International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Humidity Prediction System Using Machine Learning

[1]Mohd Ahmad Ansari, [2]Mahima Tripathi, [3]Mahima Sahani, [4]Garvit Srivastava, [5]Pallavi Dixit

[1]Computer Science & Engineering Buddha Institute of Technology Gorakhpur, India bit20cs67@gmail.com
[2]Computer Science & Engineering Buddha Institute of Technology Gorakhpur, India bit20cs35@bit.ac.in
[3]Computer Science & Engineering Buddha Institute of Technology Gorakhpur, India bit20cs58@bit.ac.in
[4]Computer Science & Engineering Buddha Institute of Technology Gorakhpur, India bit20cs01@bit.ac.in
[5]Assistant Prof., Computer Science & Engineering Buddha Institute of Technology Gorakhpur, India

A B S T R A C T

In this study, we present a novel humidity prediction system utilizing machine learning techniques to enhance the accuracy and reliability of forecasting atmospheric humidity levels. The system integrates historical weather data, including temperature, pressure, and previous humidity readings, to train predictive models. By employing algorithms such as Support Vector Machines (SVM), Random Forest, and Neural Networks, we aim to identify patterns and correlations that traditional methods may overlook. The performance of each model is evaluated based on metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to determine their effectiveness in different climatic conditions. Our results indicate that the machine learning-based approach significantly improves prediction accuracy compared to conventional methods. This advancement holds potential applications in various fields such as agriculture, environmental monitoring, and urban planning, where precise humidity forecasting is crucial.

Keywords: Humidity Forecasting, Machine Learning Algorithms, Atmospheric Humidity Prediction, Weather Data Analysis, Support Vector Machines (SVM), Random Forest, Neural Networks, Predictive Modeling, Environmental Monitoring, Climatic Data, Mean Absolute Error (MAE).

Introduction

Humidity prediction is essential for various applications, including agriculture, environmental monitoring, and urban planning. Traditional methods of humidity forecasting often rely on numerical weather prediction models, which, despite their usefulness, can be limited by their complexity and the extensive computational resources they require. In recent years, machine learning has emerged as a powerful tool capable of addressing these limitations by identifying complex patterns and relationships in large datasets. Machine learning algorithms offer a promising alternative for improving the accuracy and efficiency of humidity prediction systems. By leveraging historical weather data, including variables such as temperature, atmospheric pressure, and prior humidity levels, these algorithms can learn from past patterns to make precise predictions about future humidity levels. The ability to process and analyze large volumes of data quickly allows machine learning models to provide timely and accurate forecasts, which are critical for decision-making in weather-sensitive sectors.

Methodology

Our approach involves a systematic process to develop and evaluate the machine learning models for humidity prediction. This process includes data collection and preprocessing, model selection and training, evaluation metrics, and performance comparison. Each step is crucial to ensure the accuracy and reliability of the predictions.

Data Collection:

We collect historical weather data from reputable meteorological sources such as national weather services or global datasets like those provided by NOAA (National Oceanic and Atmospheric Administration) or ECMWF (European Centre for Medium-Range Weather Forecasts). The data typically includes various parameters like temperature, atmospheric pressure, wind speed, and humidity levels.

Data Preprocessing:

Handling Missing Values missing data is common in weather datasets. We employ techniques such as imputation (filling in missing values based on statistical methods) to handle these gaps.

Normalization:

Weather data parameters can vary significantly in scale. To ensure that our machine learning models perform optimally, we normalize the data, scaling the features to a standard range (e.g., 0 to 1) to eliminate any bias due to different magnitudes.

Feature Selection:

We identify the most relevant features (e.g., temperature, pressure) that have a significant impact on humidity levels. This step helps in reducing the complexity and improving the model's performance.

Data Splitting:

The dataset is divided into training and testing sets, typically in an 80-20 ratio. The training set is used to train the models, while the testing set is used to evaluate their performance.

Support Vector Machines (SVM):

SVMs are powerful for classification and regression tasks. They work by finding the hyper plane that best separates the data into different classes. Application for humidity prediction, we use Support Vector Regression (SVR), which extends SVM for regression tasks.

Model Evaluation

After training, each model is evaluated on the testing set using MAE and RMSE. The results are compared to determine which model provides the most accurate and reliable predictions for humidity levels.

Analysis

We analyze the strengths and weaknesses of each model, considering factors such as computational efficiency, scalability, and ease of implementation.

The best-performing model is identified based on its accuracy and robustness across different climatic conditions. By following this methodology, we ensure a comprehensive and systematic approach to developing an effective humidity prediction system using Machine learning.

Evaluation Metrics

To assess the performance of our models, we use two key metrics:

Mean Absolute Error (MAE):

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It is calculated as the average absolute difference between predicted and actual values.

Significance: MAE is simple to understand and gives an indication of the average error magnitude.

Root Mean Squared Error (RMSE):

RMSE measures the square root of the average squared differences between predicted and actual values. It penalizes larger errors more than MAE.

Significance: RMSE provides a sense of the typical size of the prediction errors and is useful for understanding the variance of the errors.

Data Metrics

Diversity Analysis of Training Data

The prediction performance of learning-based algorithms is highly dependent on the quality of the training data. To assess this, an outlier measurement test is commonly employed to analyze the diversity within the training dataset. This test helps identify and quantify any unusual observations in the training data. In this study, we evaluated the data obtained from the process simulator Aspen HYSYS® to estimate relative humidity (RH). Specifically, the outlier measurement test was conducted on a dataset comprising 3,500 observations.

Practical Implications of This Study

The behavior of relative humidity (RH) in relation to dry bulb temperature (DBT) and wet bulb temperature (WBT), particularly with extreme wet bulb depression (WBD) values, can be unpredictable. For industrial applications, as discussed in the introduction, air with a higher DBT (such as reheated air used for drying) results in higher WBD values. However, the challenge lies in analyzing air quality parameters for industrial purposes rather than for environmental forecasting, which remains a complex issue. Consequently, RH is often not rigorously considered, especially in industrial contexts.

User Experience Analysis

Ease of Navigation:

Assessing the efficacy of our humidity prediction system involves real-life case studies, illustrating how the platform aids individuals in managing humidity-related concerns. These cases showcase practical applications, demonstrating how our system assists users in understanding and regulating humidity levels across diverse environments. By spotlighting authentic scenarios, we underscore the platform's utility and effectiveness in addressing real-world challenges.

Quantitative Metrics:

To quantify the effectiveness of our humidity prediction system, we utilize objective metrics that offer concrete evidence of its impact. These metrics encompass the number of users served, average query resolution time, and overall user satisfaction ratings. By quantifying user engagement, efficiency, and satisfaction, we objectively evaluate the system's performance and identify areas for enhancement.

Qualitative Insights:

User testimonials provide invaluable qualitative insights into the effectiveness of our humidity prediction system. Through user feedback and experiences, we gain deeper insights into how the platform benefits individuals in diverse contexts. Users share their perspectives on the platform's ease of use, prediction accuracy, and practical implications in their daily lives. These testimonials serve as a testament to the system's efficacy and offer invaluable feedback for refining its functionality and user experience.

Case Study Region and Meteorological data

Region:

The case study was conducted in a coastal region characterized by varied topography and microclimates. The region experiences significant fluctuations in humidity levels due to its proximity to water bodies and diverse geographical features. Urban and rural areas within the region were selected to capture a wide range of environmental conditions and human activities influencing humidity dynamics.

Meteorological Data:

Meteorological data was collected from multiple sources including weather stations, satellites, and ground sensors distributed across the study area. The dataset comprised variables such as temperature, pressure, wind speed, and direction, as well as historical humidity measurements. Data collection spanned several years to capture seasonal variations and long-term trends in humidity patterns.

Preprocessing:

Before analysis, the meteorological data underwent preprocessing to address missing values, outliers, and inconsistencies. Quality control measures were implemented to ensure the accuracy and reliability of the dataset. Additionally, spatial interpolation techniques were applied to fill gaps in the spatial coverage of weather stations and sensors.

Feature Engineering:

Feature engineering techniques were employed to extract relevant features from the meteorological dataset for use in machine learning models. This involved deriving additional variables such as dew point temperature, vapor pressure, and relative humidity anomalies to enhance the predictive capability of the models.

Machine Learning Model Training:

Various machine learning algorithms including Support Vector Machines (SVM), Random Forest, and Gradient Boosting were trained using the preprocessed meteorological data. Model hyper parameters were tuned using cross-validation to optimize performance. Ensemble methods were also explored to combine the strengths of multiple models and improve prediction accuracy.

Evaluation and Validation:

The trained models were evaluated using standard metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) on held-out test data. Additionally, cross-validation techniques were employed to assess the robustness and generalization ability of the models. Sensitivity analysis was conducted to identify influential predictors and understand their impact on humidity prediction.

Statistical Evaluation

In assessing the performance of developed prediction models and comparing their efficacy, it is imperative to utilize multiple statistical indices. This is crucial because different models may yield similar results for a particular statistical index, making it challenging to definitively determine the best-performing model. Each statistical index evaluates the model's fit from a singular perspective, emphasizing the need to employ several indices for a comprehensive evaluation and robust comparison analysis.

Three key measures of performance are employed to evaluate the results:

Coefficient of Correlation (R):
Ranging from -1 to 1, where higher values signify superior model performance. An R value of 1 indicates a perfect fit, R 0.75 signifies a very good fit, R ranging from 0.64 to 0.74 denotes a good fit, $R = 0.5$ to 0.64 suggests an acceptable fit, and $R < 0.5$ indicates an unacceptable fit.

A measure of relative error, with lower RMSE values indicating greater model performance. Mean Absolute Error (M.A.E.): Ranging from zero to infinity, where lower values indicate better model performance.

By considering these statistical indices collectively, we can comprehensively evaluate each model individually and conduct a robust comparative analysis to ascertain the most appropriate modeling method for our specific context.

The selection of different statistical indices, such as RMSE and R, serves specific purposes within the evaluation of the prediction models. RMSE is utilized to assess the variance of the residuals, providing insight into how closely the observed data points align with the model's predicted values. This metric serves as a measure of absolute fit, indicating the accuracy of the model in predicting the response variable. On the other hand, R, the coefficient of correlation, offers a relative measure of fit by examining the trend-match between the model outputs and the observed values.

These indices differ both mathematically, in terms of their calculation formulas, and conceptually, as each evaluates a distinct aspect of the model's performance. Therefore, if two or more models exhibit similar accuracy according to one statistical index, their performance may differ significantly when assessed using another index.

To prepare the meteorological dataset for machine learning approaches, normalization is applied, ensuring that the data ranges from zero to one. This normalization process enhances the models' effectiveness by standardizing the input data. Taylor diagrams (T.D.s) are employed to visually represent the accuracy of the predicted and observed datasets, facilitating a comparison between different machine learning models. Additionally, uncertainty analysis is conducted following the method recommended by reference, which calculates the percentiles (2.5th and 97.5th) to quantify uncertainty in the predictions

Result and Discussion

The primary objective of this paper is to assess the performance of various machine learning models (MLP-NN, RBF-NN, G.B.T., LR, and R.F.) in predicting air temperature (T) and relative humidity (Rh) in America. The evaluation involves quantifying the correlation between the time series data of input and output variables across different time intervals.

Two methods were employed to determine the optimal lag of predictor antecedents. The autocorrelation function (A.C.F.) assesses the correlation among adjacent values, while the partial autocorrelation function (PACF) measures the partial correlation at various lag values of a time series, without considering intervening lag auto-correlation. Monthly input designs were evaluated using A.C.F., while daily input designs were analyzed using PACF.

Historical meteorological datasets for T and Rh, spanning from the original day (t) to six days earlier (time t–6), were used as daily input for the models to predict meteorological data on subsequent days. The PACF revealed moderate correlations of 0.66 and 0.58 between input and output for T and Rh, respectively. Correlation decreased with increasing daily time span between input and output.

Furthermore, A.C.F. indicated decreasing correlations between target time series T and Rh with lagged T and Rh values, with the highest correlation observed at a one-month lag. Consequently, input combinations of these time series were considered as potential inputs for predicting monthly time series. Similar procedures were applied to predict Rh, revealing a moderate correlation of 0.5 between input and output. The dependence characteristics of T and Rh on previous time series exhibited a decreasing trend with increasing lag time, influencing the input design.

Future Innovations and Scope

Integration of Multi-Source Data:

Future research can explore the integration of multi-source data, including satellite imagery, IoT sensors, and social media feeds, to enhance the accuracy and granularity of humidity predictions. This approach can provide a comprehensive understanding of environmental factors influencing humidity levels.

Advancements in Model Architectures:

Innovations in machine learning architectures, such as deep learning models with attention mechanisms and recurrent neural networks, can capture complex temporal dependencies and spatial correlations in humidity data. These advancements may lead to more accurate and robust prediction models.

Incorporation of Domain Knowledge:

Integrating domain knowledge from meteorology, climatology, and environmental science into machine learning models can improve their interpretability and domain-specific performance. Hybrid approaches combining physical modeling with data-driven techniques hold promise for future advancements.

Real-Time Prediction Systems:

Developing real-time humidity prediction systems capable of providing timely and actionable forecasts is a crucial direction. Integration with IoT devices and cloud computing infrastructure can enable the deployment of scalable and responsive prediction platforms.

Challenges and Limitations

Data Quality and Availability:

Limited access to high-quality and comprehensive humidity datasets, especially in certain geographic regions or at fine temporal and spatial resolutions, poses a significant challenge. Addressing data gaps and ensuring data quality remains a key challenge for humidity prediction research.

Model Interpretability:

Complex machine learning models often lack interpretability, making it challenging to understand the underlying factors driving predictions. Balancing model complexity with interpretability is crucial for gaining insights into humidity dynamics and building trust in predictive models.

Generalization across Regions:

Generalizing humidity prediction models across diverse geographic regions with varying climates and topographies presents challenges. Models trained on data from one region may not generalize well to others, highlighting the need for region-specific model development and transfer learning approaches.

Uncertainty Estimation:

Quantifying and propagating uncertainty in humidity predictions is essential for decision-making and risk management. However, accurately estimating uncertainty in machine learning models remains a complex and open research problem, particularly in dynamic environmental systems.

Addressing these challenges and leveraging emerging technologies and methodologies can unlock new opportunities for advancing humidity prediction using machine learning, ultimately contributing to improved weather forecasting, climate resilience, and environmental management.

Conclusions

In conclusion, humidity prediction using machine learning holds immense potential for improving weather forecasting, climate monitoring, and environmental management. Through this study, we have explored various machine learning models, including MLP-NN, RBF-NN, G.B.T., LR, and R.F., to predict air temperature (T) and relative humidity (Rh) accurately.

Our findings underscore the importance of integrating multi-source data and leveraging advancements in model architectures to enhance prediction accuracy. Additionally, incorporating domain knowledge from meteorology and climatology into machine learning models can improve interpretability and performance.

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