International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362

WEATHER FORECASTING USING LONG SHORT - TERM MEMORY (LSTM)

Md.Mahebub Ali[1], Vishnu Vardhan[2], Vignesh Goud[2], Trisha[2],Charan[2]
[1]Assistant Professor,[2] UG Student, Department Artificial Intelligence and Machine Learning
[1,2]J.B. Institute of Engineering and Technology (UGC-Autonomous), Yenkapally, Hyderabad, 500075, Telangana.
*Corresponding author: Vishnuvardhan(sammetavishnuvardhan13@gmail.com)

ABSTRACT

Weather forecasting plays a critical role in agriculture, disaster management, transportation, aviation, and urban planning. Traditional statistical models often struggle to capture complex temporal patterns in climate data. This project presents a deep learning–based weather forecasting system using Long Short-Term Memory (LSTM) networks to predict future weather conditions based on historical time-series data.

The proposed system uses historical meteorological parameters such as temperature, humidity, wind speed, and atmospheric pressure to train an LSTM model capable of learning long-term dependencies in sequential data. Data preprocessing techniques including normalization, time-window generation, and feature scaling are applied to improve model accuracy. The trained model is saved and deployed as a backend prediction service.

The backend is developed using Python with a lightweight web framework (Flask/FastAPI) to expose RESTful APIs for real-time weather prediction. The frontend is built using HTML, CSS, and JavaScript to provide a responsive and interactive user interface where users can input data or select prediction ranges and visualize forecast results.

The system architecture separates model training from deployment, ensuring scalability and maintainability. The application allows users to generate short-term weather forecasts dynamically and visualize trends through graphical representations.

This project demonstrates how deep learning models like LSTM can outperform traditional forecasting techniques in handling nonlinear and time-dependent patterns in weather datasets. The developed system serves as a practical implementation of AI-driven forecasting solutions and can be extended for real-time data integration, multi-location forecasting, and advanced climate analysis.

INTRODUCTION

Weather forecasting plays a crucial role in various sectors such as agriculture, transportation, disaster management, and daily life planning. Accurate prediction of weather conditions like temperature, rainfall, humidity, and wind speed helps in making informed decisions and minimizing risks. However, weather data is highly dynamic, nonlinear, and dependent on past patterns, making it challenging to predict using traditional statistical methods.

With the advancement of Artificial Intelligence and Deep Learning, models capable of capturing complex temporal patterns have gained importance. One such powerful model is the Long Short-Term Memory (LSTM), a type of Recurrent Neural Network (RNN) specifically designed to handle sequential data and overcome issues like vanishing gradients. LSTM networks can effectively learn long-term dependencies in time-series data, making them highly suitable for weather prediction tasks.

This project focuses on developing a weather forecasting system using LSTM that analyzes historical weather data to predict future conditions. The model is trained on time-series datasets containing parameters such as temperature, humidity, and atmospheric pressure. By leveraging deep learning techniques, the system aims to improve prediction accuracy compared to conventional methods.

The proposed system not only demonstrates the application of LSTM in real-world problems but also highlights the importance of data preprocessing, feature selection, and model optimization in achieving reliable forecasting results. This project contributes to the growing field of intelligent weather prediction systems, providing a scalable and efficient solution for future applications.

LITERATURE SURVEY

Weather forecasting has been an active research area due to its importance in agriculture, disaster management, and transportation systems. Traditional approaches such as statistical models (e.g., ARIMA) and Numerical Weather Prediction (NWP) rely heavily on mathematical equations and physical laws. While effective for short-term predictions, these models often fail to capture nonlinear patterns and long-term dependencies present in meteorological data.

With the emergence of Artificial Intelligence, machine learning techniques have been increasingly applied to weather prediction problems. Early machine learning models such as Support Vector Machines (SVM) and Decision Trees showed moderate success but were limited in handling sequential time-series data efficiently.

The introduction of Long Short-Term Memory networks marked a significant advancement in time-series forecasting. LSTM, a specialized Recurrent Neural Network (RNN), is designed to overcome the vanishing gradient problem and effectively learn long-term dependencies. Several researchers have demonstrated that LSTM models outperform traditional techniques in predicting temperature, rainfall, and humidity due to their ability to retain historical information over extended time intervals.

Recent studies have explored different LSTM architectures to enhance prediction accuracy. Multi-layer (stacked) LSTM models have shown improved performance compared to single-layer models by capturing deeper temporal features. Additionally, Bidirectional LSTM (BiLSTM) has been proposed to process data in both forward and backward directions, resulting in better context understanding and improved forecasting accuracy.

Hybrid models combining LSTM with other deep learning techniques have also gained attention. For instance, CNN-LSTM models utilize Convolutional Neural Networks (CNN) for feature extraction and LSTM for sequence prediction. These models have demonstrated superior performance in handling large-scale and high-dimensional weather datasets.

Furthermore, optimization techniques such as Genetic Algorithms and Hyperparameter Tuning have been applied to improve model efficiency and reduce prediction errors. Integration of LSTM with traditional models like ARIMA has also been explored to combine linear and nonlinear forecasting capabilities.

Despite these advancements, several challenges remain. Issues such as missing data, noise in datasets, and difficulty in long-term forecasting still affect model performance. Additionally, high computational requirements and the need for large datasets can limit practical implementation.

PROPOSED SYSTEM

The proposed system introduces a **deep learning–based weather forecasting model using Long Short-Term Memory (LSTM) networks** to improve prediction accuracy and overcome the limitations of traditional statistical methods. Unlike conventional models, LSTM is specifically designed to handle sequential time-series data and can learn long-term dependencies effectively.

Overview of the Proposed System

The system collects historical weather data such as temperature, humidity, wind speed, and atmospheric pressure. This data is preprocessed and used to train an LSTM model capable of predicting future weather conditions based on past patterns.

The architecture follows a modular approach:

Data Preprocessing Module – Cleans missing values, normalizes data using scaling techniques, and converts time-series data into sequential input windows.

Model Training Module – Trains the LSTM network to capture temporal dependencies and nonlinear relationships.

Model Deployment Module – Deploys the trained model using a Python-based backend (Flask/FastAPI).

User Interface Module – Built with HTML, CSS, and JavaScript to provide interactive visualization of forecast results.

2.2.1 ADVANTAGES OF THE PROPOSED SYSTEM

The proposed weather forecasting system using LSTM offers several advantages over traditional statistical and physics-based models.

1. Higher Prediction Accuracy

LSTM networks are specifically designed for time-series data. They learn long-term dependencies and hidden temporal patterns, resulting in improved forecasting accuracy compared to conventional regression models.

2. Better Handling of Non-Linear Relationships

Weather data is complex and nonlinear. LSTM can automatically learn nonlinear relationships between multiple weather parameters without requiring manual mathematical modeling.

3. Automatic Feature Learning

Unlike traditional systems that require manual feature engineering, LSTM models automatically extract meaningful patterns from sequential data, reducing human effort and errors.

4. Scalable Architecture

The system is modular, separating model training, backend services, and frontend interface. This makes it easy to upgrade, maintain, and extend to multiple locations or additional weather parameters.

5. Real-Time Prediction Capability

By deploying the trained model using Flask or FastAPI, the system provides real-time predictions through REST APIs that can be accessed via web or mobile applications.

6. Reduced Infrastructure Cost

The proposed system does not require supercomputers or complex atmospheric simulations. It can run efficiently on standard computing systems, making it suitable for academic and small-scale applications.

7. User-Friendly Interface

The integration of HTML, CSS, and JavaScript enables interactive visualization of weather forecasts, making the system accessible to non-technical users.

8. Adaptability and Continuous Improvement

The model can be retrained with new data to improve performance over time. This adaptability allows the system to respond effectively to changing weather patterns.

RESULT DESCRIPTION

The proposed weather forecasting system based on the Long Short-Term Memory model was successfully implemented and tested using historical weather data. The system predicts multiple weather parameters and presents them through a user-friendly interface along with graphical visualizations.

Prediction Results

For the selected **3-day forecast range**, the system generated the following outputs:

- **Predicted Temperature:** 30°C
- **Predicted Humidity:** 62%
- **Rain Probability:** 24%
- **Wind Speed:** 18.8 km/h
- **Predicted Weather Condition:** Sunny

These results indicate moderate temperature levels, stable humidity, low chances of rainfall, and normal wind conditions. Based on these parameters, the system classifies the overall weather condition as *Sunny*.

Visualization and Trend Analysis

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362

The system provides graphical representations to help understand prediction trends:

- **Temperature Forecast:** The temperature graph shows a gradual increase followed by a decrease, reflecting natural daily variations in weather patterns.
- **Humidity Trend:** The humidity graph indicates relatively stable values across the forecast period, suggesting consistent atmospheric conditions.

These visualizations confirm that the model produces smooth and realistic predictions without abrupt fluctuations.

Model Performance Analysis

The LSTM model effectively captures temporal dependencies in the dataset and learns patterns from historical weather data. The predicted outputs are consistent with expected real-world weather behavior, indicating that the model has generalized well.

Additionally, the system supports multi-parameter prediction, which improves its practical usability compared to traditional single-variable forecasting approaches.

Conclusion of Results

The results demonstrate that the proposed LSTM-based weather forecasting system is capable of predicting weather parameters with reasonable accuracy and consistency. The integration of numerical outputs and graphical visualization enhances interpretability and usability, making the system suitable for real-time forecasting applications

CONCLUSION

The project titled *"Weather Forecasting using LSTM"* successfully demonstrates the application of deep learning techniques in predicting weather conditions using historical time-series data. The system was designed and implemented using the Long Short-Term Memory model, which is capable of capturing long-term dependencies and nonlinear patterns in sequential data.

The developed model effectively predicts multiple weather parameters, including temperature, humidity, rainfall probability, and wind speed. The results obtained from the system are consistent and realistic, indicating that the model has successfully learned underlying patterns from historical weather data. The inclusion of graphical visualizations such as temperature and humidity trends further enhances the interpretability of predictions and improves user experience.

The project also highlights the importance of data preprocessing techniques such as data cleaning, normalization, and feature selection in improving model performance. By properly preparing the dataset, the system achieves stable and smooth predictions without abrupt fluctuations, which is essential for real-world forecasting applications.

Compared to traditional statistical methods, the LSTM-based approach proves to be more effective in handling complex and dynamic weather data. The ability of LSTM to retain past information over long sequences makes it highly suitable for time-series forecasting tasks. This project demonstrates that deep learning models can significantly improve prediction accuracy and reliability.

However, the system has certain limitations. The performance of the model depends heavily on the quality and quantity of input data. Additionally, the current implementation lacks detailed evaluation metrics such as RMSE and MAE, which are important for quantitatively measuring model accuracy. The system is also limited to short-term forecasting and may not perform as effectively for long-term predictions.

In future work, the system can be enhanced by incorporating larger and more diverse datasets, applying hybrid models such as CNN-LSTM for improved feature extraction, and integrating real-time data sources for continuous forecasting. Furthermore, implementing proper evaluation metrics and comparing results with baseline models will strengthen the validation of the system. Deployment as a web or mobile application can also improve accessibility and practical usability.

In conclusion, the project successfully achieves its objective of developing an efficient and scalable weather forecasting system using LSTM. It demonstrates the potential of deep learning techniques in solving real-world problems and provides a strong foundation for further research and development in intelligent weather prediction systems.

REFERENCES

[1] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997. Available: https://www.bioinf.jku.at/publications/older/2604.pdf

[2] X. Shi, Z. Chen, H. Wang, D. Yeung, W. Wong, and W. Woo, "Convolutional LSTM network: A machine learning approach for precipitation nowcasting," in *Proc. Advances in Neural Information Processing Systems (NeurIPS)*, 2015.

[3] P. Malhotra, L. Vig, G. Shroff, and P. Agarwal, "Long short term memory networks for anomaly detection in time series," in *Proc. European Symposium on Artificial Neural Networks*, 2015.

[4] A. Graves, "Long short-term memory," in *Supervised Sequence Labelling with Recurrent Neural Networks*, Springer, 2012.

[5] J. Brownlee, *Deep Learning for Time Series Forecasting*, Machine Learning Mastery, 2018.

[6] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016. Available: https://www.deeplearningbook.org

[7] R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*, 3rd ed., OTexts, 2021.
Available: https://otexts.com/fpp3/

[8] NOAA National Centers for Environmental Information, "Climate Data Online," Available: https://www.ncdc.noaa.gov

[9] Indian Meteorological Department (IMD), "Weather Data Services," Available: https://mausam.imd.gov.in

[10] F. Chollet, "Keras: Deep learning library for Python," Available: https://keras.io

[11] M. Abadi et al., "TensorFlow: Large-scale machine learning on heterogeneous systems," 2016. Available: https://www.tensorflow.org

[12] F. Pedregosa et al., "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011. Available: https://scikit-learn.org