Dengue prediction of Dhaka, Bangladesh

Consider weather(temperature, humidity, rainfall)

insert all necessary files and packages

In [1]:
```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, accuracy_score
from tensorflow.keras.callbacks import ModelCheckpoint
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from sklearn.svm import SVC
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.multioutput import MultiOutputClassifier
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.multioutput import MultiOutputRegressor
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

```
WARNING:tensorflow:From C:\Users\User\anaconda3\Lib\site-packages\keras\src\losses.py:2976: The name tf.loss
es.sparse_softmax_cross_entropy is deprecated. Please use tf.compat.v1.losses.sparse_softmax_cross_entropy i
nstead.
```

Import dengue cases database(2015 to 2023)

In [2]:
```
# Load dataset
df = pd.read_csv('DengueAndClimateBangladesh.csv')

df.describe()
```

Out[2]:

	YEAR	MONTH	MIN	MAX	HUMIDITY	RAINFALL	DENGUE	DEATHS
count	108.000000	108.000000	108.000000	108.000000	108.000000	108.000000	108.000000	108.000000
mean	2019.000000	6.500000	21.833830	31.047757	79.711230	206.932233	5244.648148	22.185185
std	2.594026	3.468146	4.925797	3.115912	9.747887	205.404186	14238.412507	69.020808
min	2015.000000	1.000000	11.027907	22.987097	48.826452	0.000000	0.000000	0.000000
25%	2017.000000	3.750000	18.350682	29.500630	75.216667	17.902500	44.500000	0.000000
50%	2019.000000	6.500000	23.830127	31.777857	82.441441	165.789706	320.500000	2.000000
75%	2021.000000	9.250000	25.948780	32.900000	87.229597	319.132353	2316.000000	6.250000
max	2023.000000	12.000000	31.063636	39.800000	90.222667	834.735294	79598.000000	396.000000

Split data into features and target

In [3]:
```

data = df[['YEAR','MONTH','MIN', 'MAX', 'HUMIDITY', 'RAINFALL']]
# y = df['DENGUE']  # Two target variables
y = df[['DENGUE', 'DEATHS']]  # Two target variables

```

In [4]:
```
print(data)
print(y)
```

```
     YEAR  MONTH        MIN        MAX   HUMIDITY    RAINFALL
0    2015      1  13.548485  25.300000  68.976452   10.529000
1    2015      2  17.342424  28.712121  56.465000   16.500000
2    2015      3  19.669697  31.908824  48.826452   25.823529
3    2015      4  23.503030  32.485294  78.554333  192.911765
4    2015      5  25.263636  34.111765  85.996129  171.264706
..    ...    ...        ...        ...        ...         ...
103  2023      8  25.726471  31.373529  86.110000  420.364706
104  2023      9  25.355882  31.541176  85.910000  318.220588
105  2023     10  23.638235  31.526471  83.200000  160.314706
106  2023     11  19.176471  29.529412  79.090000   42.429412
107  2023     12  14.170588  26.432353  77.970000    9.638235

[108 rows x 6 columns]
     DENGUE  DEATHS
0         0       0
1         0       0
2         2       0
3         6       0
4        10       0
..      ...     ...
103   71976     342
104   79598     396
105   67769     359
106   40716     274
107    9288      83

[108 rows x 2 columns]
```

Scaling training data using MinMaxScaler (0 to 1)

In [5]:
```
X_combined = MinMaxScaler().fit_transform(data)
print(X_combined.shape)
```

```
(108, 6)
```

create input-output pairs (sequences) fo LSTM

In [6]:
```
def create_sequences(data, target, sequence_length):
    sequences = []
    target_values = []

    # Combine data and target
    combined_data = pd.concat([pd.DataFrame(data), pd.DataFrame(target)], axis=1)

    # Shift the combined data to create sequences
    for i in range(len(combined_data) - sequence_length + 1):
        sequence_end = i + sequence_length
        if sequence_end > len(combined_data):
            break
        seq = combined_data.iloc[i:sequence_end, :-2].values
        label = combined_data.iloc[sequence_end - 1, -2:].values
        sequences.append(seq)
        target_values.append(label)

    return np.array(sequences), np.array(target_values)
```

10 consecutive time steps as input

In [7]:
```
# Define the sequence length (number of time steps to look back)
sequence_length = 1
```

Scaling(range 0 to 1) training data for fit

Input sequences and target sequnce set with 10 length

In [8]:
```
# Create sequences
X_seq, y_seq = create_sequences(np.column_stack((X_combined, y)), y, sequence_length)
print('X_seq:',X_seq.shape)
print('y_seq:',y_seq.shape)
```

```
X_seq: (108, 1, 8)
y_seq: (108, 2)
```

In [9]:
```
y_seq
```

Out[9]:
```
array([[0.0000e+00, 0.0000e+00],
       [0.0000e+00, 0.0000e+00],
       [2.0000e+00, 0.0000e+00],
       [6.0000e+00, 0.0000e+00],
       [1.0000e+01, 0.0000e+00],
       [2.8000e+01, 0.0000e+00],
       [1.7100e+02, 1.0000e+00],
       [7.6500e+02, 3.0000e+00],
       [9.6500e+02, 4.0000e+00],
       [8.6900e+02, 3.0000e+00],
       [2.7100e+02, 1.0000e+00],
       [7.5000e+01, 0.0000e+00],
       [1.3000e+01, 0.0000e+00],
       [3.0000e+00, 0.0000e+00],
       [1.7000e+01, 0.0000e+00],
       [3.8000e+01, 0.0000e+00],
       [7.0000e+01, 0.0000e+00],
       [2.5400e+02, 1.0000e+00],
       [9.2600e+02, 2.0000e+00],
```

Split the data into training and testing sets

In [10]:
```
x_train, x_test, y_train, y_test = train_test_split(X_seq, y_seq, test_size=0.2, random_state=42)
```

In [11]:
```
print('X_combined:',X_combined.shape)
print('y:',y.shape)
print('X_seq:',X_seq.shape)
print('y_seq:',y_seq.shape)
print('x_train:',x_train.shape)
print('y_train:',y_train.shape)
print('x_test:',x_test.shape)
print('y_test:',y_test.shape)
```

```
X_combined: (108, 6)
y: (108, 2)
X_seq: (108, 1, 8)
y_seq: (108, 2)
x_train: (86, 1, 8)
y_train: (86, 2)
x_test: (22, 1, 8)
y_test: (22, 2)
```

Build the LSTM model

In [12]:
```
model = Sequential()
model.add(LSTM(50, activation='relu', input_shape=(x_train.shape[1], x_train.shape[2])))#, return_sequences=Tr
model.add(Dense(2))  # Two output nodes for two target variables
model.compile(optimizer='adam', loss='mse')
```

```
WARNING:tensorflow:From C:\Users\User\anaconda3\Lib\site-packages\keras\src\backend.py:873: The name tf.get_
default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From C:\Users\User\anaconda3\Lib\site-packages\keras\src\optimizers\__init__.py:309: The
name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.
```

Define a function to checkpoint all epochs

In [13]:
```
# Define this checkpoint callback methods for draw graph of RMSE of all epoach
checkpoint_callback = ModelCheckpoint(
    filepath='weights_epoch_{epoch:02d}.h5',
    save_weights_only=True,
    save_best_only=False,
    monitor='val_loss',
    mode='min',
    verbose=1
)
```

Train the model with validation

In [14]:
```
pochs=50
history = model.fit(x_train, y_train, epochs=pochs, batch_size=30,
                    validation_data=(x_test, y_test),
                    callbacks=[checkpoint_callback],
                    verbose=2)
```

```
Epoch 1/50
WARNING:tensorflow:From C:\Users\User\anaconda3\Lib\site-packages\keras\src\utils\tf_utils.py:492: The nam
e tf.ragged.RaggedTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.


Epoch 1: saving model to weights_epoch_01.h5
3/3 - 2s - loss: 144002000.0000 - val_loss: 58641328.0000 - 2s/epoch - 536ms/step
Epoch 2/50

Epoch 2: saving model to weights_epoch_02.h5
3/3 - 0s - loss: 141746128.0000 - val_loss: 57659868.0000 - 57ms/epoch - 19ms/step
Epoch 3/50

Epoch 3: saving model to weights_epoch_03.h5
3/3 - 0s - loss: 139298848.0000 - val_loss: 56706084.0000 - 57ms/epoch - 19ms/step
Epoch 4/50

Epoch 4: saving model to weights_epoch_04.h5
3/3 - 0s - loss: 136750128.0000 - val_loss: 51559320.0000 - 50ms/epoch - 17ms/step
```

store all RMSE value of each Epoch

In [15]:
```
predictions = model.predict(x_test)
# predictions abs(predictions)
print(x_test.shape)
print(predictions.shape)
print(y_test.shape)
print(predictions)
print(y_test)
pp=predictions
```

```
1/1 [==============================] - 0s 181ms/step
(22, 1, 8)
(22, 2)
(22, 2)
[[ 8.2916864e+02  5.5640154e+00]
 [ 2.7080524e+02  3.5176158e+00]
 [ 9.1734686e+00  6.3614619e-01]
 [ 1.2104155e+03  7.5486393e+00]
 [ 2.4046598e+01  1.3755112e+00]
 [ 3.5751978e+03  2.2443621e+01]
 [ 2.8979544e+02  4.3370833e+00]
 [ 2.4110654e+03  1.4975786e+01]
 [ 5.0385703e+03  3.2288296e+01]
 [ 6.8164978e+01  1.9277180e+00]
 [ 1.5476786e+04  9.5202263e+01]
 [ 7.7062905e+03  4.7080280e+01]
 [ 4.5955598e-01 -4.3849200e-03]
 [ 7.8508130e+03  4.8211697e+01]
 [ 9.2963751e+02  5.9418459e+00]
 [ 1.2685004e+03  8.0656700e+00]
 [ 1.6861758e+04  1.0119631e+02]
 [ 4.0634850e+01  1.7414349e+00]
 [ 4.0849625e+04  2.6604910e+02]
 [ 9.5137415e+02  6.3791571e+00]
 [ 9.5151577e+00  5.2516651e-01]
 [ 2.1011465e+01  9.6816456e-01]]
[[8.2500e+02 2.0000e+00]
 [2.7100e+02 1.0000e+00]
 [1.0000e+01 0.0000e+00]
 [1.2070e+03 3.0000e+00]
 [2.7000e+01 1.0000e+00]
 [3.5670e+03 1.3000e+01]
 [2.8600e+02 1.0000e+00]
 [2.4060e+03 7.0000e+00]
 [5.0240e+03 2.7000e+01]
 [7.5000e+01 0.0000e+00]
 [1.5458e+04 4.5000e+01]
 [7.6980e+03 1.8000e+01]
 [0.0000e+00 0.0000e+00]
 [7.8410e+03 2.1000e+01]
 [9.2600e+02 2.0000e+00]
 [1.2640e+03 4.0000e+00]
 [1.6856e+04 2.5000e+01]
```

```
[4.3000e+01 0.0000e+00]
[4.0716e+04 2.7400e+02]
[9.4600e+02 5.0000e+00]
[1.3000e+01 0.0000e+00]
[2.6000e+01 0.0000e+00]]
```

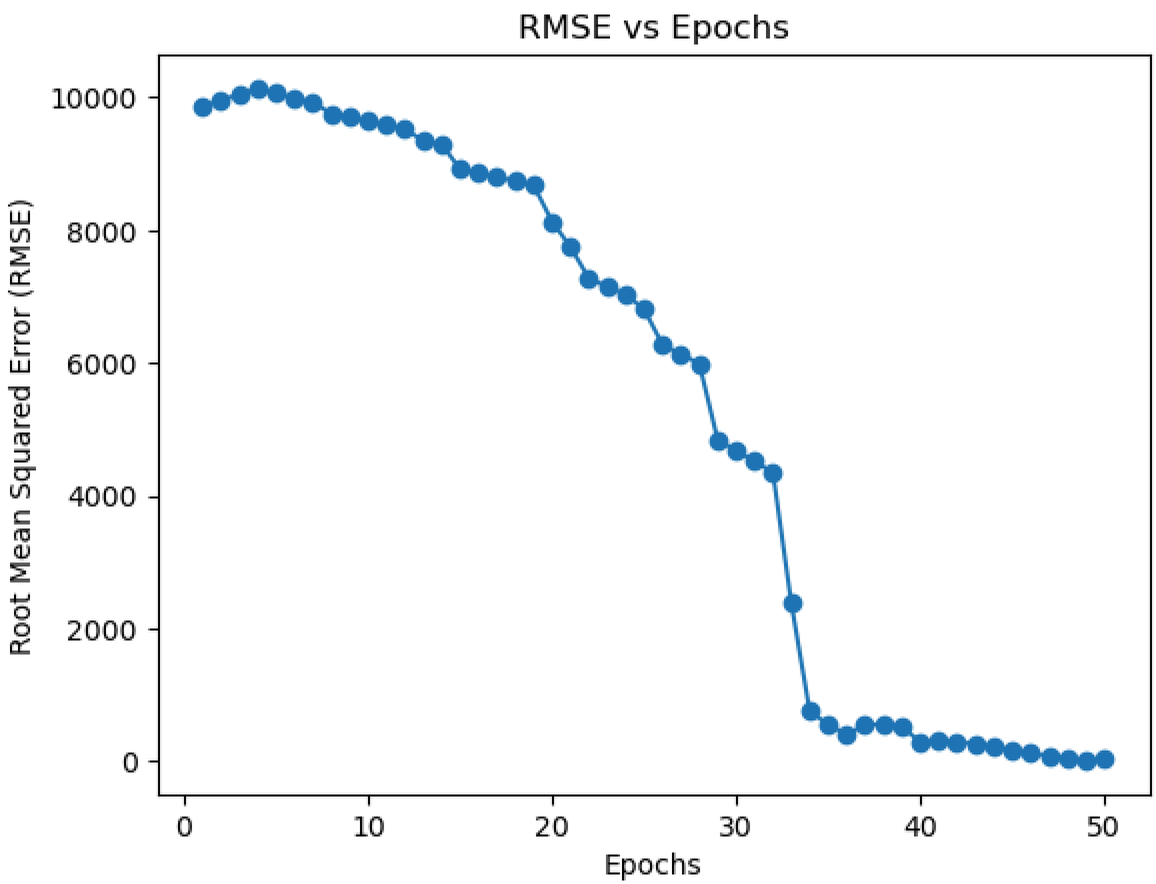
In [16]:
```
# store all RMSE values for each epoch
rmse_values_affected = []
rmse_values_deaths = []

for epoch in range(1, pochs+1):

    model.load_weights(f"weights_epoch_{epoch:02d}.h5")

    # Predictions on the test set
    predictions = model.predict(x_test)
    predictions = abs(predictions)
    # Calculate RMSE for dengue affected case
#     mse = mean_squared_error(y_test, predictions)
    mse = mean_squared_error(y_test[:, 0], predictions[:, 0])
    rmse = np.sqrt(mse)
    # Append RMSE to the list
    rmse_values_affected.append(rmse)

    # rmse for deaths
    mse = mean_squared_error(y_test[:, 1], predictions[:, 1])
    rmse = np.sqrt(mse)
    # Append RMSE to the list
    rmse_values_deaths.append(rmse)
```

```
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 32ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 15ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 11ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 35ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 39ms/step
```

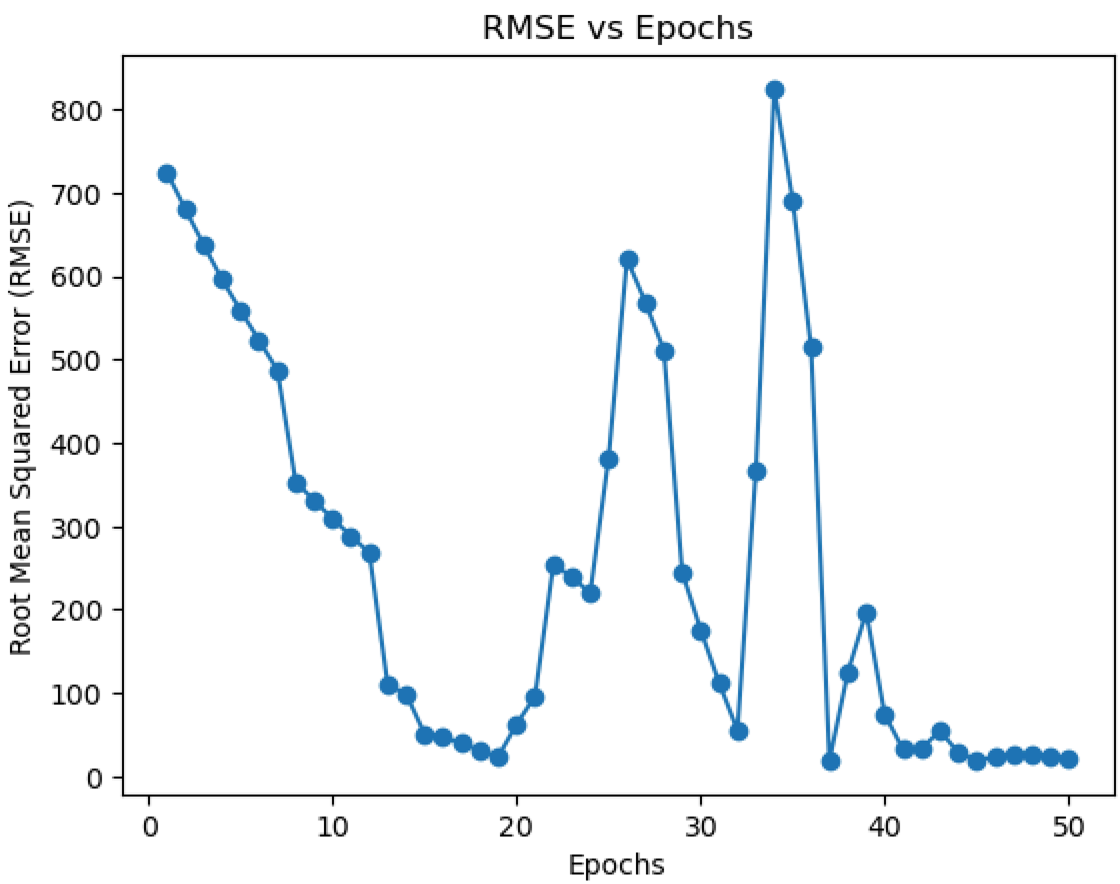
```
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 24ms/step
```

Draw RMSE vs Epochs

In [17]:
```
# Plot RMSE values for affected
plt.plot(range(1, pochs+1), rmse_values_affected, marker='o')
plt.xlabel('Epochs')
plt.ylabel('Root Mean Squared Error (RMSE)')
plt.title('RMSE vs Epochs')
plt.show()
```



In [18]:
```
# Plot RMSE values for deaths
plt.plot(range(1, pochs+1), rmse_values_deaths, marker='o')
plt.xlabel('Epochs')
plt.ylabel('Root Mean Squared Error (RMSE)')
plt.title('RMSE vs Epochs')
plt.show()
```



Predictions on the test set

In [19]:
```
#print the prediction information
predictions
```

Out[19]:
```
array([[8.2916864e+02, 5.5640154e+00],
       [2.7080524e+02, 3.5176158e+00],
       [9.1734686e+00, 6.3614619e-01],
       [1.2104155e+03, 7.5486393e+00],
       [2.4046598e+01, 1.3755112e+00],
       [3.5751978e+03, 2.2443621e+01],
       [2.8979544e+02, 4.3370833e+00],
       [2.4110654e+03, 1.4975786e+01],
       [5.0385703e+03, 3.2288296e+01],
       [6.8164978e+01, 1.9277180e+00],
       [1.5476786e+04, 9.5202263e+01],
       [7.7062905e+03, 4.7080280e+01],
       [4.5955598e-01, 4.3849200e-03],
       [7.8508130e+03, 4.8211697e+01],
       [9.2963751e+02, 5.9418459e+00],
       [1.2685004e+03, 8.0656700e+00],
       [1.6861758e+04, 1.0119631e+02],
       [4.0634850e+01, 1.7414349e+00],
       [4.0849625e+04, 2.6604910e+02],
       [9.5137415e+02, 6.3791571e+00],
       [9.5151577e+00, 5.2516651e-01],
       [2.1011465e+01, 9.6816456e-01]], dtype=float32)
```

In [20]:
```
predictions = model.predict(x_test)
# predictions= abs(predictions)
predictions
```

```
1/1 [==============================] - 0s 27ms/step
```

Out[20]:
```
array([[ 8.2916864e+02,  5.5640154e+00],
       [ 2.7080524e+02,  3.5176158e+00],
       [ 9.1734686e+00,  6.3614619e-01],
       [ 1.2104155e+03,  7.5486393e+00],
       [ 2.4046598e+01,  1.3755112e+00],
       [ 3.5751978e+03,  2.2443621e+01],
       [ 2.8979544e+02,  4.3370833e+00],
       [ 2.4110654e+03,  1.4975786e+01],
       [ 5.0385703e+03,  3.2288296e+01],
       [ 6.8164978e+01,  1.9277180e+00],
       [ 1.5476786e+04,  9.5202263e+01],
       [ 7.7062905e+03,  4.7080280e+01],
       [ 4.5955598e-01, -4.3849200e-03],
       [ 7.8508130e+03,  4.8211697e+01],
       [ 9.2963751e+02,  5.9418459e+00],
       [ 1.2685004e+03,  8.0656700e+00],
       [ 1.6861758e+04,  1.0119631e+02],
       [ 4.0634850e+01,  1.7414349e+00],
       [ 4.0849625e+04,  2.6604910e+02],
       [ 9.5137415e+02,  6.3791571e+00],
       [ 9.5151577e+00,  5.2516651e-01],
       [ 2.1011465e+01,  9.6816456e-01]], dtype=float32)
```

In [ ]:

In [21]:
```
rSquired = r2_score(y_test[:, 0], predictions[:, 0])
print(f'R-squared: {rSquired}')
```

```
R-squared: 0.99998974835348
```

In [22]:
```
r2 = r2_score(y_test[:, 1], predictions[:, 1])
print(f'R-squared: {r2}')
```

```
R-squared: 0.854275109436205
```

In [23]:
```
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(86, 1, 8)
(86, 2)
(22, 1, 8)
(22, 2)
```

In [24]:
```
print(predictions.shape)
print(y_test.shape)
```

```
(22, 2)
(22, 2)
```

In [25]:
```
print(y_test)
print(predictions)

print(type(y_test))
print(type(predictions))
```

```
[[8.2500e+02 2.0000e+00]
 [2.7100e+02 1.0000e+00]
 [1.0000e+01 0.0000e+00]
 [1.2070e+03 3.0000e+00]
 [2.7000e+01 1.0000e+00]
 [3.5670e+03 1.3000e+01]
 [2.8600e+02 1.0000e+00]
 [2.4060e+03 7.0000e+00]
 [5.0240e+03 2.7000e+01]
 [7.5000e+01 0.0000e+00]
 [1.5458e+04 4.5000e+01]
 [7.6980e+03 1.8000e+01]
 [0.0000e+00 0.0000e+00]
 [7.8410e+03 2.1000e+01]
 [9.2600e+02 2.0000e+00]
 [1.2640e+03 4.0000e+00]
 [1.6856e+04 2.5000e+01]
 [4.3000e+01 0.0000e+00]
 [4.0716e+04 2.7400e+02]
 [9.4600e+02 5.0000e+00]
 [1.3000e+01 0.0000e+00]
 [2.6000e+01 0.0000e+00]]
[[ 8.2916864e+02  5.5640154e+00]
 [ 2.7080524e+02  3.5176158e+00]
 [ 9.1734686e+00  6.3614619e-01]
 [ 1.2104155e+03  7.5486393e+00]
 [ 2.4046598e+01  1.3755112e+00]
 [ 3.5751978e+03  2.2443621e+01]
 [ 2.8979544e+02  4.3370833e+00]
 [ 2.4110654e+03  1.4975786e+01]
 [ 5.0385703e+03  3.2288296e+01]
 [ 6.8164978e+01  1.9277180e+00]
 [ 1.5476786e+04  9.5202263e+01]
 [ 7.7062905e+03  4.7080280e+01]
 [ 4.5955598e-01 -4.3849200e-03]
 [ 7.8508130e+03  4.8211697e+01]
 [ 9.2963751e+02  5.9418459e+00]
 [ 1.2685004e+03  8.0656700e+00]
 [ 1.6861758e+04  1.0119631e+02]
 [ 4.0634850e+01  1.7414349e+00]
 [ 4.0849625e+04  2.6604910e+02]
 [ 9.5137415e+02  6.3791571e+00]
 [ 9.5151577e+00  5.2516651e-01]
```

```
 [ 2.1011465e+01  9.6816456e-01]]
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
```

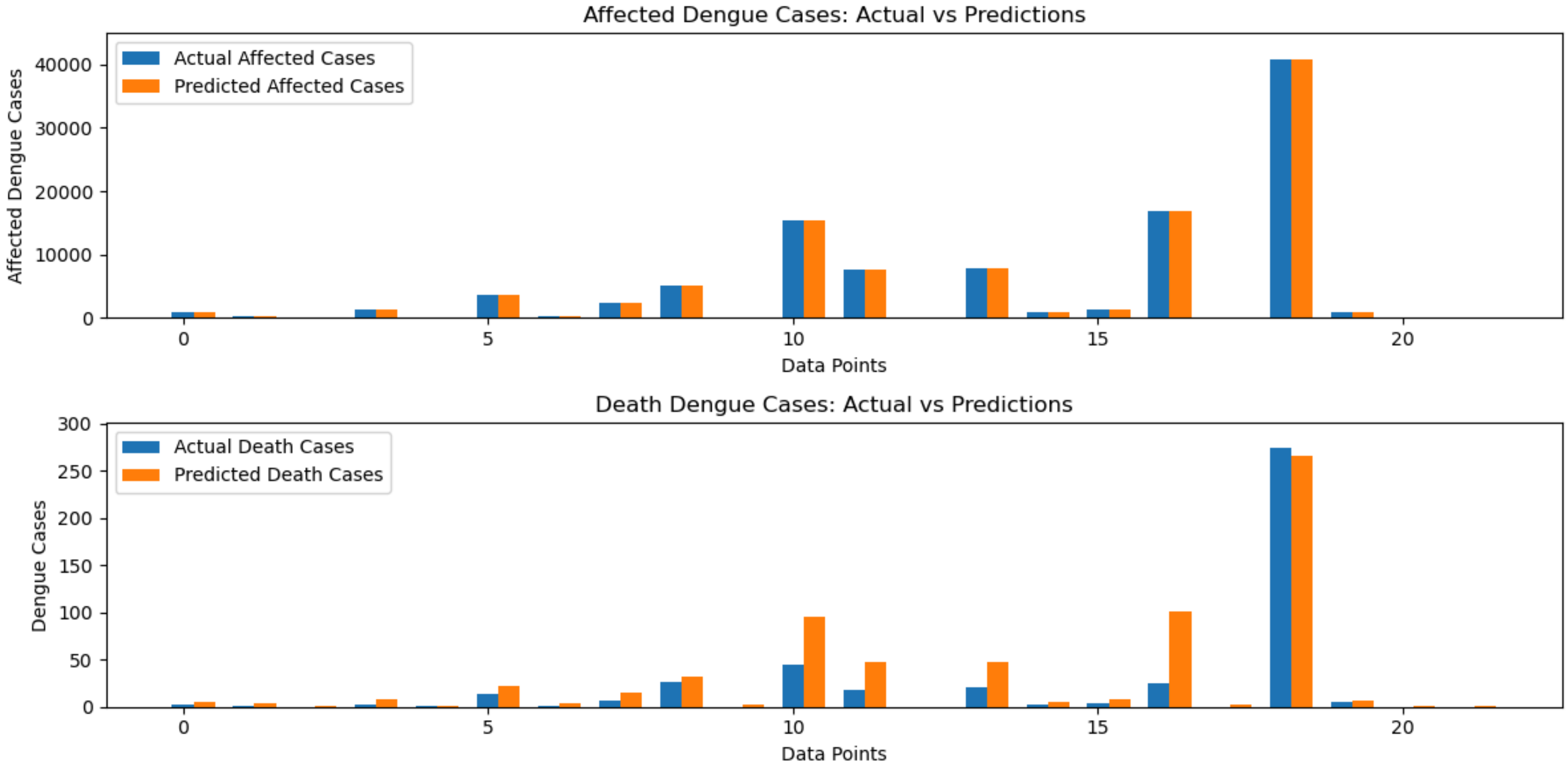
Performance mesure

Designed a bar graph of actual dengue case VS predictive dengue case

In [26]:
```
print(y_test.shape)
print(predictions.shape)
```

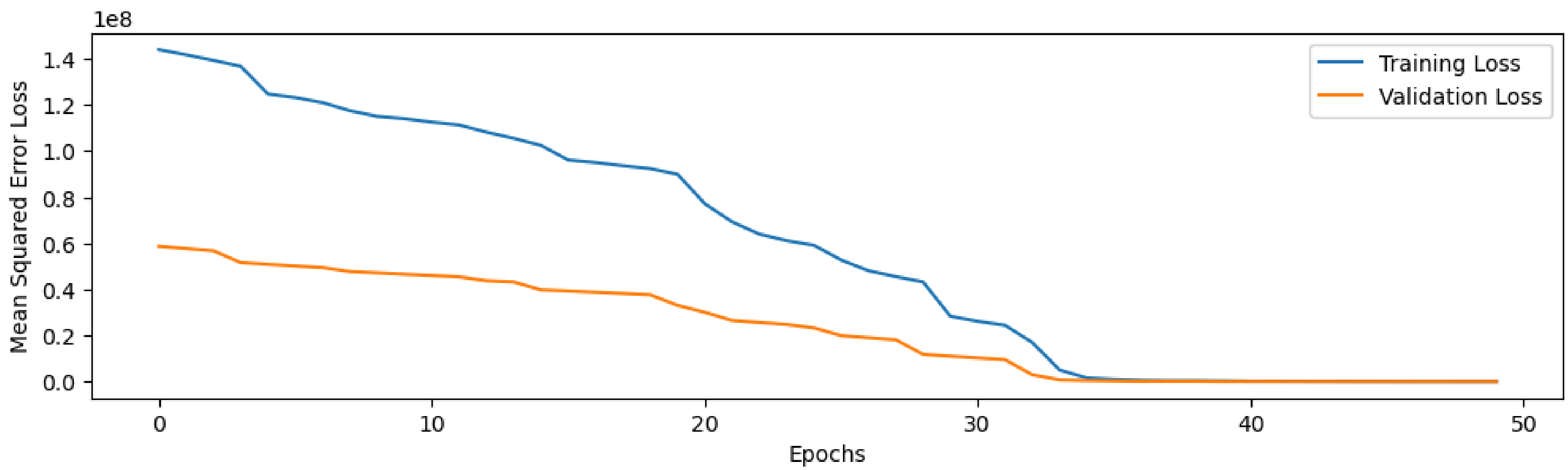
```
(22, 2)
(22, 2)
```

In [27]:
```
# Plot the bar graph for affected dengue cases
plt.figure(figsize=(12, 6))
bar_width = 0.35
plt.subplot(2, 1, 1)  # 2 rows, 1 column, 1st subplot

# Extract the first column of y_test (affected cases) for plotting
affected_actual = y_test[:, 0]  # Selecting the first column
affected_predicted = predictions[:, 0]  # Predicted affected cases

plt.bar(np.arange(len(affected_actual)), affected_actual, width=bar_width, label='Actual Affected Cases')
plt.bar(np.arange(len(affected_predicted)) + bar_width, affected_predicted, width=bar_width, label='Predicted

plt.xlabel('Data Points')
plt.ylabel('Affected Dengue Cases')
plt.legend()
plt.title('Affected Dengue Cases: Actual vs Predictions')
plt.ylim(0, max(max(affected_actual), max(predictions[:, 0])) * 1.1)  # Set y-axis limit

plt.subplot(2, 1, 2)  # 2 rows, 1 column, 2nd subplot
# Extract the actual and predicted death dengue cases
death_actual = y_test[:, 1]  # Actual death cases
death_predicted = predictions[:, 1]  # Predicted death cases
plt.bar(np.arange(len(death_actual)), death_actual, width=bar_width, label='Actual Death Cases')
plt.bar(np.arange(len(death_predicted)) + bar_width, death_predicted, width=bar_width, label='Predicted Death
plt.xlabel('Data Points')
plt.ylabel('Dengue Cases')
plt.legend()
plt.title('Death Dengue Cases: Actual vs Predictions')
plt.ylim(0, max(max(death_actual), max(predictions[:, 1])) * 1.1)  # Set y-axis limit

plt.tight_layout()  # Adjust layout to prevent overlapping
plt.show()
```


Affected Dengue Cases: Actual vs Predictions
Actual Affected Cases
Predicted Affected Cases
Affected Dengue Cases
40000
30000
20000
10000
0
0
5
10
15
20
Data Points
Death Dengue Cases: Actual vs Predictions
Actual Death Cases
Predicted Death Cases
Dengue Cases
300
250
200
150
100
50
0
0
5
10
15
20
Data Points

Designed a graph of training loss and validation loss in times of dataset passing in the model.

In [28]:
```
# Plot training and validation loss
plt.figure(figsize=(12, 3))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Mean Squared Error Loss')
plt.legend()
plt.show()
```



R-squared (R^2) ,0 to 1; higher values indicating a better fit

In [29]:
```
# Compute R-squared
r2 = r2_score(y_test, predictions)

print(f'R-squared: {r2}')
```

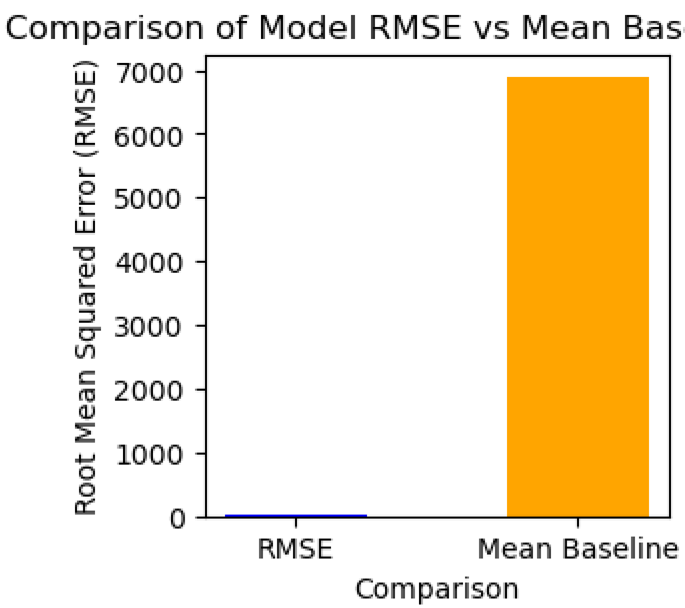
```
R-squared: 0.9271324288948425
```

RMSE VS Baseline of RMSE

In [30]:
```
# Calculate Mean Squared Error
mse = mean_squared_error(y_test, predictions)

# Calculate Root Mean Squared Error
rmse = np.sqrt(mse)
mean_baseline_predictions = np.full_like(y_test, np.mean(y_test))

# Calculate RMSE Mean Baseline
rmse_mean_baseline = np.sqrt(mean_squared_error(y_test, mean_baseline_predictions))

print('Mean Squared Error (RMSE):',mse)
print('Root Mean Squared Error (RMSE)',rmse)
print(f'Mean Baseline RMSE: {rmse_mean_baseline}')
```

```
Mean Squared Error (RMSE): 662.8707412094502
Root Mean Squared Error (RMSE) 25.74627625909134
Mean Baseline RMSE: 6901.986296179139
```

In [31]:
```
# bar difference more then better model
plt.figure(figsize=(3, 3))
plt.bar(['RMSE', 'Mean Baseline'], [rmse, rmse_mean_baseline], color=['blue', 'orange'], width=0.5)
plt.xlabel('Comparison')
plt.ylabel('Root Mean Squared Error (RMSE)')
plt.title('Comparison of Model RMSE vs Mean Baseline RMSE')
plt.show()
```



Dengue predict by other moedels

In [32]:
```
print(data)
print(y)
```

```
     YEAR  MONTH        MIN        MAX   HUMIDITY    RAINFALL
0    2015      1  13.548485  25.300000  68.976452   10.529000
1    2015      2  17.342424  28.712121  56.465000   16.500000
2    2015      3  19.669697  31.908824  48.826452   25.823529
3    2015      4  23.503030  32.485294  78.554333  192.911765
4    2015      5  25.263636  34.111765  85.996129  171.264706
..    ...    ...        ...        ...        ...         ...
103  2023      8  25.726471  31.373529  86.110000  420.364706
104  2023      9  25.355882  31.541176  85.910000  318.220588
105  2023     10  23.638235  31.526471  83.200000  160.314706
106  2023     11  19.176471  29.529412  79.090000   42.429412
107  2023     12  14.170588  26.432353  77.970000    9.638235

[108 rows x 6 columns]
     DENGUE  DEATHS
0         0       0
1         0       0
2         2       0
3         6       0
4        10       0
..      ...     ...
103   71976     342
104   79598     396
105   67769     359
106   40716     274
107    9288      83

[108 rows x 2 columns]
```

In [33]:
```
print(data.shape)
print(y.shape)

train_x, test_x, train_y, test_y = train_test_split(data, y, test_size=0.2, random_state=42)
print(train_x.shape)
print(test_x.shape)
print(train_y.shape)
print(test_y.shape)
```

```
(108, 6)
(108, 2)
(86, 6)
(22, 6)
(86, 2)
(22, 2)
```

Normalization

In [34]:
```
min_max_scaler = MinMaxScaler()
train_x = min_max_scaler.fit_transform(train_x)
test_x = min_max_scaler.transform(test_x)
```

Standardization

In [35]:
```
scaler = StandardScaler()
train_x = scaler.fit_transform(train_x)
test_x = scaler.transform(test_x)
```

In [ ]:
```

```

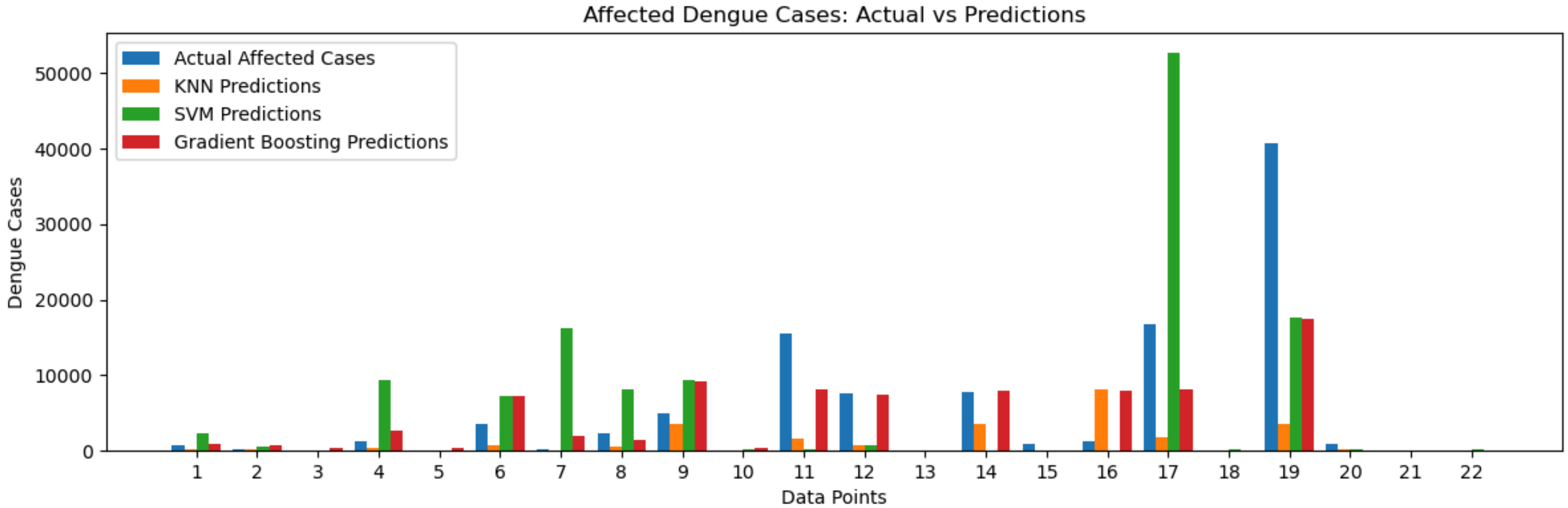
Models build

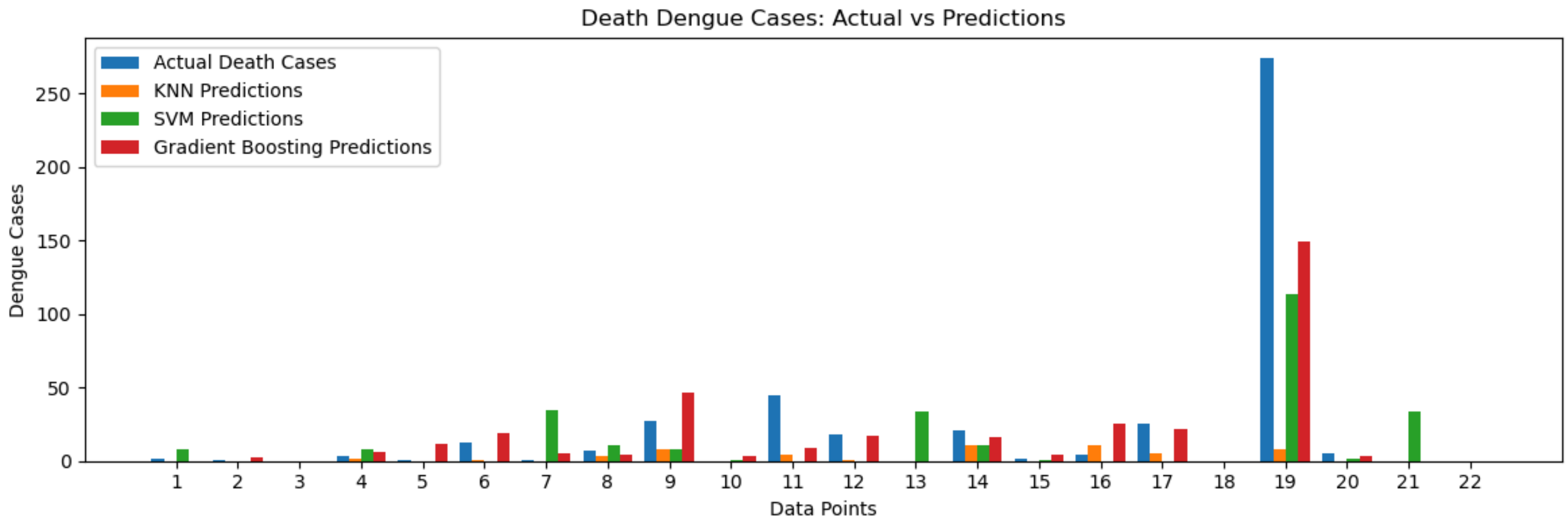
In [36]:
```
# KNN model
model_k = KNeighborsClassifier(n_neighbors=3)
model_k.fit(train_x, train_y)
predictions_k = model_k.predict(test_x)
print('shape of x test', x_test.shape)
print(predictions_k)

# SVM model
model_s = SVC(kernel='poly', degree=2, C=2.0, gamma=1)
multi_output_model = MultiOutputClassifier(model_s)
# Train the model
multi_output_model.fit(train_x, train_y)
# Make predictions
predictions_s = multi_output_model.predict(test_x)
print(predictions_s)

# Gradient Boosting Regressor model
model_g = GradientBoostingRegressor(n_estimators=100, learning_rate=0.1, max_depth=3, random_state=42)
# Wrap the model with MultiOutputRegressor to handle multiple target columns
multi_output_model_g = MultiOutputRegressor(model_g)
multi_output_model_g.fit(train_x, train_y)
predictions_g = multi_output_model_g.predict(test_x)
print(predictions_g)
```

```
shape of x test (22, 1, 8)
[[ 295    0]
 [ 145    0]
 [  38    0]
 [ 431    2]
 [   9    0]
 [ 737    1]
 [  28    0]
 [ 512    3]
 [3567    8]
 [ 126    0]
 [1571    4]
 [ 737    1]
 [  38    0]
 [3521   11]
 [  28    0]
 [8143   11]
 [1796    5]
 [  23    0]
 [3567    8]
 [ 267    0]
 [  38    0]
 [  92    0]]
[[ 2286     8]
 [  522     0]
 [   38     0]
 [ 9288     8]
 [   17     0]
 [ 7247     0]
 [16253    35]
 [ 8143    11]
 [ 9288     8]
 [  145     1]
 [  199     0]
 [  737     0]
 [   92    34]
 [   36    11]
 [   28     1]
 [   36     0]
 [52636     0]
 [  193     0]
 [17583   113]
 [  295     2]
```

```
 [   92    34]
 [  199     0]]
[[ 9.08012599e+02 -2.70780383e+00]
 [ 7.15592765e+02  2.30829448e+00]
 [ 3.33505029e+02 -6.17736507e-02]
 [ 2.61064180e+03  6.12009206e+00]
 [ 3.96890506e+02  1.21129314e+01]
 [ 7.20306272e+03  1.85527195e+01]
 [ 1.90896600e+03  5.27545758e+00]
 [ 1.43879095e+03  4.08693691e+00]
 [ 9.24702555e+03  4.65895740e+01]
 [ 3.63231529e+02  3.01934542e+00]
 [ 8.08422112e+03  9.27301081e+00]
 [ 7.49793948e+03  1.72783402e+01]
 [-2.82227088e+02 -2.15513822e+00]
 [ 7.98314233e+03  1.63552430e+01]
 [-5.20221935e+02  4.58637259e+00]
 [ 8.04725183e+03  2.52517331e+01]
 [ 8.20284647e+03  2.18172252e+01]
 [-4.02429157e+02 -1.35458575e+00]
 [ 1.74353085e+04  1.49386768e+02]
 [-4.10203546e+02  3.77904693e+00]
 [-3.02093932e+02 -4.77241627e-01]
 [-2.37507056e+02 -8.15713186e-01]]
```

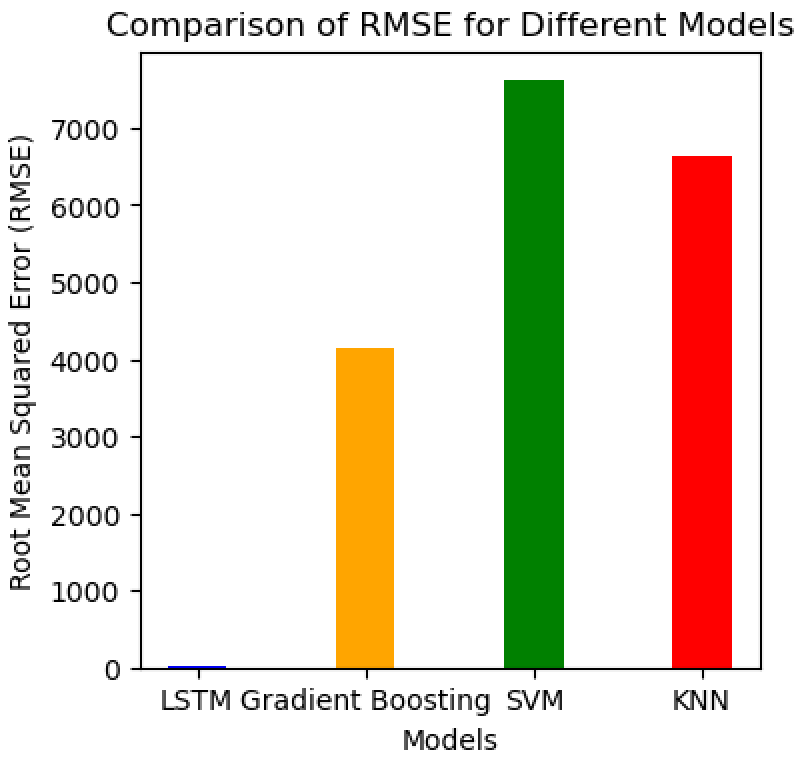
In [37]:
```
# Bar graph using subplots
plt.figure(figsize=(12, 8))

# Affected Dengue Cases subplot
plt.subplot(2, 1, 1)  # 2 rows, 1 column, 1st subplot
bar_width = 0.2
indices = np.arange(len(test_y))
# maxDeath=max(predictions_k[:, 0]),
plt.bar(indices, test_y.to_numpy()[:, 0], width=bar_width, label='Actual Affected Cases')
plt.bar(indices + bar_width, predictions_k[:, 0], width=bar_width, label='KNN Predictions')
plt.bar(indices + 2 * bar_width, predictions_s[:, 0], width=bar_width, label='SVM Predictions')
plt.bar(indices + 3 * bar_width, predictions_g[:, 0], width=bar_width, label='Gradient Boosting Predictions')

plt.xlabel('Data Points')
plt.ylabel('Dengue Cases')
plt.xticks(indices + 1.5 * bar_width, indices + 1)
plt.legend()
plt.title('Affected Dengue Cases: Actual vs Predictions')
plt.ylim(0,)  # Set y-axis limit

# Death Dengue Cases subplot
plt.subplot(2, 1, 2)  # 2 rows, 1 column, 2nd subplot
plt.bar(indices, test_y.to_numpy()[:, 1], width=bar_width, label='Actual Death Cases')
plt.bar(indices + bar_width, predictions_k[:, 1], width=bar_width, label='KNN Predictions')
plt.bar(indices + 2 * bar_width, predictions_s[:, 1], width=bar_width, label='SVM Predictions')
plt.bar(indices + 3 * bar_width, predictions_g[:, 1], width=bar_width, label='Gradient Boosting Predictions')

plt.xlabel('Data Points')
plt.ylabel('Dengue Cases')
plt.xticks(indices + 1.5 * bar_width, indices + 1)
plt.legend()
plt.title('Death Dengue Cases: Actual vs Predictions')
plt.ylim(0,)  # Set y-axis limit

plt.tight_layout()  # Adjust layout to prevent overlapping
plt.show()
```


Affected Dengue Cases: Actual vs Predictions
Actual Affected Cases
KNN Predictions
SVM Predictions
Gradient Boosting Predictions
Dengue Cases
Data Points


Death Dengue Cases: Actual vs Predictions
Actual Death Cases
KNN Predictions
SVM Predictions
Gradient Boosting Predictions
Dengue Cases
Data Points

In [38]:
```
import matplotlib.pyplot as plt

# RMSE values for each model
rmse_lstm = rmse
rmse_gb = np.sqrt(mean_squared_error(test_y, predictions_g))
rmse_svm = np.sqrt(mean_squared_error(test_y, predictions_s))
rmse_knn = np.sqrt(mean_squared_error(test_y, predictions_k))

print("LSTM(RMSE):", rmse_lstm)
print("Gradient Boosting Regressor(RMSE):", rmse_gb)
print("SVM(RMSE):", rmse_svm)
print("KNN(RMSE):", rmse_knn)

# Plotting the bar graph
plt.figure(figsize=(4, 4))  # Adjust the figure size as needed
models = ['LSTM', 'Gradient Boosting', 'SVM', 'KNN']
rmse_values_affected = [rmse_lstm, rmse_gb, rmse_svm, rmse_knn]
bar_width = 0.35

plt.bar(models, rmse_values_affected, width=bar_width, color=['blue', 'orange', 'green', 'red'])
plt.xlabel('Models')
plt.ylabel('Root Mean Squared Error (RMSE)')
plt.title('Comparison of RMSE for Different Models')
plt.show()
```

```
LSTM(RMSE): 25.74627625909134
Gradient Boosting Regressor(RMSE): 4152.8529982762575
SVM(RMSE): 7609.027770591744
KNN(RMSE): 6623.263829110237
```



In [39]:
```
rSquired
```

Out[39]:
```
0.99998974835348
```

Used SARIMAX to predict/forecast the weather for 2024.

Temperature(min, max), humidity, rainfall

SARIMAX start

In [40]:
```
data2024 = pd.read_csv('2015_to_2023.csv')
```

Convert 'YEAR' and 'MONTH' columns to datetime format

In [41]:
```
data2024['DATE'] = pd.to_datetime(data2024['YEAR'].astype(str) + '-' + data2024['MONTH'].astype(str), format=
data2024.set_index('DATE', inplace=True)

# Drop 'YEAR' and 'MONTH' columns
data2024.drop(['YEAR', 'MONTH'], axis=1, inplace=True)
```

SARIMAX parameters tunig

In [42]:
```
order = (1, 2, 1)  # ARIMA order
seasonal_order = (1, 1, 1, 12)  # Seasonal order
```

SARIMAX model design and predict

In [43]:

```
# Create a DataFrame to store the predicted values
predicted_values = pd.DataFrame()

# Fit SARIMA model for each column
for column in data2024.columns:
    # Fit SARIMA model to the entire dataset
    model_sarimax = SARIMAX(data2024[column], order=order, seasonal_order=seasonal_order)
    fitted_model = model_sarimax.fit()

    # Forecast for 2024
    forecast = fitted_model.forecast(steps=12)

    # Store the predicted values for 2024 in the DataFrame
    predicted_values[column] = forecast

# Add 'YEAR' and 'MONTH' columns
predicted_values['YEAR'] = 2024
predicted_values['MONTH'] = range(1, 13)

# Reorder the columns
predicted_values = predicted_values[['YEAR', 'MONTH'] + data2024.columns.tolist()]

# Print the predicted values for 2024
print("Predicted values for 2024:")
print(predicted_values.to_string(index=False))

# Save the predicted values to a CSV file
predicted_values.to_csv('2024-database-only.csv', index=False)
```

```
C:\Users\User\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\User\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\User\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\User\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\User\anaconda3\Lib\site-packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-invert
ible starting MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
C:\Users\User\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\User\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\User\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\User\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)

Predicted values for 2024:
 YEAR  MONTH       MIN       MAX  HUMIDITY   RAINFALL
 2024      1 12.373042 25.465648 77.909410  11.329192
 2024      2 15.755441 28.789316 70.893623  16.401124
 2024      3 20.419033 32.091233 63.376666  15.936214
 2024      4 22.938675 33.180723 75.901013  83.099795
 2024      5 24.184848 33.317984 82.372175 286.190118
 2024      6 25.435841 33.499008 88.973813 455.643578
 2024      7 25.640164 32.872642 87.934536 371.494734
 2024      8 25.804217 32.559153 87.337996 341.039926
 2024      9 25.466006 32.715513 88.343738 322.217110
 2024     10 25.079546 32.818513 85.698031 206.730428
 2024     11 18.716239 29.832275 80.305446   7.576910
 2024     12 14.365490 26.396771 76.047590  10.048108
```

SARIMAX end

2024 dengue affected and death case predict

In [44]:

```
# Define the function to create sequences
def create_sequences(data, sequence_length):
    sequences = []
    for i in range(len(data) - sequence_length + 1):
        sequence_end = i + sequence_length
        if sequence_end > len(data):
            break
        seq = data[i:sequence_end]
        sequences.append(seq)
    return np.array(sequences)

# Load the 2024 database
database2024 = pd.read_csv('2024-database-only.csv')
data = database2024[['YEAR', 'MONTH', 'MIN', 'MAX', 'HUMIDITY', 'RAINFALL']]

# Scale the features
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(data)

# Define the sequence length
sequence_length = 1

# Create sequences for training/testing
X_seq = create_sequences(X_scaled, sequence_length)
print('X_seq shape:', X_seq.shape)

# Assuming your model is already trained and loaded
# Define a placeholder for the predicted target variables
# below statement modify 2 column output is consider as 2 additional features of below code.
additional_features = np.zeros((X_seq.shape[0], X_seq.shape[1], 2))  # Assuming 2 additional features
dat = df[df['YEAR'] == 2019][['DENGUE', 'DEATHS']]
additional_features[:, :, :] = dat.values.reshape((dat.shape[0], 1, 2))

X_seq_with_additional_features = np.concatenate([X_seq, additional_features], axis=-1)

# Now X_seq_with_additional_features has shape (3, 10, 8)
# Now you can use X_seq_with_additional_features to make predictions
predictions = model.predict(X_seq_with_additional_features)

# Now you have the predictions for the target variables
print('Predictions shape:', predictions.shape)
print('Predictions:', predictions)
```

```
X_seq shape: (12, 1, 6)
1/1 [==============================] - 0s 33ms/step
Predictions shape: (12, 2)
Predictions: [[3.0668352e+01 1.2322240e+00]
 [1.4140810e+01 8.5088003e-01]
 [1.4032810e+01 9.5433062e-01]
 [5.3964756e+01 2.2007871e+00]
 [1.9494293e+02 4.4202948e+00]
 [1.8896301e+03 1.1960541e+01]
 [1.6265322e+04 9.8760445e+01]
 [5.2650754e+04 3.1597986e+02]
 [1.6862127e+04 1.0124210e+02]
 [8.1469062e+03 4.8938747e+01]
 [4.0140317e+03 2.4179747e+01]
 [1.0409282e+03 6.4539757e+00]]
```

In [ ]:

```
```

In [ ]:

```
```

In [45]:

```
# import pandas as pd

# # Read the CSV file into a DataFrame
# df = pd.read_csv('C:/Users/User/anaconda3/Dengue/Database/DengueAndClimateBangladesh.csv')

# # Filter the DataFrame for rows where the year is 2019 and select specific columns
# dat = df[df['YEAR'] == 2019][['DENGUE', 'DEATHS']]

# # Print only the values without column names and index
# print(dat.to_string(header=False, index=False))
```

In [46]:

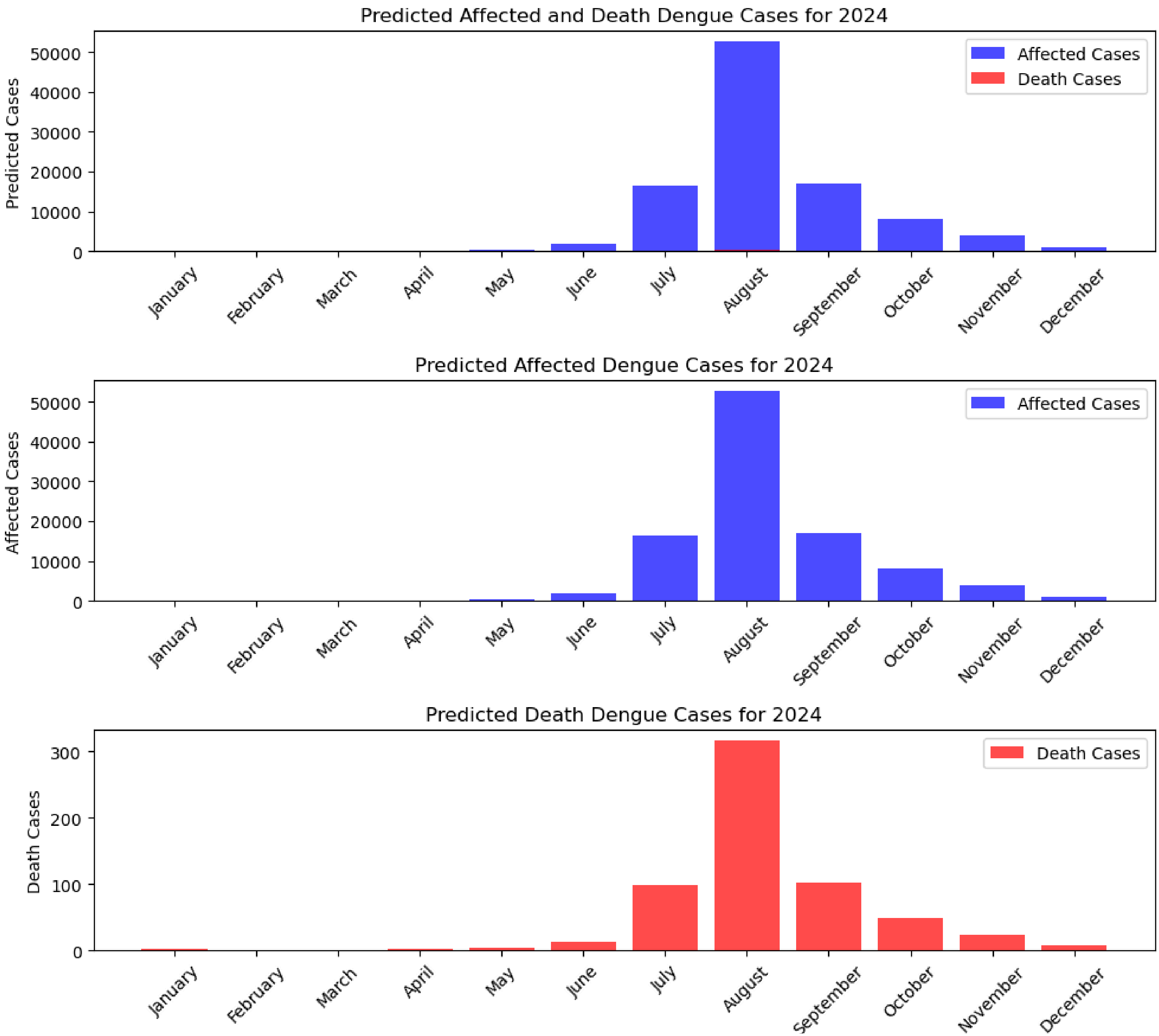
```
# additional_features[:, :, :] = dat.values.reshape((dat.shape[0], 1, 2))
# additional_features
```

In [ ]:

```
```

In [47]:
```
import matplotlib.pyplot as plt

# Months for x-axis (assuming 12 months)
months = ["January", "February", "March", "April", "May", "June", "July", "August", "September", "October", "N

# Extracting predicted values for affected and death dengue cases
predicted_affected_cases = [pred[0] for pred in predictions]
predicted_death_cases = [pred[1] for pred in predictions]

# Plotting the subplots
fig, axs = plt.subplots(3, 1, figsize=(10, 9))

# Plot for combined affected and death cases
axs[0].bar(months, predicted_affected_cases, color='blue', alpha=0.7, label='Affected Cases')
axs[0].bar(months, predicted_death_cases, color='red', alpha=0.7, label='Death Cases')
axs[0].set_ylabel('Predicted Cases')
axs[0].set_title('Predicted Affected and Death Dengue Cases for 2024')
axs[0].legend()
axs[0].set_xticklabels(months, rotation=45)
axs[0].set_ylim(0,)
# Plot for affected cases
axs[1].bar(months, predicted_affected_cases, color='blue', alpha=0.7, label='Affected Cases')
axs[1].set_ylabel('Affected Cases')
axs[1].set_title('Predicted Affected Dengue Cases for 2024')
axs[1].legend()
axs[1].set_xticklabels(months, rotation=45)
axs[1].set_ylim(0,)
# Plot for death cases
axs[2].bar(months, predicted_death_cases, color='red', alpha=0.7, label='Death Cases')
axs[2].set_ylabel('Death Cases')
axs[2].set_title('Predicted Death Dengue Cases for 2024')
axs[2].legend()
axs[2].set_xticklabels(months, rotation=45)
axs[2].set_ylim(0,)
plt.tight_layout()
plt.show()
```

```
C:\Users\Public\Documents\iSkysoft\CreatorTemp\ipykernel_1012\3821593413.py:19: UserWarning: FixedFormatter
should only be used together with FixedLocator
  axs[0].set_xticklabels(months, rotation=45)
C:\Users\Public\Documents\iSkysoft\CreatorTemp\ipykernel_1012\3821593413.py:26: UserWarning: FixedFormatter
should only be used together with FixedLocator
  axs[1].set_xticklabels(months, rotation=45)
C:\Users\Public\Documents\iSkysoft\CreatorTemp\ipykernel_1012\3821593413.py:33: UserWarning: FixedFormatter
should only be used together with FixedLocator
  axs[2].set_xticklabels(months, rotation=45)
```


Predicted Affected and Death Dengue Cases for 2024
Predicted Cases
50000
40000
30000
20000
10000
0
Affected Cases
Death Cases
January
February
March
April
May
June
July
August
September
October
November
December
Predicted Affected Dengue Cases for 2024
Affected Cases
50000
40000
30000
20000
10000
0
Affected Cases
January
February
March
April
May
June
July
August
September
October
November
December
Predicted Death Dengue Cases for 2024
Death Cases
300
200
100
0
Death Cases
January
February
March
April
May
June
July
August
September
October
November
December

In [48]:
```
# Calculate R-squared scores
print("R-squared scores (R2):",r2)
```

```
R-squared scores (R2): 0.9271324288948425
```

In [ ]:

In [ ]:

In [ ]:

In [ ]: