INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 6, June 2026 | ISSN: 2456-4184 | IJNRD.ORG

Deep Learning Model for Dew Point Prediction Using Hybrid TCN and LSTM Networks

CHALLA SRI UPENDRA
Master Of Computer Applications
Ideal College Of Arts & Sciences,
Autonomous, Affiliated To Adikavi Nannaya
University - Rajamahendravaram
Kakinada

Dr. V.S.V DEEPAK
HOD, Department of computer science
Ideal College Of Arts & Sciences,
Autonomous, Affiliated To Adikavi Nannaya
University - Rajamahendravaram
Kakinada

***Abstract*— Climate monitoring requires accurate prediction of environmental parameters to reduce the impact of sudden weather changes and natural disasters. This thesis introduces an extended dew point forecasting model using a hybrid Attention-Based Temporal Convolutional Network and Long Short-Term Memory architecture. The proposed extension improves forecasting capability by combining the temporal learning strength of TCN with the change detection ability of LSTM for handling complex climatic patterns. SHAP-based Explainable Artificial Intelligence is integrated to identify highly influential features and provide transparent prediction analysis. The system also applies feature engineering methods such as seasonal conversion, cyclical transformation, normalization, and day-night categorization to improve data representation. Experimental analysis demonstrates that the hybrid model achieved an improved R2 score of 80% with lower RMSE and MAE values when compared with existing LSTM and BiLSTM approaches. The developed framework provides efficient, interpretable, and reliable dew point forecasting for climate-related applications.**

Keywords—Dew Point, LSTM, Climate, Deep Learning

I. INTRODUCTION

Dew point temperature is an important atmospheric parameter used to measure the amount of moisture present in the air. It plays a major role in weather forecasting, climate monitoring, agriculture, environmental analysis, and disaster management. Variations in dew point temperature directly influence humidity levels, rainfall patterns, fog formation, and overall atmospheric stability. In recent years, rapid climate change and increasing global temperatures have created serious environmental challenges across many regions of the world. Sudden climatic variations, irregular rainfall, heat waves, and extreme weather conditions have increased the need for accurate environmental prediction systems.

Traditional weather forecasting methods mainly depend on statistical analysis and manual interpretation of meteorological observations. These approaches often struggle to handle large-scale climate data and complex nonlinear relationships between environmental parameters. With the growth of data collection technologies and sensor-based monitoring systems, huge amounts of climate data are generated continuously. Extracting meaningful patterns from such data using conventional techniques has become difficult and time consuming. As a result, machine learning and deep learning methods are increasingly used in climate research because of their ability to learn hidden patterns and improve forecasting accuracy.

II. RELATED WORK

Dew point temperature forecasting has gained significant attention due to its importance in climate monitoring, agriculture, environmental analysis, and weather prediction. Early research by Robinson (2000) analyzed temporal trends in dew point temperature across the United States and explained the relationship between atmospheric moisture and climatic variation. The study highlighted that dew point temperature is an important indicator for understanding long-term environmental changes and weather behavior. Around the same period, Blanco and Peña (2008) investigated the influence of acid dew point temperature on boiler performance and environmental safety. Their work demonstrated that accurate dew point estimation can improve thermal efficiency and reduce harmful emissions in industrial systems.

As environmental monitoring technologies advanced, researchers focused on intelligent computational approaches for dew point estimation. Jradi and Riffat (2014) studied dew-point cooling systems for improving thermal comfort in buildings and reducing energy consumption. Their experimental analysis showed that dew point-based systems can support efficient environmental control applications. Similarly, Kim et al. (2015) developed soft computing models for predicting daily dew point temperature using climatic parameters. Their research proved that machine learning methods can effectively capture nonlinear atmospheric relationships and provide better forecasting accuracy compared to traditional statistical methods.

Williams et al. (2015) compared different dew point estimation techniques under varying environmental conditions and emphasized the importance of selecting suitable climatic features for reliable prediction. Later, Górnicki et al. (2017) evaluated several mathematical models for dew point determination and identified the limitations of conventional forecasting approaches. Their work highlighted the growing requirement for intelligent prediction systems capable of handling complex climate patterns.

Recent studies concentrated on deep learning and artificial intelligence techniques for environmental forecasting. Bi et al. (2020) predicted flue gas acid dew point temperature distribution in industrial boilers and demonstrated the importance of intelligent forecasting for operational safety and energy efficiency. Arikan et al. (2021) applied knowledge-based forecasting models for dew point time-series analysis and showed that sequential learning methods can improve prediction reliability under changing atmospheric conditions. In the same year, Callner (2021) used artificial neural networks to predict dew point, humidity, and heat index values. The study demonstrated that neural networks can successfully learn hidden climatic relationships and improve environmental forecasting performance.

More recently, Abdullah et al. (2024) analyzed dew point temperature trends in Bangladesh and emphasized the growing need for accurate climate forecasting systems to support disaster preparedness and environmental planning. Their research highlighted the increasing importance of intelligent and interpretable forecasting techniques for handling rapidly changing climatic conditions and improving decision-making in climate-related applications.

Table: Summary of Key Literature Contributions and Their Impact on Current Research:

Author	Contribution	Impact on Research
Robinson (2000)	Studied changes in dew point temperature over time.	Helped researchers understand climate and moisture changes.
Blanco and Peña (2008)	Worked on dew point prediction in boiler systems.	Improved energy efficiency and pollution control research.
Jradi and Riffat (2014)	Developed dew-point cooling systems for buildings.	Supported energy-saving and cooling applications.
Kim et al. (2015)	Used machine learning for dew point prediction.	Showed better accuracy than traditional methods.
Williams et al. (2015)	Compared different dew point estimation methods.	Helped identify reliable forecasting techniques.
Górnicki et al. (2017)	Evaluated mathematical models for dew point calculation.	Encouraged the use of advanced prediction models.
Bi et al. (2020)	Predicted dew point temperature in industrial boilers.	Improved industrial safety and system performance.
Arikan et al. (2021)	Applied time-series forecasting for dew point data.	Improved prediction under changing climate conditions.
Callner (2021)	Used neural networks for dew point and humidity prediction.	Increased the use of AI in weather forecasting research.
Abdullah et al. (2024)	Analyzed dew point trends in Bangladesh.	Supported climate monitoring and disaster planning research.

III. PROPOSED APPROACH

Hybrid deep learning techniques are used in this work to improve the accuracy of dew point temperature forecasting under changing climatic conditions. The proposed framework combines Attention-Based Temporal Convolutional Networks (TCN) with Long Short-Term Memory (LSTM) networks to capture complex temporal relationships and sudden environmental variations from climate data. The overall system is designed to process climatic features efficiently and generate reliable forecasting results with reduced prediction error.

Initially, the collected dataset is preprocessed to remove inconsistencies and improve data quality. Climatic parameters such as dew point temperature, humidity, wind speed, date, and time are selected for analysis. Several feature engineering techniques are applied to increase model performance. Monthly values are converted into seasonal categories including winter, summer, and rainy seasons. Time information is transformed into cyclical SIN and COS values to preserve periodic relationships in climate behavior. The system also divides records into day and night categories based on hourly information. These newly generated features help the model understand environmental patterns more effectively.

After preprocessing, MinMax normalization is applied to scale all features into a uniform range. SHAP-based Explainable Artificial Intelligence techniques are then used to identify the most influential climatic parameters affecting dew point prediction. Feature selection through SHAP improves interpretability and reduces unnecessary data complexity.

The selected features are provided to the hybrid Attention-Based TCN-LSTM forecasting model. The TCN component extracts long-term temporal dependencies from sequential climate data, while the attention mechanism focuses on important feature patterns during prediction. The LSTM network further improves forecasting by capturing sudden changes and sequential environmental behavior. Finally, the system performance is evaluated using R2 Score, RMSE, and MAE metrics, where the proposed model achieves better forecasting accuracy compared to existing methods.

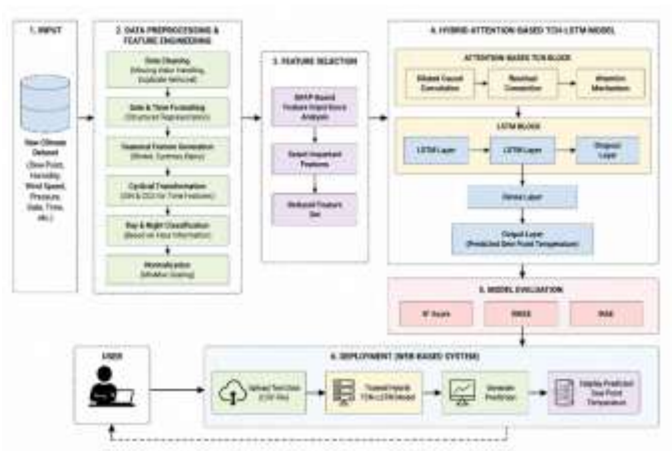

Figure 1: Dew Point forecasting workflow

IV. METHODOLOGIES

Algorithm: Hybrid Attention-Based TCN-LSTM for Dew Point Forecasting

---

Input:
Climate Dataset D
Features = {Temperature, Humidity, Wind Speed, Pressure, Date, Time}
Output:
Predicted Dew Point Temperature

Begin

1. Load climate dataset D

2. Perform data preprocessing

Remove missing values
Remove duplicate records
Convert date and time into structured format

3. Generate additional features
Convert month into seasonal features
Winter, Summer, Rainy
Apply cyclical transformation
SIN(Time), COS(Time)
Generate Day/Night feature
If hour >= 6 and <= 18
Label = Day
Else
Label = Night

4. Normalize all features using MinMax normalization

5. Apply SHAP feature selection
Calculate SHAP importance score
Select highly influential features

6. Split dataset into training and testing sets
80% → Training Data
20% → Testing Data

7. Initialize Attention-Based TCN model
Apply dilated causal convolution
Extract temporal features
Apply residual connections
Apply attention mechanism

8. Pass TCN output to LSTM network
Capture sequential dependencies
Detect sudden climate variations

9. Add dense output layer
Forecast Dew Point Temperature

10. Train hybrid TCN-LSTM model
Update weights using backpropagation
Minimize forecasting error

11. Test trained model using testing dataset

12. Calculate performance metrics
R2 Score
RMSE
MAE

13. Compare results with existing models
LSTM
BiLSTM
TCN

14. Deploy trained model in Flask web application

End

Dataset Collection

The proposed system begins with collecting climate-related data required for dew point temperature forecasting. The dataset contains important environmental parameters such as dew point temperature, humidity, wind speed, atmospheric pressure, date, and time information. Since the original dataset from the base paper was unavailable, a similar dataset was collected from the Kaggle repository. Historical environmental records are necessary because deep learning models learn forecasting patterns from previous climatic observations.

Data Preprocessing

The collected dataset is preprocessed to improve data quality and remove inconsistencies. Missing values, duplicate records, and irrelevant attributes are identified and removed. Date and time fields are converted into a structured format for easier analysis. Clean and organized data improves training performance and helps the forecasting model generate accurate results.

Seasonal Feature Generation

Environmental conditions change across different seasons, directly affecting dew point temperature. To capture these variations, month values are converted into seasonal categories such as winter, summer, and rainy seasons. Seasonal feature generation helps the model understand climate behavior during different periods of the year and improves forecasting accuracy.

Cyclical Feature Transformation

Time-based climate data follows repeating patterns. Traditional numerical values cannot effectively represent these periodic relationships. Therefore, cyclical transformation using SIN and COS functions is applied to time-related features. This transformation preserves the continuity between starting and ending time values and improves temporal pattern learning.

Step 5: Day and Night Classification

Dew point temperature changes significantly between daytime and nighttime conditions. Based on hourly information, the dataset is divided into day and night categories. Records between morning and evening are labeled as daytime, while remaining records are categorized as nighttime. This classification helps the model analyze environmental behavior more effectively.

Step 6: Data Normalization

The dataset contains features with different numerical ranges, which may affect model training. To solve this issue, MinMax normalization is applied to all selected features. Normalization scales feature values between zero and one while maintaining their relationships. This process improves training stability and reduces computational complexity.

SHAP-Based Feature Selection

SHAP-based Explainable Artificial Intelligence techniques are used to identify the most influential climatic parameters affecting dew point prediction. SHAP calculates the contribution score of each feature and ranks them according to importance. Highly influential features are selected for model training, while less relevant features are removed. This improves forecasting accuracy and model interpretability.

Training Existing Models

Before implementing the extension model, existing algorithms such as LSTM and BiLSTM are trained using the processed dataset. The dataset is divided into training and testing sets, where 80% data is used for training and 20% for testing. These models are trained to establish baseline forecasting performance for comparison purposes.

Attention-Based TCN Model

An Attention-Based Temporal Convolutional Network is developed to capture long-term temporal dependencies in climate data. The TCN architecture processes sequential environmental information using convolutional layers. The attention mechanism helps the model focus on important climatic patterns during forecasting and improves prediction reliability.

Hybrid TCN-LSTM Extension Model

The proposed extension combines Attention-Based TCN with LSTM networks to improve forecasting performance. The TCN component extracts long-range temporal patterns, while the LSTM component captures sudden environmental changes and sequential dependencies. Combining these models improves learning capability and helps achieve better forecasting accuracy with reduced prediction error.

Performance Evaluation

The trained models are evaluated using performance metrics such as R2 Score, RMSE, and MAE. The R2 Score measures prediction accuracy, while RMSE and MAE calculate forecasting error. Lower RMSE and MAE values indicate better prediction performance. Experimental results show that the hybrid model performs better than traditional forecasting methods.

VI RESULTS & DISCUSSION

	Algorithm Name	R2Score	MAE	RMSE
0	Existing LSTM	0.742843	0.083064	0.104102
1	Existing BILSTM	0.743488	0.083124	0.103972
2	Propose TCN with Attention	0.798445	0.074842	0.092163
3	Extension TCN + LSTM	0.808630	0.072806	0.089805

The experimental results demonstrate that the proposed hybrid Attention-Based TCN-LSTM model achieved better dew point forecasting performance compared to existing deep learning approaches. Performance evaluation was carried out using R2 Score, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). These metrics were used to measure prediction accuracy and forecasting error between actual and predicted dew point temperature values.

The existing LSTM model achieved an R2 Score of 0.742843 with an MAE value of 0.083064 and RMSE value of 0.104102. The prediction graph obtained from the testing phase showed noticeable differences between actual and predicted values, indicating lower forecasting accuracy under changing climate conditions. Similarly, the existing BiLSTM model produced an R2 Score of 0.743488 with MAE and RMSE values of 0.083124 and 0.103972 respectively. Although BiLSTM slightly improved sequential learning, the forecasting error remained comparatively high.

The proposed Attention-Based TCN model significantly improved forecasting performance by capturing long-term temporal dependencies from climate data. The model achieved an R2 Score of 0.798445 with lower MAE and RMSE values of 0.074842 and 0.092163 respectively. The attention mechanism helped the system focus on important climatic patterns and improved prediction reliability.

The extension hybrid TCN-LSTM model produced the best overall performance among all algorithms. The model achieved the highest R2 Score of 0.808630 with the lowest MAE value of 0.072806 and RMSE value of 0.089805. These results confirm that combining TCN with LSTM improved sequential learning, reduced prediction error, and increased dew point forecasting accuracy under varying environmental conditions.

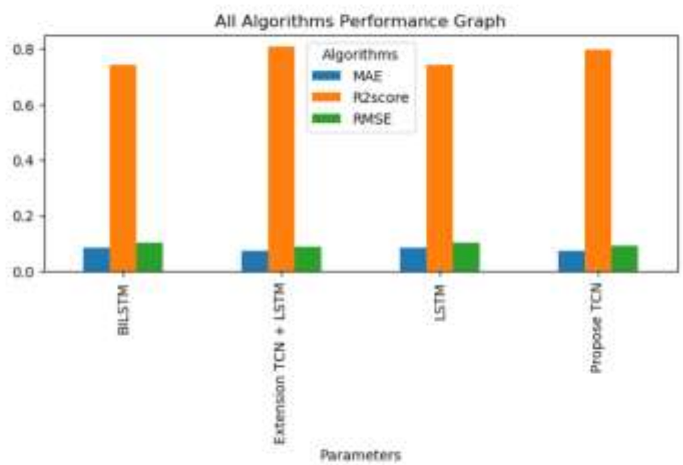

Figure 2: All Algorithms Performance Graph

The experimental analysis shows that deep learning models can effectively forecast dew point temperature when proper feature engineering and temporal learning techniques are applied. Existing LSTM and BiLSTM models achieved moderate forecasting accuracy, but their higher RMSE and MAE values indicate limitations in handling complex climate variations and long-term dependencies present in environmental data. These models were able to learn sequential information, yet they struggled to capture sudden atmospheric changes and seasonal patterns efficiently.

The proposed Attention-Based TCN model improved forecasting performance by extracting long-range temporal features from climate data. The attention mechanism further enhanced prediction quality by focusing on highly influential environmental patterns during forecasting. This resulted in improved R2 Score and reduced prediction error compared to traditional recurrent models.

The extension hybrid TCN-LSTM model achieved the best overall performance because it combines the strengths of both architectures. TCN effectively handled temporal dependencies, while LSTM captured sequential environmental variations and sudden climatic changes. The integration of SHAP-based feature selection also contributed to performance improvement by selecting highly relevant climatic features and removing unnecessary data complexity.

VII. CONCLUSION

Dew point temperature forecasting plays an important role in understanding atmospheric behavior and supporting climate-related decision making. This work developed a hybrid Attention-Based Temporal Convolutional Network and Long Short-Term Memory framework to improve forecasting accuracy under varying environmental conditions. Multiple preprocessing and feature engineering techniques, including seasonal conversion, cyclical transformation, normalization, and day-night feature extraction, were applied to enhance climate data representation. SHAP-based Explainable Artificial Intelligence techniques were used to identify the most influential climatic parameters affecting dew point prediction and improve model interpretability. Experimental results demonstrated that the extension hybrid TCN-LSTM model achieved superior performance with an R2 Score of 0.808630 and reduced RMSE and MAE values compared to existing LSTM and BiLSTM models. The combination of temporal convolution, attention mechanism, and sequential learning successfully captured long-term dependencies and sudden climate variations. The developed system provides accurate, reliable, and interpretable dew point forecasting suitable for climate monitoring and environmental analysis applications.

REFERENCES

[1] IPCC. (2023). Climate Change: The Physical Science Basis, Cambridge University Press, Contribution of Working Group I To the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. [Online]. Available: https://www.ipcc.ch/report/ar6/syr/

[2] M. Ahmed, S. Ahmad, and A. M. Kheir, ‘‘Climate change: An overview,’’ in Global Agricultural Production: Resilience to Climate Change, 2023, pp. 1–30.

[3] L. S. D. Eckstein, V. Künzel. (2021). Global Climate Risk Index 2021. Accessed: Oct. 29, 2024. [Online]. Available: https://www.germanwatch.org/en/19777

[4] M. C. Rahman, M. S. Rahaman, J. C. Biswas, N. M. F. Rahman, M. A. Islam, M. A. R. Sarkar, M. Islam, and M. Maniruzzaman, ‘‘Climate change and risk scenario in Bangladesh,’’ Asia–Pacific J. Regional Sci., vol. 7, no. 2, pp. 381–404, Aug. 2022.

[5] N. Kaushik, A. Sharma, P. Mishra, and S. Kumar, ‘‘Temperature rising, growth descending: Climate change impacts on Asian economies,’’ Global J. Emerg. Market Econ., vol. 16, no. 3, pp. 295–320, Sep. 2024.

[6] C. D. Ahrens, Meteorology Today: An Introduction to Weather, Climate, and the Environment. Boston, MA, USA: Cengage Learning, 2018.

[7] O. Kisi, S. Kim, and J. Shiri, ‘‘Estimation of dew point temperature using neuro-fuzzy and neural network techniques,

[8] P. J. Robinson, ‘‘Temporal trends in United States dew point temperatures,’’ Int. J. Climatol., vol. 20, no. 9, pp. 985–1002, 2000.

[9] S. Kim, V. P. Singh, C.-J. Lee, and Y. Seo, ‘‘Modeling the physical dynamics of daily dew point temperature using soft computing techniques,’’ KSCE J. Civil Eng., vol. 19, no. 6, pp. 1930–1940, Sep. 2015.

[10] J. M. Blanco and F. Peña, ‘‘Increase in the boiler’s performance in terms of the acid dew point temperature: Environmental advantages of replacing fuels,’’ Appl. Thermal Eng., vol. 28, no. 7, pp. 777–784, May 2008.

[11] M. Jradi and S. Riffat, ‘‘Experimental and numerical investigation of a dew-point cooling system for thermal comfort in buildings,’’ Appl. Energy, vol. 132, pp. 524–535, Nov. 2014.

[12] Y. Yang, C. Ren, C. Yang, M. Tu, B. Luo, and J. Fu, ‘‘Energy and exergy performance comparison of conventional, dew point and new externalcooling indirect evaporative coolers,’’ Energy Convers. Manage., vol. 230, Feb. 2021, Art. no. 113824.

[13] M. Ali, W. Ahmad, N. A. Sheikh, H. Ali, R. Kousar, and T. U. Rashid, ‘‘Performance enhancement of a cross flow dew point indirect evaporative cooler with circular finned channel geometry,’’ J. Building Eng., vol. 35, Mar. 2021, Art. no. 101980.

[14] M. Abdullah, S. Waheed, M. Morshed, and M. M. Hasan, ‘‘Analyzing and forecasting dew point temperature trends in Bangladesh,’’ in Proc. 2nd Int. Conf. Inf. Commun. Technol. (ICICT), Oct. 2024, pp. 165–169.

[15] B. B. Arikan, L. Jiechen, I. I. D. Sabbah, A. A. Ewees, R. Homsi, and S. O. Sulaiman, ‘‘Dew point time series forecasting at the north Dakota,’’ Knowl.-Based Eng. Sci., vol. 2, no. 2, pp. 24–34, Aug. 2021.

[16] M. D. Williams, S. L. Goodrick, A. Grundstein, and M. Shepherd, ‘‘Comparison of dew point temperature estimation methods in southwestern Georgia,’’ Phys. Geography, vol. 36, no. 4, pp. 255–267, Jul. 2015.

[17] K. Górnicki, R. Winiczenko, A. Kaleta, and A. Choińska, ‘‘Evaluation of models for the dew point temperature determination,’’ Tech. Sci., vol. 3, no. 20, pp. 241–257, May 2017.

[18] D. A. Callner, ‘‘Artificial neural networks for predicting the dew point, humidity, and the heat index,’’ in Proc. 101st Amer. Meteorol. Soc. Annu. Meeting, 2021, pp. 1–6.

[19] C. Bi, D. Li, X. Yang, Y. Lu, and J. Zhang, ‘‘Prediction of flue gas acid dew point temperature distribution range in boilers,’’ IOP Conf. Ser., Mater. Sci. Eng., vol. 721, no. 1, Jan. 2020, Art. no. 012016.

[20] K. Qaderi, B. Bakhtiari, M. R. Madadi, and Z. Afzali-Gorouh, ‘‘Evaluating GMDH-based models to predict daily dew point temperature (case study of Kerman province),’’ Meteorol. Atmos. Phys., vol. 132, no. 5, pp. 667–682, Nov. 2019.

CHALLA SRI UPENDRA is currently pursuing the MCA (Master of Computer Applications) in Ideal college of Arts and science, Vidyuth Nagar, Kakinada. His research interests include Artificial intelligence

Dr. V. S. V. Deepak is currently serving as the Head of the Department of Computer Science at Ideal College of Arts & Sciences (A). He possesses more than 18 years of academic and administrative experience in the field of Computer Science and Engineering. His areas of interest include Medical Image Processing, Cyber Security, Artificial Intelligence, Software Testing and Networking. He completed his Ph.D. research in Medical Image Processing from Swami Vivekananda University.
He has actively contributed to curriculum development, academic planning, and student mentoring. He has served as Chairman of the Board of Studies (BOS) for BCA, B.Sc. (Computer Science), B.Sc. (Artificial Intelligence), and MCA programs.