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AI-Driven Carbon Emissions Tracking and Mitigation Model

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Abstract: Climate change has become an urgent and all-encompassing concern, demanding an immediate and thorough response. In climate change mitigation, innovations and technological developments play a pivotal role in supporting sustainable practices. However, there is a scarcity of artificial intelligence innovations capable of integrating multiple mitigation strategies into a comprehensive model for tracking, educating, and mitigating climate change. This paper introduces a state-of-the-art AI-driven Carbon Emission Tracking and Mitigation Model which encompasses forecasting emissions based on user prompts, presenting descriptive scenarios to explain various climate change situations, and recommending mitigation strategies through Artificial Intelligence Large Language Models (LLMs).The model facilitates trace surveillance through drones and sensors, ensuring a thorough monitoring of emissions with real-time reporting to relevant authorities. This artificial intelligence model employs a machine learning algorithm that relies on the ARIMA model for forecasting, achieving an impressive accuracy rate of 97%. Finally, a system prototype was development serving as a tangible proof of concept for the proposed ideas contributing to a more sustainable world.

Keywords: Global warming, Climate change, Carbon Emissions, Carbon Footprint, Predictive Model, Large Language Models.

1. Introduction

Climate change, also known as global warming, is the change or shift in both weather and climate patterns of the world. This is caused by greenhouse gases that are emitted by either natural sources such as volcanoes and wildfires or human activities such as burning fossil fuels [1]. Climate change has become a general concern that requires an urgent response and needs to be addressed. It has numerous causes, with carbon emissions constituting a significant percentage of these factors. The emission of carbon, particularly in the form of carbon dioxide, is the main contributor to climate change through the greenhouse effect - the trapping of heat from the sun in the Earth's atmosphere, leading to global warming [2]. The effects and impact of global warming and climate change have been mostly negative rather than positive, spreading across various sectors, locations, and areas. The following have been adversely affected by climate change: crops affected by rising heat and global warmth, rising sea levels displacing people, increased need for energy for cooling and cooking, infectious diseases, extinction of some species, etc. In summary, climate change has adversely affected economies, renewable energy supplies, soil and seas, land use, and the psychology of both children and adults. This depicts that climate change continues to be a global concern, as it is evident from shifting weather patterns to affecting social and economic lifestyles [3]. Amazingly, Africa is a low contributor to greenhouse gases. Unfortunately, it is currently witnessing serious issues such as diseases [4], droughts [5], flash floods, hurricanes and forest fires, and locust outbreaks [6] and with the poverty in

Africa, it is rest assured that it is terrible.

The developed countries, commonly known as the G7 and BRICS, have been major contributors to greenhouse gases that accelerate climate change [7].

However, these countries have also been champions for mitigation strategies through various conferences and protocols geared towards establishing standards to be followed by them, ensuring sustainable development. Among some agreements are commitments to emission targets in the Paris Agreement, Kyoto Protocol, and the Bali Protocol for Africa [8]. Innovations are emerging to mitigate climate change such as circular economies, green innovations, and better farming practices are being promoted. However, there is also a limited number of artificial intelligence models and systems for the same purpose. This paper fully recognizes this gap and the challenges posed by climate change, delving deep to provide ways of mitigating carbon emissions urgently. It highlights the use of cutting-edge technological tools like the ones used in [9]. The AI-driven Carbon Emission Tracking and Mitigation System started as a key innovation, providing a dynamic and integrated approach to monitor, analyze, and mitigate carbon emissions. This paper will therefore endeavor to address the following objectives:

- To review climate change literature and evaluate AI technologies for carbon emission tracking and monitoring
- Propose an AI-driven carbon emission tracking and mitigation model.
- To develop an AI-driven carbon emission tracking and mitigation system

1.1 Related work

According to [10], the use of Artificial Intelligence (AI) in mitigating climate change should be pursued since it has been noted that AI has been used to effectively manage energy, and improve emission control in sectors such as transportation, agriculture and the industry. They reviewed a few algorithms but there was no model or system developed to test those algorithms. For accuracy and timely evaluation and assessment of climate data, [11] proposed an AI-driven multi-emission decision tree model that could ensure classifications were done accurately. Their system is meant to spur positive advancement in policy for the better management of the environment. They also did not develop a proof of concept for their model. The digital economy through the power of AI was proposed to help companies face climate damage on their properties hence disrupting the operations of business, therefore, [12] proposed an AI approach that could help mitigate the carbon problem by ensuring that they embrace digital economy transformations.

1.2 Proposed AI-enabled Systems

The existing systems have made efforts to curb the challenges posed by climate change. However, what makes our model and system outstanding is its thorough utilization of AI technologies (machine learning algorithms and natural language processing), the system can adapt and learn from real-time data, providing a more proactive approach to the monitoring, tracking, and mitigation of carbon emissions. The system offers both descriptive and prescriptive insights to help address the challenges posed by climate change. With a better understanding of the impacts and challenges that come with climate change, it becomes clear that a multi-dimensional approach is worth as it in this case [9]. This paper brings out the idea of the pivotal role of advanced technologies, specifically AI, in handling this issue. By incorporating predictive analytics, Large Language Models (LLMs), and innovative strategies, the proposed model aims to not only forecast emissions but also provide recommended actions for effective mitigation, all generated by the LLMs [13]. As such, the target audience extends beyond the technical community to include policymakers, environmental agencies, businesses, various international bodies, and the general public [14]. The AI-driven system catalyzes informed decision-making, promoting sustainability across various sectors. This provides collaborative morale in efforts to curb climate change.

2. Components of the Carbon Tracking and Mitigation Model

Our carbon tracking and mitigation model (Figure 1) is a comprehensive system that integrates various concepts to deliver a model that can provide various solutions in the climate change domain. The model takes advantage of LLMs that are utilized in generating textual scenarios and comments thereby helping in educating the users on various aspects of climate change and mitigation measures in various domains. The inclusion of the Contrastive Language-Image Pretraining (CLIP) enhances the model's capability of identifying images and giving insightful comments that are sustainable and directed towards conserving the environment. A time series model known as the Autoregressive Integrated Moving Average (ARIMA) model is accurate in predicting and measuring events that happen over a period of time. This is very helpful as it is used in the case of predicting the future in the context of climate change and warnings [15]. The integration of computer vision and augmented reality further makes video scanning thereby implying that it can be used by drones to scan the environment (Figure 2). The model further makes use of SMS and Email APIs for the sake of communicating strategies for conserving the environment such as carpooling and shift to green practices. The subsections below explain in detail the components of our model.

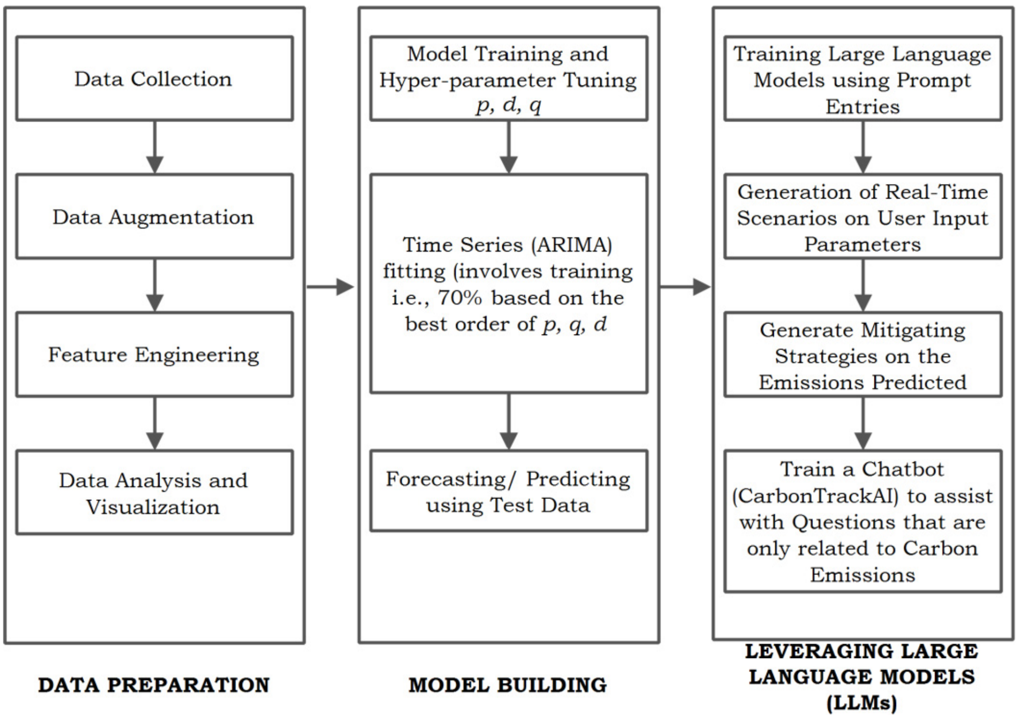


Figure 1: Carbon tracking and mitigation model with LLMs

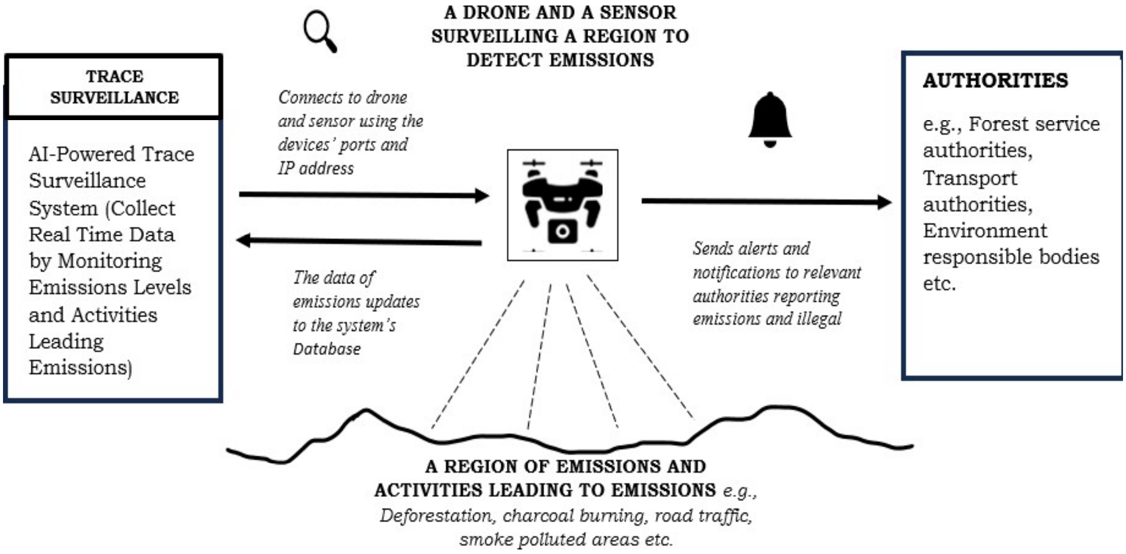


Figure 2: Trace Surveillance.

2.1 Data Collection and Preprocessing

The initial phase of our model involved gathering historical emissions datasets, capturing emissions from 1994 – 2020, from a standard dataset repository or provider known as Climate Watch[1] dataset [16]. The data includes columns i.e. ISO, Country, Data Source, Gas, Unit and Years which horizontally represented the CO2 emissions. The dataset was vertically restructured, having some features dropped, into columns of Year, Country, Sector and CO2 emissions. This data was prepared for processing based on the specific requirements. In this case, we were interested with Kenyan data which we augmented and refined to derive comprehensive carbon emissions insights tailored to the context of Kenya. Feature engineering ensured that we only use the features that we need and to ensure that the data was ready for training we visualized to ensure that there are no outliers and missing data. The Features selected were number of years and Sectors. The target Variable in this case is CO2 Emissions. The data preparation phase also known as the data processing phase ensures that data is clean and ready to be used for model training. Pre-processing ensures the accuracy and consistency of the model. The data is analyzed based on Land-Use Change and Forestry as in Figure 3 and Figure 4.

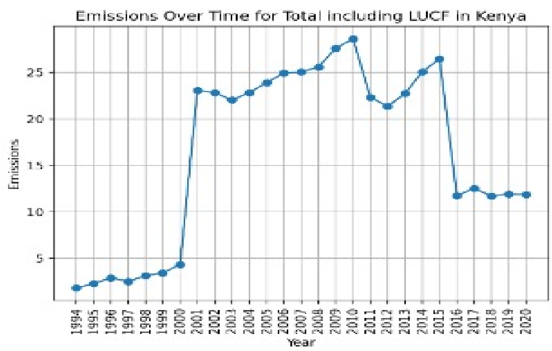


Figure 3: Emissions Over Time for Total including LUCF

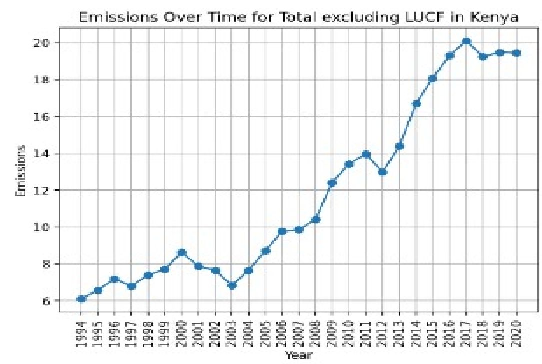


Figure 4: Emissions Over Time for Total Excluding LUCF

2.2 Model Development and Training

To train a predictive model capable of forecasting future emissions, the time series analysis algorithm known as the Autoregressive Integrated Moving Average (ARIMA) model was

[1] Climate Watch (CAIT): Country Greenhouse Gas Emissions Data | World Resources Institute (wri.org)

used to enable the model to discern patterns and trends crucial for accurate predictions. This is because the ARIMA algorithm is easy to implement and interpret and very popular in predicting time series and online data [17, 18]. Each component in ARIMA function are parameters with standard annotation. The parameters *p, q* and *d* are integer values which play a significant role in the forecasting process. The parameter values vary for all the sectors in the dataset. The model development involves developing the ARIMA model i.e. splitting the data into testing and training data, training the model and make one step prediction. The process of training and evaluation is automated by a combination of model hyperparameters. To fine tune the model, the ARIMA parameters are iterated by specifying a grid of p, q and d also known as the Grid Searching method. Below is a sample practical Use Case in the modeling process for the AI-Driven Carbon Emissions Tracking and mitigation Framework:

```
p_values = range (0,7)
q_values = range (0,7)
d_values = range (0,7)
best_score, best_order = float("inf"), None
traine_size = int(0.8 * len(sector_df))
train, test = sector_df[:train_size], sector_df[train_size]
for p in p_values:
    for d in d_values:
        for q in q_values:
            order = (p, d, q)
            model = ARIMA(train['CO2 Emissions'], order = order)
            forecast = model_fit.forecast(steps=len(test))
            rmse = sqrt(mean_squared_error(test['CO2 Emissions'], forecast))
            if rmse < best_score:
            best_order, best_score = order, rmse
if best_order is not None:
    final_model = ARIMA (sector_df ['CO2 Emissions'], order=best_order)
    final_model = final_model.fit()
    forecast = final_model_fit.forecast(steps=forecast_years)
```

2.3 Predictive Model with the LLM Technologies

The trained model was integrated with cutting-edge AI capabilities, particularly a Large Language Model (LLM). The development of the utilized LLM is in phases of OpenAI API key integration and configuration. This fusion empowered the system to generate diverse scenarios for future emissions. Leveraging the LLM, the system explains the causal factors contributing to projected emission increases or declines. Furthermore, it outlines potential mitigation strategies that can be used to curb the rising emissions [19]. This involves training the LLM with series of prompts and Keywords which intern generates scenarios, reason for rise or fall of emissions and the mitigating strategies.

2.4 User Interface Development

An intuitive and user-friendly interface was developed utilizing Stream-lit and a mobile application. These interfaces serve as the interactive platform through which stakeholders and users can access the insights generated by the system. Seamlessly integrating the pre-trained model with this interface facilitated accessible and comprehensive visualization of forecasts, scenarios, and recommended mitigation approaches.

3. Development of the Carbon Mitigation System – Proof of Concept

The development of this system involves a multi-faceted approach. It involves the use and integration of various advanced technologies and innovative tools. The cutting-edge tools used include predictive analytics, Artificial intelligence i.e., the Large Language models (LLMs), computer vision and augmented reality, SMS and Email APIs, and the Contrastive Language- image pretraining (CLIP). With all these tools integrated, the system was envisioned to provide a dynamic platform for monitoring, tracking, analyzing and mitigating carbon emissions.

3.1 Predictive Analytics Integration

This involves the development of a machine learning model that highly utilizes the ARIMA model for forecasting. From data collection to an accurate forecasting model, the process involves feature engineering selecting carbon emissions as the target variables and years and sectors as categorical variables. The model is then fine-tuned (i.e., hyper-parameter tuning) to improve the accuracy. The prediction can contribute to effective decision-making in carbon emissions mitigation

3.2 Large Language Models (LLMs) implementation

The AI is integrated into the Large Language Models (LLMs), which allows the system to process vast amounts of textual and contextual data. In this case, it provides insightful recommendations for mitigating emissions. It allows for a deep understanding of complex scenarios related to climate change. *CarbonTrackAI*, a mini-AI chatbot that was developed to answers questions that are only related to carbon emissions using Natural Language Processing capabilities. It is trained on carbon emissions vocabularies making it oriented to its goal. The AI-developed assistant tool can also accept voice inputs and give text-to-speech responses.

3.3 Computer vision, augmented reality, Contrast language-image pretraining integration

The system enables the scanning of objects and the environment by uploading an image of the emissions environment or capturing it through the camera. Drones use computer vision to trace surveillance and report to relevant authorities by sending SMS and email alerts (Figure 2).

3.4 Innovative Mitigation Strategies

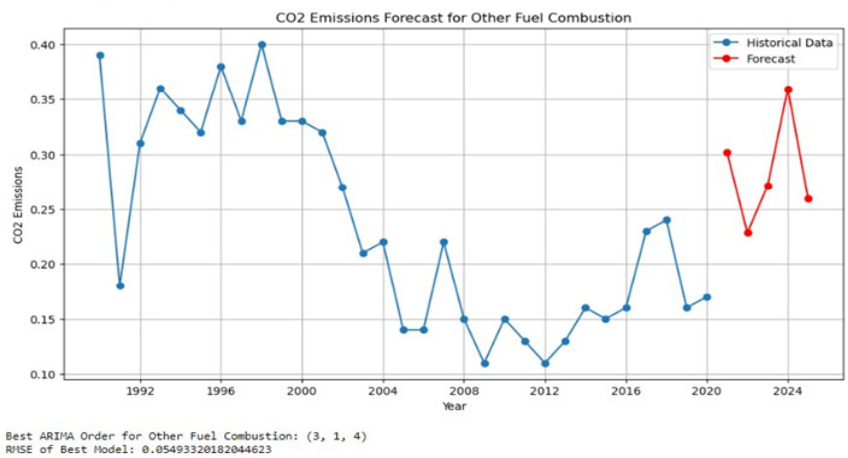
This system goes beyond the conventional approaches by combining data-driven insights with AI-generated recommendations. The system provides actionable measures to address specific sources of carbon emissions. This forward-looking approach aims to foster sustainability and resilience to challenges posed by climate change.

3.5 Business Case and Industrial Benefit

Accurate monitoring and analysis provide a competitive advantage leading to growth of demand for innovative solutions to monitor and reduce carbon emissions. The system will also help to capture environmental impact reduction, operational efficiency, cost saving, brand reputation and cooperate social responsibility.

4. Results and Discussion

When data from 1992 to 2020 was input into our model, the algorithm made predictions as indicated in Figure 5. The blue line represents the historical dataset for that period, while the red line signifies the prediction, suggesting that the levels of emissions will rise higher. The RMSE of the model was 0.05493320, and we are actively working to enhance its prediction accuracy upwards from 97.041%. The graph only represents other fuel combustion sector showing the best ARIMA order and best score in RMSE for the Other Fuel Combustion Sector.



The target variable, "CO_2 Emissions" has small range (0.40 as maximum and 0.12 as minimum Emissions for Other Fuel Combustion as one of the sectors). In this case the Root Mean Squared Error of 0.05493 stands to below with a R^2 of 0.97041 i.e., 97.041% accuracy.

Figure 5: CO2 Emissions Forecast for Other Fuel Combustion

5. Conclusions

In the midst of devastating climate change, the speed at which governments are attempting to implement solutions to mitigate climate change is slow. Therefore, there is a need to develop intelligent solutions that will help humanity quickly avert the looming crisis posed by climate change. It is on this strength that we have focused our efforts. This paper presents a model that utilizes a Large Language Model and machine learning technologies for carbon emission tracking and mitigation. The model enhances government decision-making by prioritizing high-impact areas through predictive analytics, leading to more efficient resource allocation for emission reduction. Policymakers benefit from data-driven insights, aiding in the formulation of effective environmental policies, while the community gains awareness and encouragement for sustainable practices through accessible information about carbon emissions. Accurate monitoring and analysis of the model provide a competitive advantage in the business and environmental space leading to growth of demand for innovative solutions to carb problems faced by the globe, monitor and reduce carbon emissions in particular. The model helps to capture environmental impact reduction, operational efficiency, cost saving, brand reputation and cooperate social responsibility. Besides all the benefits of the model, the LLM and Time series model requires much time to execute and run compared to other systems that are not Time Series based. Future iterations of our system might explore sentiment analysis techniques to monitor public attitudes and opinions on sustainability initiatives at the province level, in addition to these innovative capabilities. This approach acknowledges the socio-cultural environment in which these strategies are applied, which promotes sustainability and resilience.

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