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Review of Techniques and Algorithms of Temperature Prediction Using Artificial Intelligence

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ABSTRACT

This study investigates recent advancements in Artificial Intelligence (AI) techniques for temperature prediction, offering a structured review guided by five key research questions. The novelty of this work lies in its comprehensive analysis of 48 carefully selected research papers (from 2018 to 2024), screened through defined exclusion criteria, to identify dominant trends, effective methods, and future directions in AI-based weather forecasting. The results reveal that deep learning models were the most commonly applied techniques, appearing in 17 out of 48 manuscripts (35.41%). Regarding the focus of the studies, 35 papers (74.46%) employed specialized predictive algorithms tailored for temperature forecasting. Geographically, Asia was the leading region in contributions, with India alone accounting for 10 papers (20.83%). In terms of data sources, approximately 50% of the studies used sensor-based climate data, emphasizing the reliance on real-time environmental inputs. For veracity, Long Short-Term Memory (LSTM) networks and Deep Neural Networks (DNN) proved to be the most successful for time series predictions and on the other hand Random Forest (RF) and Support Vector Machines (SVM) have shown to be more appropriate for classification problems like comparative factor analysis. This article is organized systematically to offer the readers clear, concise and practical views about the utilization of AI for weather monitoring systems so that they could make use of AI in their sustainability projects.

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1. INTRODUCTION

Providing access to available, secure, and affordable energy has become animportant issue in the world for a matter of decades. While this ongoing growth of the world's energy demand (estimated to increase at a rate of some 8 % annually between 2000 and 2030) is largely met by fossil fuels, there remains (local) biophysical, environmental, and socioeconomic concerns associated with this source of energy. In this context, developed economies and developing countries begin to favour alternative energy sources, advancing towards renewable energy, such as solar and wind power, to decrease dependence on conventional energy sources and solve the environmental degradation (negative climate change) [1].

A number of factors are contributing to the worldwide transition towards clean energy, concentrations of concern directly related to fossil fuel price volatility, increased environmental consciousness, population increase, and worries about climate change [2]. To complement this transition, the development of artificial intelligence (AI), especially of machine learning (ML) and deep learning (DL), has provided new opportunities for making climate-related predictions more effective and more accurate. Nowadays, these technologies are widely used to improve energy systems, ensure the accuracy of the forecasting and for the optimal use of resources on renewable energy facilities.

In recent years, machine learning techniques have become one of the most promising approaches for climate and weather prediction, with neural networks showing particularly high accuracy. Despite these advances, challenges remain, including limited quality training data, difficulty in handling local variability, and a strong reliance on supervised learning methods. Machine learning models excel at integrating diverse data sources and detecting unusual weather events faster than traditional methods, enhancing short-term forecast accuracy.

However, limitations persist in long-term predictions and managing complex climate phenomena. Improving data quality and developing more adaptable models are essential steps toward achieving more accurate and effective climate forecasting in the future [3].

In this manuscript, we present a comprehensive (systematic review) of the main contributions in this area. An illustration of the machine learning applications in climate prediction analytics (Figure 1).

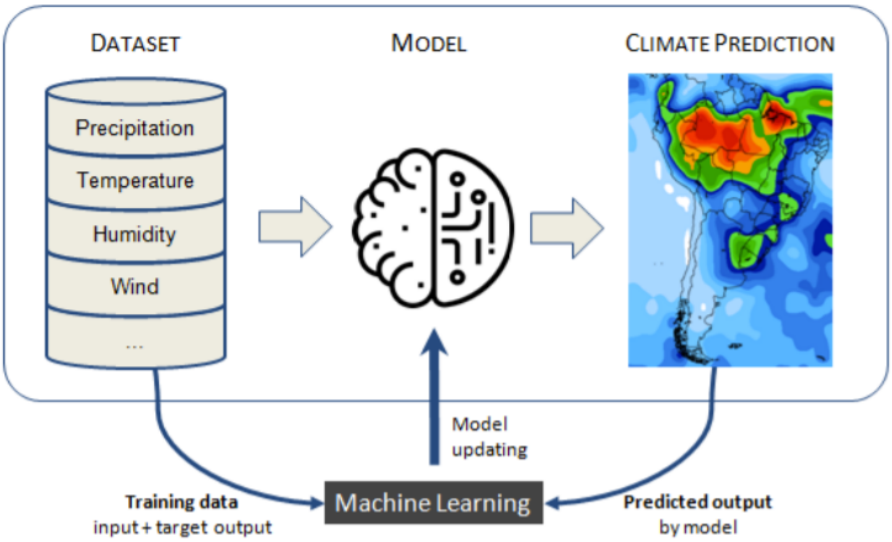

Figure .1. Machine Learning Applications in Climate Prediction Analytics [3].

This systematic review explores and evaluates the latest systems, techniques, and tools used in AI techniques, including ML and DL, in temperature and weather prediction and classification. By summarizing the current analyzing and literature the limitations and strengths of these systems, this systematic review seeks to provide valuable visions into the development and deployment of reliable solutions for weather and solar sustainability monitoring. A systematic review may guide students, researchers and industry to direct their research to meet their objectives.

This study presents a systematic review of recent developments in AI-based temperature and weather prediction techniques. The novelty of this work lies in its structured analysis of 48 peer-reviewed studies, categorized by algorithm type, data sources, geographical distribution, and performance outcomes. In this context through a critical discussion on the pros and limitations of the existing models, this review will provide a brief snapshot of the current approach of using AI in the sustainability energy planning. However, narrative literature reviews are methodologically obsolete unsound and can contain error, in contrast to the herein study that is a systematic review and meta-analysis. This would facilitate the conduct in a systematic, transparent and consistent fashion of the identification, selection and synthesis of studies of interest. The main advantage of this approach is that its prespecified sample appears to be low-biased and resulted in a clear and quantitative overview of IS in the evidence base. However, it allows for regularities and peaks of performance to be compared between different AI models, and to see which pieces are missing. It also enables one to find out (in)consistent trends and patterns across different AI models and to pinpoint what important factors (research gaps) being missing in the current literature for future research agenda. All these characteristics increase the reliability and scientific depth of the results obtained in order to provide more profound and robust results than usual reviews, or between one study analyses.

Methodology.

A comprehensive systematic review research is a structured method of extracting , analyzing and summarizing information from the current database of a defined group of questions [4]. The review was organized using the Preferred-Reporting Items-Systematic-Review-Meta-Analysis (PRISMA) checklist. It is one of the most effective ways to do deep research. It works in stages to treat problems related to artificial intelligence techniques to predict and classify climate and temperature stability. In the first phase, five questions related to current research and specific keywords and search lines were selected. While selecting the most relevant papers from selected databases, exclusion and inclusion criteria were created. Subsequently, data were extracted and summarized in response to the predefined research questions. In addition, Part 3 provides a detailed review of the current state of weather and temperature sustainability forecasting and classification systems, in addition to the potential challenges, opportunities, and limitations. The steps to conduct this survey are detailed in the following branch sections.

2.1. Research Questions

The authors created the following questions, which this paper pursues to answer through a detailed analysis. In the identification the study queries, thoughtful consideration was given to the most relevant algorithms and tools for temperature sustainability and weather forecasting and classification. The primary goal was to identify key features that improve the performance, accuracy, and energy consumption of similar systems. The queries were intended to provide a deeper understanding of the topic while offering valuable data for later studies.

RQ1: What are the AI algorithms (ML and DL) used in classification and forecasting for weather and sustainable temperature?
RQ2: What are the most commonly used tools for evaluating algorithms used in weather and temperature prediction and classification?
RQ3: What is the geographical distribution of data taken in studies?
RQ4: Types of databases used for the features involved in prediction and classification algorithms?
RQ5: The accuracy ratio or range obtained from the algorithms used after applying the evaluation tools?

2.2. Search Process

We conducted a comprehensive investigation to ensure an accurate and systematic test of algorithms for weather and temperature prediction and classification. To perform this systematic review, 4 databases widely used in the academic community, namely the Institute of Electrical and Electronics Engineers (IEEE) Xplore, ResearchGate, Science Direct and Google Scholar, were recognized. The selection of databases was guided by their credibility and their history of publishing high-quality research closely aligned with this study's focus. A carefully structured approach was adopted to guarantee the inclusion of pertinent documents. In this context, a strategic combination of search terms and topic-specific keywords facilitated an efficient and focused search process. Searches by combining the terms “Temperature Distribution”," sustainable solar", “weather prediction”, and “Climate Forecasting” were mainly executed. The search approach was applied uniformly across all four selected databases.

2.3. Inclusion and Exclusion Criteria

To ensure that the selected literature was relevant to this review, inclusion and exclusion criteria were established. These criteria helped identify the most relevant articles from the 75 studies found in the initial search (Table 1). Preference was given to manuscripts that explored climate and weather in depth. Then the inclusion of the papers has algorithms that are clear and detailed. including the papers based on artificial intelligence Finally, we highlighted manuscripts that described the algorithm development methodology to better understand the research approach. We also excluded duplicate manuscripts. Manuscripts that lacked detail or had unclear methodologies were further excluded. Finally, we excluded off-topic secondary research to encourage original empirical contributions. These criteria helped us select papers that were rigorous and relevant.

Table 1. Inclusion and exclusion criteria for systematic review.

	Inclusion Criteria (IC)		Exclusion Criteria (EC)
IC1	Publications beyond 2015	EC1	Duplicates
IC2	Inclusion of weather and climate features related	EC2	Missing focus on weather forecast
IC3	Inclusion of clear details about the used algorithms	EC3	Missing details about the used algorithms used
IC4	Items based on artificial intelligent	EC4	Missing clear design methodology
IC5	Clearly showing the algorithms design methodology	EC5	Secondary studies

2.4. Study Selection

The selected manuscripts were by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. After this step, two duplicate manuscripts were removed, leaving 74 articles for further evaluation. After applying the inclusion and exclusion criteria, 48 studies were considered eligible for inclusion in this systematic review. All studies were carefully reviewed to ensure their relevance and quality. An open and careful selection process was implemented that followed the PRISMA flowchart (Figure 2) to demonstrate accurate observations of the study design.

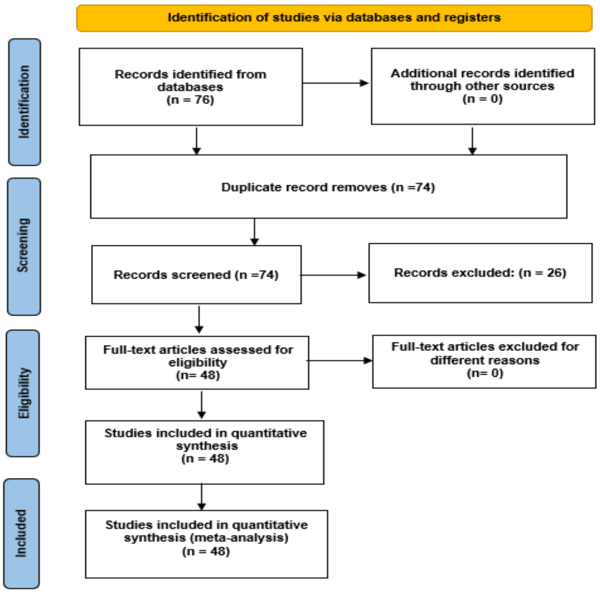

Figure 2. PRISMA flow diagram for systematic review.

2.5. Data Extraction and Synthesis

The in-principal data extraction It has been applied to all selected publications and yielded the following information; year of publication; author names; database; Artificial intelligence algorithms used (RQ1); tools for evaluating algorithms used (RQ2); Geographical distribution of data used (RQ3); dataset types used (RQ4); and the accuracy ratio or range obtained from the algorithms (RQ5). To process the research questions outlined in Part 2.1Research Questions (RQ), information integration and retrieval procedures were conducted. The selected articles underwent an initial data evaluation, which provided basic information to accurately address the search queries. The information collected included titles and abstracts of the selected publications, (author name), (year of publication), and (original database). with regard to RQ1 and RQ2, the types of algorithms used in weather and temperature sustainability forecasting and classification were identified, along with the specific evaluation metrics for these algorithms. Furthermore, geographical distribution of data taken in studies RQ3. In the RQ4, types of databases used for the features involved in prediction and classification algorithms were identified. Finally, the RQ5 showed the accuracy ratio or range obtained from the algorithms used after applying the evaluation tools.

2.6. Risk of Bias

It is important to recognize that systematic reviews, in spite of their strict methodology, are not immune to bias. In this particular review, there are several potential sources of bias that merit discussion. Several potential aspects of bias deserve discussion in this review. The first area of concern relates to the selection process, where subjectivity may occur in the application and interpretation of criteria. For example, a significant risk of bias was associated with the initial search of databases. Regarding the years of publication, the criteria for selecting articles specified what was published after 2015. Consequently, studies published before this period were not included, which may have resulted in the omission of important studies that could have contributed to a more complete understanding of sustainable AI-based temperature and weather prediction algorithms. Moreover, the search process was confined to four databases, each hosting prominent, reputable indexed journal. Nonetheless, the omission of additional databases, such as Scopus, Web of Science (WoS), PUBMED and, SpringerLink, may have introduced potential bias and excluded significant studies. It is worth emphasizing that research portals offer access to numerous high-quality journals, yet broadening the scope of future systematic reviews to incorporate these additional databases could enhance the comprehensiveness and reduce the risk of bias. Furthermore, including studies published as far back as 2015 in such reviews would provide deeper insights into the evolution and advancements in AI-driven weather forecasting algorithms and tools. However, technological progress has grown significantly in the past decade, so we do not expect significant contributions before 2015.

3. Results

Following the application of the pre-established insert Criteria (IC) and Exclusion Criteria (EC), a total of 48 studies from an initial pool of 76 were included in this systematic review. Of these, Research Gate accounted for 19 studies (38.78%), ScienceDirect contributed 11 studies (22.45%), and 10 studies (20.41%) were sourced from Google Scholar. Additionally, IEEE Xplore provided 8 relevant studies (18.37%). Notably, no studies from SpringerLink, Web of Science, Scopus, or PUBMED met the selection criteria for inclusion in this review. Figure 3 below illustrates the percentage distribution of studies across the selected databases.

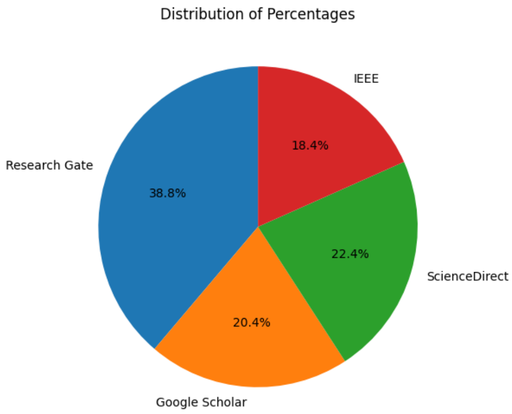

Figure 3. Percentage Distribution of Research Databases

It was also essential to identify the most concentrated years within the databases utilized for this type of research to monitor the latest updates and analyze their temporal distribution. Table 2 shows the year-wise distribution of the included studies from different databases.

Table 2. Publication distribution for each database per year.

Database	2015-2019	2020	2021	2022	2023	2024	No
Research Gate		[5][6]	[7][8][9],[10],[11], [12] ,[13]	[14],[15],[16]	[17],[18],[19]	[20],[21],[22], [23]	19
Google Scholar	[24], [25]	[26][27]	[28]	[29],[30]	[31],[32]	[33]	10
ScienceDirect	[34]	[35][36]	[37]	[38], [39]	[40]	[41],[42],[43], [44]	11
IEEE Xplore	[45][46],[47]			[48],[49],[50]	[39],[51]		8

The results in Table 2 above showed that most of the studies on the latest AI technologies used in predicting temperature sustainability were after 2020 and that studies related to it have increased significantly, which means an increase in interest in this field in the last five years, noting that the survey covered 10 years from 2015 to 2024.

3.1. Answer to RQ1

After analyzing the algorithms used in the models that were scanned, the results were as follows: The models that used deep learning algorithms had the highest percentage (35.41%) with 17 manuscripts, followed by manuscripts with a percentage (31.25%) with 15 manuscripts that used machine learning and deep learning algorithms together in their models for comparison and conclusion according to the type and size of the data. As for machine learning algorithms, they were used in 11 manuscripts with a percentage (22.91%). Finally, hybrid algorithms obtained only five manuscripts with a percentage (10.41%) because they were only used in recent years to benefit from the characteristics of more than one algorithm in one model. Table 2 below shows the details of the survey conducted on the algorithms used.

Table.3. Review of algorithms used in models

Algorithms used in the models	**References**	No
Using only machine learning algorithms	[7],[8],[21],[25],[43],[32],[10],[11],[33],[52],[53]	11
Using only deep learning algorithms	[34],[39],[14],[35],[45],[29],[54],[50],[9],[19],[12],[13],[37],[46],[28],[23],[55]	17
Using models that contain deep learning and machine learning algorithms	[41],[47],[24], [56],[15],[5],[48],[18],[49],[22],[41],[38],[6],[36],[27],	15
Using hybrid algorithms	[20],[17],[16],[30],[33]	5

3.2. Answer to RQ2

Numerous metrics are used to evaluate how well prediction and classification algorithms work. There are specialized tools for classification, such as (Accuracy, Precision, Recall, F1-Score, Confusion Matrix), and specialized tools for prediction, such as ((ME) Mean Error, Mean Square Error (MSE), Root Mean Square Error (RMSE), mean absolute percentage error (MAPE), coefficient of determination (R-square), Correlation Coefficients (CC)). In Table 4, we listed the percentages of the tools used to evaluate the performance of algorithms for manuscripts under review. The percentages are as in Table below. Firstly, the manuscripts on specialized algorithms for prediction obtained a percentage of 74.46% and a number of 35 manuscripts out of a total of 48 , then came the manuscripts specialized in evaluating classification with a percentage of 12.76% and a number of 6 manuscripts, followed by the manuscripts that used both and obtained a percentage of 4.25% and a number of two manuscripts, and finally, as for the rest of the manuscripts, direct or unclear mathematical methods were used for evaluation.

Table 4. Review of metrics used for evaluating algorithms.

Metrics Type	**References**	**No**
(ME), (MSE), (RMSE), (MAPE), (R-square), (CC).	[42],[34],[7],[47],[24],[20],[15],[17],[5],[35],[45],[48],[18],[49],[16],[54],[25],[50],[9],[42],[38],[19],[32],[10],[11],[12],[13],[33],[44],[36],[27],[46],[23],[40],[57]	35
Accuracy, Precision, Recall, F1-Score, Confusion Matrix.	[8],[14],[21],[6],[51],[29]	6
Using both types of evaluation metrics	[22],[56]	2
By using another way or without evaluation	[39],[43],[37],[28]	4

3.3. Answer to RQ3

In this analysis, as shown in table 5 below, 48 research papers were studied to identify the countries whose data were relied upon in developing machine learning models related to air quality monitoring. The results showed that Asia was the most prominent source of data, with India leading with 20.83% (10 research papers), followed by China with 14.58% (7 papers), then Japan with 4.17% (2 papers), while South Korea, Indonesia, Iran, and Turkey relied on one or two papers each, representing 2.08% and 4.17%, respectively. In North America, the United States was the main data source with 18.75% (9 papers), followed by Canada with 2.08%

(1 paper). In Europe, 7 research papers (14.58%) relied on general European data, while Germany, Norway, and Hungary came as separate sources with 2.08% each (1 paper per country). In Africa, only one paper relied on data from Mauritius, representing 2.08% of the total. Finally, 8.33% (4 papers) of studies did not specify the data source or relied on synthetic or global data sources. This distribution indicates that most research papers (91.67%) relied on specific data sources, while the remaining were unspecified. This analysis highlights the geographical distribution of data sources used and shows the disparity between regions in data reliance.

Table 5. Review of Dataset location used.

Dataset location used	References	No
Asia (India)	[7],[47],[24],[15],[48],[18],[54],[19],[6],[28]	10
Asia (China)	[34],[16],[25],[22],[32],[44],[37]	7
Asia (Japan)	[42],[23]	2
Asia (Korea)	[35]	1
Asia (Indonesia)	[39]	1
Asia (Iran)	[10]	1
Asia (Türkiye)	[39],[11]	2
North America (United States of America)	[20],[21],[50],[13], [58],[13],[36],[46],[56]	9
North America (Canada)	[43]	1
Europe	[14],[5],[30],[40],[12], [13][33]	7
Europe(Germany)	[17]	1
Europe (Norwegian)	[9]	1
Europe(Hungary)	[27]	1
Africa (Mauritius)	[38]	1
Data source is unclear or artificial or around world wide	[8], [49],[29],[51]	4

3.4. Answer to RQ4

When analysing weather and climate data, it can be seen that sensors (Sensor: a device for detecting atmospheric conditions) are the most commonly used source in research, accounting for about 50 per cent of all research. This is due to the ability to collect accurate real-time data using meteorological sensors, such as those that monitor the weather, providing a direct and complete view of weather conditions. An important source of data is Kaggle (Kaggle: knowledge and analysis of global learning and research), which accounts for 18.75 percent of studies. Many studies utilize the open datasets available on this platform due to their wide variety and ease of access. Open data (publicly available data) accounts for about 14.58% of climate research, reflecting the importance of open data provided by governments and international organizations to provide an integrated view of climate issues. Data from the National Oceanic and Atmospheric Administration (NOAA), the National Aeronautics and Space Administration (NASA), and the government (government: data from various government agencies) are important sources, but they represent a smaller share of the total. NOAA accounts for about 6.25%, while NOAA and the government each account for 4.16%. These percentages reflect the importance of these sources in supporting global climate and pollution research. Finally, data from the World Bank, such as the International Bank for Reconstruction and Development and the Intergovernmental Panel on Climate Change account for 2.08% of the total research, indicating that while these sources are important in providing data related to sustainable development and climate change, they are less utilized than other sources.

3.5. Answer to RQ5

In order to assess the accuracy of the models used, different evaluation factors were applied across the selected 48 papers. The results revealed varying accuracy ratios for each model, reflecting the differences in performance across different approaches and datasets. The results showed in [42] Both the vector autoregressive model with exogenous variables (VARX) and the deep neural network showed excellent performance in forecasting the (V) and (U) time series, with both models recording consistently high R^2 values exceeding 0.9, while achieving low mean absolute error (MAE) values.as for [34] the results indicate that the LSTM model shows a slight advantage in forecasting indoor temperature, with R^2 improvements ranging from 1% to 9.73% for 5-minute-ahead predictions.[7] The Random Forest model achieved a minimum error of 0.750 MSE and an R^2 score of 0.97, demonstrating high predictive accuracy.[8] The Naive Bayes Bernoulli model achieved 100% accuracy and the highest recall values, outperforming other classification algorithms in weather prediction. [39] LSTM predictions showed some discrepancies with actual values after 50, 150, and 250 epochs, highlighting the complexity of weather prediction.[47] The Multiple Linear Regression (MLR) model achieved an average error of 1.0782 with a correlation coefficient of 0.8119 between the actual and predicted temperatures. In comparison, the Artificial Neural Network (ANN) model recorded an average error of 1.2958 with a correlation coefficient of 0.7932, while the Support Vector Machine (SVM) model yielded an average error of 1.1371 and a correlation coefficient of 0.8110. in [24] It was determined that using Recurrent Neural Networks (RNN) for time series analysis is a more effective approach for weather forecasting. As for [14] The results suggest that combining synthetic datasets with real-world datasets can enhance the training efficiency of CNNs by up to 74%. [20]The two intelligent neural models— Sperm Swarm Optimization (SSO) and Artificial Neural Networks (ANNs) —achieved a correlation coefficient (CC) of 0.955% at 20 cm. [15] The deep neural network model (DNNM-3) achieved the highest performance, with an accuracy rate of 96.4%, surpassing the other models.[59] The suggested hybrid model produced the following results: Root Mean Squared Error (RMSE): 0.189, Mean Squared Error (MSE): 0.035, R-Squared (R^2): 0.987, and Mean Absolute Error (MAE): 0.126.[5] The results show that the Extra Trees regressor achieved the highest performance (0.058%) and average accuracy (0.97%) across all horizons. [35]Among the ANN models, LSTM from RNN were found to be more than other models suitable for time series data, as they demonstrated lower error rates compared to DNN. The RMSE for LSTM was 1.72. [39]showed the maximum R2 value obtained from the first experiment was 84.8%, with an RMSE of 125. This indicates that the recurrent neural network can be effectively used for rainfall prediction with a satisfactory level of accuracy.[48] The Root Mean Square Error (RMSE) for the RFR and LSTM models was 0.47 and 0.23, respectively, when applied to ERA5 data. Compared to the operational IFS numerical weather prediction model, the RMSE for LSTM and RFR is 65% and 83% lower, respectively. For real-time data at twenty locations, the average RMSE for both the LSTM and RFR models in forecasting temperature is 0.7. in [18] the comparison between DNN and MPR models shows that DNN models outperform MPR models, especially with a large number of input features. Among the five models, DNNM-3 achieved the best temperature prediction accuracy at 96.4%.[49]The comparison results show that the R2 value for random forest 0.992 is highest compared to other models. [16] The model genetic algorithm support vector machine (M-GASVR) got higher accuracy. RMSE (0.556%), MAE (0.452%), MAPE (0.47%), NSE (0.801%), and R^2 (0.903%) from four models used.[29] Long Short-Term Memory (LSTM) is considered one of the best models due to its high testing accuracy (100%). [21]The performance evaluation of various algorithms revealed accuracy rates as follows: Decision Tree achieved (70.07%), Random Forest (72.79%), K-Nearest Neighbors (76.87%), Support Vector Classifier (77.55%), while both Logistic Regression and Gradient Boosting Classifier reached the highest accuracy of (80.95%).[54]They empirically show that artificial neural networks yield significantly lower deviations compared to GDAS evaluations, leading to highly accurate daily weather forecast predictions. [30] ConvLSTM exhibits a higher MSE of $3.6K^2$, a lower ACC of 0.80 and SSIM of 0.65, but a slightly improved rG of 0.84.[25] The MSEs of the predicted values for SARIMA from (2015 to 2017) are (0.84), (0.89), and (0.94), respectively. [50]They observed in the LSTM model that the MAE value was 0.0625, with the RMSE 0.25. [9] The experiments demonstrate the potential of neural networks (LSTM) for weather prediction, though regional accuracy may vary due to geographical factors. A lightweight, neural network (NN)-based short-term forecasting system using weather station data could address this issue. [40] Three frameworks for air temperature forecasting were proposed: a (CNN) with video to image translation, ML models like Decision Trees, Random Forest, Lasso regression, and a CNN with Recurrence Plots for time series preprocessing. with Recurrence Plots for time series preprocessing. These methods demonstrated strong predictive performance in the Paris and Córdoba regions, proving effective for seasonal climate prediction. [22]The PBT-GRU model achieved a correlation coefficient (r) of 0.99, outperforming RF (r = 0.98), SVM (r = 0.95), GBDT (r = 0.97), and KNN (r = 0.93). [42] Both the vector autoregressive model with exogenous variables (VARX) and the deep neural network exhibited outstanding performance in time series prediction, consistently achieving R^2 scores of around 0.9 and occasionally surpassing this value. [58] The two models, Extra-Tree Regressor (ETR) and Random Forest Regressor (RFR), demonstrate nearly identical performance in the ten-city case, both yielding an RMSE close to 3.0.[38]The experiments demonstrated that the collaborative regression models resulted in a 5% reduction in Mean Absolute Percentage Error (MAPE) compared to their non-collaborative counterparts. Additionally, the Multiple Polynomial Regression (MLR) algorithm delivered superior performance, with errors ranging between 0.009% and 9% across various weather parameters. [43]They found that incorporating weather information greatly enhances the accuracy of sales forecasts, accounting for an additional 47% of the variance for individual products and up to 56% for product categories, beyond the variance explained by the baseline model. [19]by artificial neural network predict temperatures with an accuracy of (1.2°C) RMSE, MAPE of (2.9°C), CC of (0.7), and IOA of (0.8) for the validation data.[32] The Loc-PredModel, using XGBoost, predicts trip destinations and arrival times with high accuracy, achieving an RMSE of 0.208 and R^2 of 0.935, enabling personalized weather reports. [10] The accuracy ranges for the HS empirical equation and the multivariate linear regression (MLR6) mode, in terms of RMSE, were between 22–28.3 mm $month^{-1}$ and 10.8–15.1 mm $month^{-1}$, respectively. [6] The results presented in this study clearly indicate that the DNN outperforms other algorithms, including Naïve Bayes, SVM, and KNN, achieving a precision of 89.71%. [11] The R^2 values for the ANFIS, SVM, and DT models in both the testing and training phases are around 0.99, demonstrating the high success of all the models. [12] They demonstrate that employing informed model construction and deep learning techniques can significantly enhance the accuracy of global ensemble weather forecasting. In this study [13] They proposed an ensemble prediction system based on a Deep- Learning-Weather-Prediction model, which makes recursive forecasts for six important atmospheric variables at six-hour intervals. This model, designed for computational efficiency, employs convolutional neural networks on a cubed-sphere grid to generate global weather forecasts. [33] Machine learning weather prediction (MLWP) has an accuracy of 97.2% on 1,320 targets they evaluated and better predicts extreme weather, wind power, and tropical cyclone track production. [44] The (CNN-LSTM-GRU) model for (MAAT) prediction outperforms other DL models, achieving the highest correlation coefficient = 0.9879 along with the lowest root mean square error = 1.5347 and mean absolute error = 1.1830.[36] XGBoost and LSTM models demonstrated superior accuracy for load prediction, with CVRMSE values of 21.1% and 20.2%, respectively, outperforming the baseline model's 29.9% and ranking among the best in the literature. [37] The results showed that the total rainfall in weather prediction using the (Deep Q-learning) network algorithm ranged from (0.38 to 0.70), with some false alarms and missed alarms. This indicates that weather forecasts can serve as reliable inputs for the (DQN)-based irrigation decision making strategy. [27] The Model Mean Squared Error values are as follows: (ARIMA) 2.4214, (Deep Learning) 1.9006. In conclusion, deep learning models prove to be effective substitutes for ARIMA models in predicting weather parameters, such as temperature. [46] They not only discover the relationship between data volume and prediction accuracy by artificial neural networks, but also discover the relationship between data freshness and prediction accuracy. [28] The deep learning-based theoretical model exhibits a significant increase in both grids point resolution and area-averaged performance, as indicated by Pearson correlation coefficients, when compared to the operational system. This research acts as a proof-of-concept, demonstrating that residual learning-based UNET can reveal underlying physical relationships linked to precipitation. These identified physical constraints can be incorporated into dynamic operational models, leading to more accurate precipitation forecasts. [51] They achieved a maximum accuracy of (95.89%) using the Gaussian Naive Bayes algorithm.[23] This study highlights the effectiveness of utilizing Deep Neural Networks (DNNs) for temperature forecasting and emphasizes the advantages of domain adaptation through Kernel Mean Matching (KMM). [56] This study focused on the development of machine learning algorithms, such as deep neural networks, convolutional neural networks, and random forest models, to forecast frost events in the vicinity of Alcalde, NM. The models exhibited strong accuracy, with a 6-hour RMSE between 1.53°C and 1.72°C for predicting frost and minimum temperatures.

After Analysing the above results, it can be observed that deep models such as DNN and LSTM showed the best performance in short-term weather forecasting, especially when predicting temporal data involving variables such as temperature or climate. Random Forest and SVM models also performed well in predicting environmental conditions with high classification accuracy. The Naive Bayes model showed excellent results in classifying data containing independent variables with balanced distributions. On the other hand, hybrid models such as ConvLSTM and GRU showed a slight improvement in performance but were not the best in predicting complex weather factors compared to other models. Thus, LSTM and DNN are recommended for tasks requiring accurate weather forecasting, while random forest and SVM are recommended for applications requiring accurate classification and comparison of different factors.

2. CONCLUSION

In summary, in this paper, we have conducted a comprehensive and systemic survey of recent advances in AI methods for temperature prediction and RE systems. The comparison to other methods reveals that deep learning models, in particular deep neural networks and short-term memory networks, are the most successful ones and present high prediction accuracy and are due to their promising ability for capturing temporal patterns. The majority of papers used prediction models for the prediction of temperature; similarly, one-third of the studies used real-time weather data from sensors, highlighting the importance of accurate environmental inputs. The geographical distribution of research indicates significant contributions from Asia, particularly India.These findings highlight the importance of AI as a scalability factor in addressing renewable energy challenges through integration of climate data and energy system optimization over regions. Metaloproteinases such as random forests and support vector machines provide predictive models with adequate proxies for data classification and comparison as well. Overall, the results of the study underscore the importance of creating precise and robust AI algorithms, which are adapted to distinct renewable energy and environmental monitoring requirements. This work offers a solid foundation for future research by identifying key trends, strengths, and limitations in AI applications for climate prediction.

In future studies, reviewed studies can be made more comprehensive by employing more databases and a greater period of coverage to provide more comprehensive findings. More research questions, in greater numbers, will give more detailed insights into new issues and issues of solutions. Furthermore, establishing clear and transparent exclusion criteria, preferably by an impartial committee, will reduce bias and improve systematic review validity. These efforts will work to advance the field further in offering more robust, precise, and transferable AI solutions for climate prediction and renewable energy technology.

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