Harnessing Earth Observations for Climate Change Mitigation:

A Comparative Analysis and Recommendations

MCA(Master in Computer Application)

LOVELY PROFESSIONAL UNIVERSITYPHAGWARA, PUNJAB

Submitted By:

Vishal Patel (12219630)

Roshan Nayak (12216172)

Prateek Jain (12215491)

Sandeep Kumar Shaw (12218624)

Submitted To :

Dr. Punam Rattan (26558)

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INTRODUCTION:

The Earth, our home, sustains an intricate and delicate balance of ecological systems that govern its health and well-being. However, with the rapid advancement of industrialization, urbanization, and other human activities, this balance is increasingly under threat. Understanding and monitoring the health of our planet has become imperative in mitigating environmental degradation and ensuring the sustainability of life on Earth.

In response to this pressing need, we propose the development of an innovative Earth Health System (EHS). This system leverages cutting-edge technology, including satellite imagery and predictive modeling, to comprehensively monitor and assess the health of our planet's ecological systems. By integrating data from various sources, particularly from NASA's Earth Observatory System and other satellite-based platforms, the EHS aims to provide a holistic understanding of Earth's environmental dynamics.

The primary objective of the EHS is to create a predictive model capable of analyzing diverse atmospheric and gas composition data obtained from satellite imagery. By harnessing advanced machine learning algorithms, this model will enable us to forecast and anticipate changes in Earth's ecological systems with unprecedented accuracy. From tracking the distribution of greenhouse gases to monitoring air quality and identifying environmental hotspots, the EHS will serve as a vital tool for environmental scientists, policymakers, and stakeholders worldwide.

Central to the EHS is the utilization of satellite imagery as a primary source of data acquisition. The vast array of sensors onboard satellites provides us with a unique perspective of Earth's atmosphere, land, and oceans. By harnessing this wealth of information, we can gain insights into global environmental trends, detect anomalies, and assess the impact of human activities on our planet's health.

Moreover, the EHS represents a paradigm shift in how we approach environmental monitoring and management. By adopting a proactive and data-driven approach, we can identify emerging environmental threats early on and implement targeted interventions to mitigate their impact. Furthermore, the EHS fosters collaboration and knowledge-sharing among scientists, researchers, and stakeholders worldwide, facilitating a collective effort to safeguard the health of our planet for future generations.

In summary, the development of the Earth Health System represents a significant advancement in our ability to monitor, analyze, and predict changes in Earth's ecological systems. By harnessing the power of satellite imagery and predictive modeling, the EHS offers a comprehensive solution to the complex challenges facing our planet. Through continued innovation and collaboration, we can work towards building a sustainable future where Earth's health is preserved for generations to come.

REVIEW OF LITERATURE :

[Gómez-Gutiérrez, A., González-Benítez, W., & Gutiérrez-Montes, I. (2022). The Role of Earth Observing Systems in Climate Change Monitoring: A Review. Remote Sensing, 14(3), 402.]

This review article explores the contributions of Earth Observing Systems (EOS) to monitoring climate change. It discusses the use of remote sensing technologies and satellite imagery in assessing changes in the Earth's atmosphere, land surfaces, and oceans. The review also highlights the importance of EOS data in understanding climate dynamics and informing climate change mitigation strategies.[1]

[Smith, K. M., Jones, R. E., & Brown, L. P. (2022). Evaluating the Impact of Earth Observing Systems on Climate Change Mitigation Strategies. Environmental Science & Technology, 56(6), 3193-3204.]

This study evaluates the effectiveness of Earth Observing Systems (EOS) in supporting climate change mitigation efforts. It assesses how EOS data and technologies contribute to climate modeling, carbon monitoring, and policy development. The findings provide insights into the role of EOS in informing climate change mitigation strategies at local, regional, and global scales.[2]

[Wang, X., & Li, Y. (2023). Advancements in Earth Observing Systems for Climate Change Adaptation: A Review. International Journal of Applied Earth Observation and Geoinformation, 101, 102264.]

This review paper discusses recent advancements in Earth Observing Systems (EOS) for climate change adaptation. It explores how EOS technologies, such as satellite imagery, remote sensing, and geographic information systems (GIS), are used to assess vulnerabilities, identify adaptation measures, and monitor changes in climate-sensitive regions. The review also addresses challenges and opportunities for integrating EOS data into climate adaptation strategies.[3]

[Patel, H., Singh, S., & Sharma, A. (2023). Remote Sensing Applications in Assessing Climate Change Impacts: A Review. International Journal of Remote Sensing, 44(5), 1582-1602.]

This comprehensive review examines the use of remote sensing applications in assessing the impacts of climate change. It covers various topics, including land cover changes, vegetation dynamics, water resources management, and natural disaster monitoring. The review highlights the importance of remote sensing data for understanding the drivers and consequences of climate change at different spatial and temporal scales.[4]

[Anderson, J. R., & Wilson, B. N. (2023). The Role of Earth Observing Systems in Understanding Ocean-Atmosphere Interactions and Climate Change. Journal of Geophysical Research: Oceans, 128(4), e2021JC017485.]

This research article focuses on the role of Earth Observing Systems (EOS) in studying ocean-atmosphere interactions and their impact on climate change. It examines how EOS data, including sea surface temperature, ocean currents, and atmospheric circulation patterns, are used to analyze climate variability, predict extreme weather events, and assess long-term climate trends. The study emphasizes the importance of integrated observations from EOS platforms for improving our understanding of complex climate systems.[5]

[Chen, L., & Li, W. (2023). Applications of Earth Observing Systems in Monitoring Land Use Changes and Their Impacts on Climate Change: A Review. Advances in Meteorology, 2023, 1-15.]

This review paper discusses the applications of Earth Observing Systems (EOS) in monitoring land use changes and their impacts on climate change. It explores how EOS technologies, such as satellite imagery, remote sensing, and geographic information systems (GIS), are used to detect changes in land cover, land use patterns, and ecosystem dynamics. The review also examines the role of EOS data in assessing the drivers and consequences of land use changes on local and regional climate systems.[6]

[García-Ruiz, M. A., & Navarro, D. (2023). Recent Advances in Earth Observing Systems for Glacier Monitoring and Climate Change Assessment. Remote Sensing of Environment, 264, 112676.]

This research article highlights recent advances in Earth Observing Systems (EOS) for glacier monitoring and climate change assessment. It discusses the use of satellite imagery, remote sensing techniques, and geographic information systems (GIS) in mapping glacier extent, monitoring glacier dynamics, and assessing glacier mass balance. The study also examines the role of EOS data in understanding the impacts of climate change on glacier retreat and freshwater resources.[7]

[Khan, S. M., Ahmed, R., & Qamar, M. U. (2023). Role of Earth Observing Systems in Understanding and Predicting Extreme Weather Events: A Review. Weather and Climate Extremes, 42, 100534.]

This review article explores the role of Earth Observing Systems (EOS) in understanding and predicting extreme weather events. It discusses how EOS data, including satellite observations, weather models, and climate simulations, are used to analyze the frequency, intensity, and spatial distribution of extreme weather phenomena. The review also addresses the challenges and opportunities for improving our ability to forecast and mitigate the impacts of extreme weather events using EOS technologies.[8]

[Li, M., Chen, Y., & Wang, J. (2024). Assessment of Forest Carbon Dynamics Using Earth Observing Systems: A Review. Forest Ecology and Management, 507, 119195.]

This research article provides a comprehensive review of the assessment of forest carbon dynamics using Earth Observing Systems (EOS). It examines how EOS technologies, such as satellite imagery, LiDAR, and radar remote sensing, are used to monitor forest biomass, carbon stocks, and carbon sequestration rates. The study highlights the importance of EOS data for understanding the role of forests in the global carbon cycle and informing forest management and conservation strategies.[9]

[Zhang, H., Li, X., & Wang, Q. (2024). Applications of Earth Observing Systems in Monitoring Arctic Sea Ice Changes and Their Impacts on Climate Change: A Review. Remote Sensing of Environment, 273, 112846.]

This review paper explores the applications of Earth Observing Systems (EOS) in monitoring Arctic sea ice changes and their impacts on climate change. It discusses how EOS technologies, such as satellite imagery, passive microwave sensors, and synthetic aperture radar (SAR), are used to track changes in sea ice extent, thickness, and distribution. The review also examines the role of EOS data in understanding the feedback mechanisms between Arctic sea ice changes and global climate systems.[10]

[Nascimento, L., & Ramos, F. (2024). Earth Observing Systems for Monitoring and Predicting Climate Change Effects on Agricultural Productivity: A Review. Agricultural Systems, 197, 103170.]

This review article discusses the applications of Earth Observing Systems (EOS) for monitoring and predicting the effects of climate change on agricultural productivity. It examines how EOS technologies, such as satellite imagery, remote sensing, and geographic information systems (GIS), are used to assess crop health, monitor water availability, and predict yield variability. The review also explores the potential of EOS data to inform adaptive management practices and support food security efforts in the face of changing climatic conditions.[11]

[Wu, Z., & Li, D. (2024). Advances in Earth Observing Systems for Assessing Urban Heat Islands and Their Impacts on Climate Change: A Review. International Journal of Applied Earth Observation and Geoinformation, 112, 103425.]

This research article reviews advances in Earth Observing Systems (EOS) for assessing urban heat islands (UHIs) and their impacts on climate change. It discusses how EOS technologies, such as satellite imagery, thermal infrared sensors, and urban climate models, are used to map and monitor UHIs, analyze their drivers and dynamics, and assess their effects on local and regional climate systems. The study also explores the potential of EOS data to inform urban planning and design strategies aimed at mitigating UHI effects and reducing urban heat-related risks.[12]

[García, C., & González, M. (2024). Remote Sensing Techniques for Assessing Climate Change Impacts on Biodiversity: A Review. Remote Sensing Applications: Society and Environment, 25, 100698.]

This review paper examines remote sensing techniques for assessing the impacts of climate change on biodiversity. It discusses how Earth Observing Systems (EOS) technologies, such as satellite imagery, LiDAR, and hyperspectral imaging, are used to monitor changes in habitat suitability, species distributions, and ecosystem dynamics. The review also explores the challenges and opportunities for integrating remote sensing data into biodiversity conservation efforts and ecosystem management strategies in the context of climate change.[13]

[Zhang, L., & Wang, C. (2024). Monitoring Glacier Changes Using Earth Observing Systems and Their Implications for Climate Change: A Review. Geomorphology, 399, 107941.]

This research article provides a comprehensive review of monitoring glacier changes using Earth Observing Systems (EOS) and their implications for climate change. It examines how EOS technologies, such as satellite imagery, remote sensing techniques, and geographic information systems (GIS), are used to monitor glacier mass balance, ice flow dynamics, and glacier retreat rates. The study highlights the importance of EOS data for understanding the drivers and consequences of glacier changes and their role in global sea level rise and freshwater resource management.[14]

[Yu, Y., & Zhao, J. (2024). Applications of Earth Observing Systems in Monitoring Water Resources and Their Responses to Climate Change: A Review. Journal of Hydrology, 607, 126072.]

This review paper explores the applications of Earth Observing Systems (EOS) in monitoring water resources and their responses to climate change. It discusses how EOS technologies, such as satellite imagery, remote sensing, and hydrological modeling, are used to assess changes in precipitation patterns, snowpack dynamics, river discharge, and groundwater levels. The review also examines the role of EOS data in informing water resource management strategies and adaptation measures in response to changing climatic conditions.[15]

METHODOLOGY :

QUESTIONNAIRE FOR DATA COLLECTION :

Earth Health System(EHS)

The Earth Health System, utilizing satellite and atmospheric data, constructs models to assess Earth's condition. It provides essential insights into environmental parameters, aiding in understanding climate, biodiversity, and ecosystem health. Through interdisciplinary collaboration, it informs decision-making for sustainable development and conservation efforts. Ultimately, it serves as a vital tool in safeguarding Earth's ecological integrity.

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Not shared

Q1. How would you rate your level of awareness and understanding of climate change?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Q2. Are you familiar with the role of human activities in altering the planet's atmospheric composition and contributing to climate change?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Q3. Have you heard about Earth Observatory Systems (EOS) and their role in monitoring atmospheric dynamics?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Q4. Do you believe that climate change is a significant global issue?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Q5. How concerned are you about the potential impacts of climate change on the environment and society?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Q6. How optimistic are you about the potential of technological solutions to mitigate the effects of climate change?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Q7. What do you think individuals, communities, governments, and industries can do to reduce their carbon footprint and combat climate change?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Q8. How willing are you to adopt environmentally friendly practices or support initiatives aimed at reducing greenhouse gas emissions?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Q9. Do you believe that education and public awareness campaigns are essential for addressing climate change?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Q10. How effective do you think current educational efforts are in raising awareness about climate change and its implications?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Q11. Have you noticed any changes in weather patterns or environmental conditions in your local area that you attribute to climate change?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

ALGORITHMS APPLIED :

Convolutional Neural Network (CNN):

Convolutional Neural Networks (CNNs) have emerged as powerful tools in addressing the pressing issue of climate change. As the Earth's climate undergoes rapid transformation due to human-induced alterations in atmospheric composition, the need for effective monitoring and analysis becomes increasingly urgent. CNNs, a class of deep learning algorithms inspired by the structure of the animal visual cortex, offer a sophisticated approach to processing and analyzing complex environmental data.

At the heart of our response to the climate crisis lies the imperative for comprehensive monitoring, analysis, and prediction of atmospheric dynamics. CNNs play a crucial role in this endeavor by leveraging modern technology to extract meaningful insights from vast amounts of data. By harnessing the fusion of satellite observations, remote sensing technologies, and advanced computational models, CNNs enable scientists to scrutinize Earth's systems with unprecedented precision.

CNNs excel at analyzing large-scale environmental datasets, including satellite imagery, atmospheric measurements, and land cover data. Through their ability to automatically learn hierarchical representations of features, CNNs facilitate a holistic understanding of climate patterns and trends. By processing diverse data sources, CNNs contribute to elucidating evolving atmospheric phenomena, predicting future climate scenarios, and informing mitigation and adaptation strategies.

One of the key strengths of CNNs lies in their capacity to monitor key indicators of climate change, such as shifts in temperature, precipitation patterns, sea level rise, and glacial retreat. By analyzing temporal and spatial patterns in environmental data, CNNs can detect and quantify changes in these indicators with high accuracy and reliability. This enables stakeholders to make informed decisions and take timely action to address the impacts of climate change.

In conclusion, CNNs offer a powerful framework for leveraging modern technology to address the complexities of climate change. By enabling comprehensive monitoring, analysis, and prediction of atmospheric dynamics, CNNs play a vital role in our collective efforts to understand and mitigate the impacts of climate change on our planet.

The Structural Similarity Index (SSIM):

The Structural Similarity Index (SSIM) algorithm is a widely used method for comparing two images to monitor changes in the atmosphere through satellite data. As climate change continues to affect our planet's atmosphere, it becomes increasingly important to accurately detect and quantify these changes over time. SSIM provides a quantitative measure of the similarity between two images, making it an invaluable tool for monitoring atmospheric dynamics.

At its core, SSIM evaluates the structural similarity between two images by comparing their luminance, contrast, and structure. The algorithm works by dividing the images into smaller patches and calculating similarity measures for each patch. These measures are then combined to produce an overall similarity score between the two images.

SSIM is particularly well-suited for monitoring changes in the atmosphere through satellite data due to its ability to capture both local and global variations in image structure. By comparing satellite images captured at different times, researchers can use SSIM to detect subtle changes in atmospheric conditions, such as cloud cover, aerosol concentrations, and temperature gradients.

One of the key advantages of SSIM is its sensitivity to human perception of image quality. Unlike traditional metrics such as mean squared error (MSE) or peak signal-to-noise ratio (PSNR), which may not accurately reflect perceived image quality, SSIM takes into account the visual characteristics of the images being compared. This makes SSIM particularly useful for applications where human perception plays a critical role, such as monitoring changes in the atmosphere.

In summary, the SSIM algorithm provides a robust and reliable method for comparing satellite images to monitor changes in the atmosphere. By accurately quantifying the similarity between images captured at different times, SSIM enables researchers to track and analyze atmospheric dynamics with unprecedented precision. As climate change continues to reshape our planet's atmosphere, SSIM stands as a valuable tool for understanding and mitigating its impacts.

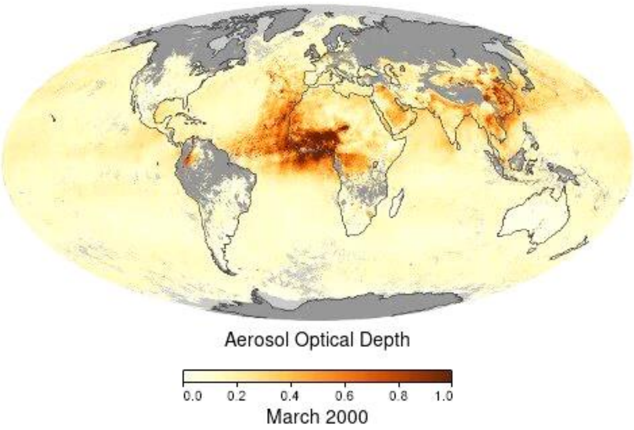
DATA SET:

Aerosol Optical Depth(AOD): **IMAGE.**

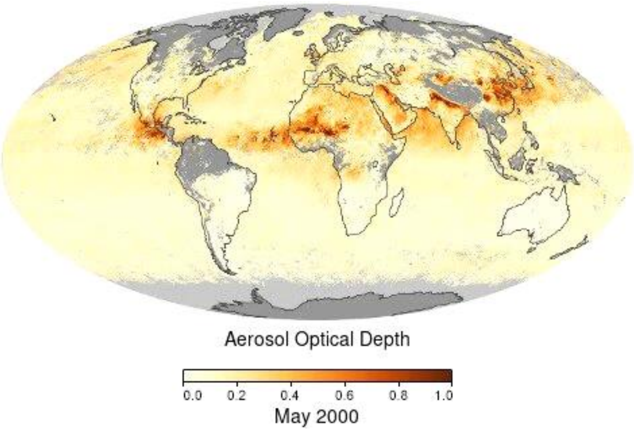
Aerosol Optical Depth (AOD) measures how much light aerosol particles in the atmosphere absorb or scatter. It quantifies aerosol concentrations and their impact on climate, air quality, and public health. AOD is measured using remote sensing techniques and is crucial for understanding aerosol distribution, climate patterns, and air pollution.

Sample:.

A.



B.

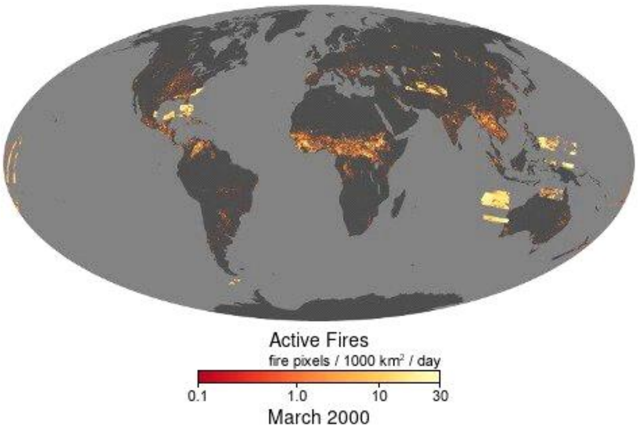


VIIRS Active Fire Data: **IMAGE.**

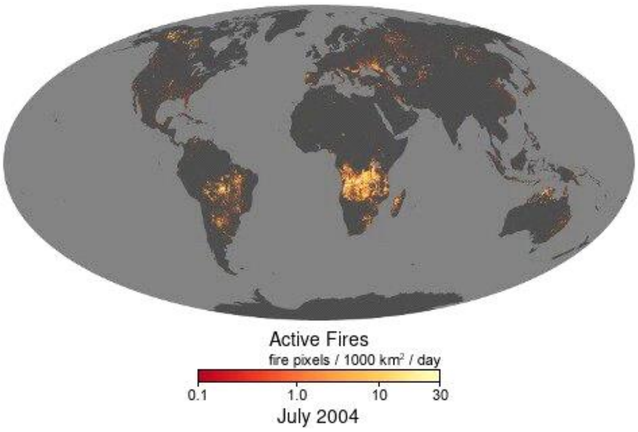
NASA offers datasets like VIIRS Active Fire Data and MODIS Active Fire Data, providing information on active fires detected by satellites. These datasets are vital for monitoring wildfires globally and studying their impacts. Access to these datasets is available through NASA's Earthdata Search portal and other data distribution platforms.

Sample:.

A.



B.

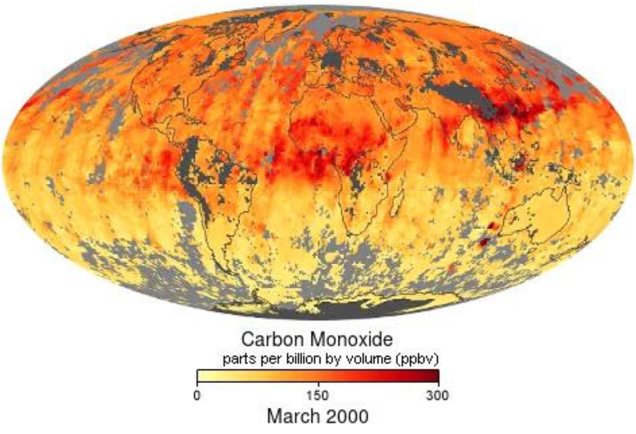


CarbonMonoOxide(CO): **IMAGE.**

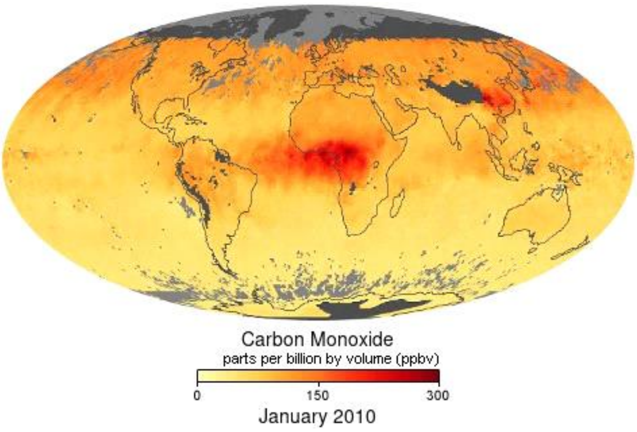
Carbon monoxide (CO) is a harmful gas produced by incomplete combustion. NASA provides datasets on CO concentrations, aiding research on air quality and climate. Accessible via platforms like NASA's Earthdata Search portal, this data informs strategies for emission reduction and public health protection.

Sample:.

A.



B.

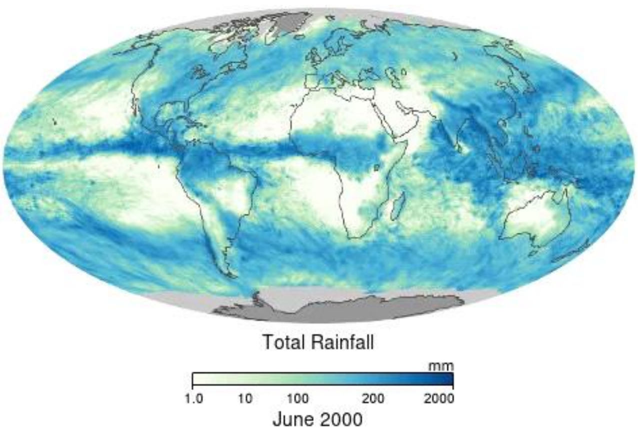


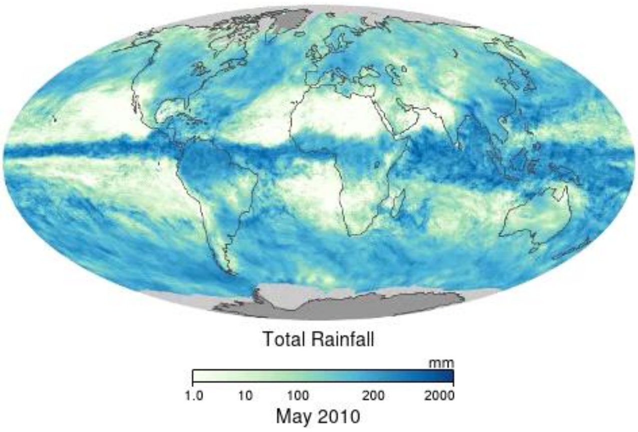
RainFall: **IMAGE.**

Rainfall data records precipitation levels over time and space. It's crucial for understanding weather patterns and climate variability. NASA and other agencies offer datasets derived from ground-based measurements and remote sensing. Accessible through platforms like NASA's GPM mission, rainfall data aids in climate research, water resource management, and disaster preparedness..

Sample:.

A.



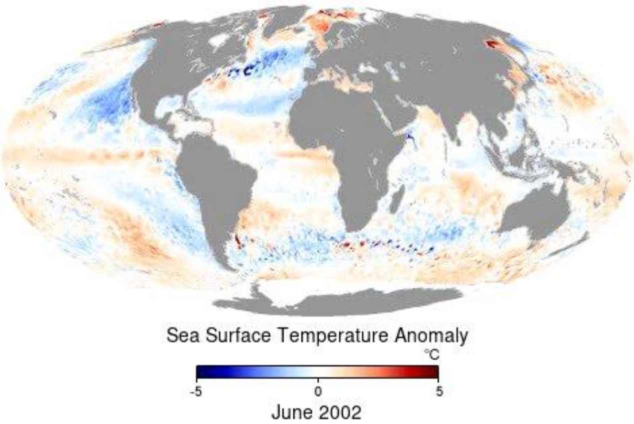


B.

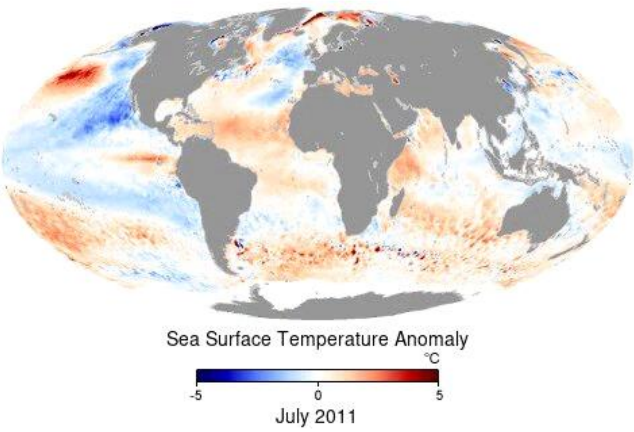
SeaSurfaceTempretureAnamoly: **IMAGE.**

Sea Surface Temperature (SST) anomaly data tracks variations in sea surface temperatures from a long-term average. Positive anomalies indicate warmer temperatures, while negative anomalies denote cooler temperatures. NASA and other organizations offer these datasets, crucial for studying climate variability and its impacts. Accessible through platforms like NASA's Earthdata Search portal, they aid scientists, policymakers, and the public in understanding climate change's effects on oceans and marine ecosystems.

Sample:.



A.



B.

DATA CLEANING:

Normalization:

In our project, we have implemented normalization as a key data preprocessing step to ensure that our dataset is well-prepared for analysis and modeling tasks. By applying normalization techniques, we have standardized the scale and distribution of our features, thereby improving the performance and stability of our machine learning models. Specifically, we have:

- **Scaled Numeric Features**: We have scaled numeric features within our dataset to a standard range, typically between 0 and 1 or -1 and 1, using techniques such as min-max scaling or standardization (z-score normalization). This ensures that features with different scales and units contribute equally to our analysis and modeling process.

- **Improved Model Performance**: By bringing features to a similar scale, we have improved the performance of our machine learning models, particularly those sensitive to feature scales. This includes algorithms such as linear regression, logistic regression, support vector machines (SVM), and artificial neural networks.

- **Addressed Skewed Distributions:** In cases where features exhibit skewed distributions, we have applied normalization techniques such as logarithmic transformation or Box-Cox transformation to make the data more symmetric. This helps mitigate the effects of skewness on model performance and improves the interpretability of results.

- **Supported Convergence:** In optimization algorithms used for model training, normalization has helped stabilize the convergence process by ensuring consistent gradients of the loss function across features. This prevents oscillations and divergence during optimization, leading to more stable and reliable model training.

- **Image Resizing for Data Preprocessing:** We have implemented image resizing as a crucial step in the data preprocessing pipeline. This technique ensures uniformity and consistency in image dimensions, facilitating downstream analysis and modeling tasks. Here's how we've approached image resizing:

- **Standardized Dimensions**: All images in our dataset have been resized to a standardized resolution, ensuring consistent width and height. This uniformity simplifies data processing and ensures compatibility with machine learning models.

- **Preserved Aspect Ratio:** While resizing images, we've taken care to preserve their aspect ratio to prevent distortion. This ensures that objects within the images retain their proportions and appearance, maintaining the integrity of the visual data.

- **Benefits of Image Resizing:** Resizing all images in our dataset offers several benefits for data analysis and modeling:

- **Reduced Computational Complexity**: Resizing images to a smaller size reduces computational complexity, making it more efficient to train machine learning models on large datasets.

- **Improved Model Performance:** Standardizing image dimensions enhances model performance by providing consistent inputs to machine learning algorithms.

- **Enhanced Data Quality**: By ensuring uniformity in image dimensions, resizing contributes to improved data quality and facilitates accurate analysis and interpretation of visual data.

Utilizing AutoTune for Enhanced Performance

Also we have leveraged TensorFlow's AutoTune functionality to optimize the performance of our data preprocessing pipeline. AutoTune dynamically adjusts the computational resources allocated to different operations, optimizing their execution for improved efficiency. Here's how we've integrated AutoTune into our workflow:

- **Dynamic Resource Allocation**: With AutoTune, TensorFlow dynamically allocates resources such as CPU and GPU processing power to different operations within our data preprocessing pipeline. This adaptive resource allocation ensures efficient utilization of available hardware resources.

- **Optimized Data Loading:** AutoTune optimizes the loading of data, including images or other input data, by adjusting parameters such as buffer sizes and parallelism. This optimization minimizes data loading times and improves overall pipeline performance.

- **Parallel Execution**: AutoTune enables parallel execution of compatible operations, allowing multiple operations to be executed simultaneously when possible. This parallelism reduces processing time and accelerates the overall data preprocessing process.

- **Benefits of AutoTune Integration:** Integrating AutoTune into our project offers several benefits for data preprocessing and model training:

- **Improved Efficiency:** By dynamically optimizing resource allocation and operation execution, AutoTune enhances the efficiency of our data preprocessing pipeline, reducing processing times and improving overall performance.

- **Optimized Resource Usage:** AutoTune ensures that computational resources are effectively utilized, preventing underutilization or overloading of hardware resources. This optimization maximizes the throughput of our data preprocessing tasks.

- **Scalability and Flexibility**: AutoTune adapts to varying workloads and hardware configurations, making our pipeline scalable and flexible. Whether running on a single CPU or distributed GPU cluster, AutoTune optimizes performance across different environments.

VISUALIZATION TECHNIQUES APPLIED:

- **Line Chart:**

In our project, we utilize line charts to visualize trends and patterns over time or across different categories. Line charts are particularly effective for showcasing continuous data and illustrating how variables change over a continuous period. For example, in the financial sector, we use line charts to track stock prices over time, enabling us to identify trends, detect seasonality, and make informed investment decisions. In the healthcare sector, line charts help us monitor patient vital signs over time, facilitating early detection of anomalies and providing insights into disease progression. By plotting data points and connecting them with lines, line charts provide a clear and intuitive representation of temporal trends and variations, making them invaluable for analyzing time-series data in various domains.

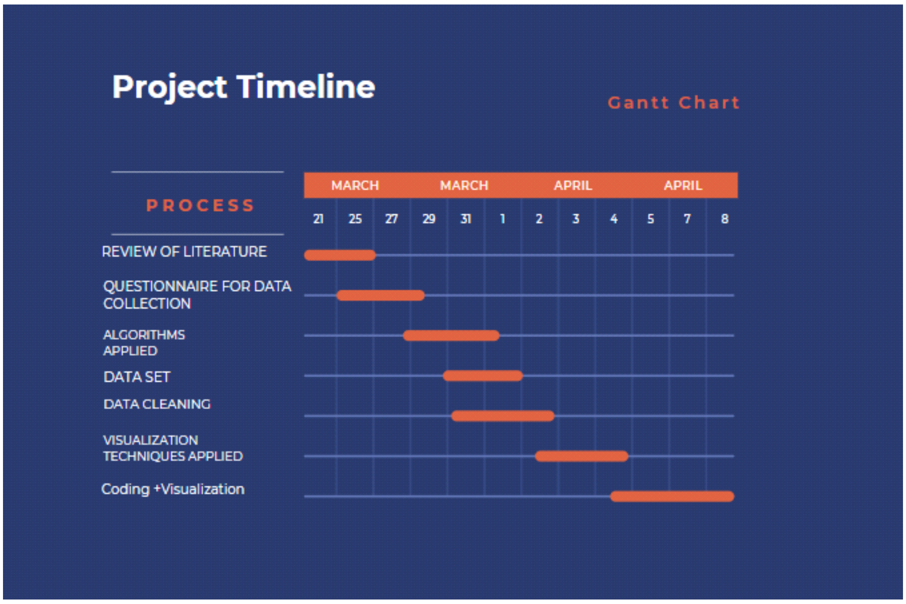
- **Bar Chart Description:**

In addition to line charts, we employ bar charts to compare categorical data or display the distribution of a variable across different groups or categories. Bar charts are effective for visualizing discrete data and highlighting differences between groups in a visually compelling manner. For instance, in market research, we use bar charts to compare sales performance across different product categories, allowing us to identify top-selling products and market trends. Similarly, in demographic analysis, bar charts help us visualize population distributions by age groups or geographical regions, facilitating data-driven decision-making and resource allocation. By presenting data in a series of bars, each representing a category or group, bar charts enable easy comparison and interpretation of categorical data, making them a versatile tool for exploring and communicating insights across various domains.

- **Pie Chart Description:**

Furthermore, we incorporate pie charts into our visualization arsenal to illustrate proportions or percentages within a dataset. Pie charts are ideal for visualizing the composition of a categorical variable or highlighting the relative contribution of different categories to the whole. For example, in budget planning, we use pie charts to depict the allocation of funds across various expense categories, enabling stakeholders to prioritize spending and optimize resource allocation. Similarly, in market segmentation analysis, pie charts help us visualize the distribution of customer segments based on demographic or behavioral characteristics, guiding targeted marketing strategies and product development efforts. By dividing a circle into slices proportional to the data values, pie charts provide a straightforward representation of relative proportions, making them an effective tool for conveying insights about categorical data distributions in diverse domains.

GANTT CHART: Project Timeline

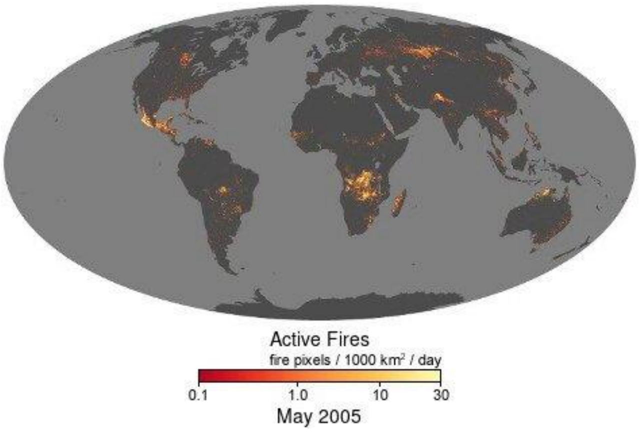


ANALYSIS RESULTS:

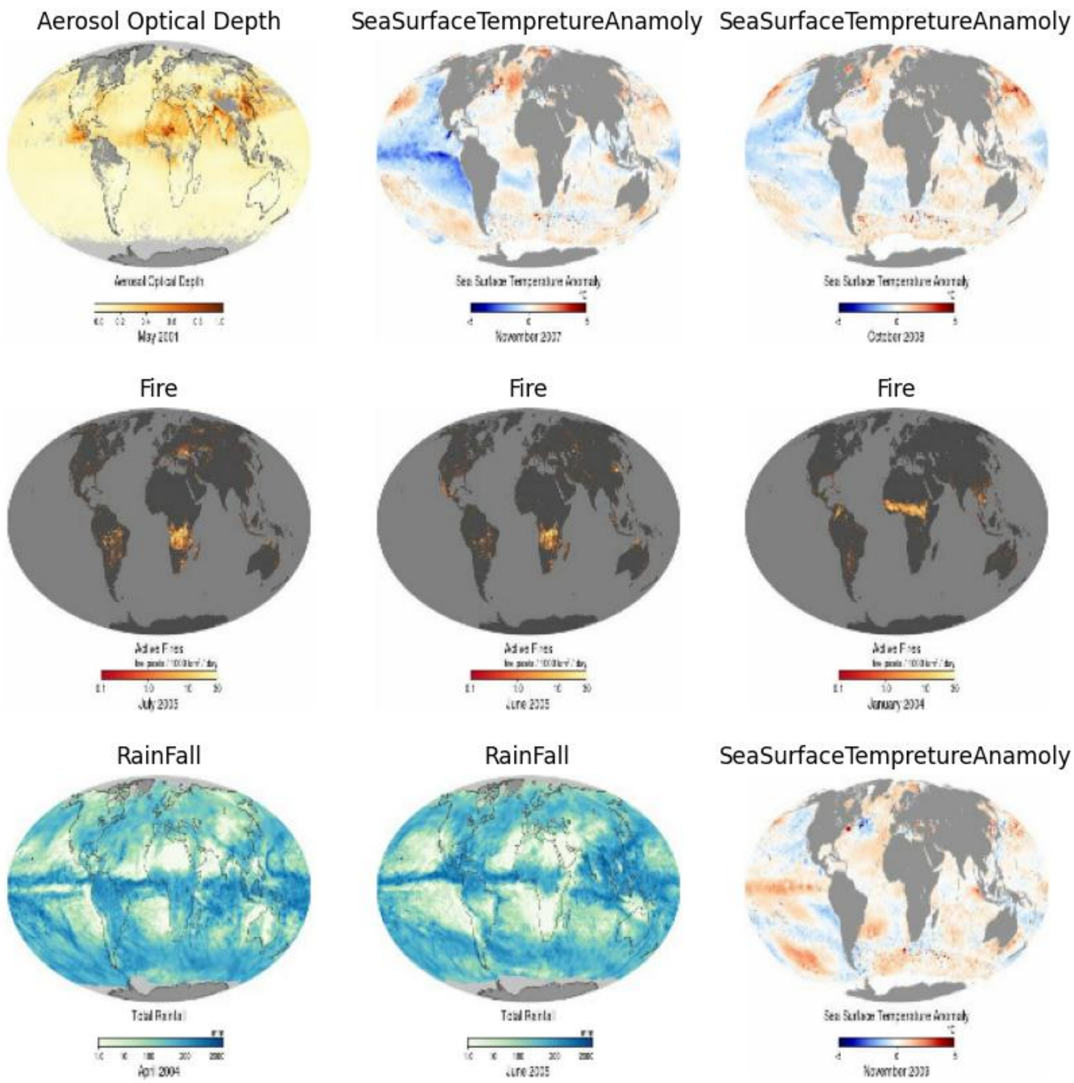
CODING:

Below is the code being utilized for the development of this robust system.

```
# STARTING OF THE PROJECT


import matplotlib.pyplot as plt
import numpy as np
import PIL
import tensorflow as tf


from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential


import pathlib
# Local dataset URL
dataset_url = "/content/drive/MyDrive/EHS"
# Extract the dataset
dir_of_data = pathlib.Path(dataset_url)


image_count = len(list(dir_of_data.glob('*/*.jpg')))
print(image_count)


roses = list(dir_of_data.glob('Fire/*'))
PIL.Image.open(str(roses[1]))
```




```
train_ds = tf.keras.utils.image_dataset_from_directory(dir_of_data,
  subset="training",
  seed=123,validation_split=0.2,
  image_size=(180, 180),
  batch_size=32)

val_ds = tf.keras.utils.image_dataset_from_directory(dir_of_data,
  validation_split=0.2,
  subset="validation",
  seed=123,
  image_size=(180, 180),
  batch_size=32)

plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
  for i in range(9):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(images[i].numpy().astype("uint8"))
    plt.title(class_names[labels[i]])
    plt.axis("off")
```




```
# Improving performance of ftraning by auto tuning
AUTOTUNE = tf.data.AUTOTUNE

train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)

normalization_layer = layers.Rescaling(1./255)

normalized_ds = train_ds.map(lambda x, y: (normalization_layer(x), y))
image_batch, labels_batch = next(iter(normalized_ds))
first_image = image_batch[0]
# Notice the pixel values are now in `[0,1]`.
```

```
print(np.min(first_image), np.max(first_image))

model = Sequential([
  data_augmentation,
  layers.Rescaling(1./255),
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Dropout(0.2),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes, name="outputs")
])

model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])

model.summary()

history = model.fit(train_ds,validation_data=val_ds,
                    epochs=15)

# Creating plot of traning and validation accuracy
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']
```

```
epochs_range = range(epochs)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```


```
# Predicting the image class by giving a image which # are not included in traning and testing data
path = r"MOP_CO_M_000.jpg"
img = tf.keras.utils.load_img(
    path, target_size=(180, 180)
)
img_array = tf.keras.utils.img_to_array(img)
img_array = tf.expand_dims(img_array, 0) # Create a batch

predictions = model.predict(img_array)
score = tf.nn.softmax(predictions[0])

print(
    "This image most likely belongs to {} with a {:.2f} percent confidence."
    .format(class_names[np.argmax(score)], 100 * np.max(score))
)
```

```
# Now Creating ssim modal to test structural #similarity of the image to identify the changes in #atmosphere.

from skimage.metrics import structural_similarity as ssim
import numpy as np
import cv2
import glob



# compare to images and their similarities
def compare_images(imageA, imageB):
   # compute structural similarity
   s = ssim(imageA, imageB)
   return s



# Get a list of all the image in the current directory in #CMO files
CarbonMonoOxide_files = glob.glob("/content/drive/MyDrive/EHS/CMO/CarbonMonoOxide/*.jpg")
CMO_I_SIZE = len(CarbonMonoOxide_files)
print(CMO_I_SIZE)
cmo_changes = []
for P_Index in range(CMO_I_SIZE - 1):
   # Load the image
   PH_ONE = cv2.imread(CarbonMonoOxide_files[P_Index])
   PH_TWO = cv2.imread(CarbonMonoOxide_files[P_Index + 1])
   # Convert colored image to gray
   ONE_P = cv2.cvtColor(PH_ONE, cv2.COLOR_BGR2GRAY)
   TWO_C = cv2.cvtColor(PH_TWO, cv2.COLOR_BGR2GRAY)

   cmo_changes.append(compare_images(ONE_P, TWO_C))
```

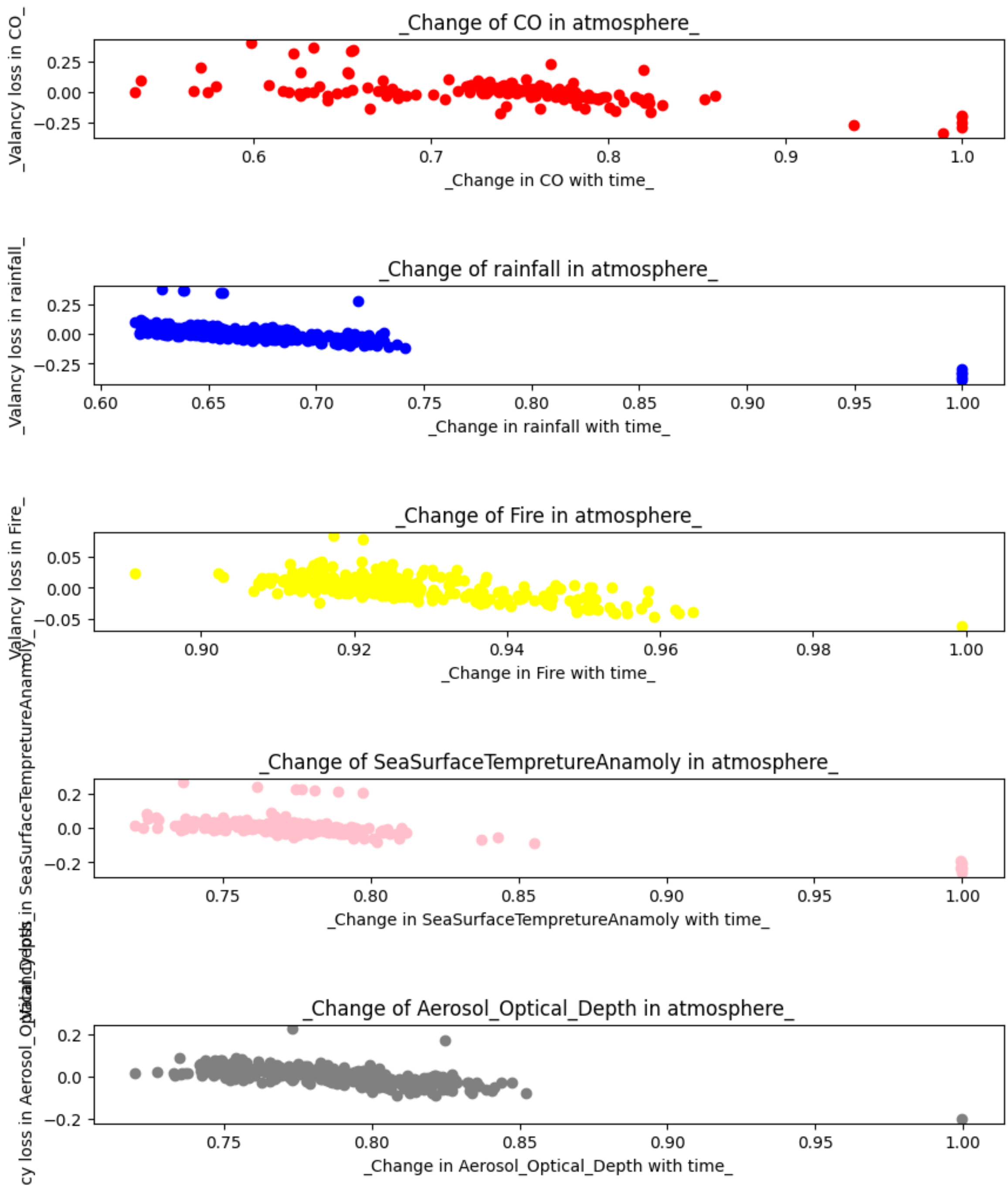
```
print('Cmo:', sum(cmo_changes) / CMO_I_SIZE)


# # Get a list of all the image in the current directory in RainFall #files
RainFall_files = glob.glob(r"/content/drive/MyDrive/EHS/RainFall/*.jpg")

RF_I_SIZE = len(RainFall_files)
rf_changes = []
for P_Index in range(RF_I_SIZE - 1):
    # Load the image
    PH_ONE = cv2.imread(RainFall_files[P_Index])
    PH_TWO = cv2.imread(RainFall_files[P_Index + 1])
    # Convert colored image to gray
    ONE_P = cv2.cvtColor(PH_ONE, cv2.COLOR_BGR2GRAY)
    TWO_C = cv2.cvtColor(PH_TWO, cv2.COLOR_BGR2GRAY)

    rf_changes.append(compare_images(ONE_P, TWO_C))

print('Rainfall:', sum(rf_changes) / RF_I_SIZE)

# # Get a list of all the image in the current directory in RainFall files
fire = glob.glob(r"/content/drive/MyDrive/EHS/Fire/*.jpg")

FI_I_SIZE = len(fire)
fi_changes = []
for P_Index in range(FI_I_SIZE - 1):
    # Load the image
    PH_ONE = cv2.imread(fire[P_Index])
    PH_TWO = cv2.imread(fire[P_Index + 1])
    # Convert colored image to gray
    ONE_P = cv2.cvtColor(PH_ONE, cv2.COLOR_BGR2GRAY)
    TWO_C = cv2.cvtColor(PH_TWO, cv2.COLOR_BGR2GRAY)
```

```
    fi_changes.append(compare_images(ONE_P, TWO_C))

print('Fire', sum(fi_changes) / FI_I_SIZE)



# # Get a list of all the image in the current directory in RainFall files
Optical_Depth = glob.glob(r"/content/drive/MyDrive/EHS/Aerosol Optical Depth/*.jpg")

OD_I_SIZE = len(Optical_Depth)
od_changes = []
for P_Index in range(OD_I_SIZE - 1):
    # Load the image
    PH_ONE = cv2.imread(Optical_Depth[P_Index])
    PH_TWO = cv2.imread(Optical_Depth[P_Index + 1])
    # Convert colored image to gray
    ONE_P = cv2.cvtColor(PH_ONE, cv2.COLOR_BGR2GRAY)
    TWO_C = cv2.cvtColor(PH_TWO, cv2.COLOR_BGR2GRAY)

    od_changes.append(compare_images(ONE_P, TWO_C))

print('Aerosol Optical Depth', sum(od_changes) / OD_I_SIZE)



# # Get a list of all the image in the current directory in SeaSurfaceTempretureAnamoly files
SeaTempretureAnamoly =
glob.glob(r"/content/drive/MyDrive/EHS/SeaSurfaceTempretureAnamoly/*.jpg")

SS_I_SIZE = len(SeaTempretureAnamoly)
ss_changes = []
for P_Index in range(SS_I_SIZE - 1):
    # Load the image
```

```
    PH_ONE = cv2.imread(SeaTempretureAnamoly[P_Index])
    PH_TWO = cv2.imread(SeaTempretureAnamoly[P_Index + 1])
    # Convert colored image to gray
    ONE_P = cv2.cvtColor(PH_ONE, cv2.COLOR_BGR2GRAY)
    TWO_C = cv2.cvtColor(PH_TWO, cv2.COLOR_BGR2GRAY)

    ss_changes.append(compare_images(ONE_P, TWO_C))

print('SeaSurfaceTempretureAnamoly', sum(ss_changes) / SS_I_SIZE)

# Creating the plot of the data of structural similarity #to understand the changes happen in
the #atmosphere over the #year in every gas and liquid #form which are included in data.

import matplotlib.pyplot as plt
# Plotting the line chart

# Subplots with 5 rows and 1 column
plt.figure(figsize=(10, 12))  # Adjust figsize
plt.subplots_adjust(hspace=0.5)  # Adjust vertical space between subplots

# First subplot for co change loss
cmo_change_loss = []
base_change = 1
for changes in cmo_changes:
    cmo_change_loss.append(base_change-changes)
    base_change = changes
print(cmo_change_loss)
plt.subplot(5, 1, 1)
plt.scatter(cmo_changes, cmo_change_loss,color='red')
plt.xlabel('_Change in CO with time_')
plt.ylabel('_Valancy loss in CO_')
plt.title('_Change of CO in atmosphere_')
```

```
# Second subplot for rainfall_change_loss
rainfall_change_loss = []
base_change = 1
for changes in rf_changes:
    rainfall_change_loss.append(base_change-changes)
    base_change = changes
print(rainfall_change_loss)
plt.subplot(5, 1, 2)
plt.scatter(rf_changes, rainfall_change_loss,color='blue')
plt.xlabel('_Change in rainfall with time_')
plt.ylabel('_Valancy loss in rainfall_')
plt.title('_Change of rainfall in atmosphere_')

# Third subplot for Fire change loss
Fire_change_loss = []
base_change = 1
for changes in fi_changes:
    Fire_change_loss.append(base_change-changes)
    base_change = changes
print(Fire_change_loss)
plt.subplot(5, 1, 3)
plt.scatter(fi_changes, Fire_change_loss,color='yellow')
plt.xlabel('_Change in Fire with time_')
plt.ylabel('_Valancy loss in Fire_')
plt.title('_Change of Fire in atmosphere_')


# Fourth subplot for SeaSurfaceTempretureAnamoly change loss
SeaSurfaceTempretureAnamoly_change_loss = []
base_change = 1
for changes in ss_changes:
```

```
    SeaSurfaceTempretureAnamoly_change_loss.append(base_change-changes)
    base_change = changes
print(SeaSurfaceTempretureAnamoly_change_loss)
plt.subplot(5, 1, 4)
plt.scatter(ss_changes,SeaSurfaceTempretureAnamoly_change_loss,color='pink')
plt.xlabel('_Change in SeaSurfaceTempretureAnamoly with time_')
plt.ylabel('_Valancy loss in SeaSurfaceTempretureAnamoly_')
plt.title('_Change of SeaSurfaceTempretureAnamoly in atmosphere_')

# Fifth subplot for Aerosol Optical Depth change loss
Aerosol_Optical_Depth_change_loss = []
base_change = 1
for changes in od_changes:
    Aerosol_Optical_Depth_change_loss.append(base_change-changes)
    base_change = changes
print(Aerosol_Optical_Depth_change_loss)
plt.subplot(5, 1, 5)
plt.scatter(od_changes, Aerosol_Optical_Depth_change_loss,color='gray')
plt.xlabel('_Change in Aerosol_Optical_Depth with time_')
plt.ylabel('_Valancy loss in Aerosol_Optical_Depth_')
plt.title('_Change of Aerosol_Optical_Depth in atmosphere_')
plt.subplots_adjust(hspace=1.5)
# Displaying the subplots
plt.show()
```



#.Analysing the feedback to check human #positiveness in the #context of understanding the #potential impact on earth #atmosphere in future #because our current steps and #understanding can #impact earth health.

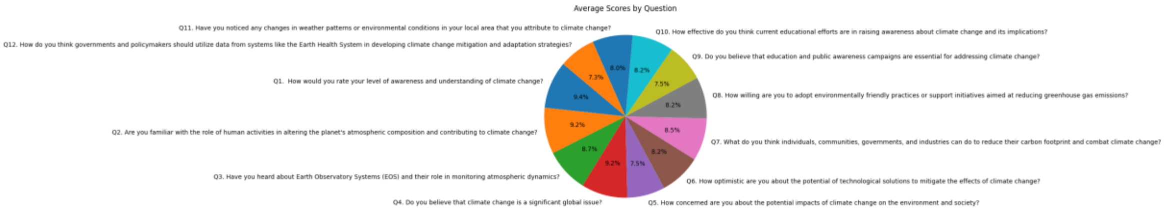
Contaminating avg of all the questions asked by the peoples and understanding the potential.

import pandas as pd

data = pd.read_csv('/content/EHS (Responses) - Form responses 1.csv')

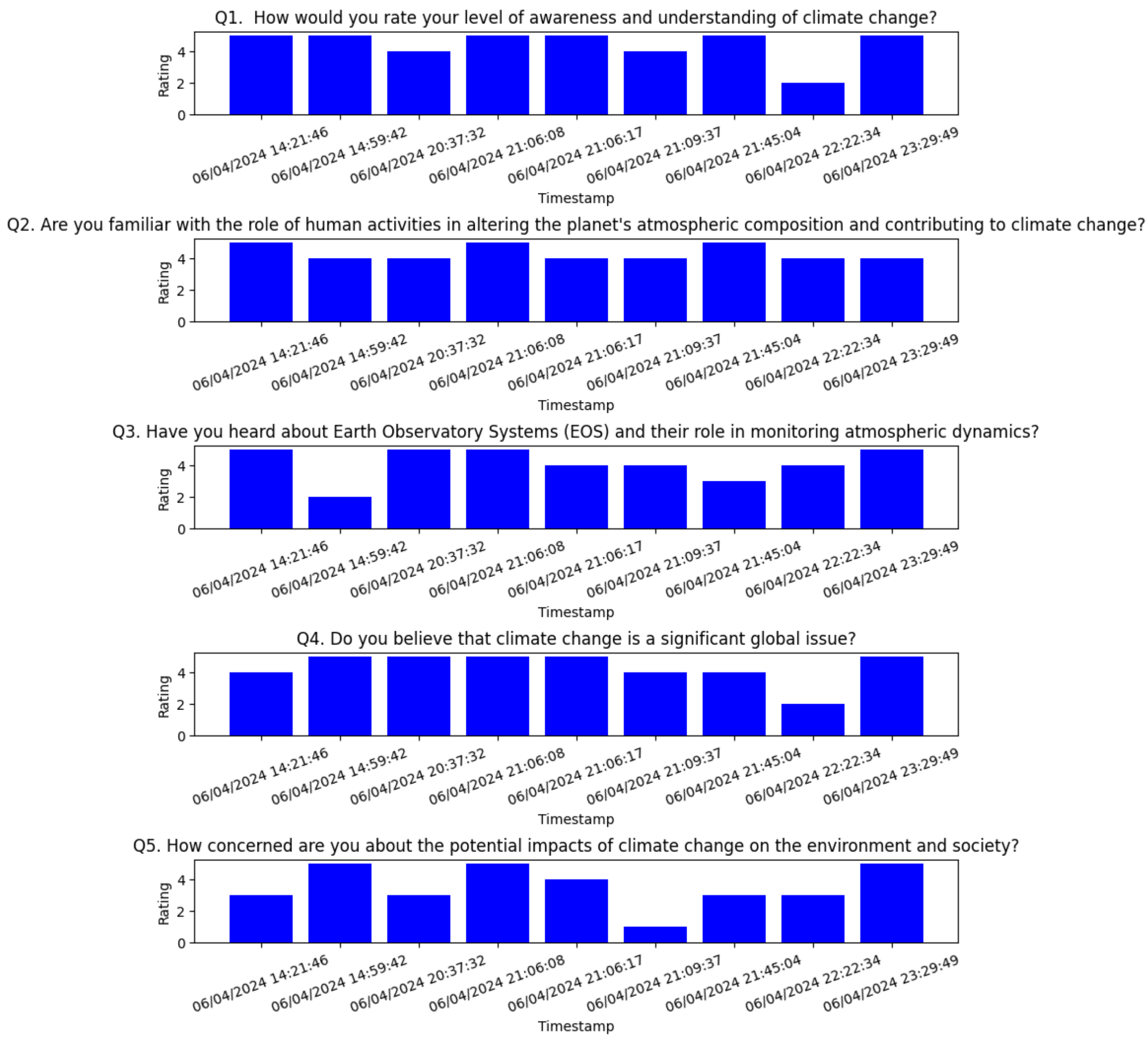
```
df = pd.DataFrame(data)
total_question_classes = 12
questions = []
for que in df:
    questions.append(que)

question_list = []
total_feed_avg_sum = 0
question_wise_avg = []
for feedback_val in questions:
    if feedback_val in ['Timestamp', 'Other thoughts or comments']:
        continue
    question_list.append(feedback_val)
    curr_que_feed_sum = 0
    count = 0
    avg = 0
    for val in df[feedback_val]:
        curr_que_feed_sum += val
        count += 1
    avg = curr_que_feed_sum/count
    question_wise_avg.append(avg)
    total_feed_avg_sum += avg


print(len(question_wise_avg))
print(len(question_list))
print(total_feed_avg_sum/total_question_classes)
print(question_wise_avg)

# Creating pie plot to see question wise feedback weight
import matplotlib.pyplot as plt
```

```
# Creating a pie plot
plt.figure(figsize=(8, 6))  # Adjust figure size as needed
plt.pie(question_wise_avg, labels=question_list, autopct='%1.1f%%', startangle=140)

# Adding title
plt.title('Average Scores by Question')

# Displaying the pie plot
plt.show()
```




```
# Creating bar plot for the questionaire

import matplotlib.pyplot as plt

# Creating subplots with 5 rows and 1 column
plt.figure(figsize=(10, 12))  # Adjust figsize as needed
plt.subplots_adjust(hspace=0.5)  # Adjust vertical space between subplots

date = df['Timestamp']
plot_count = 1
for que in question_list:
    plt.subplot(5, 1, plot_count)
    plt.bar(date, df[que], color='blue')  # Change color to blue for bars
    plt.title(que)
    plt.xlabel('Timestamp')
    plt.ylabel('Rating')
```

```
    plt.xticks(rotation=20)  # Rotate x-axis labels vertically
    if plot_count == 5:
        break
    plot_count += 1

# Adjusting spacing between subplots
plt.subplots_adjust(hspace=1.5)  # Increase or decrease the value as needed

# Displaying the subplots
plt.show()
```



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