APPPLIED DATA SCINECE PROJECT

PROJECT TITLE: PREDICTION OF CO2 EMISSION IN VEHICLES

TEAM MEMEBERS - 12

- 1. Ch.V.Abhijeet
- 2. Mohammed Afzal
- 3. M Venkat Anvay Reddy
- 4. Vikas Yadav

- 1. Introduction
 - a. Overview
 - b. Purpose
- 2. Literature Survey
 - a. Existing Problem
 - b. Proposed Solution
- **3.** Theoretical Analysis
 - a. Block diagram
 - b. Hardware/Software designing
- 4. Experimental Investigations
- 5. Flowchart
- **6.** Result
- 7. Advantages and Disadvantages
- **8.** Applications
- 9. Conclusion
- 10. Future Scope
- 11.Bibliography
- 12. Appendix
 - a. Source code
 - b. UI output Screenshot

1. Introduction

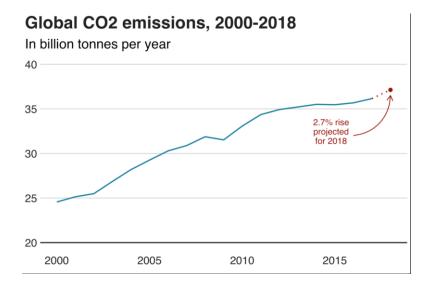
Overview: The project was to predict the emission of CO2 in vehicles this dataset contains official CO2 emissions data for various cars of different features over the period of 2014 to 2020. It has 7385 samples and has a total of 11 features.

Purpose: The main purpose of the project was to find the rate of CO2 emission in vehicles and to find which type of cars and depending on the fuel consumption which cars emit the less CO2.

2. Literature Survey

Existing Problem: Our personal vehicles are a major cause of global warming, collectively cars and trucks account for nearly one-fifth of emissions, emitting around 24 pounds of carbon dioxide and other global-warming gases for every gallon of gas.

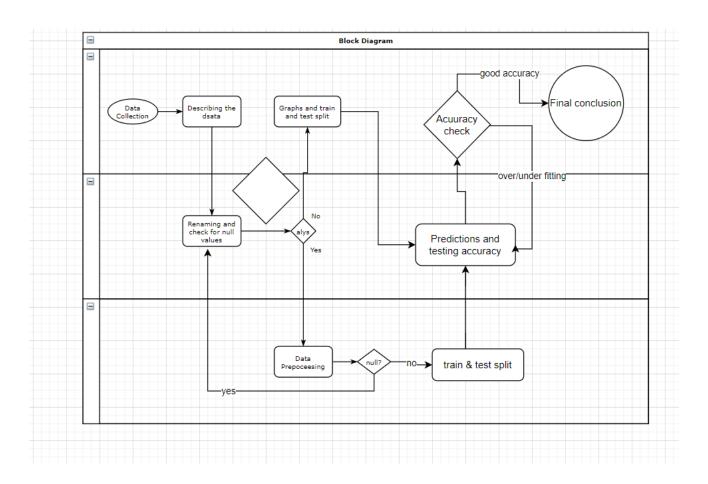
Most of the gases comes from the extraction, production, and delivery of the fuel, while the great bulk of heat-trapping emissions more than 19 pounds per gallon comes right out of a car's tailpipe.



Proposed Solution: The idea is to take the data from the past 10 years and the data set includes different kinds of vehicles and their CO2 emissions based on the fuel consumption and if we are able to calculate the vehicles which produce more CO2 as compared to other vehicles which have same engine size and fuel consumption we can decrease or stop the production of such vehicles and based on the predictions we can come to form a formidable conclusion on what to do.

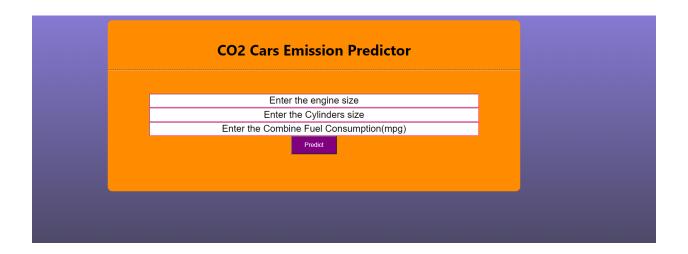
3. Theoretical Analysis

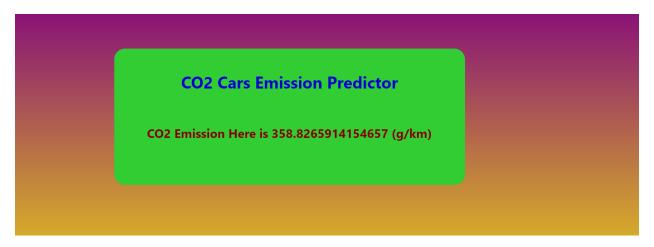
Block Diagram:



Hardware/ Software Designing:

We designed a web page which is used to predict the Co2 based on Combine Fuel Consumption and engine, cylinder size.





The hardware components required for the project are:

8GB RAM

The software components required for the project are:

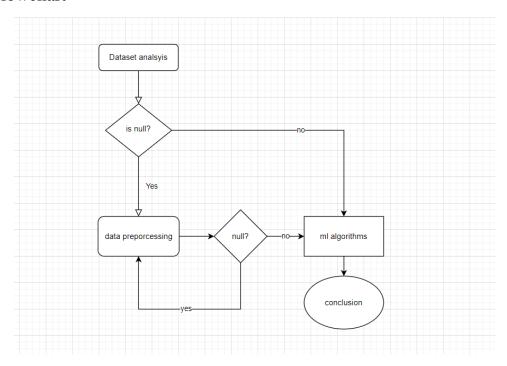
Anaconda prompt

Spyder

4. Experimental Investigations

During the project analysis we first observed what kind of data we had and as there were few empty spaces in the names we replaced the names values and checked for null values if there are any and we preprocessed the data and made few more observations and calculated the correlation and based on that we extracted the columns we need and then train and test splitting of data was done we applied different algorithms and based on the accuracy prediction we came to a conclusion that Linear regression gives good accuracy.

5. Flowchart



6. Result

Based on the algorithms we applies we came the conclusion that linear regression is giving good predictions compared to other algorithms which were either under or over fitting.

7. Advantages

The main advantage of this project is that we will be able to predict which cars are environment supportive and which cars emit less CO2.

Disadvantages

Though there are certain advantages we may not be able to predict which car gives consumes less CO2 though the accuracy is 86 we might not be able to give exact accuracy which may be improved if we collect a much larger dataset and run it in a data warehouse.

8. Applications

- They may be useful for the production of vehicles which emit less CO2.
- They will be helpful for the better development of engine size.
- They may be useful for checking the ration of engine to fuel consumption which emit less CO2.

9. Conclusion

We came to a final conclusion that engine size, cylinder size and fuel consumption directly affect the amount of CO2 which is being released into the atmosphere.

10. Future Scope

If we are able to calculate the collect much larger and amount of dataset and test the engine components for various items and how much fuel is being consumed by them and if we run the dataset in a **DATAWAREHOUSE** and deploy a machine learning model and algorithms then we may improve accuracy and give better results.

11. Bibliography

- https://www.kaggle.com/debajyotipodder/basic-eda-of-the-co2-emissions-by-vehicle-dataset
- https://www.google.com/search?q=increase+in+co2+emission+d%3Due+to
 +cars&sxsrf=ALeKk02YNk-M1K4CbYgCAeix1TesXB8BA:1627795169822&source=lnms&tbm=isch&sa=X&ved=2ahUKEwi1zP
 TGiY_yAhWIA3IKHSsBD_EQ_AUoAnoECAEQBA&biw=1536&bih=722
 #imgrc=Fx1zQE03huyuhM
- https://www.ucsusa.org/resources/car-emissions-global-warming
- https://sso.teachable.com/secure/teachable_accounts

12. Appendix Source Code

```
Renaming the Columns
 In [3]: renamed col = {
    'Vehicle Class': 'vehicle_class',
    'Engine Size(L)': 'engine_size',
    'Fuel Type': 'fuel_type',
    'Fuel Consumption City (L/100 km)': 'fuel_cons_city',
    'Fuel Consumption Hoy (L/100 km)': 'fuel_cons_mny',
    'Fuel Consumption Comb (I/100 km)': 'fuel_cons_comb',
    'Fuel Consumption Comb (mg9)': 'mggfuel_cons_comb',
    'CO2 Emissions(g/km)': 'co2'
                  dataset.rename(renamed_col, axis='columns', inplace=True)
                 Checking For Null Values
  In [4]: dataset.isnull().any()
 Out[4]: Make
Model
Welcle_class
engine_size
Cylinders
Transmission
fuel_type
fuel_cons_city
fuel_cons_cmb
mpgfuel_cons_comb
co2
                                                     False
atype: bool

In [5]: dataset.isnul

Out[5]: Hake
Hodel
Wehicle_class
engine_size
Cylinder:
Cylinder:
Gylinder:
Fuel_cons_city
fuel_cons_comb
mpgfuel_cons_comb
co2
dtype: int64
                  co2
dtype: bool
  In [5]: dataset.isnull().sum()
  Information of Dataset
               In [8]: dataset.describe()
                          engine_size Cylinders fuel_cons_city fuel_cons_hwy fuel_cons_comb mpgfuel_cons_comb

        count
        7385.00000
        7385.00000
        7385.00000
        7385.00000
        7385.00000
        7385.00000
        7385.00000

        mean
        3.160083
        5.615030
        12.556534
        9.041706
        10.975071
        27.481652
        250.584899

        std
        1.354170
        1.828307
        3.500274
        2.224456
        2.802506
        7.231679
        58.512679

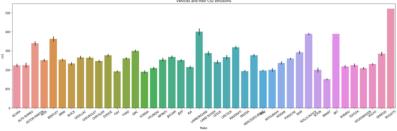
                                                                                            4.000000
                    min 0.900000 3.000000
                                                                      4.200000
                                                                                                                   4.100000
                                                                                                                                               11.000000 96.000000
                 25% 2.000000 4.000000 10.100000
                 75% 3,70000 6,00000 12,10000 10,20000 12,60000 27,00000 246,00000 275,00000 28,00000 10,20000 12,800000 32,000000 28,000000 10,200000 12,800000 32,000000 288,000000
                   max 8.400000 16.000000 30.600000 20.600000
                                                                                                                                              69.000000 522.000000
                                                                                                                 26.100000
```

Data Visualization

```
In [9]: dataset.Make.unique()
```

Make VS CO2 Emission

```
In [10]: f, ax = plt.subplots(figsize=(25,7))
             x = dataset.Make.value_counts().sort_values()
             ax = sns.barplot(data-dataset,x='Make',y='co2')
plt.title('Vehicles and their Co2 emissions')
plt.xticks(rotation=35)
plt.show()
```



Model Building Using Decision Tree

```
In [52]: from sklearn.tree import DecisionTreeRegressor from sklearn.model_selection import GridSearchCV
```

- In [53]: dt_model=DecisionTreeRegressor(criterion='mse',random_state=0)
- In [54]: dt_model.fit(x_train,y_train)

In [55]: y_pred=dt_model.predict(x_test) y_pred

- Out[55]: array([300. , 176.25 , 286.25 323.55555556, 250.5625]) , ..., 246.76190476,
- In [56]: np.sqrt(mean_squared_error(y_test,y_pred))

Out[56]: 7.420156024586886

- In [58]: dt_model = DecisionTreeRegressor(random_state = 42)

Using GridSearch for hyperparameter tuning

```
In [59]: dt_cv_model = GridSearchCV(dt_model, dt_params, cv = 10, n_jobs = -1, verbose = 2)
```

In [60]: dt_cv_model.fit(x_train, y_train)

Fitting 10 folds for each of 36 candidates, totalling 360 fits

```
Scaling
In [39]: from sklearn.preprocessing import StandardScaler
         import joblib
sc=StandardScaler()
x=sc.fit_transform(x)
          joblib.dump(sc,'standard.save')
Out[39]: ['standard.save']
          Splitting the Dataset into train and test
In [40]: from sklearn.model_selection import train_test_split
    x_train,x_test,y_train,y_test*train_test_split(x,y,test_size=0.2,random_state=0)
          Model Building Using Multiple Linear Regression
In [41]: from sklearn.linear_model import LinearRegression
In [42]: mr=LinearRegression()
          Fitting the model to training data
In [43]: model=mr.fit(x_train,y_train)
          Making Predictions
In [44]: y_pred=mr.predict(x_test)
y_pred
Out[44]: array([373.41938679, 172.7802348 , 272.18033419, ..., 241.51011101, 321.57600975, 233.59796301])
In [45]: y_test
Out[45]: 553
```

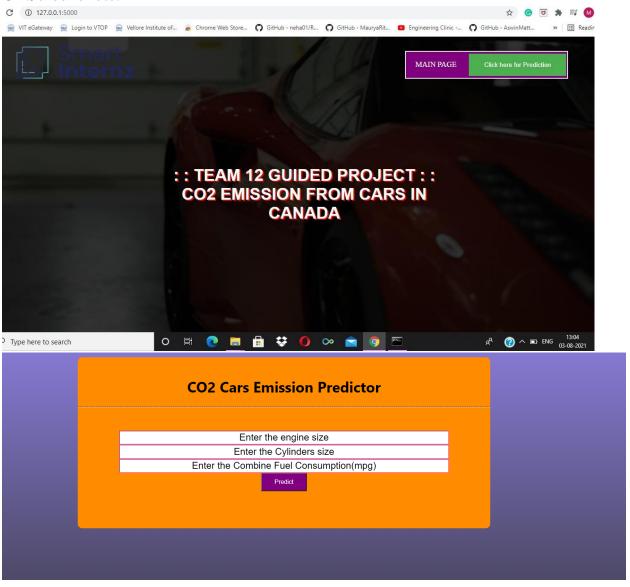
```
In [60]: dt_cv_model.fit(x_train, y_train)
                Fitting 10 folds for each of 36 candidates, totalling 360 fits
                [Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done 25 tasks | elapsed: 4.5s
[Parallel(n_jobs=-1)]: Done 322 tasks | elapsed: 5.3s
                [Parallel(n_jobs=-1)]: Done 360 out of 360 | elapsed: 5.4s finished
Out[60]: GridSearchCV(cv=10, error_score=nan,
estimator=DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse',
                                                                                           max_depth=None, max_features=None,
max_leaf_nodes=None,
                                                                                           max_lear_inues=nume,
min_impurity_decrease=0.0,
min_impurity_split=None,
min_samples_leaf=1,
min_samples_split=2,
min_weight_fraction_leaf=0.0,
presort='deprecated',
                                                                                           random_state=42, splitter='best'),
                                     random_state=42, splitter="best
ide"deprecated', n_jobs=-1,
param_grid={'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9],
"max_features': [3, 5, 10, 15]},
pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
scoring=None, verbose=2)
In [61]: dt_cv_model.best_params_
Out[61]: {'max_depth': 9, 'max_features': 3}
In [63]: dt_tuned.fit(x_train, y_train)
Out[63]: DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=9,
                                                    (ccp_aipha=e.o, criterion= mse , max_deptn=9,
max_features=3, max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, presort='deprecated',
random_state=None, splitter='best')
In [64]: np.sqrt(mean_squared_error(y_test, y_pred))
Out[64]: 7.420156024586886
```

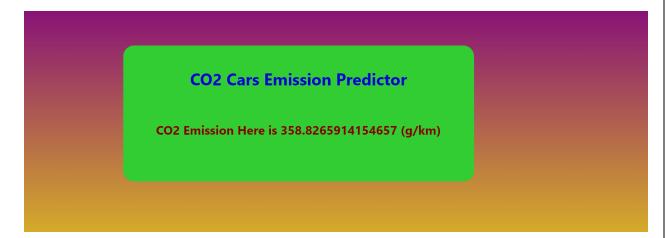
Checking the Score of The Model

```
In [65]: from sklearn.metrics import r2_score
r2_score(y_test,y_pred)
Out[65]: 0.9814724059217347
In [66]: from io import StringID
from IPython.display import Image
from Stlaern.tree import export_graphvir
import pydotplus
dot_data = StringIO()
export_graphvir(dt_tuned_out_file-dot_data,
filed-frue, rounded-frue,
special_characters-True)
graph = pydotplus_graph from_dot_data(dot_data.getvalue())
Image(graph.create_png())
                   dot: graph is too large for cairo-renderer bitmaps. Scaling by 0.600777 to fit
Out[66]:
                                                                      alanda arabakan adda walanda arabaka arabaka arabaka arabaka ada walanda wa walanda arabaka araba walanda arab
In [67]: pred=dt_tuned.predict(x_test)
frames = [pred,y_test]
result_pred = pd.DataFrame(data=frames)
result_pred=result_pred.T
                  result_pred_Dt-result_pred_rename(columns=(0: 'Pred_DT',1: 'Real'))
result_pred_Dt['Pred_DT']-result_pred_Dt['Pred_DT'].map(lambda x:round(x,2))
result_pred_Dt['Diff']-result_pred_Dt['Pred_DT']-result_pred_Dt['Real']
result_pred_Dt['Diff'']-result_pred_Dt['Diff'']
result_pred_Dt['Diff'']-result_pred_Dt['Diff'']).mean())
result_pred_Dt.head(20)
                  Mean Diff: 3.6608868715083807
Out[67]:
                          Pred_DT Real Diff
                  0 308.02 290.0 18.02
                    2 285.07 287.0 -1.93
                      3 272.93 274.0 -1.07
                    4 186.26 188.0 -1.74
                      5 209.57 211.0 -1.43
```

```
Fitting 10 folds for each of 144 candidates, totalling 1440 fits
              [Parallel(n\_jobs=-1)] \colon \mbox{ Using backend LokyBackend with 8 concurrent workers.}
               [Parallel(n_jobs=-1)]: Done 25 tasks
[Parallel(n_jobs=-1)]: Done 146 tasks
                                                                             elapsed: 2.8s
elapsed: 12.2s
              Out[76]: GridSearchCV(cv=10, error_score=nan, estimator=RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse', max_depth=None, max_features='auto', max_leaf_nodes=None, max_samples=None, min_impurity_decrease=0.0,
                                                                             min_impurity_decrease=0.0,
                                                                             min_impurity_decrease=0.0,
min_impurity_split=None,
min_samples_leaf=1,
min_samples_split=2,
min_weight_fraction_leaf=0.0,
n_estimators=100, n_jobs=None,
oob_score=False, random_state=42,
verbose=0, warm_start=False),
                                In [77]: rf_cv_model.best_params_
 Out[77]: {'max_depth': 9, 'max_features': 3, 'n_estimators': 500}
 In [78]: rf_tuned = RandomForestRegressor(max_depth = 9,
                                                            max features =
                                                            n_estimators =500)
 In [79]: rf_tuned.fit(x_train, y_train)
 Out[79]: RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                                             max_depth=9, max_features=3, max_leaf_nodes=None,
max_samples=None, min_impurity_decrease=0.0,
                                             min_impurity_split=None, min_samples_leaf=1,
min_samples_split=2, min_weight_fraction_leaf=0.0,
                                             n_estimators=500, n_jobs=None, oob_score=False, random_state=None, verbose=0, warm_start=False)
```

UI Screenshots:





```
Editor - A:\Internship\INternship\FINAL PROJECT\finalsite.py
finalsite.py
                indexnew.html
  1 # -*- coding: utf-8 -*-
  3 Created on Sat Jul 31 14:30:10 2021
  5 @author: M VENKAT ANVAY REDDY
  8 from flask import Flask, request, render_template
  9 import joblib
 10 model = joblib.load('fourtune.save')
 11 trans=joblib.load('scproject.save')
 13 app = Flask(__name__)
 14
 15
 16 @app.route('/')
 17 def home():
       return render_template('home.html')
 18
 19 @app.route('/Prediction', methods=['POST', 'GET'])
 20 def prediction():
        return render_template('indexnew.html')
 22 @app.route('/Home', methods=['POST', 'GET'])
 23 def my_home():
        return render_template('home.html')
 25 @app.route('/predict',methods=["POST","GET"])
 26 def predict():
 27
        x_test=[[float(x) for x in request.form.values()]]
       x_test=trans.transform(x_test)
 28
 29
       y_pred=model.predict(x_test)
 30
       output=y_pred[0]
 31
        return render_template('resultnew.html',prediction='{}'.format(output))
 32
 33
 34 if __name__ == '__main__':
 35
        app.run(debug=True)
```