COMPONENT 1

Design of Intelligent Agents

Abstract
An intelligent agent is a stand-alone programme or object that communicates with its surroundings by sensing the environment and acting on it with actuators (Simplilearn, 2022). This report dwells on the different environments, actuators and sensors, and analyses the properties therein related to the agent. Such agents include office productivity assistant, cancer detector, and physical theft alarm system.

1.0 Introduction

Artificial intelligence is a technique for teaching a computer, a robot operated by a computer, or software to think critically and creatively like a human mind. AI is achieved through examining the cognitive process and researching the patterns of the human brain. These research projects produce systems and software that are intelligent (Simplilearn, 2022).
This report aims to analyse the following task environments, office productivity, climate change, chemically hazardous environment, cancer detection, physical theft prevention and brain surgery.

2.0 Breakdown of the Agent
2.1 The task environments
The task environ is the problem which the rational agent seeks to solve (Ojie, 2022).
The task environments are:

1. Office productivity
2. Climate change
3. Hazardous environment (chemical)
4. Cancer detection
5. Physical theft prevention
6. Brain surgery

Table 1: The PEAS description for the above task environments

Agent type	Performance measures	Environment	Actuators	Sensors
Office productivity assistant (software)	Set reminders, maximize calendar use, meeting booking and date suggestions, achieve proper time management and cost saving	Client, Employer, Employee, office, and home	Visual display of texts, audio output (reminder alarm)	Keyboard, digital clock accelerometer, calendar, microphone
Climate change simulator	Correct predictions of future outcomes, Pictorial representation, reduced cost,	Visual data (photos to train the algorithm), dataset input of change in weather, outdoors, and home	Visual animation of future outcome, audio output (descriptive narration)	Camera, keyboard input of prediction date needed

	suggestive measures			
Hazardous environment (chemical) sensor	Accurate warning of hazard levels, preventive predictions of hazards, suggestive measures	Outdoors (soil, air humidity, visibility), chemical waste, and factory	Visual warning sign display, alarm sound and descriptive narration	Camera, pH meter, air quality measuring device
Cancer detector	Accurate detection and diagnosis, reduced cost, and good reputation	Patient, medical staff, and home	Visual display of information, descriptive narration, visual animation of located cancer	Biomarker, keyboard input of patient medical history, electrochemical biosensor
RFID theft detector	Timely theft warning/alarm, accurately sensing when an item is removed without authority or purchase, cost saving, timely security alert	Store, home, storage unit, shopping centre, device/item/product	Visual display of warning signs, alarm sound	RFID sensor, camera, confirmation of purchase, microphone
Brain surgery assistant (Software)	Precise guide during the operation, accurate malignant tissue identification, accurate prediction of prognosis, optimizes surgical plan, reduced cost, good reputation	Patient, medical staff, surgeon, operating theatre, and hospital	Descriptive narration, visual display of warning systems	Radiomic tumour marker, input of dataset of information via keyboard, patient medical history, camera

2.2. The percepts

The percept refers to the input provided to the system. The inputs are:

Table 2: Percepts of the task environments

Task Environ	Office productivity assistant	Climate change simulator	Hazardous environment (chemical) sensor	Cancer detector	RFID theft detector	Brain surgery assistant (Software)
Percepts	• Password • Username •Calendar events •Time input •Determined goals to be achieved	•Location •Date •Calendar month •Calendar year	•Location •Calendar month •Calendar day	•Blood samples •Bio-factor •Body tissues •Patient medical history	•QR code •Purchase information	•Patient medical history •Patient

2.3. The external stimuli that could affect the agent

These are factors that can affect the agent.

Table 3: External Stimuli

Task Environ	Office productivity assistant	Climate change simulator	Hazardous environment (chemical) sensor	Cancer detector	RFID theft detector	Brain surgery assistant (Software)
Stimuli	•Electricity supply •Internet connectivity	•Internet connectivity •Electric surge	•Sensor trips •Electric surge	•Inadequate blood sample •Sensor damage	•Server connectivity •Electric surge •Interference	•Server connectivity •Electric surge

2.4. Properties of the task environment

The properties of the task environment refer to the states the agent can exist in.

Table 5: Properties of the task environment

Task Environ	Observable	Agents	Deterministic	Episodic	Static	Discrete
Office productivity assistant	Fully	Multi	Stochastic	Sequential	Static	Continuous
Climate change simulator	Partially	Single	Stochastic	Sequential	Static	Continuous
Hazardous environment (chemical) sensor	Partially	Single	Nondeterministic	Sequential	Static	Continuous
Cancer detector	Fully	Single	Deterministic	Sequential	Static	Discrete
RFID theft detector	Fully	Multi	Nondeterministic	Sequential	Static	Discrete

Brain surgery assistant	Partially	Multi	Deterministic	Sequential	Static	Discrete

Fully observable; this is because all the complete states of the environment, at each point in time, are provided by the sensor. Partially observable; this is because part of the states of the environment, at each point in time, are provided by the sensor (Ojie, 2022).

2.5. The kind of agent program

1. Office productivity assistant: Goal based agent. The agent maximizes productivity and efficiency of work (Ojie, 2022).

2. Climate change simulator: Model-based reflex agent. The agent depends on the percept history of task environment (Ojie, 2022).

3. Hazardous environment (chemical) sensor: Utility based agent. The agent compares the different states of the environment and gives a measure of the difference (Ojie, 2022).

4. Cancer detector: Model-based reflex agent. The agent maintains some internal states that depend on the percept history of the environment (Ojie, 2022).

5. RFID theft detector: Simple reflex agent. The agent's action is dependent on the current percept (Ojie, 2022).

6. Brain surgery assistant: Model-based reflex agent. The agent depends on the percept history of task environment (Ojie, 2022).

3.0. Conclusion

The information to build several agents was described. It consisted of the agent's: percepts, PEAS, and properties all suitable for the given task environment. Sensors, actuators, performance measure and external stimuli that could affect their behaviour were discussed alongside the type of agent that fits the various environments (Ojie, 2022).

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COMPONENT 2

Fuel Consumption Rating Report

This fuel consumption rating report aims to categorise the vehicles based on categorical and numerical criteria and predict the CO_2 emission of the vehicles. Several data science approaches were used to make this prediction, including data cleaning, categorical data encoding, separating the dataset into training and testing sets, training the model, and finally forecasting the test set outcomes.

Data Cleaning

The census data was cleaned to make sure it was accurate, consistent, and usable for creating our model and generating predictions afterwards. This procedure entails locating data mistakes, fixing them, and switching the data types of the columns to the proper data types. The Jupyter Notebook that is attached to this report has a detailed description of each data cleaning procedure. Below is a description of the columns in the dataset and their data types:

	MAKE	MODEL	VEHICLECLASS	TRANSMISSION	FUELTYPE
0	ACURA	CSX	COMPACT	AS5	X
1	ACURA	CSX	COMPACT	M5	X
2	ACURA	CSX	COMPACT	M6	Z
3	ACURA	MDX AWD	SUV	AS6	Z
4	ACURA	RDX AWD TURBO	SUV	AS5	Z
...	...	...	...	...	...
5354	VOLVO	XC60 AWD	SUV - SMALL	AS6	X
5355	VOLVO	XC60 AWD	SUV - SMALL	AS6	X
5356	VOLVO	XC70 AWD	SUV - SMALL	AS6	X
5357	VOLVO	XC70 AWD	SUV - SMALL	AS6	X
5358	VOLVO	XC90 AWD	SUV - STANDARD	AS6	X

FUELCONSUMPTIONCITY(L/100 km)	FUELCONSUMPTIONHWY(L/100 km)	FUELCONSUMPTIONCOMB(L/100 km)	FUELCONSUMPTIONCOMB(mpg)	CO2EMISSIONS(g/km)
10.9	7.8	9.5	30	219
10.0	7.6	8.9	32	205
11.6	8.1	10.0	28	230
14.8	11.3	13.2	21	304
13.2	10.3	11.9	24	274
...	...	...	...	...
13.4	9.8	11.8	24	271
13.2	9.5	11.5	25	264
13.4	9.8	11.8	24	271
12.9	9.3	11.3	25	260
14.9	10.2	12.8	22	294

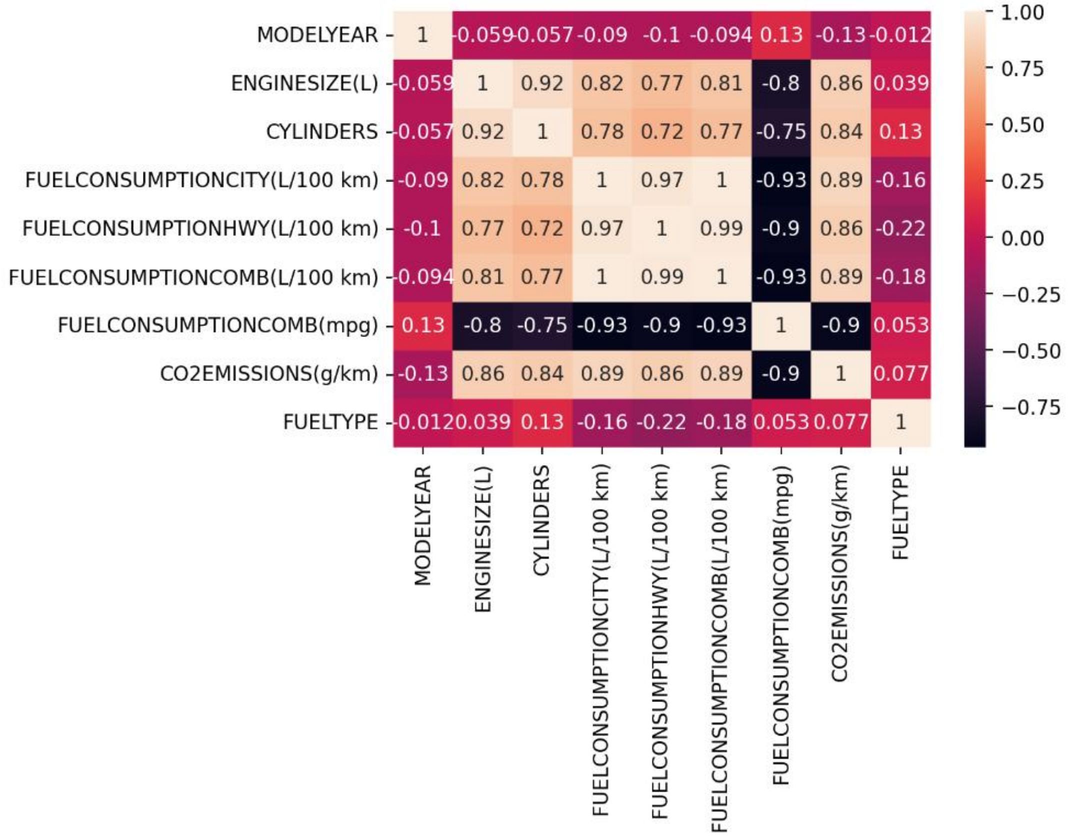
Steps Required to Train a Model

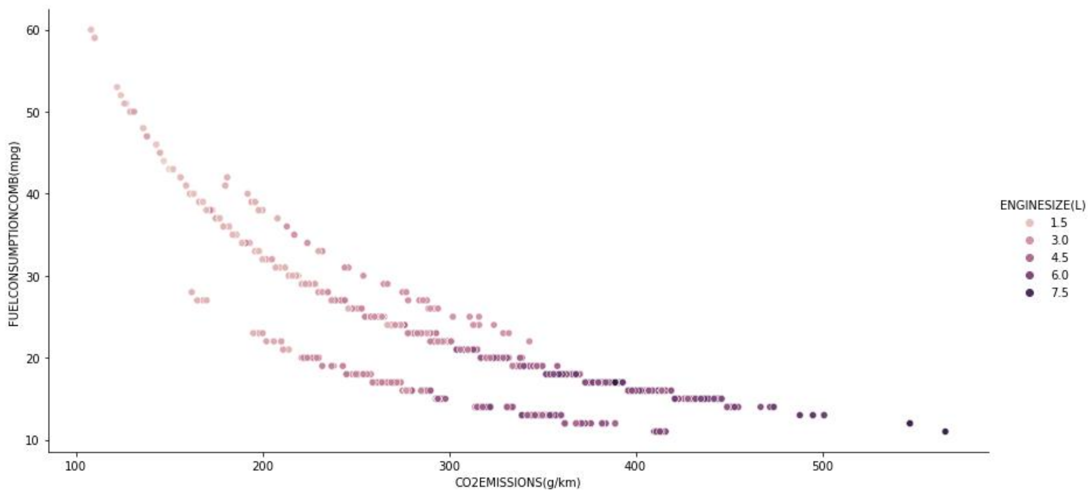
1. Importing the libraries
2. Importing the dataset
3. Cleaning the dataset
4. Encoding categorical data
5. Splitting the dataset into the Training set and Test set

6. Training the Multiple Linear Regression model on the Training set
7. Predicting the Test set results
8. Getting the final linear regression equation with the values of the coefficients
9. Making a prediction from the linear regression equation based on a given set of independent variables

Building a Model Based on the Numerical Continuous Variables

We had to extract every numerical information from the fuel consumption set and assign it to a new variable in order to build a model based on the numerical variables. 'ENGINESIZE', 'FUELCONSUMPTION CITY', 'FUELCONSUMPTION HWY', 'FUELCONSUMPTION COMB', 'FUELCONSUMPTION COMB MPG', and 'CO2EMMISSIONS' are among the numerical variables in our dataset. With the exception of "CO2EMMISSIONS," which is the dependent variable, all numerical variables are independent. In particular "FUELCONSUMPTION COMB MPG", the heatmap figures demonstrate a substantial connection between the dependent and independent variables.





The exploratory data analyses show in the particular graph above, that high mileage and smaller engine sizes produce lower CO2 emissions.

We scaled the characteristics of the independent variables in order for the predictors to have a mean of 0 as is frequently advised in order to develop our multiple linear regression utilising numerical data. After creating the regression model, we used metrics such as Mean Squared Error, Mean Absolute Error, and R-Squared or Coefficient of Determination to assess the model's performance in the regression study.

Multiple Linear Regression Using Subset Numerical Data

Subset 1: This subset uses all the columns in the Dataframe except CO2 emissions and the Model year for our features for multiple linear regression. From our regression analysis, the mean absolute error, root mean squared error and coefficient of determination are 15.03, 21.51, and 0.89 respectively.

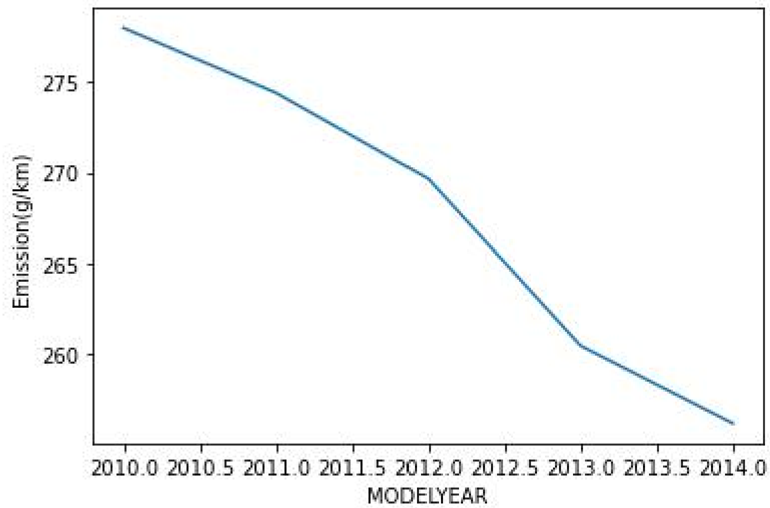
Subset 2: This subset uses all except ['CO2EMISSIONS(g/km)', 'FUELCONSUMPTIONCITY(L/100 km)', 'FUELCONSUMPTIONHWY(L/100 km)', 'FUELCONSUMPTIONCOMB(L/100 km)'] for our features for multiple linear regression. From our regression analysis, the mean absolute error, root mean squared error and coefficient of determination are 15.51, 22.64, and 0.88 respectively.

Simple Linear Regression

Subset 3: This subset uses [‘ENGINESIZE(L)’] for our features for multiple linear regression. From our regression analysis, the mean absolute error, root mean squared error and coefficient of determination are 24.48, 33.08, and 0.73 respectively.

Note that Subset 1 performed better than both subset 2 and subset 3.

CO2 Emissions Between Year 2010 to 2014



As is shown in the graph above, the CO2 trended down as the year progressed.

COMPONENT 3

EMERGENCY VEHICLE IDENTIFICATION

1.0.

The steps I took into consideration before creating this classification model include:
Explain the issue: The first step involved outlining the problem that the model was meant to address as well as its aims and objectives. In order to guarantee that the model was created to answer the particular demands of the application, this was done.
Using a data import method in pandas, the data was imported from the directory. After the data has been imported, I use the application to access and modify it.
In order to make the data suitable for training the model, preprocessing was done to clean out any flaws or inconsistencies. Data labelling: Data labelling is the process of giving each data point in the dataset that was used to train the classification model a string or text label. Usually, this was done to make it simpler to comprehend, interpret, and assess the model's output and performance.
Choose and build the model: After the data was prepared, the process moved on to choosing the classification model to be utilised and building the model's hyperparameters to enhance performance. This was commonly accomplished by training the model on a dataset that had been labelled, meaning that each data point had been given a particular class or category. The model learned the correlations between the data points using this training data to understand the connections between the data points and the classifications they belong to, and then applied this understanding to forecast future data. Model construction: The optimizer and loss function to be utilised in the learning process were specified. The loss function gauges how well the model is doing on the training data, while the optimizer decides how the model will adjust its internal parameters based on the data it gets. I make sure the model is configured properly for training or evaluation when I put it together.
Model training: I gave the model labelled data and used an iterative procedure to let it discover the connections between the data and the relevant classes. In order to attain the greatest performance, this often entails modifying the model's hyperparameters. A second test dataset was used to evaluate the model's performance after training in order to gauge its accuracy and other performance indicators. This was done to assist find any problems with the model and, if necessary, fine-tune it even more.
Launch the model: On the new dataset, the model was used to make predictions.

2.0.

The performance of our model was enhanced by the addition of more layers. Although adding more layers is advantageous, it can also be harmful if the model learns more intricate patterns in the data and becomes overly complicated with numerous parameters. Overfitting could become more likely as a result.

3.0.

It's encouraging that the data performs well on our validation data because it means that the model is not overfit. The training accuracy and validation accuracy were both utilised to be sure, and since neither was greater than the other, there was no overfitting.

4.0.

I am particularly interested in using the accuracy score as a performance measure when working on these classification models because it gives the ratio of the number of accurate predictions the model made on a dataset to the total number of predictions. This model's accuracy score is 0.77, which means that out of 100 predictions, 77 were accurate, indicating good performance.

COMPONENT 4

Ethical Challenges in AI Systems

Abstract

This report discusses the ethical challenges faced using AI in certain fields as it has a potential to either contribute positively, or aid in the further deterioration of the world we live in.

1.0 Introduction

There is often an underlying premise that we are talking about immoral things when we discuss AI's ethical concerns. Artificial intelligence (AI) has impressive capabilities, but it also raises a lot of ethical concerns. Although governments and businesses have developed several AI ethics rules to prevent unethical behaviour by AI, the impact has been modest, possibly as a result of the guidelines' ambiguity. Of course, these morally troubling outcomes are at the centre of most of the AI debate (Stahl, 2021; Mengyi, 2022). This report will be identifying five (5) challenges AI is facing with regard to ethics.

2.0. AI Ethical Challenges

2.1. Disappearance of Jobs

AI has a tendency to raise unemployment, particularly among those with a medium level of education. Predictions show a nearly totally automated economy that would produce a surplus of products and services at a marginal cost of close to zero within the next two decades, with an estimate of a 47% high potential for automated jobs (Bordot, 2022). Although AI and related technologies shouldn't result in widespread technical unemployment, our analysis indicates that they may well produce significant changes in the UK's employment structure across occupations, industries, and regions. Over the next five years, the consequences might be negligible, but over the following ten to twenty years, they might grow more significant. Analyses conducted by Gov.uk has shown that these technology advances may likely to favour persons with greater education and skill levels, who also tend to have higher salary levels, which may further exacerbate income inequality (Gov.uk, 2022).

An example of such jobs that may be taken over by AI is Data Entry Clerking. If you were to think of adjectives to describe a data entry job, "repetitive" and "dull" probably came to mind first. The need for data entry clerks won't go away given the massive volume of data that both businesses and individuals generate. But the notion that a business must pay a person an hourly wage to convert data into another format or to compile it in one location—and maybe get a few (perhaps significant) errors tossed in for good measure. This ascribes to replacement with AI (Dormehl, 2018).

Turning a job that is going away into a promotion with a higher salary by adding abilities to one’s professional résumé, such as the ability to supervise the data input machines or by accepting the data science component of the position is plausible way to address such ethical issues (Dormehl, 2018).

2.2. Lack of Privacy

Data gathered with AI poses privacy concerns such as freely given informed consent, the ability to opt out, collection restrictions, explanations of the nature of AI processing, and even the ability to remove data upon request. But how would the individuals whose data was gathered, potentially as a result of a spillover effect, even be aware that their information had been taken in order to contact companies about their own data or ask for it to be deleted? AI privacy considerations are different from ordinary data privacy considerations. Developing appropriate policies that protect privacy without limiting advancements in AI technology is one of the difficulties in preserving privacy in artificial intelligence. As well as the nature of the data itself and how it is used to develop the AI capabilities, the data contexts at issue include the scanning mechanisms that allow the AI tools to learn about their settings. Artificial intelligence's ability to reproduce, reinforce, or magnify undesirable prejudices is a major worry. Depending on the method used to acquire the data, these biases may spread (Pearce, 2021).

According to Pearce (2021), AI poses several privacy challenges, such as:

- Data persistence - Due to affordable data storage, data persists longer than the human people who created it.
- Data repurposing – Data repurposing refers to the use of data for purposes other than those originally intended.
- Data spillovers – Information gathered about individuals who are not the subject of the data collection.

An example is when a US company, Clearview AI, violated Canadian privacy laws by taking photos of Canadian adults and even children without their consent for the purpose of mass surveillance, facial recognition, and commercial sale only serves to further erode public confidence in the ability of the AI industry to handle privacy- and AI-related issues responsibly. In Australia and the UK, independent, concurrent investigations into Clearview AI are taking place. The Office of the Privacy Commissioner (OPC) of Canada noted in a study on the issue that the information scraping appears to be against the terms of service of websites like Facebook, YouTube, Instagram, Twitter, and Venmo. Furthermore, the OPC concludes that express authorization is necessary in the case of particularly sensitive biometric information, despite Clearview AI's contention that the information is widely available on the internet and that no consent is necessary and/or when the individual's reasonable expectations are not met by the collection, use, or disclosure. Facial information is without a doubt one of the most sensitive types of personal data, but would a reasonable person really consent to having their biometric data, which is also one of the most sensitive types, used by a for-profit organisation where the data could be used for anything and where the purpose could change into anything else indefinitely in the future (because data is forever in the digital world)? No, definitely not (Pearce, 2021).

While most firms may be concerned with privacy compliance and ethics when using sensitive personal data, the problems in artificial intelligence might differ greatly in terms of both scope and content. To guarantee that these AI-based privacy concerns are the subject of adequate oversight, it is the responsibility of both the IT governance professional and the privacy expert. This is one of numerous ways to address the salient issues in the privacy ethics of AI (Pearce, 2021).

2.3. Bias and Discrimination

Initiatives to address and improve fairness in AI systems have grown significantly in recent years, and a growing body of research has focused on this issue (Giovanola et al, 2022).

An example is the requirement for fairness in ML, and more specifically in healthcare ML algorithms (HMLA), has become a highly essential and urgent challenge as machine-learning (ML) algorithms are increasingly used and relied upon to execute jobs, offer services, and make choices in the fields of health and healthcare. Even though the discussion of fairness in HMLA and the ethics of artificial intelligence (AI) has expanded greatly over the past ten years, the fundamental idea of fairness as an ethical value has not yet received enough attention (Giovanola et al, 2022).

Insofar as AI advances the formation of a society of social justice by promoting respect for all people and a fairer allocation of opportunity for all, particularly the least fortunate. Every person must be treated equally, given equal opportunities, and given real authority over knowledge and behaviour in order to advance the common good. By adhering to the updated AI ethics principle of fairness, HMLA can serve as an example for the advancement of a society that is more just and inclusive and in which AI can really be a force for good (Giovanola et al, 2022).

2.4. Use in Warfare

National defence science and technology laboratories across many nations have held open contests for AI applications, demonstrating the potential for AI to be used in the military. In a war situation, the capacity of AI to extract insights from both historical and real-time streaming data for better decision-making offers clear value. Military AI applications currently frequently concentrate on automation processes, optimization processes, or some mixes of the two when the speed of operations and the volume of data to be used cannot be managed by humans without significant automation (Hallaq et al, 2017).

For instance, the US Department of Defense Algorithmic Warfare Cross-Functional Team's Project Maven, which was established in April 2017. Its goal was to hasten DoD's use of big data and machine learning in order to quickly transform the vast amount of data at its disposal into usable intelligence and insights. To be more precise, the project's initial stage involved developing, training, and ultimately deploying machine-learning technologies to sort through the numerous hours of data that had been gathered through the military's various surveillance methods (Davis, 2022). This poses an ethical issue as surveillance guidelines and boundaries are usually overlooked.

A taxonomy of DoD uses of AI based on their ethical, safety, and legal risk considerations ought to be established in order to overcome this ethical dilemma. This taxonomy should prioritise greater caution and inspection in applications that are less mature and/or potentially have more major negative effects and encourage and reward the quick adoption of mature technologies in low-risk applications.

2.5. Environmental Ethics

Deep learning necessitates a lengthy training period for AI. For instance, in order to teach an AI to recognise different sorts of photos, it may be necessary to process millions of images. Large amounts of computer power are needed for this training process, which in turn uses a lot of energy. According to one study, the greenhouse gas emissions from training a single AI model can be similar to the lifetime emissions from one or more cars. The usage of ever-increasing computational power is crucial for expanding the capabilities of cutting-edge AI systems. This begs the question of when investing in AI is worthwhile given how much energy it uses. Environmental ethics theories like the ecological footprint and the social cost of carbon can be used to provide an answer to this query (Baum et al, 2022).

Gaining a deeper understanding of the types of biases and distortions that influence decision-making processes will help clarify the circumstances in which we may be certain that we have at least approached a consensus. This makes it possible to more effectively address ethical concerns for the environment (Thomson, 1997).

3.0. Conclusion

Salient ethical issues in AI are numerous and often overwhelming. With the advancement of technology, AI will continue to grow and be embraced. However, the measures put in place in present time will affect the correct or otherwise use of AI in the future, therefore discussions of what those correct uses are in present day is vital.

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