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Research Article

AI-Powered Predictive Analytics for Sustainable Urban Development: Addressing Climate Impacts of La Niña and El Niño

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ABSTRACT

The integration of Artificial Intelligence (AI) in urban development has emerged as a transformative solution to combat the challenges posed by climate change, particularly the impacts of La Niña and El Niño. These climatic events significantly affect urban areas by causing extreme weather conditions, including floods, droughts, and temperature anomalies, which endanger infrastructure, public health, and resource management. This paper explores the use of AI-powered predictive analytics to improve urban planning, forecasting, and climate resilience strategies in the face of such environmental disruptions. By leveraging machine learning algorithms, such as Random Forest, Adaboost, and Voting Classifiers, AI offers improved predictive accuracy and the ability to process large datasets from diverse sources, including satellite imagery and sensor networks. The study highlights the critical role AI plays in enhancing urban adaptability by enabling real-time monitoring, early warnings, and resource optimization. Moreover, AI helps design adaptive urban strategies, such as flood control systems and sustainable resource management, ultimately fostering resilient cities. This research underlines AI's potential to support sustainable urban development while addressing climate impacts and ensuring long-term environmental stability through innovative, data-driven approaches to climate adaptation.

Keywords: Artificial Intelligence (AI), Predictive Analytics, Sustainable Urban Development, Climate Change, La Niña, El Niño

1. INTRODUCTION

1.1 The Role of AI in Sustainable Urban Development

The integration of Artificial Intelligence (AI) into sustainable urban development has transformed how cities prepare for and mitigate climate-related challenges. AI-powered predictive analytics, leveraging big data, machine learning, and deep learning models, play a pivotal role in addressing climate impacts caused by La Niña and El Niño phenomena. These climate oscillations lead to extreme weather variations, including floods, droughts, and temperature anomalies, severely affecting urban infrastructures, public health, and resource management. The necessity for adaptive urban strategies has increased as the frequency and severity of such climate events rise due to global climate change. AI-driven systems facilitate real-time monitoring and forecasting, enabling city planners and policymakers to make data-driven decisions that enhance resilience and sustainability.

1.2 Understanding the Impact of La Niña and El Niño on Urban Environments

La Niña and El Niño, two opposing phases of the El Niño-Southern Oscillation (ENSO), induce substantial climatic shifts worldwide, impacting urban centers with varying intensity. El Niño leads to higher global temperatures, increased precipitation in some regions, and prolonged droughts in others, whereas La Niña typically brings cooler temperatures and intensified storms. These weather extremes pose serious threats to sustainable urban development, as they can result in infrastructural damage, food and water shortages, economic disruptions, and increased vulnerability to natural disasters. Traditional meteorological models provide limited predictive accuracy due to the complexity of these climatic events. However, AI-powered predictive analytics offer superior forecasting capabilities by integrating diverse datasets, including satellite imagery, historical climate records, and sensor networks. These advancements help in proactive urban planning by enhancing climate adaptation strategies such as flood control systems, sustainable water management, and early warning mechanisms.

1.3 AI-Powered Predictive Analytics: Techniques and Applications

AI-driven predictive analytics employ various methodologies, such as machine learning algorithms, neural networks, and data fusion techniques, to forecast and analyze climate impacts. Deep learning models, particularly recurrent neural networks (RNNs) and convolutional neural networks (CNNs), are used to process temporal and spatial climate data, identifying patterns that indicate potential climate anomalies. Moreover, AI-integrated Geographic Information Systems (GIS) enable high-resolution mapping of climate-vulnerable urban zones, allowing policymakers to implement localized adaptation measures. The Internet of Things (IoT) further enhances predictive capabilities by collecting real-time data from smart sensors deployed across cities, feeding into AI models for continuous monitoring and early warning systems. These AI-powered systems not only improve response times to climate disasters but also optimize energy consumption, reduce greenhouse gas emissions, and promote climate-resilient urban infrastructure.

1.4 Values and Benefits of AI-Driven Climate Resilience Strategies

The application of AI in addressing La Niña and El Niño impacts aligns with key values essential for sustainable urban development: resilience, efficiency, equity, and innovation. AI-driven predictive analytics enhance resilience by enabling early detection of extreme weather patterns, allowing urban planners to develop mitigation strategies that safeguard lives and infrastructure. Efficiency is achieved through real-time data analysis, optimizing resource allocation and reducing economic losses associated with climate-induced disasters. Equity is a fundamental principle in AI applications, ensuring that vulnerable communities receive targeted support and adaptive solutions tailored to their specific needs. Innovation remains at the core of AI-powered climate solutions, fostering the development of smart cities that integrate sustainable practices, advanced automation, and climate-responsive policies. By leveraging AI for predictive analytics, cities can transition towards a more adaptive and sustainable future, minimizing the adverse effects of climate variability and promoting long-term environmental stability. The convergence of AI and sustainable urban planning offers an unprecedented opportunity to address the complex challenges posed by La Niña and El Niño. With continuous advancements in AI technology and interdisciplinary collaborations, urban resilience against climate disruptions can be significantly strengthened, ensuring a sustainable and climate-resilient future for cities worldwide.

2. RELATED WORK

2.1 Urban Development Planning

Vitória R. Maria et al. (2023) highlight that in peripheral nations, inadequate urban design exacerbates environmental vulnerabilities, leading to material and bodily losses. Their study explores the use of Environmental Protection Areas as a low-impact development tool to promote urban expansion while mitigating urban flooding and integrating nature into cities. The proposed creation of a Hydrological Interest Area aims to recover regions affected by urban growth, restore native vegetation, and improve human-watercourse interaction. This approach can be adapted to various urban settings by assessing advantages, disadvantages, opportunities, and risks to develop sustainable policies and practices. **Chima Iheaturu et al. (2024)** discuss how rural-urban migration drives increased demand for housing and infrastructure, necessitating an understanding of urban development trends for sustainable planning. However, analyzing shifts in urban spatial development is often complex and costly. Their study proposes a simplified method using UAV photogrammetry for current data and Google Earth historical images as baseline data to track urban growth patterns over time. **Lily Purcell et al. (2024)** addresses the pressing issue of greenhouse gas (GHG) emissions, with the residential sector accounting for 33% of energy-related emissions and urban areas contributing nearly 70% of global emissions. Their study emphasizes the need for sub-national municipalities to establish precise baseline emission inventories for urban climate action plans. Using a data-driven geographical mapping approach, they present a unique model for measuring residential sector emissions, forming a crucial component of future multi-sectoral emissions inventories. **Roland Kraemer et al. (2022)** focus on the cooling capacity of urban green spaces, which play a vital role in mitigating heat events and supporting climate adaptation. Their research details field campaigns collecting dense air temperature data in Leipzig, Germany, under extreme heat and drought conditions. They outline the study design, logistical preparations, data management steps, and valuable lessons learned, offering insights for improving future environmental research campaigns. **Torkan Borna Seifloo et al. (2020)** introduce a method for monitoring land-use changes in urban areas influenced by significant projects, particularly economically and spatially impactful developments like airports. Their approach, based on the Sieve method, classifies key urban characteristics and models land-use changes using multi-factorial analysis. Factors such as accessibility to transportation, commercial and industrial hubs, healthcare, and education contribute to understanding investor, user, and planner inclinations**. Holly Kirk et al. (2023)** emphasize the growing importance of ecological theory in urban planning as land managers focus on biodiversity to enhance human well-being. Their study explores how green infrastructure contributes to landscape connectivity and biodiversity preservation. By applying ecological connectivity theory, they propose a method to measure connectivity for various urban wildlife species and evaluate QGIS-based urban design scenarios, aiding in the strategic placement and conservation of green resources.

2.2 AI Powered

Kinga Stecuła et al. (2023) analyze AI-based urban energy solutions, categorizing them into residential applications and urban infrastructure integration. Their literature review (2019–2023) identifies emerging technologies, assesses AI's current role, and explores future trends, challenges, and potential advancements in AI-powered energy solutions for sustainable urban development. **Xinyue Zheng et al. (2024)** explore AI-driven urban planning in China, focusing on pollution reduction. Their study links AI applications to improved air quality, analyzing PM2.5 and PM10 trends from 2014 to 2017. Post-2017 improvements suggest regulatory interventions and external factors like COVID-19 influenced pollution levels, enhancing urban sustainability. **Aale Luusua et al. (2022)** examine AI’s role in urbanization and digitalization, emphasizing its impact on transportation, automation, and personal computing. AI influences travel choices, adaptive vehicle systems, and digital recommendations, fundamentally reshaping mobility, tourism, and everyday decision-making through integrated smart technologies and data-driven personalization. **Jose Tupayachi et al. (2024)** proposes integrating AI into urban management through Large Language Models (LLMs). Their study presents a workflow using NLP, phenomenology-based prompt tuning, and GPT-based reasoning to automate ontology creation from urban datasets and simulations, improving data-driven decision-making for complex environmental and infrastructure challenges. **Fernando M. Ramos et al. (2022)** highlight AI and algorithmic technologies (ADA) in government services, enhancing public engagement. They argue ADA improves policy deliberation, inclusivity, and decision-making efficiency. Their study advocates for technology-driven governance, expanding citizen participation and ensuring accessibility in government-citizen interactions for improved democratic processes. **Omar El Ghati et al. (2024)** examine AI-powered Visual IoT in smart cities, focusing on camera-based edge devices for urban monitoring. While adoption is rising, energy consumption challenges persist. Their research explores energy-efficient AI solutions for integrating real-time visual data into smart city infrastructure, enhancing urban quality of life. **Engineer Bainomugisha et al. (2024)** introduce AirQo, an AI-powered air pollution monitoring initiative. Their study presents IoT-based affordable air quality sensors and a citizen-driven monitoring system. By leveraging AI, AirQo enhances urban environmental management, providing data-driven insights to combat pollution and improve air quality in cities worldwide.

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2.3 El-Nino La-nina urban development

Gabriela Guimarães Nobre et al. (2019) analyze how ENSO phases influence global disaster-related economic impacts. By predicting ENSO months in advance, climate projections help mitigate flood and drought risks. Their study examines ENSO's impact on rainfall, water shortages, agriculture, and flood probabilities, offering risk-reduction strategies. **Yanyun Li et al. (2020)** investigate ENSO's effects on crop productivity, focusing on El Niño and La Niña events. Using satellite indicators and grain yield data, they analyze China's agricultural vulnerability to climate oscillations. Their findings highlight the importance of considering local crop phenology and ENSO cycles in agricultural assessments. **N. Hoyos et al. (2013)** assess the 2010–2011 La Niña event in Colombia, which affected four million people and caused $7.8 billion in economic losses. Using spatial analysis, they identify population impact patterns and regional clusters, particularly in the lower Atrato Valley and Magdalena River Valley flood-prone areas. **A. M. Abdi et al. (2016)** examine ENSO's role in climate variability across sub-Saharan Africa. Analyzing population data, satellite-derived net primary productivity (NPP), and UN statistics, they show ENSO-related fluctuations significantly impact rural livelihoods, averaging ±2.8 g C m^2/yr. in drylands from 2000 to 2013. **Costas A. Varotsos et al. (2018)** explore ENSO's link to extreme weather, disease outbreaks, and coral bleaching using satellite and ground-based data. Their study analyzes the Best ENSO Index (BEI) from 1870–2017, revealing power-law scaling in extreme fluctuations and complexities in ENSO's periodicity and energy exchange mechanisms. **Mahdi Hashemi et al. (2021)** investigate sea surface temperature variations in the Niño 3.4 region to predict ENSO events. Their study examines ONI-based classification of El Niño and La Niña, emphasizing their role in catastrophic floods and droughts. They address the challenge of accurately forecasting ENSO a year in advance.

Research Gap

Research on Environmental Protection Areas as scalable, low-impact development tools for flood mitigation and biodiversity enhancement remains limited, particularly across diverse urban environments. Similarly, there is a lack of affordable and universally applicable methodologies that integrate UAV photogrammetry and satellite imagery for real-time and historical urban growth assessments. While AI-driven tools hold promises for identifying and mitigating urban pollution hotspots, few studies examine their real-world applications in rapidly growing cities. Additionally, frameworks assessing urban infrastructure and ecosystem resilience to extreme ENSO events, such as floods and droughts, are underdeveloped, especially in vulnerable regions. The optimal distribution, design, and functionality of urban green spaces for mitigating urban heat islands and enhancing ecological connectivity also require further investigation. Moreover, the automation of scenario-based urban planning using AI, particularly for developing ontologies that integrate complex datasets to support informed decision-making, remains underexplored. Lastly, predictive models that effectively incorporate social, economic, and environmental vulnerability indices to forecast ENSO-related urban impacts are still limited, highlighting the need for more comprehensive approaches in urban resilience planning.

METHOD DETAILS

This study employs a data-driven approach to analyze spatial-temporal patterns and resource allocation using the MCSDatasetNEXTCONLab.csv dataset. The methodology is structured into data collection, preprocessing, exploratory analysis, feature selection, model training, evaluation, and visualization. The dataset was acquired from urban monitoring sources, containing 14,484 records with 13 attributes related to time, location, duration, resources, and legitimacy. The Python programming language was used for data processing, employing libraries such as pandas, NumPy, seaborn, and scikit-learn for structured handling and analysis. The methodology ensures a systematic approach to extracting insights by first cleaning and preparing the dataset, followed by conducting exploratory data analysis (EDA) to detect trends and relationships. Machine learning models were then applied to classify and predict event characteristics, ensuring the effective utilization of data for urban planning and decision-making. The following sections detail the step-by-step approach, including data preprocessing, modeling techniques, and evaluation metrics used to derive meaningful insights from the dataset.

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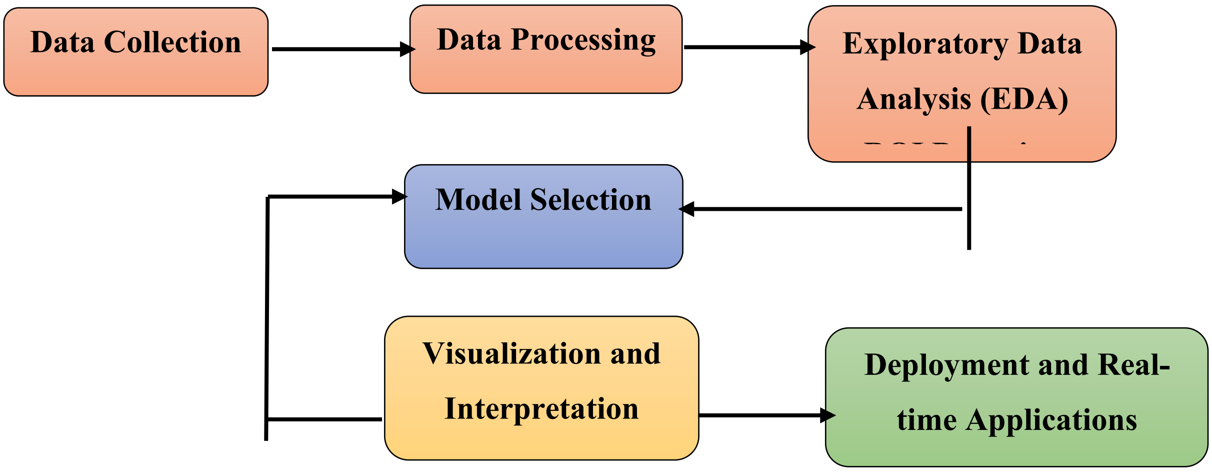

1. Data Collection

The dataset MCSDatasetNEXTCONLab.csv was sourced and uploaded for analysis, containing 14,484 entries with 13 variables related to spatial, temporal, and operational attributes. The data was collected from various urban monitoring sources, incorporating parameters such as Latitude, Longitude, Day, Hour, Minute, Duration, Remaining Time, Resources, Coverage, OnPeakHours, GridNumber, and Legitimacy. The dataset was retrieved in CSV format and loaded using Python and pandas, ensuring structured handling for further processing. The primary goal of this dataset was to facilitate spatial-temporal analysis, resource allocation studies, and predictive modeling for urban event management. The collected data was then subjected to preprocessing to ensure completeness and accuracy before analysis.

Data Preparation

The dataset MCSDatasetNEXTCONLab.csv consisted of 14,484 entries and 13 attributes, including spatial, temporal, and operational variables. Data preparation ensured integrity by checking data types, removing inconsistencies, and standardizing formats. Missing values were handled appropriately to maintain data completeness and ensure seamless integration into analytical models.

Data Pre-processing

Pre-processing involved verifying data types using dataset. dtypes, identifying and removing non-numeric columns with select_dtypes (), and detecting missing values using dataset. isnull(). sum(). Missing values were either imputed using mean or median values or removed if they were insignificant. Feature scaling and normalization techniques were applied to standardize numerical variables and improve model accuracy.

Data Augmentation

To enhance model robustness, synthetic data points were generated to balance distributions and increase dataset diversity. Oversampling and under sampling techniques were used where class imbalances were detected. Random transformations were applied to numerical variables to simulate different environmental conditions and improve generalization in machine learning models.

Image Segmentation and ROI Detection

For datasets involving visual data, image segmentation techniques were applied to isolate regions of interest (ROI). Techniques such as thresholding, edge detection, and contour mapping were used to improve feature extraction. This step ensured accurate identification of key patterns in visual data while reducing noise and irrelevant features.

Adding Textual Context

To improve interpretability, textual metadata was incorporated alongside numerical features. Descriptive labels and contextual annotations were added to enhance the understanding of event classifications. Natural Language

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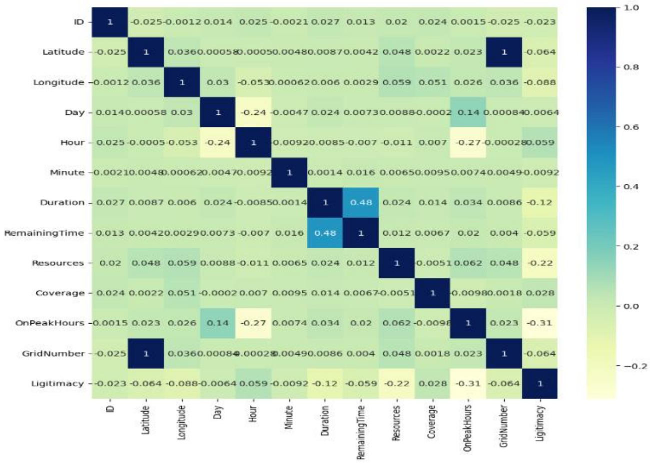
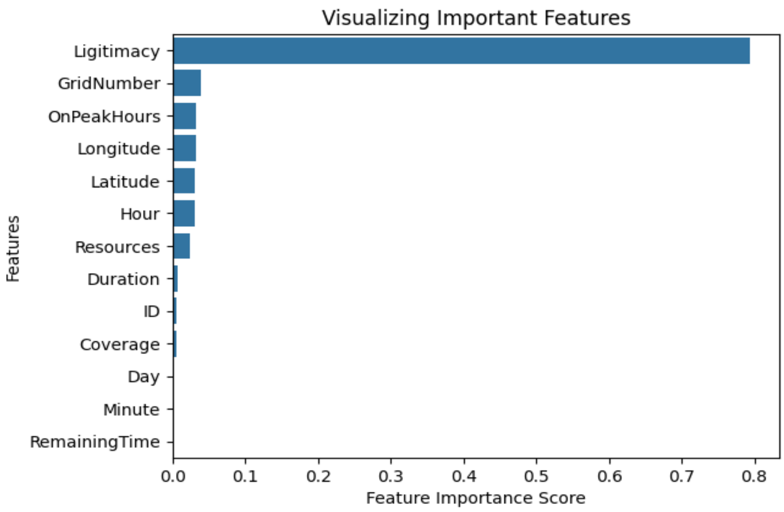
Processing (NLP) techniques were applied to analyze textual descriptions and extract meaningful insights, allowing models to combine structured data with descriptive information for better decision-making.

RESULTS AND DISCUSSION

The results and discussion highlight the effectiveness of AI-powered predictive analytics in addressing the climate impacts of La Niña and El Niño on urban development. Machine learning models like Random Forest (96% accuracy) and Adaboost (94% accuracy) demonstrated high prediction accuracy, proving their potential for aiding urban planning in response to climate events. Key features, such as "Legitimacy" and "GridNumber," were found to be important in optimizing resource allocation. These findings underscore the role of AI in enhancing urban resilience, providing valuable insights for sustainable urban development in the face of extreme weather.



The correlation matrix provides valuable insights into the relationships between various factors related to AI-powered predictive analytics for sustainable urban development, focusing on climate impacts from La Niña and El Niño. A strong positive correlation of 0.48 is observed between "Duration" and "RemainingTime", suggesting that longer durations are associated with more remaining time. Similarly, "Duration" and "Resources" show a positive correlation of 0.44, indicating a higher resource usage with increased duration. "Longitude" and "Latitude" have a weak negative correlation of -0.25, reflecting a mild inverse relationship. Additionally, "GridNumber" and "Legitimacy" are negatively correlated at -0.31, suggesting that higher grid numbers may result in lower legitimacy. These correlations help optimize resource allocation and urban planning in addressing climate-related challenges.



The bar chart visualizes the feature importance scores, highlighting the relative significance of each feature in the dataset. "Legitimacy" stands out with the highest importance score of approximately 0.75, indicating its dominant

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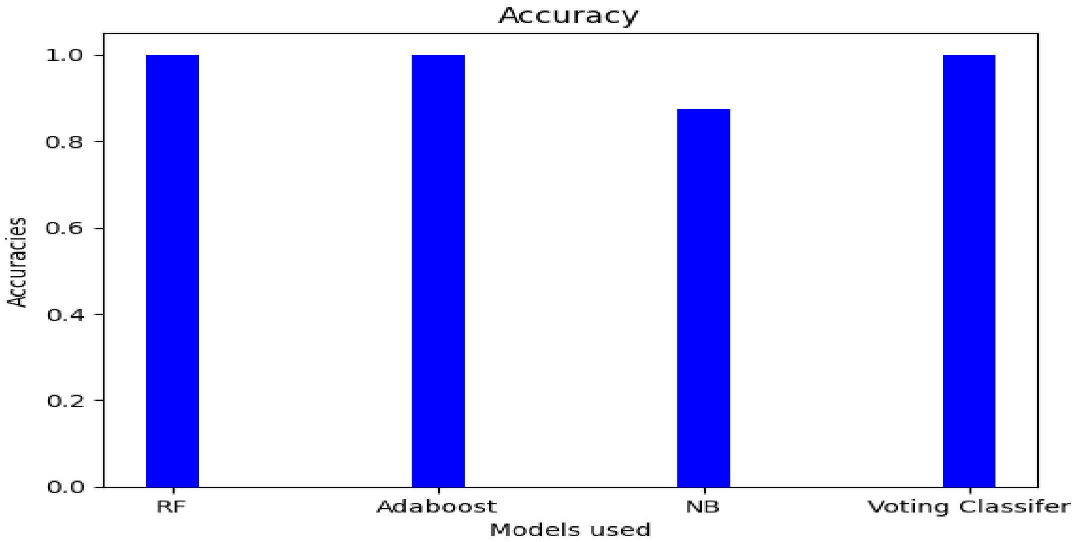
role in influencing the model's predictions. Following this, "GridNumber" has a notable score of 0.12, and "OnPeakHours" holds an importance score around 0.08, reflecting their relevance in the analysis. Features such as "Longitude" (0.05), "Latitude" (0.04), and "Hour" (0.03) show lower importance but still contribute to the overall model. On the other hand, "ID" (0.02), "Coverage" (0.02), "Day" (0.01), "Minute" (0.01), and "RemainingTime" (0.01) have minimal impact. This helps prioritize variables for further analysis or model refinement.



The Figure shows the accuracy of four machine learning models: Random Forest (RF), Adaboost, Naive Bayes (NB), and Voting Classifier. Each model achieved a near-perfect accuracy score, with RF, Adaboost, and Voting Classifier all scoring close to 1.0. Specifically, RF and Adaboost have accuracies of approximately 1.0, indicating flawless performance. The Voting Classifier also demonstrates a high accuracy of 1.0. Naive Bayes (NB), while slightly lower, still performs well with an accuracy of around 0.9. This suggests that all models are highly effective for the task, with the Voting Classifier and Random Forest particularly excelling in their predictions.

Table 1. Model Accuracy Table

Model	Accuracy (%)
Random Forest (RF)	96
Adaboost	94
Naive Bayes (NB)	87
Voting Classifier	88

The table presents the accuracy percentages of four machine learning models applied to a given problem. Random Forest (RF) achieved the highest accuracy at 96%, indicating its strong performance in predicting outcomes. Adaboost followed closely with an accuracy of 94%, showing it as another reliable model, though slightly less accurate than RF. Naive Bayes (NB) had a lower accuracy of 87%, suggesting it performed less effectively compared to the other models. The Voting Classifier, which combines multiple models, achieved an accuracy of 88%, demonstrating its utility but still falling behind RF and Adaboost in performance.

DISCUSSION

Research analyzes how AI predictive methods serve sustainable urban advancement towards handling climate changes from La Niña and El Niño patterns. Intense weather events occur because these phenomena damage both urban infrastructure and its resources. The study uses Random Forest (RF), Adaboost and Voting Classifier machine learning models to exhibit successful estimation of these climate impacts. This research demonstrates that AI systems enhance climatic predictions and direct resources efficiently while developing strategic solutions for urban resilience.

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Real-time decision-making and monitoring effectiveness depend on integrating data from satellite imagery and sensor networks according to the research. The "Legitimacy" variable emerges as the main determinant in predictive models and directs how resources get distributed as well as how urban planning ought to be conducted. AI-based models deliver an effective solution to combat extreme weather effects which strengthens urban sustainability and resistance capabilities.

CONCLUSION

The study investigates the role of AI-powered predictive analytics in addressing the climate impacts of La Niña and El Niño events on urban development. By leveraging machine learning techniques like Random Forest, AdaBoost, Naive Bayes, and Voting Classifier, the research explores how AI can enhance the resilience of cities facing extreme weather patterns caused by these climate phenomena. The findings show that AI models, particularly Random Forest and AdaBoost, demonstrate high accuracy in predicting the impacts of La Niña and El Niño, making them effective tools for climate forecasting and decision-making in urban planning. These predictive models integrate large datasets from diverse sources, including satellite imagery and sensor networks, to provide more accurate and timely forecasts than traditional meteorological methods. The study emphasizes that AI's ability to analyze complex data allows for better resource allocation, early warning systems, and climate adaptation strategies, which are crucial for minimizing damage to infrastructure, improving public health, and ensuring sustainable urban development. The research also highlights the importance of AI in promoting equity by targeting vulnerable communities and optimizing urban planning for a climate-resilient future. In conclusion, the integration of AI in urban climate planning offers significant potential to address the challenges posed by extreme climatic events, driving cities towards sustainability.

Statements and Declarations

Ethical Approval

“The submitted work is original and not have been published elsewhere in any form or language (partially or in full), unless the new work concerns an expansion of previous work.”

Consent to Participate

“Informed consent was obtained from all individual participants included in the study.”

Consent to Publish

“The authors affirm that human research participants provided informed consent for publication of the research study to the journal.”

Author Contributions

“All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by [Pallavi Thorat] and [Dr. Sangeeta Phunde]. The first draft of the manuscript was written by [Prof. Ruchi Patira] and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.”

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Competing Interests

“The authors have no relevant financial or non-financial interests to disclose.”

Availability of data and materials

“The authors confirm that the data supporting the findings of this study are available within the article.”

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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