Chemotronix: IOT device enabled with AI for carbon reduction

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Abstract

Energy is a crucial need for the world. We all need energy to carry out activities as individuals, organizations, etc. The Oil and Gas Industry has been the major supplier of energy for years, which has been a major source of carbon emissions. There is an urgent need to decarbonize the energy sector especially concerning sources of fossil fuels. The development of energy sources is essential for agriculture, transportation, waste collection, information technology, communications etc. Reducing the amount of carbon dioxide in the atmosphere is critical for achieving the aims of the Paris Agreement produced at COP21, keeping a global temperature rise well below 2˚C this century, and driving efforts of a 1.5˚C limit above pre-industrial levels. But much of the damage already has been done; seasonally adjusted concentrations of carbon dioxide in Earth's atmosphere have risen dramatically in the past half-century and continue to creep upward. Carbon dioxide has become a major business liability, decreasing a firm's value by $212,000 for every 1,000 metric tons produced, according to KPMG.

Introduction

The energy sector contributes about 40% of global emissions of CO2. Three-quarters of those emissions come from six major economies of the world. Although coal-fired plants account for just 40% of world energy production, they were responsible for more than 70% of energy-sector emissions in 2010. Despite improvements in some countries, the global CO2 emission factor for energy generation has hardly changed over the last 20 years. Nigeria has experienced a 271% increase in Greenhouse Gas emission, CO2 emission makes a vast majority (75%) of Greenhouse Gas emissions.

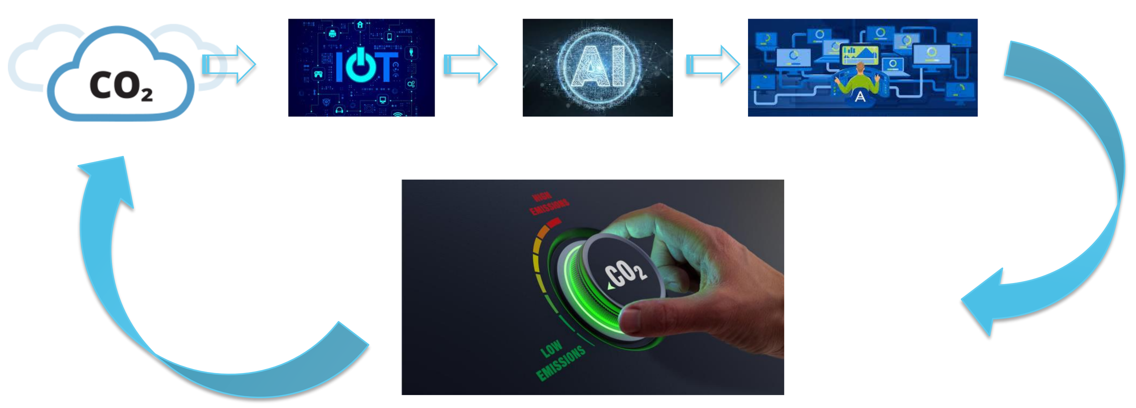
We discovered Nigeria does not have a comprehensive dataset available, so we built an IoT device enabled with AI to monitor and predict carbon emissions which can be deployed anywhere. Our solution would help individuals, organizations and the government to monitor carbon emissions since they will have access to real time data. This data would guide in decision making regarding solutions to be deployed such as planting of trees, use of Carbon Capture and Storage depending on the resources available and the most appropriate as the case may be.

AI would help to predict emissions at various locations and for future dates based on the data available. This would help in making quality decisions.

Methodology.

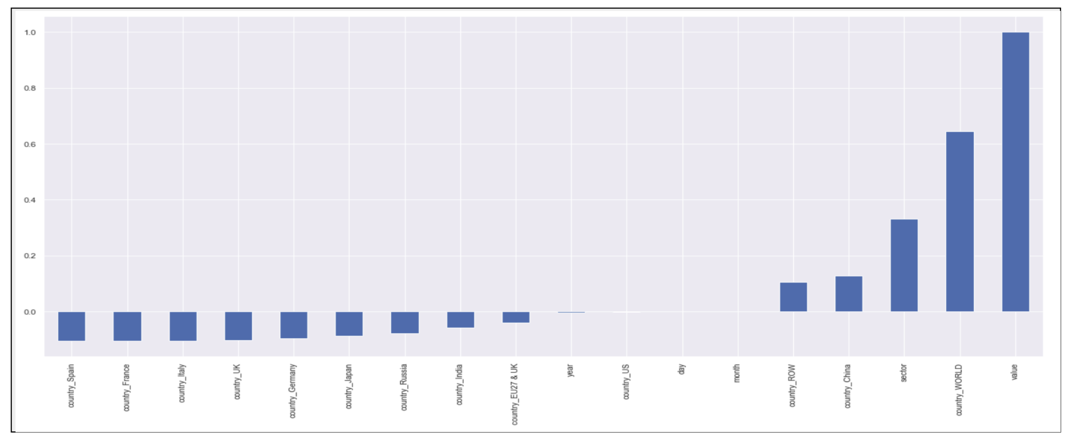
Our methodology is quite simple, it entails:

- Detecting Co2 emissions via IoT sensing device.
- Passing Detections through A.I model
- Predict when and where emissions will be massive
- Deploy carbon capture options based on predictions.



Data Pre-processing.

The dataset used to create the initial A.I model was fetched from carbonmonitor.org. The datasets consist of four columns which include; date, country, sector, timestamp, and respective carbon concentration values.
During preprocessing, the timestamp column was deleted, the sector column was encoded according to their mean value(carbon emissions), three new columns were created from the date column which includes; day, month and year. The date column itself was dropped. The country column was label encoded with numerical values using the one-hot-encoding scheme.



On correlating the features, we found statistically, that the sector where emissions are recorded has a strong correlation to the concentration of carbon.

Modelling

To create an A.I model for this problem, we used the CatBoost algorithm which is a gradient boosting on decision trees. We also used grid-search, a sklearn library to choose the best hyperparameters for the model. We used a max_depth of 10, and a learning rate of 0.1. The model was trained under 100 iterations.

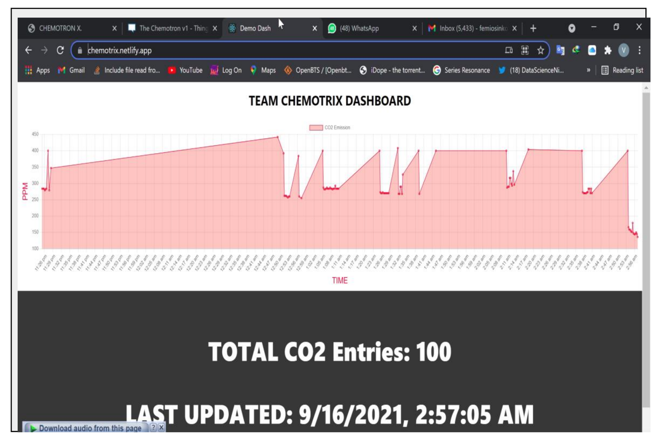
Adedayo19/Chemotronix: A Machine Learning model that predicts CO2 emissions values for a specified place and time (github.com)

Results

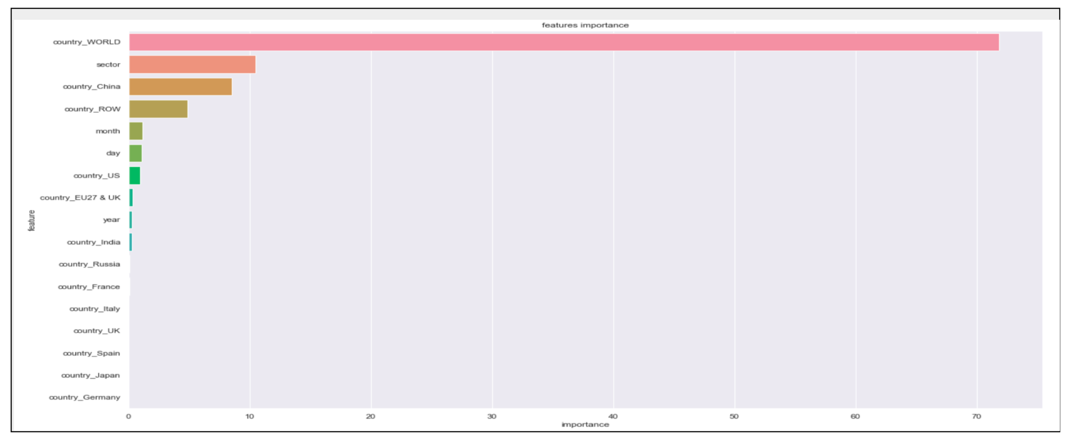
To analyze and score the model, we used root mean square error which measures the differences between values predicted by the model or an estimator and the values observed. We had a root mean square error (RMSE) of 0.44 on our validation set. The average runtime for each is 0.0328 seconds.

The data was also tested on some unseen data taken out of the original dataset initially. The model returned values with a 0.1 change in root mean square error.

The Latency of the model is precisely 7.02 seconds, therefore the throughput of the model caught up to be 0.14 per second.



Readings of IoT fetched via API endpoints created for public use.



From the model, we were also able to determine the most important features driving the predictions of the A.I model.

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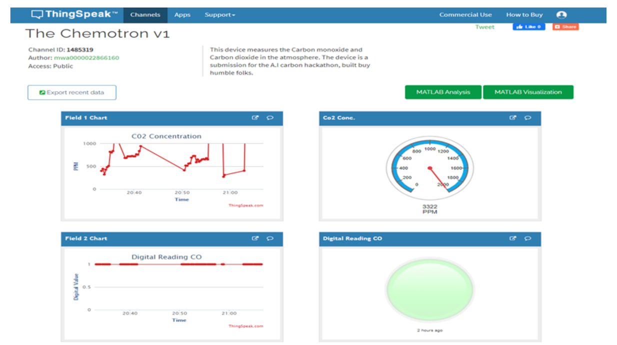
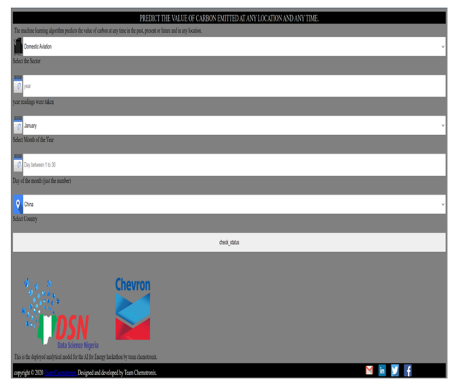
Deliverables

Here are the deliverables we've worked on thus far to complete the pipeline from detection to prediction.

1. IoT device sensing carbon concentration



2. Admin dashboard for visualization



3. Deployed A.I model making predictions.

Conclusion

The backbone cyclic methodology which we've described in this poster is the A.I model, as it influences the efficiency of the carbon reduction strategy. This means that more local data need to be collected to build A.I algorithms that predict more accurately.

Deployment

The link to the deployed A.I model is:
https://chemotron-x.herokuapp.com/

Link to public admin dashboard for the IoT device:
https://thingspeak.com/channels/1485319

References

1. Carbon monitor
2. Artificial Intelligence Has an Enormous Carbon Footprint | by Emil Walleser | Towards Data Science
3. The Role of Digitalization in Decarbonizing the Oil and Gas Industry | SPE Nigeria Annual International Conference and Exhibition | OnePetro