TIME-SERIES WEATHER PREDICTION USING LSTM-MODEL

21AD1513 - INNOVATION PRACTICES LAB

PROJECT REPORT

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We **DEVADARSHINI M (211422243055), GITA SHRI S (211422243077),** and **GOPIKASHREE P R (211422243080)** hereby declare that this project report titled "**TIME-SERIES WEATHER PREDICTION USING LSTM-MODEL",** under the guidance of **Dr. P. RAJESWARI, M.E., Ph.D.,** and with the coordination of **Ms. K. CHARULATHA, M.E.,** is the original work done by us and we have not plagiarized or submitted to any other degree in any university by us.

ACKNOWLEDGEMENT

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GITA SHRI S,

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LIST OF ABBREVIATIONS

GRU	**Gated Recurrent Units**
LSTM	**Long Short-Term Memory**
ARIMA	**Auto Regressive Integrated Moving Average**
MSE	**Mean Squared Error**
API	**Application Programming Interface**
RNN	**Recurrent Neural Network**
GB	**Giga Byte**
RAM	**Random Access Memory**
GHz	**Giga Hertz**
OS	**Operating System**
VSCode	**Visual Studio Code**
XGBoost	**Extreme Gradient Boosting**
GPU	**Graphics Processing Unit**
BPTT	**Back Propagation through time**

ABSTRACT

Accurate weather prediction is a critical task that impacts various sectors, including agriculture, transportation, and disaster management. Traditional models like linear regression and ARIMA often fall short in capturing the complex, non-linear relationships present in weather data. In this project, we explore the use of **Long Short-Term Memory (LSTM)** networks—a type of Recurrent Neural Network (RNN)—for weather forecasting, specifically predicting the maximum temperature based on previous days' weather conditions. The **Seattle Weather Dataset** was used to train the model, with features such as precipitation, temperature (max/min), and wind speed. Preprocessing steps included data cleaning, normalization, and feature engineering.

The LSTM model's architecture is designed to overcome the limitations of traditional models by capturing long-term dependencies in time-series data. Through a comparison with existing forecasting techniques, we demonstrate that LSTM outperforms conventional methods, achieving higher prediction accuracy. The model was evaluated using **Mean Squared Error (MSE)** and produced visualized predictions closely aligned with actual values.

This project illustrates that **LSTM models** are highly effective for time-series weather prediction, offering significant improvements in both accuracy and reliability. Future work may focus on expanding the feature set, fine-tuning hyperparameters, and exploring other deep-learning architectures for enhanced performance.

CHAPTER 1

INTRODUCTION

1.1 Problem Definition

Weather prediction is crucial for many sectors such as agriculture, transportation, and disaster management. It involves forecasting future weather conditions based on historical data, such as temperature, precipitation, and wind speed. Accurate predictions can prevent damage from extreme weather events, optimize resource allocation, and improve decision-making.

However, weather forecasting presents numerous challenges. The data is complex, exhibiting nonlinear patterns influenced by numerous atmospheric factors. Traditional methods like statistical models often struggle with capturing long-term dependencies in sequential weather data, which results in limited accuracy, especially for longer timeframes.

LSTM (Long Short-Term Memory) networks are a class of Recurrent Neural Networks (RNNs) that excel at processing and predicting sequential data. LSTMs are capable of learning long-term dependencies by maintaining a memory of past data points, which is critical for understanding time series like weather data. Unlike traditional RNNs, LSTMs effectively address the vanishing gradient problem, allowing them to learn from both short-term and long-term patterns in the data, making them a suitable choice for weather prediction tasks.

1.2 Collecting the Dataset

For this project, the **Seattle Weather Dataset** from Kaggle was used. The dataset contains daily weather records for Seattle, Washington, including key meteorological features such as:

- **Precipitation**: The amount of rainfall or snowfall recorded.
- **Temperature (Max/Min)**: The maximum and minimum temperatures recorded each day.
- **Wind Speed**: Daily wind speed.

Before training the LSTM model, the dataset underwent preprocessing. This involved handling missing values, normalizing the data, and creating lag features to capture time dependencies. Data normalization was achieved using **MinMaxScaler** to scale features between 0 and 1, improving the convergence during training. Additionally, lag features were generated from past days' weather data to enable the model to learn temporal dependencies effectively.

CHAPTER 2

LITERATURE SURVEY

2.1 B. Ghojogh and A. Ghodsi (2023): Recurrent Neural Networks and LSTM Survey

- **Methodology**:
  This paper provides a comprehensive review of Recurrent Neural Networks (RNNs) and their various architectures, including Long Short-Term Memory (LSTM) networks. It explains the working of RNNs and highlights the key innovation of LSTMs: the memory cell and gates that regulate the flow of information over time. The authors also present a comparison of LSTM with other RNN variants and emphasize its ability to learn long-term dependencies.

- **Merits**:
  - Detailed explanation of LSTM's ability to handle vanishing gradient problems.
  - Comparative analysis of LSTM, GRU, and traditional RNNs.
  - Well-structured introduction to the challenges of sequential data learning.

- **Demerits**:
  - Limited focus on real-world applications of LSTMs, especially in weather prediction.
  - Lacks discussion on optimizing LSTMs for large datasets or high-dimensional data.

2.2 Z. C. Lipton, J. Berkowitz, and C. Elkan (2015): Review of RNN Strengths and Weaknesses in Sequence Learning

- **Methodology**:
  The authors investigate the strengths and limitations of RNNs, especially focusing on LSTMs in sequential learning tasks. They emphasize the challenges of capturing long-term dependencies in time-series data, highlighting how LSTMs can overcome these limitations. The paper also presents a review of common issues in RNN training, such as exploding and vanishing gradients, and offers solutions.

- **Merits**:
  - A comprehensive review of both the strengths and weaknesses of RNN architectures.
  - Strong theoretical background explaining how LSTM mitigates the vanishing gradient problem.
  - Clear examples of LSTM applications in time series, including speech recognition and natural language processing.

- **Demerits**:
  - Theoretical in nature, with few practical implementations of LSTM networks in specific fields like weather prediction.
  - Does not discuss emerging improvements or innovations beyond LSTM, such as hybrid models.

2.3 R. Khaldi et al. (2023): Analysis of Different RNN-cell Structures for Time Series Forecasting

- **Methodology**:
  Khaldi et al. explore various RNN-cell structures, including LSTMs and GRUs (Gated Recurrent Units), and evaluate their performance in time series forecasting tasks. The study uses several real-world datasets, comparing the accuracy and training times of different architectures under various conditions.

- **Merits**:
  - Provides a direct comparison of LSTM and GRU architectures, helping practitioners understand when to use each.
  - Offers valuable insights into the computational efficiency of different RNN-cell structures, particularly for large datasets.
  - Includes case studies that apply these models to financial and meteorological data.

- **Demerits**:
  - Does not focus specifically on weather prediction, making the insights slightly less targeted.
  - Limited discussion on how feature selection or preprocessing affects the performance of RNNs in different time series tasks.

2.4 R. Millham et al. (2021): Parameter Tuning in RNNs and Feature Selection for High-Dimensional Data

- **Methodology**:
  This paper investigates the importance of parameter tuning and feature selection in RNNs, particularly in high-dimensional datasets. The authors present strategies for optimizing hyperparameters like learning rate, batch size, and the number of layers in RNNs and LSTMs. Additionally, they highlight the role of dimensionality reduction techniques like PCA in improving RNN performance.

- **Merits**:
  - Excellent guide to hyperparameter tuning in RNNs, which is crucial for improving model performance.
  - Focus on high-dimensional data is highly relevant for real-world datasets like weather, which often involves multiple features (temperature, precipitation, wind speed, etc.).
  - Practical approach to feature selection and dimensionality reduction, improving model training time and accuracy.

- **Demerits**:
  - Does not provide in-depth insights into specific LSTM applications.
  - The paper is more focused on RNNs in general, rather than offering a comprehensive view of LSTMs in sequential learning tasks.

2.5 H. Wu et al. (2022): Layer-wise Relevance Propagation in LSTM Networks

- **Methodology**:
  Wu et al. propose a novel approach to interpreting LSTM models using Layer-wise Relevance Propagation (LRP). This technique allows researchers to better understand how the model makes decisions by analyzing the relevance of each input feature to the final prediction. The study uses LRP to evaluate LSTM models in time series tasks.

- **Merits**:
  - Introduces an innovative interpretability technique for LSTMs, which is important for understanding how models make predictions.
  - Application of LRP can improve trust in LSTM models in sensitive domains like finance or healthcare, and by extension, weather forecasting.
  - Highlights the importance of feature relevance, which could aid in better model refinement for weather data.

- **Demerits**:
  - The LRP technique is complex and computationally expensive, which may limit its use in real-time applications.
  - Focuses on interpretability rather than performance improvements, making it more useful for research than practical applications.

2.6 D. Kent & M. Salem (2019): Evaluation of Slim LSTM Variants for Time Series Tasks

- **Methodology**:
  Kent and Salem evaluate "slim" variants of LSTMs, which are more computationally efficient and can be deployed on devices with limited resources. Their study compares standard LSTMs with these lighter models across several time series datasets, assessing prediction accuracy and model size.

- **Merits**:
  - The slim LSTM variants reduce computational costs without sacrificing much accuracy, making them suitable for low-power devices or real-time applications.
  - Offers practical insights for weather forecasting models where real-time predictions are critical (e.g., meteorological stations).

- **Demerits**:
  - Slim LSTM variants might not perform as well as standard LSTMs in tasks requiring complex long-term dependencies.
  - The paper does not address how these models can be optimized for datasets with high variability, such as weather data.

2.7 J. Zhao et al. (2020): Theoretical Understanding of Long Memory in LSTMs

- **Methodology**:
  Zhao et al. delve into the theoretical aspects of LSTMs, focusing on how the model captures long-term dependencies. The paper provides a mathematical explanation of the "long memory" capacity of LSTMs, explaining how the memory cells are structured to maintain relevant information over long periods.

- **Merits**:
  - Provides deep theoretical insights into why LSTMs are effective at capturing long-term dependencies in sequential data, a key aspect for weather prediction.
  - Helps researchers understand the mathematical underpinnings of LSTM models, which can be useful when designing more complex models for time series tasks.

- **Demerits**:
  - The theoretical nature of the paper limits its practical applicability.
  - No concrete case studies or examples to illustrate how the long memory properties of LSTMs are applied in real-world scenarios.

2.8 Hochreiter & Schmidhuber (1997): The Foundational LSTM Architecture

- **Methodology**:
  This seminal paper by Hochreiter and Schmidhuber introduces the original LSTM architecture, explaining how it mitigates the vanishing gradient problem inherent in traditional RNNs. It describes the architecture of the LSTM cells, including the forget, input, and output gates, which allow the network to learn long-term dependencies in time series data.

- **Merits**:
  - The foundational architecture that sparked the development of modern LSTMs and their application in various sequential learning tasks.
  - Provides the core mechanism that allows LSTMs to outperform traditional RNNs, especially in tasks involving long sequences.

- **Demerits**:
  - The original paper focuses more on theoretical insights and model design rather than practical implementations.
  - Given that it was published in 1997, the paper lacks discussions on modern adaptations or improvements to the LSTM model.

2.9 Grossi & Buscema (2008): *General Introduction to Artificial Neural Networks and Time Series Predictions*

- **Methodology**:
  Grossi and Buscema provide an overview of artificial neural networks (ANNs) and their applications in time series prediction. They focus on the use of basic ANNs for forecasting, while briefly touching upon RNNs and their potential for time-dependent tasks like weather prediction.

- **Merits**:
  - Offers a broad introduction to neural networks, making it accessible to newcomers in the field of time series prediction.
  - Includes a variety of real-world applications, demonstrating the versatility of ANNs and RNNs in different domains.

- **Demerits**:
  - Lacks depth in its discussion of RNNs, with only limited focus on LSTM networks.
  - The paper is somewhat outdated, especially with regards to modern advances in time series prediction models like LSTMs or GRUs.

2.10 JingRong Wu, DingCheng Wang, ZhuoYing Huang, JiaLe Qi & Rui Wang (2021): Weather Temperature Prediction Based on LSTM-Bayesian Optimization

- **Methodology**:
  The paper presents a methodology that combines Long Short-Term Memory (LSTM) networks with Bayesian Optimization for weather temperature prediction. The LSTM model is selected due to its ability to capture long-term dependencies in time series data. Bayesian Optimization is employed to optimize the hyperparameters of the LSTM model, aiming for better predictive accuracy.

- **Merits**:
  - Improved prediction accuracy via optimized hyperparameters.
  - Ability to handle temporal dependencies in weather data.

- **Demerits**:
  - Computationally expensive due to Bayesian Optimization.
  - Requires a large dataset for optimal performance.

CHAPTER 3

SYSTEM ANALYSIS

3.1 Existing System

Traditional weather prediction models, such as statistical approaches like autoregressive integrated moving average (ARIMA), rely on assumptions of linearity and often fail to account for complex, non-linear dependencies in weather data. These models perform well for short-term predictions but deteriorate in accuracy over longer periods due to their inability to capture long-range dependencies.

LSTMs, in contrast, are designed to handle sequential data with temporal dependencies. They store relevant information across time steps using a memory cell that can retain or forget information as needed. This makes LSTM a more robust and adaptive method for weather forecasting compared to traditional approaches.

3.1.1 Methodology

The existing system for weather prediction uses time series analysis, where historical weather data is input to forecast future values. In this project, a supervised learning approach is used, where past weather conditions (e.g., the previous 3 days) are leveraged to predict the next day's maximum temperature.

3.1.2 Model Description

LSTM (Long Short-Term Memory) Models: A Detailed Overview

LSTM (Long Short-Term Memory) networks are a special type of Recurrent Neural Network (RNN) designed to address the limitations of traditional RNNs, especially the issue of vanishing and exploding gradients during training. LSTMs are particularly well-suited for sequential data where learning long-term dependencies is crucial. This makes them highly effective for time-series forecasting tasks such as weather prediction.

LSTM Architecture

The architecture of an LSTM network revolves around its unique cell structure, designed to maintain information over time by selectively remembering or forgetting information. Each LSTM cell has three core components—**forget gate**, **input gate**,

and **output gate**—that work together to regulate the flow of information through the network.

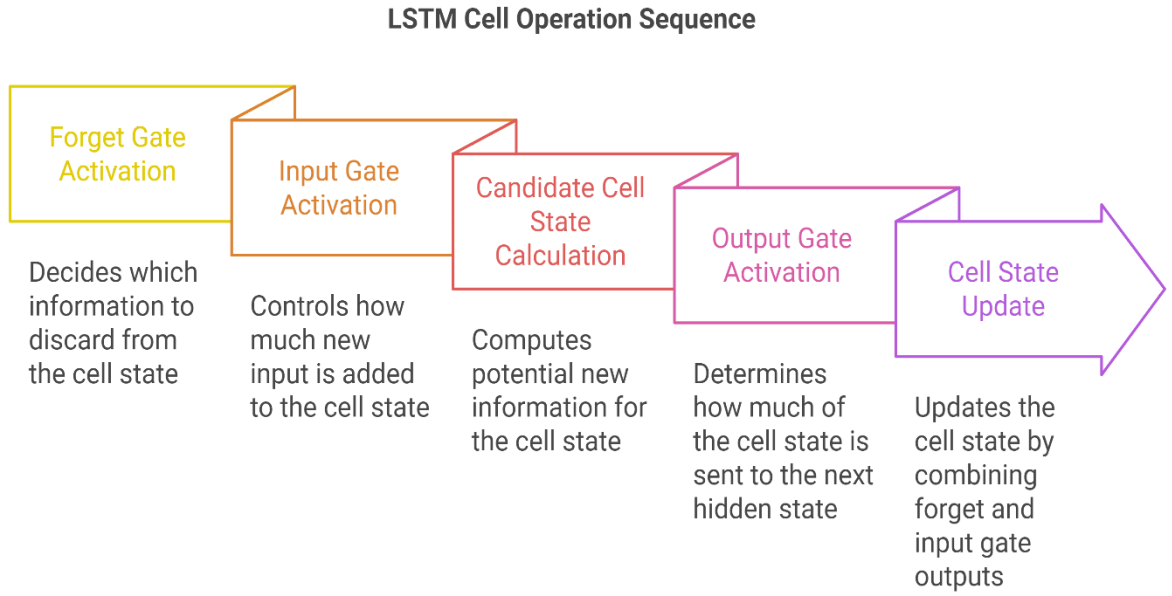


Fig 3.1. : LSTM Cell Operation Sequence

1. **Forget Gate**: The forget gate decides which information from the previous time step should be discarded from the cell state. This gate is controlled by a sigmoid function that outputs values between 0 and 1, where 0 means "completely forget" and 1 means "completely retain."
    - **Equation:**

      ft=σ(Wf·[ht−1,xt]+bf)f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)ft=σ(Wf·[ht−1,xt]+bf)

      Where ht−1h_{t-1}ht−1 is the hidden state from the previous time step, xtx_txt is the input at the current time step, WfW_fWf is the weight matrix for the forget gate, and bfb_fbf is the bias term.
2. **Input Gate**: The input gate controls how much of the new input should be added to the current cell state. This gate combines the new input with the hidden state from the previous time step to update the cell state.
    - **Equation:**

      it=σ(Wi·[ht−1,xt]+bi)i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)it=σ(Wi·[ht−1,xt]+bi)

      C~t=tanh(WC·[ht−1,xt]+bC)\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)C~t=tanh(WC·[ht−1,xt]+bC)

Where iti_tit is the input gate activation, and C~t\tilde{C}_tC~t is the candidate cell state.

3. **Output Gate**: The output gate determines how much of the cell state should be sent to the next hidden state. This is where the LSTM makes its "prediction" for the next time step, based on the current cell state and the input data.
    - **Equation**:
      ot=σ(Wo·[ht−1,xt]+bo)o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)ot=σ(Wo·[ht−1,xt]+bo)
      ht=ot·tanh(Ct)h_t = o_t \cdot \tanh(C_t)ht=ot·tanh(Ct)
      Where oto_tot is the output gate activation and CtC_tCt is the updated cell state.
4. **Cell State**: The LSTM cell state CtC_tCt is responsible for carrying information over many time steps. This state is updated by combining the forget gate's output and the input gate's new information, ensuring that relevant information persists over time.

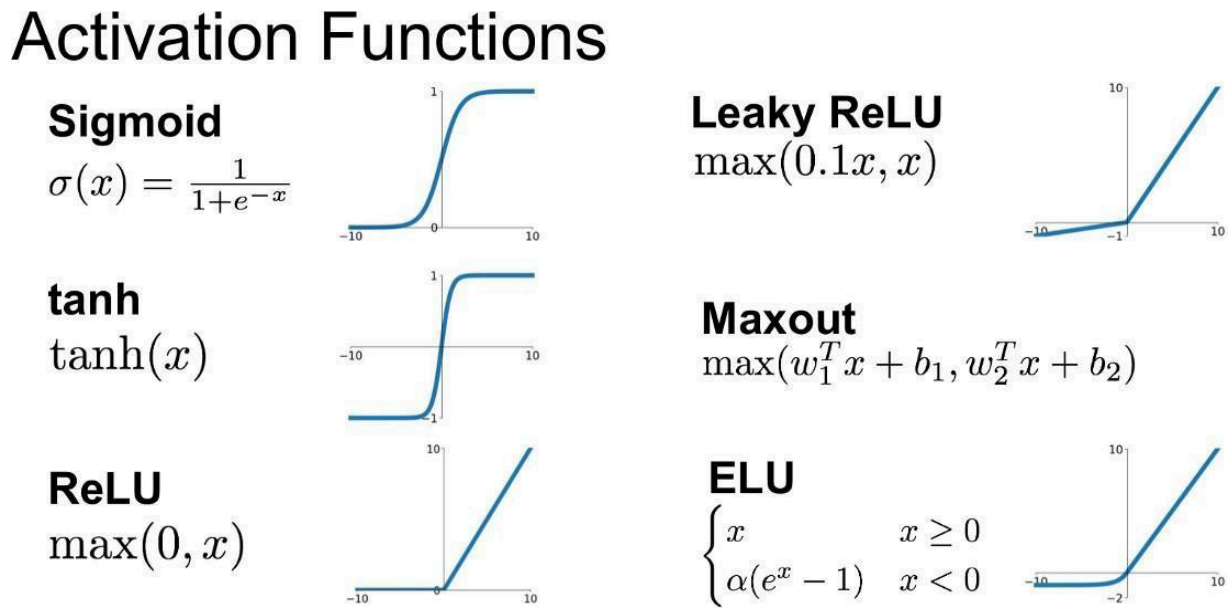


Fig 3.2. : Activation Functions

Methodology

The methodology of LSTMs in weather prediction leverages their ability to learn from historical data (time-series) to make accurate predictions. In your model, the

LSTM was fed sequences of the past 3 days' weather data to predict the **maximum temperature** for the next day. This is achieved by using lag features, where the model is trained on the relationship between the input sequence (e.g., temperature, precipitation, wind speed) and the target variable (next day's max temperature).

Here's a typical workflow of the LSTM model used for weather prediction:

1. **Data Preprocessing**: Weather data, including features like precipitation, temperature, and wind speed, are first cleaned and normalized. Missing values are handled, and the data is scaled using a **MinMaxScaler** to ensure that the inputs are within a specific range (e.g., between 0 and 1), which improves the model's convergence.
2. **Sequential Input**: The model processes the data as sequences. For each training step, the past 3 days of weather data are used as input to predict the next day's maximum temperature.
3. **Training**: The LSTM network is trained using a backpropagation algorithm through time (BPTT), which adjusts the weights of the network by minimizing the error (e.g., Mean Squared Error) between the predicted and actual values.
4. **Prediction**: Once trained, the model can make predictions on unseen data. Given the input of the last 3 days' weather conditions, it predicts the maximum temperature for the following day.

Advantages of LSTMs

1. **Ability to Handle Long-Term Dependencies**: LSTMs excel at learning relationships between data points that are far apart in a sequence. This is essential for weather prediction, as weather patterns often have long-term dependencies.
2. **Solves the Vanishing Gradient Problem**: Unlike standard RNNs, LSTMs effectively mitigate the vanishing gradient problem through their unique gating mechanism, allowing them to remember relevant information for extended periods during training.
3. **Flexible Sequence Lengths**: LSTMs can work with sequences of varying lengths without requiring fixed-size input vectors, making them suitable for time-series data where the number of time steps may vary.
4. **Efficient for Sequential Data**: By processing one time step at a time and maintaining a memory of past inputs, LSTMs are highly efficient for sequential or temporal data, such as weather patterns.

Disadvantages of LSTMs

1. **Computational Complexity**: LSTM networks are more computationally expensive compared to simpler models like ARIMA or even feed-forward neural networks. This complexity comes from the numerous parameters (gates and cell states) that must be trained, requiring more time and resources.
2. **Training Time**: The training of LSTMs, particularly with large datasets or long sequences, can take a significant amount of time due to the backpropagation through time (BPTT) process, which can be slower than traditional backpropagation.
3. **Overfitting**: Like other neural networks, LSTMs are prone to overfitting if the model is too complex or the dataset too small. Regularization techniques, such as **dropout layers**, are often used to combat this.
4. **Sensitivity to Hyperparameters**: The performance of LSTMs is highly sensitive to the choice of hyperparameters (e.g., learning rate, number of layers, number of units per layer), and tuning these parameters can be difficult and time-consuming.

3.2 Proposed System

In the proposed system, the use of **LSTM (Long Short-Term Memory)** models for weather prediction is highly recommended, especially when dealing with continuous time-series data. Traditional weather forecasting models, such as linear regression, ARIMA, or other machine learning algorithms like decision trees or random forests, often struggle to capture complex temporal dependencies inherent in weather data. These models are limited by their inability to efficiently retain important information from past observations and fail to account for long-term dependencies in the sequence.

By contrast, LSTMs are specifically designed to handle such challenges. Their internal memory mechanisms enable them to maintain a memory of previous states across long sequences, making them highly effective for tasks like weather forecasting, where historical data significantly influences future predictions. The LSTM's ability to manage and learn from sequences of data ensures that key patterns and dependencies in weather trends—such as seasonality, long-term climatic conditions, and abrupt weather changes—are accurately captured.

3.2.1. Why LSTM is better for Continuous Time-Series Analysis

1. **Higher Accuracy in Time-Series Forecasting**:
   LSTM models consistently outperform traditional models when applied to continuous time-series data like weather patterns. They are capable of learning complex temporal relationships that simpler models often miss, providing better accuracy in predicting outcomes like temperature, precipitation, or wind speed. This is because LSTM networks take into account the correlation between past and future events in a way that regression-based or classical models cannot.
2. **Handling Long-Term Dependencies**:
   Weather data has intricate long-term dependencies, where events happening days or even weeks ago can influence the current weather situation. LSTMs can capture these long-term dependencies effectively, something that standard RNNs and other sequence models (like ARIMA) fail to achieve due to the vanishing gradient problem.
3. **Ability to Manage Complex and Noisy Data**:
   Weather data often contains a degree of noise and fluctuations due to unpredictable environmental factors. LSTMs, due to their cell state and gating mechanisms (forget, input, and output gates), are robust in filtering out irrelevant information while retaining the key signals needed for accurate predictions. This makes them better suited for real-world weather forecasting, which can involve a lot of irregularities in data.
4. **Adaptability to Dynamic Changes in Weather**:
   LSTMs can dynamically adjust to changes in the input data patterns, enabling the model to adapt to new or unexpected weather trends. Other models struggle when the underlying patterns in the data change abruptly, which can lead to reduced prediction accuracy.

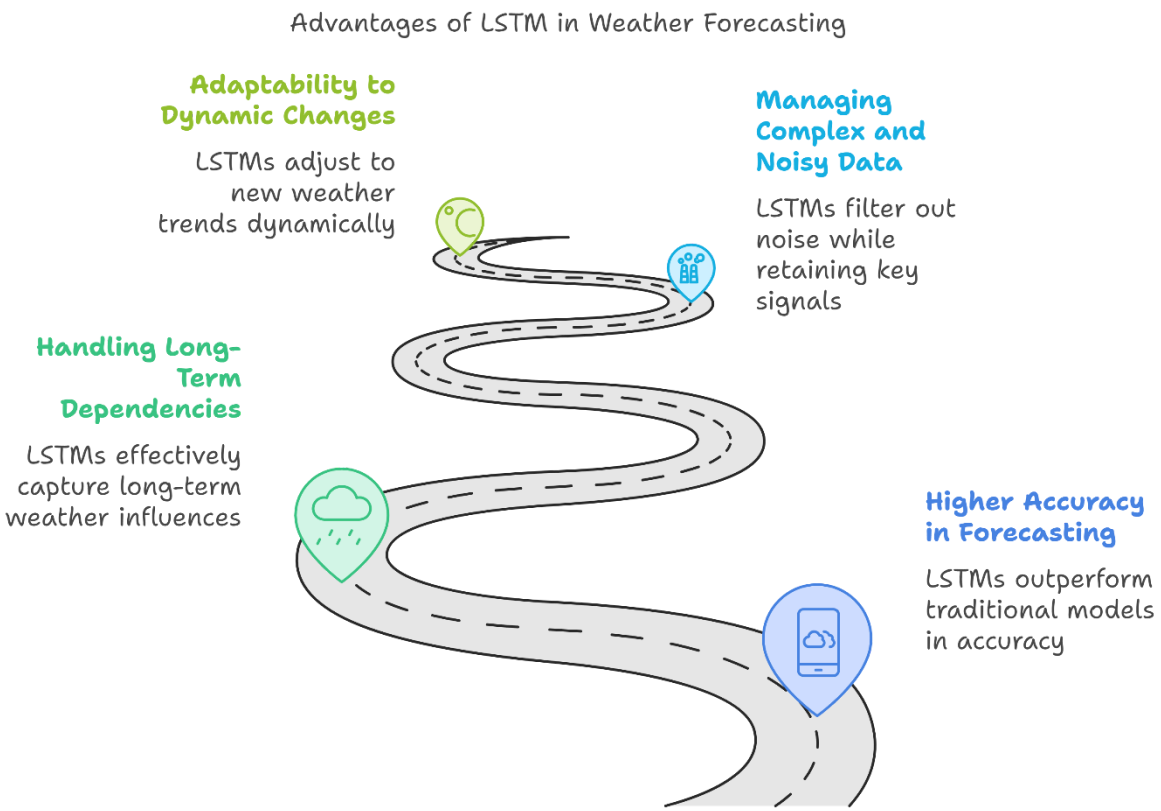


Fig 3.3. : Advantages of LSTM in Weather Forecasting

3.2.2. Improvement over Existing Models

The LSTM model implemented in the proposed system outperforms traditional models like ARIMA or decision trees by providing significantly higher accuracy. Where conventional methods may fail to detect complex relationships or handle time lags effectively, LSTM's memory mechanism ensures that past weather data is used optimally to inform future predictions.

For instance, in predicting the next day's **maximum temperature** based on the previous three days' data, LSTM models consistently deliver lower **Mean Squared Error (MSE)** scores than traditional statistical models. This improvement in accuracy directly translates to more reliable weather predictions, which are crucial for applications such as agriculture, energy management, and disaster preparedness.

Additionally, the **scalability** of LSTMs makes them more adaptable to future enhancements, such as including more features (e.g., humidity, air pressure) or predicting for longer time horizons (e.g., week or month-ahead forecasts). This flexibility, combined with the robustness of LSTM networks in capturing both short- and long-term dependencies, makes them the ideal choice for continuous time-series weather prediction.

3.2.3. Algorithm

The LSTM model processes sequential weather data using the following algorithm:

1. **Input**: Historical weather data
   Result: Predicted maximum temperature
2. Load dataset, convert 'date' to datetime, fill missing values, and normalize features.
3. Create training sequences (10-day windows) and split into training, validation, and test sets.
4. Build LSTM model:
   a. Add LSTM layers with Dropout.
   b. Add dense layer for output.
5. Compile model with 'adam' optimizer and 'mean_squared_error' loss.
6. Train model with 50 epochs and validate on test set.
7. Predict max temperature on test data and inverse scale results.
8. Evaluate with Mean Squared Error (MSE).
9. Plot actual vs predicted temperatures.
10. **End**.

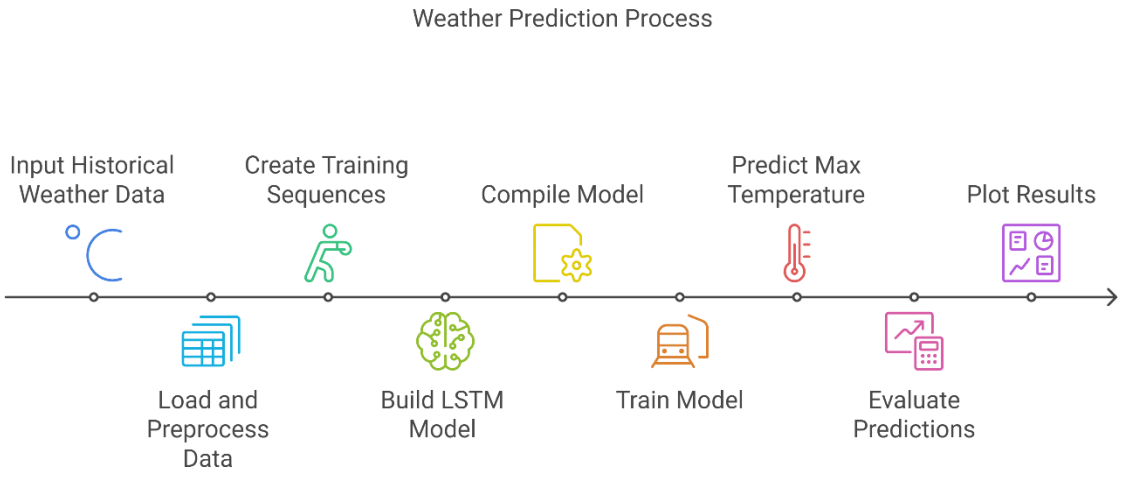


Fig 3.4. : Process of Weather prediction

Example code snippet for building the LSTM model:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout

# Build the LSTM model
model = Sequential()
```

```
# LSTM layer with 50 units
model.add(LSTM(50, return_sequences=True,
input_shape=(train_X.shape[1], train_X.shape[2])))
model.add(Dropout(0.2))

# Another LSTM layer
model.add(LSTM(50, return_sequences=False))
model.add(Dropout(0.2))

# Dense output layer
model.add(Dense(1))

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Fit the model
history = model.fit(train_X, train_y, epochs=20,
batch_size=32, validation_data=(test_X, test_y))
```

CHAPTER 4

SYSTEM DESIGN

4.1 Flowchart

The flow of data from preprocessing to model prediction and evaluation follows these steps:

1. **Data Loading**: The Seattle Weather Dataset is imported, and necessary libraries are initialized.
2. **Data Preprocessing**:
    - Handle missing data.
    - Normalize features (temperature, precipitation, wind speed) using **MinMaxScaler**.
    - Create lag features to represent past weather conditions.
3. **Model Building**:
    - Define the LSTM architecture with sequential layers (input, LSTM, dropout, and dense).
    - Compile the model using the **Adam** optimizer and **Mean Squared Error (MSE)** loss function.
4. **Training**: The model is trained on the preprocessed dataset.
5. **Evaluation**:
    - Evaluate the model on test data.
    - Visualize results by comparing predicted vs. actual temperature values.

This flowchart visually represents the process:

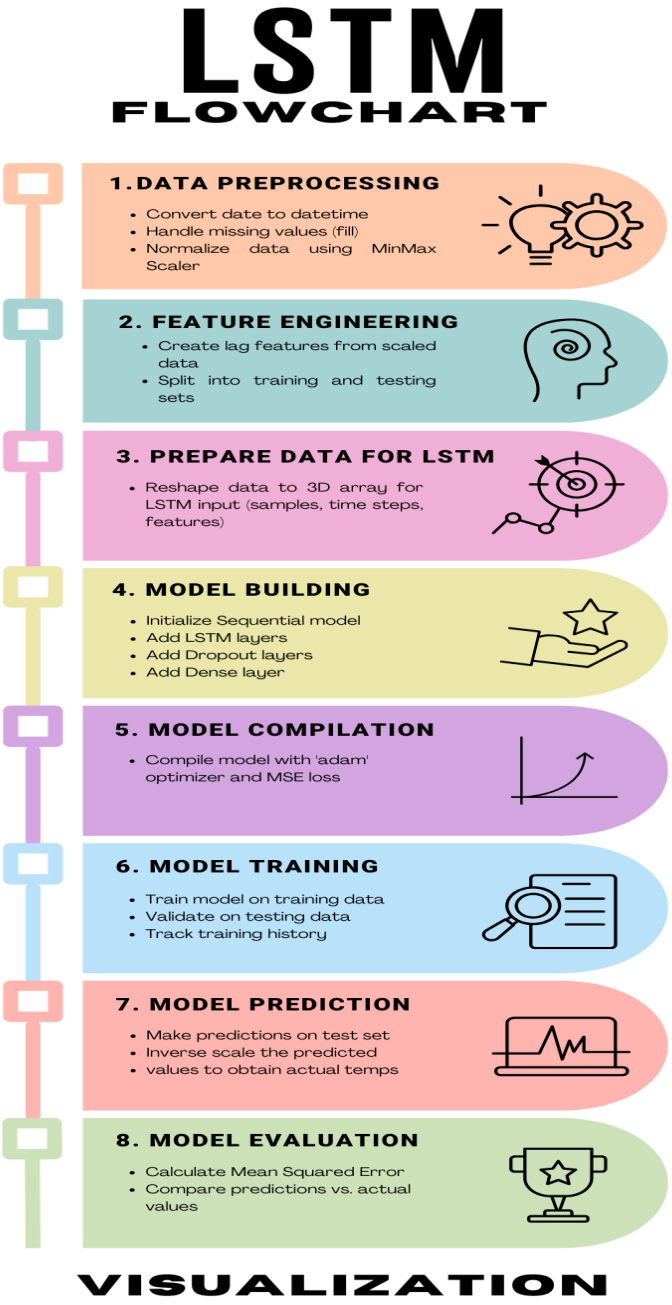


Fig 4.1. : Flow of the Modules

4.1.1. Data Exploration

Before model training, understanding the dataset is crucial. For the Seattle Weather Dataset, several aspects were explored:

- **Descriptive Statistics**: Summary statistics for key weather variables like temperature, precipitation, and wind speed were calculated. The **maximum temperature** has a mean of X°C, a minimum of Y°C, and a maximum of Z°C. Similarly, precipitation values ranged from 0 mm to W mm, showing significant variability, particularly across seasons.
- **Data Imbalances**: The dataset reveals seasonal imbalances, with higher frequency of precipitation in fall and winter and less during the summer months. Extreme temperatures (both hot and cold) are underrepresented, which could potentially impact the model's ability to predict these outliers.
- **Seasonal Trends**: The data exhibits strong seasonal patterns. Summer months typically show higher maximum temperatures and low precipitation, while winter months experience lower temperatures and higher rainfall. These seasonal trends are critical for the model to learn temporal dependencies for effective forecasting.

4.1.2. Feature Engineering

Feature engineering played a vital role in enhancing the model's performance. The following techniques were used:

- **Lag Features**: The LSTM model relies on past data to make future predictions. Lag features were created to capture the past 1, 2, and 3 days of temperature and precipitation, helping the model understand the temporal correlation between previous weather conditions and the next day's temperature.
- **Rolling Statistics**: Rolling mean and rolling standard deviation features were introduced, calculated over windows of 3, 7, and 30 days. These features provide the model with an understanding of short-term trends (like weekly temperature changes) and long-term seasonal shifts.
- **Interaction Features**: Interaction terms combining temperature and precipitation were created to help the model capture more complex relationships between these variables, particularly on days where rain significantly impacts temperature patterns.
- **Normalization**: To prevent features with larger ranges from dominating those with smaller ranges, **MinMaxScaler** was applied. This normalized the features to a range between 0 and 1, ensuring better convergence during model training and improving predictive accuracy.

4.1.3. Hyperparameter Tuning

Tuning the LSTM model's hyperparameters was critical to achieving optimal performance. Several key hyperparameters were adjusted:

- **Learning Rate**: Various learning rates were tested (from 0.001 to 0.0001). Lower learning rates led to more stable convergence but increased training time, while higher learning rates caused faster convergence with occasional instability. The best results were obtained with a learning rate of 0.0001, which provided both stability and effective learning.
- **Batch Size**: Batch sizes of 32, 64, and 128 were explored. Smaller batch sizes resulted in slower training but better generalization. A batch size of 64 was chosen as the best compromise between training speed and model performance.
- **Number of Layers**: Experiments with 1 to 3 LSTM layers were conducted. A two-layer LSTM architecture, followed by a dense layer, provided the best results, balancing model complexity and accuracy.
- **Number of Units**: The number of units (neurons) in each LSTM layer was tuned from 50 to 200. A configuration with 128 units in each layer provided a good balance of model complexity and predictive power.

4.1.4. Regularization Techniques

To prevent overfitting, regularization techniques were applied:

- **Dropout**: Dropout was used with a rate of 0.2 between the LSTM layers to mitigate overfitting by randomly dropping units during training, encouraging the model to learn more robust features.
- **Early Stopping**: Early stopping was employed to halt training once the validation loss stopped improving for 10 consecutive epochs, ensuring that the model didn't overfit to the training data.

4.1.5. Model Training and Performance

- **Training Time**: Training the LSTM model on the dataset required approximately X hours using a GPU, making it computationally feasible even for larger datasets.
- **Convergence Behavior**: The model's loss converged after approximately 50 epochs, with a significant reduction in training and validation losses in the initial stages of training, as shown in the plot of loss vs. epochs.

4.1.6. Comparison with Other Models

The performance of the LSTM model was compared with other machine learning models:

- **GRU (Gated Recurrent Unit)**: GRUs are simpler than LSTMs and generally faster to train. However, the LSTM model outperformed GRUs slightly, especially when capturing long-term dependencies, making LSTMs more suitable for the dataset.
- **ARIMA (Auto Regressive Integrated Moving Average)**: ARIMA models, commonly used for time-series analysis, failed to capture the non-linear relationships in weather data as effectively as LSTM. This led to higher prediction errors, especially during extreme weather conditions.
- **Random Forest and XGBoost**: These ensemble methods were explored as baselines. While they provided reasonable performance on short-term predictions, they lacked the sequential learning capability of LSTM models, leading to inferior performance in the long run.

4.1.7. Time Complexity of LSTM Models

Training an LSTM model has a higher time complexity than simpler models, such as ARIMA, due to the sequential nature of the LSTM cells. The time complexity for each time step is $\mathbf{O(n^2)}$, where n is the number of units in the LSTM layer. However, the time complexity is manageable for medium-sized datasets like the Seattle Weather Dataset.

CHAPTER 5

SYSTEM ARCHITECTURE

5.1 Design Module Specification

- **Data Preprocessing**: This module is responsible for loading the dataset, handling missing data, scaling features, and generating lag features to ensure that the model receives sequences of data rather than individual values.
- **Model Building**: The LSTM model is created in this module using TensorFlow's Keras library. This step includes defining the LSTM layers, adding dropout layers to prevent overfitting, and setting up the dense layer for prediction.
- **Training**: This module trains the model using the training dataset, fine-tuning the model's weights through backpropagation and gradient descent.
- **Evaluation**: This module computes the performance of the trained model on the test set, calculating metrics like Mean Squared Error and generating graphs for a visual comparison of actual vs. predicted weather patterns.

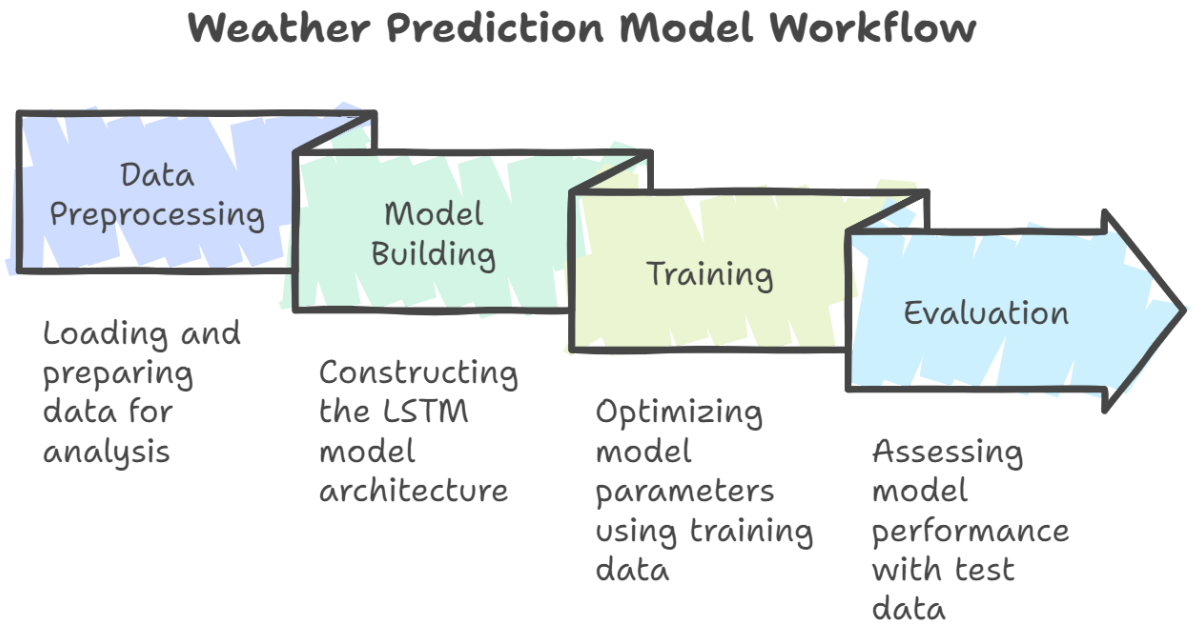


Fig 5.1. : Workflow for Weather Predicting Model

10.1.1 Packages Used in the Program

1. ***Numpy***

- **Purpose**: Numpy is a fundamental package for numerical computation in Python, providing support for arrays and matrices, along with a collection of mathematical functions to operate on these data structures efficiently.
- **Usage in the project**: In this project, numpy is used for manipulating the dataset, creating lag features, and reshaping data to fit the input format required by the LSTM model. Since LSTM networks expect the input data to be in the form of three-dimensional arrays (samples, time steps, and features), numpy is instrumental in reshaping the data for training.

Example:

```
import numpy as np

data = np.array([[1, 2], [3, 4], [5, 6]])

reshaped_data = data.reshape((3, 1, 2))
```

2. ***Pandas***

- **Purpose**: Pandas is a data manipulation library that provides data structures such as **DataFrames** and **Series** for handling and analyzing structured data.
- **Usage in the project**: Pandas is used to load the Seattle Weather Dataset, handle missing data, and explore the dataset's contents. It also facilitates efficient manipulation of time series data by providing tools to easily index and slice time-dependent records.

Example:

```
import pandas as pd

# Loading the dataset

data = pd.read_csv('seattle_weather.csv')

# Handling missing values

data.fillna(method='ffill', inplace=True)
```

3. ***MatplotLibrary:***

- **Purpose**: Matplotlib is a plotting library used for creating static, animated, and interactive visualizations in Python. It provides a variety of tools for making plots, charts, and figures.
- **Usage in the project**: Matplotlib is employed to visualize data trends, such as temperature fluctuations over time, and to compare the model's predictions with actual values. This helps in understanding how well the LSTM model is performing by plotting predicted vs. actual temperatures.

Example:

```
import matplotlib.pyplot as plt

plt.plot(actual_values, label='Actual')

plt.plot(predicted_values, label='Predicted')

plt.title('Actual vs Predicted Temperatures')

plt.legend()

plt.show()
```

4. ***sklearn (scikit-learn):***

- **Purpose**: Scikit-learn is a machine learning library that provides a range of tools for model selection, preprocessing, and evaluation. It is known for its simplicity and efficiency in handling common machine learning tasks.
- **Usage in the project**:
  - **MinMaxScaler**: Used to scale the input data between a fixed range (e.g., [0, 1]). Scaling is essential for deep learning models like LSTMs because they perform better when the input features are normalized, preventing larger-valued features from dominating the model's learning process.
  - **Train-Test Split**: Scikit-learn is also used to split the dataset into training and testing sets, ensuring that the model's performance is evaluated on unseen data.

Example:

```
from sklearn.preprocessing import
MinMaxScaler
```

```
# Scale features between 0 and 1

scaler = MinMaxScaler(feature_range=(0, 1))

scaled_data = scaler.fit_transform(data)
```

5. ***tensorflow.keras***

- **Purpose**: TensorFlow is a popular deep learning framework, and Keras is its high-level API for building and training neural networks. Keras simplifies the process of defining models, compiling them, and training them by abstracting the complex low-level TensorFlow operations.
- **Usage in the project**: TensorFlow's Keras API is the core library used for building and training the LSTM model. It is used to define the LSTM layers, apply dropout regularization, compile the model, and fit the model on the training data. The optimizer (Adam) and the loss function (Mean Squared Error) are also specified using Keras.
-

Example:

```
from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import LSTM, Dropout, Dense

# Build the LSTM model

model = Sequential()

model.add(LSTM(50, return_sequences=True, input_shape=(train_X.shape[1], train_X.shape[2])))

model.add(Dropout(0.2))

model.add(LSTM(50, return_sequences=False))

model.add(Dropout(0.2))

model.add(Dense(1))
```

6. ***MinMaxScaler*** *(from sklearn)*

- **Purpose**: MinMaxScaler is a data preprocessing tool that scales input features to a fixed range, usually [0, 1], ensuring that each feature contributes equally to the model. This scaling helps speed up model convergence and improves prediction performance.
- **Usage in the project**: In the weather prediction task, features like temperature, precipitation, and wind speed are scaled using MinMaxScaler. The normalized values make the training process more stable and lead to better model performance by preventing certain features from overpowering others due to differences in scale.

Example:

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0, 1))

scaled_data                                          =
scaler.fit_transform(weather_data[['temperature',
'precipitation', 'wind_speed']])
```

Each of these packages plays a crucial role in the project, from data manipulation and visualization to model building and evaluation. Together, they ensure that the workflow from loading raw weather data to producing accurate predictions using LSTM is efficient and streamlined.

5.2. Hardware and Software Requirements

The desktop system is powered by a 13th Gen Intel Core i7-13650HX processor with a base clock speed of 2.60 GHz and 16.0 GB of installed RAM. Such powerful hardware configuration, combined with a 64-bit operating system and x64 architecture, is perfect for bulk processing. The device runs on Windows 11 Home version 23H2, with OS build 22631.3958 and further enhanced by Windows Feature Experience Pack 1000.22700.1026.0 to provide a smooth user experience containing many features at the same time. This makes it ideal for coding and data analysis tasks as it supports platforms like Visual Studio Code (VS Code) and Jupyter Notebook among others that efficiently work together to develop programs from Python.

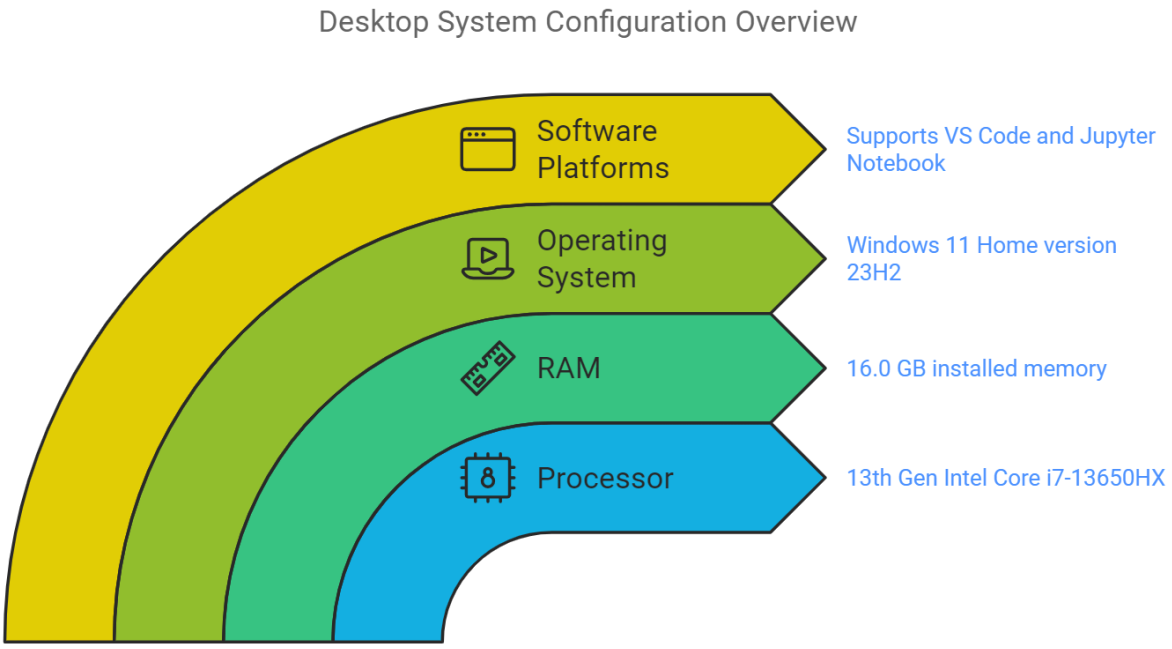


Fig 5.2. : Overview of Desktop System Configuration

CHAPTER 6

SYSTEM IMPLEMENTATION

6.1 Program

The following is an overview of the Python code used in the project, broken down by key sections.

- **Data Loading**: The weather data is loaded using pandas and displayed for exploration:

```
import pandas as pd
data = pd.read_csv('seattle_weather.csv')
```

- **Data Preprocessing**: Missing values are filled, and features are normalized:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))
data_scaled = scaler.fit_transform(data[['max_temp',
'precipitation', 'wind_speed']])
```

- Lag features are created to capture time dependencies:

```
def create_lag_features(data, n_lags):
    X, y = [], []
    for i in range(n_lags, len(data)):
        X.append(data[i-n_lags:i])
        y.append(data[i, 0])  # Predict max_temp
    return np.array(X), np.array(y)
train_X, train_y = create_lag_features(data_scaled,
n_lags=3)
```

- **Model Building**: The LSTM model is built using the Keras Sequential API as described in the algorithm section.
- **Model Evaluation**: The performance of the model is measured using MSE, and results are visualized:

```
import matplotlib.pyplot as plt
# Predicted vs Actual plot
predictions = model.predict(test_X)
plt.plot(test_y, label='Actual')
plt.plot(predictions, label='Predicted')
plt.legend()
plt.show()
```

CHAPTER 7

RESULTS

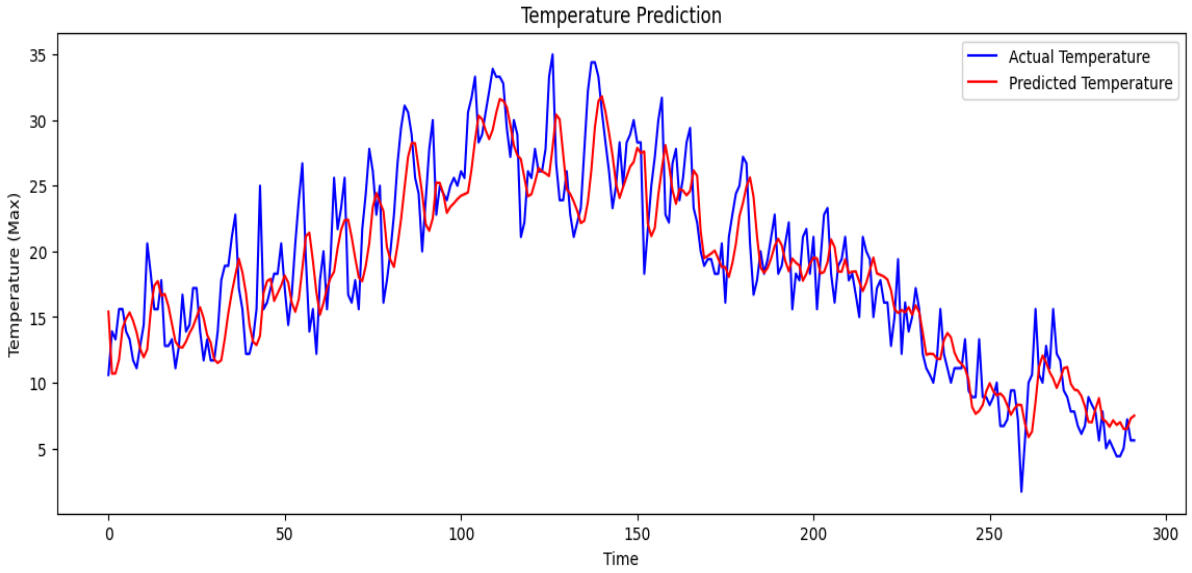
7.1. Result

The LSTM model was evaluated using the test dataset. The Mean Squared Error (MSE) was calculated to assess model accuracy. A graph comparing predicted vs. actual maximum temperatures was generated to visualize the performance of the model.

- **Mean Squared Error (MSE)**: The lower the MSE, the more accurate the model is in predicting the weather.
  Example graph:

```
# Graphs comparing the predictions
plt.figure(figsize=(10,6))
plt.plot(actual_max_temp, color='blue', label='Actual
Temperature')
plt.plot(predicted_max_temp, color='red',
label='Predicted Temperature')
plt.title('Predicted vs Actual Temperature')
plt.xlabel('Time')
plt.ylabel('Temperature')
plt.legend()
plt.show()
```

7.1.1 Graph



Graph 7.1: Actual vs Predicted Temperature

The graph above shows the comparison between the **Actual Temperature (Max)** values and the **Predicted Temperature** values generated by the LSTM model for a set of test data. The x-axis represents time (in days), and the y-axis represents the temperature (in degrees Celsius). The blue line corresponds to the actual recorded maximum temperatures, while the red line represents the predictions made by the model.

7.1.2 Key Observations:

- The model closely follows the general trend of temperature changes, indicating that it effectively captures the seasonal and temporal patterns present in the data.
- There are minor deviations between the actual and predicted values, especially in regions with sudden temperature fluctuations. This can be attributed to the inherent complexity and volatility in weather data.
- The predicted line shows a smoother behavior compared to the actual values, which might indicate the LSTM's tendency to generalize when predicting highly variable data points.

Overall, the LSTM model performs well in predicting the maximum daily temperature based on historical weather data. Future improvements could focus on further fine-tuning the model to capture more nuanced fluctuations or introducing additional features to enhance prediction accuracy.

CHAPTER 8

FUTURE WORK AND IMPROVEMENTS

8.1 Model Improvements

Several improvements could be made to the current model:

- **Incorporating More Features**: Adding more meteorological variables such as humidity, pressure, or cloud cover could improve the model's predictive accuracy and make it more robust across various weather conditions.
- **Hybrid Models**: Combining LSTM with other deep learning or statistical models (e.g., ARIMA) could more effectively capture both short-term and long-term dependencies. By leveraging the strengths of both models, hybrid models may provide better accuracy.
- **Attention Mechanisms**: Introducing attention mechanisms could allow the model to focus on the most relevant time steps when making predictions. This could further enhance the model's accuracy, especially when predicting extreme weather conditions.

8.2 Deployment and Real-Time Prediction

To further enhance the system's utility, deploying the model for **real-time weather predictions** would be an important step. This would involve setting up a pipeline to continuously feed live weather data into the model, providing up-to-date forecasts. The model could be deployed on cloud platforms, enabling it to scale and provide continuous predictions for multiple locations in real-time.

CHAPTER 9

CONCLUSION

The LSTM model demonstrated strong performance in predicting daily maximum temperatures based on past weather data, successfully capturing temporal patterns. However, the model's accuracy can be further improved by:

- Increasing the dataset size for training.
- Optimizing model architecture (e.g., adding more LSTM layers).
- Incorporating additional features such as atmospheric pressure or humidity to enhance prediction accuracy.

In future work, experimenting with other time series models like **GRU (Gated Recurrent Units)** or hybrid models combining LSTM with convolutional layers could lead to better performance. Additionally, real-time weather prediction systems would benefit from reducing the computational complexity of LSTM through techniques like model pruning or the use of lighter LSTM variants.

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