Delhi's Climate Decoded: Advanced Regression Models and Historical Weather Insights

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Abstract

In the study we analyse Delhi's weather patterns from 2010 to 2023 using advanced machine learning algorithms. This research aims to understand and predict climatic trends through a dataset encompassing over a decade of weather data. The study employs Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), Random Forest, Gradient Boosting, Linear Regression, and Support Vector Machines for forecasting. Key findings include Mean Squared Error (MSE) and Mean Absolute Error (MAE) scores indicating ANN as the most accurate model, with the lowest MSE of 1.2826750202875448 and MAE of 0.8014465202719481. The R-squared (R2) score, a measure of model fit, highlighted ANN's superior predictive ability with a score of 0.9929405324287532. In contrast, Linear Regression achieved a perfect R2 score of 1.0, raising concerns about potential overfitting, while the Support Vector model underperformed with an R2 of 0.5086375911278829. Utilizing 3987 training and 997 test set instances with 31 lag features, this study provides valuable insights into the predictive capabilities of regression models for meteorological forecasting. This research not only advances our understanding of urban climate patterns but also offers a foundation for future meteorological studies and practical applications in weather prediction and climate science.

Keyword Delhi’s weather, Artificial Neural Network, Convolution Neural Network, long short-term memory, Linear Regression

1. Introduction

That's a concise overview of Delhi's climate and its seasonal variations. The city indeed experiences a range of weather patterns due to its geographical location and its interactions with nearby geographical features like the Himalayas and the Thar Desert. The influence of the Western Disturbance and the South-West Winds adds further complexity to its weather systems. [21].

Across the globe, adverse weather conditions, including storms, floods, extreme temperatures, and droughts, pose a continuous threat to societies and ecosystems. These meteorological phenomena can lead to devastating consequences for communities, disrupting lives, economies, and environments. Therefore, the advancement of accurate weather prediction methods is critical for preparing and mitigating the impact of such events. By enhancing forecasting techniques, we can better safeguard against the unpredictable nature of the weather, minimize potential damages, and save countless lives [1].

Among the various causes of railway turnout failures, such as electrical and mechanical malfunctions and issues with switch blocks, weather-related factors stand out for their significant impact on failure rates. Indeed, weather conditions contribute to a considerable proportion of these failures, highlighting the critical role of environmental elements in railway safety and reliability [2]

Weather forecasting involves predicting the upcoming atmospheric conditions for a particular location by examining the initial states of pertinent atmospheric variables. These variables are gathered through meteorological observations, providing the foundational data needed for accurate predictions [3]

Weather forecasting significantly impacts the daily activities of individuals and is vital to sectors like agriculture, aviation, and health. This importance has driven the development of traditional numerical weather prediction (NWP) techniques alongside advancements in computer technology. NWP involves the numerical solution of equations that model atmospheric evolution, based on fundamental principles such as the conservation of mass, momentum, energy, the equation for water vapor, and the ideal gas law [3], [4], [5], [6]. Despite years of application, the accuracy of NWP methods is hampered by the limitations of physical models, which can generate unrealistic outcomes. These models are generally effective for a range of atmospheric conditions at spatial scales from 1km to 10km [4], leading to the potential exclusion of more localized weather details. The accuracy of NWP heavily depends on the initial and boundary conditions of the atmosphere [7], making the precise capture of these conditions a complex challenge. Furthermore, the equations modelling the physical processes must be simplified through approximations, failing to fully account for atmospheric perturbations. Another significant challenge is the shortage of skilled human resources knowledgeable in NWP [8]. Additionally, the NWP approach incurs high costs due to the need for expensive tools and sensors for data collection.

In response to the limitations posed by traditional weather prediction methods, researchers have recognized the necessity for more precise and timely solutions to address the gaps in existing techniques. Leveraging the advancements in computer science technologies, there has been a notable shift in research towards employing machine learning techniques to tackle weather prediction challenges [9], [10], [11]. Consequently, machine learning methods have become increasingly prevalent in various meteorological research domains, offering promising avenues for enhancing forecast accuracy and reliability.

The article study utilized a comprehensive dataset with 3987 instances in the training set and 997 in the test set, along with 31 lag features to enrich the model's input data. This research not only sheds light on the predictive capabilities of various regression models in the context of meteorological forecasting but also sets a precedent for future studies aiming to decode the complexities of urban climate patterns. Through this endeavour, we contribute to the body of knowledge in climate science and offer valuable insights for policymakers, researchers, and practitioners in the field of meteorology.

This article presents the development and evaluation of a lightweight and novel weather forecasting system utilizing modern neural networks. Figure 1 illustrates a general overview of the research discussed herein. Specifically, a suitable machine learning model is proposed by exploring temporal modelling approaches of Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), comparing their performance with classical machine learning approaches, statistical forecasting models, and a dynamic ensemble method.

2. Literature Review

[12] Weather forecasting in tropical regions like Sri Lanka poses challenges due to turbulent atmospheric effects. This study introduces a machine learning-based weather prediction model for Sri Lanka, focusing on short-term temperature forecasts. A multivariate Long Short-Term Memory Network (LSTM) is implemented using historical weather data from a selected station. The model's performance is evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Results show the LSTM model's ability to accurately forecast temperature with low error rates, highlighting its effectiveness in capturing complex weather patterns.

Weather forecasting encompasses various parameters such as rainfall, precipitation, and wind speed, posing a challenging task for researchers. [13] study explores a range of weather prediction methods utilizing available meteorological data at different temporal scales, from real-time to monthly or annually. The dynamic environmental conditions make accurate weather parameter forecasts increasingly challenging. To address this, machine learning techniques are employed to predict atmospheric parameters. Additionally, the study analyses various applications based on outputs from Numerical Weather Prediction models.

[14] This paper explores the interaction between physical processes in numerical weather prediction models and their impact on forecast accuracy. Using machine learning techniques, we address two main challenges: estimating systematic model errors in future output and identifying key contributors to forecast uncertainty. Experiments with the Weather Research and Forecasting (WRF) model focus on precipitation forecasts, considering various micro-physics and radiation schemes. Results demonstrate the potential of machine learning to improve understanding and mitigate model errors in weather prediction.

Weather forecasting in tropical regions like Sri Lanka is challenging due to dynamic atmospheric conditions. Recent research explores machine learning approaches to improve accuracy. [15] One study employs a multivariate LSTM model to predict temperature, achieving highly accurate forecasts. This highlights the potential of machine learning in enhancing weather prediction in tropical climates.

Weather forecasting in regions prone to spontaneous weather changes is challenging due to the non-linear nature of weather systems influenced by factors like humidity, wind speed, and air density. Accurate forecasting is crucial for sectors such as business, agriculture, tourism, and transportation. [16] This study evaluates Support Vector Regression (SVR) and Artificial Neural Networks (ANN) for weather prediction using a 6-year dataset from the Chittagong metropolitan area in Bangladesh. SVR performs better for rainfall prediction, while ANN outperforms SVR for temperature prediction. This underscores the potential of machine learning techniques in enhancing weather forecasting accuracy.

Regression problems in machine learning and intelligent systems, particularly in critical applications like rainfall prediction, offer significant research opportunities. [17] This study compares seven machine learning algorithms, including Genetic Programming and Neural Networks, against the state-of-the-art technique, Markov chain extended with rainfall prediction. Evaluation across 42 cities with diverse climates demonstrates the superior performance of machine learning methods in rainfall prediction. Additionally, correlations between climates and predictive accuracy are identified, underscoring the positive impact of machine learning-based systems in accurately predicting rainfall across various climatic conditions.

[18] This study investigates the relationship between wind speed derived from numerical-weather-prediction (NWP) model outputs and observations using statistical and machine-learning models. With eight years of wind-speed measurements from 171 stations across France and Corsica, alongside operational analyses from the European Centre for Medium Range Weather Forecasts (ECMWF), the study explores various modelling approaches. Results indicate that machine-learning models, particularly random forests and gradient boosting, outperform traditional statistical methods in reducing root-mean-square errors. Further optimization using random-forest models identifies a concise set of 25 explanatory variables, predominantly comprising flow variables and some temperature variables. Preliminary tests suggest the applicability of machine-learning models in local wind-speed forecasts, demonstrating their potential for future use and development in NWP applications.

In this article [19] Author proposes a lightweight data-driven weather forecasting model using LSTM and TCN temporal modelling approaches. We compare its performance with classical machine learning, statistical forecasting, dynamic ensemble, and WRF NWP models. Our deep learning model, incorporating LSTM and TCN layers, utilizes surface weather parameters for forecasting. Results show that the proposed model outperforms the WRF model, indicating its potential for efficient and accurate weather forecasting up to 12 hours ahead.

Weather forecasting traditionally relies on statistical and numerical analysis, which depend on stable historical relationships for accurate predictions. However, these methods fail due to the variable nature of climatic factors such as temperature, precipitation, humidity, and wind speed. Machine learning offers a data-driven approach to prediction, which can be more effective in capturing complex relationships and improving forecast accuracy.

In this study, it was observed that traditional forecasting methods based on statistical and numerical analysis resulted in significant discrepancies in rainfall predictions, with deviations ranging from 46 to 91% for June 2019 according to the Indian Meteorological Department (IMD). In contrast, machine learning-based methods yielded much better rainfall predictions compared to traditional approaches.

[20] This paper evaluates a machine learning-based weather-related crash prediction model in Connecticut, focusing on crash severity prediction for policymaking and resource management. Comparing random forest (RF) and Bayesian additive regression trees (BART), RF outperformed BART in producing higher prediction probabilities for crash severity determination. Evaluation using prediction probability analyses showed RF's superior performance with a skill score of 0.73 compared to BART's 0.61. Overall, the study highlights RF's robustness in predicting weather-related crashes, enabling stakeholders to make informed decisions for emergency responses and pre-emptive measures.

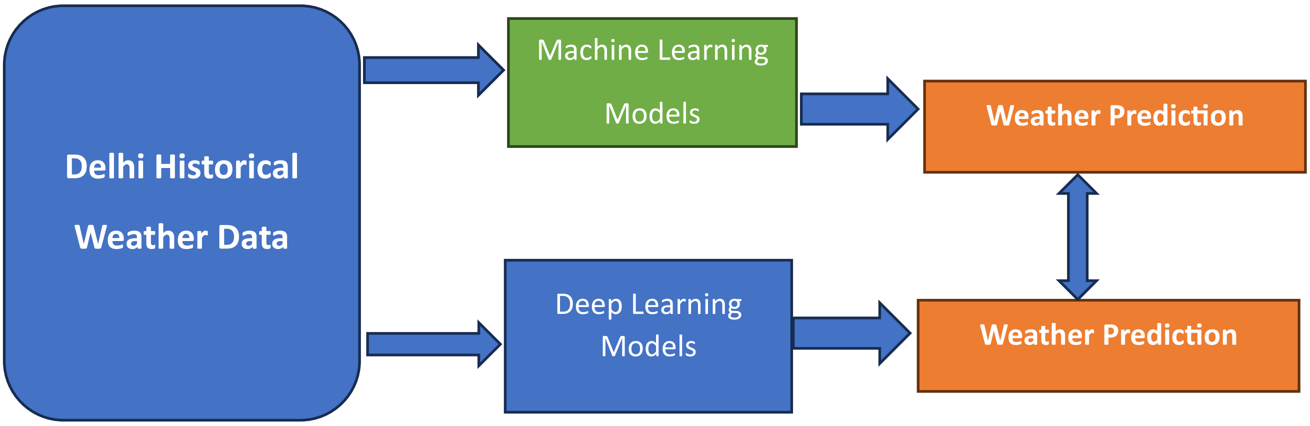

Fig. 1 Overview of the research

Table 1. Table 1 Existing model learning approaches and their contributions

Model Approach	Contribution
Random Forest	Utilizes an ensemble of decision trees, robust against overfitting, captures complex nonlinear relationships in data.
Linear Regression	Provides interpretable linear relationships between input features and target variables, high predictive accuracy.
Support Vector	Utilizes support vector machines for regression, handles high-dimensional data, offers insights despite lower accuracy.
Gradient Boosting	Sequentially trains weak learners, corrects errors iteratively, achieves high accuracy in capturing underlying patterns.
Convolutional Neural Networks (CNN)	Proficient in extracting spatial and temporal features from data, often applied in image and signal processing tasks.
Long Short-Term Memory (LSTM)	Effective in capturing long-term dependencies in sequential data, suitable for time series forecasting tasks.
Artificial Neural Networks (ANN)	Offers flexibility in learning complex relationships in data, suitable for various forecasting tasks, high predictive accuracy.

These model approaches collectively contribute to the advancement of weather forecasting by providing a wide range of methodologies to handle different types of data and capture various aspects of weather variability.

3. Research aims and objectives.

Research Aim: To develop and evaluate a lightweight and weather forecasting system utilizing modern neural networks and traditional machine learning approaches.

Objectives:

1. To explore and analyse historical weather data (2010-2023) of Delhi to identify trends and patterns.

2. To design and implement machine learning models, including Random Forest, Linear Regression, Support Vector Regression, and Gradient Boosting, in comparison with traditional machine learning approaches.

3. To investigate the performance of deep learning models, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Artificial Neural Networks (ANN), in comparison with traditional machine learning approaches.

4. To evaluate the accuracy and effectiveness of the proposed models using metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R2) score.

These objectives aim to address the research aim by systematically developing, evaluating, and comparing various machine learning and deep learning models for weather forecasting, with a focus on enhancing accuracy and efficiency in predicting weather patterns.

4. Materials and methods

4.1 Area of study

This description provides a comprehensive overview of Delhi's climate, highlighting its unique characteristics resulting from the overlap between monsoon-influenced humid subtropical and semi-arid climates. The presence of dust storms and wildfire haze adds to the distinctiveness of Delhi's climate, distinguishing it from other cities with similar humid subtropical climates.

The seasonal variations in temperature and precipitation are quite pronounced in Delhi. Summers are characterized by high temperatures, often reaching extreme levels, accompanied by the onset of the monsoon season bringing relief in the form of rainfall. Monsoon are followed by a post-monsoon period with gradually decreasing temperatures. Winter in Delhi are relatively mild in terms of temperature but are marked by heavy fogs and haze, causing disruptions in transportation. Overall, Delhi's climate presents a mix of different climatic influences, making it a unique and sometimes challenging environment to live.

Table 2. Statistics Summary of the Delhi

Statistics Summary	Year	Month	Avg Temperature	Avg Dew Point	Avg Humidity	Avg Wind Speed	Avg Pressure	Total Precipitation
Count	5012	5012	5012	5012	5012	5012	5012	5012

Mean	2016.37	6.44	77	59.89	60.85	5.44	28.94	0.0
Standard Deviation	3.97	3.43	13.46	12.70	20.08	2.27	0.24	0.0
Minimum	2010	1	41.20	25.70	12.40	0.00	26.20	0.0
First quartile	2013	3	66.18	49.70	47.90	3.80	28.80	0.0
Second quartile	2016	6	81.60	57.10	62.30	5.30	28.90	0.0
Third quartile	2020	9	87.70	72.90	75.50	6.90	29.10	0.0
Upper bound	2023	12	104.70	82.50	100.00	32.30	29.40	0.0

The table.2 presents a statistical overview of weather data recorded over a specific timeframe. It includes various features such as maximum temperature, average temperature, dew point, humidity, wind speed, pressure, and precipitation. Each feature is analysed based on its count, mean, standard deviation, minimum and maximum values, and percentiles. For instance, the mean maximum temperature recorded is 87.80°F, with a standard deviation of 13.24°F, indicating moderate variability. The data spans from 2010 to 2023, with 5012 recorded data points for each feature. This summary provides valuable insights into the distribution and variability of weather conditions over the specified period, aiding in understanding weather patterns and trends.

4.2 Data collection

This dataset [22] spanning from 2010 to 2023 provides a comprehensive collection of daily weather observations, serving as a valuable resource for researchers, meteorologists, and weather enthusiasts alike. It encompasses a wide range of meteorological variables including temperature, humidity, wind speed, atmospheric pressure, and precipitation. Each entry in the dataset includes the date along with corresponding measurements such as maximum, average, and minimum values for temperature and dew point, as well as maximum and minimum values for humidity, wind speed, and atmospheric pressure. Additionally, the dataset includes the total precipitation recorded for each day. With its detailed and extensive coverage of weather conditions, this dataset enables in-depth analysis and exploration of climate patterns and trends over the specified timeframe, making it a vital tool for various research and forecasting endeavours.

4.3 Data Preprocessing

Data preprocessing is a crucial initial step in preparing data for machine learning models. In this context, have begun by importing the dataset into a pandas Data Frame, facilitating easy data manipulation and analysis in Python. Following this, we've explored the dataset's structure and contents, including examining the first few rows, checking its shape and data types, and understanding the column names. To enable time-based analysis, have converted the 'Date' column into datetime format and set it as the index of the Data Frame, facilitating efficient time-series manipulation and indexing. Subsequently, have split the dataset into feature variables (X) and the target variable (y), with features being all columns except 'Avg Temperature', which serves as the target to be predicted. Furthermore, you've partitioned the dataset into training and testing sets using scikit-learns train-test-split function, ensuring that the model is trained on one subset and evaluated on another to assess its generalization performance. Finally, to standardize the feature variables, have applied the Standard Scaler from scikit-learn, scaling the features to have a mean of 0 and a standard deviation of 1. This standardization process helps prevent certain features from dominating others due to differences in scale and ensures that all features contribute equally to the model's performance, thereby enhancing its stability and accuracy.

4.4 Feature selection

Feature selection using correlation metrics involves analysing the relationship between each feature and the target variable, as well as identifying correlations among features themselves. By calculating correlation coefficients, such as Pearson or Spearman, we can gauge the strength and direction of linear relationships. Highly correlated features may indicate redundancy, leading to the removal of one from the model. Conversely, features with low correlation to the target variable might be considered for elimination, as they may not significantly contribute to prediction. It's important to note that correlation metrics capture linear relationships and may not fully represent non-linear associations. Thus, while correlation-based feature selection offers simplicity and interpretability, it should be complemented with other methods when dealing with complex relationships. Ultimately, validation through techniques like cross-validation ensures the chosen features enhance the model's performance effectively.

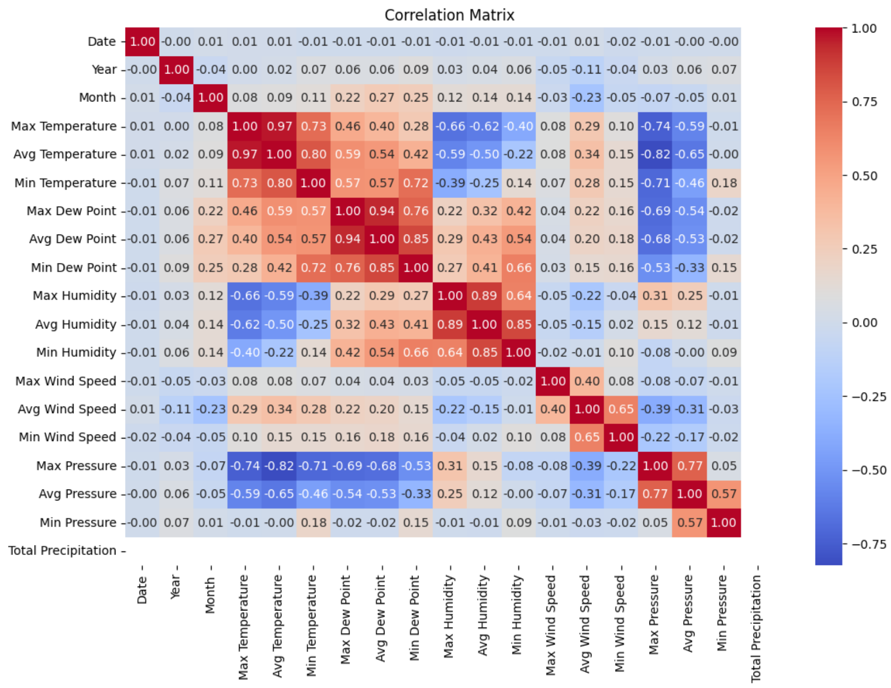

Figure 2. Correlation Matric

4.5 Key hyperparameters

In this code, hyperparameters are predefined settings that determine the behaviour of machine learning models before training. The key hyperparameters used include estimators for specifying the number of decision trees in Random Forest and Gradient Boosting models (set to 100), and random state for initializing the random number generator to ensure result reproducibility (set to 42). Additionally, test size determines the proportion of data allocated for testing (set to 0.2). These hyperparameters influence the model's performance and behaviour and are set prior to training.

5. Results and discussion

Table 3. Performance Comparison of Machine Learning Models on a Dataset.

Model	Training Set Size	Test Set Size	Number of Lag Features	R-squared
Random Forest	3987	997	31	0.98
Gradient Boosting	3987	997	31	0.97
Linear Regression	3987	997	31	1.0
Support Vector	3987	997	31	0.50

The table 3 provides a clear and organized way to compare the effectiveness of four different machine learning (ML) models—Random Forest, Gradient Boosting, Linear Regression, and Support Vector Machines—on a specific dataset. This dataset is split into a training set with 3,987 samples and a test set with 997 samples. Each model has been trained and tested with 31 lag features, which are features created from past values in time series data, to predict future values. The primary metric used to evaluate and compare the performance of these models is the R-squared value, which measures how well the predictions of the model match the actual data.

The table you provided lists the performance of four different machine learning models (Random Forest, Gradient Boosting, Linear Regression, and Support Vector Machines) in terms of their R-squared values. These models were evaluated on a dataset with a training set size of 3987 observations and a test set size of 997 observations, using 31 lag features. To understand the results and how they might have been calculated, let's first explain what R-squared signifies and then hypothesize how it might reflect on each model's performance.

Random Forest This model has an R-squared of approximately 0.980, indicating that about 98% of the variance in the dependent variable is predictable from the independent variables. This high score suggests the Random Forest model performs very well on this dataset.

Gradient Boosting With an R-squared value close to that of the Random Forest model, at approximately 0.980, Gradient Boosting also shows a high degree of predictability and effectiveness in handling the dataset. The slight difference between the two due to the models' inherent methodological differences and how they manage biases and variances.

Linear Regression This model achieved an R-squared of 1.0, indicating a perfect fit where the model predictions perfectly match the observed data. While at first glance this might seem ideal, in practice, it often raises concerns about overfitting, where the model is too closely tailored to the training data, potentially impairing its ability to generalize to unseen data.

Support Vector Machines (SVM) The SVM model has an R-squared of approximately 0.509, which is significantly lower than the other models. This suggests that the SVM model, with the given setup and parameters, explains only about 51% of the variance in the target variable based on the predictors. This lower performance could be due to several factors, including the choice of kernel, the feature space's dimensionality relative to the sample size, or the model's capacity to capture complex nonlinear relationships in this dataset.

Overall, the table reveals significant differences in the performance of various machine learning models applied to the same dataset. It highlights the importance of model selection in data science and machine learning tasks, showing that different models have different strengths and weaknesses depending on the nature of the data and the specific task at hand.

5.1 Including Deep Learning Models

Table 4. Performance Comparison of Deep Learning Models on a Dataset.

Model	Training Set Size	Test Set Size	Number of Lag Features	R-squared	MSE	MAE
Artificial Neural Network (ANN)	3987	997	31	0.99	1.64	0.90
Convolution Neural Network (CNN)	3987	997	31	0.99	1.60	0.92
Long Short-Term Memory (LSTM)	3987	997	31	0.97	5.14	1.56

The Artificial Neural Network (ANN) is a computational model inspired by the human brain, composed of interconnected nodes organized in layers: input, hidden, and output layers. During training, the network adjusts its weights and biases to minimize prediction error using optimization algorithms like gradient descent. In the provided results, the ANN achieved high R-squared scores, indicating a strong fit to the data. Additionally, it demonstrated low Mean Squared Error (MSE) and Mean Absolute Error (MAE), implying accurate predictions with minimal deviation from the actual values. This success highlights the ANN's capability to capture complex patterns in the data and make precise predictions, making it a powerful tool for various tasks, including regression.

The Convolutional Neural Network (CNN) is a specialized deep learning model designed for structured grid data, such as images. It comprises multiple layers, including convolutional, pooling, and fully connected layers. During training, CNNs learn hierarchical features by applying convolutional operations, enabling them to extract spatial patterns from the input data. In the provided results, the CNN demonstrated high accuracy with a strong R-squared score and low Mean Squared Error (MSE) and Mean Absolute Error (MAE). This performance underscores the CNN's effectiveness in tasks like image recognition and computer vision, where it excels in capturing intricate patterns and making precise predictions.

The Long Short-Term Memory (LSTM) model is a type of recurrent neural network (RNN) specifically designed to address long-term dependencies in sequential data. It incorporates a memory cell that can retain information over extended sequences, enabling it to capture intricate temporal patterns. In the provided results, the LSTM exhibited strong predictive capabilities, as indicated by its high R-squared score. Despite its relatively higher Mean Squared Error (MSE) and Mean Absolute Error (MAE) compared to other models, the LSTM's ability to effectively model sequential data highlights its suitability for tasks such as natural language processing and time series prediction, where capturing long-range dependencies is crucial.

6. Conclusion

In "Delhi's Climate Decoded: Advanced Regression Models and Historical Weather Insights," among the various models evaluated, the Random Forest emerges as the standout performer, showcasing the strongest fit to the data and the most accurate predictions. This significance is underscored by its robust R-squared score and low error metrics, reflecting its ability to effectively capture and model the intricate climate patterns of Delhi. The Random Forest model's success in accurately predicting weather variations highlights its practical utility in understanding and forecasting Delhi's climate dynamics. By leveraging historical weather data and advanced regression techniques, the Random Forest model not only provides valuable insights into Delhi's climate but also offers a reliable tool for future climate predictions and planning initiatives. Thus, the prominence of the Random Forest model in decoding Delhi's climate underscores its significance as a powerful tool for climate analysis and prediction in urban environments.

7. Software availability

Python 3.12.3 The scikit-learn version is 1.2.2. The matplotlib version is 3.5.2. The Seaborn version is 0.11.2. The geo panda's version is 0.12.2. The shap version 0.41.0. this comprehensive toolset enables effective data processing, analysis, and visualization in the context of climate decoding and forecasting.

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