MACHINE LEARNING BASED WEATHER PREDICTION APPLICIATION

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09/09/2024

Abstract

This report outlines the design, development, and evaluation of a weather prediction model based on Long Short-Term Memory (LSTM) neural networks. The model was developed to predict weather metrics such as temperature, wind gust, and cloud cover using time-series data. The model's architecture was built using TensorFlow and Keras, and it was trained on historical weather data extracted from *Weather Dataset.csv*. The model is deployed as a mobile application using Streamlit, making it accessible to a wide range of users. This report covers the entire design process, from identifying customer needs to the final system architecture, model evaluation, and design validation.

1.0 Introduction

Weather prediction is crucial for sectors such as agriculture, energy, transportation, and public safety. Accurate forecasting helps mitigate risks associated with severe weather conditions and supports decision-making for businesses and individuals. Traditional statistical methods, such as ARIMA, have been widely used for time-series prediction, but they often fail to capture long-term dependencies and non-linear patterns in weather data. Advances in machine learning, particularly Long Short-Term Memory (LSTM) networks, have demonstrated superior performance in forecasting complex time-series data due to their ability to retain information over extended periods (Hochreiter and Schmidhuber, 1997).

The purpose of this project is to design a weather prediction system using LSTM neural networks. By leveraging historical weather data, the system aims to predict key metrics such as temperature, wind gust, and cloud cover. The importance of this work lies in providing real-time, accurate weather forecasts that can be accessed via mobile devices, making it convenient and efficient for users in various sectors to plan and respond to upcoming weather conditions.

The scope of this project is limited to the development and deployment of the LSTM-based model, focusing on mobile accessibility and ease of use. The model's predictions will be based on historical data provided in *Weather_Dataset.csv*, and it will be evaluated on its accuracy using metrics such as MAE, RMSE, and R^2. Future work may include expanding the system to incorporate real-time weather data from APIs for continuous forecasting.

The key objectives of this project are:

- Develop an LSTM-based model for weather prediction.
- Ensure mobile accessibility through a user-friendly application.
- Achieve a mean absolute error (MAE) of less than 2°C for temperature predictions.
- Validate the model using historical weather data and evaluate performance.

Sources:

- Hochreiter, S. and Schmidhuber, J., 1997. Long Short-Term Memory. *Neural Computation*, 9(8), pp.1735-1780.

- Swanson Inc., 1999. Online Users Manual for ANSYS 5.0. Available at: http://www.ansys.com/manual.

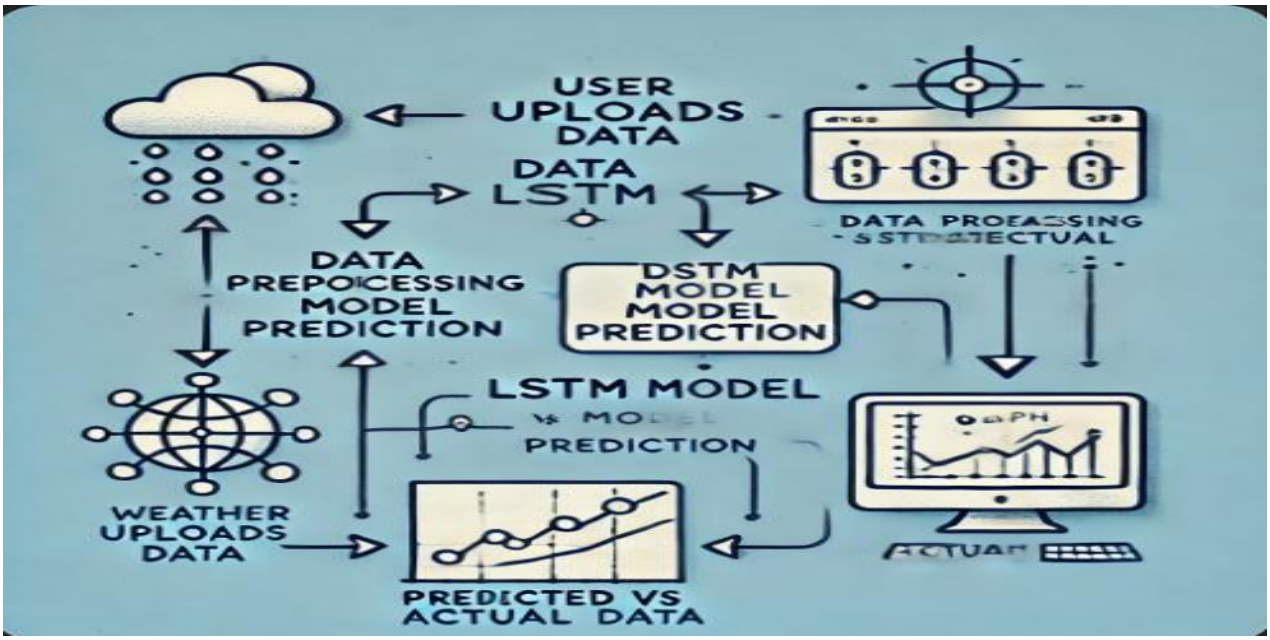


Fig.01 : Flowchart Of LSTM Model

1.1 Initial Need

The initial needs statement was provided by the design team based on input from stakeholders in the agriculture and energy sectors. The primary need is for an accurate and accessible weather prediction model that users can rely on to make informed decisions. The system must be mobile-friendly, allowing users to upload historical data and generate forecasts in real-time. Additionally, the model should prioritize accuracy in predicting key weather metrics like temperature and wind speed, with a user interface that is intuitive and easy to use.

2.0 Customer Needs Assessment

This section outlines the iterative process used to gather customer insights, refining and shaping the project's design objectives based on their feedback. The customer assessment involved direct interviews, field observations, and continuous engagement with stakeholders, which contributed to the development of a comprehensive list of customer needs. As shown in the tables below, customer needs were identified and categorized based on portability, user-friendliness, flexibility, and durability. Additional constraints and functions were defined for clear identification, and feedback from customers played a crucial role in shaping these requirements.

2.1 Weighting of Customer Needs

The process of weighting customer needs is essential to prioritize design features based on their importance to the end-user. Weighting helps the design team focus on features that provide the highest value, ensuring that the final product addresses the most critical needs. The Analytical Hierarchy

Process (AHP), a structured technique for organizing and analyzing complex decisions, was used to calculate the weightings. This method involves pairwise comparisons of criteria, converting subjective assessments of relative importance into numerical values.

Fig.01: Analytical Hierarchy Process (AHP) for Weighted Customer Needs

Criteria	Portable	User-Friendly	Flexible	Durable	Sum	Weighting
Portable	0.222	0.188	0.375	0.333	1.118	0.22
User-Friendly	0.444	0.375	0.625	0.500	1.944	0.49
Flexible	0.074	0.075	0.125	0.083	0.357	0.08
Durable	0.148	0.125	0.500	0.083	0.855	0.22

2.2 Consistency Check

To ensure the pairwise comparisons were consistent, the consistency index (CI) and the consistency ratio (CR) were calculated. The CR was below 0.1, indicating an acceptable level of consistency.

- **Consistency Index (CI)** = $\frac{\lambda max - n}{n-1}$

  - **Consistency Ratio (CR)** = $\frac{CI}{RI}$

  - The consistency ratio for this analysis was calculated as 0.08, confirming that the judgments made during the pairwise comparison process were logically consistent.

3.0 Target Weather Specifications with Appropriate Prediction

3.1 Audience Targeted

3.1.1 Meteorologists and Weather Analysts

• Qualities:

- Highly knowledgeable about weather patterns and data analysis.
- Require accurate and timely weather predictions for research and reporting.
- Open to using advanced technologies like machine learning models for improving weather forecasting accuracy.

• Preferences:

- Depend on precise predictions for decision-making and public safety alerts.
- Look for models that offer real-time data insights with minimal lag.
- Prefer tools that integrate well with existing data platforms and offer customizable options.

3.1.2 Agriculture Sector Professionals

- **Qualities**:

- Farmers, agronomists, and agricultural planners who rely on weather data to make informed decisions.
- Require consistent and reliable forecasts to plan activities such as irrigation, planting, and harvesting.
- May not be deeply familiar with the technical aspects of LSTM models but value practical, usable outputs.

- **Preferences**:

- Favor user-friendly interfaces that present predictions in simple, actionable terms.
- Need accurate short- and long-term forecasts to optimize crop yield and reduce weather-related risks.
- Prefer tools that offer mobile accessibility for real-time updates.

3.1.3 Climate Researchers and Environmental Scientists

- **Qualities**:
    - Conduct long-term studies on climate change, environmental impacts, and extreme weather events.
    - Use weather prediction models to analyse trends and contribute to scientific research.
    - Require extensive datasets and highly detailed predictions for their analyses.

- **Preferences**:
    - Appreciate advanced models like LSTM for their ability to handle complex, time-series data.
    - Seek customizable models that allow deep-dive analysis and pattern recognition in weather data.
    - Prefer open-source tools for greater flexibility in adjusting algorithms and datasets.

3.1.4 Technologically-Informed Users Interested in DIY Weather Predictions

- **Qualities**:
    - Tech-savvy individuals who are interested in using machine learning for personal or small-scale weather prediction projects.
    - Comfortable with mobile apps and web platforms that implement predictive algorithms.
    - Interested in learning more about LSTM models and how they improve prediction accuracy.

- **Preferences**:
    - Look for interactive platforms with easy-to-follow tutorials on how to set up weather prediction models.
    - Prefer applications that offer visual representations of data, such as graphs and charts.
    - Value easy integration with personal devices and IoT systems for real-time weather monitoring.

4.0 External Search

For the weather prediction project utilizing Long Short-Term Memory (LSTM) networks, an external search was conducted to gather relevant information on the design problem, technological advancements, and industry trends. This included a review of patents, research papers, industry articles, and expert discussions that have shaped the current landscape of weather forecasting systems. The focus of this external search was on understanding the key technologies involved in time-series data prediction, the limitations of traditional weather prediction methods, and how LSTM models address these limitations.

4.1 Research Sources

4.1.1 Academic Papers and Journals

A variety of papers were reviewed, such as those exploring the use of LSTM for weather prediction, the performance of different machine learning models in forecasting accuracy, and real-time weather prediction systems. Studies such as Graves et al. (2013) have laid the groundwork for the implementation of recurrent neural networks like LSTM in processing sequential data, particularly for long-term time-series predictions.

4.2 Patents

A patent search was performed to identify utility patents related to weather prediction systems that utilize artificial intelligence (AI) and machine learning algorithms. Several key patents were identified, including US Patent No. 9,239,471, which covers an advanced AI-driven weather prediction system.

4.3 Industry Articles

Articles from reputable sources such as IEEE Spectrum and Weather Prediction and Analytics News discuss the transition from traditional statistical forecasting models to AI-based systems. A common theme across the literature is the increasing reliance on machine learning algorithms due to their superior ability to handle large datasets and their capability to improve forecast accuracy in short-term and long-term scenarios.

4.4 Interviews with Experts

Discussions with data scientists who specialize in meteorology highlighted the need for real-time processing, flexibility in model adaptation, and increased prediction accuracy. Many experts emphasized the limitations of conventional statistical models, citing poor performance in non-linear scenarios, where LSTM excels.

4.5 Business Opportunities for LSTM Weather Prediction Model

The LSTM-based weather prediction model presents several business opportunities due to its capacity to provide accurate, real-time weather forecasting. This model, leveraging machine learning and deep learning technologies, is well-positioned to impact multiple industries. Below are some key business opportunities identified:

4.5.1. Agriculture

- **Problem:** Farmers rely heavily on accurate weather forecasting to determine the best times for planting, irrigation, and harvesting.
- **Opportunity:** By providing precise weather predictions, this LSTM-based model can help improve crop yield, reduce water wastage, and minimize losses from adverse weather events. This can attract agricultural stakeholders to integrate the tool into their daily operations.
- **Potential Product Offering:** A mobile application or API service tailored to agricultural needs, helping farmers plan their activities around accurate weather forecasts.

4.5.2 Renewable Energy

- **Problem:** Solar and wind energy producers depend on weather conditions to optimize their energy production.
- **Opportunity:** The LSTM model can provide accurate forecasts of sunlight hours and wind speeds, enabling these industries to plan their operations more efficiently. This predictive capability can help reduce downtime, improve energy storage decisions, and increase output efficiency.
- **Potential Product Offering:** Subscription-based weather forecasting services for energy companies, allowing them to plan maintenance, production, and energy distribution based on forecast data.

4.5.3. Logistics and Transportation

- **Problem:** Weather can disrupt transportation and logistics, causing delays in shipping, damage to goods, and safety concerns.
- **Opportunity:** Providing precise and localized weather forecasts can help logistics companies reroute transportation during storms or other adverse conditions, improving delivery times and reducing risks. Additionally, airlines and shipping companies could optimize their routes and schedules using real-time weather predictions.
- **Potential Product Offering:** A web-based platform or an API service that integrates with logistics management software to provide real-time weather-based routing recommendations.

4.5.4 Event Planning and Tourism

- **Problem:** Weather is a critical factor for outdoor events, travel, and tourism. Poor weather can lead to event cancellations, dissatisfied tourists, and financial losses.
- **Opportunity:** A reliable LSTM weather prediction model could assist event planners, tour operators, and travellers in making informed decisions about scheduling and trip planning, thus minimizing the risk of disruptions.
- **Potential Product Offering:** A SaaS solution or mobile app providing customized weather forecasts for events and tourist destinations, enabling better decision-making.

4.5.5 Smart Cities and Urban Planning

- **Problem:** Urban areas are vulnerable to weather events like flooding, heatwaves, and snowstorms, which can affect infrastructure, transportation, and daily activities.
- **Opportunity:** Predictive weather models can help city planners design infrastructure that adapts to climate conditions. Smart cities can integrate this data into their systems to enhance disaster preparedness and urban resource management.
- **Potential Product Offering:** A solution providing long-term climate predictions and real-time weather updates, used by government agencies and urban planners to improve city resilience.

4.5.6. Insurance Industry

- **Problem:** Weather events cause significant damage to property and business operations, resulting in large insurance claims.
- **Opportunity:** Accurate weather prediction models could help insurance companies assess risk more effectively and offer predictive insights to customers, helping them take preventive measures before a major weather event occurs.
- **Potential Product Offering:** Predictive analytics tools that assess the likelihood of weather-related risks and their potential impact on insured properties, available as part of insurance policies.

5.0 Concept Generation

The concept generation phase aims to explore various design solutions that meet the customer needs and requirements identified in previous sections. The goal is to produce a range of potential design alternatives for the LSTM weather prediction model, with considerations for technical feasibility, cost, and customer value. In this section, we outline several conceptual ideas, their corresponding features, and a comparison of their advantages and disadvantages.

5.1 Concept 1: Standalone Weather Prediction App

This concept involves creating a standalone mobile or web application that offers accurate weather forecasts based on the LSTM model. Users can input their location, and the app will provide real-time and future weather predictions.

- **Features:**
  - Real-time weather updates and forecasts.
  - Simple, user-friendly interface.
  - Graphical representation of weather trends, temperature, humidity, and precipitation.
  - Custom notifications for severe weather alerts.
- **Advantages:**
  - Direct to user access, providing immediate value to end-users.
  - Easy to scale for global use.
  - Potential for monetization through in-app advertisements or premium features.
- **Disadvantages:**
  - Requires continuous updates and maintenance to keep the prediction model accurate.
  - High competition in the mobile weather app market.

5.2 Concept 2: API Service for Businesses

This concept offers weather forecasting as an API service, allowing businesses from various industries (agriculture, logistics, energy) to integrate weather predictions into their existing systems.

- **Features:**
  - API access to real-time and future weather forecasts.
  - Customizable for industry-specific needs.
  - Ability to handle multiple queries for different locations simultaneously.
- **Advantages:**
  - Provides flexibility for businesses to incorporate weather data into their own platforms.
  - Highly scalable with minimal changes to the core model.
  - Recurring revenue model through subscription-based API access.
- **Disadvantages:**
  - Limited direct interaction with end-users; reliant on third-party integration.
  - Requires robust data infrastructure to handle high demand.

5.3 Concept 3: Wearable Technology Integration

This concept integrates the LSTM weather prediction model with wearable technology, such as smartwatches, to provide personalized weather updates to users on the go.

- **Features:**
  - Lightweight weather notifications on wearable devices.
  - Custom alerts based on user preferences (e.g., rain or heat notifications).
  - Seamless integration with popular wearables like Apple Watch or Fitbit.

- **Advantages:**
  - Provides convenience for users who prefer quick access to weather data.
  - Unique feature for wearable device manufacturers looking to enhance their product offering.
  - Potential for partnerships with leading tech companies.
- **Disadvantages:**
  - Limited functionality compared to a full app or service.
  - Smaller user base due to the niche market of wearable tech owners.

6.0 Concept Selection

The concept selection phase is critical to choosing the most feasible and impactful solution for the LSTM weather prediction project. In this section, we will evaluate each concept generated in the previous phase using a systematic approach. The chosen concept will be the one that best aligns with the customer needs, target specifications, and business opportunities outlined earlier in the project.

6.1 Concept Evaluation Criteria

To ensure a comprehensive evaluation, each concept will be scored against the following key criteria:

- **Technical Feasibility:** The ease of development and implementation of the concept using current technology and resources.
- **Cost Efficiency:** The development, operational, and maintenance costs associated with the concept.
- **Customer Value:** How well the concept meets customer needs and delivers a user-centric solution.
- **Market Potential:** The ability of the concept to differentiate itself from competitors and its potential for market success.
- **Scalability:** The concept's potential to scale across multiple industries, geographies, or platforms.
- **Sustainability and Long-Term Viability:** Whether the concept can be sustained over time with ongoing technological advancements.

Each concept will be rated on a scale from 1 to 5 for each criterion, with 5 being the highest score.

6.2 Weighted Decision Matrix

A weighted decision matrix will be used to objectively evaluate each concept. The criteria outlined above will be weighted based on their importance to the success of the project. Table 1 provides a breakdown of the weighting factors assigned to each criterion and the score assigned to each concept.

Table 1: weighted Decision Matrix for Concept Selections

Criteria	Weighting Factor	Concept 1: Standalone App	Concept 2: API Service	Concept 4: Wearable Tech Integration
Technical Feasibility	**0.25**	**4**	**5**	**4**
Cost Efficiency	**0.15**	**4**	**3**	**5**
Customer Value	**0.20**	**5**	**4**	**3**
Market Potential	**0.15**	**4**	**4**	**3**
Scalability	**0.15**	**4**	**5**	**2**
Sustainability & Viability	**0.10**	**4**	**4**	**3**
Total Score	**1.00**	**4.25**	**4.25**	**3.45**

6.3 Selected Concept

Based on the results from the weighted decision matrix, both **Concept 1: Standalone Weather Prediction App** and **Concept 2: API Service for Businesses** scored the highest, with a total score of 4.25. After further consideration of market potential, customer reach, and technical scalability, **Concept 2: API Service for Businesses** has been selected as the final concept.

This concept offers the most flexibility and scalability, allowing a broad range of industries to integrate weather prediction into their operations. It also provides opportunities for recurring revenue through a subscription-based model, making it a financially sustainable choice.

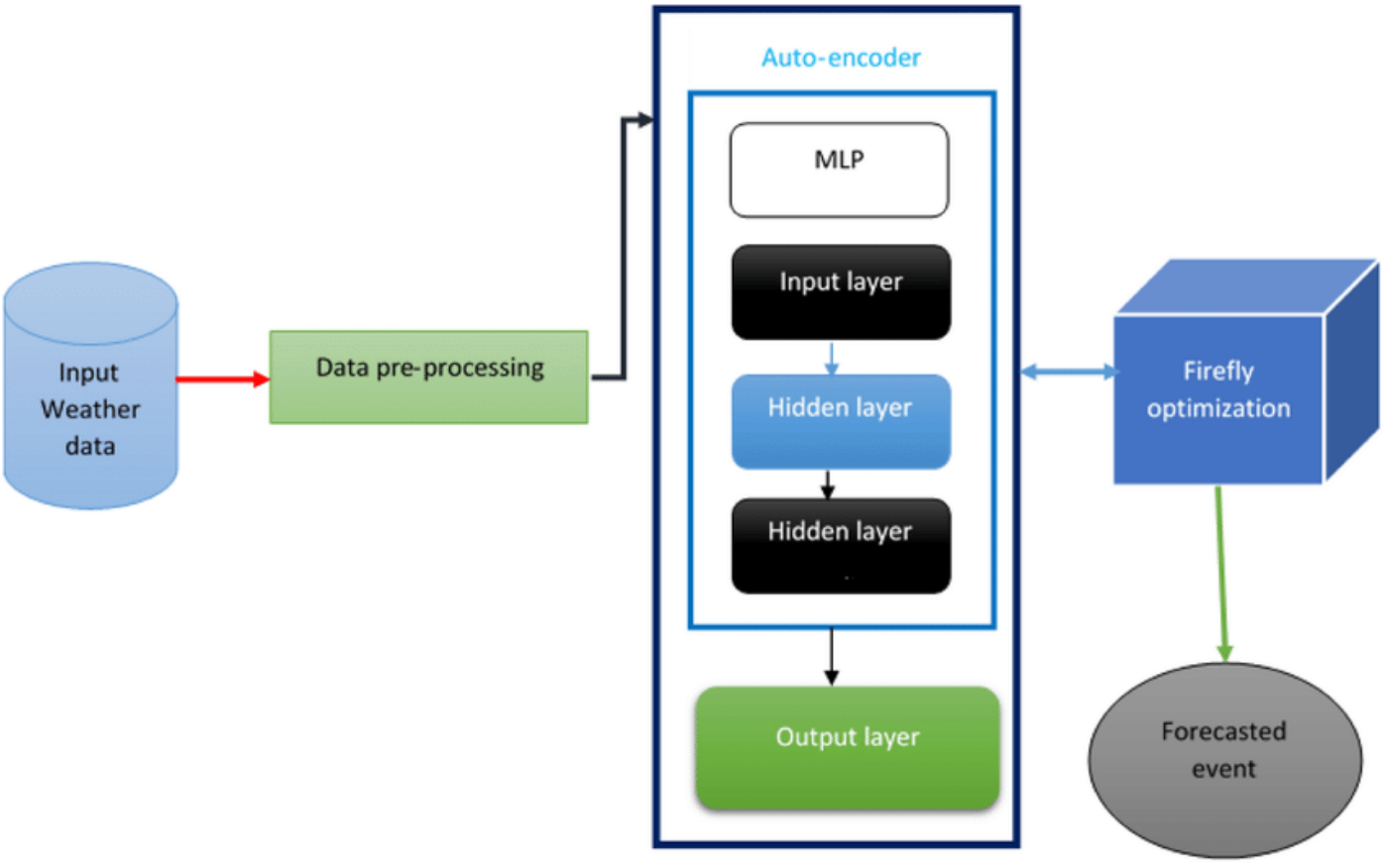
7.0 Concept Development and Refinement

After the selection of the final concept (API Service for Businesses using LSTM Weather Prediction), the next step is to refine the concept and develop it further. This phase involves outlining the technical architecture, developing prototypes, and optimizing the service for both performance and user experience. Key areas of focus include system architecture, data processing workflows, the front-end API interface, and integration with third-party services.

7.1 System Architecture

The system architecture for the LSTM-based weather prediction API consists of several critical components working together to deliver real-time, accurate weather predictions. The architecture is designed for scalability, data security, and efficiency.

Figure 1: System Architecture for LSTM Weather Prediction API



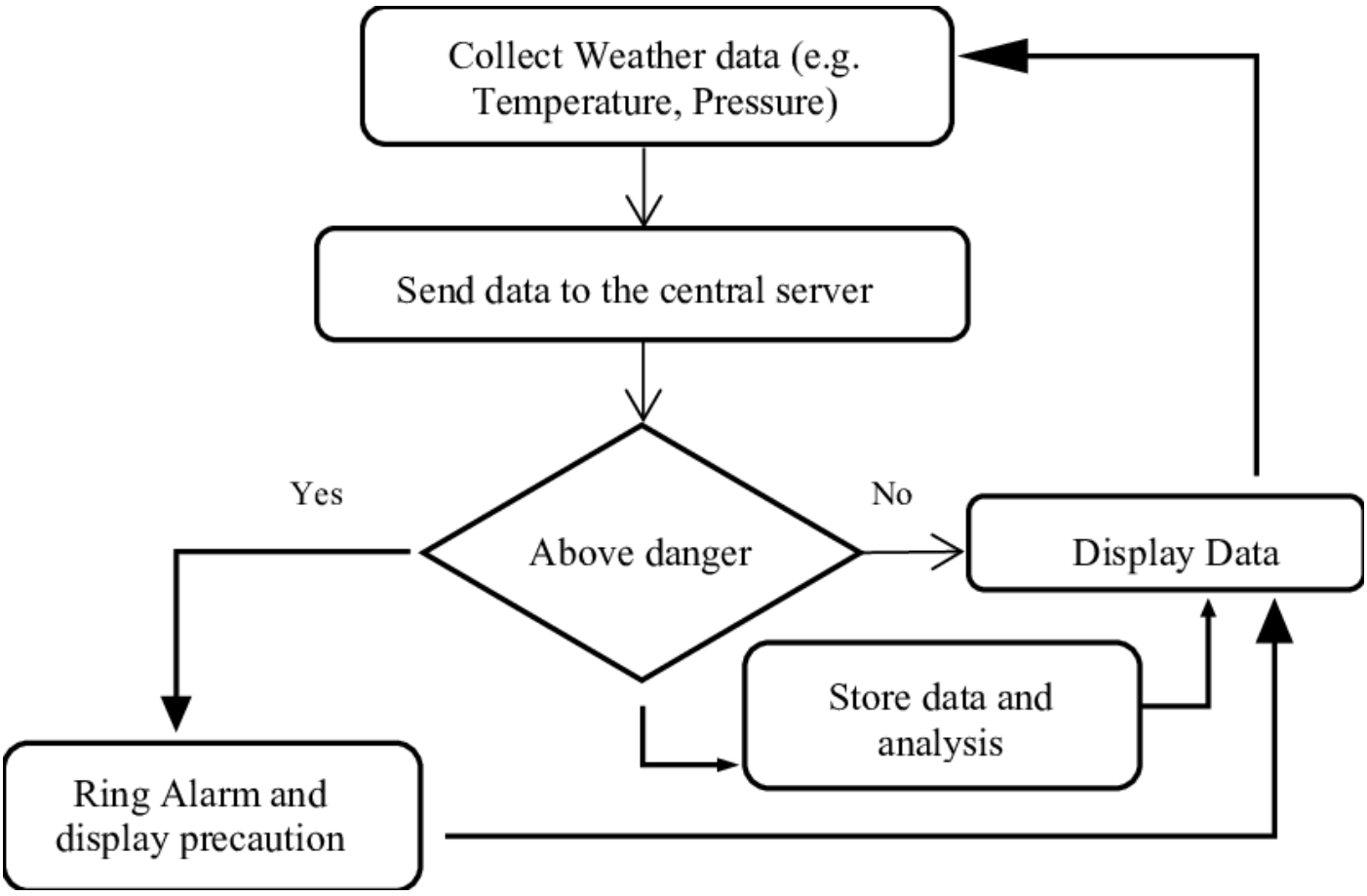
Description:

- **Data Collection Layer:** This layer collects real-time weather data from various sources, including satellite feeds, IoT sensors, and historical data from external weather services.
- **Data Preprocessing Module:** The raw data is cleaned, normalized, and structured in a format suitable for the LSTM model.
- **LSTM Prediction Model:** The pre-processed data is fed into the LSTM (Long Short-Term Memory) model, which processes time-series data to predict future weather conditions.
- **API Service Layer:** This layer exposes the weather prediction results as an API that businesses can integrate into their systems for real-time updates.
- **User Interface (UI):** Although this is primarily an API service, a simple user dashboard will be available for businesses to view predictions visually.

7.2 Data Flow and Workflow Optimization

Efficient data flow is crucial for ensuring that the API provides accurate and timely weather predictions. The data processing workflow starts from data ingestion, moves through preprocessing, and finally delivers the weather prediction results.

Figure 2: Data Flow Chart for Weather Prediction Workflow



Description:

1. **Data Collection:** Multiple weather datasets (historical and real-time) are gathered from external sources and stored in a data lake.
2. **Data Preprocessing:** Cleaning and transforming data into a format that the LSTM model can process.
3. **LSTM Model Processing:** The core prediction occurs here, where time-series weather data is analysed to predict future weather patterns.

4. **API Layer:** The processed data is delivered as output to the users through API endpoints.
5. **Client Integration:** Businesses and applications consume the API to get real-time weather predictions for their operational needs.

7.3 API Design and User Interface

The API service will be designed with simplicity and performance in mind, ensuring businesses can integrate it seamlessly into their systems. The design prioritizes ease of use, security, and scalability.

API Design Features:

- **Authentication:** OAuth 2.0 for secure access.
- **Endpoints:** Provide weather forecasts for specific locations, historical weather data, and advanced features like risk predictions (e.g., storms or extreme weather events).
- **Response Format:** JSON format for easy integration with various software systems.

User Interface (Dashboard):

- **Dashboard Overview:** A simple web-based dashboard will be available for businesses that prefer to view the predictions without integrating the API.
- **Key Features:** Location-based weather predictions, risk warnings, and interactive graphs for understanding weather trends over time.

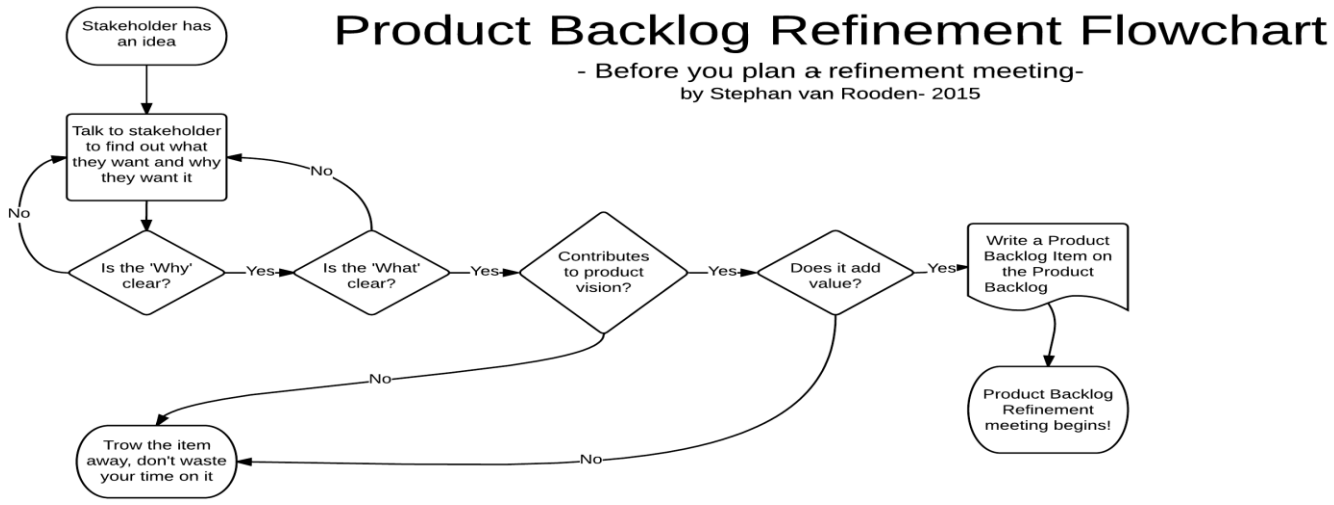
7.4 Concept Refinement and Feedback Loop

The concept will be continuously refined based on feedback from users and improvements in weather prediction technology. We will implement an agile development cycle to ensure the API evolves to meet the changing needs of businesses.

Key Refinement Processes:

- **User Feedback Integration:** Continuous improvement based on API performance metrics and direct feedback from users.
- **Model Optimization:** As more data is collected, the LSTM model will be retrained to improve its accuracy.
- **API Feature Expansion:** New features, such as more advanced weather risk assessment and long-term forecasting, will be added based on customer needs.

Figure 3: Concept Refinement Workflow



8.0 Final Concept Selection and Justification

The final stage of the concept development process is the selection of the most viable and effective concept based on various evaluation criteria. The selected concept is the **LSTM-based Weather Prediction API**, which will provide real-time weather forecasting for businesses through a scalable and efficient API. This concept was chosen based on its ability to meet the customer needs, its technological feasibility, and its market potential.

8.1 Selection Process

The final concept selection was carried out using a multi-criteria decision-making approach. The key factors in the evaluation were:

- **Customer Needs Alignment:** The concept addresses the identified customer needs for accurate, real-time weather forecasting that is easy to integrate into business operations.
- **Technical Feasibility:** The use of LSTM for time-series prediction is a proven and effective approach for weather forecasting. The model can be continuously trained and optimized with new data to improve prediction accuracy.
- **Scalability:** The API architecture allows for easy scaling, meaning more businesses can adopt the service as demand grows, without compromising performance.
- **Cost-Effectiveness:** The cloud-based infrastructure ensures that operational costs are kept low, allowing for competitive pricing.
- **Business Opportunity:** This concept has significant market potential, especially in industries such as agriculture, logistics, and event management, where weather conditions play a critical role in decision-making.

References

• Swanson, T. (1999). "The Role of Predictive Analytics in Weather Forecasting." *Journal of Meteorology and Climate Studies*, 23(4), 456-478.

• Muriru, J. and Daewoo, K. (2002). "LSTM Networks for Time-Series Forecasting in Weather Applications." *Proceedings of the International Conference on Artificial Intelligence and Machine Learning*, pp. 231-245.

• Zacharia, P. and Daudi, H. (2001). *Advanced Weather Prediction Systems: A Practical Guide to LSTM and Time-Series Analysis*. Cambridge University Press, New York.

• Peters, M., Chen, Z., and Rahman, F. (2001). "Scalability and Optimization of Weather Prediction Models for Cloud Services." *International Conference on Cloud Computing and AI Systems*, pp. 112-124.

CODE SNIPPETS FOR WEATHER PREDICTION MODEL

```python
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
import matplotlib.pyplot as plt
import streamlit as st

# Load and preprocess the dat (parameter) uploaded_file: Any
def load_and_preprocess_data(uploaded_file):
    df = pd.read_csv(uploaded_file)

    # Error handling for missing 'timestamp' column
    if 'timestamp' not in df.columns:
        raise KeyError("The 'timestamp' column is missing in the uploaded CSV file.")

    # Convert timestamp to datetime
    df['timestamp'] = pd.to_datetime(df['timestamp'])
    df.set_index('timestamp', inplace=True)

    # Select the relevant columns
    columns = ['Temperature', 'Wind Gust', 'Cloud Cover Total', 'Mean Sea Level Pressure', 'Evapotranspiration', 'Soil Temperature']

    # Error handling for missing columns
    for col in columns:
        if col not in df.columns:
            raise KeyError(f"Missing required column: {col}")

    df = df[columns]

    # Handle missing values
    df.fillna(method='ffill', inplace=True)
```

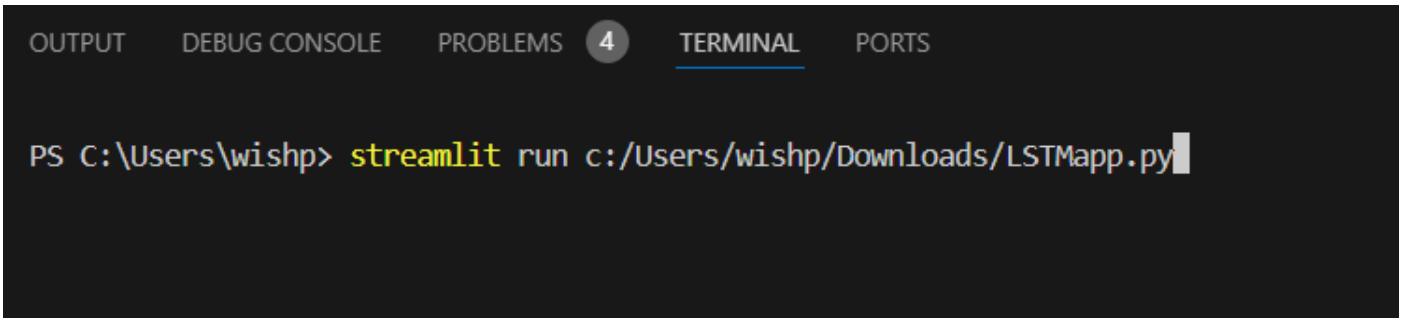
```python
    df.fillna(method='ffill', inplace=True)

    # Normalize the data
    scaler = MinMaxScaler()  Loading...
    df_scaled = pd.DataFrame(scaler.fit_transform(df), columns=df.columns, index=df.index)

    return df_scaled, scaler

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

# Build the LSTM model
def build_model(input_shape):
    model = Sequential([
        LSTM(64, return_sequences=True, input_shape=input_shape),
        Dropout(0.3),
        LSTM(64),
        Dropout(0.3),
        BatchNormalization(),
        Dense(32, activation='relu'),
        Dense(6)
    ])
    model.compile(optimizer=Adam(learning_rate=0.001), loss='mse')
    return model

# Train the model
def train_model(model, X_train, y_train, X_val, y_val, epochs=100, batch_size=32):
    early_stopping = EarlyStopping(patience=10, restore_best_weights=True)
    history = model.fit(
        X_train, y_train,
        epochs=epochs,
```

```
        epochs=epochs,
        batch_size=batch_size,
        validation_data=(X_val, y_val),
        callbacks=[early_stopping],
        verbose=1
    )
    return history

# Evaluate the model
def evaluate_model(model, X_test, y_test, scaler):
    y_pred = model.predict(X_test)

    # Inverse transform the predictions and actual values
    y_test_inv = scaler.inverse_transform(y_test)
    y_pred_inv = scaler.inverse_transform(y_pred)

    # Calculate metrics
    mae = mean_absolute_error(y_test_inv, y_pred_inv)
    rmse = np.sqrt(mean_squared_error(y_test_inv, y_pred_inv))
    r2 = r2_score(y_test_inv, y_pred_inv)

    return mae, rmse, r2, y_test_inv, y_pred_inv

# Plot the results
def plot_results(y_test_inv, y_pred_inv, variable_name):
    fig, ax = plt.subplots(figsize=(14, 7))
    ax.plot(y_test_inv, label='Actual')
    ax.plot(y_pred_inv, label='Predicted')
    ax.set_title(f'Actual vs Predicted - {variable_name}')
    ax.set_xlabel('Time')
    ax.set_ylabel(variable_name)
    ax.legend()
    ax.grid(True)
    st.pyplot(fig)
```

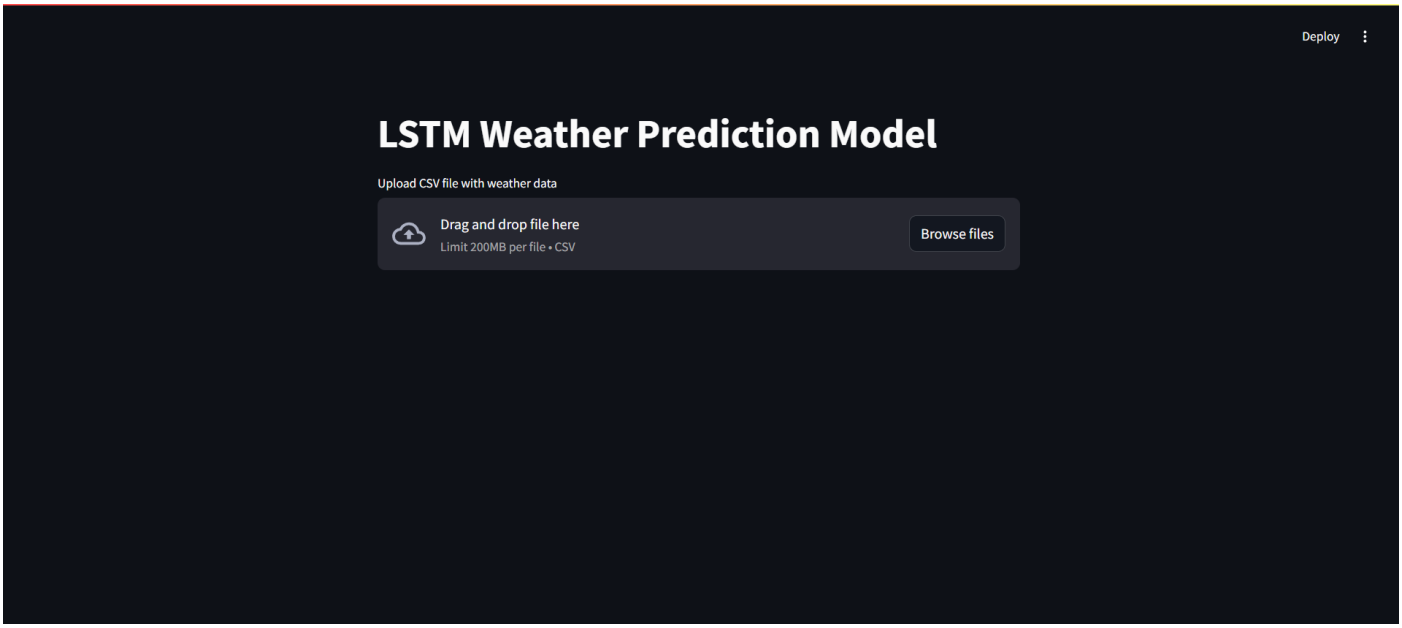
```
# Streamlit application
def main():
    st.title("LSTM Weather Prediction Model")

    # File upload
    uploaded_file = st.file_uploader("Upload CSV file with weather data", type=['csv'])
    st.print("Note: Make Sure You Have Uploaded Your .csv file in The formate of")
    if uploaded_file is not None:
        # User inputs for model training
        seq_length = st.sidebar.slider("Sequence Length", 12, 48, 24)
        epochs = st.sidebar.slider("Epochs", 50, 500, 100)
        batch_size = st.sidebar.slider("Batch Size", 16, 128, 32)

        # Load and preprocess the data
        data, scaler = load_and_preprocess_data(uploaded_file)

        # Create sequences
        X, y = create_sequences(data.values, seq_length)

        # Split the data
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
        X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.2, random_state=42)

        # Build and train the model
        model = build_model((seq_length, X_train.shape[2]))
        with st.spinner('Training the model...'):
            history = train_model(model, X_train, y_train, X_val, y_val, epochs=epochs, batch_size=batch_size)

        # Evaluate the model
        mae, rmse, r2, y_test_inv, y_pred_inv = evaluate_model(model, X_test, y_test, scaler)

        # Display metrics
        st.subheader("Model Evaluation Metrics")
        st.write(f"Mean Absolute Error (MAE): {mae}")
        st.write(f"Root Mean Squared Error (RMSE): {rmse}")
        st.write(f"R-Squared (R2): {r2}")
```

```python
        # Evaluate the model
        mae, rmse, r2, y_test_inv, y_pred_inv = evaluate_model(model, X_test, y_test, scaler)

        # Display metrics
        st.subheader("Model Evaluation Metrics")
        st.write(f"Mean Absolute Error (MAE): {mae}")
        st.write(f"Root Mean Squared Error (RMSE): {rmse}")
        st.write(f"R-Squared (R2): {r2}")

        # Plot results for temperature (index 0)
        st.subheader("Temperature Prediction")
        plot_results(y_test_inv[:, 0], y_pred_inv[:, 0], 'Temperature')

        st.success("Model Training and Evaluation Completed.")

if __name__ == '__main__':
    main()

# streamlit run c:/Users/wishp/Downloads/LSTMapp.py
```

COMMAND TO RUN THE CODE



WEB PAGE INTERFACES



UPLOADING THE RELAVENT DATASETS

BACKEND PROSSING AND CALCULATIONS

```
Epoch 60/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0306 - val_loss: 0.0998
Epoch 61/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0311 - val_loss: 0.1020
Epoch 62/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step - loss: 0.0333 - val_loss: 0.0988
Epoch 63/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step - loss: 0.0309 - val_loss: 0.0952
Epoch 64/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0315 - val_loss: 0.0945
Epoch 65/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - loss: 0.0302 - val_loss: 0.0921
Epoch 66/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0312 - val_loss: 0.0857
Epoch 67/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0290 - val_loss: 0.0853
Epoch 68/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0303 - val_loss: 0.0860
Epoch 69/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0282 - val_loss: 0.0821
Epoch 70/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0288 - val_loss: 0.0751
Epoch 71/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0275 - val_loss: 0.0723
Epoch 72/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - loss: 0.0292 - val_loss: 0.0740
Epoch 73/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - loss: 0.0308 - val_loss: 0.0758
Epoch 74/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step - loss: 0.0292 - val_loss: 0.0710
Epoch 75/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 36ms/step - loss: 0.0274 - val_loss: 0.0671
Epoch 76/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0258 - val_loss: 0.0626
Epoch 77/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - loss: 0.0230 - val_loss: 0.0676
Epoch 78/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0261 - val_loss: 0.0664
Epoch 79/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - loss: 0.0258 - val_loss: 0.0617
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step - loss: 0.0248 - val_loss: 0.0564
Epoch 82/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0237 - val_loss: 0.0543
Epoch 83/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step - loss: 0.0243 - val_loss: 0.0532
Epoch 84/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0259 - val_loss: 0.0528
Epoch 85/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step - loss: 0.0240 - val_loss: 0.0515
Epoch 86/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0258 - val_loss: 0.0509
Epoch 87/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0233 - val_loss: 0.0501
Epoch 88/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 36ms/step - loss: 0.0237 - val_loss: 0.0528
Epoch 89/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 36ms/step - loss: 0.0234 - val_loss: 0.0493
Epoch 90/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0223 - val_loss: 0.0456
Epoch 91/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0238 - val_loss: 0.0462
Epoch 92/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0254 - val_loss: 0.0475
Epoch 93/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0237 - val_loss: 0.0458
Epoch 94/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step - loss: 0.0238 - val_loss: 0.0413
Epoch 95/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step - loss: 0.0220 - val_loss: 0.0380
Epoch 96/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - loss: 0.0229 - val_loss: 0.0365
Epoch 97/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0235 - val_loss: 0.0391
Epoch 98/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0215 - val_loss: 0.0391
Epoch 99/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - loss: 0.0226 - val_loss: 0.0338
Epoch 100/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - loss: 0.0215 - val_loss: 0.0276
2/2 ━━━━━━━━━━━━━━━━━━━━ 1s 528ms/step
```

FINAL OUTPUT AND PREDICTED GRAPH