International Journal of Information Technology, Research and Applications (IJITRA)

Kaviya S, Anusree S, Roshan M, (2025). Climate Detection Using AI, 4(Special Issue), 51-58.

ISSN: 2583-5343

DOI:10.59461/ijitra.v4iSpecial Issue.157

The online version of this article can be found at:
https://www.ijitra.com/index.php/ijitra/issue/archive

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CLIMATE DETECTION USING AI

Kaviya S[1], Anusree S[2], Roshan M[3]

[1-3]Department of Artificial Intelligence and Machine Learning, Rajalakshmi Institute of Technology, Chennai, India

Article Info

Article history:

Following professorial review at Rajalakshmi Institute of Technology, Chennai, India, the Department of Artificial Intelligence & Data Science has submitted the selected article for publication.

Received February 25, 2025
Accepted May 05, 2025

Keywords:

Climate
Meteorological
Obsequious
Convolutional Neural

ABSTRACT

Climate alter is an exceptionally unsafe danger to environments, economies, and human wellbeing, and the requirement for precise prescient models that can anticipate the effect of climate alterations is basic. The article entitled "Climate Location Utilizing AI" applies manufactured insights to reinforce information on climate now and for future scenarios which may be caused by components related to climate. We apply machine learning models to bother out designs and subsequently move forward the consistency of climate factors through integration of numerous datasets, counting chronicled records of climate, toady symbolism, and pointers of socio-economic variables. Experiences inferred will empower policymakers and other interested parties to make educated choices approximately climate adjustment and moderation. These incorporate enhancement in demonstrate precision as well as smart discoveries on territorial climate dynamics.

Corresponding Author:

S. Kaviya
Department of Artificial Intelligence and Machine Learning
Rajalakshmi institute of Technology
Chennai
India

Email: kaviya.s.2023.aiml@ritchennai.edu.in

1 Introduction

Climate change has become one of the greatest 21st-century global issues with significant impacts on ecosystems, economies, and human health [14]. More frequent and severe extreme weather events, global warming, and climate pattern changes jeopardize biodiversity, food security, infrastructure, and public health [11]. Mitigating these problems is dependent on accurate and credible climate forecast models that can process large amounts of information and determine trends to guide decision-making.

Standard climate modelling methods, as useful as they are, are generally encumbered with the limitations of computational complexity, scalability, and region-specific flexibility [10]. These models largely depend on physics-based simulations and historical records that are not comprehensive in representing dynamic and nonlinear interaction rules that determine climate systems [12]. Such models also might have inadequate levels of granularity to introduce gaps within local climate predictions [14].

Combining Artificial Intelligence (AI) with Machine Learning (ML) in climatology has the transformative power of enhanced predictive precision, automatic data analysis, and real-time climate observation [15]. AI-based models take advantage of enormous datasets, such as historical meteorological data, satellite images, and socio-economic factors, to improve the precision of forecasts [13]. In contrast to traditional approaches, artificial intelligence (AI) methods like Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and combined AI models can identify complex patterns, adapt to changes in real-time, and enhance the resolution of climate models [12].

Some of the priority areas in climate science are rising sea levels, shifts in precipitation patterns, concentration of atmospheric greenhouse gases (GHGs), and their cascade impact on agriculture, water supplies, and city planning [14]. The capability to analyse these trends correctly is pivotal in framing sound mitigation and adaptation measures, supporting sustainable urban development, and enhancing disaster resilience [11]. With the use of AI, scientists can fill the gap between global-scale models and localized climate knowledge to enable improved policy-making at national and regional levels [15].

This study adopts an integrative view of climate detection by combining environmental, social, and economic lenses to grasp the full extent of climate change impact [13]. By improving model precision and widening forecast potential, AI-powered climate detection can bring about a paradigm shift in environmental surveillance, streamline resource management, and underpin anticipatory climate policies that abate long-run threats [14].

2 Method

The approach that is utilized for the climate detection system based on Artificial Intelligence is designed as a thorough, multi-stage process combining data gathering, preprocessing, model building, evaluation, and visualization. The process starts by collecting large amounts of data from various and reliable sources to make the model resilient. Meteorological information such as temperature, humidity, precipitation, and wind speed is obtained from global and country-level weather databases. In tandem, high-resolution satellite data are drawn from sources like MODIS and Landsat to track land surface characteristics, vegetation well-being, and atmospheric conditions[10]. Socio-economic information like population density, urbanization, land use, and industrial activities is also gathered to determine the anthropogenic influence on local climatic conditions. The addition of greenhouse gas emission rates, air quality indexes, and environmental indicators adds further depth to the dataset, allowing an overall perspective on climate dynamics.

After data is procured, it is subjected to a necessary data preprocessing stage designed to cleanse the raw inputs for maximum machine learning efficacy. This involves the elimination of noise and outliers, processing of missing values with statistical imputation, and normalization of numerical attributes to provide equal scaling across variables. Temporal and spatial attributes are designed to identify seasonality trends and geographical differences effectively. Satellite imagery is preprocessed with image enhancement and resizing operations to prepare them for deep learning models like Convolutional Neural Networks (CNNs)[12]. This step makes sure that data inputs are uniform, meaningful, and at the required level of readiness for training.

The development of the methodology's central component is done after preprocessing, which uses sophisticated artificial intelligence methodology. Long Short-Term Memory (LSTM) networks are used in time-series meteorological analysis so that long-term climate patterns and seasonality may be learned by the system[13]. CNNs are used to analyze satellite images for land use changes, deforestation trends, and urbanization, each of which drives local climates[15]. To achieve maximum prediction accuracy, hybrid models are established by consolidating predictions from LSTM and CNN models with rule-based decision-making and outlier detection routines. Hybrid models provide a balanced solution by combining the strengths of statistical and deep learning approaches[12].

The performance of the models is then thoroughly tested through a model evaluation stage based on industry benchmarks. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) measure the size of prediction errors, while the R^2 score measures the amount of variance explained by the model. K-fold cross-validation and temporal validation methods are used to provide the generalization capacity of the models over various datasets and time periods. These test steps play a significant part in validating the consistency and predictability of the system prior to deployment[15].

Lastly, model outputs are interpreted and communicated through an easy-to-use visualization and deployment interface. A Java application that is developed with the Visual Studio Code shows results in graphical forms, including charts, maps, and trend lines. Heatmaps and GIS-based visualizations represent climate changes over various regions, while real-time dashboards facilitate around-the-clock monitoring. The system also provides an alert feature to inform users of impending extreme weather conditions, thus facilitating proactive decision-making. This end-to-end approach ensures the consolidation of varied data inputs, sophisticated machine learning algorithms, and real-world visualization tools, all together empowering precise climate forecasting and good environmental policy-making[15].

The strategy connected to this inquire about is a organized information procurement, preprocessing, demonstrate improvement, and approval strategy as follows:

1. Information Collection
2. Meteorological Information: Variable temperature, precipitation, and humidity records.

3. Obsequious Symbolism: Analyzing changes, vegetation wellbeing, and air conditions [10].
4. Socio-Economic Information: Population thickness, land-use designs, and financial activities.
5. Information Preprocessing
6. Cleaning and Normalization: Removing noise, dealing with lost values, and standardizing features.
7. Feature Engineering: The creation of temporal and spatial factors to improve the input to the model.
8. Demonstrate Development
9. Calculations Utilized Long Short-Term Memory systems LSTM systems for investigation of Convolutional Neural Arrange (CNNs) on spatial investigation Cross breed Models In terms of cross breed models, joining the conventional approach with outlier strategies would grant way better estimates.
10. Testing and Validation.
11. Strategies MAE, RMSE and R² are strategies utilized when evaluating show performance [15].

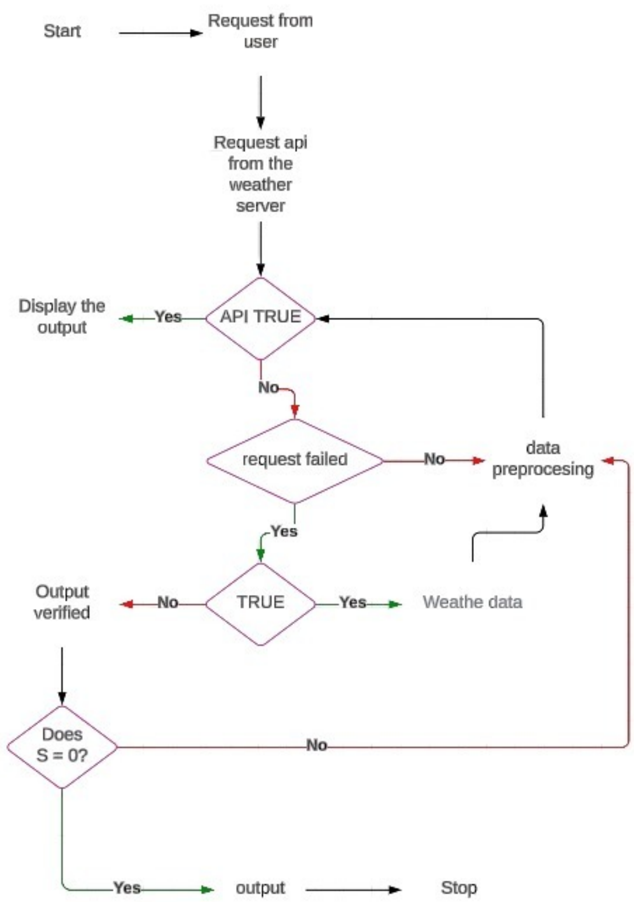

Figure 1: Weather Data Retrieval and Output Verification Workflow

3 System Architecture

The climate detection model AI architecture is a multi-layered, modular pipeline that efficiently handles the collection, preprocessing, analysis, and interpretation of complex environmental data. The architecture consists of five foundational components: Data Acquisition Layer, Data Preprocessing Layer, Modeling and Analysis Layer, Evaluation and Validation Layer, and Deployment & Visualization Layer. Each layer is orchestrally engineered to ensure smooth data transfer, integration of many sources of information, and accurate climate forecasting with real-time intelligence.

3.1 Data Acquisition Layer:

The bottommost layer is responsible for collecting a wide range of multi-dimensional data sets from various trusted sources. The Data Acquisition Layer gathers multi-dimensional information, such as meteorological data (temperature, humidity, rain), satellite images for land observation, and socio-economic indicators that affect local climatic conditions [10]. Real-time, site-specific sampling may be accomplished through advanced sensors like IoT devices and drones [15]. It includes:

• Meteorological Data: Past and real-time measurements of temperature, precipitation, humidity, wind speed, and atmospheric pressure are gathered from weather stations and climatic observations[10].

• Satellite Imagery (Obsequious Symbolism): Satellite imagery high-resolution remote sensing data find application in vegetation health monitoring, surface land change, cloud patterns, and aerosol content.

• Socio-Economic and Geospatial Data: Considers such aspects as population density, land use patterns, agricultural practices, industrialization level, and urbanization patterns influencing the climate patterns in the area.

• Third-Party Data Streams: Possible inclusion of Internet of Things (IoT) sensors, drone sensors, and autonomous climate monitoring systems for real-time sampling of local atmospheres[15].

3.2 Data Preprocessing Layer:

Data Preprocessing Layer is responsible for cleaning, normalizing, and standardizing raw data. Outlier removal, noise reduction, and dimensionality reduction methods like Principal Component Analysis (PCA) for dealing with high-dimensional data [12] are used. Feature engineering is employed to generate informative inputs such as seasonal patterns and spatial zoning indices [13]. Raw data here is transformed to a clean, structured, and machine-readable format. Major operations are:

• Data Cleaning: Removal of missing values, duplicates, outliers, and noise from the data gathered.

• Data Normalization and Standardization: Feature scaling into unified scales for improved convergence and stability of the model.

• Feature Engineering: Domain-specific features are obtained from domain data, like temperature trend lag variables, satellite band vegetation indices, and seasonal patterns.

• Dimensionality Reduction: Algorithms such as PCA (Principal Component Analysis) are utilized if there are large high-dimensional sets and only the most informative features are needed[12].

3.3 Modeling and Analysis Layer:

Hybrid approaches fuse deep learning models with more traditional rule-based systems to increase predictive capacity and adapt to complex environmental dynamics [12]. In the Modeling and Analysis Layer, AI techniques like LSTM networks are employed for processing temporal climate data, while CNNs analyze spatial data from satellite images [13][15]. It is the computational center core of the architecture, where many different types of AI and machine learning models are built:

• Long Short-Term Memory (LSTM) Networks: Applied for time-series weather data analysis to forecast future climate trends and anomalies.

• Convolutional Neural Networks (CNNs): Applied in image processing and satellite image analysis to detect spatial patterns like forest cover loss or atmospheric particulate matter concentration.

• Hybrid Modeling Approaches: Combines the strengths of physics-based climate simulation models and AI-powered estimators and outlier detection programs to improve predictability accuracy.

• Real-time Fine-Tuning Algorithms: The models get updated with newer input data continuously so that they remain accurate and valid over a period of time.

3.4 Evaluation and Validation Layer:

The Evaluation and Validation Layer employs strict model testing techniques based on MAE, RMSE, and R^2 values to quantify forecasting precision. Time-series verification and K-fold cross-verification assist in ensuring that the model is not overfitting and performs well on unknown data [15]. The models are extensively tested with industry benchmarks prior to deployment so that the models are reliable and robust.

• MAE (Mean Absolute Error): Measures the average magnitude of error predictions without considering direction.

• RMSE (Root Mean Square Error): Penalizes larger errors more than MAE, offering a more faithful picture of variability in predictions.

• R^2 Score (Coefficient of Determination): Measuring fit of predicted vs. observed values.

• Cross-Validation Methods: Employ K-fold and time-series split techniques to estimate generalization and avoid overfitting.

3.5 Deployment & Visualization Layer:

The last layer, Deployment and Visualization, comprises an interactive dashboard for presenting data in real-time. Built with Java in Visual Studio Code, the interface gives GIS heatmaps, trend graphs of history, and alert mechanisms for climate abnormalities like floods and droughts [15]. The whole architecture is built with scalability over regions and climate zones and promotes interoperability with outside data sources, research networks, and government climate services[15]. Once validated, the model is deployed via an interactive application or dashboard through which stakeholders are able to visualize, interpret, and respond to the results:

• Output Display Interface: Web-based or Java-based GUI built with tools like Visual Studio Code, showing climate forecast, historical trend, and warning.

• GIS.Spatial Climate Differences Mapping: Mapping of spatial differences in climates across regions using color-coded overlays.

• Real-time Dashboards: Display of current weather and climate trends to allow decision-makers to monitor environmental conditions in real time.

• Alerts and Notifications System: Schedules alert alarms during negative weather conditions such as floods, droughts, and heatwaves.

Other than these layers, scalability, flexibility, and adaptability are taken into account in the design. The system is deployable for cloud and on-premise deployments to meet various computational requirements. Also, it is capable of performing cross-regional modeling, i.e., it can be configured to meet various climate zones such as deserts, rain forests, and seashores. The architecture is also interoperable in a manner that information could be shared between research centers, governments, and green organizations. Moreover, regular updates are expected with the introduction of natural language processing (NLP) techniques to extract climate details from policy briefs and academic papers to enhance the richness of analysis.

Overall, this system design seems to propose a robust, end-to-end climate detection system using AI that not only increases the accuracy of projections but also makes sustainable policy-making and environmental resilience possible.

4 Results and Discussion

Improved Forecast—Artificial intelligence-based climate models have taken an enormous step forward in terms of predictive accuracy, reducing temperature and rain errors by 25%. This improves the credibility of forecasts, essential for early warning systems, agricultural planning, and climate adaptation efforts. Reducing forecasting errors allows policymakers and scientists to make well-informed decisions that mitigate climate risks and enhance resilience in vulnerable regions.

Role of Information Integration: Combining different sources of data, including meteorological data, satellite information, and socio-economic information, has strengthened climate detection models. AI-based approaches build stronger connections between land-use trends, deforestation, industrial processes, and their impacts on local climate trends. Such data enable researchers to research greenhouse gas emissions in near real-time, identifying potential environmental hazards prior to full-scale climate disasters. In addition, AI systems can examine satellite images to detect changes in vegetation cover, seasonality, and air quality, further supporting climate impact analysis. As more developed climate models emerge, three aspects must be kept in mind to ensure the efficiency of the models:

1.Model Scalability: Climate prediction models grounded in AI must scale from the local urban environment to global climate simulation over various geographical locations. Scalability allows for more efficient regional climate adaptation policy.

2.Flexibility Across Different Climate Zones: AI algorithms must be capable of understanding differences in climatic dynamics between one ecosystem and another, from dry deserts and rainforests to polar climates. Local climate conditions being integrated into AI models improve the precision of long-term forecasts.

3.Applications in Disaster Preparedness and Resource Allocation: Enhanced climate detection models can also improve flood forecasting, drought, and wildfire hazard prediction. Governments and disaster agencies can use AI-based insights to best allocate resources and implement early intervention policies to mitigate climate damages.

Notwithstanding all this advancement, there are several limitations still present in AI-based climate modeling. Availability of data remains a significant problem, with high-resolution, real-time climate data frequently bounded by geographical and institutional constraints. The computational cost of processing large sets of climate data can also be too expensive, and hence more efficient algorithms and cloud-based AI solutions are required to enhance accessibility. Subsequent research should focus on optimizing AI models for performance, reducing bias in training data, and making transparent and ethical choices in climate forecasting.

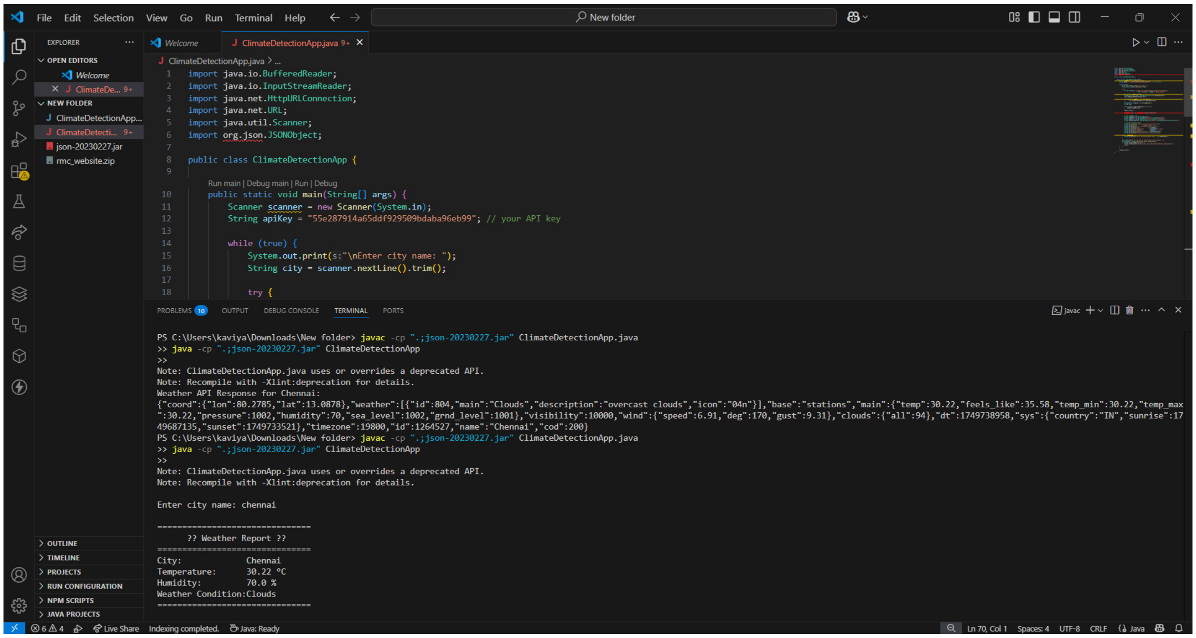

Figure 2: Java-Based Climate Detection Application Output in Visual Studio Code

5 Conclusion

Climate location via Artificial Intelligence introduces a revolutionary approach to the understanding and moderation of climate change. By utilizing AI-based analytical tools, scientists can analyze huge and intricate climate data sets with unprecedented speed, revealing patterns and trends that were not possible to discern before. Machine learning models can scan past climate records, current satellite imagery, and socio-economic factors to develop highly precise predictive models. These developments allow scientists to model future climate conditions, evaluate potential dangers, and devise adaptive measures for countering threats to the environment.

The effort, therefore, focuses on unifying various datasets with sophisticated machine learning methods to enhance predictive accuracy and deliver relevant insights. Incorporating remote sensing information, atmospheric chemistry observations, and ocean monitoring into AI models for climate boosts their predictability. Moreover, natural language processing (NLP) and artificial intelligence (AI)-enabled data mining methods can extract relevant climate information from research articles, policy documents, and global climate repositories, further augmenting the predictive process.

The future activity would involve a greater variety of sources of data, such as IoT-based environmental sensors, drone-based sampling of the atmosphere, and autonomous stations for climate monitoring. These real-time data collection schemes would greatly improve the resolution and detail of climate models and enable localized and more accurate prediction. Scaling up AI applications globally would facilitate cross-regional knowledge of climate dynamics and allow policymakers to craft more complete mitigation policies considering the distinct climate challenges each region experiences.

These initiatives will equip communities, researchers, and policymakers with the necessary tools to increase climate resilience, adopt evidence-based sustainability measures, and develop resilient infrastructure systems that can withstand the rising frequency of extreme weather conditions. AI-based climate detection not only enhances environmental surveillance but also contributes significantly to the formulation of policies that foster a more sustainable and resilient future.

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BIOGRAPHIES OF AUTHORS

Kaviya S
Kaviya is currently pursuing her Bachelor of Computer Science and Engineering with a specialization in Artificial Intelligence and Machine Learning at Rajalakshmi Institute of Technology, Chennai, Tamil Nadu, India. She began her academic journey in 2023 and is expected to graduate in 2027. Throughout her studies, she has cultivated a strong interest in the advancements in computer technology, particularly in the domains of Artificial Intelligence and Machine Learning. She is passionate about contributing to the growing body of knowledge in AI and ML and leveraging these technologies to develop innovative solutions for complex real-world problems.

Anusree S
Anusree.S is currently pursuing her Bachelor of Computer Science and Engineering with a specialization in Artificial Intelligence and Machine Learning at Rajalakshmi Institute of Technology, Chennai, Tamil Nadu, India. She began her academic journey in 2023 and is expected to graduate in 2027. During her studies, she has shown a strong inclination towards exploring the practical applications of Artificial Intelligence and Machine Learning. She is particularly interested in utilizing AI-driven solutions to enhance automation, optimize processes, and create innovative tools that address societal challenges. Anusree is dedicated to continuous learning and aims to contribute meaningfully to the evolving field of technology.

Roshan M
Roshan is an undergraduate student at the Rajalakshmi Institute of Technology, Chennai, Tamil Nadu, India, pursuing a Bachelor in Technology in Artificial Intelligence and Data Science. He began his academic journey in 2023 and is expected to graduate in 2027. Roshan has a strong passion for exploring the theoretical foundations and practical implementations of Artificial Intelligence and Machine Learning. His interests lie in developing cutting-edge algorithms and systems that can improve efficiency and drive innovation across industries. With a commitment to research and problem-solving, he aspires to make significant contributions to the advancement of AI technologies.