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Integration of Sensors and Predictive Analysis with Machine Learning as a Modern Tool for Economic Activities and a Major Step to Fight Against Climate Change

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Abstract: Environmental issues have remained one of the most challenging social-economic impacts on the world and most countries. Tackling these challenges has remained an underlying issue as a concise approach, method, and policy are yet to be globally made available. Machine learning (ML) with support from IoTs, big data, NLP, and cloud computing is radicalizing the development of a modern-day economy via human support systems. With technical devices, systems, and processes intricately oriented to human understanding. Little environmental needs have been developed to give humans a comfortable place. Even though sensors capture and satisfy human needs, global ecosystem barriers have weighed beyond. Following changes in the world today, automated restrictions and barriers have been seen limiting humans from enjoying opportunities offered by IoTs, big data, NLP, and cloud computing due to environmental impact. Machine learning with capabilities to help humans become more informed is insignificantly exploited on the environmental needs. To suggest an integrated system, method, and areas that IoTs, big data, NLP, and cloud computing should focus on to fight negative environmental impact as a major step to fight climate change. In the study, two research questions and a hypothesis were used. Daily data on emission accusations was collected and used to respond to research questions and hypotheses. In 30 minutes per day and within a month, 412 diesel cars emitted 54,384 g CO_2/km, 636 petrol cars emitted 76,320 g CO_2/km, and 157 LPG cars emitted 9,577 g CO_2/km. Predictions and forecasts were determined based on the data collected. Data accusations reveal they worsen the future impact as both hypotheses and research questions positively support findings that integration of sensors with machine learning can predict future climate situations. Improved gardens are needed, limit artificial items and diesel cars, and improved afforestation is needed in this city.

Keywords: Machine learning; Sensor; Internet of Things; Cloud computing; Big data; Natural language processing; Carbon emissions; Environmental changes; Climate change

1. Introduction

From the advanced use of sensors, the development of materials and devices that cohabitate with humans by trying to give a sense of understanding. Today, ranging from homes, cars, computers, public transport systems, and many others, many human needs have been greatly observed with the help of sensors. People can predict, understand, and implement actions with great support from electronics, systems, and materials around them.

Million electronics have been developed with little attention to their impact on the economy. According to world health organization 2021, coronavirus originated from the animal [1]. The use of big data networks said the Americas and the Caribbean have 85% of the forest area and 80% of forest types that are potentially threatened by climate change [2]. Big data has the capability to disrupt senior management by giving opportunities to make rapid and prompt decisions [3]. With the level of technology development sensors can detect variances in the COVID-19 pandemic that could have been limited with the help of technology. The importance of big data is improving our understanding of different interactions between biological systems and global environmental changes [4]. Following this development, it is high time modern systems developed systems that monitor humans, plants, and animals. It is easy to say technology before COVID-19 has been biasing as it pays more attention only to human needs. The Internet of things, big data, and cloud computing have orchestrated the production of advanced materials that hold high sensors, promptness, and relativity to things around humans. A project carried out to determine the impact of IoTs through cloud computing said that the collaboration between IoTs and cloud computing technology is capable to present how a smart environment service domain can help smart city citizens [5]. He further says this information can be sent to citizens via emails with the help of cloud computing. These elements and devices allowed more simulations with little consideration for environmental impact. Modern cars with higher emissions, highly polluted processes within industrial enterprises, and high-large structures that occur on land reserved for habitats. Reinforcement can lead to increasing 5G endpoints by accelerating digitalization in smart cities which are good applications among smart environmental monitoring systems [6]. The advanced use of internet of things devices has the potential capability to transform multiple fields ranging from healthcare to environmental monitoring, and digital agriculture [7]. The study identifies gas emissions as one of the most impacting elements that promote environmental challenges. Today, almost every system and application consume energy and generates gases that go a long way to contaminate cyberspace. Two research questions were used to develop the paper and test the hypothesis.

The study examines technological drivers like AI, ANNs, smart fuzzy logic systems, smart genetic algorithms, smart IoTs, and smart expert systems to effectively and efficiently evaluate CO_2 emissions. These software-defined systems can radicalize a positive impact on the issues of climate change and environmental challenges. The cyber-physical space is where companies require free cyberspace for smooth internet connection, remote sensing, and simulations. Without free cyberspace, it is very difficult to achieve a stable internet, cloud base systems, remote sensors, and virtual simulations. Following industry 4.0, smart digitalization and now virtualization and remote sensing have been escalated into cloud base systems, big data technologies of 6G, simulators, and robot swarms. Cyberspace is a safe harbor for most companies nowadays that rely on remote activities and there's a need to secure it.

1.1 Data Centers and Energy Consumption

The need for remote Servers has led to the deployment of thousands of computers connected to cloud systems. Advanced cloud-based systems have led to increased storage and communication devices that lead to high energy utilization and carbon emissions [8]. Renewable energy resources are highly needed to replace fossil fuels-based grid energy to effectively reduce carbon emissions generated by cloud data centers. Servers and cooling systems consume a huge amount of energy which alternatively emit a lot of carbon [9]. The authors suggested that a modification of the distribution of power architecture of data servers and cooling systems will go a long way to serve some energy consumption. There is a need for more data energy centers due to the coming of Cloud computing and web emerging applications [10]. Restrictions are better ways to handle carbon emissions than the allocation of allowance [11]. They argue that investment policy leads to bias, operations, and product pricing decisions which leads to increased costs. Power models developed for operating systems, virtual machines, and software applications generate heat that turns system devices to emit carbon dioxide [12]. Information centers are an example of energy-hungry infrastructures that allow large-scale.

Internet-based services to connect with systems and generate carbon emissions. Carbon footprints have been pushing data center operators to cap energy consumption [13]. This can be achieved naturally by capping energy with main concerns about their impact on the environment.

1.2 Machine Learning Techniques for Climate Change

The need to reduce greenhouse gas emissions to assist society to adapt to a changing climate has remained a challenge [14]. Machine learning algorithms have smart grids that can detect disasters and manage them by identifying high-impact areas. Spatio-temporal fields of land-atmosphere surveys obtained from field survey data-driven models can work similarly to process-based land surface models [15]. Machine learning algorithms can simultaneously predict carbon dioxide from several different sources such as latent heat, sensible heat, and net radiation fluxes across different ecosystems. A sensible heat on a remote sensing area indices, climate, and meteorological data and provide information on land use [16]. The energy efficiency and productivity achieved so far still fall below because of the use of chemical feedstocks which use both CO_2 and renewable energy to build solar panels and wind energy [17]. Copper has been the predominant electrocatalyst for this reaction which instead should be focused on ethylene. The advancements in technology and related applications, devices, and systems will create more data about 90% and this capacity will be too high for humans to manage [18]. There is a need for system algorithms like machine learning. There is a need to reduce costs and improve equity in NLP research and practice due to the cost associated with training models and developing algorithms like machine learning for climate change challenges [19].

1.3 Technology Innovation Expectations for Climate Change

The role of digital technologies has the main solution center to managing challenges in addressing climate change lies with three objectives [20]. The following objectives can effectively manage the challenges the world faces with the environment and climate.

The first objective is the need for a blended behavioral change with technological innovation. The collection of valuable physiological data has a great way to change our thoughts and educate us on our surroundings with iMotions. There is a need for a holistic technology that cohabitates with humans and the existing environment. Machine learning is one of the technologies that have this approach but little training has been provided to the general public. Even with open access, remote areas still fall below requirement due to a lack of internet access to benefit from open libraries like Jupiter, anaconda, tensor flow, and many others. The World-leading behavioral analysis software for human behavior research should emphasize the need for all to know, have access and talk with a specialist.

The second object identifier lies with the socio-technical drivers that will accelerate low-carbon transitions. One of the effective ways to mitigate the impact of climate change will require far-reaching transformations of electricity, heat, and transport autonomous systems. The amalgamation towards a sustainable system that is fully free or with fewer carbon emissions can be achieved by focusing efforts to change our attitude towards climate issues. Climate change should be a global affair and not for a select few tech companies. The government should be fully engaged in the fight against climate change. Climate change issues should not be limited by industrial policies, cultural norms, and political motivations.

The last objective is the need for digital technologies that provide access to information, challenges, and impact on the globe. The world needs to respond better and faster to environmental, climate, health, and market changes with intelligent automation. Optimizing climate relationship management with Intelligent servers, services, systems, and applications is what the world needs to timely respond to growing climate change. Digital Factory solutions should engage together with consultancy. The reason is that digital solutions and consultancy are both ICT tools are should collaborate to better share human needs and environmental impact on humans. Access to information and communication technology differ considerably across the globe with heavy impact. Many efforts made to close this digital divide and if successful, a better harmonize approach to fight climate change.

1.4 Objectives of the Study

Artificial intelligence (AI) is a system or field that deals with machine learning (ML) to provide artificial behavior to situations around us in the living environment. This field of study help humans easily understands certain things difficult to be understood easily, humans. With the strong relationship between AI and ML, it is therefore important to use some algorithms to collect data about the environment and present it to the general public as a means of signaling caution about the dangers of our activities. The following objectives are used in this study to help the readers understand the study and to act as a caution to the general public on the dangers of our activities in the living environment.

(1) To explain how the integration of sensors and predictive analytics to control the negative impact of climate change.

(2) To examine and provide data on how the integration of sensors and machine learning algorithms can help predict future climate situations.

1.5 Questionnaires

Two research questions were developed and tested with hypotheses. Based on the daily statistic, the author was able to respond to survey questions and hypotheses.

(1) Can the integration of sensors and predictive analysis control the negative impact of climate change?

(2) Can the integration of sensor and machine learning algorithms help predict future climate situations?

1.6 Hypothesis

The study had to run a hypothesis for the primary data collected to determine the degree of acceptance of integration or sensor and the role of machine learning in the fight against climate change.

Hypothesis Analysis. Two basic hypotheses were applied that represent the two research questions and also directly represent the study objective. The hypothesis was abbreviated as H and numbers represent the following words Yes or No signs. Yes=1 while No=No. H1=hypothesis. Yes and H0=hypothesis No.

H1=Yes, H0=No. The study will determine if:

(1) If Yes or No the integration of sensors and predictive analysis can control the negative impact of climate change.

(2) If Yes or No the integration of sensor and machine learning algorithm help predict future climate situation.

1.7 Current Global State of Climate

With advanced orientation on human needs, more artificial devices, systems, processes, and psychological needs have been developed that give the most needed desires to humans. Modern tools that make life easier for humans have been greatly exploited. Little attention has been placed on plants, animals, and biomedical sciences that sustain lives. The intergovernmental panel on climate change 2022 [21], said preparing comprehensive assessment reports about the state of scientific, technical, and socio-economic knowledge on climate change helps impacts the world and exposes future risks with an option for reducing the rate at which climate change is taking place. Climate change scenarios predict additional stresses on wetlands [22]. According to global average surface temperature [23], earth's temperature has risen by 0.14° Fahrenheit (0.08° Celsius) per decade since 1880. These changes go a long way to affecting the ozone layer. This study couldn't access information about emissions and even try to request daily statistics but fail. The main problem with global climate change is due to different governmental policies. The authors of this manuscript decided to run a primary search to document in their way the impact of climate change on our environment based on carbon emissions. No state will be able to achieve sufficient climate action alone as it seems to be a central feature of the current global order that cooperation is required [24]. Because the world requires a global approach, this study embarks in search of possibilities to remotely fight climate change with the integration of sensors and predictive analysis of machine learning techniques.

2. Related Literature

The use of ML in this study is observed in three major directions, supervised learning, unsupervised learning, and reinforcement learning. Many systems predict and use sensors to capture environmental issues like digital stethoscopes and home-based spirometry tests [25]. With the advancement in technology, ML learning is becoming a great tool that can be trained to handle environmental issues. A system that answers the need on how to construct computers that improve automatically through past use or instruction [26]. The part of technology that encompasses a broad range of algorithms and modeling data techniques tools that can be used for a vast large quantity of data processing tasks is ML. Environmental issues are one of the broadest areas of humanity as they are where every technological system circulates. There is a need to use this technology of ML to make this environment where every system rest to be comfortable for users and the technology itself.

We classify machine learning into three categories. We observed supervised learning to be that section that involves the daily data of emissions produced by transport cars between Zabrze and Krakow highways.

We computed CO_2 produced by transport cars in this study as input data classified as supervision and letting the computer know how it is running, performing, and the machine is responsible for learning the rules and instructions by annotated samples. While on the other hand, we see unsupervised learning as daily emissive data from the highway of Zabrze and Krakow. In this section we let ourselves be like a school in which the student starts to see the data and tries to figure it out without supervision. The process of data collection was not trained or predetermined. We observed this data silently without signaling the authorities or city users of the city of Krakow. The (fine-tuned predictive analysis model) plays along as a regression linear algorithm and was able to help us recognize a pattern that is impossible for a human to discover which we used to simplify it for general public understanding. Lastly, reinforcement learning, which we observed to be a type of learning that provides feedback in terms of reward or punishment with the help of a regression linear algorithm is learning.

2.1 Application of Machine Learning with the Support of IoTs, Big Data, NLP, and Cloud Computing on Climate Change

Effective integration of sensors embedded in an AI can use many applications to capture changes in the environment. We know the disasters that can happen around us be they man-made or naturally from nature [27]. Mobile apps are critical elements that work with embedded sensors to help users in daily environmental situations. Sensors enable a very important role in our daily activities as they provide an essential component for Internet of Things (IoT) based application systems. Sensors help us to collect information to make smart decisions based on intelligent feedback from a mobile application.

Figure 1, NLP act as a channel of data input. Big data technology act as access and permissible quality of the internet of 5G for data collected to be treated. The IoTs provide a cyber-physical object of real-world permissibility between environmental activities and humans. The IoTs give access to GPS and actuators to record daily activities using various sensors. The AI here acts as autonomous and swarm robots that capture information based on instructions. These instructions can be through text commands, voice commands, and remote commands which are aspects of NLP. Cloud computing technology gives access to monitor and capture data remotely without living in our comfort zones. Here most drones and remote sensors can display what is happening around us.

Natural Language processing and climate prediction. The application of NLP help communicated the activities related to environmental activities that let to global effects. Before information circulates in any society or system it is passed through text messages, video charts audio records, emails, and calls. To effectively fight climate change and accurately predict, the whole globe requires advanced implementation of the NLP system.

Big data and climate prediction. The system act as a channel that provides accurate, fast, and reliable access. With the advancement of technology, big data technology can handle a large amount of data and give access to good internet and 5G network that can access a good number of environmental issues.

Internet of Things and climate prediction. This system helps connect with an object and gives a human sense of real-world existence. The IoTs are a cost-effective and efficient way to manage and control climate [28]. With IoTs, it is possible to connect with many objects that can give feedback on daily occurrences like emissions, and uses of environmental elements that advance the effects of climate change.

Artificial intelligence and climate prediction. It is a system of modern technology that most companies are adopting now to replace human sources. This system is fast in executing commands but little use of this system has been put in place to alert the users of environmental effects or daily emissions.

Artificial Intelligence on mobile apps and climate predictions.

Cloud computing is the most used in the field of environmental activities. With the advancement in sensors, 3D technology that capture real-world activities uses cloud computing. Machine learning can use knowledge from cloud computing to educate students and the general public by way of simulation. Today, most activities are moving remotely and the knowledge of cloud computing is greatly needed.

This section explains the challenges that modern technology has indirectly or directly put on the economy which is negatively affecting humanity. Many changes have occurred in the universe in the past years due to advances in technology. The excesses of technology for competitive reasons have put humanity on an imbalanced scale of laughter from the best of beautiful environments and tears of global warming.

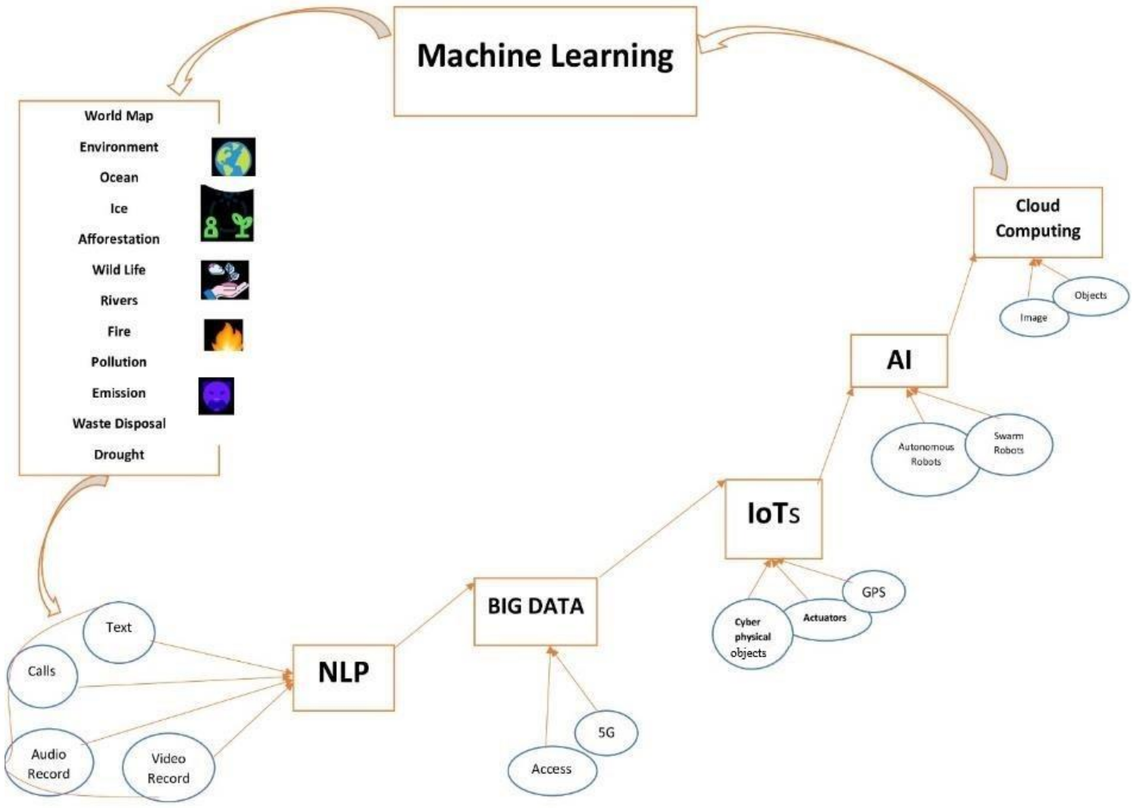


Figure 1. Application of machine learning with the support of IoTs, big data, NLP, and cloud computing on climate

Table 1. General statistics for diesel, petrol and LPG emissions Zabrze-Krakow highway

Details month	**Time**	**Zabrze-Katowice diesel 5 liters/100 km**			**Zabrze-Katowice petrol 5 liters/100 km**			**Zabrze-Katowice LPG 5 liters/100 km**		
Date	11:00-11:30AM	Diesel daily record	Fixed g CO_2/km Zabrze-Krakow	Total diesel daily records	Petrol daily record	Fixed g CO_2/km Zabrze-Krakow	Total daily records	LPG daily record	Fixed g CO_2/km Zabrze-Krakow	Total LPG daily records
12/4/2022	11:00-11:30AM	18	132 g CO_2/km	2376	30	120 g CO_2/km	3600	5	61 g CO_2/km	305
13/04/2022	11:00-11:30AM	16	132 g CO_2/km	2112	18	120 g CO_2/km	2160	4	61 g CO_2/km	244
14/04/2022	11:00-11:30AM	17	132 g CO_2/km	2244	23	120 g CO_2/km	2760	5	61 g CO_2/km	305
15/04/2022	11:00-11:30AM	17	132 g CO_2/km	2244	27	120 g CO_2/km	3240	3	61 g CO_2/km	183
16/04/2022	11:00-11:30AM	18	132 g CO_2/km	2376	23	120 g CO_2/km	2760	10	61 g CO_2/km	610
17/04/2022	11:00-11:30AM	12	132 g CO_2/km	1584	20	120 g CO_2/km	2400	11	61 g CO_2/km	671
18/04/2022	11:00-11:30AM	16	132 g CO_2/km	2112	28	120 g CO_2/km	3360	2	61 g CO_2/km	122
19/04/2022	11:00-11:30AM	13	132 g CO_2/km	1716	25	120 g CO_2/km	3000	7	61 g CO_2/km	427
20/04/2022	11:00-11:30AM	14	132 g CO_2/km	1848	21	120 g CO_2/km	2520	5	61 g CO_2/km	305
21/04/2022	11:00-11:30AM	20	132 g CO_2/km	2640	29	120 g CO_2/km	3480	8	61 g CO_2/km	488
22/04/2022	11:00-11:30AM	21	132 g CO_2/km	2772	30	120 g CO_2/km	3600	9	61 g CO_2/km	549
23/04/2022	11:00-11:30AM	16	132 g CO_2/km	2112	27	120 g CO_2/km	3240	3	61 g CO_2/km	183
24/04/2022	11:00-11:30AM	9	132 g CO_2/km	1188	27	120 g CO_2/km	3240	5	61 g CO_2/km	305
25/04/2022	11:00-11:30AM	14	132 g CO_2/km	1848	28	120 g CO_2/km	3360	8	61 g CO_2/km	488
26/04/2022	11:00-11:30AM	7	132 g CO_2/km	924	21	120 g CO_2/km	2520	4	61 g CO_2/km	244
27/04/2022	11:00-11:30AM	21	132 g CO_2/km	2772	19	120 g CO_2/km	2280	7	61 g CO_2/km	427
28/04/2022	11:00-11:30AM	23	132 g CO_2/km	3036	15	120 g CO_2/km	1800	4	61 g CO_2/km	244
29/04/2022	11:00-11:30AM	11	132 g CO_2/km	1452	17	120 g CO_2/km	2040	3	61 g CO_2/km	183
30/04/2022	11:00-11:30AM	15	132 g CO_2/km	1980	11	120 g CO_2/km	1320	7	61 g CO_2/km	427
1/5/2022	11:00-11:30AM	19	132 g CO_2/km	2508	25	120 g CO_2/km	3000	8	61 g CO_2/km	488
2/5/2022	11:00-11:30AM	10	132 g CO_2/km	1320	23	120 g CO_2/km	2760	6	61 g CO_2/km	366
3/5/2022	11:00-11:30AM	20	132 g CO_2/km	2640	26	120 g CO_2/km	3120	3	61 g CO_2/km	183
4/5/2022	11:00-11:30AM	14	132 g CO_2/km	1848	14	120 g CO_2/km	1680	5	61 g CO_2/km	305
5/4/2022	11:00-11:30AM	17	132 g CO_2/km	2244	28	120 g CO_2/km	3360	8	61 g CO_2/km	488
6/5/2022	11:00-11:30AM	8	132 g CO_2/km	1056	30	120 g CO_2/km	3600	6	61 g CO_2/km	366
7/5/2022	11:00-11:30AM	9	132 g CO_2/km	1188	24	120 g CO_2/km	2880	4	61 g CO_2/km	244
8/5/2022	11:00-11:30AM	17	132 g CO_2/km	2244	27	120 g CO_2/km	3240	7	61 g CO_2/km	427
		412		**54384**	**636**		**76320**	**157**		**9577**

Excess application of simulators and systems. Nowadays, most experiments are off the field. Modern tools are in advance used with little consideration to field activities. This alone has taken the world unaware with a very high impact. The simulator presented in the paper was without real-time execution capability adjusted to reproduce the output voltage characteristic of a Relion SR-12 500-W PEM FC stack most experiments that were at first carried out on the field are nowadays examined, determine, and concluded based on simulators and systems results [29]. Following this advance used of software and systems, real threatening situations have been undermined. Many real situations are verily considered because little close human attached nerfs of the environment have been undermined.

Excess artificial tools and devices. Today, the high demand for beautiful cities, transport systems, and infrastructure has made it a highly desirable loyalty for artificial devices. In the past, many infrastructures were often complimented with the most natural sceneries. Following technological development's influence and needs, many developers have turned to paying more attention to artificial things like flowers, lights, carpets, and many others. The most challenging and demanding task in science today is to utilize new energy to make renewable and clean fuels from abundant and easily accessible resources [30]. These elements are highly appreciated and limelight for humans but negatively impact our environment for there is no timely approach to handle such identify challenges.

Reclamation and mining of lands. Many years ago, biological experiments were that most organisms that have a friendly impact on human lives are very close to the human inhabitants. Mining has left an extensive environmental impact [31]. With technological development and the growth of the population, many infrastructure techniques have been developed. Planes like swarms, valleys, and wet weather are now being reclaimed. Most organisms that live in these places have been destroyed. Many diseases and hazards of different natures have been developed that impact our well-being negatively. Land reclamation areas pose a threat to ecosystems and also have effects on the local climate [32].

Higher consumable electronics. High-tech support devices that allow the spot need and desires have prompted the growth of non-recycled electronics. Today because of human needs and wants, technology has resulted in advanced material products very infrastructure and friendly to the environment. IoTs, big data, and cloud computing have ensured a perfect fit design to fulfill the needs of humans from different backgrounds and classes. With higher needs enhancement, little considerations are seen in the environmental impact assessment applied. There are difficulties in clarifying a particular identify optimal strategy for plastic waste management [33]. From the publisher, we can likely say that there is a real impact on the economy and there should be readjustment. Following advancements in technology, there has been an increase in plastic items.

Exaggeration of human needs. Nowadays we see cars that respond to owners' commands, we see infrastructure responses to human needs ranging from health to wellness issues. But no technology has been seen responding to the extinction of habitats that provide basic elements that sustain life and protect the environment. The extent to which environmental and climate change has been exploited [34]. They find out that about 15,963 publications are available on health and climate change-related issues predominantly in the areas of Air quality and heat stress. Nowadays, we see modern systems that help to reproduce.

3. Results

This section responds to the research question and confirmation of a positive or negative hypothesis. The standard of application of Yes or No surely depends on the data collected and the result from the re-enforcement approach of machine learning applied and the regression approach to data computation. The following questions were determined.

RQ1: Can the integration of sensors and predictive analysis control the negative impact of climate change? Based on the literature [35], a repeated occurrence can be documented and used as a lesson to others. In the survey about rainfall and natural disaster. This is true because of the rule of sensitization. The study uses (fine- tuned predictive analysis model). The said data can be used to document the rule of sensors by capturing reoccurrences. Statistics assembled by this study can help as an eye-opener for the government of Poland to promote afforestation to help cope with gas emissions from transport cards to fight against climate change.

RQ2: Can the integration of sensor and Machine learning algorithms help predict future climate situations? Based on Figure 3, Yes, it's possible to base on the approach (fine-tuned predictive analysis model) applied in this study. From (Figure 2), we can see a sample analysis of data for the first 10 days of the month. On a scale of 100% emission, the below statistic indicates 18% LPG cars summing up to 50% of g CO_2/km already capture from the data. From the 10 days of emission from LPG cars, we can predict to have more emissions as days go by. This question also responds to the hypothesis. With the high rate of emission within 10 days of the month, it is likely to observe more emissions.

Another sample to predict the number of cars to be recorded according to statistics for data needed was put to test. From (Figure 3) above, follows the statistic needed within a time interval of a month. When a sample was run using ML data analysis to predict how many likely numbers of cars will be identified under the list diesel category, the sample analysis indicate that 412 cars will be identified for one month. This prediction was accurate as 412 cars using diesel were identified (Figure 3 and Table 1). The sample survey also indicated that within ten days of the month that is from 12th April 2022 and 20th April 2022, 147 diesel cars will be identified. This was also actually identified as a reference (Figure 3 and Table 1). The said number of cars using diesel was identified on the highway between Zabrze and Krakow. This amount was verified from the filling station XXX on the highway road number A4 Zabrze to Krakow. The above (Figure 2 and Figure 3), has determined that, Yes, the integration of sensors and predictive analysis can control the negative impact of climate change. These, therefore, respond to hypothesis one. The second hypothesis has confirmed that, Yes, the integration of sensor and Machine learning algorithms can help predict future climate situations.

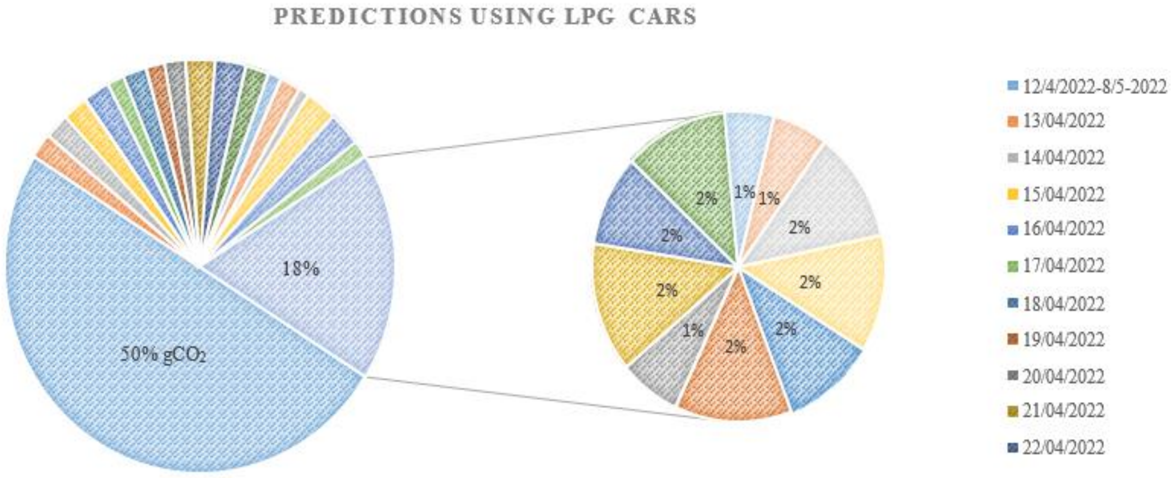


Figure 2. LPG cars emission predict future climate situation

Diesel daily record on predictive analysis and control mechanism. Following the two research questions. Sample analysis was attempted with the help of statistics from cars using diesel. The following statistics were assembled.

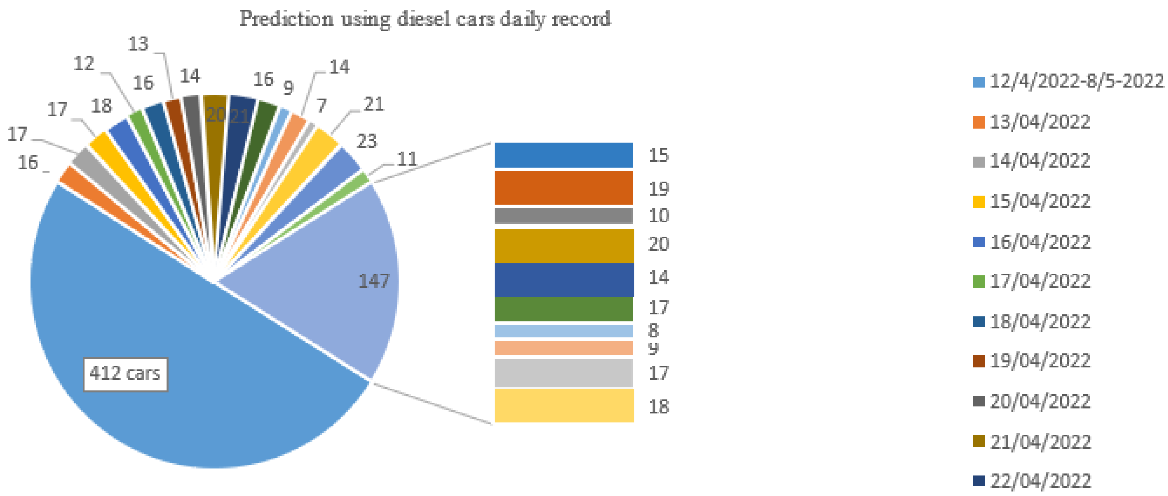


Figure 3. Prediction using diesel cars daily records

3.1 Comparative Regression Analysis of the Results

This section of the result presents a comparative analysis of the three selected brands ranging from the worst car brand fuel system with the highest level of Emission. Diesel Daily analysis: This Figure 4 below gives detailed emissions of day-day pollution of diesel cars and the amount of CO_2 produced between 12th April 2022 and 8th April 2022 on Zabrze and Krakow highway in an interval time scale of 11:00-11:30 AM.

The Figure 4 detail how many cars were recorded per day and the amount of CO_2 product, using diesel flying on the road of Zabrze and Krakow. The statistics are limited to data for just time intervals of 11:00-11:30 AM from the 12th of April 2022 and the 8th of May 2022.

Petrol monthly analysis: Figure 5 below gives detailed emissions of day-day pollution of petrol cars and the amount of CO_2 produced between 12th April 2022 and 8th April 2022 on Zabrze and Krakow highway in an interval time scale of 11:00-11:30 AM.

The Figure 5 detail how many cars were recorded per day and the amount of CO_2 product, using petrol flying the road of Zabrze and Krakow. The statistics are limited to data for just time interval of 11:00-11:30 AM from the 12th April 2022 and 8th May 2022.

LPG monthly analysis: This Figure 6 below gives detailed emissions of day-day pollution of LPG cars and the amount of CO_2 produced between 12th April 2022 and 8th April 2022 on Zabrze and Krakow highway in an interval time scale of 11:00-11:30 AM.

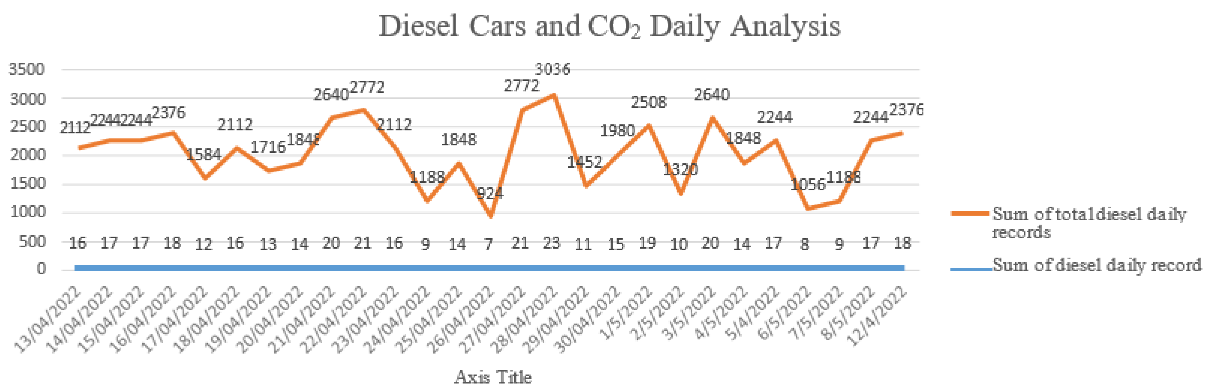


Figure 4. Daily analysis of CO_2 and diesel cars records per day

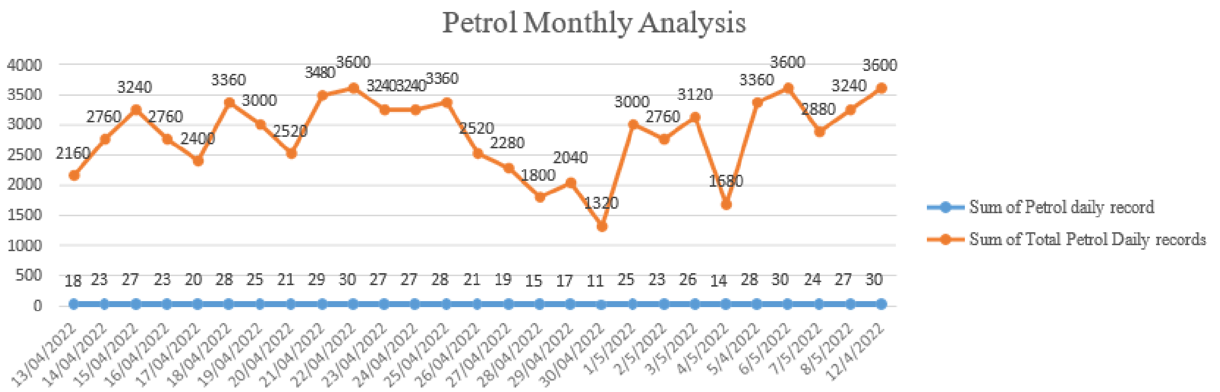


Figure 5. Daily analysis of CO_2 and petrol cars records per day

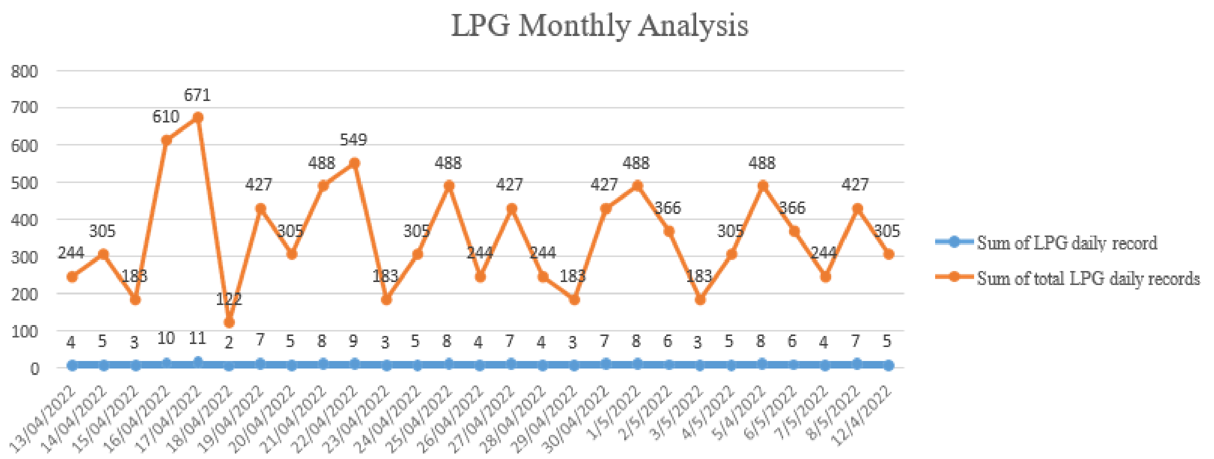


Figure 6. Daily analysis of CO_2 and LPG cars records per day

The above Figure 6 detail how many cars were recorded per day and the amount of CO_2 product, using LPG flying the road of Zabrze and Krakow. The statistics are limited to data for just time intervals of 11:00-11:30 AM from the 12th of April 2022 and the 8th of May 2022. From the representative graph, we can see a fluctuation in the number of cars and CO_2 plotted on the diagram.

NB: From the above comparative analysis, the following statistics indicate 412 diesel cars emitted 54,384 g CO_2/km, 636 petrol cars emitted 76,320 g CO_2/km, and 157 LPG cars emitted 9,577 g CO_2/km. The movement of the graph can also help us understand the busiest days that have the higher emissions than others. Total findings shows that petrol cars are the highest carbon emittance. This can also help in planning a regulatory mechanism. The results from Figure 4, Figure 5 and Figure 6 can help persons suffering from lung diseases to be able to determine which days of the month they require precautions and which they don't require such.

4. Applied Method

The use of machine learning (ML) in this study is observed in three major directions, supervised learning, unsupervised learning, and reinforcement learning. Firstly, supervised learning. We observed supervised learning to be that section that involves the daily data of emissions produced by transport cars between Zabrze and Krakow highways. We computed CO_2 produced by transport cars in this study as input data classified as supervision and letting the computer know how it is running, performing, and the machine is responsible for learning the rules and instructions by annotated samples. While on the other hand, we see unsupervised learning as daily emissive data from the highway of Zabrze and Krakow. In this section we let ourselves be like a school in which the student starts to see the data and tries to figure it out without supervision. The process of data collection was not trained or predetermined. We observed this data silently without signaling the authorities or city users of the city of Krakow. The (fine-tuned predictive analysis model) plays along as a regression linear algorithm and was able to help us recognize a pattern that is impossible for a human to discover which we used to simplify it for general public understanding. Lastly, reinforcement learning, which we observed to be a type of learning that provides feedback in terms of reward or punishment with the help of a regression linear algorithm is learning.

The data in this section was collected on the highway between Zabrze and Katowice. Between these midways, all cars were considered to take up 100 km and utilized 5 liters of fuel consumed. During the survey, 30 minutes were spent on this highway for one month. A fixed particular time was taken into consideration (11:00-11:30 AM). Based on car circulation, statistics were collected that determine the rate of emission per day for a period of one month (Table 1). Each type of car was confirmed with filling station XXX. To confirm if it is petrol, diesel, or LPG type of fuel was monitored as the only evidence of the exact category.

The following mathematical summations methods were used to calculate the CO_2 emission from the fuel consumption. CO_2 was arranged from the highest consumption system to the lowest. In the findings diesel top the list, petrol second, and LPG last.

$$\boldsymbol{Ea} = \frac{Average\ consumption\ liters}{Kilometers} \times CO_2\ arams$$

where,

FA) Diesel:

::::) 1 liter of diesel weighs 835 grams.

::::) Diesel consist for 86,2% of carbon, or 720 grams of carbon per liter diesel.

::::) To combust this carbon to CO_2, 1,920 grams of oxygen is needed.

::::)) The sum of 720 = 2,640 grams of CO_2/liter diesel.

::::)) An average consumption of 5 liters/100 km then corresponds to 5 L x 2,640 g/L / 100 (per km) = 132 g CO_2/km.

FB) Petrol:

::::) 1 liter of petrol weighs 750 grams.

:::)) Petrol consists for 87% of carbon, or 652 grams of carbon per liter of petrol.

:::)) To combust this carbon to CO_2, 1,740 grams of oxygen is needed.

:::)) The sum of 652 = 2,392 grams of CO_2/liter of petrol.

:::)) An average consumption of 5 liters/100 km then corresponds to 5 L x 2,392 g/L / 100 (per km) = 120 g CO_2/km.

$$\boldsymbol{EaDiesel} = \frac{Average\ consumption\ liters}{Kilometers} \times CO_2\ arams$$

$$\boldsymbol{Eq} = \frac{5}{100} \times 2640 = 132\ g\ CO_2/km$$

$$\boldsymbol{EaPetrol} = \frac{Average\ consumption\ liters}{Kilometers} \times CO_2\ arams$$

$$\boldsymbol{Eq} = \frac{5}{100} \times 2392 = 120\ g\ CO_2/km$$

FC) LPG:

:::)) 1 liter of LPG weighs 550 grams.

:::)) LPG consists for 82,5% of carbon, or 454 grams of carbon per liter of LPG.

:::)) To combust this carbon to CO_2, 1,211 grams of oxygen is needed.

:::)) The sum of 454 = 1,211 grams of CO_2/liter of LPG.

:::)) An average consumption of 5 liters/100 km then corresponds to 5 L x 1,211 g/L/ 100 (per km) =61 g CO_2/km.

$$\boldsymbol{EqLPG} = \frac{Average\ consumption\ liters}{Kilometers} \times CO_2\ arams$$

$$\boldsymbol{Eq} = \frac{5}{100} \times 1211 = 61\ g\ CO_2/km$$

The result presented in this section were applied throughout the study to obtain data that was uses to developed section 3, 3.1 and 4.1. Section 3 is the result of the findings and analysis of questionnaires and hypothesis. Section 3.1 is the comparative regression analysis of the results while section 4.1 is the applied method and the equation uses to calculated all the input results.

4.1 Analysis of Applied Method of Data Collected

This section detailed the sum total of cars identified by the study between 12th April 2022 and 8th April 2022 using the Zabrze and Krakow highways between 11:00-11:30 AM respectively. Details are given below for petrol, gas, and LPG.

Diesel cars. In a period of one month, 412 cars and 4,384 g CO_2/km were recorded on measurement of 100 km of highway between Zabrze to Krakow consuming 5 liters. The total number of cars per recorded time scale (11:00-11:30 AM) was multiple by 132 grams (g) of Carbon dioxide (CO_2) of 100 kilometers (km) journey between the Zabrze-Krakow highway.

Table 2. General statistics for diesel emissions Zabrze-Krakow Highway per month

Details month	Time scale	Zabrze-Katowice DIESEL 5 liters/100 km		
Date	11:00-11:30AM	Diesel daily record	Fixed g CO_2/km Zabrze-Krakow	Total diesel daily records emission
12/4/2022 to 8/5/2022	11:00-11:30AM	412	132 g CO_2/km	5,4384 g CO_2/km

From Table 2 above, 412 diesel cars and 54384 g CO_2/km on a fixed 132 g CO_2/km were recorded between 12th April 2022 and 8th May 2022. This tells us how much the rate of emission was from diesel cars and how much effect was exposed to the environment.

Petrol cars. In a period of one month, 636 Petrol cars and 76,320 g CO_2/km were recorded on measurement of 100km of highway between Zabrze to Krakow consuming 5 liters. The total number of cars per recorded time scale (11:00-11:30 AM) was multiple by 120 grams (g) of Carbon dioxide (CO_2) of 100 kilometers (km) journey between the Zabrze-Krakow highway.

Table 3. General statistics for petrol emissions Zabrze-Krakow highway per month

Details month	Time scale	Zabrze-Katowice DIESEL 5 liters/100 km		
date	11:00-11:30AM	Petrol daily record	Fixed g CO_2/km Zabrze-Krakow	Total Petrol Daily records emission
12/4/2022 to 8/5/2022	11:00-11:30AM	636	120 g CO_2/km	76,320 g CO_2/km

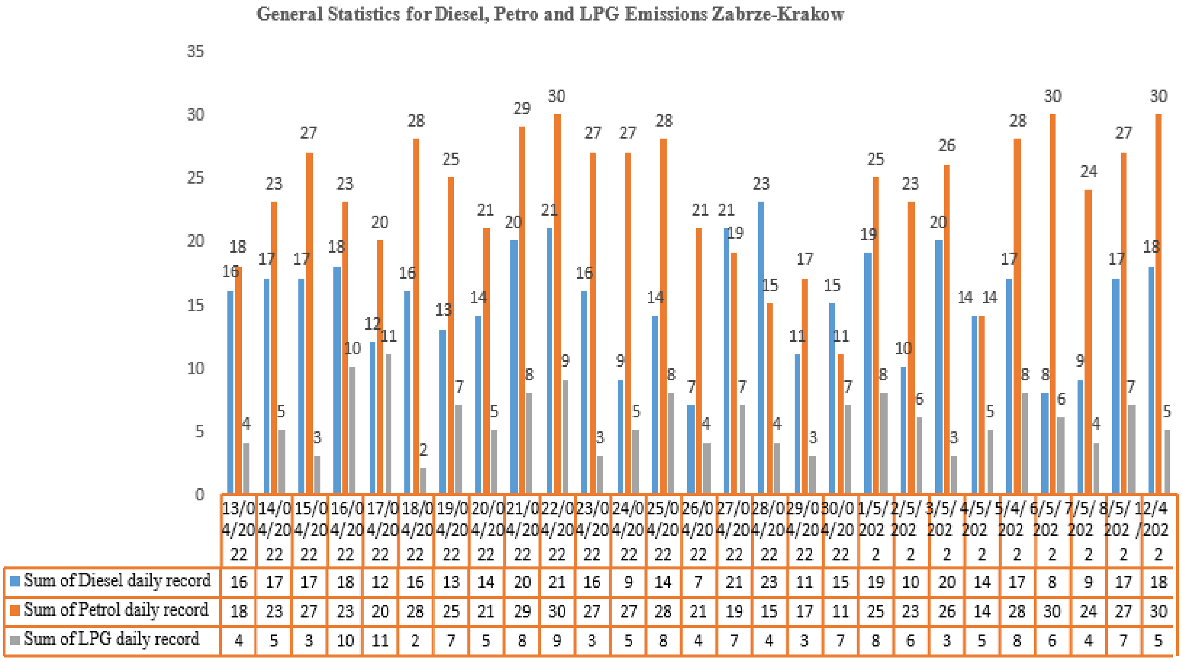
From Table 3 above, 636 petrol cars and 76,320 g CO_2/km on a fixed 120 g CO_2/km were recorded between 12th April 2022 and 8th May 2022. This tells us how much rate of emission was from Petrol cars and how much effect was exposed to the environment.

LPG cars. In a period of one month, 157 LPG cars and 9,577 g CO_2/km were recorded on measurement of 100km of highway between Zabrze to Krakow consuming 5 liters. The total number of cars per recorded time scale (11:00-11:30 AM) was multiple by 61 grams (g) of Carbon dioxide (CO_2) of 100 kilometers (km) journey between the Zabrze-Krakow highway.

Table 4. General statistics for LPG emissions Zabrze-Krakow Highway per month

Details month	Time scale	Zabrze-Katowice LPG 5 liters/100 km		
Date	11:00-11:30AM	LPG daily record	Fixed g CO_2/km Zabrze-Krakow	Total LPG daily records emission
12/4/2022 to 8/5/2022	11:00-11:30AM	157	61 g CO_2/km	9,577 g CO_2/km

From Table 4 above, 157 LPG cars and 9,577 g CO_2/km on a fixed 61 g CO_2/km were recorded between 12th April 2022 and 8th May 2022. This tells us how much the rate of emission was from LPG cars and how much effect was exposed to the environment.



	13/04/2022	14/04/2022	15/04/2022	16/04/2022	17/04/2022	18/04/2022	19/04/2022	20/04/2022	21/04/2022	22/04/2022	23/04/2022	24/04/2022	25/04/2022	26/04/2022
Sum of Diesel daily record	16	17	17	18	12	16	13	14	20	21	16	9	14	7
Sum of Petrol daily record	18	23	27	23	20	28	25	21	29	30	27	27	28	21
Sum of LPG daily record	4	5	3	10	11	2	7	5	8	9	3	5	8	4

	27/04/2022	28/04/2022	29/04/2022	30/04/2022	1/5/2022	2/5/2022	3/5/2022	4/5/2022	5/4/2022	6/5/2022	7/5/2022	8/5/2022	12/4/2022
Sum of Diesel daily record	21	23	11	15	19	10	20	14	17	8	9	17	18
Sum of Petrol daily record	19	15	17	11	25	23	26	14	28	30	24	27	30
Sum of LPG daily record	7	4	3	7	8	6	3	5	8	6	4	7	5

Figure 7. Statistics of g CO_2/km of movement of cars from Zabrze to Krakow

From Figure 7 above, we can see the various amount of emissions for diesel, petrol, and LPG cars for the period of one month. These statistics were calculated with the help of the standard formulas from the point (FA, FB, and FC) above. To derive the statistics data of Figure 7 above, for instant Diesel daily records, the final answer for FA (132 g CO_2/km) was multiplied with daily records as in (Figure 7). The same activity was carried out for all the statistics above to compute the final emission of each car category.

5. Discussion of System Implementation

This section explains how various software proposed by the study can be used to forecast and predict climate change. Simulation systems and remote sensing are innovative modern devices that help us accurately predict and map effects on soil status and identify specific policies to minimize the risk of land degradation [36]. This is an innovative system that helps preserve environmental sustainability standards. The section also explains how the impact assessment system of IoTs, big data, and cloud computing on the environment can help fight and mitigate the effects of climate change. The section also gives in brief environmental and remote sensing casework and how it can help to mitigate the effects of climate change. Lastly, the section explains how machine learning algorithms technology can be used to address issues related to climate change. Deep learning technologies can be used here to realize needed re-enforcement to evaluate learning techniques best suited for the best elements of IoTs, big data, and cloud computing. A well classifies method can help extract relevant features from waterbodies with the use of remote sensing imagery to capture drought [37].

5.1 Environmental and Remote Sensing

Emissions, carbon, nitrous, and methane oxide can be determined and detected with the help of sensors. With basic elements light high quantity of cars, stem engines and locomotive systems predominantly of diesel. It is very easy to detect the atmospheric conditions of the place without necessarily using sensors. Modern technology has come up with systems that are capable of sensing and communicating climate change. Figure 8 represents environmental and remote sensing actuator that can help in determining environmental impacts.

Geostationary satellites. They are placed in n spins and orbits in the earth's rotation. They have capabilities by using cloud computing systems to sense and compare low-altitude satellite and high resolution then provide details on the flow every 30 minutes.

Atmospheric emissions monitor. Radiative activities such as greenhouse gases can be monitored using LiDARs. To measure such, a scattering optical property is required to have a specific size, thermal system, internet access, moisture land, plants, and sensors.

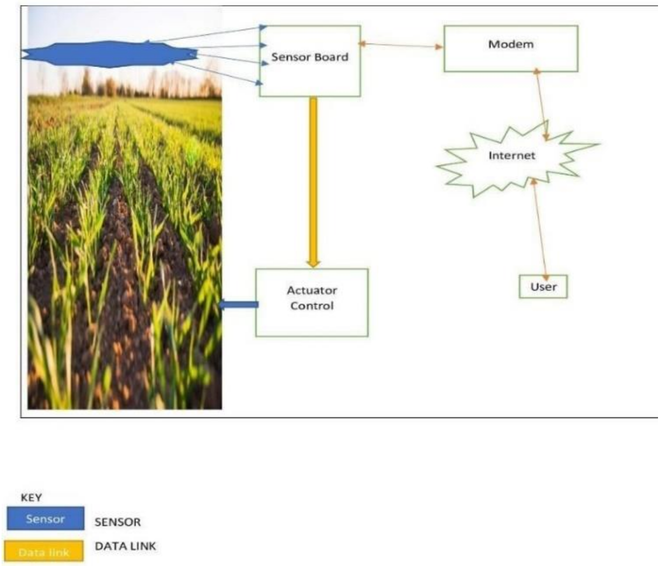


Figure 8. Environmental remote sensing

5.2 Forecasting and Prediction Model

The said model classified elements of environmental systems into different ICT tool. The system put every element on a given data set to facilitate and initiate accuracy. With global ecosystem many challenges have been observed with merging of different natural sceneries with single ICT tools. The system determines and classified different environmental sustainability paradigm into level base on needs.

The naval sensor method measures the system cloud on real-time dimensions by indicating prototype integrated systems that classified environmental impact on three different layers. Elements to tackle climate change by cloud computing, IoTs, and big data technologies. From the suggested system, the environmental sustainability paradigm of IoTs prototype can check, predict and forecast. Drought, desertification, warmness, heatwave, and temperature. With the environmental sustainability paradigm of the cloud computing prototype, it's possible to check, predict and forecast air quality, weather conditions, and wind pressure. While with the environmental sustainability paradigm of big data it is possible to check, predict and forecast acidification, glaciers, storm surge, and rise and fall of ties.

5.3 Device and Tools for Predicting and Forecasting

This section lists items that can be examined to determine the environmental impact on humans. Many elements create real-time negative impacts on society but little attention is placed on them.

- LiDARs
- Wind profiling SODAR
- Leilometer
- Radar
- Meteorological satellites and radiometers

5.4 Machine Learning Algorithms and Environmental Impact Assessment

Machine learning algorithms technology can be used to address issues related to IoTs.

Deep learning technologies can be used here to realize needed re-enforcement to evaluate learning techniques best suited for the best elements of IoTs, big data, and cloud computing. Artificial intelligence and machine learning are capable of transforming the scientific disciplines of environmental impact, but their full potential for climate change mitigation remains elusive [38]. Machine learning algorithms monitor the various components of IoTs, big data, and cloud computing by stating the entire machine learning efforts needed to enable the following possibilities.

- Means that promotes multiple benefits that IoTs used to achieve efficiency.
- Security and privacy concerns are needed for a wireless environment.
- Integration of artificial intelligence and data transactions.
- Capabilities of sensors and predictive analytics.

5.5 Preprocessing Prototype

The system below describes how machine learning can be applied in data processing acquisition of emissions from source to software-define system explained figure detail machine learning types of supervised learning, unsupervised learning, and reinforcement learning machine learning.

From Figure 9, we can see a self-explanatory diagram that details machine learning types and how gas emissions can be applied to. From the above figure supervised learning type deals with the collection and imputation of data into the system while the unsupervised learning type deal with the system running of executing and command task and the reinforcement learning type deals with system execution based on program type without human intervention. A self-organizing maps (SOM) machine learning model of deep learning can accurately predict CO_2 emissions based on the economic growth of a nation [39]. A good plan and documented dataset can help in predicting and evaluating the level of emission [40].

Artificial neural network (ANN) applications use different types of systems to capture information from the environment. This data capture advances human health and ameliorates living conditions. ANN depends on the physical space to capture data using pattern recognition, signal filtering, data segmentations, data compressions, data mining, and adaptive control strategies. ANN learns using an iterative process, unlike ML with the help of AI. As ANN uses iterative process classified into supervised learning, unsupervised learning, and reinforcement learning respectively, these is a similar pattern of activities performed by ML for its daily users.

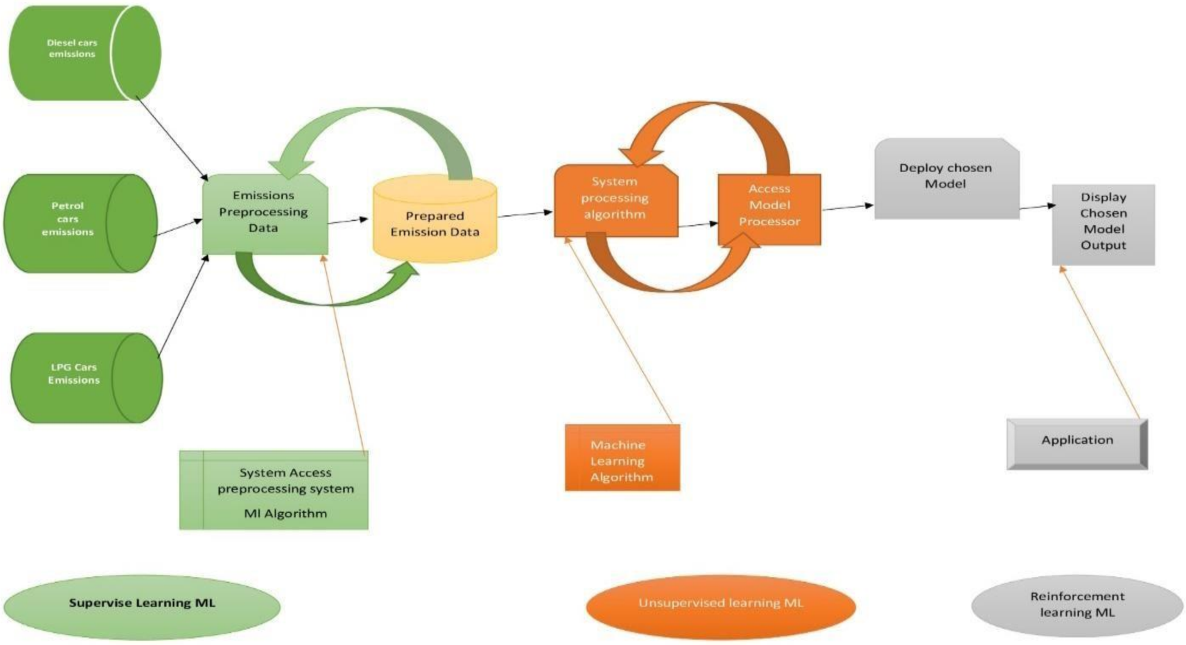


Figure 9. Emissions preprocessing prototype

Figure 10 is cyber space. Due to large data generated, management systems, strategies, and transmission signals respectively are transforming the world into virtual systems. All the above items depend on cyberspace and rely on free environmental space for smooth functioning. There is a need to keep the physical space clean and pure to enable the free and smooth function of sensors. There is a need to activate systems that reduce the level of emission as they go directly to physical space which goes a long way to hinder and slow the level of sensors. TV sets, GPS signals, WIFI signals, and many other technological systems rely on cyberspace to transmit data. Today, there is too much data generated and this data is moving to the virtual management system. With the outbreak of COVID-19, many activities have advanced to virtual space, and management system storing is shifting as well. To ease and prevent future challenges, we need to effectively control the emission of gases. The emission of gases doesn't just cause environmental harm to human health, it also changes climate. Today, more earth quarks and natural disasters are weaknesses because of the fast movement of plate tectonics. As the surface of the earth gets heated, so too does plate tectonics fast split and cause natural hazards.

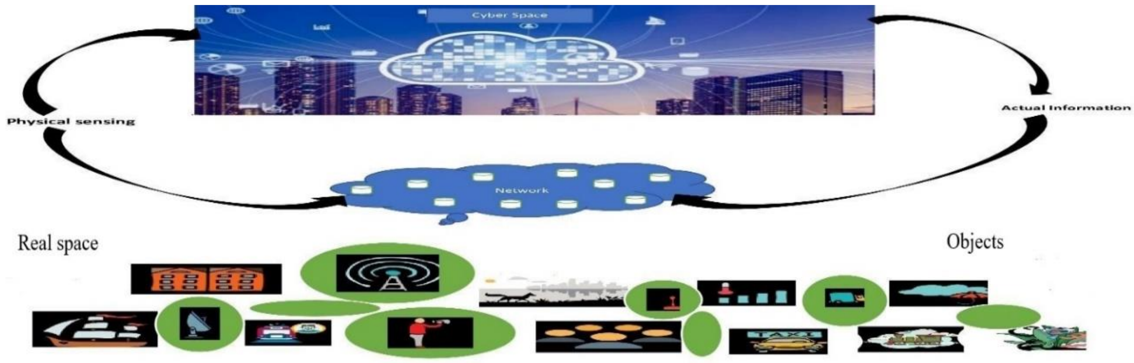


Figure 10. Cyber space

6. Conclusion

Based on the objective to enable an integrated system, method, and areas of IoTs, Big data, NLP, and cloud computing with machine learning that can focus on fighting negative environmental impact as a major step to fight climate change, the study via research questions and a hypothesis were used. Daily data on emission accusations was collected and used to respond to research questions and hypotheses. In an interval of 30 minutes per day and within a month, 412 diesel cars emitted 54,384 g CO_2/km, 636 petrol cars emitted 76,320 g CO_2/km, and 157 LPG cars emitted 9,577 g CO_2/km. Predictions and forecasts were determined based on the data collected. Data accusations reveal they worsen the future impact as both hypotheses and research questions positively support findings that integration of sensors with machine learning can predict future climate situations.

Artificial intelligence and applied machine learning techniques are great systems to advance a clean Energy System. Cyber physical required good accessibility for all types of sensors, remote monitoring, and control evaluation of CO_2 emissions. Clean energy systems stand as one of the global issues that will achieve a smart sustainable economy by 2035. The positive response of IoTs, big data, NLP, and cloud computing to the environment are permutable with the available technology. IoTs, big data, NLP, and cloud computing are effective elements to tackle climate change and give environmental impact a positive view. The advancement in technology gives it a positive role to monitor and sense the quantity of carbon monoxide in an environment. With monitoring and sensors' ability and capabilities, greenhouse gases from fossil burns can be detected and tackled. Carbon rates can be monitored and controlled. With the capabilities to develop devices from the system that monitors humans from advanced material, it's equally possible to develop devices that cohabitate with environmental hazards. Modern technology can predict, communicate, and help the user's data from the literature review reveal. With the available literature review, the hypothesis was applied to ascertain the result from questionnaires. A real scenario according to the H1, and H0 analysis integration system was critically examined based on RQ1 and RQ2. The study determined that, if a common method influence exists, (1) results emerge from analysis with the view that the integration of sensors and predictive analysis can control the negative impact of climate change (positive hypotheses), or (2) statistical data emerge accounting for the fact that integration of sensor and Machine learning algorithms help predict future climate situations (positive results) and a conclusion will take into account supporting motion. In the study, all the questions captured the motion that the integration of sensors can predict climate change situations. No single factor did emerge with an indicator integration of sensors and Machine learning algorithms cannot help predict future climate situations. Therefore, technology development of machine learning influences an achieved positive impact on economic activities via transport logistics system as its own way to fight climate change.

7. Limitation

The study realized that for any challenges in the regulations at the national level, the approach to the study must be upgraded. Other findings should continue to investigate the impact of climate change as the situation might be different in different countries.

The study is limited to findings in Poland and other findings should be carried out using a similar approach for different countries.

The study realized that there is little or no access to data regarding carbon emissions for open-access source programmable languages. Most governments are very sensitive when it comes to issues of carbon emissions and this was a big challenge for this study. We were not able to obtain open-source files with data on various car emissions for this venous city in Poland. Sourcing primary data for this study was very challenging and tough. It is costly, time-consuming, and cumbersome as we had to manually source data and analyzed using the modern computer system.

The study realized that there are no available applications to remotely source data emissions. Even with the many advancements in technology, we were unable to identify any mobile applications that can provide data on global or national carbon emissions.

The study also realized that the national and local governments do restrict open-source data about emissions. Especially heavily industrial cities that solely depend on industrialization.

The study realized a lack of willingness amongst stakeholders in matters of carbon emission as there is no concise approach to handle such a situation. The transport sector definitely is willing to give a listening ear to global climate change but they don’t have an alternative system that will follow if they will practically undertake the prescribed measures to fight climate change.

8. Recommendations

Further findings should be carried out for different countries and states. The findings of this study were limited to Poland. The study understands that when it comes to climate issues different countries hold different policies.

Further studies should investigate the level of impact of a country, city, and local community's heavy investment in an artificial system, recreational facilities, and garden as opposed to a natural system, natural recreational facilities, and natural gardens. This study understands that the situation of climate change in urban centers is worse than in local centers and the reason is the heavy investments in the artificial system, recreational facilities, and gardens.

Further studies should investigate whether the standard of different cars of diesel, petrol, and LPG are similar to the one used in this study or they are the same and what suggestions can be made to help the transport sector fully engage in the fight against climate change.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

I certify that I have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. We have no financial or proprietary interests in any material discussed in this article.

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