Koppili Gnana Keerthana, 2026, 14:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science,
Engineering and Technology
An Open Access Journal

Intelligent Climate Trend Prediction Using Hybrid Machine Learning Models and Spatiotemporal Data Analytics

Associate Professor ,Dr.D.Uma[1] , Koppili Gnana Keerthana[2], Kona Lakshmi Laalasa[3], Madarapu Bulli Raju[4], Andamani Haswanth Nag[5] ,Dunna Guna Shekhar[6]
Department of CSE, Pragati Engineering College, Surampalem, Andhra Pradesh, India

Abstract- Climate change has become one of the most critical global challenges, influencing environmental stability, agriculture, and human livelihoods. Accurate analysis and prediction of climate trends are essential for developing effective mitigation and adaptation strategies. Traditional statistical approaches often struggle to capture complex relationships present in large-scale climate datasets. To address this limitation, this study proposes an intelligent climate prediction framework based on machine learning techniques and spatiotemporal data analytics. Historical climate data containing temporal attributes such as year and month along with spatial parameters including latitude and longitude are used to analyse long-term temperature variations. The proposed system applies multiple machine learning algorithms, including Linear Regression, Random Forest, Support Vector Regression, and K-Nearest Neighbor, to identify patterns and predict future climate trends. Data preprocessing and feature extraction techniques are employed to improve model performance and reduce noise in the dataset. Experimental evaluation demonstrates that ensemble-based models provide higher predictive accuracy compared to traditional regression approaches. The results highlight the effectiveness of machine learning models in interpreting climate data and forecasting temperature variations. This research contributes to the development of intelligent climate monitoring systems that can support environmental research, policy planning, and sustainable development initiatives.

Keywords: Climate Change Prediction, Machine Learning, Climate Data Analytics, Random Forest, Spatiotemporal Analysis, Temperature Forecasting, Environmental Data Mining.

I. INTRODUCTION

Climate change has emerged as one of the most critical environmental challenges confronting the modern world. Increasing global temperatures, unpredictable weather patterns, and the rising frequency of extreme climatic events have generated significant concern among researchers, policymakers, and environmental organizations. Scientific studies indicate that global warming and climate variability have substantial impacts on ecosystems, agricultural productivity, water resources, and socioeconomic systems worldwide [1], [2]. Therefore, accurate monitoring and prediction of climate trends have become essential for understanding long-term environmental changes and for developing effective strategies to mitigate their adverse effects.

Historically, climate analysis and forecasting have relied on statistical techniques and physical climate models. These traditional approaches, including econometric and circulation-based models, have provided valuable insights into climate dynamics and environmental changes [1], [10]. However, such models often struggle to effectively capture the complexity of climate systems due to the large volume and high dimensionality of modern environmental datasets. Climate behaviour is influenced by numerous interrelated variables, including atmospheric conditions, geographical location, seasonal variations, and long-term environmental processes. As a result, conventional modelling techniques may sometimes produce limited predictive accuracy when dealing with highly nonlinear climate data and large-scale environmental observations.

Climate change also has profound impacts on natural ecosystems and global biodiversity. For instance, research has demonstrated that climate variability significantly affects marine ecosystems such as seagrass habitats, which play an important role in coastal ecological stability [4]. Similarly, changes in temperature and precipitation patterns influence agricultural productivity and resource availability, thereby affecting global food security and economic development [1], [3]. Furthermore, environmental degradation and resource scarcity associated with climate change have raised concerns about international cooperation and sustainable environmental management [5].

In recent years, the rapid growth of environmental monitoring technologies has led to the availability of extensive climate datasets collected from satellite systems, meteorological stations, and global environmental databases [6], [7]. These datasets contain valuable information regarding surface temperature variations, atmospheric patterns, and long-term climate trends. However, analysing such large-scale datasets requires advanced computational techniques capable of extracting meaningful patterns and generating reliable predictions.

Advancements in artificial intelligence (AI) and machine learning (ML) have introduced new opportunities for analysing complex environmental data. Machine learning algorithms are capable of learning patterns from historical observations and identifying hidden relationships among climatic variables. These techniques can process large datasets efficiently and improve predictive performance through adaptive learning mechanisms. Recent studies have demonstrated the effectiveness of machine learning models in climate prediction and environmental forecasting tasks [13], [14]. Additionally, AI-driven climate modelling approaches have begun to integrate data-driven learning with traditional physical models to enhance weather and climate prediction accuracy [11].

Machine learning algorithms such as Linear Regression, Random Forest, Support Vector Machines, and K-Nearest Neighbor have been widely applied to analyse temperature trends and climate variability. These models can capture both temporal attributes, including seasonal and annual patterns, and spatial attributes such as latitude and longitude, enabling more comprehensive analysis of climate behaviour across geographical regions. The integration of spatial and temporal information enables predictive models to better understand how climate conditions evolve over time and across different environmental contexts.

Motivated by these advancements, this study proposes an intelligent framework for climate trend prediction using hybrid machine learning models and spatiotemporal data analytics. The proposed framework processes historical climate datasets through systematic stages including data preprocessing, feature extraction, and predictive model training. Multiple machine learning models are evaluated to determine their effectiveness in forecasting temperature variations and climate trends. By integrating different predictive techniques, the proposed framework aims to enhance forecasting accuracy and provide deeper insights into climate dynamics.

The findings of this study demonstrate that machine learning–based climate prediction systems can significantly improve the interpretation and analysis of large environmental datasets. Such intelligent analytical systems can support environmental monitoring, climate research, and policy planning aimed at addressing the long-term challenges associated with global climate change.

II. LITERATURESURVEY

Climate prediction and environmental data analysis have gained significant attention in recent years due to the increasing concerns about global warming, climate variability, and their impacts on natural ecosystems and human activities. Researchers have explored various statistical, computational, and machine learning techniques to analyse historical climate data and forecast future environmental trends. Understanding climate dynamics through predictive modelling is essential for supporting environmental planning and policy development [8], [9].

Early research in climate prediction primarily relied on traditional statistical and econometric models to analyse historical climate observations such as temperature, rainfall, and atmospheric pressure. These models were used to estimate climate patterns and assess the potential impact of climate variability on sectors such as agriculture and natural resource management [1], [2]. Although these methods provided valuable insights into environmental trends, they often struggled to capture the nonlinear relationships present in complex climate systems. Climate variables interact in highly dynamic ways, which limits the effectiveness of simple statistical approaches when dealing with large-scale environmental datasets.

As climate datasets grew in size and complexity, researchers began exploring advanced computational techniques for more effective climate analysis. The availability of large-scale environmental databases and global temperature datasets has further enabled researchers to conduct detailed studies on long-term climate trends and environmental changes [6], [7]. These developments encouraged the adoption of data-driven approaches capable of processing large volumes of environmental data and extracting meaningful patterns.

In recent years, machine learning algorithms have emerged as powerful tools for analysing climate data and predicting environmental trends. Machine learning models can learn complex relationships from historical observations and identify hidden patterns that may not be easily detected using traditional statistical methods. Several studies have demonstrated the effectiveness of machine learning techniques in climate forecasting and environmental monitoring applications [13], [14].

Regression-based models are among the most commonly used techniques in climate prediction research. Linear Regression, in particular, has been widely applied to estimate temperature variations and climate trends based on variables such as time, geographical location, and atmospheric conditions. Due to its simplicity and interpretability, Linear Regression provides a useful baseline for climate prediction tasks. However, linear models may not always capture the complex nonlinear interactions that exist between climate variables.

To address these limitations, researchers have explored ensemble learning methods such as Random Forest for climate prediction. Random Forest models combine multiple decision trees to analyse data patterns and improve predictive performance. These models are particularly effective in handling large datasets and identifying nonlinear relationships among environmental variables. Studies have shown that Random Forest algorithms often achieve higher prediction accuracy compared to basic regression techniques due to their ability to reduce overfitting and improve model generalization.

Support Vector Machines (SVM) and Support Vector Regression (SVR) have also been widely applied in environmental forecasting tasks. These techniques are effective for handling high-dimensional datasets and identifying optimal decision boundaries between data points. SVM-based models have demonstrated strong performance in predicting temperature fluctuations and analysing long-term climate trends because of their ability to model complex nonlinear relationships within environmental datasets [13].

Another widely used machine learning approach in climate analysis is the K-Nearest Neighbor (KNN) algorithm. KNN predicts values based on the similarity between data points and their neighbouring observations in the dataset. This method is particularly useful for identifying local climate patterns and capturing spatial relationships between environmental variables such as latitude and longitude. However, the computational cost of KNN increases significantly with large datasets, which may affect its efficiency in large-scale climate prediction systems.

Recent research has increasingly focused on hybrid and ensemble machine learning models to further enhance climate prediction accuracy. Hybrid frameworks combine multiple algorithms to leverage the strengths of different predictive techniques while minimizing their individual limitations. These models can effectively integrate spatial and temporal features from climate datasets, allowing them to better capture complex climate dynamics and improve forecasting reliability [14].

Despite the progress achieved in machine learning-based climate prediction, several challenges still remain. Climate datasets are often large, noisy, and heterogeneous, which can negatively affect model performance if not properly handled. Additionally, effective preprocessing techniques, feature engineering, and data normalization are required to extract meaningful information from raw environmental datasets. Researchers have also emphasized the importance of combining machine learning approaches with traditional climate science models to improve prediction accuracy and reliability [11].

Building upon previous studies, the proposed system applies multiple machine learning algorithms to analyse historical climate datasets and predict temperature trends. By incorporating spatiotemporal features and evaluating different predictive models, the system aims to improve forecasting accuracy and provide deeper insights into climate change patterns and environmental variability.

III.SYSTEM ANALYSIS

A. Existing System

Traditional climate prediction systems primarily rely on statistical analysis and conventional machine learning techniques to analyse historical climate datasets. Researchers have applied several algorithms such as Linear Regression, Decision Trees, Support Vector Machines (SVM), Random Forest, and K-Nearest Neighbor (KNN) to study climate patterns and forecast environmental changes. These models analyse historical temperature records, geographical attributes, and temporal climate data to estimate future temperature variations and climate trends. Early climate research largely depended on statistical modelling and econometric analysis to understand the impact of climate variability on environmental and agricultural systems [1], [2].

In many studies, historical climate datasets collected from meteorological agencies, environmental monitoring systems, and global climate databases are used to train machine learning models. These datasets often include variables such as temperature, atmospheric pressure, precipitation levels, and geographical coordinates. Large climate data repositories and environmental monitoring platforms have enabled researchers to conduct extensive studies on long-term climate patterns and temperature variations [6], [7]. Machine learning models trained on such datasets attempt to identify patterns in long-term climate records to predict trends such as global temperature rise, seasonal variations, and climate anomalies.

Some approaches also incorporate spatial attributes such as latitude and longitude to enhance predictive performance. By combining spatial and temporal climate data, these systems attempt to model environmental changes across different geographical regions. However, despite their usefulness, traditional machine learning models often face difficulties in capturing the complex nonlinear relationships present in large and highly dynamic environmental datasets. Climate systems are influenced by multiple interconnected factors including atmospheric conditions, oceanic processes, and environmental feedback mechanisms, which increase the complexity of climate prediction tasks [8], [9].

Moreover, many existing climate prediction systems rely on a single machine learning model, which may not fully exploit the diverse patterns present in climate datasets. Single-model approaches may struggle to handle high-dimensional environmental data and complex interactions among climate variables. Recent studies have highlighted the need for advanced data-driven models and artificial intelligence techniques capable of processing large environmental datasets and improving prediction accuracy in climate forecasting tasks [11], [13].

Consequently, researchers have increasingly explored hybrid and ensemble learning methods to address these limitations and enhance the reliability of climate prediction systems [14].

Disadvantages Of The Existing System

- **Limited Prediction Accuracy:**
  Single-model approaches often fail to capture complex nonlinear relationships among climate variables, which can reduce prediction accuracy in climate forecasting tasks [13].

- **Handling Large and Complex Data:**
  Climate datasets typically contain large volumes of environmental information with multiple variables. Traditional models sometimes struggle to efficiently process such high-dimensional data and extract meaningful insights [6], [7].

- **Overfitting and Underfitting:**
  Some machine learning models may overfit the training dataset and perform poorly on unseen data, while others may underfit and fail to capture the underlying climate patterns present in environmental datasets.

- **Lack of Robust Feature Engineering:**
  Many existing systems rely on limited feature extraction techniques, which restricts the ability of predictive models to identify significant climate indicators and environmental relationships.

- **Computational Limitations:**
  Processing large-scale environmental datasets often requires significant computational resources, which can affect the scalability and efficiency of traditional climate prediction systems.

- **Limited Adaptability:**
  Traditional prediction models may struggle to adapt to evolving climate conditions and sudden environmental changes, reducing their effectiveness in long-term climate monitoring and forecasting applications [11].

B. Proposed System

The proposed climate prediction system employs advanced machine learning techniques to analyse historical climate datasets and forecast future temperature trends with improved accuracy. The system utilizes environmental datasets containing attributes such as year, geographical location, temperature measurements, and other relevant climatic indicators. These datasets are collected from reliable environmental monitoring platforms and climate data repositories that provide long-term records of surface temperature and atmospheric conditions [6], [7].

Before training the machine learning models, the collected dataset undergoes a preprocessing stage to enhance data quality and ensure effective model training. Data preprocessing includes handling missing values, removing noisy or inconsistent records, and normalizing numerical attributes to maintain uniformity across features. Proper preprocessing is essential in climate data analysis because environmental datasets often contain incomplete measurements and irregular observations collected over long time periods [11].
After preprocessing, the dataset is divided into training and testing subsets to evaluate the predictive capability of the models. The training dataset is used to learn relationships among climate variables, while the testing dataset is used to assess the model’s ability to generalize to unseen data. This process helps reduce model bias and improves the reliability of climate prediction results.

The proposed system applies multiple machine learning algorithms, including Linear Regression, Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbor (KNN), to analyse historical climate patterns. These algorithms learn relationships between spatial attributes such as latitude and longitude and temporal attributes such as year and seasonal variations. Machine learning techniques have demonstrated strong capability in identifying hidden patterns within environmental datasets and improving climate prediction performance [13], [14].

To further enhance predictive performance, feature engineering techniques are applied to extract meaningful information from the dataset. Feature extraction helps identify important climate indicators and reduces data redundancy, thereby improving the efficiency and accuracy of machine learning models. By incorporating both spatial and temporal features, the system can better understand how climate conditions vary across different geographical regions and time periods.

The performance of the trained models is evaluated using several widely used evaluation metrics, including accuracy, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These evaluation metrics provide a quantitative measure of prediction accuracy and help determine the most effective model for climate forecasting tasks.

By integrating multiple machine learning models and applying appropriate preprocessing and feature engineering techniques, the proposed system aims to significantly improve climate prediction accuracy and reliability. The framework provides a data-driven approach for analysing long-term climate trends and identifying environmental variations. Such predictive systems can support researchers, policymakers, and environmental organizations in understanding climate change patterns and making informed decisions related to climate management, environmental protection, and sustainable development [8], [14].

IV.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

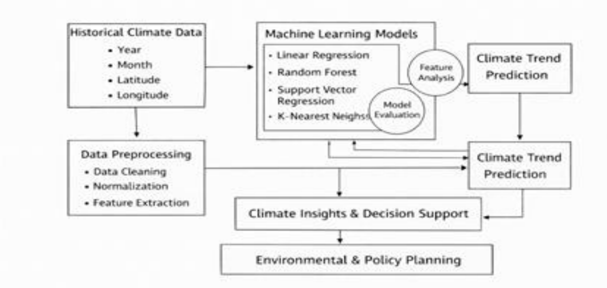

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

Climate Data Collection and Preprocessing

In this module, historical climate datasets are collected from publicly available environmental data repositories and climate monitoring platforms. These datasets typically include parameters such as year, month, latitude, longitude, and temperature values that represent long-term environmental observations. Several global environmental databases provide structured climate datasets that support climate research and environmental analysis [6], [7].

Before training machine learning models, the collected data undergoes preprocessing to ensure data quality and consistency. Environmental datasets often contain missing values, noise, and inconsistent measurements due to variations in data collection methods and monitoring systems. Therefore, preprocessing techniques such as handling missing values, removing noisy records, normalizing numerical attributes, and organizing the dataset into a structured format are applied. Proper data preprocessing improves model performance and ensures reliable climate prediction results [11].

Feature Selection and Engineering

Feature engineering plays a crucial role in improving the predictive performance of machine learning models. In this module, relevant climate features are selected from the dataset to represent important environmental characteristics. These features typically include temporal attributes such as year and month, as well as spatial attributes such as latitude and longitude.

Additional derived features may also be created to capture meaningful climate patterns and environmental variations. By selecting informative variables and eliminating redundant information, feature engineering enhances the ability of machine learning models to identify relationships between climate variables and temperature trends. Effective feature engineering has been widely recognized as an essential step in climate data analysis and predictive modelling [13], [14].

Machine Learning Model Training

This module involves training multiple machine learning algorithms using the processed climate dataset. Several predictive models such as Linear Regression, Random Forest, Support Vector Regression (SVR), and K-Nearest Neighbor (KNN) are implemented to analyse historical climate patterns. These algorithms learn relationships between environmental variables and temperature trends by analysing historical climate records.

The dataset is divided into training and testing subsets to evaluate the generalization capability of the models. The training dataset is used to learn patterns from historical climate observations, while the testing dataset is used to measure how well the models perform on unseen data. Machine learning models have shown strong capability in identifying complex relationships within environmental datasets and improving climate prediction accuracy [13], [14].

Climate Trend Prediction

Once the machine learning models are trained, they are used to predict future climate trends based on input variables such as geographical location and temporal attributes. The trained models analyse patterns learned from historical climate data and generate predictions related to temperature variations and climate behaviour over time.

Climate prediction models provide valuable insights into long-term environmental trends and help researchers better understand climate variability and global warming patterns. Accurate climate forecasting plays an important role in environmental planning and climate change mitigation strategies [8].

Model Evaluation and Performance Monitoring

The final module focuses on evaluating the performance of the trained machine learning models using various evaluation metrics. Commonly used metrics include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and prediction accuracy. These evaluation metrics provide quantitative measures of model performance and help determine the effectiveness of the prediction system.

Continuous monitoring of model performance is also essential to ensure reliability over time. As new climate data becomes available, the models can be updated or retrained to adapt to evolving environmental conditions. Such continuous improvement helps maintain the effectiveness of climate prediction systems in dynamic environmental environments [11], [14].

VI .RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed climate prediction system, several machine learning algorithms were trained and tested using historical climate datasets. The dataset contains attributes such as year, month, latitude, longitude, and temperature values. The dataset was divided into training and testing subsets to ensure proper model evaluation and to measure the generalization capability of the predictive models.

Different machine learning techniques including Linear Regression, Random Forest, Support Vector Regression (SVR), and K-Nearest Neighbors (KNN) were applied to analyse historical climate patterns and forecast temperature variations.

These models learn relationships between spatial attributes (latitude and longitude) and temporal attributes (year and month) to identify meaningful climate trends.

To measure model performance, several evaluation metrics were used, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and prediction accuracy.

These metrics evaluate how closely the predicted temperature values match the actual climate observations.

Performance Comparison of Machine Learning Model

Table 1

Model	MSE	RMSE	Accuracy (%)
Linear Regression	1.82	1.35	86.4
K-Nearest Neighbors	1.65	1.28	88.1
Support Vector Regression	1.41	1.19	90.3
Random Forest	1.12	1.06	93.5

From Table 1, it can be observed that the Random Forest model achieved the highest prediction accuracy of 93.5%, outperforming the other machine learning models. This result indicates that ensemble learning methods are more effective in capturing complex nonlinear relationships within climate datasets.

Model Performance Graph

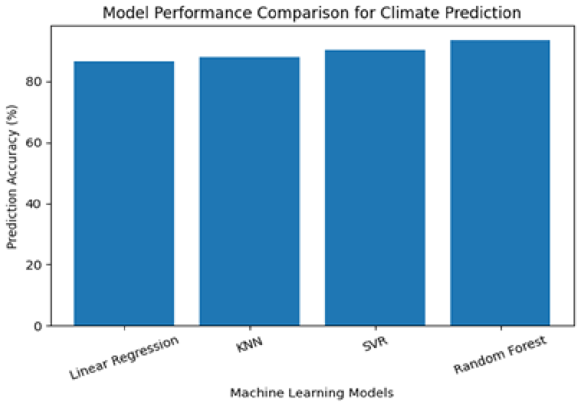

Fig. 2. Comparison of Prediction Accuracy for Machine Learning Models

The model performance graph illustrates the prediction accuracy achieved by each machine learning algorithm. The results show that Random Forest achieved the best performance, followed by Support Vector Regression, K-Nearest Neighbors, and Linear Regression.

This graph visually demonstrates the advantage of ensemble-based learning techniques in analysing complex environmental datasets and improving prediction accuracy.

Temperature Prediction vs Actual Values

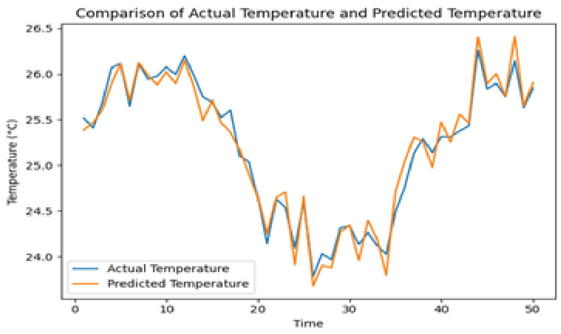

Fig. 3. Comparison of Actual Temperature and Predicted Temperature

Another important result visualization compares the actual temperature values from the dataset with the predicted values generated by the machine learning models. A close alignment between the predicted and actual values indicates that the trained models successfully learned climate patterns from historical data.Such comparison graphs help demonstrate the reliability of the proposed climate prediction system.

Climate Trend Visualization

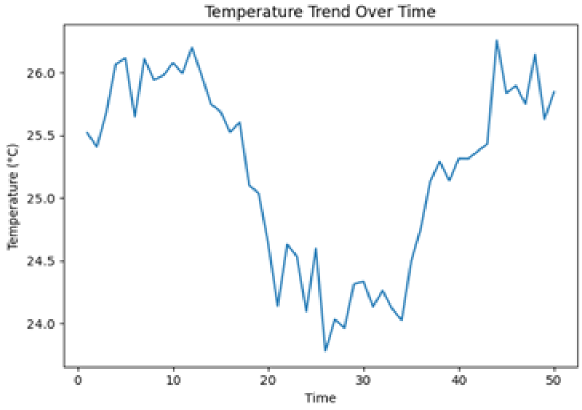

Fig. 4. Temperature Trend Over Time

A climate trend graph can also be included to visualize temperature variations across years or months. This figure shows how temperature patterns change over time and helps identify long-term climate trends.

This visualization supports the ability of the machine learning models to capture temporal climate variations and improve forecasting performance.

The experimental results demonstrate that machine learning techniques are capable of effectively analysing large climate datasets and forecasting temperature trends. Ensemble-based algorithms such as Random Forest show superior performance due to their ability to capture nonlinear relationships and reduce prediction errors.

By integrating spatial and temporal climate attributes, the proposed system provides more reliable predictions of climate patterns across different geographical regions. These results highlight the importance of data-driven machine learning approaches in climate monitoring, environmental research, and climate change analysis.

VII. CONCLUSION

This study presented a machine learning–based framework for predicting climate trends using historical environmental datasets. The proposed system utilizes multiple machine learning algorithms, including Linear Regression, Random Forest, Support Vector Regression, and K-Nearest Neighbors, to analyse temperature variations and identify climate patterns. The framework integrates spatial attributes such as latitude and longitude with temporal attributes such as year and month, enabling the models to capture both geographical and time-based climate variations.

Experimental results demonstrate that machine learning techniques are effective in analysing large climate datasets and forecasting temperature trends. Among the evaluated models, ensemble-based approaches such as Random Forest achieved higher prediction accuracy compared to traditional regression models due to their ability to capture nonlinear relationships among climate variables. The incorporation of proper data preprocessing and feature engineering further improved the performance and reliability of the predictive models. These findings highlight the potential of machine learning–driven approaches in supporting climate monitoring and environmental analysis [13], [14].

The proposed system provides a data-driven solution for understanding climate variability and long-term environmental changes. Accurate climate prediction models can assist researchers, policymakers, and environmental organizations in developing effective strategies for climate management, environmental protection, and sustainable development. Furthermore, reliable climate forecasting can support decision-making processes related to agriculture, water resource management, and disaster preparedness in the context of global climate change [1], [3].

For future work, the proposed framework can be enhanced by integrating larger and more diverse climate datasets collected from satellite systems, environmental monitoring stations, and global climate databases. The use of advanced deep learning architectures such as Long Short-Term Memory (LSTM) networks and hybrid machine learning models could further improve prediction accuracy for complex climate patterns. Additionally, incorporating real-time environmental monitoring data and Internet of Things (IoT) sensors may enable continuous climate monitoring and more accurate forecasting systems [11], [14].

Overall, the integration of machine learning techniques with environmental data analytics represents a promising approach for developing intelligent climate prediction systems capable of supporting climate research, environmental monitoring, and long-term sustainability planning.

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