**Assignment 4**

**1. Objective**

The goal of this project is to build a **deep learning-based weather forecasting model** that predicts daily temperatures using a synthetic dataset. The model applies **LSTM networks** which are effective for sequential and time-dependent data like weather conditions.

**2. Dataset**

* A synthetic dataset was created to simulate **daily temperature readings** from **2010 to 2020** (11 years).
* The temperature follows a sinusoidal pattern to simulate **seasonal changes** with added Gaussian noise to mimic real-world weather fluctuations.
* Features:
  + **Date**: Ranging from 01-01-2010 to 31-12-2020.
  + **Temperature**: Simulated daily temperature values.

**3. Data Preprocessing**

* Converted temperature data into a **time series** format indexed by date.
* Normalized the data using **MinMaxScaler (0–1)** for stable neural network training.
* Created **sequences of 60 days (time steps)** as input to predict the next day’s temperature.
* Split the dataset into **training (80%)** and **testing (20%)** sets.

**4. Model Architecture**

The model was built using **Keras Sequential API** with the following layers:

1. **LSTM Layer (50 units, return sequences=True)** – captures long-term dependencies in temperature patterns.
2. **LSTM Layer (50 units, return sequences=False)** – compresses features for final prediction.
3. **Dense Layer (25 units)** – adds non-linearity.
4. **Dense Layer (1 unit)** – final output: predicted temperature.

* **Loss Function**: Mean Squared Error (MSE)
* **Optimizer**: Adam
* **Batch Size**: 32
* **Epochs**: 20

**5. Training**

* The model was trained on the training dataset.
* Training process minimized the **MSE loss** while learning temperature patterns.

**6. Evaluation**

* Predictions were made on the **test set**.
* The results were compared with actual temperature values.
* **Visualization**:
  + Blue line: Actual temperatures
  + Red line: Predicted temperatures

The plot showed that the model successfully captured the **seasonal variations and short-term fluctuations** of the synthetic weather data.

**7. Conclusion**

* The LSTM model performed well in forecasting daily temperatures using time series data.
* The model can be extended to real-world datasets for practical weather prediction tasks.
* Future improvements may include:
  + Adding multiple weather features (humidity, wind speed, pressure).
  + Hyperparameter tuning (layers, neurons, epochs).
  + Using Bidirectional LSTMs or GRUs for better performance.