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UNDERSTANDING ARTIFICIAL INTELLIGENCE

771763-2022/2023

ASSIGNMENT: COMPONENT 1

ABSTRACT

In this report we will examine the breakdown structure of various agents and how they perform in their environment.

1.0 INTRODUCTION

A decision or action can be made by an agent based on its own evaluation of the surrounding circumstances and the data it has access to. In the case of computer agents, there is more emphasis about their performance in an environment *[Russell and Norvig, 2016].*

2.0 METHODOLOGY

This shows the breakdown structure of the agent, including pictorial representation using microsoft paint to show the agent's behaviour in an environment and some pseudocode demonstration for the agent function.

2.1 THE TASK ENVIRONMENT

Table 1. This is the list of the task environment for each agent.

AGENT TYPE	THE TASK ENVIRONMENT
Motion Detection Agent	Improve Office Productivity
Solar Power Agent	Reduce CO2 Emission Usage
Human Agent	Detect Hazard in an Environment
Motion Detection Security Agent	Prevent Physical Theft Prevention
Magnetic Resonance Imaging (MRI) Agent	Display Irregularities in the Brain
Computed Tomography (CT) Scan Agent	Display Cancer Tumors in the body

2.2 THE PEAS DESCRIPTION

Table 2. The PEAS (Performance Measures Environment Actuators Sensors)

AGENT TYPE	PERFORMANCE MEASURES	ENVIRONMENT	ACTUATORS	SENSORS
Motion Detection	The accuracy of the motion prediction.	The office space and people	Lightening and Heating systems.	Infrared and Ultrasonic

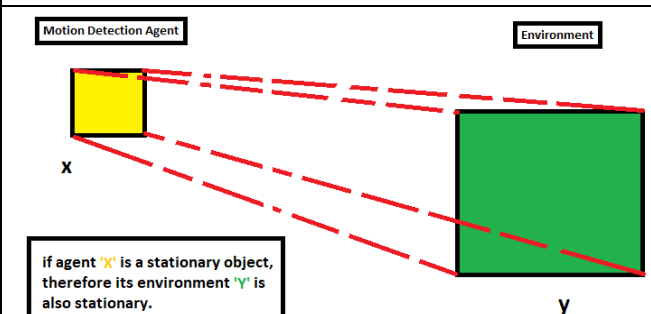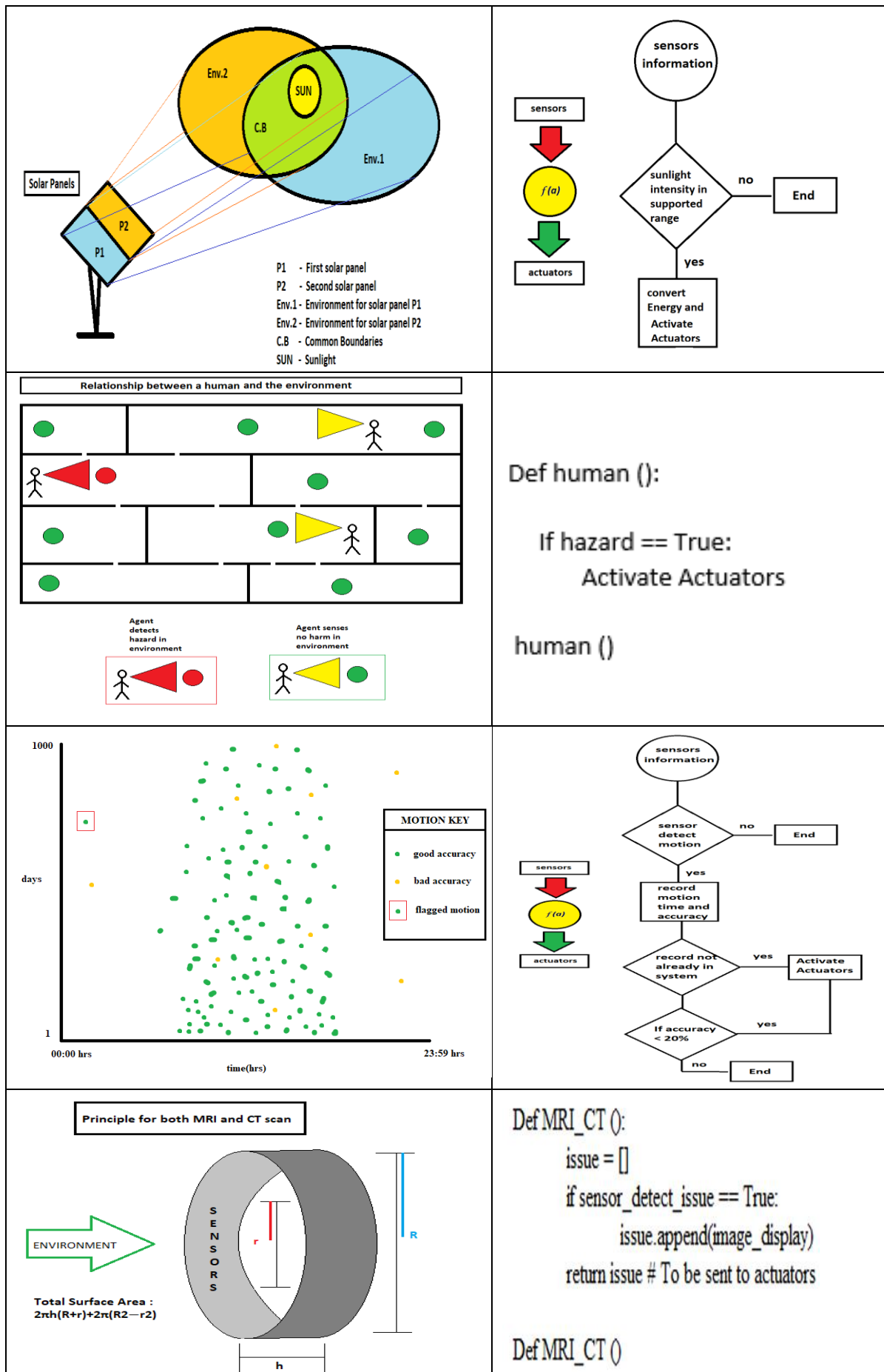| Solar Power | The efficiency of the energy from sunlight. | Sunlight and trees. | Batteries and Inverters. | Solar Panels. |
Human	The accuracy in detecting hazard.	People and equipment.	Human Actions	Human Eyes Human Noise
Security Motion Detection	The accuracy of the motion prediction.	People and stationary objects.	Security light and Alarm bells.	Infrared and Ultrasonic
Brain Surgery MRI	Clear 3D image of a patient facial organs	patient head, patient facial organs	3D Image display and Sound	Fiber Optic Temperature sensors
(CT) Scan for Cancer Detection	Clear 3D image of a patient body organs	Patient body and organs	3D Image display and Sound	Image sensor

2.3 PERCEPTS OF THE AGENT

Table 3. The percept refers to the input provided to the system.

AGENT TYPE	PERCEPTS
Office motion detection agent	Human motion in the environment
Solar power agent	Sunlight intensity
Human agent	Hazard in the environment
Security motion detection agent	Human motion in the environment and time of motion
Brain surgery MRI agent	Images in the environment
CT scan for cancer detection agent	Images in the environment

2.4 AGENT FUNCTION

Table 4. Some pictorial representation of sensors behavior in an environment and a code demonstration of the agent function.

SENSOR AND ENVIRONMENT	PSEUDOCODE DEMONSTRATION

Motion Detection Agent — Environment — x — if agent 'X' is a stationary object, therefore its environment 'Y' is also stationary. — y	if sensor_detect_movement == True:
	    RESET timer
	    if actuator == OFF:
	        ON actuator
	elif timer == 0 and actuator == ON:
	    OFF actuator

Panel 1 (top-left)

Env.2
SUN
C.B
Env.1
Solar Panels
P2
P1

P1 - First solar panel
P2 - Second solar panel
Env.1 - Environment for solar panel P1
Env.2 - Environment for solar panel P2
C.B - Common Boundaries
SUN - Sunlight

Panel 2 (top-right)

sensors information

sensors
$f(a)$
actuators

sunlight intensity in supported range — no → End

yes

convert Energy and Activate Actuators

Panel 3 (second row, left)

Relationship between a human and the environment

Agent detects hazard in environment

Agent senses no harm in environment

Panel 4 (second row, right)

```
Def human ():

    If hazard == True:
        Activate Actuators

human ()
```

Panel 5 (third row, left)

1000

days

1

00:00 hrs   23:59 hrs

time(hrs)

MOTION KEY

● good accuracy
● bad accuracy
□ flagged motion

Panel 6 (third row, right)

sensors information

sensor detect motion — no → End

yes

record motion time and accuracy

record not already in system — yes → Activate Actuators

If accuracy < 20% — yes

no → End

sensors
$f(a)$
actuators

Panel 7 (bottom-left)

Principle for both MRI and CT scan

ENVIRONMENT

SENSORS

r
R
h

Total Surface Area :
$2\pi h(R+r)+2\pi(R2-r2)$

Panel 8 (bottom-right)

```
Def MRI_CT ():
    issue = []
    if sensor_detect_issue == True:
        issue.append(image_display)
    return issue # To be sent to actuators


Def MRI_CT ()
```

2.5 EXTERNAL STIMULI

Table 5. External stimulus (actions) could affect (trigger) the behaviour of the agents.

AGENT TYPE	EXTERNAL STIMULI
Motion Detection Agent for Office Productivity	Obstruction and Rapid Distance
Solar Power Agent for Climate Change Solutions	Weather condition Trapped dirt on the solar panel
Human Agent for Hazardous Environment	Poor sight to see clearly and Emotional stimuli
Motion Detection Security Agent for Physical Theft Prevention	Camera placement and Movement in the environment
Magnetic Resonance Imaging (MRI) for Brain Surgery	Metal objects, Patient movement, Patient size
Computed Tomography (CT) Scan for Cancer Detection	Bad electronic component (IC), Patient size, Patient movement

2.6 PROPERTIES OF THE TASK ENVIRONMENT

Table 6. The properties of the task environment of the agents

TASK ENVIRONMENT	OBSERVABLE	AGENTS	DETERMINISTIC	EPISODIC	STATIC	DISCRETE
Motion Detector	Fully observable	Single agent	Deterministic	Episodic	Dynamic	Discrete
Solar Power System	Fully observable	Single agent	Non-deterministic	Episodic	Dynamic	Continuous
Human	Partially observable	Multi-agent	Non-deterministic	Episodic	Dynamic	Discrete
Security Motion Detector	Fully observable	Single agent	Deterministic	Sequential	Dynamic	Discrete
Brain MRI	Fully observable	Single agent	Deterministic	Episodic	Static	Discrete
CT Scan Cancer Detector	Fully observable	Single agent	Deterministic	Episodic	Static	Discrete

2.7 AGENT STRUCTURE

Table 7. Agent program category

AGENT TYPE	AGENT PROGRAM
Motion Detection Agent for Office Productivity	SIMPLE REFLEX AGENT
Solar Power Agent for Climate Change Solutions	SIMPLE REFLEX AGENT
Human Agent for Hazardous Environment	LEARNING AGENT
Motion Detection Security Agent for Physical Theft Prevention	MODEL-BASED FLEX AGENT
Magnetic Resonance Imaging Agents for Brain Surgery	SIMPLE REFLEX AGENT
Computed Tomography (CT) Scan for Cancer Detection	SIMPLE REFLEX AGENT

2.8 RESULT/JUSTIFICATION

The performance measures for humans and motion detection for both office productivity and security depends on the accuracy to ensure correct actions by the actuators while MRI and CT depend on clarity for easy operation of the patient. The sensor receives percepts from the environment and gives output to the agent function, while the agent function does the mathematical computation that activates the actuators.

For both motion detection agents, the sensor is interested in the percept involving human motion to feed the agent function for an accurate output. In the case of human and solar power system agent, we are looking at the hazard and sun intensity respectively as they are the requirement needed for the agent function after detected by a sensor. The MRI and CT agent percepts are images of the environment detected by the sensors for the agent function to take further action.

Motion detectors, solar power system, MRI and CT scan agent are all fully observable because they can see the whole environment at every instant, and they are static. These set of agents are also single agent as they all operate alone in the environment. Human on the other hand is not static and they could be multiple agents in the environment. For this purpose, human and solar power system are non-deterministic because they are independent of the environment previous state while the rest of the agent are. Due to there action from previous step, all are episodic except security motion detector being sequential. MRI and CT environment does not change unlike others. All are discrete except solar power system due to their finite or infinite steps.

3.0 CONCLUSION

We were able to describe what constituted in our agents such as the percepts, task environment, PEAS, environment, and properties of the task environment.

REFERENCES

NHS Choices (2021). *CT scan*. [online] NHS. Available at: https://www.nhs.uk/conditions/ct-scan/.

Russell, S.J. and Norvig, P. (2016). *Artificial intelligence: a modern approach*. Upper Saddle River: Pearson.

ASSIGNMENT: COMPONENT 2

ABSTRACT

In order to prevent serious environmental implications in the future, CO2 emission must be tackled. In this report, our aim is to see how to predict the CO2 emission of vehicles in a dataset and find steps to classify the vehicles based on the categorical variables.

1.0 INTRODUCTION

Carbon dioxide (CO2) is produced through the production and burning of fossil fuels like coal, oil, and natural gas as well as during wildfires and other natural processes *[NASA, 2017]*. The amount of CO2 emitted by a vehicle depends on several factors which we will examine using various models.

2.0 METHODOLOGY

2.1 STEPS REQUIRED TO TRAIN A MODEL

There are various steps required for us to start training testing and validating models as shown below:

- **Data cleaning and preparation** is the process of fixing or removing incorrect data within a dataset.
- **Data visualization and analysis** gives a true representation of our dataset. Using Exploratory Data Analysis (EDA), we can detect variable performance which is necessary for feature selection.
- **Feature selection** is the process of selecting a subset of relevant features for use in model construction.
- **Model selection** is the process of building a machine learning model best fit for a task.

2.2 REGRESSION MODEL SELECTION PROCESS AND ANALYSIS

It is important to know that not all numerical variables are continuous. After selecting my numerical continuous variables, I decided to scale the data before imploring a model.

Using Multiple linear regression model to predict CO2 emission, the root mean squared error RMSE was **23.5**. The lower the RMSE the more accurate the model. Comparing RMSE for different regression models using cross validation we were able to see that the decision tree regressor performance was the best as shown in figure 1 below.

	Model	cv_score 1	cv_score 2	cv_score 3	cv_score 4	cv_score 5	avg_score
0	Linear_R	23.184607	24.847968	24.909708	23.021667	23.427049	23.878200
1	Dtree	12.387146	12.203859	8.318004	5.946689	8.611148	9.493369
2	SVR	26.258449	27.391193	28.665844	25.727745	25.377219	26.684090

Figure 1. *Cross validation RMSE for regression models before EDA and Feature selection.*

After undergoing Exploratory Data Analysis, I decided to drop either the Fuel_Consumption_COMB (L/100 km) or Fuel_Consumption_City (L/100 km) since they had a perfect correlation as shown in figure 2.
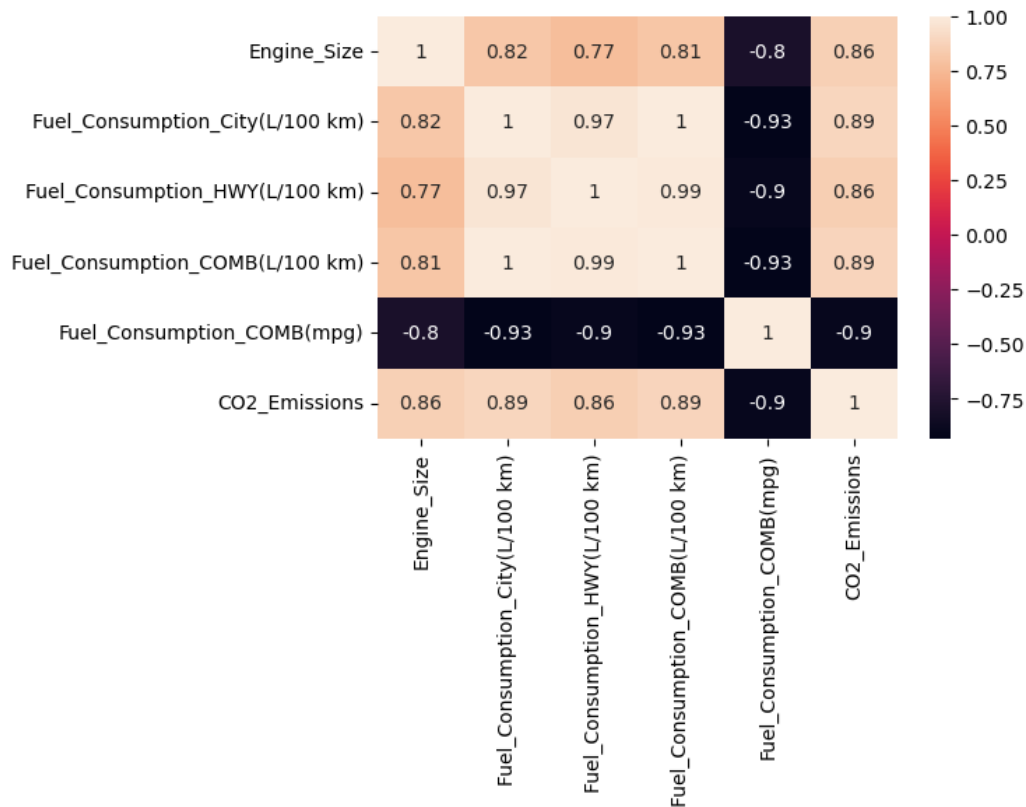

Figure 2. *Exploratory data analysis (EDA) using heatmap*

A new subset was created to repeat the procedure after dropping Fuel_Consumption_City (L/100 km), the result is shown in figure 3 below.

	Model	cv_score 1	cv_score 2	cv_score 3	cv_score 4	cv_score 5	avg_score
0	Linear_R	23.181949	24.844155	25.004827	23.058002	23.524561	23.922699
1	Dtree	10.706445	12.904897	6.432219	6.379179	8.124584	8.909465
2	SVR	25.736334	26.763897	28.040629	25.527637	24.933863	26.200472

Figure 3. *Cross validation RMSE for regression models after EDA and Feature selection.*

From the above comparison, the decision tree regressor is the best model as clearly shown in the visualization in figure 4 below.
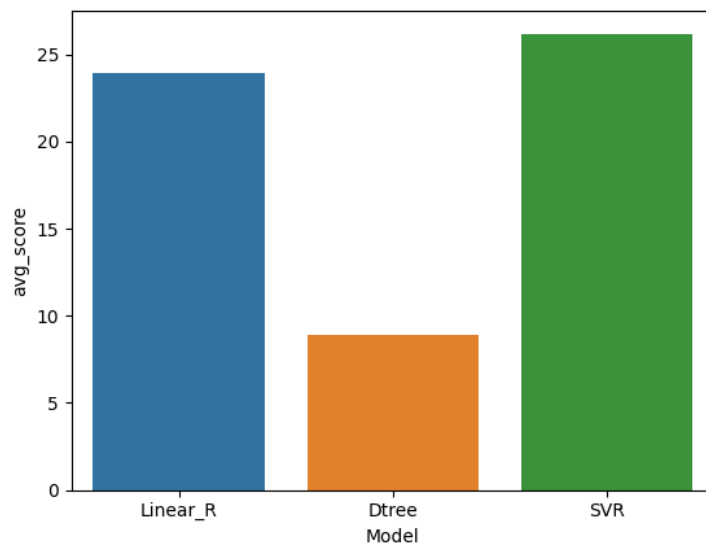
Figure 4. *Bar plot showing the regression models performance.*

In terms of the performance, we can see that the RMSE is **slightly more accurate from 9.49 to 8.91** for the decision tree regressor after using a subset of the input data. This performance was further improved to **7.92** using Hyperparameter.

2.3 CHANGE IN CO2 EMISSION FROM YEAR 2010 TO YEAR 2014

To know the change in CO2 Emission from the year 2010 to 2014, we will need to plot both data for the model year and CO2 Emissions. From the average CO2 Emissions per year between 2010 to 2014 as shown in figure 5, there is a decrease in CO2_Emissions from 279 to around 255, respectively.
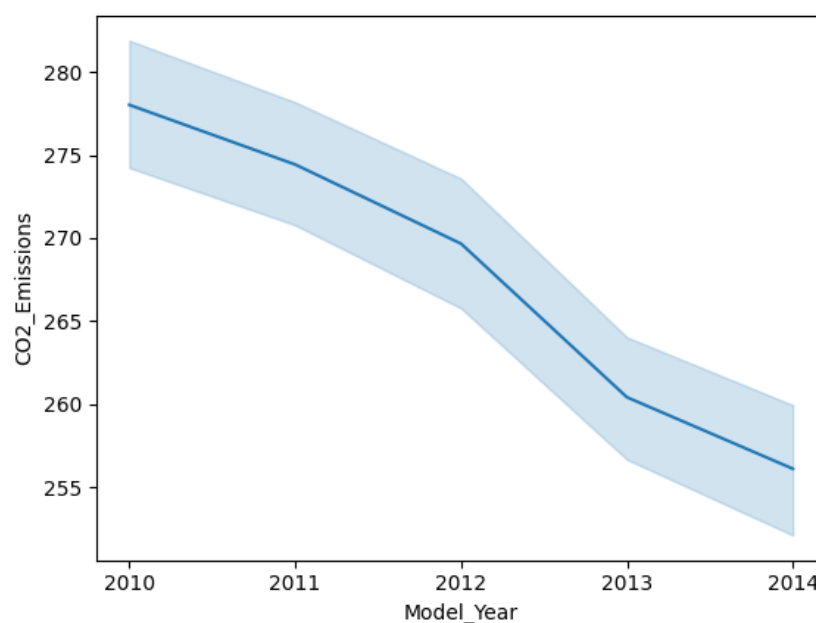
Figure 5. *Average CO2 Emissions per year between 2010 to 2014.*

2.4 CATEGORICAL VARIABLE COMPARISON BY CLASSIFYING THE DATASET

For us to determine the variable that performs best in classifying the dataset, we will first choice a model by using cross validation on a single categorical variable e.g., 'Fuel'. Synthetic Minority Oversampling Technique was first applied to our categorical variable before training and cross validation. After applying cross validation, it is observed that Random Forest Classifier (RF) performed best as shown in figure 6 below.

model	cv score1	cv score1	cv score1	cv score1	cv score1
LR	0.760997	0.749817	0.785033	0.776229	0.827586
KNN	0.8761	0.856933	0.868672	0.870873	0.866471
Dtree	0.934751	0.942773	0.953778	0.937638	0.949376
SVC	0.359971	0.336757	0.338225	0.362436	0.376376
RF	0.942815	0.946442	0.954512	0.949376	0.955246

Figure 6. *Cross validation accuracy for classification models*

Selecting RF as the model, there was a need to create a function that accepts two categorical data X_train and y_train which returns both test data and predicted data. From figure 7 below we can see the Confusion Matrix and accuracy of the categorical data. The **'Fuel' variable seems to have the best classification accuracy of 98%** and it takes less computational power due to the low number of categories.
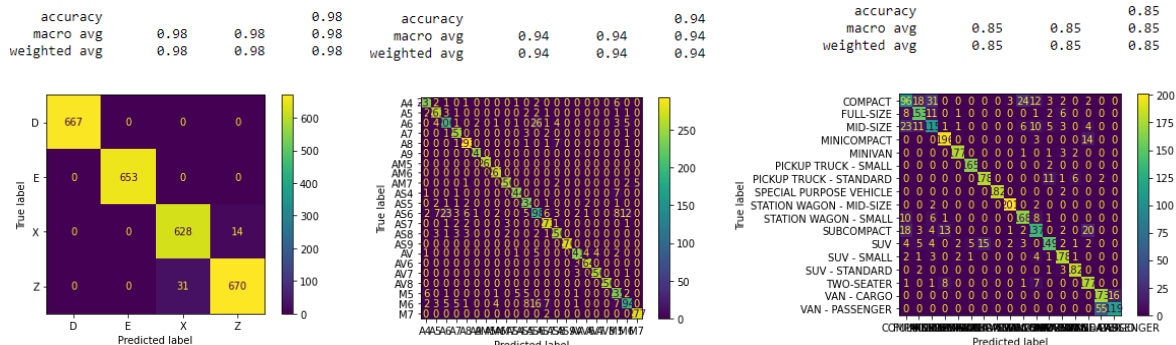

Figure 7. *Shows the confusion matrix and classification accuracy of the categorical data.*

2.5 OVERFIT CHECK

Over fitting check was done in both our regession and classification model . **Cross Validation Check** was the way I checked for over fitting. The model is probably overfitting if it performs noticeably better on training data than on the validation data.
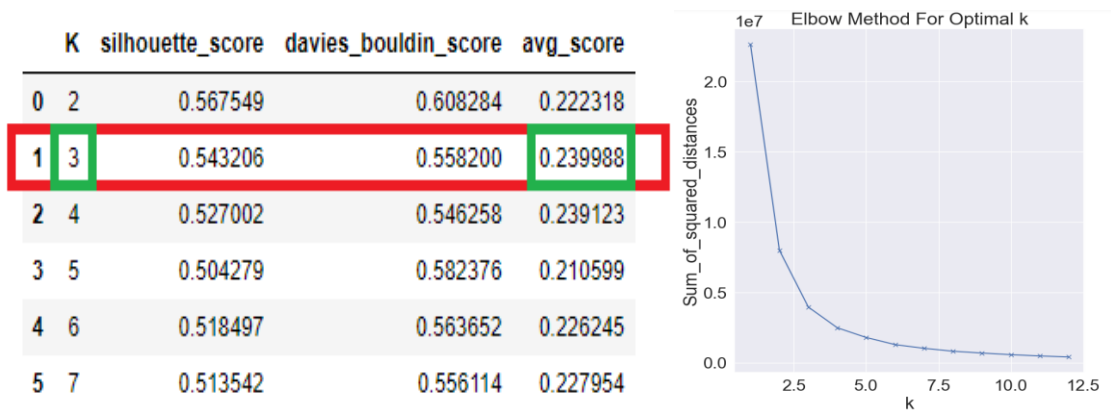
2.6 PERFORMANCE MEASURE(S)

- For Regression, **root mean squared error** was prefered because it mantains the original data unit making it easy to interpret.
- For Classification, **Accuracy** was perfered because it is easy to understand and we have a balanced dataset.

2.7 MODEL DEPLOYABILITY

The models are deployable for both regression and classification. In both cases, the selection of the models was done using cross validation and the results were accurate and reliable. The regression RMSE was 7.92 and classification had an accuracy of 98%.

2.8 CATEGORICAL VARIABLE DESCRIPTION USING INTERNAL AND EXTERNAL EVALUATION METRICS

For internal evaluation metrics, it is using data that was used to train the model. For the evaluation, I made use of both Davies-Bouldin score and Silhouette score to determine the number of clusters. Elbow method was also used to visually confirm the optimal number of clusters needed.

	K	silhouette_score	davies_bouldin_score	avg_score
0	2	0.567549	0.608284	0.222318
1	3	0.543206	0.558200	0.239988
2	4	0.527002	0.546258	0.239123
3	5	0.504279	0.582376	0.210599
4	6	0.518497	0.563652	0.226245
5	7	0.513542	0.556114	0.227954

Figure 8. *Internal Evaluation Outcomes.*

For External evaluation metrics, it is using data that was not used to train the model. V-measure score was used as an external evaluation metric for a clustering algorithm as shown in figure 9. The highest score is the Model.

object variable	rand_score	v_measure_score
Model_Year	0.768387	0.013544
Make	0.912525	0.276378
Model	0.945891	0.512122
Vehicle_Class	0.872974	0.231854
Transmission	0.84806	0.176471
Fuel	0.594292	0.200315

Figure 9. *External evaluation metrics using V-measure score outcomes and rand_score.*

3.0 CONCLUSION

We were able to predict the CO_2 emission of vehicles in a dataset and find steps to classify the vehicles based on the categorical variables.

REFERENCES

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ASSIGNMENT: COMPONENT 3

ABSTRACT

For the purpose of identifying cars as either "emergence" or "non-emergence" based on images, this report proposes a convolutional neural network (CNN) method. The suggested CNN model is trained using a sizable dataset consisting of automobiles photos in both emergence and non-emergence modes. After testing the trained model on a different test dataset, its performance will be assessed.

1.0 INTRODUCTION

Convolutional neural networks (CNNs) are a form of deep learning model that are especially made for processing data having a grid-like layout, like photographs [Hirohara, 2018].

A sizable collection of labelled photos of automobiles in both emergent and non-emergent stages would be required to train a CNN for this purpose. The CNN would then be trained using supervised learning on this dataset, where the annotated photos would be used to teach the model to distinguish between the two classes of automobiles. After training, the model can then be used to categorise new pictures of automobiles as emerging or not.

2.0 METHODOLOGY

2.1 STEPS CONSIDERED BEFORE BUILDING THE MODEL?

Before building a model, there are steps that can be considered.

- Firstly, we will need to define the problem we want to build a model for, this will help to know the possible best approach for our model.
- Secondly, we will get our data which will be used for the model selection.
- After getting our data, we will need to clean and pre-process the data to make sure that in the right format for the model.
- Selecting a model architecture which defines the layers and other component of the model.

Figure 1 below shows a clear illustration of the data distribution.
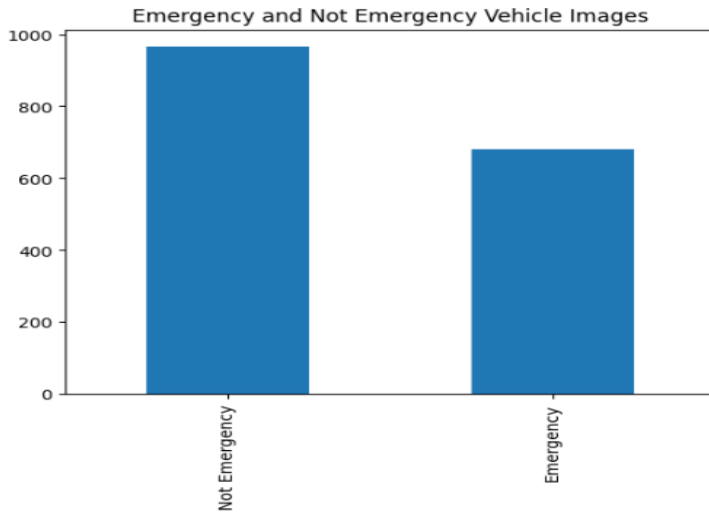
Figure 1. *This shows the number of emergency and non-emergency vehicle image in our training dataset.*

Selecting a model architecture which defines the layers and other component of the model. This may involve repeated trials to achieve aim.

## 2.2 NUMBER OF LAYERS EFFECT ON THE MODEL'S PERFORMANCE AND TIME?

The performance of a convolutional neural network (CNN) may be enhanced by adding more layers, which enables the model to learn more intricate characteristics from the input data. The model's training process may take longer and use more computer resources as a result, though. I observed that there was a decrease in performance after adding more layers to the single layer initially done which was expected. Using three additional layers, the performance is shown in figure 2 below.
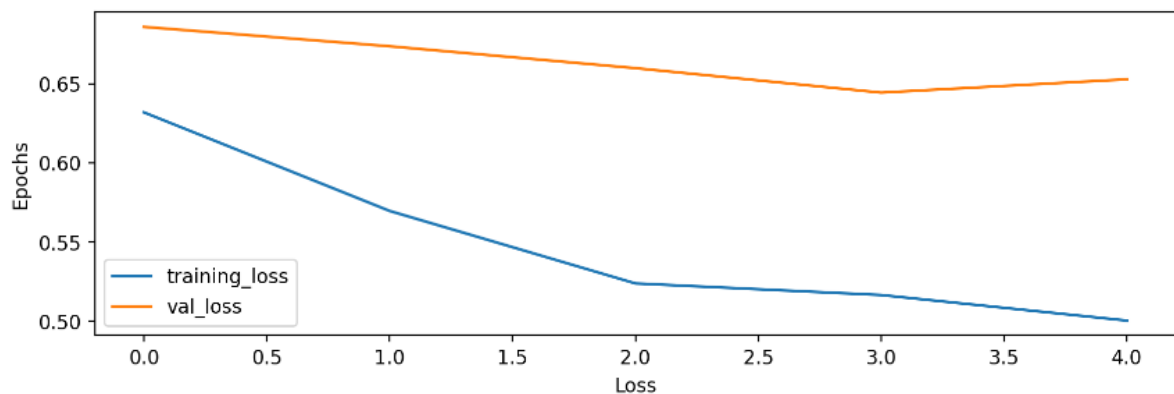

Figure 2 *Using loss (or error) to check for overfitting using three layers.*

2.3 CASE OF OVERFITTING IN THE MODEL

Plotting the training and validation loss as a function of the quantity of training epochs is one method of using loss (or error) to examine a convolutional neural network (CNN) for overfitting. Also, an indication that the network is overfitting is when the training accuracy rises farther than the validation accuracy stays the same or starts to fall [Gavrilov, 2018]. During are first model training, we were able to control the behaviour of the model using hyperparameters settings. This may involve alternating the learning rate, batch size, and number of training epochs. For our first training model I used 10 epochs and there was no sign of overfitting as shown in figure 3.

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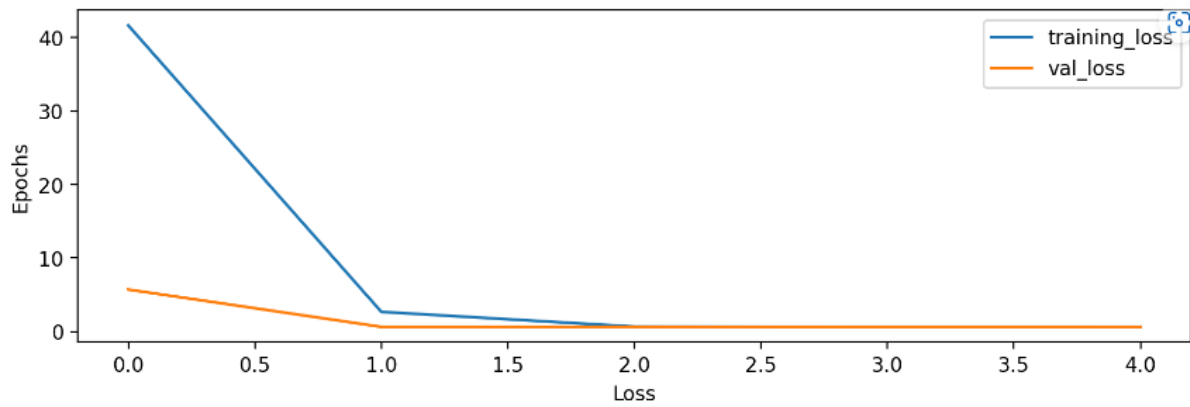
Figure 3a. *Using loss (or error) to check for overfitting using one layer.*
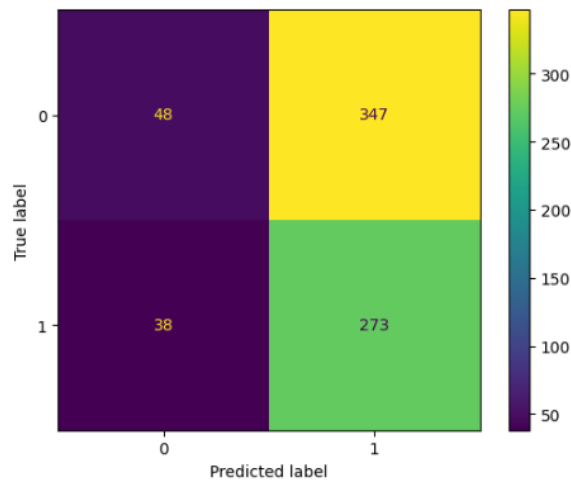
Figure 3b Confusion Matrix Display

2.4 PERFORMANCE MEASURE

There are several performance measures that can be used to evaluate the performance of a convolutional neural network (CNN) as shown below.

Accuracy: By dividing the total number of forecasts by the number of right predictions, the accuracy of the network's predictions is determined.

Precision: This is the percentage of accurate positive predictions, is computed by dividing the total number of positive predictions made by the network by the number of actual positive predictions.

Recall: it is Calculated by dividing the total number of genuine positive predictions by the total number of real positive cases, recall is the percentage of positive cases that were correctly anticipated.

F1 score: Calculated by using the harmonic mean of precision and memory, the F1 score is a measure of accuracy and recall.

Accuracy was used for this model because it is that it is easy to understand and interpret. It provides a simple and clear measure of how well the model is performing.

3.0 CONCLUSION

In summary, this research shows how well a convolutional neural network (CNN) can categorise vehicles as either "emergence" or "non-emergence" based on visual input. The accuracy of the suggested CNN model was evaluated after training it on a sizable dataset of labelled pictures.

REFERENCE

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Hirohara, M., Saito, Y., Koda, Y., Sato, K. and Sakakibara, Y. (2018). Convolutional neural network based on SMILES representation of compounds for detecting chemical motif. *BMC Bioinformatics*, 19(S19). doi:10.1186/s12859-018-2523-5.

ASSIGNMENT: COMPONENT 4

ABSTRACT

Several significant ethical issues are brought up by the creation and application of artificial intelligence (AI), which require serious consideration and resolution. We will cover five various ethical issues in this study, along with potential solutions.

1.0 INTRODUCTION

Artificial intelligence (AI) is a fast-growing field that has the potential to improve many aspects of our lives. However, the development and use of AI has given rise to important ethical concerns that need to be considered and addressed accordingly.

2.0 FIVE MAJOR ETHICAL CHALLENGES AND SOLUTIONS

Five major ethical challenges in AI which we will focus on are:

- FAIRNESS AND BIAS
- PRIVACY AND SECURITY
- HARMFULNESS AND ACCOUNTABILITY
- ENVIRONMENTAL IMPACT
- SINGULARITY

2.1 BIAS AND DISCRIMINATION

The quality of AI systems depends on the data they are trained on, so if the data contains biases, the AI system may also inherit those biases. ***For example, a machine learning algorithm trained on data that is predominantly from a certain African country of 99% black people may be more accurate at recognizing black people than any other race.*** This could lead to AI systems that are unfairly biased against certain groups of people, which could have serious consequences in fields such as criminal justice and employment.

To address the issue of bias and discrimination in AI, it is important to carefully evaluate the data that is used to train AI systems and to ensure that it is representative of the population. In addition,

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it is important to develop methods for detecting and mitigating bias in AI systems, such as using fairness metrics to evaluate the performance of AI systems.

2.2 PRIVACY AND SECURITY

As AI systems become more advanced and can process vast amounts of data, they may also be able to access and potentially misuse sensitive information about individuals. This could lead to serious privacy violations and could be exploited by malicious actors for nefarious purposes*. For example, using a social media application on a smart device where user data are utilized for monetary gain can pose as a privacy and security concern*. Ensuring that AI systems are secure, and that individuals' personal information is protected is a crucial ethical concern.

To address the issue of privacy and security, Strong security measures must be put in place to prevent AI systems from accessing or abusing sensitive data such as encryption to ensure that they are not accessing or using data in unauthorized ways.

2.3 HARMFULNESS AND ACCOUNTABILITY

Another major ethical challenge is the possibility of using AI for bad reasons. Since A.I System is dependent on the data it receives, there is every possibility it could be used for the wrong reason. *For example, AI systems could be used to automate cyberattacks which is a major challenge in this computer age.* Even if the A.I was built on ethical grounds with full autonomy, accountability becomes a problem when an error occurs.

In order to ensure that the A.I systems are aligned with ethical values to prevent their misuse, it is important to carefully evaluate their goals and objectives. As well as creating systems for accountability and monitoring, this may entail creating ethical frameworks or rules for the creation and application of AI.

2.4 ENVIRONMENTAL IMPACT

The computer centres that run our cloud infrastructure require a lot of power to be able to function optimally and this can pose an environmental challenge. *For Example, AI systems can contribute to greenhouse gas emissions and climate change which poses an environmental threat to our planet.*

The recommended steps to mitigate environmental impact would include investing in clean energy, promoting sustainable practices, and ensuring that AI systems are designed and used ethically and responsibly.

2.5 SINGULARITY

According to the singularity theory, once artificial intelligence reaches systems with human-level intellect, these systems will subsequently produce AI systems that are more advanced than human intelligence, making them super intelligent. ***For Example, AlphaGo, a computer program that uses DeepMind Technology, defeated a human who was the reigning champion in a board game called Go*** [Malachy, 2020]. Long-term consideration of superintelligence raises the concern of an existential danger, or the possibility that superintelligence may result in the annihilation of the human species. [Muller, 2020].

Building AI systems that are inherently limited in their capabilities and scope, to prevent them from becoming too powerful or uncontrollable. It would also be advised to approach AI systems development and usage with caution, and to carefully consider the potential consequences of creating highly advanced AI systems.

3.0 CONCLUSION

The development and use of AI raises several important ethical challenges, the key to addressing these challenges is to approach its development and use with caution, and to carefully consider the potential consequences of creating advanced AI systems.

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