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Original Article

AI-Enabled Big Data Analytics for Climate Change Prediction and Environmental Monitoring

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Abstract - Climate change poses an escalating global challenge, demanding accurate forecasting and continuous environmental monitoring. As climate-related information provided by satellites, weather stations, sensors, etc. is growing exponentially, the role of Artificial Intelligence (AI) and Big Data Analytics integration has become critical. In this paper, an Artificial Neural Network (ANN) based framework that predicts the climate patterns utilizing ten years of weather data is presented using AI. The ANN model was trained and validated after intensively cleaning, normalizing and engineering the data. It recorded excellent performance measures of R^2 of 96.25, MSE of 0.0175, RMSE of 0.194, and MAE of 0.155 and surpassed MLR and Deep CNN. These findings prove the model to be very satisfactory in terms of its ability to capture non-linear climatic associations as well as its capacity to produce credible predictions. This will enable policymakers and environmental scientists to make sustainable climate strategies in real-time by improving the predictive accuracy.

Keywords - Artificial Intelligence, Climate Change Prediction, Environmental Monitoring, Deep Learning, Predictive Analytics.

1. Introduction

The climate of the globe is a complex and dynamical system that establishes long-term averages for many meteorological factors, including temperature, humidity, air pressure, wind, and precipitation. This system is very important in the formation of natural ecosystems, the maintenance of biodiversity, water cycle maintenance, as well as the maintenance of agricultural yield and the lives of people [1]. In stable conditions, the climate has smooth variability due to natural forces like sun radiation, volcanic forces and ocean circulation. However, human activity has been the main contributor to the notable and unusual changes in the climate during the past few decades. In particular, deforestation, the burning of fossil fuels, and extensive industrialization have all contributed to the rise in greenhouse gas concentrations in the atmosphere. Sea levels are rising, more frequent and severe weather events, changing precipitation patterns, the melting of the polar ice caps, and impacted ecosystems are all severe consequences [2][3]. These changes are dangerous not only to the environmental equilibrium but also to the socio-economic stability, food security, and the health of global populations.

To address these rising issues, the concept of environmental monitoring has come out as a crucial tool in the comprehension and control of the effects of climate changes it is the organized gathering, examination and elucidation of data on significant environmental variables, including atmospheric composition, land use, sea surface temperature and biodiversity indicators in both spatial and temporal scales [4][5]. Nevertheless, the growing complexity and dimensions of climate systems pose great challenges to traditional monitoring methods as they are commonly hampered by poor data integration, resolution, and latency. The fast development of big data technologies has brought new horizons in expanding the possibilities of climate monitoring [6]. Nowadays, there are enormous streams of environmental data that are constantly produced by a large diversity of sources, such as satellite images, remote sensors, climate modeling, and IoT-based observation systems.

Although such data is ripe with possible discoveries, deriving useful patterns and usable intelligence out of these big-volume, big-variety data sets needs more sophisticated analytic structures. This is the role that AI cannot do without [7][8]. ML and DL, AI methods are especially effective at identifying patterns, building sophisticated nonlinear models, and creating predictive models based on big data with many dimensions. As a climatologist and environmental scientist, AI has been utilized in predicting extreme weather patterns, identifying variations in land cover, tracking pollution, and real-time analysis of satellite imagery. AI will allow creating more precise, scalable, and responsive climate change forecasting and environmental monitoring systems when combined with big data analytics.

1.1. Motivation and Contribution

The increasing effects of climatic changes, the capacity to effectively predict climatic trends is becoming progressively significant in efficient environmental observation and authorities' intervention. Conventional statistical models are frequently insufficient to estimate nonlinear and complicated interactions in huge climate data. The driving force behind this research is the demand of having smart, automated and scalable climate prediction systems capable of learning based on a wide range of environmental cues. Big data analytics, AI in particular, is an attractive option to simulate complex climate behaviors and enable proactive decision-making. The following are the study's main contributions:

- Leveraging a structured weather dataset to develop an AI-based framework for climate change prediction.
- To improve model performance, comprehensive data preparation is carried out, including cleaning, normalization, and feature engineering.
- Using an ANN to predict non-straightforward climatic relationships and tendencies.
- The separation of data into training and testing groups to validate the model's precision and ability to generalize.
- Evaluating predictive performance using metrics such as R^2, RMSE, MSE, and MAE.
- The suggested AI-driven method's substantial improvement in climate forecasting accuracy and dependability, contributing to more effective environmental monitoring and strategic climate planning.

1.2. Novelty of the Paper

This paper's novelty lies in its AI-driven framework for climate prediction that integrates an ANN with extensive weather data preprocessing techniques, specifically engineered for real-world environmental monitoring. This work harnesses DL strength in modeling nonlinear patterns and demonstrates superior performance metrics. Its comparative evaluation and scalability for future real-time applications position it as a transformative approach in climate analytics.

1.3. Organization of the Paper

The remainder of the document is organized as follows: Work connected to Section II. The suggested technique is described in Section III. Experimental data are presented in Section IV, and Section V discusses important findings and future directions.

2. Literature Review

In this section, the article discusses the recent developments in climate change forecasting and environmental observation by using AI and big data analytics. The studied publications also emphasize the variety of data-driven modeling approaches to improving the precision, scalability of climate-related predictions and environmental analyses the reviewed studies involve:

- Heshmati et al. 2019 Summaries about the ways that the invasive plant Prosopis multiflora is impacted by climate change. The research assesses how climate change affects species distribution using maximum entropy and species distribution modelling. With the Mediterranean Basin, Middle East, and North America most at danger of an expansion in range, the results show that climate change affects the species' capacity to occupy geographic regions. According to the study, assessing how climate change is affecting the global spread of invasive species might be a useful tool for setting up extensive monitoring programs in natural spaces[9].
- Huntingford et al. 2019 emphasizes the role that ML and AI should play in climate analysis. ML could help to detect complicated feedbacks in Earth System models, whereas AI could give more detailed warnings about the approaching weather features. The approach would help to better comprehend and utilize the available data and simulations in The climate change context and societal adaptability [10]
- Teja Reddy Gatla et a. (2019) The study explores the ways in which AI might support efforts to combat climate change and adapt to environmental changes. AI has the potential to stabilize complex systems, process big data and generate actionable insights, allowing advanced climate modelling, optimization of renewable energy production and advanced agriculture. Nonetheless, AI has other obstacles, including information security, bias in algorithms, and inequality. The article aims to provide a comprehensive review of AI's revolutionary potential and address ethical issues that arise throughout the global adoption of AI technology [11].
- Crane-Droesch (2018) A semiparametric DNN is used in this approach to yield a model to forecast how agricultural production would be impacted by climate change. This approach performs better than completely nonparametric neural networks and conventional statistical approaches, demonstrating significant detrimental effects on maize production that are less severe than those of classical statistical methods, especially in warm climates [12].
- Sing (2018) highlights the significance of efficient conservation and monitoring methods in combating climate change. AI has the potential to improve conservation efforts, forecast environmental changes, and monitor ecosystems. However, to guarantee sustainable management of natural resources, issues including data quality, model interpretability, and scalability must be resolved [13].
- O'Gorman and Dwyer (2018) study explores simulations of climate change using ML. They use idealized tests to train ML-based parameterizations on conventional output, ensuring energy conservation and surface precipitation is not negative. The study shows how ML may be used to capture climate change between warm and control areas [14].

A comprehensive summary of important studies on AI and big data analytics for environmental monitoring and climate change prediction is given in Table I. It summarizes the main contributions, limitations, and highlights potential directions for future improvements.

Table 1. Summary of Recent Studies on Ai in Climate Change Prediction and Environmental Monitoring

Author	Approach	Dataset	Main Contributions	Limitations	Future Work
Heshmati et al. (2019)	Species Distribution Modeling (MaxEnt)	Global bioclimatic variables (BIO1, BIO12, BIO2), GCM outputs	Evaluated the invasive species Prosopis juliflora's present and potential worldwide spread in light of climate change scenarios; strong prediction accuracy (AUC 0.854)	Focus on a single invasive species; uncertainty in climate projections; limited to bioclimatic variables	Extend to other invasive species; integrate more environmental variables; develop early-warning systems for invasions
Huntingford et al. (2019)	Climate System Analysis Using Machine Learning	Earth System Model simulations, observational climate data	Demonstrated ML's potential to uncover complex climate teleconnections; proposed AI for enhanced weather and extreme event prediction	Lack of generic application across entire climate system; complexity of integrating ML with Earth System Models (ESMs)	Develop comprehensive ML frameworks for full climate system understanding; improve integration with ESMs
Teja Reddy Gatla (2019)	Review of AI for Climate Adaptation & Mitigation	Various (big data, climate models, renewable energy data)	Highlighted AI's role in climate modeling, renewable energy optimization, agriculture, and disaster response; discussed ethical and social issues	Generalized review without empirical validation; ethical issues like bias and social inequality require more study	Develop equitable, transparent AI frameworks; address data privacy and algorithmic bias in climate solutions
Crane-Droesch, (2018)	Semi-parametric Using Deep Neural Networks to Model Crop Yield	US Midwest corn yield data, climate model scenarios	Improved crop yield prediction under climate change; showed less pessimistic impacts in warm scenarios than classical models	Focused on one crop and region; model generalizability to other crops and regions uncertain	Extend models to other crops and regions; incorporate socioeconomic factors for yield prediction
Sing (2018)	AI applications in Environmental Monitoring and Conservation	Wildlife, forest, climate change monitoring datasets	Demonstrated AI's transformative potential in ecosystem monitoring, species conservation, and environmental prediction	Challenges with data quality, interpretability, and scalability; lack of standardized AI tools	Develop scalable, interpretable AI models; improve data integration and quality for conservation applications
O'Gorman and Dwyer, (2018)	ML-based Parameterization in Climate Models	High-resolution model outputs, GCM simulations	ML convective parameterization improves climate and precipitation modeling; captures climate change effects when trained on diverse climates	Training dependency on data coverage; limited understanding of ML parameterization behavior in complex climate models	Enhance ML parameterization robustness; explore interpretability and transferability across climate regimes

3. Methodology

This methodology presents a structured approach to predicting climate change using AI-enabled models in Figure 1. It begins with the collection of a weather dataset, which is then subjected to a comprehensive data preprocessing phase. Data cleaning is performed to eliminate missing values, inconsistencies, and irrelevant records, ensuring the dataset is accurate and reliable. Simultaneously, feature engineering is applied to extract and construct relevant variables that enhance the predictive capability of the model. The refined data is then normalized to standardize the feature scales, followed by splitting the dataset into two sets: 20% for testing and 80% for training. The suggested ANN model is developed using the training set to capture complicated, nonlinear patterns within the weather data. The model's predictive power and generalization are assessed using the testing set. Finally, important assessment measures including R^2, RMSE, MSE, and MAE are used to gauge the model's performance. This AI-powered framework aims to provide robust climate change prediction and support environmental monitoring efforts

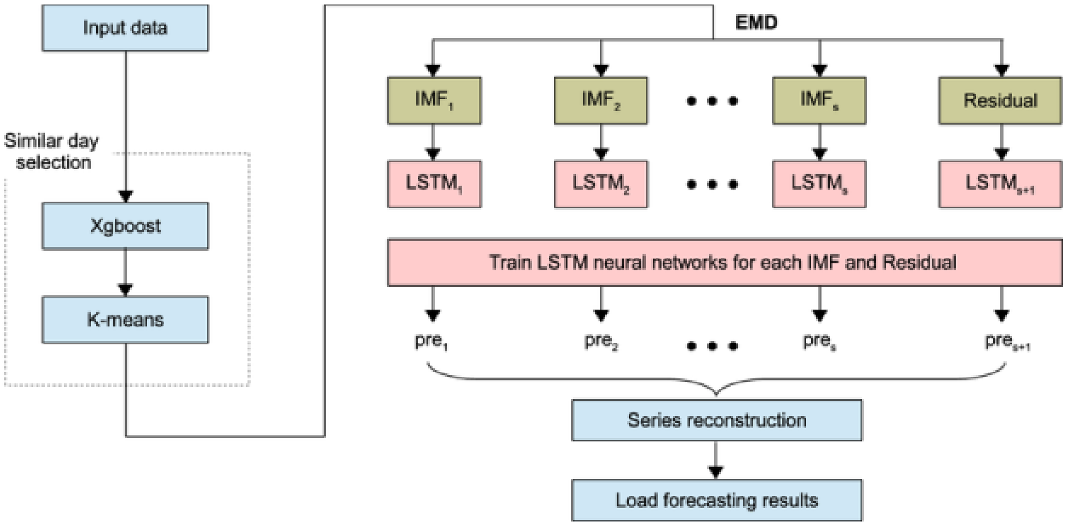

Figure 1. Proposed AI-Based Climate change prediction Workflow

3.1. Dataset Description

This dataset includes information of the region's atmosphere. The Weather data for Istanbul covering the years 2009 to 2019 includes climate such as air pressure, temperature, humidity, wind speed, and precipitation. Over ten years, it makes it possible to study seasonal variations, climate changes and forecast future weather. The data visualizations are provided below:

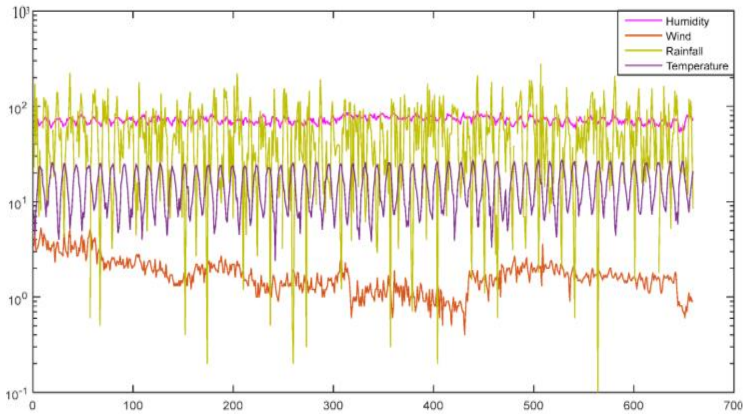

Figure 2. Log-Scaled Time Series Plot of Weather Parameters

This Figure 2 presents a log-scaled time series visualization of four weather parameters Humidity, Wind, Rainfall, and Temperature over time. Each variable is color-coded for clarity. The log scale on the y-axis highlights variations and periodic trends in the data, making subtle changes more observable and helping compare magnitudes across variables with different ranges and volatility.

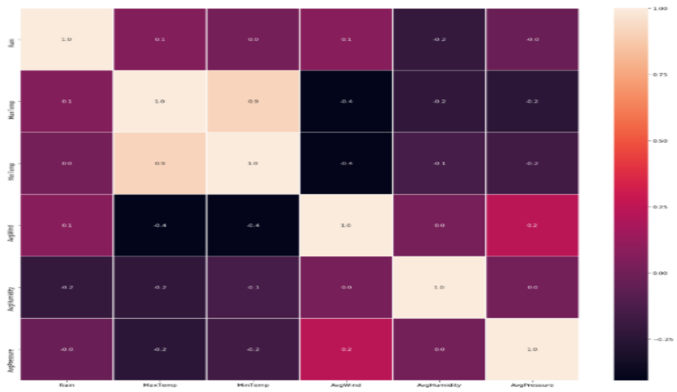

Figure 3. Correlation Heatmap of the Dataset

Figure 3. is a correlation heatmap displaying numerical relationships between six variables. Each cell shows The correlation coefficient is a number between -1.0 and 1.0. Stronger positive correlations are shown by warmer colours, whereas weaker or negative correlations are indicated by cooler or darker colours. The diagonal shows perfect positive correlations of 1.0, as variables are perfectly correlated with themselves.

3.2. Data Preprocessing

Data preprocessing involves a series of methods applied to raw data to clean, transform, and organize it for analysis or modeling. This process enhances data quality and ensures it is properly formatted for use with machine learning algorithms. The key steps include:

- The act of finding, fixing, or eliminating erroneous, lacking, inconsistent, or unnecessary data from a dataset in order to increase its quality and dependability is known as data cleaning.
- Address missing values by eliminating records with a high percentage of missing data or by imputing them using statistical or ML techniques.
- Remove duplicate records to ensure data integrity and prevent redundancy.
- Identify and fix mistakes (e.g. outliers via Z-score), and resolve inconsistencies in timestamp formats, units of measurement, and categorical labels.

3.3.Feature Engineering

Feature engineering is the process of developing new variables from the available data in order to improve machine learning models' ability to identify pertinent patterns and correlations. It includes putting raw data into forms that more closely capture cyclical or seasonal features, e.g. by expressing months or seasons in terms of sine and cosine terms to capture the fact that these reoccur over the year. Derived features may also be used to measure departures of long-term averages, e.g. temperature anomalies, to point out exceptional conditions. Also, the continuous variables, such as rainfall, may be grouped into levels of intensity to make the complex distribution of data simplified and enable more efficient analysis.

3.4. Normalization

A data preparation technique called normalization is used to scale and distribute numerical data characteristics to a similar range and form while preserving the distinctions between the value scales. Min-Max Normalization is a particular type of normalization that rescales a feature's values to fall inside a predetermined range, often 0 to Equation (1). This is the Min-Max Normalization formula:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

3.5. Data Splitting

In order to train AI-driven analytics models aimed at environmental monitoring and climate change prediction, the dataset is divided into 80%, with 20% of the total is reserved for evaluating and confirming the correctness of the model.

3.6. Proposed Artificial Neural Network Model

ANNs are mathematical algorithmic models that do distributed information processing in parallel and mimic the behavior of animal brain networks. These networks process information by altering a great number of interconnected interactions between nodes, depending on the complexity of the system [15]. At least three major components make up the ANN system: The input layer comes first, then the output layer and the hidden layer (at least one lfayer that processes the input layer). The sigmoid function was used in this study to calculate weights, and training influenced how many hidden layers were used [16]. In Figure 4, the neural network's structure is displayed.

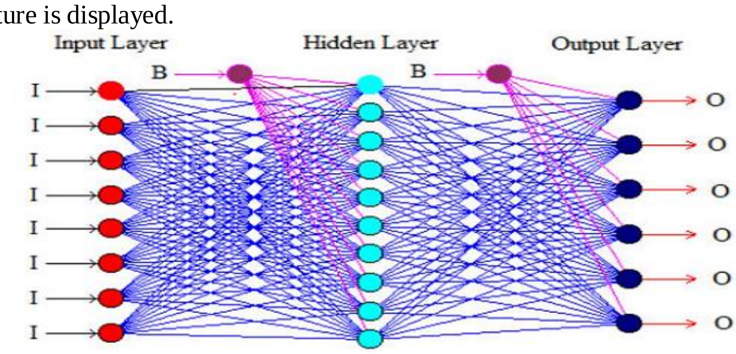

Figure 4. Structure of the ANN Model [17]

There are two phases involved in calculating each neuron's output. To utilize the following Equation (2), the first step is to determine the input data's overall weight.

$$T_i = \sum_{j=1}^{n} x_{ij} i_i + c_j$$

When c_j specifies the middle node's bias-related weight, x_{ij}indicates the input node's weight, and t_i displays the input data number. The ANN model's output was obtained in the second step by applying the activation function. For activation functions, there are several approaches. The sigmoid function, which is computed using Equation 3, has been used in this investigation:

$$Q_j(x) = \frac{1}{1+e^{-z_j}}$$

The output is then determined by the subsequent Equation (4)

$$Out_i = \sum_{j=1}^{n} x_{kj} i_i + c_k$$

3.7. Performance Measurement Parameters

The main assessment metrics used to gauge how successfully regression models predict property insurance rates are described in this section [18]. These metrics offer quantifiable evaluations of the model's accuracy and effectiveness:

3.7.1. Mean Absolute Error (MAE)

The absolute error is the sum of the predicted errors. The average of all absolute mistakes is known as the average absolute error [19]. The mathematical calculation is the Equation (5):

$$MAE = \frac{1}{n} \sum_{i=1}^{n} y_i - \hat{y}_i$$

3.7.2. Mean Squared Error (MSE)

The square of the number of mistakes is measured by MSE. When the model produces a single, really bad prediction, MSE excels at giving those points greater weights. MSE contains the variance and bias of the estimator appearing in Equation (6).

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

3.7.3. Root Mean Squared Error (RMSE)

The observations of the mean of the squares of the variations between the expected and actual values, as indicated by Equation (7), are measured by RMSE.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

3.7.4. Coefficient of Determination (R-square)

A standard determination coefficient R^2 Equation. (8) provides the percentage of variability of predictands that is explained by the empirical model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y_i})^2}$$

These assessment indicators, when combined, provide a comprehensive assessment of the model's predictive power.

4. Result Analysis and Discussion

The paper discusses how advanced ML methods can be applied to climate change forecasting and environmental surveillance, and especially how ANN may be used. Python, running in a Jupyter Notebook environment, was used to develop and evaluate models, and this was done on a high-performance computing system, with 32 GB of RAM and GPU acceleration to work with large-scale climate simulation data and remote sensing inputs. Modeling workflow was done with the help of powerful libraries, including TensorFlow, Keras, NumPy, Pandas, and Scikit-learn. The ANN model attained a coefficient of determination (R2) of 96.25, MSE of 0.0175, RMSE of 0.194 and MAE of 0.155 as shown in Table II. These findings confirm the high predictive performance of the ANN model and indicate that this data-driven method is suitable to be used in assisting with environmental monitoring and predicting the effects of climate change.

Table 2. Performance Evaluation of the Ann for Climate Change Prediction

Metrics	Artificial Neural Network
R2	96.25
MSE	0.0175
RMSE	0.194
MAE	0.155

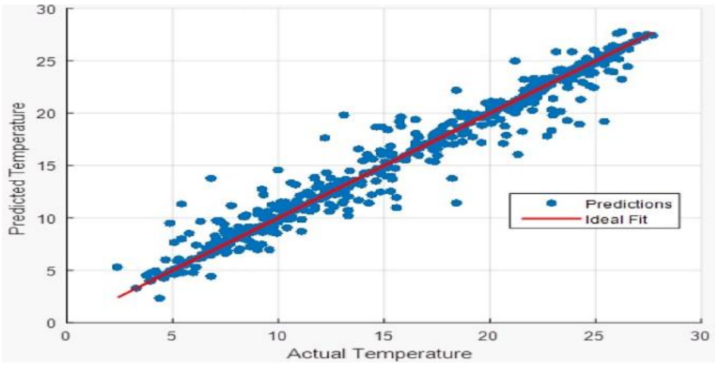

Figure 5. Regression Analysis of Predicted vs. Actual Temperature of ANN Model

A regression study of the ANN model's anticipated vs actual temperature is shown in Figure 5 below, which has a high R2 of 96.25. This means that the model effectively captures temperatures, which is essential in determining and predicting trends of climate change and its effects.

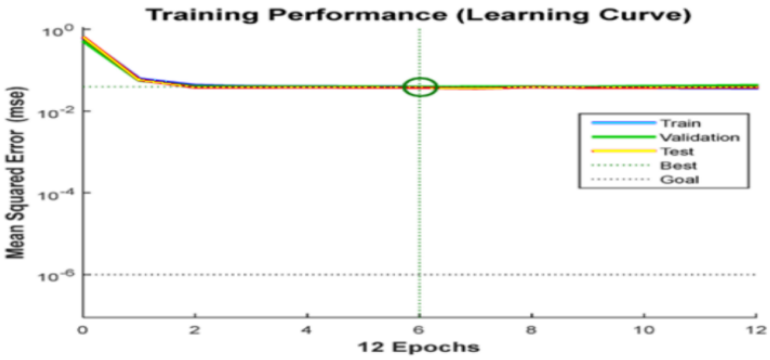

Figure 6. Training Performance (Learning Curve) of the ANN Model

Figure 6 illustrates the MSE on training, validation and test sets after 12 epochs. The curves soon reduce and level off, showing that the error in the model is stabilized. The dot of green color at around 6 epochs represents the point of the best performance. This is the learning curve that is important in evaluating the performance of a model that could be used in predicting climate change.

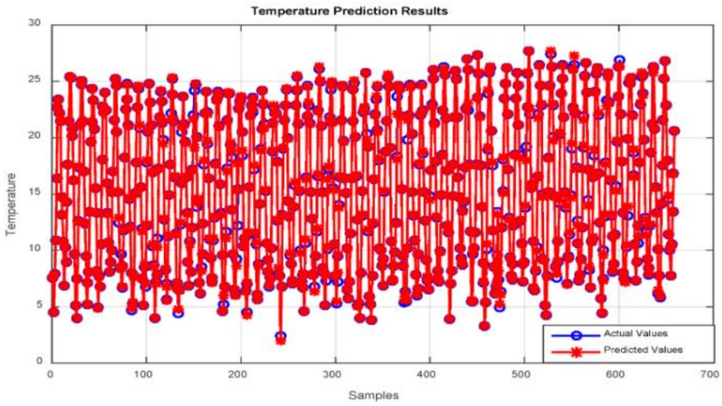

Figure 7. Comparison of Actual and Predicted Temperature Values from the ANN Model

Figure 7 displays the ability of a model to predict temperature across many samples. The red "Predicted Values" closely follow the blue "Actual Values" which means that it is very accurate. Such a high predictive power is important in the investigation of climate change.

4.1. Comparative Analysis

This part focuses on a comparative study of ML models on climate change forecasting with big data analytics. Table III demonstrated that the ANN model represented the best coefficient of determination (R2) value of 96.25, which implies its predictive accuracy over the other assessed models. Conversely, MLR and Deep CNN obtained an R2 of 92 and 89, respectively. Although these models still performed quite well, the lower R2 values compared to ANN indicate a loss of accuracy in capturing the nonlinear relationships that often occur in climate data.

Table 3. Comparative Performance of Machine Learning Models For Climate Change Prediction

Models	R2
Artificial Neural Network	96.25
MLR[20]	92
Deep CNN[21]	89

The projected ANN climate change forecasting model will have the capability of effectively computing complicated non-linear relationships among climatic variables using high-dimensional big data. The model also had a high coefficient of determination (R2) value of 96.25 which implies that it has a strong predictive accuracy. The key advantage of the proposed ANN model is its superior ability to capture complex, nonlinear dependencies within climate data, offering more reliable forecasts and supporting informed decision-making in climate impact assessments and mitigation strategies.

5. Conclusion and Future Scope

Accurate prediction of climate change trends is essential for environmental sustainability, disaster preparedness, and policy-making. This research demonstrates the potential of combining big data analytics with AI to develop an effective and scalable solution for climate change forecasting. In order to increase sustainability, the design of cloud data centres, issues with energy use, and possible renewable energy sources including solar, wind, hydropower, and geothermal were all examined in this study. Even though integrating renewable energy in cloud computing has a lot of potential, the results show that issues like infrastructure, cost, and resource unpredictability need to be fixed.

Utilizing a ten-year weather dataset, the ANN model exhibited exceptional predictive capabilities, with a high R^2 of 96.25, MSE of 0.0175. The approach not only aids in precise climate trend estimation but also supports proactive environmental planning. Future research will concentrate on expanding the dataset to incorporate real-time and multi-regional inputs, integrating external variables such as socio-economic factors, and deploying ensemble and hybrid models for enhanced accuracy. Additionally, explainable AI techniques could be applied to increase transparency in model predictions. These advancements can contribute to developing comprehensive early warning systems and actionable climate policies across different regions.

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