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Impact of the Intersection of Artificial Intelligence and the Reduction of Carbon Footprints

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***Abstract*— This study contributes to an understanding of the potential of AI in achieving a sustainable environment. In this paper, we investigate various machine learning algorithms in the context of supply chain management to determine which machine learning algorithms are best suited for predictive maintenance and CO2 emissions prediction. We highlight the practical application of this model combined with ISO-14064 by demonstrating how organizations can reduce their carbon footprints while optimizing and enhancing operational efficiency.**

***Keywords*— Artificial Intelligence, Machine Learning, supply chain management, ISO-14064, predictive maintenance**

I. Introduction

Carbon emissions, the greenhouse effect, and climate change are the most catastrophic environmental issues worldwide. Organizations make benefits by shifting all or part of their supply chain activities to countries with less stringent CO2 emissions regulations to avoid high compliance costs. This affects the climate through the increase of greenhouse gases as organizations expand their business operations and profit from lax regulations in these countries. Countries have established international agreements, such as the Paris Agreement, to limit global warming to 2 degrees by 2050 and carbon dioxide emissions to 2 tons per person by 2050. In our research, we examine the case study of a German company operating in Tunisia. There are approximately three hundred German companies engaged in part of their supply chain activities in Tunisia. We analyze the current situation of CO2 emissions in Tunisia and how AI could assist countries and organizations in reducing their CO2 emissions based on ISO 14064.

II. Literature Review

A review paper by [1], based on ISO 14064 and the Greenhouse Gas Protocol, aims to comprehend, assess, supervise, document, and verify greenhouse gas emissions while suggesting mitigation plans for organizations. A study by [2] presents an overview of the carbon footprint and explains how ISO 14067:2018, based on its principles, requirements, and guidelines, could support organizations in measuring and reporting a product's carbon footprint.

The 2022 sustainability report of the German multinational company 'DRÄXLMAIER' [3], which develops and manufactures wiring systems, interiors, and battery systems and has a significant presence in Tunisia, aims to make the future of mobility sustainable by reducing the CO2e footprint of its products. Research by [4] Integrating Artificial Intelligence investigates the role of artificial intelligence and predictive analytics in optimizing supply chain management, leading to a minimized carbon footprint using the Random Forest algorithm, one of the better-performing machine learning techniques.

Despite significant advancements in CO2 emission prediction based on AI and machine learning techniques, there remains a lack of research on preparing the data required for calculating the carbon footprint using ISO 14064 while obtaining appropriate insights from AI and machine learning techniques to optimize the application of these standards.

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III. RESEARCH OBJECTIVE

The primary objective of this research is to investigate the current situation of carbon dioxide emissions of Tunisia and to examine the intersection of Artificial Intelligence with ISO 14064 to reduce GHG emissions and enable minimal carbon footprint of supply chain operations.

IV. RESEARCH METHODOLOGIES

The research approach of this paper employs a mixed-method strategy. It involves a critical examination of various studies regarding Tunisian politics on reducing carbon emissions. A case study of a German company operating in Tunisia will be analyzed to illustrate how AI could be incorporated into the supply chain process to reduce carbon emissions.

V. TUNISIAN POLITICS OF REDUCING CARBON EMISSIONS

In 2021, Tunisia emitted 37.1 million tonnes of CO2 equivalent and belongs to the World's 100th largest emitter with 0.08% of global emissions and 3.14 tonnes of CO2 equivalent per person. However, Germany emitted 681.18 million tonnes of CO2 equivalent representing 1.43% of global emissions and 8.19 tonnes of CO2 equivalent per person [5].

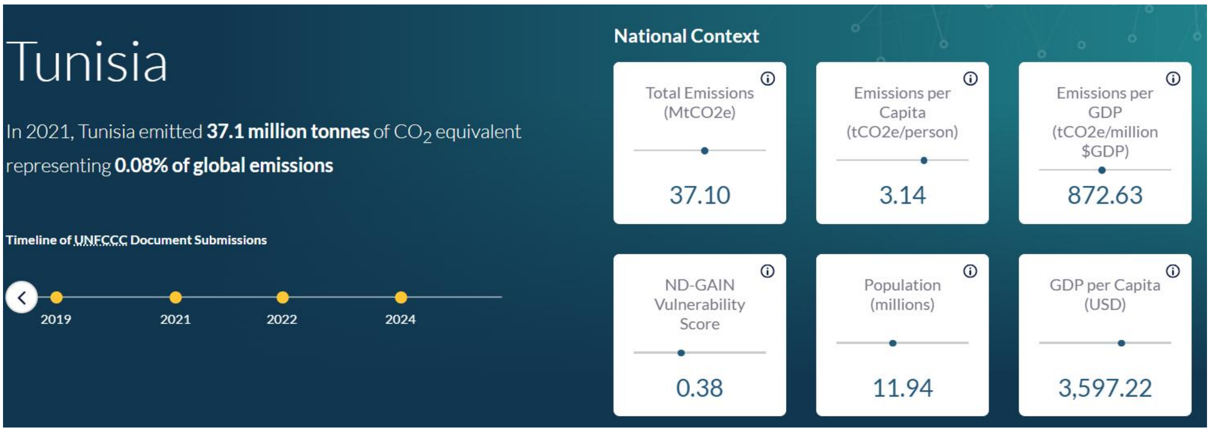

Figure 1 Tunisia's CO2 emissions in 2021

In 2021, Tunisia emitted 29,61 MtCO2 emissions from the energy sector, 6.15 MtCO2 emissions from the industrial processes, and 4,72 MtCO2 emissions from the agriculture sector. [5]. Tunisia's registered motor vehicles were reported at 1,450,000 units in December 2015. [6].

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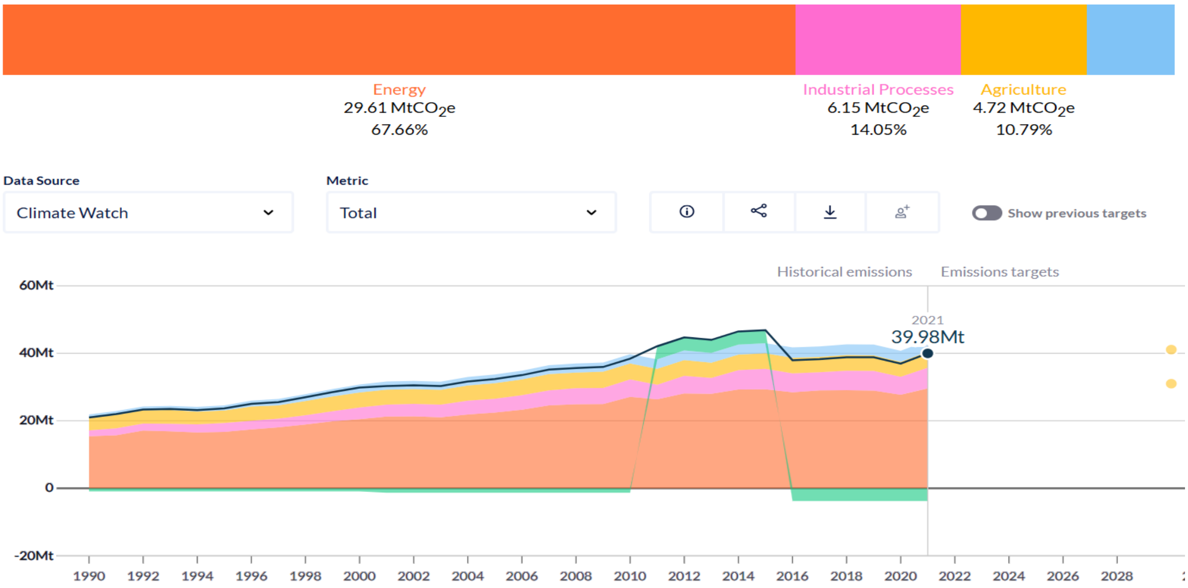

Figure 2 Tunisian Global Historical GHG Emissions from 1990 to 2021

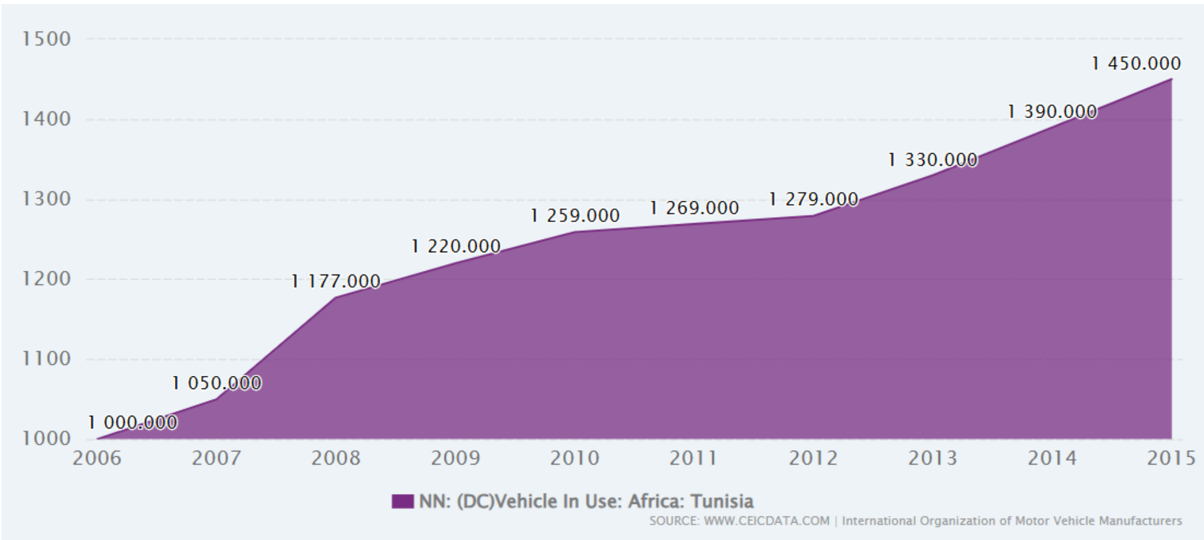

Figure 3
Tunisia's Registered Motor Vehicles from 2005 to 2015

As shown in Fig. 2 and Fig. 3, 2015 was a record year with 1,450,000 units and 46,87 MtCO2 emissions. Tunisia's forest development initiative in 2015 contributed to a change, with approximately 6.7% of the country's territory, producing positive effects on CO_2 emissions. Forests are carbon sinks as they absorb CO_2 from the atmosphere, which helps mitigate climate change. Tunisia is increasingly affected by the consequences of global climate change and has set ambitious goals within the scope of the Paris Climate Agreement to reduce CO2 emissions to 41 percent by 2030 compared with 2010. [7]. Fig. 4 shows that the majority of global GHG emissions worldwide come from the energy sector, accounting for 34%. The industrial and transport sectors together represent 39% of global GHG emissions. [8]. The predictive maintenance of vehicles and industrial machines aims to minimize GHG emissions from all related sectors, optimize supply chain operations, and reduce costs.

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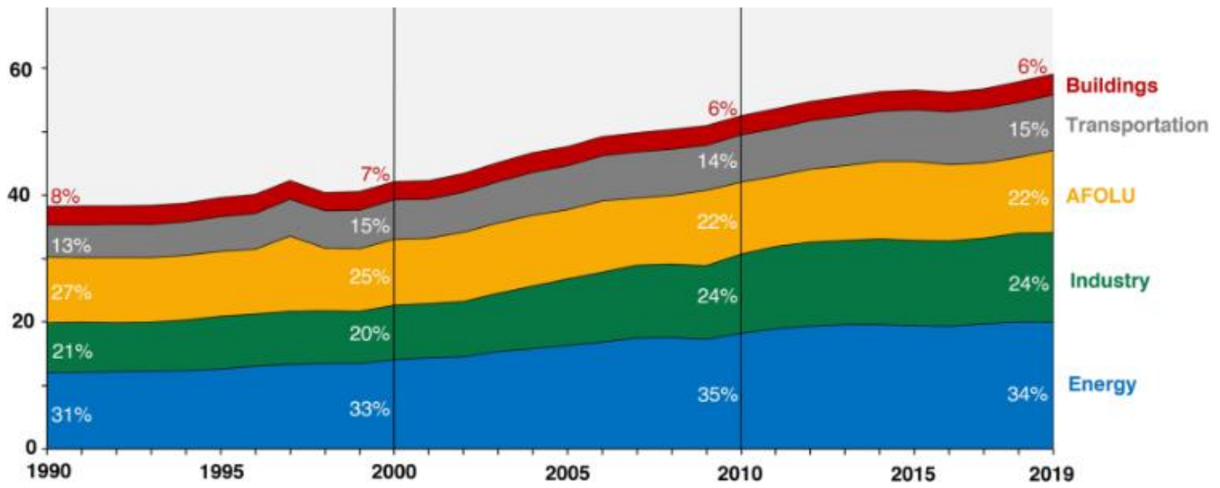

Figure 4 Global GHG emissions by sector in Gt CO2-eq from 1990 to 2019

VI. ISO 14064: CASE STUDY OF DRÄXELMAIER GROUP

ISO 14064 is a set of international standards for greenhouse gas (GHG) auditing and validation. It provides support for organizations on quantifying and reporting their GHG emissions and establishes the framework for managing the reduction of these emissions. The standard is divided into three main parts:

- ISO 14064-1: specifies the requirements at the organization level for calculating and reporting GHG emissions.
- ISO 14064-2: guides organizations involved in climate mitigation projects to reduce their GHG emissions.
- ISO 14064-3: provides requirements for the validation and verification of GHG assertions, ensuring accuracy and transparency in communicating the report.

Organizations typically implement frameworks for greenhouse gas (GHG) inventory reporting by following structured steps that ensure standardized reporting.

A. Selecting a reference year

Organizations choose a reference year that forms the basis for emissions reporting. The selection of the reference year affects the calculation´ s accuracy of the emission and the future comparisons. In our study, we choose 2022 as a reference year for emissions reporting of Dräxlmaier Group.

B. Defining Boundaries

Organizations identify all direct and indirect emissions scope across the organization. Table I provides insights into three scope categories of greenhouse gas emissions.

TABLE I GREENHOUSE GAS EMISSIONS SCOPES

Scope 1	Scope 2	Scope 3
Direct GHG emissions owned by an organization and arise from direct combustion processes at the company's own locations, including emissions from the company's vehicle fleet and from heating.	Indirect GHG emissions from purchased electricity, steam, heat, and cooling, linked to the energy supplier.	Indirect GHG emissions from activities in an organization's value chain, such as transportation and waste management.

C. Detecting Emission Sources

They collect a list of all potential emission sources of their activities. This includes for example emissions from raw materials, production, energy use, transportation, and waste management. Table II details the sources of greenhouse gas emissions by scope.

TABLE II SOURCES OF GREENHOUSE GAS EMISSIONS BY SCOPE

Scope 1	Scope 2	Scope 3
Emissions from burning natural gas	Emissions from electricity generation	Upstream Activities:

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for heating in a company building. Emissions from a gas-fired boiler used for production processes. Emissions from a company fleet of vehicles (e.g., trucks, cars) using gasoline or diesel.	at power plants that supply energy to the company's facilities. Emissions associated with the steam generated by a utility that provides heating for a company's production facilities.	Transportation and distribution (upstream). Purchased goods and services. Capital goods. Fuel- and energy-related activities not already included in Scope 1 or 2. Waste generated in operations. Employee commuting and business travel. Downstream Activities: Transport and distribution (downstream). Processing of sold products. Use of sold goods. End-of-life treatment of sold products. Leased assets. Investments.

D. Applying the relevant method

Organizations utilize standardized methodologies for calculating their GHG emissions. The Greenhouse Gas Protocol offers best practices for various industries. Organizations use two methods for calculating Scope 2 emissions. The location-based method refers to the average emission intensity of the national electricity grid, while the market-based method relies on specific emission factors from contracts with electricity suppliers.

E. Gathering activity information

This step involves the collection of relevant data of energy consumption, raw materials used, and logistics operations that contribute to GHG emissions. This includes gathering energy invoices, production data, and transportation route information necessary for more precise calculations.

F. Calculating GHG emissions

Organizations calculate their total GHG emissions from the identified sources based on emission factors related to different fuels and processes. According to Table III, the Dräxelmaier Group's highest CO2 emissions come from Scope 3, totaling 2,900,010 t CO_2e, of which 113,524 t CO_2e arise from upstream transportation and distribution. [3]

TABLE III SOURCES OF GREENHOUSE GAS EMISSIONS BY THE SCOPE OF THE DRÄXELMAIER GROUP

Company	**Scope 1**	**Scope 2**	**Scope 3**
Dräxelmaier Group	Total Scope 1 Emissions: 17,521 t CO_2e	Total Scope 2 Market-based emissions: 8,798 t CO_2e. Total Scope 2 location-based emissions: 139,430 t CO_2e.	Total Scope 3 Emissions 2,900,010 t CO_2e Purchased goods and services: 2,342,573 t CO_2e Capital goods: 274,056 t CO_2e Fuel and energy-related activities (not included in Scope 1 or 2): 9,072 t CO_2e Upstream transportation and distribution: 113,524 t CO_2e Business travel: 1,802 t CO_2e Employee commuting: 82,443 t CO_2e End-of-life treatment of sold products: 2,605 t CO_2e

G. Validation, Verification, and Reporting GHG emissions

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An independent audit may conduct a review to ensure the accuracy of the GHG emissions inventory. This is crucial for establishing transparency, credibility and compliance with regulatory requirements. The completed inventory is reported and communicated to relevant stakeholders, such as management, authorities, and the public.

H. Establishing goals for reduction of GHG emissions

Organizations set goals for emissions reduction based on the previous report. These goals are crucial for guiding future strategies and decisions. The DRÄXLMAIER Group has established goals for the reduction of greenhouse gas (GHG) emissions as part of their future sustainability plan. It aims to reduce Scope 1 and 2 emissions by 66% between 2021 and 2029, which aligns with the Paris Agreement commitments to combat climate change. [3]

I. Evaluating and adjusting

Continuous evaluating of emissions and periodic adjusting to the inventory are important to optimize operations and emissions sources precisely.

VII. DISCUSSION

The supply value chain often represents the largest portion of total emissions across the three scopes. AI technology leads to the optimization of the supply chain by enhancing demand forecasting, transport shipping routes, predictive maintenance, waste management and recycling, pollution management, energy efficiency, environmental surveillance, risk management, and automation of repetitive tasks. The integration of AI in the supply chain process aims to optimize trade operations and reduce carbon emissions. The return on investment in integrating AI-powered solutions in supply chain management brings benefits through the analysis of historical and real-time data and the application of predictive analytics to make sustainable decisions regarding demand forecasting, logistics, recycling, and carbon footprint monitoring. In this research, we focus on how AI could support predictive maintenance of vehicles to reduce CO2 emissions in the supply chain.

A. Predictive maintenance

Predictive maintenance is a preventive maintenance strategy based on data analysis and predictive analytics to identify the condition of equipment and predict when maintenance should occur. Predictive maintenance enables organizations to operate efficiently and on demand by keeping track of equipment problems before they arise, thus preventing possible downtime. Doing this saves energy, optimizes the use of equipment, reduces maintenance costs, and CO2 emissions generated by emergency work.

1) Data Collection: Data are basically collected from three sources: sensors, historical records, and environmental conditions. Sensor data relates to the collection of real-time data such as the engine´s revolutions per minute. When this value is too low or high, it may signal engine´s failure. Another relevant value are the lubricating oil pressure and temperature. In this context, low pressure means oil starvation, which could burn up the engine; too high temperature is a risk of oil breakdown, and too low temperature indicates inadequate lubrification. Further data include the coolant pressure and temperature, which measure the pressure in the coolant system to maintain the proper temperature of the engine and avoid overheating. Finally, the fuel pressure expresses the pressure of fuel supplied to the engine, which affects the Combustion quality and engine performance. Our dataset includes one label, which is the engine condition. It indicates the operational state of the engine, which is influenced by the previous features. AI based on the potential of machine learning algorithms used for the classification, enables us to predict the future state of the engine derived from historical data of the features. In our research, we utilized a dataset called [9] which includes six features. Fig. 5 provides an overview of engine´s data based on the engine´s revolutions per minute, the lubricating oil pressure and temperature, the coolant pressure and temperature and the fuel consumption to predict the engine condition label. It includes 19535 rows and 7 columns.

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	Engine rpm	Lub oil pressure	Fuel pressure	Coolant pressure	lub oil temp	Coolant temp	Engine Condition
0	700	2.493592	11.790927	3.178981	84.144163	81.632187	1
1	876	2.941606	16.193866	2.464504	77.640934	82.445724	0
2	520	2.961746	6.553147	1.064347	77.752266	79.645777	1
3	473	3.707835	19.510172	3.727455	74.129907	71.774629	1
4	619	5.672919	15.738871	2.052251	78.396989	87.000225	0
...	...	...	...	...	...	...	...
19530	902	4.117296	4.981360	4.346564	75.951627	87.925087	1
19531	694	4.817720	10.866701	6.186689	75.281430	74.928459	1
19532	684	2.673344	4.927376	1.903572	76.844940	86.337345	1
19533	696	3.094163	8.291816	1.221729	77.179693	73.624396	1
19534	504	3.775246	3.962480	2.038647	75.564313	80.421421	1

19535 rows × 7 columns

Figure 5 Engine Health Dataset Overview

2) Predictive analytics: classification: The supervised learning refers to the training of a model using feature data to predict the label for the new data. The label in our case study is known in advance, so the supervised learning algorithms is suitable for our research methodologies. There are multiple algorithms behind machine learning, particularly for classification problems. Some of the ones that are often used by supply chain professionals include: KNeighborsClassifier (KNN), Decision Tree, RandomForestClassifier, Logistic Regression, Support Vector Machines (SVM). These algorithms have their strengths and weaknesses based on the problem to be solved and the nature of the dataset. For example, in applications like supply chain management, the selected algorithm may be influenced by data correlation, operational requirements, and technical restrictions. Algorithms such as Random Forest work well for complex environments using ensemble methods for tasks like predicting likely future states or simply using Logistic Regression to gain insight on a binary classification task. [4]

TABLE IV METRICS RESULTS OF THE CLASSIFICATION MACHINE LEARNING ALGORITHMS FOR THE ENGINE HEALTH DATASET

		precision	**recall**	**f1-score**	**Accuracy**
RandomForestClassifier	0	0.62	0.29	0.40	0.66700
	1	0.68	0.89	0.77	
LogisticRegression	0	0.60	0.30	0.40	0.661632
	1	0.68	0.88	0.76	
DecisionTreeClassifier	0	0.57	0.41	0.48	0.664704
	1	0.70	0.82	0.75	
KNeighborsClassifier	0	0.48	0.42	0.45	0.611722
	1	0.68	0.72	0.70	
SVM (kernel='linear')	0	0.61	0.20	0.30	0.652674
	1	0.66	0.93	0.77	
SVM (kernel=poly)	0	0.64	0.09	0.15	0.63885
	1	0.64	0.97	0.77	

Refer to Table IV, the RandomForestClassifier has the best accuracy at 0.66700 compared to the other tested machine learning algorithms. In our case study, 0.66700 is still not a good accuracy value for an optimized outcome; however, if the dataset is expanded, the RandomForestClassifier could be better trained and achieve better accuracy. Fig. 2 shows the confusion matrix used for evaluating the accuracy of

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RandomForestClassifier to understand how well our model is predicting classes. As an example, RandomForestClassifier has correctly predicted 2177 positive class.

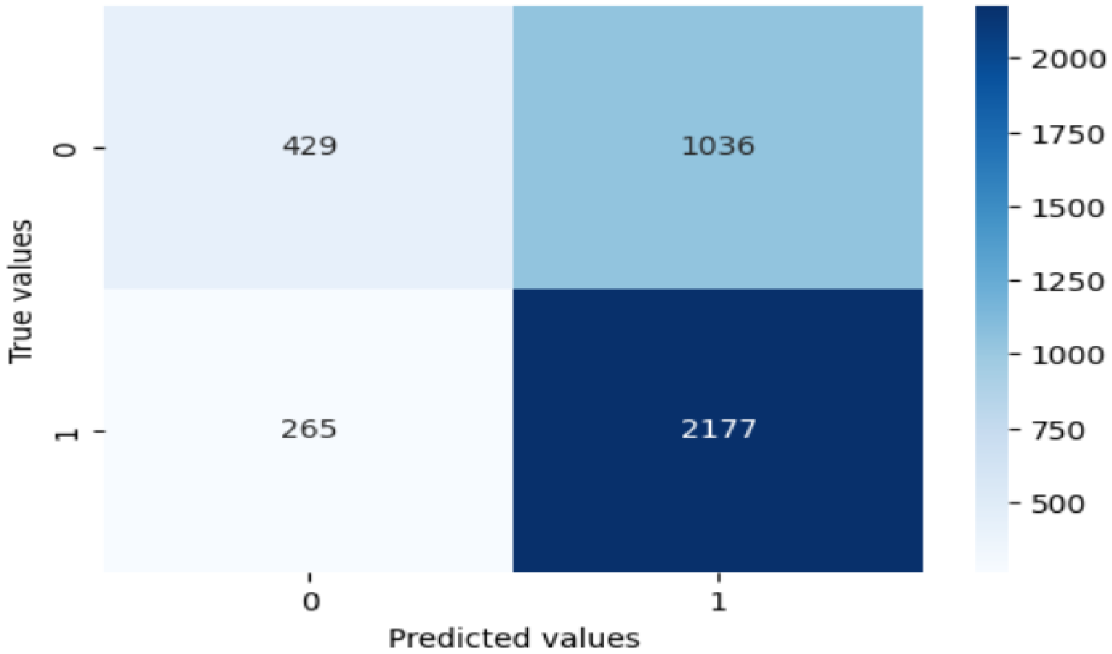

Figure 6 Confusion Matrix of the RandomForestClassifier

B. CO2 emission prediction of automobile vehicles

This is a unique research area that is heavily based on mechanical engineering, environmental science, and data analytics, helping to predict and monitor carbon dioxide emission rates from automobiles. By utilizing advanced data analytics, machine learning models, and real-time monitoring technologies, stakeholders can gain insights into emissions performance to reduce their environmental impact and ensure regulatory compliance more effectively.

1) Data Collection: Data are primarily collected from three sources: sensors, historical records, and traffic conditions. Sensor data refers to the collection of real-time data related to engine performance, fuel consumption, and CO2 emissions. Historical data involves the gathering of historical emissions data from automotive manufacturers. Traffic and driver behavior condition data indicate the traffic status, speed, and driver behavior that impact the CO2 emissions. In our research, we utilized a dataset called [10], which includes eleven features. Fig. 7 provides an overview of data for every vehicle class and engine size, including the fuel type and fuel consumption in both city and highway conditions, used to predict the CO2 emissions label. It comprises 7,385 rows and 12 columns.

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	Make	Model	Vehicle Class	Engine Size(L)	Cylinders	Transmission	Fuel Type	Fuel Consumption City (L/100 km)	Fuel Consumption Hwy (L/100 km)	Fuel Consumption Comb (L/100 km)	Fuel Consumption Comb (mpg)	CO2 Emissions(g/km)
0	ACURA	ILX	COMPACT	2.0	4	AS5	Z	9.9	6.7	8.5	33	196
1	ACURA	ILX	COMPACT	2.4	4	M6	Z	11.2	7.7	9.6	29	221
2	ACURA	ILX HYBRID	COMPACT	1.5	4	AV7	Z	6.0	5.8	5.9	48	136
3	ACURA	MDX 4WD	SUV - SMALL	3.5	6	AS6	Z	12.7	9.1	11.1	25	255
4	ACURA	RDX AWD	SUV - SMALL	3.5	6	AS6	Z	12.1	8.7	10.6	27	244
...	...	...	...	...	...	...	...	...	...	...	...	...
7380	VOLVO	XC40 T5 AWD	SUV - SMALL	2.0	4	AS8	Z	10.7	7.7	9.4	30	219
7381	VOLVO	XC60 T5 AWD	SUV - SMALL	2.0	4	AS8	Z	11.2	8.3	9.9	29	232
7382	VOLVO	XC60 T6 AWD	SUV - SMALL	2.0	4	AS8	Z	11.7	8.6	10.3	27	240
7383	VOLVO	XC90 T5 AWD	SUV - STANDARD	2.0	4	AS8	Z	11.2	8.3	9.9	29	232
7384	VOLVO	XC90 T6 AWD	SUV - STANDARD	2.0	4	AS8	Z	12.2	8.7	10.7	26	248

7385 rows × 12 columns

Figure 7 CO_2 Emissions Dataset Overview

2) Predictive analytics: regression: Linear regression can be used for simpler relationships where emissions are expected to be proportional to certain features, such as fuel consumption. Random forests and support vector machines can be employed for regression tasks to predict CO2 emissions based on input features, including vehicle type, engine size, cylinders, fuel type, and fuel consumption in the city and on the highway; these models manage non-linear relationships. Refer to Table V, the RandomForestRegressor has the best R-Squared (R^2) at 0.9687 compared to the other tested machine learning algorithms.

TABLE V METRICS RESULTS OF THE REGRESSION MACHINE LEARNING ALGORITHMS FOR THE CO2 EMISSIONS DATASET

	Mean Absolute Error (MAE)	**Mean Squared Error (MSE)**	**Root Mean Squared Error (RMSE)**	**R-Squared (R^2)**
RandomForestRegressor	4.6000	106.6837	10.3288	0.9687
LinearRegression	13.5136	410.8422	20.2692	0.8793
PolynomialFeatures	8.9617	255.4188	15.9818	0.9250
DecisionTreeRegressor	5.1828	115.1643	10.7315	0.9662

VIII. CONCLUSION

The preservation of our climate is a mission for our countries, organizations, and people. Everyone is involved in this mission to protect our climate for future generations. Artificial intelligence-powered solutions support organizations in calculating and reducing their GHG emissions while optimizing their supply chains. Predictive maintenance is not only relevant for the industry and transport sectors but also for the entire country, considering the number of vehicles in Tunisia as an example. In this context, the Random Forest machine learning algorithm performs well for predictive maintenance and the prediction of failure and CO2 emissions.

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