CARBON FOOTPRINT MONITORING SYSTEM

USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

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Abstract

India is one of the world's largest producers of greenhouse gases (GHGs), and its emissions are projected to continue to grow in the forthcoming years. The country is susceptible to climate change's effects, which include rising sea levels, more frequent and severe extreme weather events, and food and water scarcity. By following the carbon footprint, India can take action to lower its GHG emissions and lessen the effects of climate change by paying attention to its carbon footprint. In comparison to 2005 levels, the nation wants to reduce its carbon GHG emission (the amount of CO2e per unit of GDP) to 33–35% before 2030. This goal is part of India's commitment to the Paris Agreement, which seeks to keep the rise of temperature worldwide to less than 20C above pre-industrial levels. To overcome this problem, the emission of greenhouse gases is calculated and analyzed using Machine Learning Models. To monitor the real-time environment, we profound an IoT device to capture the real-time data in the nearby locality and predict the GHG emission using the Birch and LSTM model. The model shows the emission of greenhouse gases in the current scenario and also predicts the future environment.

Keywords: Carbon Footprint, Carbon Footprint Monitoring System, Air Quality Index, AQI Bucket, Machine learning, Deep Learning, Birch Clustering, LSTM

I. INTRODUCTION

The temperature and biosphere of the Earth are significantly impacted by greenhouse gases. These gases trap heat from the sun when they are released into the atmosphere, raising the temperature of the Planet. The greenhouse effect, which keeps the earth warm enough for us to survive, is a phenomenon that is vital to supporting life on Earth. Yet, due to human activities like deforestation, industrial operations, and burning fossil fuels for electricity and transportation, the concentration of greenhouse gases in the atmosphere has increased dramatically, enhancing the greenhouse effect. As a result, the world's temperatures have increased, melting ice caps and raising sea levels, among other effects.

Carbon dioxide (CO2), Methane (CH4), Nitrous oxide (N2O), and fluorinated gases are the primary greenhouse gases. CO2 is the most significant

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contributor to the enhanced greenhouse effect and is primarily released through the burning of fossil fuels like coal, oil, and natural gas. Methane is emitted through agricultural activities like livestock farming and rice cultivation, while N2O is released from fertilizers and industrial processes. This GHG emission leads to the concept of Carbon Footprint.

Carbon footprint is a method to calculate the greenhouse gas (GHG) emissions associated with an entity's activities. Carbon footprint measurement involves estimating the amount of GHG emissions (primarily carbon dioxide, but also including other GHGs such as methane and nitrous oxide) that are released as a result of an entity's activities. Many governments and organizations are implementing carbon reduction policies and initiatives, and carbon footprint monitoring systems can play a key role in helping to achieve these goals. By providing accurate and reliable information about greenhouse gas emissions, these systems can enable individuals and organizations to make informed decisions about reducing their environmental impact and working towards a more sustainable future.

There are many calculators to calculate the amount of carbon footprint. These calculators take the user input and process output. There are set of questions available in the applications and the user has to manually feed the input. The questions may include the usage of electricity, transport, food, etc. By using these applications, users can calculate their carbon footprint level for a particular period (year, month). The drawback of these calculators only focuses on user input, our proposed model focuses on the atmospheric gases for a particular place and calculates the carbon footprint. The real-time data will be taken from the IoT device and then the analysis will take place using Supervised and Un-Supervised Techniques. This model helps to create awareness and helps to minimize GHG emissions.

II. SCOPES OF CARBON FOOTPRINT

The scopes of carbon footprint refer to the different categories of emissions that contribute to an entity's total carbon footprint. There are three main scopes of carbon footprint:

- ***Scope 1:*** Direct emissions from an entity's activities, such as emissions from burning fossil fuels for heat or transportation.
- ***Scope 2:*** Indirect emissions produced by the entity's use of purchased electricity, steam, or heat. These emissions are generated by the power plants that generate the electricity or heat that the entity consumes.
- ***Scope 3:*** Indirect emissions from an entity's value chain, including the production of goods and services, transportation of goods and people, waste management, and use of sold products. These emissions are often the largest and most challenging to calculate, as they include emissions from suppliers, customers, and other stakeholders.

We are concentrating on the Scope 1 emission. The implementation of a carbon footprint monitoring system for Scope 1 emissions can provide organizations with valuable insights into their direct greenhouse gas emissions. By accurately measuring and tracking these emissions over time, organizations can identify areas where emissions can be reduced and develop strategies to achieve emissions reductions.

III. LITERATURE REVIEW

[1] The Mau carbon footprint calculator using Android is developed by Girish Bekaroo. The user has to create a profile in this app. The user gives input for the questions asked by this app. After all the questions were answered we will get the percentage of the carbon footprint value by a single person. The authors gave the options to calculate the carbon footprint for a particular period.

[2] R. Rahul et al studied carbon footprint in their college. They classified the emission of the data into 3 forms: Direct, Indirect, and other indirect emissions. The data from direct emission is obtained by the generator. Electricity and Transportation were the indirect and other indirect sources. They used IPCC for the carbon footprint assessment and obtained the major emission from other indirect sources 10,53,471 CO_2 Kg per annum, contributing 27.89% of the overall factor for carbon emission. From the indirect emission they obtained 5,94,000 CO_2 Kg per annum and direct is 4,82,265 CO_2 Kg per annum.

[3] Dr.M.Newlin Rajkumar et alimplemented an IoT device using Raspberry pi to measure the CO_2 emission from transports, industries, and forest fires. The sensor detects any one of the sources and stores it in the remote server via the GSM module. The result of the atmospheric status will be viewed from a user

application. If the current status is higher than the given range it will alert using a buzzer otherwise it does not provide any action. In this model, we can able to know the variety of factors like temperature, humidity, and smoke range from the source.
[4] Ashish M. Husain et al proposed an IoT device for air quality monitoring. They used gas sensors like MQ-9, MQ-135, and the dust sensor GP2Y1010AU0F. Using this device, we can able to identify the concentration of dust particles in the air. The sensors detect the source and send the data to the Arduino Mega 250 microcontroller. We can able to view the result through a computer or mobile phone. [5] The authors implemented an IoT for detecting greenhouse gases in the wireless sensor network environment. There are two nodes: Transmitter and Receiver node. On the transmitter side, they were used different types of sensors – CO sensor, CH_4 sensor, CO_2 sensor, and temperature sensor along that there used GPS module and the XBee wireless module are connected to a microcontroller. On the receiver side, they used a microcontroller and XBee wireless module. When the source is detected by the sensors, it will send the data to the microcontroller and send the data to the receiver side using the XBee wireless module. From the receiver side, we can able to see the data from the cloud platform. [6] The authors analyzed the air using an IoT device. The author gives the result of the variation in the air. They used MQ 135 sensor, Arduino UNO, Display screen, and Potentiometer. When the smoke is detected by the sensor it sends the range of real-time value to the micro-controller where the author divides the range into 3 categories: If the value is lesser than 80 ppm then it is fresh air, if the value is greater than 80 ppm and lesser than 200 ppm then the air is polluted, if it is greater than 200 ppm then the air is very polluted. The result will be displayed on to display screen according to the level of the ppm from the source.

According to the study, several limitations have been identified,

1. The Carbon footprint can be calculated by using a Carbon Footprint Calculator. The calculators are available in both web & mobile applications. The user has to feed the input corresponding to the questions and then the amount of consumption will be displayed.
2. Greenhouse gases are detected by the IoT device which calculates the range of the input gases. The wireless sensor system helps to detect GHG. In this system, there are two types of nodes: Transmitter and receiver. On the transmitter side, we detect the air through the sensor and send the value to the microcontroller. The microcontroller sends the value to the receiver using an XBee wireless module where we can view the result.
3. The air quality can be calculated by using an IoT device. The IoT device consists of a power supply, sensors, a microcontroller, and a Wi-Fi module. When the sensor detects the source (smoke), it will give the data to the microcontroller in the form of analog data. Then the microcontroller converts the data into digital and sends it to the cloud platform where we can view the range of the air in ppm.

In the existing system, all the above-mentioned issues do not have the feature to calculate the real-time data in the environment.

IV. METHODOLOGY

In the above existing model, the models were only focused on only single GHG gas or measured the air quality but in this proposed model we focused on all the primary greenhouse gases. The gases are sensed by the sensor and send the value to the microcontroller. When the real-time data is fetched, then we will do our further analysis.

Our model helps organizations and individuals understand their emissions and identify areas for improvement. By accurately measuring and monitoring their carbon footprint, they can make informed decisions about reducing their emissions and becoming more sustainable.

The sources were taken from 5 different places Agaram Then, Chromepet, Kundrathur Pallavaram, and Tambaram. When the smoke (source) detects by the different sensors it will give the range of ppm to the microcontroller as analog data. The microcontroller sends the data to the cloud platform via a Wi-Fi module in the form of digital data. The sources can be smoke or gas from a vehicle or industries. The sensors will detect the type of gas and collect their range. If anyone of the sensor didn't detect the gas then it will give the value as '**0 ppm**'. Through the cloud platform, we can able to download real-time data in the form of CSV or Excel for further analysis.

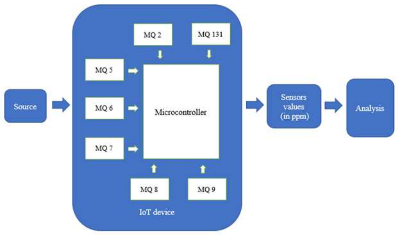


Fig. 1. Flow of work

The Carbon Footprint Monitoring System is created using a variety of approaches and techniques, as detailed below.

A.Setting Up the Hardware

The ESP32 has a single Analog pin, so we attached it to the ESP32 Shield. The different types of sensors are connected to the shield. The Vcc of the MQ – 131 is connected to the 5V Vcc of the shield then the Gnd of the MQ – 131 is connected to the GND of the shield and the Analog pin of the MQ – 131 is connected to the IO13 of the shield. Likewise, connect all the sensors to the shield.

Analog Pin Numbers:

1. MQ – 131 : 13
2. MQ – 5 : 12
3. MQ – 6 : 27
4. MQ – 9 : 04
5. MQ – 7 : 33
6. MQ – 2 : 35
7. MQ – 8 : 34

When all the analog pins are connected, then we can test the kit. The overall power supply of the kit is 5V so the power from the laptop or computer to start the connection.

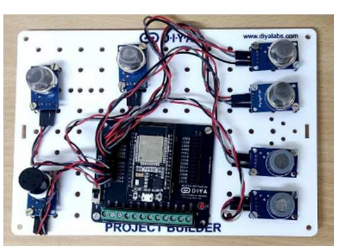


Fig. 2. Hardware Setup

After getting the data from the IoT kit, we convert the data into a CSV file as shown below:

Location	Date	Time	CO2	CH4	CO	H	N2O	O3	CFC
Chromepet	23/03/2023	09.12.11	36	81	19	17	13	19	0
Chromepet	23/03/2023	09.12.12	50	100	15	27	13	20	0
Chromepet	23/03/2023	09.12.13	66	114	23	28	18	35	1
Chromepet	23/03/2023	09.12.14	81	125	27	21	22	50	1
Chromepet	23/03/2023	09.12.15	75	103	51	39	24	54	0
Chromepet	23/03/2023	09.12.16	89	141	37	29	19	41	0
Chromepet	23/03/2023	09.12.17	74	126	21	26	9	44	0
Chromepet	23/03/2023	09.12.18	68	121	25	29	15	50	0
Chromepet	23/03/2023	09.12.19	63	128	23	25	12	39	0
Chromepet	23/03/2023	09.12.20	69	127	23	26	11	31	0
Chromepet	23/03/2023	09.12.21	77	139	25	29	14	39	0
Chromepet	23/03/2023	09.12.22	76	125	15	24	14	37	0
Chromepet	23/03/2023	09.12.23	80	111	15	27	12	31	0
Chromepet	23/03/2023	09.12.24	71	151	17	26	14	35	0
Chromepet	23/03/2023	09.12.25	102	155	21	25	14	41	0
Chromepet	23/03/2023	09.12.26	108	174	34	27	18	51	0
Chromepet	23/03/2023	09.12.27	106	159	23	32	14	56	0
Chromepet	23/03/2023	09.12.28	104	122	25	31	14	64	0
Chromepet	23/03/2023	09.12.29	107	187	22	31	12	44	0
Chromepet	23/03/2023	09.12.30	137	208	32	29	14	45	0
Chromepet	23/03/2023	09.12.31	147	209	68	30	24	56	0
Chromepet	23/03/2023	09.12.32	148	195	42	30	15	45	0
Chromepet	23/03/2023	09.12.33	153	214	49	59	40	52	1

Fig. 3. Dataset

B.Dataset

The dataset is taken from the IoT device which has 73199 rows x 10 columns. The columns represent different variables that were measured, including Location, Date, Time, CO2, CH4, CO, H, N2O, O3, and CFC. The sources were taken from 5 different places Agaram Then, Chromepet, Kundrathur Pallavaram, and Tambaram. We collected the data for 1 month, and each day we collect the data three times: Morning, Afternoon, and Evening. When the smoke (source) is detected by the different sensors it will give the range of ppm to the microcontroller as analog data. The microcontroller sends the data to the cloud platform via a Wi-Fi module in the form of digital data. The sources can be smoke or gas from a vehicle or industries. The sensors will detect the type of gas and collect their range. If anyone of the sensor didn't detect the gas then it will give the value as '**0**'. Through the cloud platform, we downloaded the real-time data in the form of CSV.

Location: Refers to the area where the data was collected, in this case, it is Chromepet.

- **Date:** Refers to the date when the data was collected, in the format DD/MM/YYYY.
- **Time:** Refers to the time when the data was collected, in the format HH.MM. SS.
- **CO2, CH4, CO, H, N2O, O3, CFC:** Refers to different gases that were measured during the monitoring process. These are all greenhouse gases that can contribute to climate change and affect air quality.

Location	Date	Time	CO2	CH4	CO	H	N2O	O3	CFC
Chromepet	23/03/2023	09.12.11	36	81	19	17	13	19	0
Chromepet	23/03/2023	09.12.12	50	100	15	27	13	20	0
Chromepet	23/03/2023	09.12.13	66	114	23	28	18	35	1
Chromepet	23/03/2023	09.12.14	81	125	27	21	22	50	1
Chromepet	23/03/2023	09.12.15	75	103	51	39	24	54	0
Chromepet	23/03/2023	09.12.16	89	141	37	29	19	41	0
Chromepet	23/03/2023	09.12.17	74	126	21	26	9	44	0
Chromepet	23/03/2023	09.12.18	68	121	25	29	15	50	0
Chromepet	23/03/2023	09.12.19	63	128	23	25	12	39	0
Chromepet	23/03/2023	09.12.20	69	127	23	26	11	31	0
Chromepet	23/03/2023	09.12.21	77	139	25	29	14	39	0
Chromepet	23/03/2023	09.12.22	76	125	15	24	14	37	0
Chromepet	23/03/2023	09.12.23	80	111	15	27	12	31	0
Chromepet	23/03/2023	09.12.24	71	151	17	26	14	35	0
Chromepet	23/03/2023	09.12.25	102	155	21	25	14	41	0
Chromepet	23/03/2023	09.12.26	108	174	34	27	18	51	0
Chromepet	23/03/2023	09.12.27	106	159	23	32	14	56	0
Chromepet	23/03/2023	09.12.28	104	122	25	31	14	64	0
Chromepet	23/03/2023	09.12.29	107	187	22	31	12	44	0
Chromepet	23/03/2023	09.12.30	137	208	32	29	14	45	0
Chromepet	23/03/2023	09.12.31	147	209	68	30	24	56	0
Chromepet	23/03/2023	09.12.32	148	195	42	30	15	45	0
Chromepet	23/03/2023	09.12.33	153	214	49	59	40	52	1

Fig. 4. Initial Dataset

After getting the value from the IoT device, we have to calculate the AQI value for all the rows. AQI (Air Quality Index) is a measure used to assess the air quality of an area. It provides a numerical value to indicate how polluted the air is, and the associated health effects. We calculate the AQI value and the AQI Bucket for the above dataset and add the columns in the dataset. The formula is as per CPCB's (Central Pollution Control Board) official AQI Calculator.

Location	Date	Time	CO2	CH4	CO	H	N2O	O3	CFC	AQI Value	AQI Bucket
Chromepet	23/03/2023	09.12.11	36	81	19	17	13	19	0	84	Satisfactory
Chromepet	23/03/2023	09.12.12	50	100	15	27	13	20	0	104	Moderate
Chromepet	23/03/2023	09.12.13	66	114	23	28	18	35	1	131	Moderate
Chromepet	23/03/2023	09.12.14	81	125	27	21	22	50	1	165	Moderate
Chromepet	23/03/2023	09.12.15	75	103	51	39	24	54	0	176	Moderate
Chromepet	23/03/2023	09.12.16	89	141	37	29	19	41	0	172	Moderate
Chromepet	23/03/2023	09.12.17	74	126	21	26	9	44	0	137	Moderate
Chromepet	23/03/2023	09.12.18	68	121	25	29	15	50	0	131	Moderate
Chromepet	23/03/2023	09.12.19	63	128	23	25	12	39	0	132	Moderate
Chromepet	23/03/2023	09.12.20	69	127	23	26	11	31	0	115	Moderate
Chromepet	23/03/2023	09.12.21	77	139	25	29	14	39	0	151	Moderate
Chromepet	23/03/2023	09.12.22	76	125	15	24	14	37	0	180	Moderate
Chromepet	23/03/2023	09.12.23	80	111	15	27	12	31	0	183	Moderate
Chromepet	23/03/2023	09.12.24	71	151	17	26	14	35	0	193	Moderate
Chromepet	23/03/2023	09.12.25	102	155	21	25	14	41	0	224	Poor
Chromepet	23/03/2023	09.12.26	108	174	34	27	18	51	0	268	Poor
Chromepet	23/03/2023	09.12.27	106	159	23	32	14	56	0	253	Poor
Chromepet	23/03/2023	09.12.28	104	122	25	31	14	64	0	208	Poor
Chromepet	23/03/2023	09.12.29	107	187	22	31	12	44	0	211	Poor
Chromepet	23/03/2023	09.12.30	137	208	32	29	14	45	0	246	Poor
Chromepet	23/03/2023	09.12.31	147	209	68	30	24	56	0	319	Very Poor
Chromepet	23/03/2023	09.12.32	148	195	42	30	15	45	0	317	Very Poor
Chromepet	23/03/2023	09.12.33	153	214	49	59	40	52	1	310	Very Poor

Fig. 5. Dataset after adding AQI value and AQI bucket

The IoT device is used to fetch real-time data from the environment. After getting the data, it is converted into standardized data for further analysis.

V. MACHINE LEARNING ANALYSIS

Fig. 6. Machine learning analysis

For machine learning, we use the Birch algorithm. BIRCH is a scalable clustering technique based on hierarchical clustering that only needs to be scanned once, making it quick when working with big datasets. The CF (clustering features) tree is the foundation for this approach. Additionally, this approach builds clusters using a tree-structured summary. The BIRCH algorithm creates the Clustering feature tree (CF tree), which is a tree structure for the provided data.

A. Dataset

The dataset is collected from our IoT kit which consists of 10 columns, Location, Date, Time, CO2, CH4, CO, H, N2O, O3, and CFC. After calculating the AQI Value and AQI Bucket, the dataset will consist of 12 columns. Initially, the dataset consists of 73199 rows.

B. Preprocessing

- *Removing the Null sets*

Null sets or missing data can significantly impact the analysis and modeling of a dataset. Preprocessing is a crucial step in data analysis, which involves cleaning and preparing the data for further analysis. One of the key objectives of data preprocessing is to handle missing data effectively. Removing the null sets is a common approach in preprocessing to ensure that the dataset is complete and accurate. After removing the null sets, we have 64527 rows and 12 columns.

- *Normalization*

There are different methods of normalization that can be used in the BIRCH clustering algorithm, such as z-score normalization, min-max normalization, and log normalization. The choice of the normalization method depends on the data and the clustering task. The goal of normalization in the BIRCH clustering algorithm is to improve the clustering performance by making the data more suitable for the clustering process.

C. Feature Extraction

Feature extraction in the BIRCH algorithm involves reducing the dimensionality of the data by selecting a subset of the most important features for the clustering process.

D. Birch Model

BIRCH algorithm uses a clustering criterion called CF (Clustering Feature), which is a combination of the feature values and their squared distances to the centroid. In our model, we create 6 clusters based on the 7 different types of gases. We predict the AQI value for each and every element of the gases.

	AQI Bucket
0	2
1	5
2	4
3	4
4	4
5	4

Fig. 7. Predicting the AQI Value

VI. DEEP LEARNING ANALYSIS

Fig. 8. Deep learning analysis

For deep learning analysis, we use the LSTM model. **Long Short-Term Memory (LSTM)** is a type of recurrent neural network (RNN) that is designed to handle long-term dependencies in sequential data. LSTM networks are particularly well-suited for tasks such as speech recognition, natural language processing, and time series prediction.

A. Dataset

The dataset is collected from our IoT kit which consists of 10 columns, Location, Date, Time, CO_2, CH_4, CO, H, N_2O, O_3, and CFC. After calculating the AQI Value and AQI Bucket, the dataset will consist of 12 columns. Initially, the dataset consists of 73199 rows.

B. Preprocessing

- *Removing the Null sets*

Null sets or missing data can significantly impact the analysis and modeling of a dataset. Preprocessing is a crucial step in data analysis, which involves cleaning and preparing the data for further analysis. One of the key objectives of data preprocessing is to handle missing data effectively. Removing the null sets is a common approach in preprocessing to ensure that the dataset is complete and accurate. After removing the null sets, we have 64527 rows and 12 columns.

- *Normalization*

Normalizing the data is an important step in preparing the data for an LSTM program. It can improve convergence, reduce overfitting, speed up training, and improve the performance of the model. Normalization techniques such as min-max scaling normalization are used to normalize the data before feeding it to the LSTM model.

C. Defining The Training and Testing Data

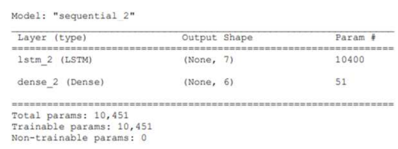
The data is divided into two sets: training data and test data. The training data is used to train the LSTM model, and the test data is used to evaluate the performance of the model. The separation of data into training and test sets is a fundamental aspect of deep learning, which enables the model to learn from the data and make accurate predictions on new and unseen data.

Table 1: Dataset

CATEGORY	TASK	NO. OF DATA
Training Data	Used to train the network	61234
Testing Data	Used to evaluate the final network	3292

D. LSTM Model

The model is defined using the Sequential API in Keras. The first layer added to the model is an LSTM layer with 50 units and a ReLU activation function. The input shape to this layer is a 2D tensor with shape (n_steps, n_features), where n_steps is the number of time steps in the input sequence, and n_features is the number of features in each time step. After the LSTM layer, a Dense layer with six output units is added to the model. This layer uses a linear activation function by default. Finally, the model is compiled with the Adam optimizer, mean squared error (MSE) loss function, and accuracy metric.



```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 7)                 10400

 dense_2 (Dense)             (None, 6)                 51

=================================================================
Total params: 10,451
Trainable params: 10,451
Non-trainable params: 0
_________________________________________________________________
```

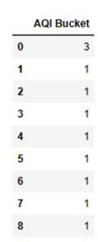
Fig. 9. Model Summary

VII. RESULT AND DISCUSSION

A. Birch model

AQI Bucket Clustering

To group the AQI values into six categories based on the Birch Clustering algorithm, you can see the data is formed into 6 clusters based on their similarity.



	AQI Bucket
0	3
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1

Fig. 9. Predicting the data points

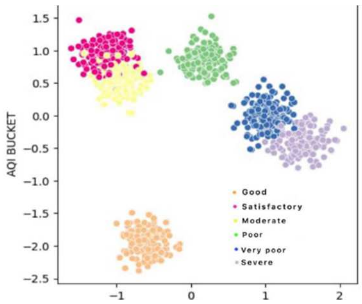


Fig. 10. Categorized into six clusters based on AQI Bucket

The number of data points that occupy each of the six clusters in the Birch algorithm will depend on the specific dataset and the parameters used in the clustering process.

```
Good: 2875
Satisfactory: 18761
Moderate: 17089
Poor: 8989
Very Poor: 7542
Severe: 17944
```

Fig. 11. How many data points are occupied in six clusters

B.LSTM model

Accuracy

The results of the model were also evaluated with the predominant deep learning approaches in the applied methodology has shown significant results with an average training accuracy is 0.6088.

Loss

Loss value measures the dissimilarity between predicted and actual outputs during training. In this model, the average loss for is 0.4349.

Epoch

An epoch refers to one complete pass through the entire training dataset during training. In this model, I used 10 epochs for training the data.

```
Epoch 1/10
1912/1912 [==============================] - 6s 2ms/step - loss: 0.5671 - accuracy: 0.3231 - val loss: 0.7513 - val accurac
y: 0.6088
Epoch 2/10
1912/1912 [==============================] - 4s 2ms/step - loss: 0.5572 - accuracy: 0.3987 - val loss: 0.7048 - val accurac
y: 0.6088
Epoch 3/10
1912/1912 [==============================] - 4s 2ms/step - loss: 0.5423 - accuracy: 0.4360 - val_loss: 0.6542 - val_accurac
y: 0.6088
Epoch 4/10
1912/1912 [==============================] - 4s 2ms/step - loss: 0.5327 - accuracy: 0.4897 - val_loss: 0.6084 - val_accurac
y: 0.6088
Epoch 5/10
1912/1912 [==============================] - 4s 2ms/step - loss: 0.4910 - accuracy: 0.5563 - val_loss: 0.5729 - val_accurac
y: 0.6088
Epoch 6/10
1912/1912 [==============================] - 3s 2ms/step - loss: 0.4956 - accuracy: 0.5238 - val_loss: 0.5183 - val_accurac
y: 0.6088
Epoch 7/10
1912/1912 [==============================] - 4s 2ms/step - loss: 0.4859 - accuracy: 0.5238 - val_loss: 0.5091 - val_accurac
y: 0.6088
Epoch 8/10
1912/1912 [==============================] - 4s 2ms/step - loss: 0.4804 - accuracy: 0.5238 - val loss: 0.4963 - val accurac
y: 0.6088
Epoch 9/10
1912/1912 [==============================] - 4s 2ms/step - loss: 0.4762 - accuracy: 0.5238 - val loss: 0.4489 - val accurac
y: 0.6088
Epoch 10/10
1912/1912 [==============================] - 4s 2ms/step - loss: 0.4762 - accuracy: 0.5238 - val loss: 0.3912 - val accurac
y: 0.6088
```

Fig. 12. Model Epoch

- *Accuracy graph and Loss graph*

ii. *Accuracy*

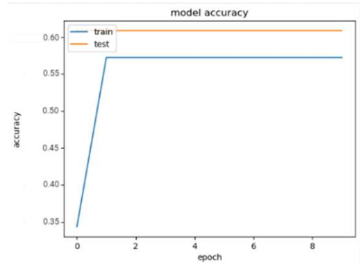


Fig. 13. Model Accuracy

In this graph, the accuracy is calculated based on every epoch cycle of training and testing accuracy.

Table 2: Training and Testing accuracy of the model

NUMBER OF EPOCHS	TRAINING ACCURACY	TESTING ACCURACY
10	0.5238	0.6088

iii. *Loss*

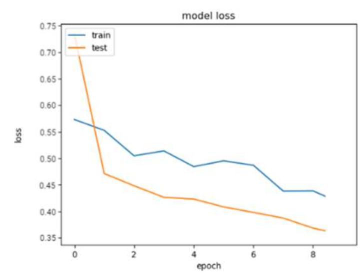


Fig. 14. Model Loss

In this graph, the accuracy is calculated based on every epoch cycle of training and testing accuracy.

Table 3: Training and Testing loss of the model

NUMBER OF EPOCHS	TRAINING LOSS	TESTING LOSS
10	0.4762	0.3912

- *Result of GUI*

In this application, the user is required to select an algorithm and provide gas values obtained from an IoT device. Once the data is entered, the system will predict the appropriate AQI Bucket for the given input.

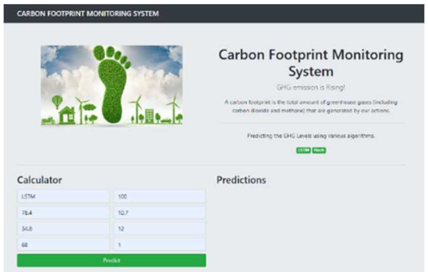


Fig. 15. Data entry

Fig. 16. Output

VIII. COMPARISON

We have developed a carbon footprint monitoring system that leverages both machine learning and deep learning techniques. Specifically, we have used the Birch algorithm for machine learning and the LSTM model for deep learning.

The Birch algorithm is a clustering algorithm that is well-suited for large datasets. It has the advantage of being computationally efficient and memory-efficient, making it a good choice for applications with limited computational resources. In this system, the Birch algorithm has achieved an accuracy of 72%, indicating that it is effective in identifying patterns in the data.

On the other hand, the LSTM model is a deep learning technique that is specifically designed for time-series data, making it an ideal choice for our carbon footprint monitoring system. LSTM models are known for their ability to capture long-term dependencies. In this system, the LSTM model has achieved an accuracy of 60%, indicating that it is effective in predicting future carbon footprint values. Currently, the LSTM algorithm provides lower accuracy compared to the BIRCH algorithm. However, in the future, we will endeavor to enhance the accuracy of LSTM.

Overall, our carbon footprint monitoring system is a powerful tool for organizations to track their carbon emissions and identify areas for improvement.

```
Accuracy score of Birch Algorithm is 0.7289410220030839
```

Fig. 17. Accuracy score – Birch Algorithm

```
Accuracy score of LSTM Algorithm is 0.60880280
```

Fig. 18. Accuracy score – LSTM Algorithm

IX. CONCLUSION

The model has a significant impact on lowering greenhouse gas emissions and lessening the effects of climate change. By providing real-time data on carbon emissions, businesses and individuals can make informed decisions about reducing their environmental impact. The carbon footprint monitoring system consists of sensors, data analytics software, and user interfaces that allow for the collection, processing, and visualization of carbon footprint data. In order to track their carbon emissions and pinpoint areas for improvement, a variety of businesses, including transportation, industry, and agricultural, can employ these systems.

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