International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 5, 2025
https://theaspd.com/index.php

Trend Analysis And Machine Learning Based Short – Term Forecasting Of Heat Index And Temperature – A Case Study In Urban Chennai

Dr.K.Selvavinayaki[1], K.Rizvanaparvin[2]
[1]Associate professor, Department of Computer Applications, Nehru Arts and Science College, Thirumalayampalayam, Coimbatore -641 105. nascselvavinayaki@nehrucolleges.com
[2]Guest Lecturer, Government Arts and Science College, Kottur-625 534 Theni-Dt, parvinrizvana1@gmail.com

Abstract
Analyzing the weather particularly heat waves in a urban city like Chennai has become essential since the temperature is high leading to high heat index particularly in hot summer April – June. Forecasting the weather parameters such as temperature and heat index will aid the humans to take necessary precautions for themselves, their pets etc. This necessitates a ease model that would predict next day or next week parameters. The proposed model is developed for short term prediction of temperature and heat index based on machine learning techniques. The proposed model is trained using historical weather data from January 2017 till May 2025 and immediate next day metrics are predicted using Random Forest regression. Since the dataset contains time information like year, days and months Long Short-Term Memory technique best fits the training and upon implementation the metrics for one week is predicted. The model is evaluated using error metrics Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The training efficiency is validated using regression R^2. An average of 0.85 is the R^2 for Random Forest and 0.87 for LSTM. Similarly, the RSME value is less for LSTM. Hence LSTM network outperforms than Random Forest leading to prediction of increased number of days.
Keywords: *Weather Forecasting, Short-term Forecast, Machine Learning, Artificial Intelligence, Urban Chennai, Temperature, Heat Index, Humidity, Windspeed.*

1. INTRODUCTION

Forecasting of weather conditions is typically uncertain and is crucial to predict. Prediction of weather conditions are of much importance in aiding people of various fields and public to be given an alert. Warnings in case of heavy storms, cyclones and high heat index could be cautioned. There are totally 25 weather monitoring stations across India located in various states of the country which works in S, C and X band [1]. In recent days climate changes are prone to uncertainty due to global warming and urbanization effects [2]. These climatic variations are essentially to be monitored continuously and alert has to be given in time. Traditionally weather prediction is being done based on numerical weather prediction techniques which involves atmospheric simulations. Recent advances in Machine learning techniques play a vital role in the development of prediction model based on the historical information of weather parameters [3,10-11]. Though many researchers work in Artificial intelligence model to forecast the weather conditions, the model requires more accuracy. In urban regions like Chennai where there exists a hot climate in summer and mid-summer. Hence analysis of heat index in such a hot region becomes essential. Heat index has greater impact on human health as it completely depends on temperature and humidity of that particular region [3]. Heat index in Vietnam has been taken for study and it is identified that in the months of June, July, and August the heat index in Vietnam exceeds 41 ºC. It is predicted that there is a likely increase in heat index in the forthcoming years. Same scenario arises in various parts of India especially in urban Chennai.

Weather could be monitored continuously using various monitoring techniques. Short term prediction of weather is achievable by development of exclusive device based on image processing techniques [4]. The images of the various locations are captured and trained for identifying the weather conditions such as possible occurrence of rainfall and status of temperature low or high. This AI based monitoring system is a complete device that predicts temperature and rainfall. The network used for training Combinational Neural Network. Recent researchers are focusing on IoT based weather monitoring and prediction system for applications such as agriculture, surveillance and other meteorological parameters [5-8]. Weather prediction is also done based on the historical data available for decades. One such methodology adopted for prediction is Gencast Machine learning algorithm [9]. This probabilistic Gencast approach is able to forecast weather for next 15 days with a greater accuracy.

The weather prediction models can be developed using three various methodologies such as statistical method, AI based model, Hybrid or Ensemble model. The AI based models makes use of Regression, classification and Numerical Weather Prediction model. These models make use of LSTM, ANN, RF, RNN, SVM and clustering algorithms for training the network. The collected data is initially pre-processed for making the data suitable for training. Interpolation and normalization techniques are frequently adopted for enhancing and uniform distribution of inputs. In such models, biases are reduced to precisely forecast parameters such as rainfall, windspeed etc. Accuracy is increased in these proposed models thereby decreasing R^2 and RMSE [12-17,21].

LSTM techniques are popularly used for weather prediction model as the model has memory within the model. This model is incorporated with two hidden units with long- and short-term memory [18]. From the studies it is evident that there is necessity of extensive geoscience data to develop a data driven machine learning model for weather forecasting. Forecasting of weather 15 days ahead is possible through these approaches. The predicted value is also more accurate and closer to the reality [19]. Studies also confirm that Naive Bayes Bernoulli algorithm outperforms in prediction of temperature, windspeed etc. as the approach is probabilistic. In few research, the network is trained with lesser number of raw data [20]. The research is also carried out with the datasets collected from Kaggle where rule-based algorithm, Convolution neural network and logistic regression is implemented and tested for accuracy of prediction [22]. The overall accuracy of 87.35% is achieved using Logistic regression getting a promising prediction. The algorithm with time series reduces the error in prediction. Time series RNN outperforms than ANN and SVM [23]. Studies is also extended to logistic regression model to make statistical studies and status of prediction for weather data [24].

Prediction of weather for various countries has been carried out by the researcher. The research carried out for Bangladesh weather data has implemented the prediction model using novel ensemble-based regression. The metrics estimated for validation are Root Mean Square Error, Mean Absolute Error and F1 score. The rainfall forecasting ensemble classifier outperforms with 83.4 % accuracy [25]. Researchers carry over many research for weather prediction particularly using rainfall data along with temperature, humidity, windspeed using Artificial Intelligence techniques. These techniques make use of both classification and regression models based on their requirement of prediction. The models developed lack in use of more raw data. Few researchers worked with raw data. Also concluding remark of amount of rainfall or occurrence of rainfall is not discussed elaborately. The training accuracy of the model is estimated and the performance of the developed model in term of accuracy is discussed. **Hence the proposed study analyses the historical patterns of climate and its impact with the information available in the dataset. The scope of the work is to develop a machine learning based model for short term predication of weather parameters temperature and heat index.**

2. METHODS AND MATERIALS

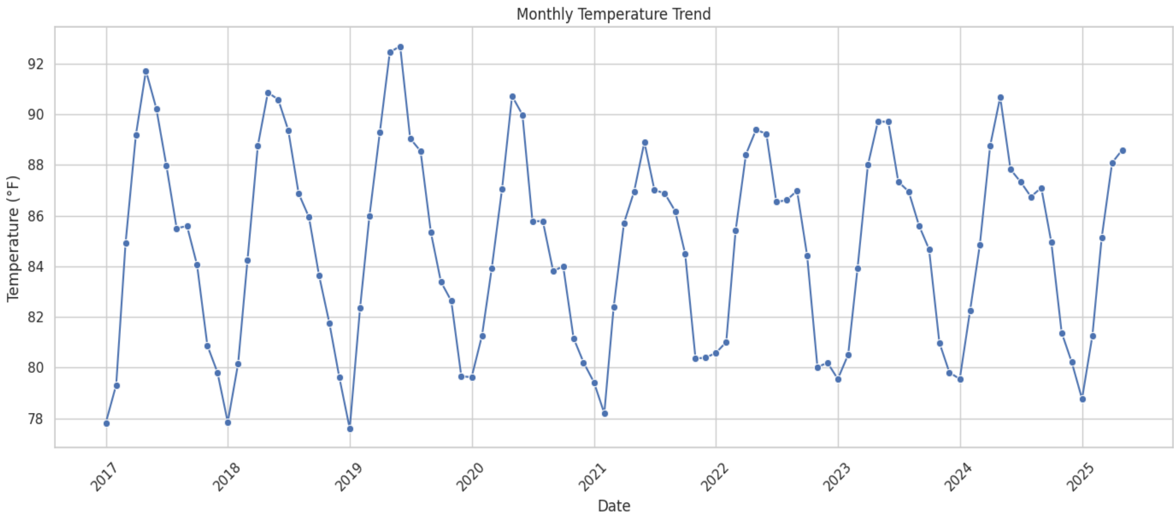
2.1Data Exploration

The information collected has years, months, days, temperature (°F), Humidity (%), Dew Point (°F) and windspeed (mph) as the parameters taken for study. Totally 3072 data have been collected which contains raw data acquired from Chennai International Airport Monitoring station [26] from the year 2017 – 2025 for all months and days of the academic year. For the year 2025 information till 31st May have been considered.

2.2Trend Analysis Parameters that impact Weather

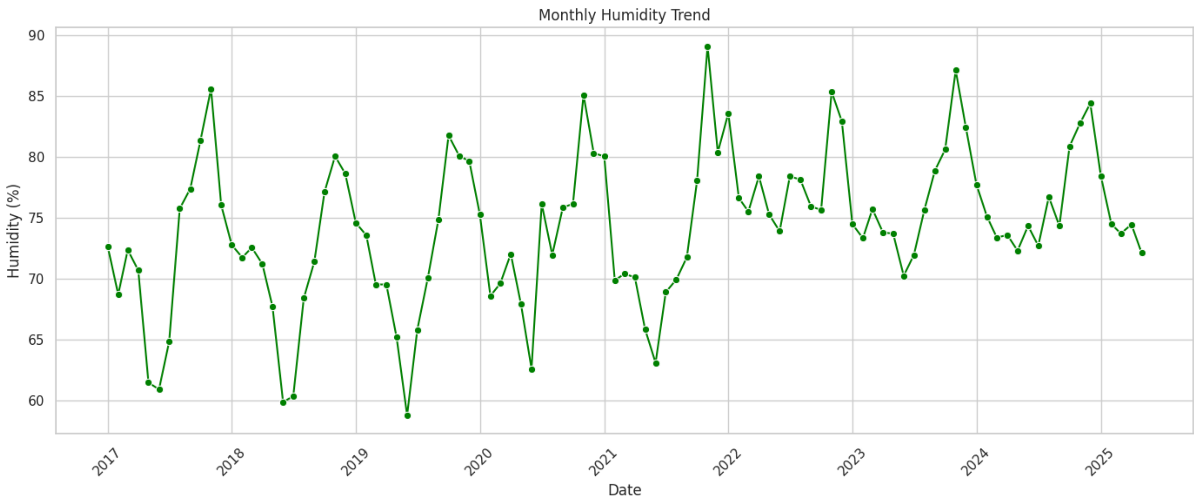
The trends of various parameters are analyzed for the available dataset. Form the temperature data it is evident that the climatic cycle does not fluctuate over years, it remains stable as predicted. The temperature rises to its peak during May and June of every year whereas in the months of December and January it remains low. The maximum temperature achieved in the year 2019 ranging between an average

value of 90 °F – 93 °F. It is observed that there are possibilities of temperature to increase during peak summer. The average monthly temperature from the year 2017 – 2025 is given in Figure 1.
The monthly observations of humidity ranges from 58 % to 89 % for the year 2017 – 2025. The humidity level is relatively stable from the year 2012 whereas during the year 2017 – 2020 it is slightly higher. From the monthly average chart, it is evident that there is no long term sustained variations in the trends of increasing or decreasing level of humidity. The average monthly trend chart of humidity from the year



2017-2025 is given in Figure 2.

Figure 1 Average Monthly Temperature from the year 2017 – 2025 from Chennai International Airport Monitoring Station



•

Figure 2 Average Monthly Humidity from the year 2017 – 2025 from Chennai International Airport Monitoring Station.

It is observed from Figure 1 and 2 that the temperature and humidity is in increasing ranges and is sustainable for longer period of months in a year. Hence an analysis of heat index is taken in to account. The heat index is estimated from the temperature and humidity and is given in equation 1.

$$HI = K_1 + K_2 T + K_3 H + K_4 TH + K_5 T^2 + K_6 H^2 + K_7 T^2 H + K_8 TH^2 + K_9 H^2 T^2 \qquad (1)$$

Where HI – Heat Index, T – Temperature in °F, H – Relative Humidity in %
The coefficients are
K_1 = - 42.379, K_2 = 2.0490, K_3 = 10.1433, K_4 = -0.2247, K_5 = -6.8378 X 10^{-3}, K_6 = -5.4817 X 10^{-2}
K_7 = 1.2287 X10^{-3}, K_8 = 8.5282 X10^{-4}, K_9 = -1.00X10^{-6}

The equation 1 is based on temperature effect, humidity effect and its non-linear effects on extreme conditions.
The trend chart for estimated monthly average heat index is given in Figure 3.

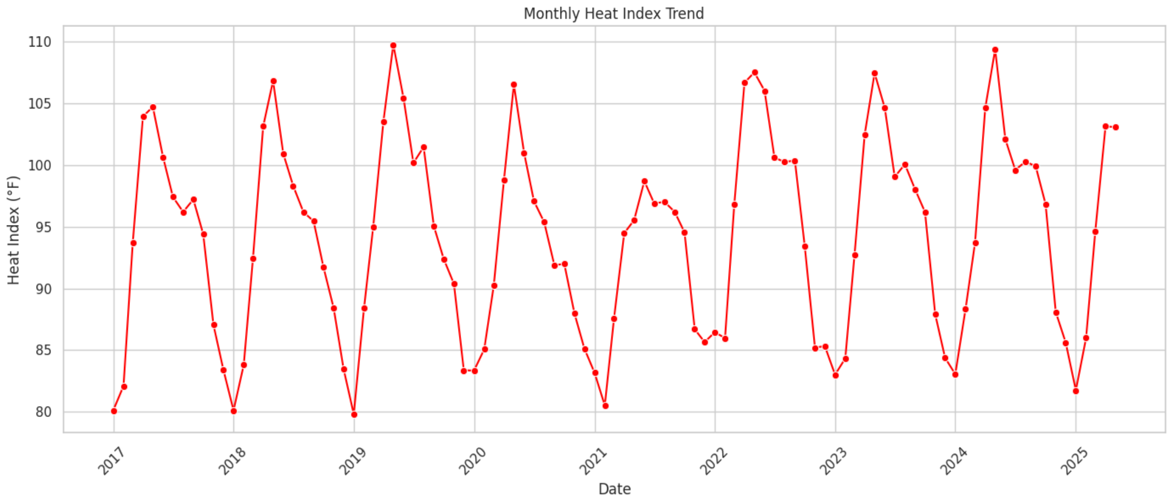


Figure 3 Average Monthly Estimated Heat Index based on Temperature (⁰ F) and Humidity (%) from the year 2017 – 2025.

The average monthly heat index is high in the hot summers May - June and in the months of December - January is relatively low indicating the cool comfort. In hot summer the heat index reaches consistently 105°F. But in the year 2019 and 2024 the heat index has reached a peak there by reaching 110°F. Monthly average heat index heat map is given in Figure 4. From the heat index map it is evident that in urban Chennai the months April – September heat exists leading to discomfort for humans. In the year 2019 and 2022 the heat started in the month of March itself. Hence it is observed that an average of 4 months alone in urban Chennai there is comfort for human since the heat index is considerably reduced, remaining 8 months there is a discomfort to human leading to most discomfort for 3 months in the month of April, May and June every year. Hence it is inferred that there is consistent trend in temperature and humidity of urban Chennai.
The proposed work aims to develop a machine learning prediction model that contributes short – term prediction of temperature and heat index over next 7 days. This prediction would help humans to know about the heat level. This awareness on heat level can make the humans to take necessary precautions for themselves and their pets. It can also help the volunteers and staffs working in service to safeguard wild animals.

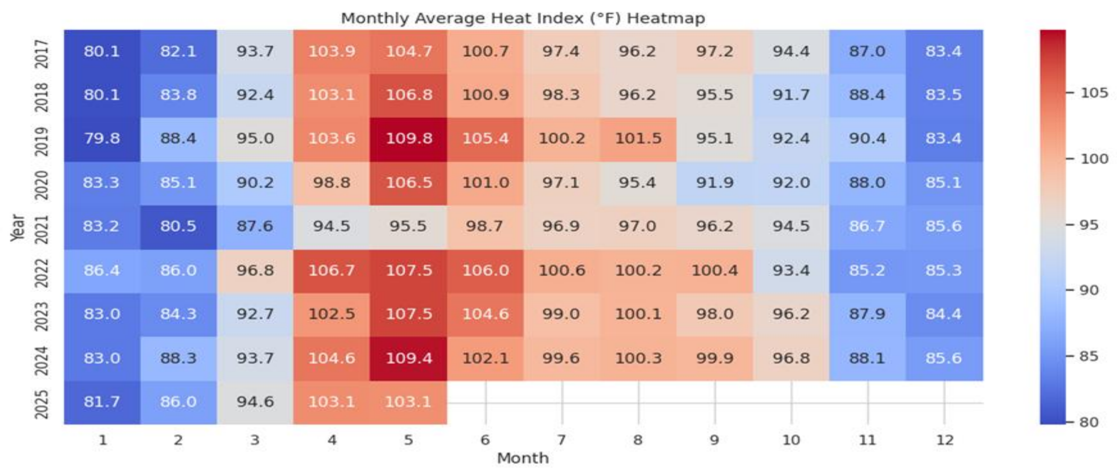


Figure 4 Monthly Average Heat Index Map from the year 2017 – 2025.

2.3Proposed Study

The proposed model aims to develop artificial intelligence based short term prediction model to predict the temperature and humidity 3 in advance. The developed model uses 80: 20 ratios for training and testing the data. Table 1 depicts the algorithm of the proposed study and Figure 5 shows the flow chart of the study.

Table 1 Algorithm – Proposed Model

Algorithm – Proposed Model

```
BEGIN
  # Step 1: Data Exploration
   Collect_Raw Data() # Raw data collected is directly used no preprocessing is done

   # Step 2: Load the Dataset
   Short – Term WPM = Load_Dataset()

   # Step 3: Training Features
   Temperature,  Humidity, Windspeed and Heat Index

   # Step 4: Network Training
   Model = Initialize_Model()
   Training_Successful = False


   WHILE NOT Training_Successful:
                  Train_Model(Temperature,  Humidity, Windspeed and Heat Index)
                  Parameter_Tuning(Model)
                 Training_Successful = Check_Training_Success(Model)

   # Step 5: Testing and Performance Evaluation
   IF Training_Successful:
       Test_Model(Model)
       Performance = Estimate_Performance(Model)

   # Step 6: End Process
   STOP

END
```

2.4Short – Term Weather Prediction Model (Short – Term WPM)

The proposed Short – Term WPM is implemented using Randon Forest Regression algorithm and LSTM technique.

2.4.1 Random Forest Regression

Random forest is a supervisory learning algorithm that combines multiple decision trees to obtain the final regression output. Each decision tree is formed with the random selection of subset from the entire parameters in the data set. Every decision tree has multiple nodes, and training is done for the randomly chosen data subset as given in equation 2.

$$I_{train} = \{(X_j, Y_j)\}j_1^P \qquad (2)$$

Where

X_j - the training parameters

Y_j - Targets for every value of j varying from 1 to P samples.

Every decision tree provides prediction based on the data subset considered for training. The predictions of all independent trees are averaged to get the final prediction as given in equation (8).
The final prediction is given by the equation (3).

$$Y_{pred} = \frac{1}{T_{tot}} \sum_{i=1}^{M} T_i \ (x) \tag{3}$$

T_{tot} - total number of trees in the network
Y_{pred} - Final predicted output
$T_i(x)$ - Prediction of i^{th} decision tree.

2.4.2 Long Short-Term Memory

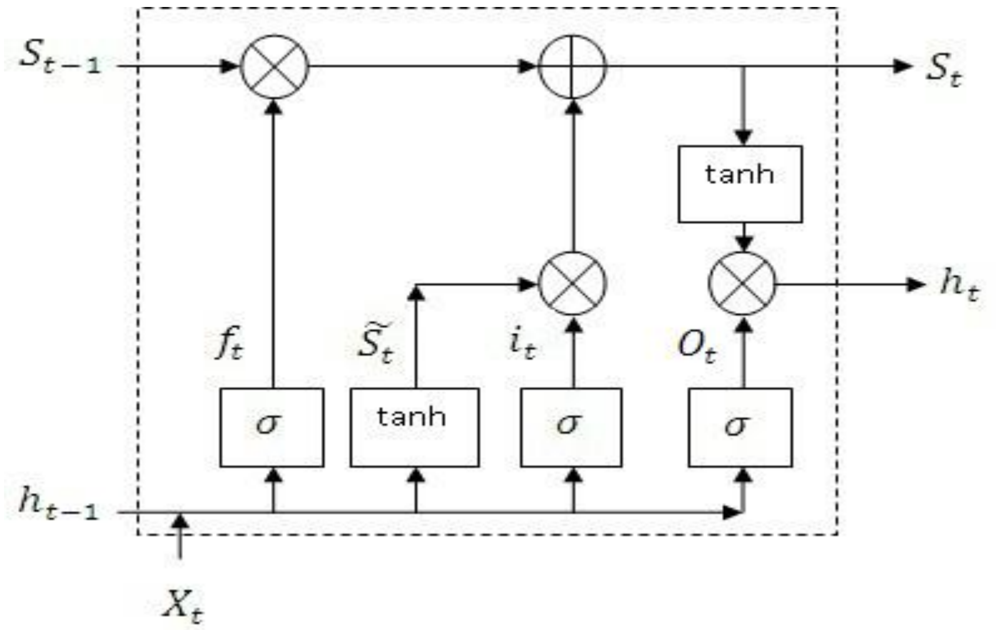


Figure 6 Architecture of LSTM network

Long Short Term Memory (LSTM) network is a type of Recurrent Neural Network (RNN) that cannot have long term dependencies. LSTM network functions in three phases. In the first phase, decision is taken on the previous state information for computing the output of current state. This decision is performed in forget gate. In second phase, learning or updating the information takes place in memory cell. In the last phase, the updated information from the current state is passed to the next state. All the phases together constitute a single time step as shown in figure 6. This process will be repeated for every time step to get the final output.

LSTM network contains memory cells which retain information over long periods of time and has three gates namely the input gate, forget gate, and output gate. The input gate (i_t) decides on the new information that has to be stored in the cell state as per equation (4). The memory cell state is updated and output gate (O_t) decides the information that has to influence the output as given in equation (5). The forget gate (f_t) decides on the information that has to be discarded from the cell state as expressed in equation (6). This input gate involves two parts such as sigmoid layer and tanh layer. A sigmoid layer decides on which values are to be updated and a tanh layer generates a vector to sum up to the state.

$$i_t = \sigma(W_i h_{t-1} + U_i X_t + b_i) \tag{4}$$

Where W_i,U_i and b_i are the parameters to be learned which connects each state, input to the state and bias respectively with respect to the input gate

$$O_t = \sigma(W_o h_{t-1} + U_o X_t + b_o) \tag{5}$$

Where W_o, U_o and b_o are the parameters to be learned which connects each state, input to the state and bias respectively with respect to the output gate

$$f_t = \sigma(W_f h_{t-1} + U_f X_t + b_f) \tag{6}$$

Where W_f, U_f and b_f are the parameters to be learned which connects each state, input to the state and bias respectively with respect to the forget gate

There are three states in the LSTM architecture such as temporary state, previous state and current state.

$\widetilde{S_t}$ is a temporary state which is computed based on equation (7),

$$\tilde{S}_t = Wh_{t-1} + UX_t + b \quad (8)$$

Where W, U and b are the learning parameters

St is the current state that is computed based on equation (9),

$$S_t = f_t \cdot S_{t-1} + i_t \cdot \tilde{S}_t \quad (9)$$

Output of the current block h_t is computed based on equation (10),

$$h_t = O_t \cdot \tanh(S_t) \quad (10)$$

2.5 Hyper – Parameter Tuning

The hyper parameters are tuned for optimization in LSTM. The number of LSTM units considered for training is 16,31,64,128 in which 64 units gives better prediction than the other values. The number of layers is trialled with 1, 2 and 3 layers in which 2 layers gives better results. After several trials the learning rate is fixed as 0.01with ADAM optimizer. The loss function considered is MSE and the training is completed efficiently with 50 epochs. When tried for more than 50 epochs overfitting occurs. The hyper - parameter tuning is done by manual search method. In Random Forest regression model the number of estimators are fixed with 50, 100 and 150 where 100 estimators performs better and number of leaf node is 5.

3. RESULTS AND DISCUSSION

The proposed model is predicted for next day temperature and humidity using Random Forest Regression technique. Also to validate the prediction the error metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) is estimated. With the training data from 1st January 2017 till 31st May 2025, the weather for next six days is predicted and Tabulated in Table 3.

Table 3 Predicted and Estimated Errors for Next Day June 1st 2025

Error Estimate	**Temperature (°F)**	**Humidity (%)**	**Heat Index (°F)**
Predicted	88.68	77.99	102.89
RMSE	3.54	1.57	3.35
MAE	3.14	1.18	2.37
R^2	0.87	0.817	0.853

From the table it is evident that the temperature and humidity predicted are 88.68 and 77.99. To further validate the results linear regression is applied on the available data set and for both temperature and heat index, plot is plotted between actual Vs predicted values and is given in Figure 7. From the figure it is inferred that the data points fall on the regression line without much deviation. The data points are not scattered beyond there is only minimum scattering of data points. This indicates the prediction accuracy for both the parameters of the proposed model is high and confirming no significant outliers, thereby it ensures the validity of proposed model. The proposed model is also validated by predicting the 2025 calendar year data for the month of January to May and is given in Figure 8 (a-e).

The comfort level of humans based on these weather conditions are categorized in to various levels of comfort. If the estimated heat index exceeds 129 °F it is considered as Danger state whereas temperature less than 80.6 °F is comfortable for humans and various ranges of comfort state is listed in Table 4. Hence for the predicted heat index listed in Table 3 the comfort level is Extreme Caution.

Table 4 Heat Index Vs Comfort Level

Temperature (°F)	**Comfort Level**
Less than 80.6	Comfortable
80.6 to 89.6	Caution
89.6 to 105	Extreme Caution
105 to 129	Danger
Greater than 129	Extreme Danger

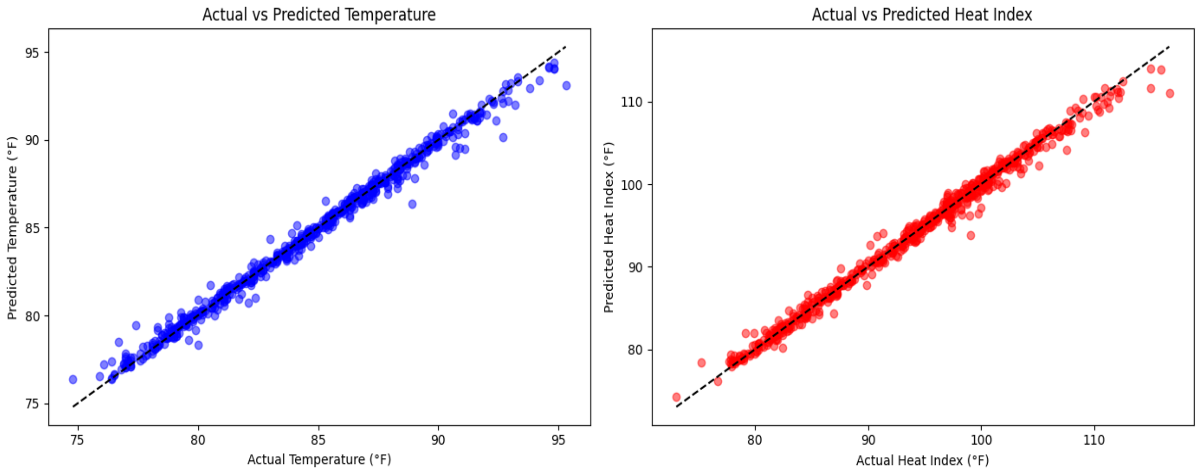
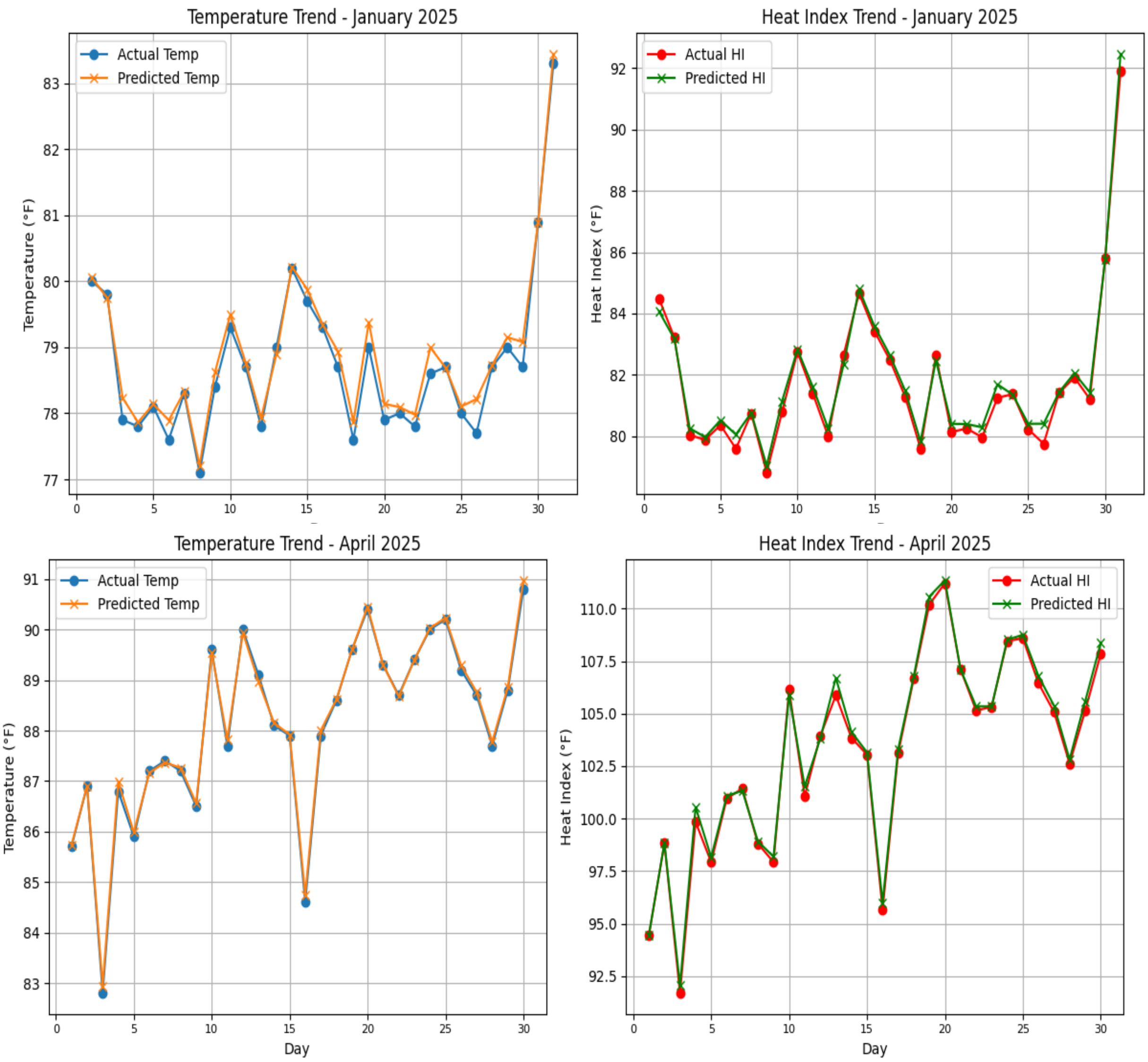
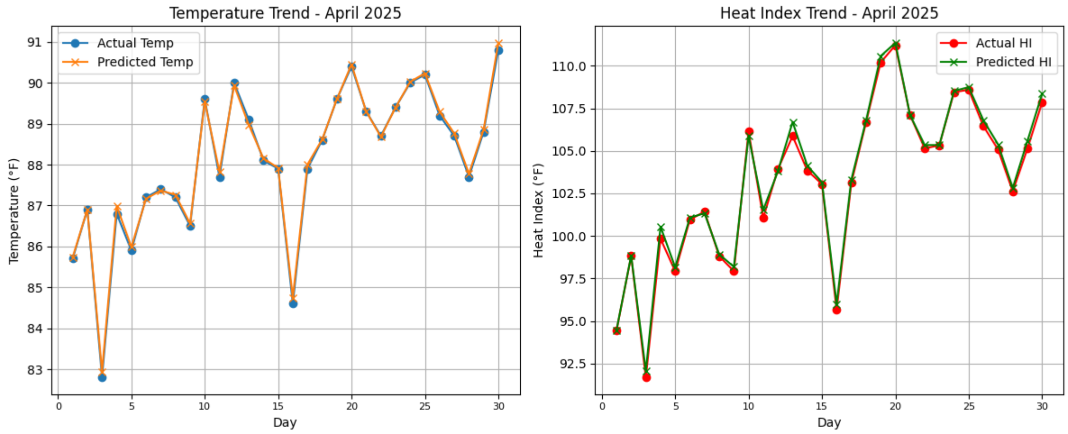


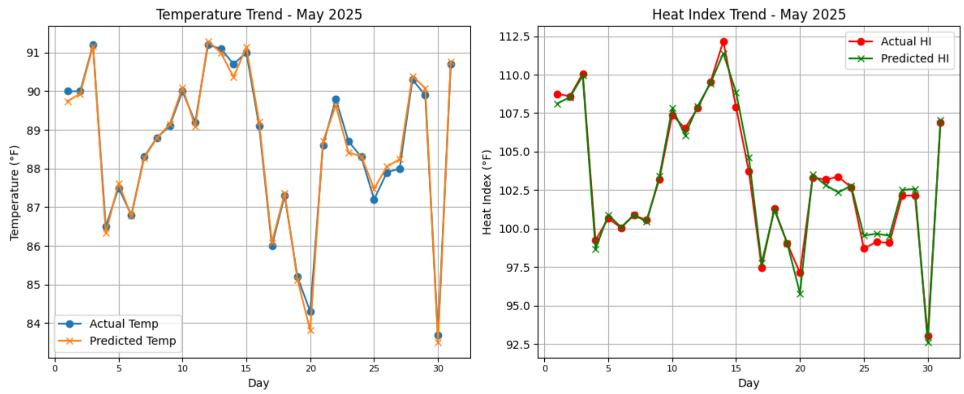
Figure 7 Regression plot between actual and predicted temperature and Heat index.



(a)



(d)



(e)

Figure 8 (a- e) Actual Vs Predicted data points for Temperature and Heat Index for Jan 2025 to May 2025.

On training the network with LSTM technique, with 200 epochs the network is trained on 75 epochs and it is able to estimate for next 7 days. The estimated temperature and heat index is given in Figure 9.

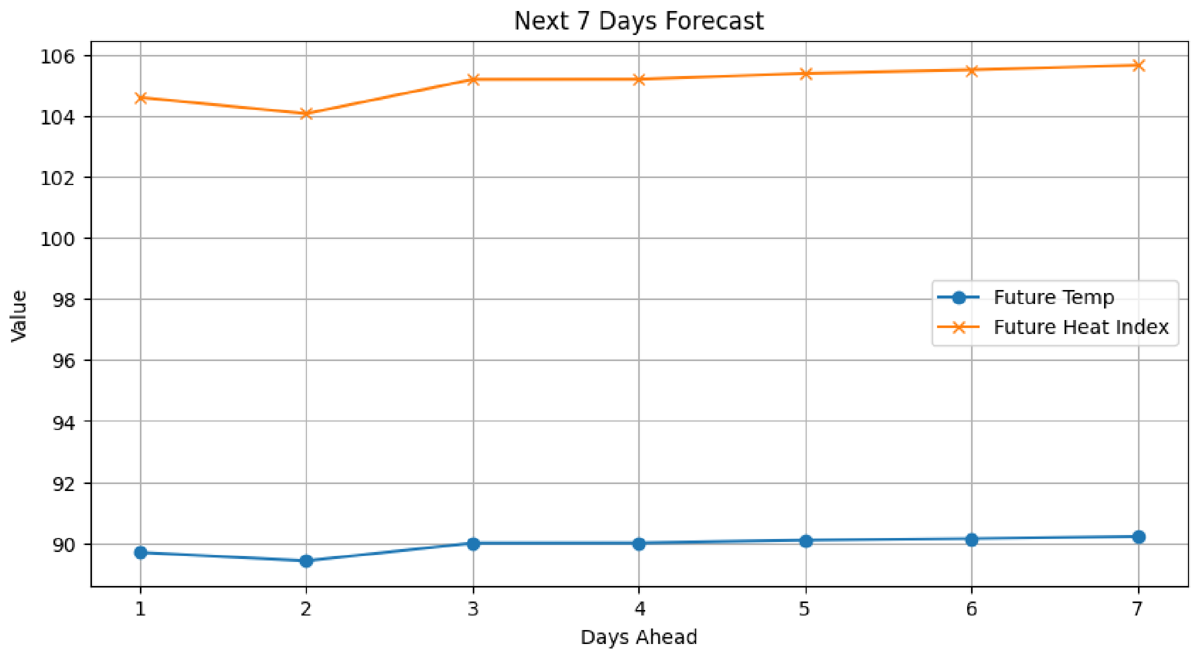


Figure 9 Estimated Heat Index and Temperature using LSTM Network

he error metrics for the developed LSTM network is given in Table 5.

Table 5 Error Metrics for LSTM Network

Evaluation Metrics	Temperature		Heat Index	
	LSTM	Random Forest	LSTM	Random Forest
RMSE	1.61	3.54	3.26	3.35
R^2	0.851	0.87	0.882	0.852

Form Table 5 it is evident that both LSTM and Random Forest equally contributes in prediction. But when used Random Forest technique the prediction for next 1 day is appropriate where the error increases on further future days predictions. Whereas the prediction using LSTM network outperforms by predicting successfully for next 7 days. Since LSTM network has Long Short-Term Memory it is best suited for time series data.

4. CONCLUSION

Temperature, wind speed, humidity are the major parameters that aids in identifying the weather conditions of a region. These parameters for a period of eight years are collected and since the information collected is from urban area Chennai, normally it is known that it will be hot in summer season. Hence the heat index is estimated for all the collected information. Using machine learning technique Random Forest and LSTM technique. In Random Forest temperature, humidity and heat index is predicted for next day. The data set contains data till 31st May 2025 and the parameters are predicted for 1st June 2025. The predicted values of temperature, humidity and heat index are 88.68, 77.99 and 102.89 respectively. The actual value of temperature and humidity on the same day is 92.57 and 78.12 respectively. Hence form the forecast it is identified it is able to predict the values closer. LSTM network forecast the temperature for next 7 days with 89.56, 89.74, 90.26, 90.26, 90.29, 90.32 and 90.38 respectively. The actual temperatures on those 7 days are 91.1, 91.3, 90.8, 90.5, 91.1, 91.0 and 93.0 respectively there by predicting more accurately than Random Forest. The RMSE of LSTM network is 1.61 for prediction of temperature. The results are further validated by predicting every next day values of 2025 for the months of January – May. The predicted results show not much deviation. Also, the data points through the regression analysis of actual and predicted data is not scattered, rather the data points approximately lie in the same linear line representing the accuracy of training.

5. Limitations and Future Work

The developed model aids in predicting only the next day and next 7 days weather conditions based on the past information. This prediction could be enhanced for next weeks with highly accurate prediction. Features such as rainfall, wind speed and heat index could be added to bring a more precise model.

REFERENCES

[1]. https://mausam.imd.gov.in/imd_latest/contents/imd-dwr-network.php

[2]. M Balasubramanian and V Dhulasi Birundha, Climate Change and Its Impact on India, The IUP Journal of Environmental Sciences, Vol. VI, No. 1, 2012.

[3]. Hoang TLT, Dao HN, Cu PT, Tran VTT, Tong TP, Hoang ST, Vuong VV and Nguyen TN (2022), Assessing heat index changes in the context of climate change: A case study of Hanoi (Vietnam). Front. Earth Sci. 10:897601. doi: 10.3389/feart.2022.897601.

[4]. K. Murugan, R. K. Tiruveedhi, D. R. Ramireddygari, D. Thota and C. Neeli, "AI based Weather Monitoring System," 2022 Second International Conference on Advanced Technologies in Intelligent Control, Environment, Computing & Communication Engineering (ICATIECE), Bangalore, India, 2022, pp. 1-5, doi: 10.1109/ICATIECE56365.2022.10047380.

[5]. Luciana Nieto, Rai Schwalbert, P.V. Vara Prasad Bradley , "An integrated approach of field, weather, and satellite data for monitoring maize phenology," Sci Rep 11, p. 15711, 2021.

[6]. S.. Narasimha Swamy, C.N.Sowmyarani. , "Repeated data management framework for IoT: A case study on weather monitoring and forecasting," in 4th International Conference on Recent Advances in Information Technology (RAIT) , IEEE, 2018.

[7]. Pertab Rai and Murk Rehman, "ESP32 Based Smart Surveillance System," in International Conference on Computing, Mathematics and Technologies – iCoMET 2019, 2019.

[8]. Kalpana Murugan and Jenitha.R, "Long Range IoT for Agricultural Acquisition Through Cloud Computing," CRC Press, Taylor & Francis Group, vol. I st Edition, 2022.

[9]. Price, I., Sanchez-Gonzalez, A., Alet, F. et al. Probabilistic weather forecasting with machine learning. Nature 637, 84–90 (2025). https://doi.org/10.1038/s41586-024-08252-9.
[10]. Waqas, M., et al., 2024b. Advancements in daily precipitation forecasting: a deep dive into daily precipitation forecasting hybrid methods in the tropical climate of Thailand. MethodsX 12, 102757.
[11]. Brotzge, J. A., and Coauthors, 2023: Challenges and Opportunities in Numerical Weather Prediction. Bull. Amer. Meteor. Soc., 104, E698–E705, https://doi.org/10.1175/BAMS-D-22-0172.1.
[12]. Muhammad Waqas, Usa Wannasingha Humphries, Bunthid Chueasa, Angkool Wangwongchai,Artificial intelligence and numerical weather prediction models: A technical survey,Natural Hazards Research,Volume 5, Issue 2,2025,Pages 306-320,ISSN 2666-5921, https://doi.org/10.1016/j.nhres.2024.11.004.
[13]. Sayeed, A., et al., 2021. A deep convolutional neural network model for improving WRF simulations. IEEE Transact. Neural Networks Learn. Syst. 34 (2), 750–760.
[14]. Zheng, Y., et al., 2014. Urban computing: concepts, methodologies, and applications. ACM Transactions on Intelligent Systems and Technology (TIST) 5 (3), 1–55.
[15]. Liu, Y., et al., 2023. A WRF/WRF-Hydro coupled forecasting system with real-time precipitation–runoff updating based on 3Dvar data assimilation and deep learning. Water 15 (9), 1716.
[16]. Christoforou, E., et al., 2023. Spatio-temporal deep learning for day-ahead wind speed forecasting relying on WRF predictions. Energy Systems 14 (2), 473–493.
[17]. Feng, J., et al., 2023. Capturing synoptic-scale variations in surface aerosol pollution using deep learning with meteorological data. Atmos. Chem. Phys. 23 (1), 375–388.
[18]. P. Nazareth, A. K. Konnur, A. M. Chavan and K. M. D. Shetty, "Weather Forecasting Using Machine Learning Approach," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-7, doi: 10.1109/ICCCNT61001.2024.10726201.
[19]. Zhang, H.; Liu, Y.; Zhang, C.; Li, N. Machine Learning Methods for Weather Forecasting: A Survey. Atmosphere 2025, 16, 82. https://doi.org/10.3390/atmos16010082
[20]. Uday Patkar, Mr. Sanskar Maske and Mr. Saffa Ahmad , Mr. Rushikesh Mengade, Mr. Gaurav Sadawarti, Weather Prediction using Machine Learning, GIS Science Journal, Vol. 8(12), 2021, PP 118-125.
[21]. Ruyi Yang, Jingyu Hu, Zihao Li, Jianli Mu, Tingzhao Yu, Jiangjiang Xia, Xuhong Li, Aritra Dasgupta, Haoyi Xiong, Interpretable machine learning for weather and climate prediction: A review, Atmospheric Environment, Volume 338,2024,120797, ISSN 1352-2310, https://doi.org/10.1016/j.atmosenv.2024.120797.
[22]. Yadav, K.; Malviya, S.; Tiwari, A.K. Improving Weather Forecasting in Remote Regions Through Machine Learning. Atmosphere 2025, 16, 587. https://doi.org/10.3390/atmos16050587.
[23]. Singh, Siddharth and Kaushik, Mayank and Gupta, Ambuj and Malviya, Anil Kumar, Weather Forecasting Using Machine Learning Techniques (March 11, 2019). Proceedings of 2nd International Conference on Advanced Computing and Software Engineering (ICACSE) 2019, Available at SSRN: https://ssrn.com/abstract=3350281 or http://dx.doi.org/10.2139/ssrn.3350281
[24]. Kaiwei Shen. 2024. Applying Machine Learning Technology for Weather Forecasting: A Case Study of the Logistic Regression Model. In Proceedings of the International Conference on Image Processing, Machine Learning and Pattern Recognition (IPMLP '24). Association for Computing Machinery, New York, NY, USA, 572–576. https://doi.org/10.1145/3700906.3700998.
[25]. Adil Hussain, Ayesha Aslam, Sajib Tripura, Vineet Dhanawat, and Varun Shinde, "Weather Forecasting Using Machine Learning Techniques: Rainfall and Temperature Analysis," Journal of Advances in Information Technology, Vol. 15, No. 12, pp. 1329-1338, 2024.
[26]. https://www.wunderground.com/history/daily/in/saidapuramu/ICHENN51/date/2023-9-7