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AI-DRIVEN CLIMATE IMPACT ESTIMATOR TO PREDICT ECONOMIC EFFECTS OF CLIMATE CHANGE ON VARIOUS INDUSTRIES

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Abstract:

The advent of the Artificial Intelligence (AI) age offers numerous potentials for predicting regional GDP growth and transportation dynamics. This article presents an in-depth overview of the AI and empirical modeling techniques used in this area, emphasizing the significant possibilities that AI presents and discussing potential obstacles. The use of AI is essential in managing complicated data, allowing for effective analysis of detailed regional economic trends. This capacity will be essential for making economic policies and plans that respond to each region's specific needs and capabilities. This paper first explores the relationship and impact of different modes of transportation and regional economic growth. Subsequently, the different empirical models and methods including factors used for studied economic analysis were comprehensively discussed and summarized. In the last part, the discussion focuses on the potential role of AI to revolutionize regional economic research using different AI approaches. This includes its capacity to handle vast and intricate databases, its ability to forecast future patterns using historical and current data, and its assistance in advanced decision making. The present study enhances our awareness of how AI is revolutionizing the field of regional economic growth study, shedding light on both its current application and future possibilities. This study will help in the development of AI predictive models in decision making for predicting regional economic growth across the globe. The impact of climate change on various industries has become a pressing global concern, necessitating the development of advanced predictive tools to assess its economic consequences. The advent of Artificial Intelligence (AI) provides significant opportunities for estimating these effects, enabling data-driven insights into regional GDP growth, industrial productivity, and transportation dynamics. This study presents an AI-driven Climate Impact Estimator that leverages machine learning and empirical modeling techniques to analyze and predict economic shifts caused by climate change across different sectors.

1. INTRODUCTION

Climate change has emerged as one of the most critical challenges of the 21st century, affecting various industries, economies, and ecosystems worldwide. India, being one of the fastest-growing economies, is highly vulnerable to climate-related risks such as extreme temperatures, erratic monsoons, rising sea levels, and increased frequency of natural disasters. According to the Reserve Bank of India (RBI) report, climate change could reduce India's GDP by 2.5% to 4.5% annually by 2030. The World Bank estimates that unmitigated climate change could push 600 million Indians into extreme heat conditions by 2050, significantly affecting agriculture, infrastructure, and industrial productivity. The agriculture sector, which contributes around 18% to India's GDP and employs nearly 50% of the workforce, is particularly sensitive to climate variability. Likewise, the transportation sector, responsible for 12% of India's greenhouse gas (GHG) emissions, faces risks from rising fuel costs and infrastructure damage due to extreme weather. AI-driven climate impact estimators offer the potential to revolutionize economic forecasting by integrating large datasets, analyzing trends, and providing actionable insights. By leveraging machine learning and empirical modeling, this research aims to create a robust, data-driven decision support system to predict climate-induced economic shifts, helping policymakers, industries, and investors plan for a more resilient future

2. LITERATURE SURVEY

Artificial Intelligence (AI) has significantly impacted different sectors in the recent past, including the health sector education, transport, recreation, and logistics

Bickley et al.,[1] Economic growth has had a substantial impact on local, national, and global economies. Regional economic growth focuses on enhancing economic operations within a specific region to boost its economic effectiveness, labor force, and overall quality of life. Economic growth is impacted by various elements including infrastructures health, schooling, environmental conditions, industrial expansion, and technological advancements

Ding et al., [2]. Similarly, the application of different AI algorithms including Machine Learning (ML) approach and Deep Learning (DL) models

Zhang et al., [3], provides sophisticated and effective techniques for data interpretation, trend identification, economic assessment

Pu et al.,[4] and predictive modeling

Jiang [5].These systems are capable of processing substantial amounts of complex and diverse data, offering useful insights into economic patterns at a regional scale. AI techniques can improve economic prediction, performance assessment, and legislative decision-making, ultimately fostering economic progress and growth

Okewu et al.,[6]. Recently, numerous research projects have investigated the application of AI techniques for local economic research. Different approaches, such as econometric evaluation and techniques based on ML, have been used to study the impacts of educational institutions on economic growth around the globe

Bertoletti et al.,[7]. Models developed using deep learning have been developed to analyze factors influencing economic development in the region

Cheng and Huang, [8], and reinforcement-learned models have been proposed for forecasting regional Economy

Li et al.,[9]. The authors have used multi-graph neural networks to predict local economic patterns

Xu et al., [10]. The impact of future innovations like 5G along with the Internet of Things (IoT) on the regional economy has been studied in the context of AI. An efficient transportation system plays a crucial role in promoting GDP growth and social welfare by enhancing productivity .

3. PROPOSED METHODOLOGY

The Supply Chain Disruption Analysis using Long Short-Term The dataset used for this project is the Climate-Risk-Index-1 dataset. This dataset contains information related to climate change, economic losses, and their impact on various industries. The data includes attributes such as country identifiers, economic indicators, and climate-related variables that influence GDP loss. The dataset is loaded into the system and is analyzed to understand its structure, number of records, and attribute distributions. The key purpose of using this dataset is to analyze patterns in climate-related economic losses and develop a machine learning model that can predict future losses based on input variables.

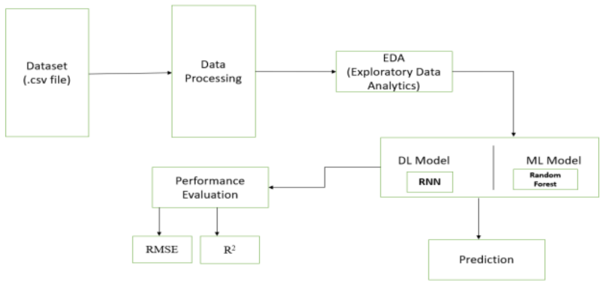

Fig. 1: Architectural Block Diagram of the proposed system.

Data preprocessing is a crucial step in machine learning to ensure the dataset is clean, structured, and ready for training models. In this project, the dataset is loaded and examined for inconsistencies such as missing values, duplicate entries, and outliers. Initially, a summary of the dataset is generated using statistical functions to understand the distribution of features. Missing values are handled by replacing them with the mean of the respective column to maintain data consistency. Certain categorical features, such as country codes and country names, are encoded into numerical representations using a Label Encoder to make them compatible with machine learning models. Feature scaling is applied using StandardScaler to normalize numerical values, ensuring that all features contribute equally during model training. Additionally, polynomial feature transformation is used to enhance the dataset's complexity and capture non-linear relationships between variables.

Proposed Algorithm: RNN Regressor

What is RNN Regressor?

A Recurrent Neural Network (RNN) Regressor is a deep learning model designed to process sequential data and predict continuous values. Unlike traditional neural networks, RNNs have memory, allowing them to learn temporal dependencies in time-series data, making them suitable for regression tasks involving sequential patterns.

How It Works?

- **Input Sequence** – The model takes sequential data as input, such as time-series energy usage or financial trends.

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— **Recurrent Connections** – Hidden states store information from previous time steps, enabling the model to learn temporal dependencies.

— **Backpropagation Through Time (BPTT)** – The model updates weights using a specialized backpropagation method that considers past states.

— **Regression Output** – The final layer generates a continuous value prediction based on the learned temporal patterns.

Architecture of RNN Regressor

4. EXPERIMENTAL ANALYSIS

The figure 1 displays the graphical user interface (GUI) where the *climate-risk-index-1* dataset is uploaded for processing. The interface provides an overview of the dataset structure, including columns such as *country, cri_rank, fatalities_per_100k_total, losses_per_gdp_total, GDP loss*, and other relevant climate risk indicators. The dataset is analyzed to ensure completeness, consistency, and correctness before proceeding with further steps.

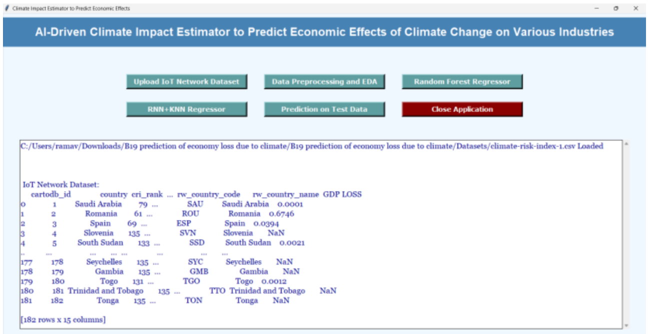


Fig. 1: Upload and Analysis of the Climate Risk Index Dataset

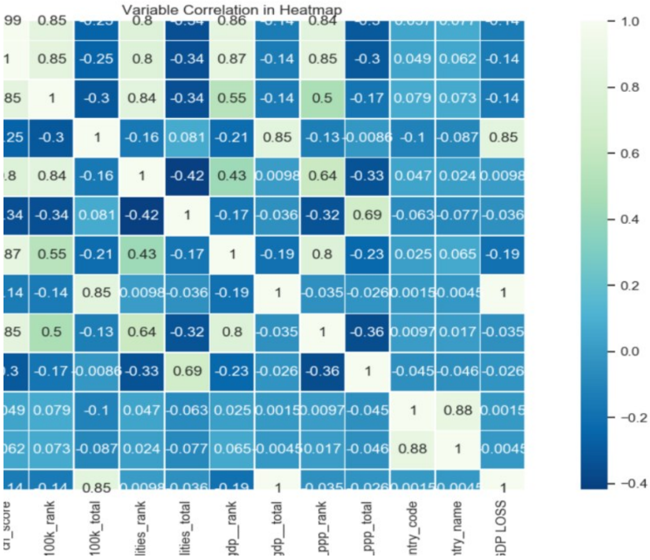
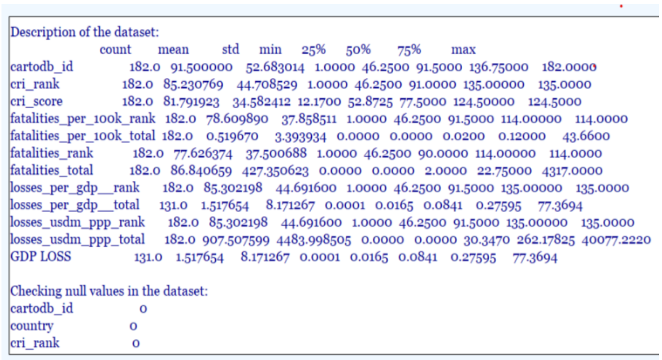


Fig. 2: Exploratory Data Analysis (EDA) Plots

The figure 2 presents various EDA visualizations generated to understand the dataset's distribution and relationships. Histograms, box plots, and scatter plots illustrate the spread of different features, identifying patterns, correlations, and outliers. Feature distributions of GDP loss, fatalities per 100k, andtotal losses are visualized to observe trends and potential predictors for economic loss estimation.



Description of the dataset:

	count	mean	std	min	25%	50%	75%	max
cartodb_id	182.0	91.500000	52.683014	1.0000	46.2500	91.5000	136.75000	182.0000
cri_rank	182.0	85.230769	44.708529	1.0000	46.2500	91.0000	135.00000	135.0000
cri_score	182.0	81.791923	34.582412	12.1700	52.8725	77.5000	124.50000	124.5000
fatalities_per_100k_rank	182.0	78.609890	37.858511	1.0000	46.2500	91.5000	114.00000	114.0000
fatalities_per_100k_total	182.0	0.519670	3.393934	0.0000	0.0000	0.0200	0.12000	43.6600
fatalities_rank	182.0	77.626374	37.500688	1.0000	46.2500	90.0000	114.00000	114.0000
fatalities_total	182.0	86.840659	427.350623	0.0000	0.0000	2.0000	22.75000	4317.0000
losses_per_gdp__rank	182.0	85.302198	44.691600	1.0000	46.2500	91.5000	135.00000	135.0000
losses_per_gdp__total	131.0	1.517654	8.171267	0.0001	0.0165	0.0841	0.27595	77.3694
losses_usdm_ppp_rank	182.0	85.302198	44.691600	1.0000	46.2500	91.5000	135.00000	135.0000
losses_usdm_ppp_total	182.0	907.507599	4483.998505	0.0000	0.0000	30.3470	262.17825	40077.2220
GDP LOSS	131.0	1.517654	8.171267	0.0001	0.0165	0.0841	0.27595	77.3694

Checking null values in the dataset:

cartodb_id	0
country	0
cri_rank	0

Fig. 3: Data Preprocessing in the GUI

The figure 3 showcases the preprocessing steps applied to the dataset. Missing values are handled, categorical variables are encoded, and numerical features are normalized to optimize model performance. The interface highlights transformations like outlier detection, feature scaling, and data balancing to improve prediction accuracy. The pre-processed dataset is displayed before feeding it into the machine learning models.

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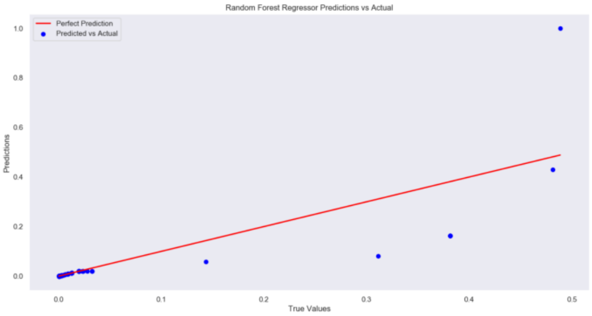

Fig. 4: Performance Metrics and Regression Scatter Plot – Random Forest Regressor

The figure 4 provides a detailed evaluation of the *Random Forest Regressor* model. The scatter plot visualizes actual vs. predicted values, indicating the model's effectiveness in estimating *GDP loss*. The performance metrics reveal:

- **Mean Absolute Error (MAE):** 0.0103
- **Mean Squared Error (MSE):** 0.0028
- **Root Mean Squared Error (RMSE):** 0.0531
- **R-squared (R^2):** 0.5400

Model Predicted value in test data:

	cri_rank	cri_score	fatalities_per_100k_rank	...	rw_country_code	rw_country_name	Predicted
0	79	72.50	18	...	2	2	0.002683
1	61	61.50	112	...	1	1	0.030875
2	69	66.33	74	...	0	7	-0.024467
3	135	124.50	114	...	6	4	0.032671
4	133	117.33	114	...	5	6	0.018283
5	102	88.50	42	...	3	3	0.021453
6	33	45.67	84	...	7	5	-0.015342
7	83	75.50	114	...	4	0	-0.020239

[8 rows x 13 columns]

Fig. 6: Model Prediction on Test Data

5. CONCLUSION

The research successfully develops an AI-driven approach to estimating the economic impact of climate change on various industries using machine learning techniques. The dataset is processed to extract meaningful insights, and two predictive models—Random Forest Regressor (existing) and RNN Regressor (proposed)—are implemented for estimating GDP loss due to climate-related factors. The comparative analysis highlights the efficiency of deep learning-based regression in capturing complex dependencies between climate risk indicators and economic losses. The proposed RNN model demonstrates improved predictive accuracy compared to the traditional Random Forest Regressor, showcasing the potential of deep learning in economic impact forecasting.

The results emphasize the significance of data-driven approaches in understanding climate change consequences. The insights derived from this study can assist policymakers, economists, and environmental agencies in devising strategies to mitigate economic losses and improve disaster preparedness. The research also highlights the necessity of incorporating more advanced AI models for better predictive performance in climate-related risk assessments.

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