainfall Forecasting

In [20]:
```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming you have your data loaded in 'weekly_da'

# Extract rainfall data
rainfall_data = weekly_da['rain'].values.astype(float)

# Normalize data
scaler = MinMaxScaler(feature_range=(-1, 1))
rainfall_data_normalized = scaler.fit_transform(rainfall_data.reshape(-1, 1))

# Define sequence length
seq_length = 5

# Create sequences
def create_sequences(data, seq_length):
    xs = []
    ys = []
    for i in range(len(data) - seq_length):
        x = data[i:i+seq_length]
        y = data[i+seq_length]
        xs.append(x)
        ys.append(y)
    return np.array(xs), np.array(ys)

xs, ys = create_sequences(rainfall_data_normalized, seq_length)

# Split data into training and testing sets
train_size = int(len(xs) * 0.8)
test_size = len(xs) - train_size
train_X, test_X = xs[:train_size], xs[train_size:]
train_y, test_y = ys[:train_size], ys[train_size:]

# Flatten the sequence dimension while keeping the other dimensions intact
train_X_flat = train_X.reshape(train_X.shape[0], -1)
test_X_flat = test_X.reshape(test_X.shape[0], -1)

# Define the parameter grid
param_grid = {
    'kernel': ['rbf', 'linear'],  # Different kernel types
    'C': [0.1, 1, 10],  # Regularization parameter values
    'gamma': ['scale', 'auto']  # Gamma parameter for RBF kernel
}

# Initialize SVR model
svm_model = SVR()
```

```
# Perform grid search with cross-validation
grid_search = GridSearchCV(estimator=svm_model, param_grid=param_grid, cv=3, scorin
grid_search.fit(train_X_flat, train_y)

# Get the best model
best_svm_model = grid_search.best_estimator_

# Make predictions on the test set using the best model
svm_predictions = best_svm_model.predict(test_X_flat)

# Inverse transform the predictions
svm_predictions_inv = scaler.inverse_transform(svm_predictions.reshape(-1, 1))
test_y_inv = scaler.inverse_transform(test_y.reshape(-1, 1))

# Calculate Mean Squared Error (MSE) for rainfall
mse_rainfall_svm = mean_squared_error(test_y_inv, svm_predictions_inv)
print("MSE for Rainfall (SVM):", mse_rainfall_svm)

# Plot predictions vs actual rainfall
plt.plot(test_y_inv, label='Actual Rainfall')
plt.plot(svm_predictions_inv, label='Predicted Rainfall (SVM)')
plt.xlabel('Time')
plt.ylabel('Rainfall')
plt.title('Actual vs Predicted Rainfall (SVM)')
plt.legend()
plt.show()

# Get the best hyperparameters
best_params = grid_search.best_params_
print("Best Hyperparameters:", best_params)

# Extract grid search results
results = pd.DataFrame(grid_search.cv_results_)

# Pivot the dataframe to have hyperparameters as columns
pivot_table = results.pivot_table(index='param_kernel', columns='param_C', values='

# Plot the heatmap
plt.figure(figsize=(4, 2))
sns.heatmap(pivot_table, annot=True, cmap="YlGnBu", cbar_kws={'label': 'Mean Test S
plt.title("Grid Search Results")
plt.xlabel("C (Regularization Parameter)")
plt.ylabel("Kernel")
plt.show()

# Create a DataFrame for hyperparameters, validation losses, and training times
svm_data = []
for kernel in param_grid['kernel']:
    for C in param_grid['C']:
        for gamma in param_grid['gamma']:
            idx = param_grid['kernel'].index(kernel) * len(param_grid['C']) * len(p
                  param_grid['C'].index(C) * len(param_grid['gamma']) + param_grid[
            svm_data.append({
                'Kernel': kernel,
                'C': C,
                'Gamma': gamma,
                'Validation Loss': grid_search.cv_results_['mean_test_score'][idx],
                'Training Time': grid_search.cv_results_['mean_fit_time'][idx]
            })

df_hyperparameters_svm = pd.DataFrame(svm_data)
```

```
# Display the DataFrame
print(df_hyperparameters_svm)
```

```
C:\Anaconda\Lib\site-packages\sklearn\utils\validation.py:1183: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
C:\Anaconda\Lib\site-packages\sklearn\utils\validation.py:1183: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
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```

```
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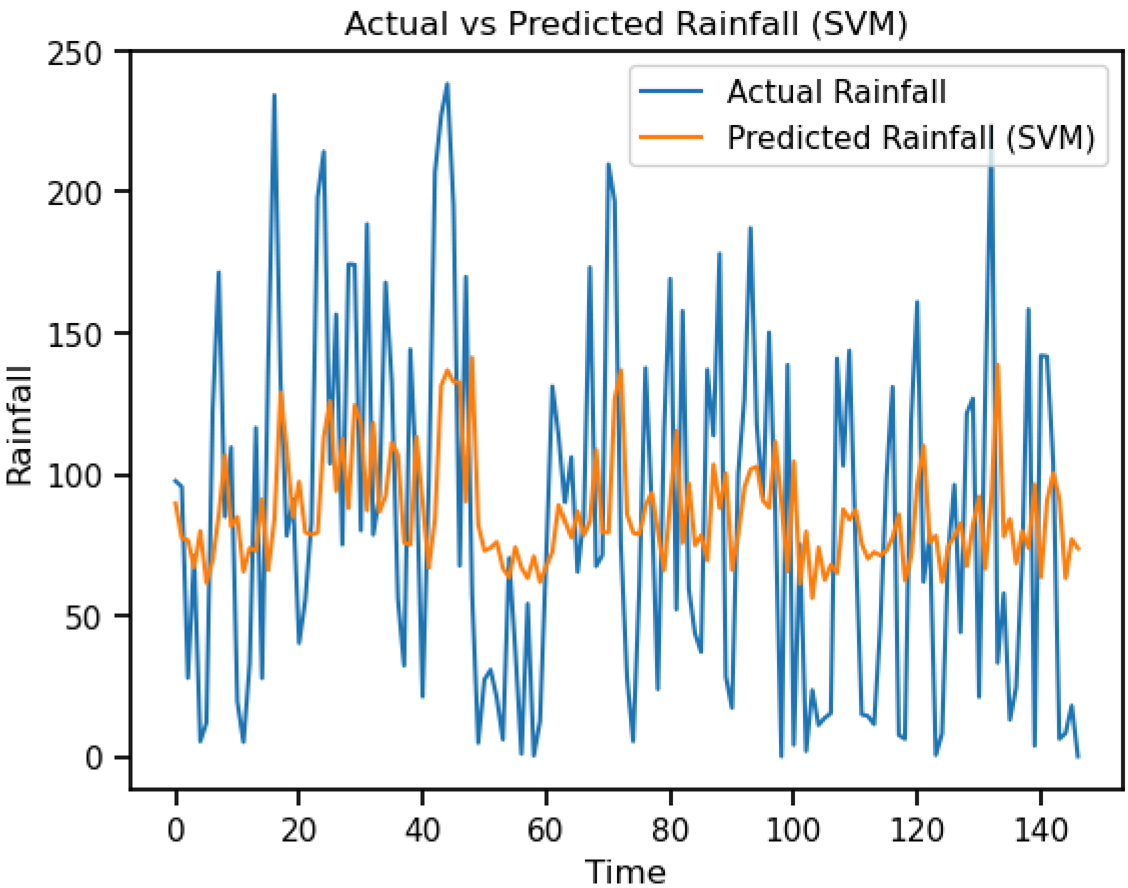
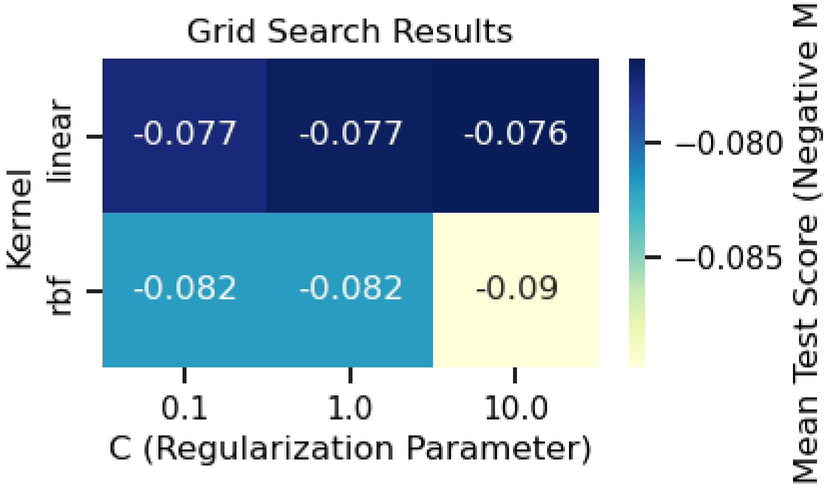
shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
MSE for Rainfall (SVM): 3602.8760644338677
```




```
Best Hyperparameters: {'C': 1, 'gamma': 'auto', 'kernel': 'rbf'}
```




```
    Kernel     C  Gamma  Validation Loss  Training Time
0      rbf   0.1  scale        -0.084488       0.007221
1      rbf   0.1   auto        -0.077342       0.005333
2      rbf   1.0  scale        -0.079407       0.005712
3      rbf   1.0   auto        -0.077342       0.004985
4      rbf  10.0  scale        -0.087609       0.009035
5      rbf  10.0   auto        -0.076622       0.007643
6   linear   0.1  scale        -0.076276       0.007269
7   linear   0.1   auto        -0.076622       0.007356
8   linear   1.0  scale        -0.100665       0.020695
9   linear   1.0   auto        -0.076409       0.014989
10  linear  10.0  scale        -0.078939       0.011009
11  linear  10.0   auto        -0.076409       0.015631
```

In [21]:
```
#This line of code is generated to draw the hyperparameter comparison (using a df t
#df_hyperparameters_svm.to_excel('df_hyperparameters_svm_rain.xlsx')
```

SVM - Temperature Forecasting

In [22]:
```
# Extract temperature data
temperature_data = weekly_da['temp'].values.astype(float)

# Normalize data
scaler_temp = MinMaxScaler(feature_range=(-1, 1))
temperature_data_normalized = scaler_temp.fit_transform(temperature_data.reshape(-1

# Create sequences for temperature
xs_temp, ys_temp = create_sequences(temperature_data_normalized, seq_length)

# Split data into training and testing sets for temperature
train_size_temp = int(len(xs_temp) * 0.8)
test_size_temp = len(xs_temp) - train_size_temp
train_X_temp, test_X_temp = xs_temp[:train_size_temp], xs_temp[train_size_temp:]
train_y_temp, test_y_temp = ys_temp[:train_size_temp], ys_temp[train_size_temp:]

# Flatten the sequence dimension while keeping the other dimensions intact for temp
train_X_flat_temp = train_X_temp.reshape(train_X_temp.shape[0], -1)
test_X_flat_temp = test_X_temp.reshape(test_X_temp.shape[0], -1)

# Perform grid search with cross-validation for temperature
grid_search_temp = GridSearchCV(estimator=svm_model, param_grid=param_grid, cv=3, s
grid_search_temp.fit(train_X_flat_temp, train_y_temp)

# Get the best model for temperature
best_svm_model_temp = grid_search_temp.best_estimator_

# Make predictions on the test set using the best model for temperature
```

```
svm_predictions_temp = best_svm_model_temp.predict(test_X_flat_temp)

# Inverse transform the predictions for temperature
svm_predictions_inv_temp = scaler_temp.inverse_transform(svm_predictions_temp.resha
test_y_inv_temp = scaler_temp.inverse_transform(test_y_temp.reshape(-1, 1))

# Calculate Mean Squared Error (MSE) for temperature
mse_temperature_svm = mean_squared_error(test_y_inv_temp, svm_predictions_inv_temp)
print("MSE for Temperature (SVM):", mse_temperature_svm)

# Plot predictions vs actual temperature
plt.plot(test_y_inv_temp, label='Actual Temperature')
plt.plot(svm_predictions_inv_temp, label='Predicted Temperature (SVM)')
plt.xlabel('Time')
plt.ylabel('Temperature')
plt.title('Actual vs Predicted Temperature (SVM)')
plt.legend()
plt.show()

# Get the best hyperparameters for temperature
best_params_temp = grid_search_temp.best_params_
print("Best Hyperparameters for Temperature:", best_params_temp)

# Extract grid search results for temperature
results_temp = pd.DataFrame(grid_search_temp.cv_results_)

# Pivot the dataframe to have hyperparameters as columns for temperature
pivot_table_temp = results_temp.pivot_table(index='param_kernel', columns='param_C'

# Plot the heatmap for temperature
plt.figure(figsize=(4, 2))
sns.heatmap(pivot_table_temp, annot=True, cmap="YlGnBu", cbar_kws={'label': 'Mean T
plt.title("Grid Search Results for Temperature")
plt.xlabel("C (Regularization Parameter)")
plt.ylabel("Kernel")
plt.show()

# Create a DataFrame for hyperparameters, validation losses, and training times for
svm_data_temp = []
for kernel in param_grid['kernel']:
    for C in param_grid['C']:
        for gamma in param_grid['gamma']:
            idx = param_grid['kernel'].index(kernel) * len(param_grid['C']) * len(p
                  param_grid['C'].index(C) * len(param_grid['gamma']) + param_grid[
            svm_data_temp.append({
                'Kernel': kernel,
                'C': C,
                'Gamma': gamma,
                'Validation Loss': grid_search_temp.cv_results_['mean_test_score'][
                'Training Time': grid_search_temp.cv_results_['mean_fit_time'][idx]
            })

df_hyperparameters_svm_temp = pd.DataFrame(svm_data_temp)

# Display the DataFrame for temperature
print(df_hyperparameters_svm_temp)

#This line of code is generated to draw the hyperparameter comparison (using a df t
#df_hyperparameters_svm_temp.to_excel('df_hyperparameters_svm_temp.xlsx')
```

```
C:\Anaconda\Lib\site-packages\sklearn\utils\validation.py:1183: DataConversionWarn
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```

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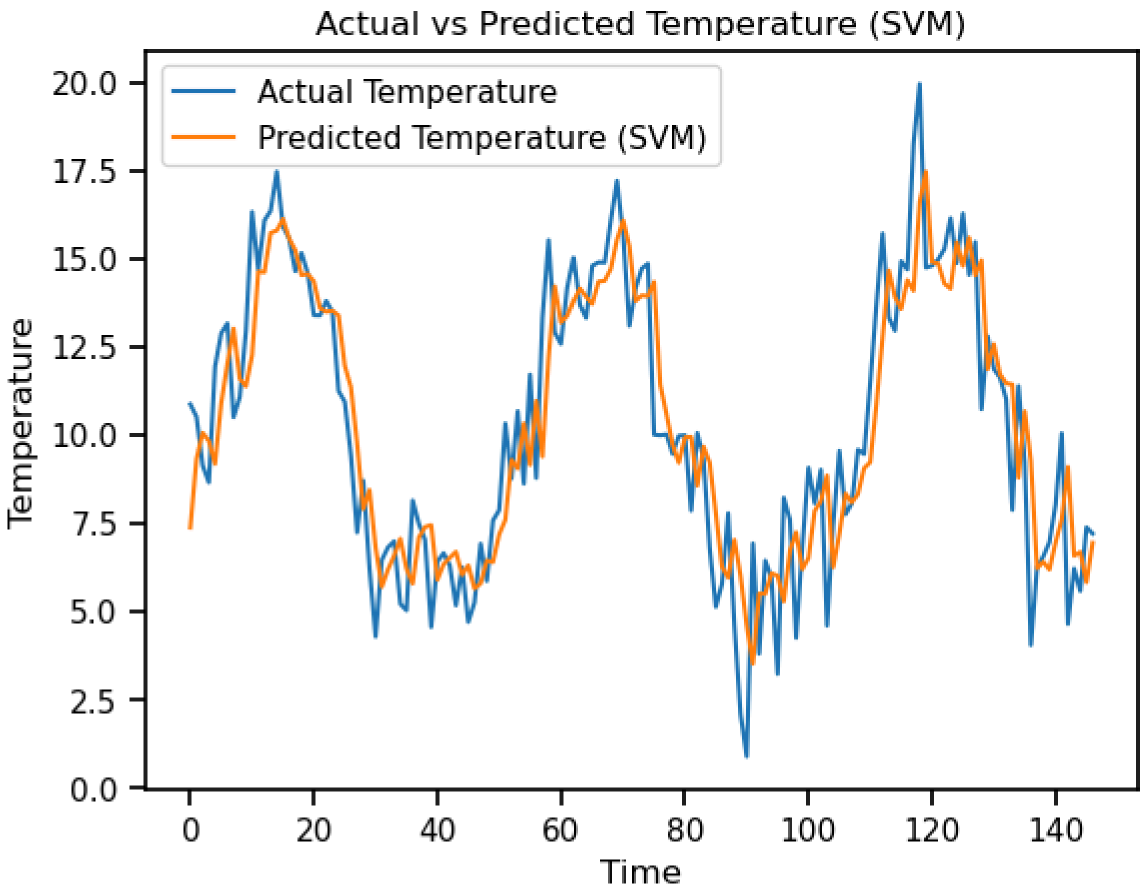
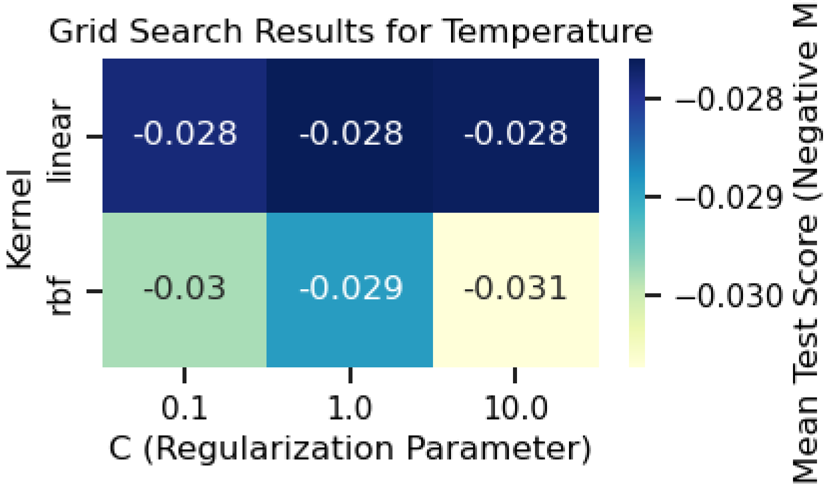
shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
MSE for Temperature (SVM): 3.5063773157897056
```




```
Best Hyperparameters for Temperature: {'C': 1, 'gamma': 'auto', 'kernel': 'rbf'}
```



	Kernel	C	Gamma	Validation Loss	Training Time
0	rbf	0.1	scale	-0.031030	0.004668
1	rbf	0.1	auto	-0.027808	0.003674
2	rbf	1.0	scale	-0.028554	0.004379
3	rbf	1.0	auto	-0.027808	0.003957
4	rbf	10.0	scale	-0.030811	0.007997
5	rbf	10.0	auto	-0.027592	0.008041
6	linear	0.1	scale	-0.026985	0.005362
7	linear	0.1	auto	-0.027592	0.007663
8	linear	1.0	scale	-0.033502	0.015662
9	linear	1.0	auto	-0.027631	0.014617
10	linear	10.0	scale	-0.028005	0.009333
11	linear	10.0	auto	-0.027631	0.017263

Saving the Model files for SVM - Rainfall & Temperature

In [23]:
```
# Save the best SVM model for rainfall prediction
dump(best_svm_model, 'best_svm_model_rainfall.joblib')

# Save the best SVM model for temperature prediction
dump(best_svm_model_temp, 'best_svm_model_temperature.joblib')
```

Out[23]: ['best_svm_model_temperature.joblib']

Results and Findings - SVM VS LSTM

MSE PLOTS - Rainfall and Temperature

In [24]:
```
# Calculate Mean Absolute Error (MAE) for rainfall predictions
mae_rainfall_svm = mean_absolute_error(test_y_inv, svm_predictions_inv)
mae_rainfall_lstm = mean_absolute_error(test_y_inv, best_test_predictions_rain_lstm

# Calculate Mean Absolute Error (MAE) for temperature predictions
mae_temperature_svm = mean_absolute_error(test_y_inv_temp, svm_predictions_inv_temp
mae_temperature_lstm = mean_absolute_error(test_y_inv_temp, best_test_predictions_l

# Calculate the MSE values for SVM models for temperature and rainfall predictions
lowest_temp_svm = mse_temperature_svm
lowest_rain_svm = mse_rainfall_svm

# Calculate the MSE values for LSTM models for temperature and rainfall predictions
lowest_temp_lstm = mse_df_temp_lstm['mse_temperature'].min()
lowest_rain_lstm = mse_df_rain_lstm['mse_rainfall'].min()

# Plotting subplots for MSE and MAE comparison for temperature and rainfall
```

```
# Create a figure and subplots
fig, axs = plt.subplots(2, 2, figsize=(12, 10))

# Temperature MSE comparison
axs[0, 0].bar(['SVM', 'LSTM'], [lowest_temp_svm, lowest_temp_lstm], color=['orange'
axs[0, 0].set_xlabel('Model')
axs[0, 0].set_ylabel('MSE')
axs[0, 0].set_title('Temperature MSE (SVM vs LSTM)')
# Annotate values
for i, v in enumerate([lowest_temp_svm, lowest_temp_lstm]):
    axs[0, 0].text(i, v + 0.01, str(round(v, 2)), ha='center', va='bottom')

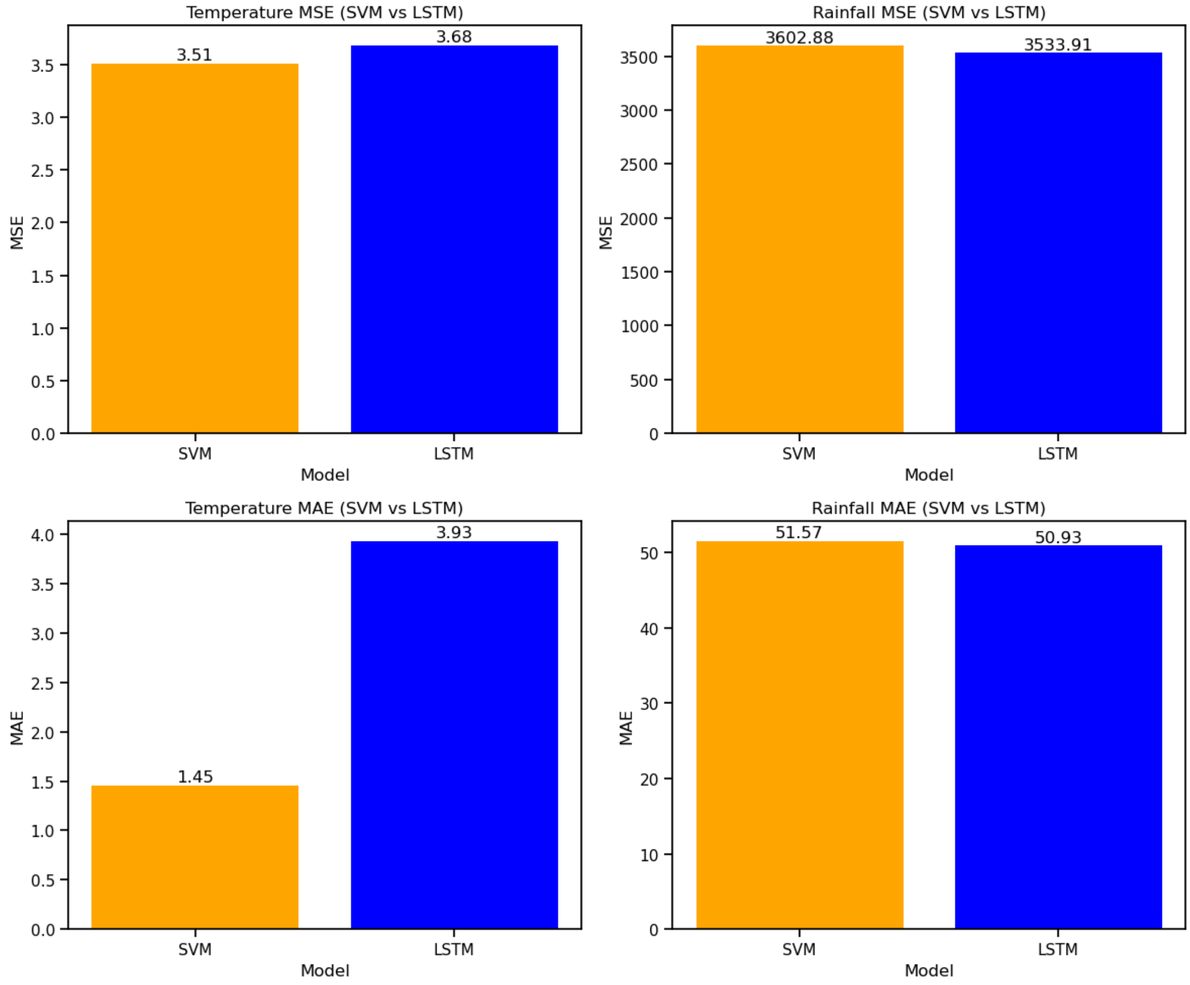
# Rainfall MSE comparison
axs[0, 1].bar(['SVM', 'LSTM'], [lowest_rain_svm, lowest_rain_lstm], color=['orange'
axs[0, 1].set_xlabel('Model')
axs[0, 1].set_ylabel('MSE')
axs[0, 1].set_title('Rainfall MSE (SVM vs LSTM)')
# Annotate values
for i, v in enumerate([lowest_rain_svm, lowest_rain_lstm]):
    axs[0, 1].text(i, v + 0.01, str(round(v, 2)), ha='center', va='bottom')

# Temperature MAE comparison
axs[1, 0].bar(['SVM', 'LSTM'], [mae_temperature_svm, mae_temperature_lstm], color=[
axs[1, 0].set_xlabel('Model')
axs[1, 0].set_ylabel('MAE')
axs[1, 0].set_title('Temperature MAE (SVM vs LSTM)')
# Annotate values
for i, v in enumerate([mae_temperature_svm, mae_temperature_lstm]):
    axs[1, 0].text(i, v + 0.01, str(round(v, 2)), ha='center', va='bottom')

# Rainfall MAE comparison
axs[1, 1].bar(['SVM', 'LSTM'], [mae_rainfall_svm, mae_rainfall_lstm], color=['orang
axs[1, 1].set_xlabel('Model')
axs[1, 1].set_ylabel('MAE')
axs[1, 1].set_title('Rainfall MAE (SVM vs LSTM)')
# Annotate values
for i, v in enumerate([mae_rainfall_svm, mae_rainfall_lstm]):
    axs[1, 1].text(i, v + 0.01, str(round(v, 2)), ha='center', va='bottom')

# Adjust layout
plt.tight_layout()

# Show plot
plt.show()
```



Residual plots - SVM VS LSTM

In [25]:
```
# Calculate residuals for SVM temperature prediction
residuals_svm_temp = svm_predictions_temp - test_y_inv_temp.flatten()
residuals_svm_rain = svm_predictions_inv.flatten() - test_y_inv.flatten()
# Calculate residuals for LSTM temperature prediction
best_test_predictions_lstm_temp = best_test_predictions_lstm_temp.flatten()
residuals_lstm_temp = best_test_predictions_lstm_temp - test_y_inv_temp.flatten()
best_test_predictions_rain_lstm = best_test_predictions_rain_lstm.flatten()
test_y_inv_rain = scaler.inverse_transform(test_y.reshape(-1, 1))
residuals_rain_lstm = best_test_predictions_rain_lstm.flatten() - test_y_inv_rain.f
# Create a figure with subplots for rainfall and temperature predictions
plt.figure(figsize=(10, 8))
# Subplot for rainfall predictions
plt.subplot(2, 1, 1)

# Residual plot for SVM rainfall prediction
plt.scatter(svm_predictions_inv, residuals_svm_rain, color='orange', alpha=0.5, lab
plt.axhline(y=0, color='red', linestyle='--')
plt.title('Residual Plot for Rainfall Prediction')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.grid(True)
plt.legend()

# Residual plot for LSTM rainfall prediction
plt.scatter(best_test_predictions_rain_lstm, residuals_rain_lstm, color='blue', alp
plt.axhline(y=0, color='red', linestyle='--')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.grid(True)
```

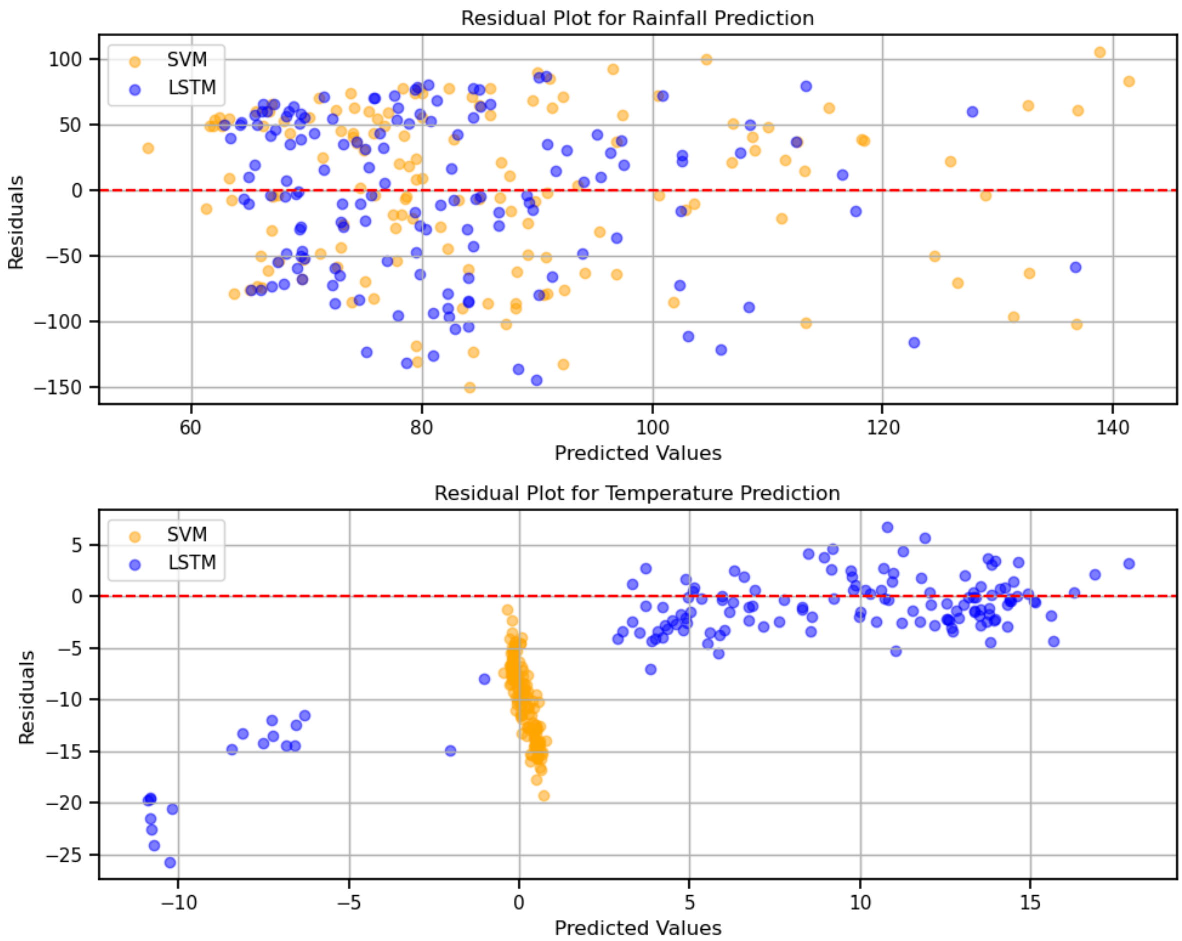
```
plt.legend()

# Subplot for temperature predictions
plt.subplot(2, 1, 2)

# Residual plot for SVM temperature prediction
plt.scatter(svm_predictions_temp, residuals_svm_temp, color='orange', alpha=0.5, la
plt.axhline(y=0, color='red', linestyle='--')
plt.title('Residual Plot for Temperature Prediction')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.grid(True)
plt.legend()

# Residual plot for LSTM temperature prediction
plt.scatter(best_test_predictions_lstm_temp, residuals_lstm_temp, color='blue', alp
plt.axhline(y=0, color='red', linestyle='--')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.grid(True)
plt.legend()

plt.tight_layout()
plt.show()
```



In [ ]: