COMPONENT 1 SOLUTION

A. **Building an Intelligent Agent for Office Productivity**: This presents a productivity agent which helps users schedule and block out time on their calendar to focus on important tasks, monitor and intervene with distractions.

1.1 The Task environment: This refers to the problem that the agent intends to solve. The task environment is Office Productivity Analysis.

The PEAS description for the agent

S/N	DOMAIN (AGENT TYPES)	PERFORMANCE MEASURES	ENVIRONMENT	ACTUATORS	SENSORS
1	Text-Based Office Agent	Prioritize user schedules, occlude distractions, monitor delivery.	Laboratories, Workshops, Offices, People.	Standalone desktop, keyboards, PCs, Mouse.	Sensing software, Agent dialog, Display cards, Microsoft outlook.

1.2 The Percepts

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

- Client's information (staff encrypted details)
- Time proportions (Scheduled time, active time detected by the sensors)
- Outlook calendars (work reminders, targets displayed)

1.3 The environment

The environment is fully observable because the sensors detect all aspects that are relevant to the choice of action.

1.4 The external stimuli that could affect the agent

- Power failure
- System (Hardware) failure

1.5 The properties of the task environment

S/N	Task environment	Observable	Agents	Deterministic	Episodic	Static	Discrete
1	Office Productivity Analysis	Fully	Multiagent	Stochastic	Sequential	Dynamic	Continuous

1.6 The Kind of agent Program

Goal-based agent; because the agent needs some sort of goal information that describes situations that are desirable (Russell & Peter,2010, p.71).

B. Building an Intelligent Agent for Climate Change: According to Joanna Haigh (2011) Variations in the composition and intensity of incident solar radiation hitting the Earth have produced significant changes in global and regional climate. In this exercise the design of an agent for analysis of solar activities as it impacts climate change is discussed.

2.1 The Task environment is Solar Activity Analysis.

The PEAS description for the agent

S/N	DOMAIN (AGENT TYPES)	PERFORMANCE MEASURES	ENVIRONMENT	ACTUATORS	SENSORS
2	Solar Activity Analysis.	To Analyse the activities of Sun as it impacts climate change.	Sun, earth, planetary system.	Orbits, Solar Flares, solar wind,	Telescope, solar flux sensor, pyranometer

2.2 The Percepts

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

- Sunspots Numbers (perceived via flux sensor)
- Solar flux data (displayed flux energy spectrum)
- Radiation paths (captured radar waves)

2.3 The environment

The environment is fully observable because agent’s sensor provides access to the complete state of the environment at each point in time.

2.4 The external stimuli that could affect the agent

- Carbon emission
- Geomagnetic storms
- Satellite drags
- The coupled magnetosphere-ionosphere-atmosphere system (Keith P. 1994)

2.5 The properties of the task environment

S/N	Task environment	Observable	Agents	Deterministic	Episodic	Static	Discrete
2	**Solar Activity Analysis.**	**Fully**	**Multi-agents**	**Deterministic**	**Episodic**	**Semi-static**	**Continuous**

2.6 The Kind of agent Program

Model-based reflex agent; It keeps track of the current state of the world using an internal model. It then chooses an action in the same way as the reflex agent. (Russell & Peter,2010, p.78).

C. Building an Intelligent Agent for Hazardous environment (Chemical): In this exercise the design of an agent for the Control and elimination of poisonous chemicals (CO_2) is discussed.

3.1 The Task environment is Carbon Capture Analysis.

The PEAS description for the agent

S/N	DOMAIN (AGENT TYPES)	PERFORMANCE MEASURES	ENVIRONMENT	ACTUATORS	SENSORS
3	Carbon Capture Agent	To reduce emission of poisonous chemicals (CO_2)	Air, People, Facilities, tanks, vessels.	Flare header, steam jets, burner tip, valves, pipes.	Metering units, indicators, gas detectors.

3.2 The Percepts

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

- Oxygen level (indicated via metering unit)
- CO_2 contents (shown via indicators)
- Fuel composition (displayed via metering unit)

3.3 The environment is partially observable because some parts are simply missing from the sensor data.

The external stimuli that could affect the agent

- Process and operations activities.
- Standard practices, policies and regulation.
- Raw materials compositions.

3.4 The properties of the task environment

Table 6.

S/N	Task environment	Observable	Agents	Deterministic	Episodic	Static	Discrete
3	Carbon capture Agent	Partially	Multi-agents	Stochastic	Sequential	Dynamic	Continuous

3.5 The Kind of agent Program

Goal-based agent; because the agent needs some sort of goal information that describes situations that are desirable.

D. Building an Intelligent Agent for Cancer Detection: In this exercise the design of an agent for improvement of accuracy and speed of diagnosis is discussed.

4.1 The Task environment is Improved Accuracy and Speed for Cancer diagnosis.

The PEAS description for the agent

S/N	DOMAIN (AGENT TYPES)	PERFORMANCE MEASURES	ENVIRONMENT	ACTUATORS	SENSORS
4	Improved Accuracy and Speed for Cancer diagnosis.	To improve the accuracy and speed of diagnosis.	Patients, Hospital, insurers, Laboratories.	Screen display, emails, treatments, diagnoses, tests.	Magnetic resonance Imaging, findings, entry of symptoms, positron emission tomography, mouse, patients' answers, scan results.

4.2 The Percepts

The inputs are:

- Severity (indications from entries)
- Likelihood (possible outcome of the tests)
- Trace Cycles (Root cause analysis via answers)

4.3 The environment is fully observable because agent's sensor provides access to the entire state of the domain at each point in time.

4.4 The external stimuli that could affect the agent

- Technological breakthroughs
- Research modifications

4.5 The properties of the task environment

S/N	Task environment	Observable	Agents	Deterministic	Episodic	Static	Discrete
4	Improved Accuracy and Speed for Cancer diagnosis.	Partially	Single	Stochastic	Sequential	Dynamic	Continuous

4.6 The Kind of agent Program

Utility-based agent; because it provides a way in which likelihood of success can be weighed against the importance of goals. (Russell & Peter,2010, p.72).

E. Building an Intelligent Agent for Physical Theft Prevention: In this exercise the design of an agent for Physical Theft Prevention Analysis is discussed.

5.1 The Task environment is Physical Theft Prevention System (**PTPS**).

The PEAS description for the agent

S/N	DOMAIN (AGENT TYPES)	PERFORMANCE MEASURES	ENVIRONMENT	ACTUATORS	SENSORS
5	Physical Theft Prevention System	Theft detection, Certainty, Response time.	Building structures, Facilities, People.	Notifications, Alarms, Blocking connections, Deactivating panels.	CCTvs, Passive Infrared Sensors, Magnetic Switches, Glass Break Detectors.

5.2 The Percepts

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

- Images (captures from camera)
- Timelines (observed incident time)
- Movements and Patterns (captures from camera)
- Finger & Footprints (detections from IR sensors)

5.3 **PTPS** is fully observable because agent's sensor provides access to the complete state of the environment at each point in time.

5.4 The external stimuli that could affect the agent

- Power failure
- Camera resolution
- Hardware failure

The properties of the task environment

S/N	Task environment	Observable	Agents	Deterministic	Episodic	Static	Discrete
5	Physical Theft Prevention System	Fully	Single	Deterministic	Sequential	Static	Discrete

5.5 The Kind of agent Program is a **Simple reflex agent** because its decision making is based only on the current input data.

F. Building an Intelligent Agent for Brain Surgery: In this exercise the design of an agent for improved accuracy in Brain surgery is discussed.

6.1 The Task environment is Improved accuracy in Brain surgery.

The PEAS description for the agent

S/N	DOMAIN (AGENT TYPES)	PERFORMANCE MEASURES	ENVIRONMENT	ACTUATORS	SENSORS
6	Improved Accuracy in Brain surgery.	To improve the accuracy in brain surgery	Patients, Hospital, insurers, laboratories, surgery center.	Computers, Human Brain, Tissues, diagnoses, tests, referrals.	Magnetic resonance Imaging, X-ray, Positron emission tomography, Computerized tomography, findings.

6.2 The Percepts

The inputs are:

- Diagnosis Optimization (via trained imagery)
- Risk stratification (severity sensed via rational test)
- Imaging sequence (detected images)

- Predicting the prognosis and recurrence.

6.3 Improved accuracy in Brain surgery is fully observable because its sensor provides access to the complete state of the environment at each point in time.

6.4 The external stimuli that could affect the agent

- Ethics
- Scientific evaluation
- Clinical acceptability (Hugo 2021, p.17)

6.5 **The properties of the task environment**

S/N	Task environment	Observable	Agents	Deterministic	Episodic	Static	Discrete
6	Improved Accuracy in Brain surgery	Fully	Single	Stochastic	Sequential	Dynamic	Discrete

6.6 The Kind of agent Program

Utility-based agent; because it presents a way in which likelihood of success can be weighed against the importance of goals.

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COMPONENT 2 FUEL CONSUMPTION

1

Training a model simply means learning (determining) good values for all the weights and the bias from labelled sample data. The goal of **training a model** is to find a set of weights and biases that have low loss, on average, across all sample data. The building of machine learning models consists of various **steps listed below**:

- Import the necessary Libraries/functions
- Load the data
- Examine and cleaning the data
- Separate the target variables
- Extract categorical and numerical columns
- Impute missing data
- Encode categorical columns
- Split dataset into train and validation sets
- Define model
- Fit the model
- Predict and evaluate on the validation set
- Generate test prediction

STEP -1: The required libraries and functions are imported accordingly.

STEP -2: The dataset provided is read or called to enable us to parse the file.

STEP -3: Here the file is examined taking into consideration its shape, columns, heads to enable us to have a known dimension, labels, integers, categorial variables on the dataset.

STEP-4: Separate the targets variables by distinguishing the dependent variables from the independent variables. There is need to drop missing target variables at this point.

STEP-5: Extract the categorical and numerical columns; thus, dividing the columns labels into categorical, numerical and columns_to_drop respectively.

STEP-6: Fix missing data; adjust and make corrections to the missing data where required taking note of common denominators across given dataset.

STEP-7: Encode categorical columns. There are two basic types of categorical feature encoding namely Label encoding and OneHot Encoding. This enable data pre-processing to place else it is seen as an error in machine learning.

STEP-8: Here the dataset is split into train and validation sets respectively though test set already provided.

STEP-9: Define the model to be implemented. This could be done using Random Forest, Decision tree, Extra tree and Bagging Regressors respectively.

STEP-10: Fit the model; it means training the model on the training data.

STEP-11: Predict and evaluate model on the validation set. The testing of trained model is done on the validation set whereby the predictions on validation data, mean absolute errors are all evaluated.

STEP-12: Final step is the generation of test prediction. This is also stored commonly as ‘preds_test’.

2

NUMERICAL ATTEMPT TO PREDICT CO2 EMISSION

MODEL	COEFFICIENT OF DETERMINATION	MEAN ABSOLUTE ERROR	ROOT MEAN SQUARE ERROR	FEATURES
MODEL 1	0.88	14.98	21.42	MODEL YEAR, CYLINDERS, FUEL_CONSUMPTION_CITY, FUEL CONSUMPTION_HWY, FUEL COMSUMPTION COMB, FUEL CONSUMPTION MPG, ENGINE SIZE

SUBSET OF VARIABLES ATTEMPT TO PREDICT CO2 EMISSION

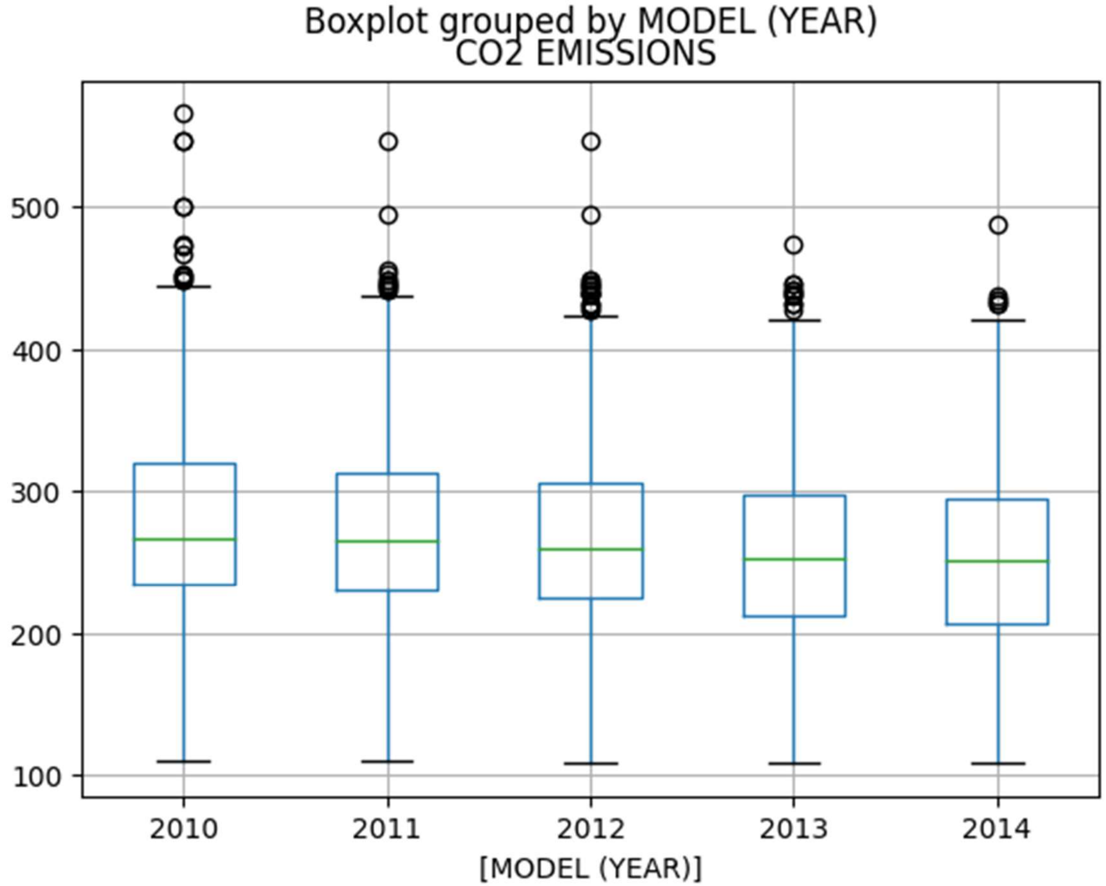
MODEL	COEFFICIENT OF DETERMINATION	MEAN ABSOLUTE ERROR	ROOT MEAN SQUARE ERROR	FEATURES
MODEL 2	0.87	15.62	22.27	'CYLINDERS', 'ENGINE_SIZE', AND 'FUEL_CONSUMPTION_COMB_MPG'

MODEL 3	0.86	16.20	23.38	ENGINE_SIZE AND FUEL_CONSUMPTION _COMB_MPG
MODEL 4	0.87	15.60	22.31	CYLINDERS AND FU EL_CONSUMPTION_C OMB_MPG
MODEL 5				ENGINE SIZE
MODEL 6	0.79	20.17	28.85	'FUEL_CONSUMPTIO N CITY
MODEL 7	0.72	24.53	33.01	'FUEL_CONSUMPTIO N_COMB_HWY'
MODEL 8	0.83	17.58	25.87	'FUEL_CONSUMPTIO N_COMB_MPG'
MODEL 9	0.77	20.92	29.70	'FUEL_CONSUMPTIO N_COMB_

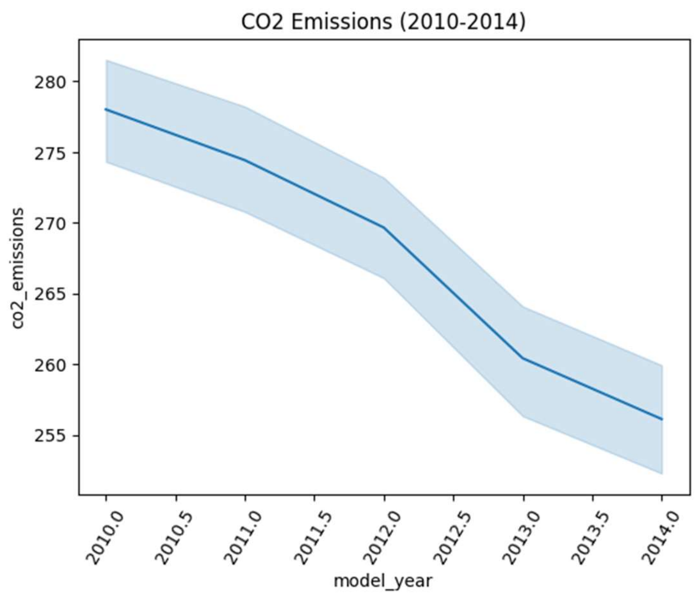
It could be observed that the Multiple linear regression performed better than simple linear regression. Model 1 with the feature ['FUEL CONSUMPTION COMB (mpg)','CYLINDERS'] performs best among the multiple linear regression models. We could notice that it has the least weighted errors of **14.98** within the same linear scale. In model 5 we have the highest coefficient of 0.88 which shows how the model is fit. The fitness is much better than the other models.

3

<AxesSubplot:title={'center':'CO2 EMISSIONS '}, xlabel='[MODEL (YEAR)]'>



<AxesSubplot: title={'center': 'CO2 Emissions (2010-2014)'}, xlabel='model_year', ylabel='co2_emissions'>



In the boxplot above, there is a reduction in the CO_2 emission across the years from 2010 to 2014 as indicated in the plot above. Also, counts of outliers were significantly reduced across the years. Some of the outliers were identified with the following models- Veyron, E350 Wagon and Avertador Roadster with Veyron having most counts in the first three years. Hence there is a noticeable drop in the CO_2 emission across the years.

<u>USING CATEGORICAL VARIABLES AS TARGET VARIABLES TO PREDICT CO_2 EMISSION</u>

<u>CYLINDERS</u>

MODEL CLASSIFICATION	ACCURACY
DECISION TREES	0.99
SUPPORT VECTOR	0.91
RANDOM FOREST	1.00
LOGISTIC REGRESSION	0.83
K-NEIGHBORS	0.97

*Ranom Forest has the best accuracy because it detects the highest rightful predictions.

*Random Forest also has the best performance metric for efficiency thus has less bias.

*Random Forest has low error possibility.

*In Random Forest, K-Neighbors and Decision Trees, it indicated via the standard deviations of 0.00 that there are high clustering within the mean value across the dataset.

CROSS VALIDATION FOR MODEL 1

MODEL CLASSIFICATION	MEAN ACCURACY	STANDARD DEVIATION
DECISION TREES	0.99	0.00
SUPPORT VECTOR	0.53	0.02
RANDOM FOREST	1.00	0.00
LOGISTIC REGRESSION	0.62	0.01
K-NEIGHBORS	0.95	0.00

FUEL TYPE

MODEL CLASSIFICATION	ACCURACY
DECISION TREES	0.95
SUPPORT VECTOR	0.84
RANDOM FOREST	0.96
LOGISTIC REGRESSION	0.81
K-NEIGHBORS	0.92

CROSS VALIDATION FOR MODEL 2

MODEL CLASSIFICATION	MEAN ACCURACY	STANDARD DEVIATION
DECISION TREES	0.95	0.01

SUPPORT VECTOR	0.37	0.03
RANDOM FOREST	0.96	0.00
LOGISTIC REGRESSION	0.77	0.01
K-NEIGHBORS	0.88	0.01

MODEL YEAR

MODEL CLASSIFICATION	ACCURACY
DECISION TREES	0.28
SUPPORT VECTOR	0.25
RANDOM FOREST	0.29
LOGISTIC REGRESSION	0.24
K-NEIGHBORS	0.23

Conclusion: Cylinders performed best based on its accuracies across the supervised learning algorithms especially Random Forest (1.00), Decision Trees (0.99) and mean accuracy of 1 in Random Forest regressor. Cylinder offers the best performance for our categorical variables.

5

I checked that the model is not overfitted by carrying out **cross validation** on the models. This allows me to tune hyperparameters with the original set thus keeping test set as a truly unseen dataset for final model selection.

6

For Linear regression models, my main interested lies in the mean absolute error as it is best for numerical continuous variables.

In classification, I was most interested in accuracy, recall and precision because of the discrete variables involved. It also provides a more conditional appearance for me.

7

The models can be deployed efficiently to predict CO2 emissions as demonstrated. They can as well used for classification to a good extent provided, they are applied on validation set.

8

Cylinders best described the group formed.

COMPONENT 3

1

STEPS TAKEN PRIOR TO BUILDING EMERGENCY IDENTIFICATION MODEL

1. Importing the necessary libraries.
2. Identification and assignment of train and test directory for the model.
3. Read the first image and parsing.
4. Preprocessing using image data generator for augmentation of image.
5. Reading the training set
6. Converting the training set to Strings
7. Training stage
8. Test or checks for Overfitting
9. Evaluation stage

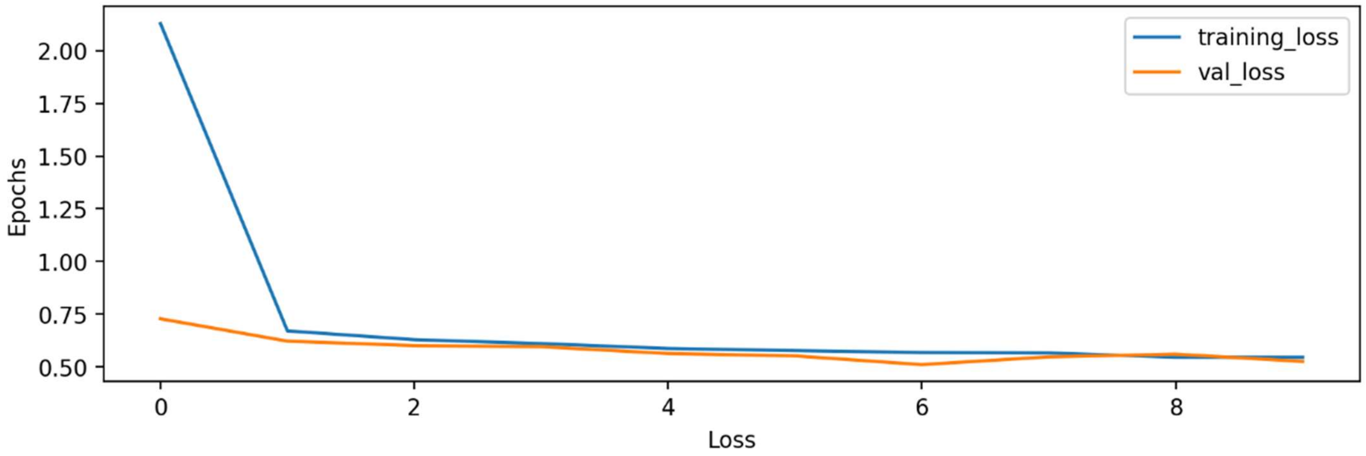
2

Increasing the hidden layers improved the accuracy of the model.

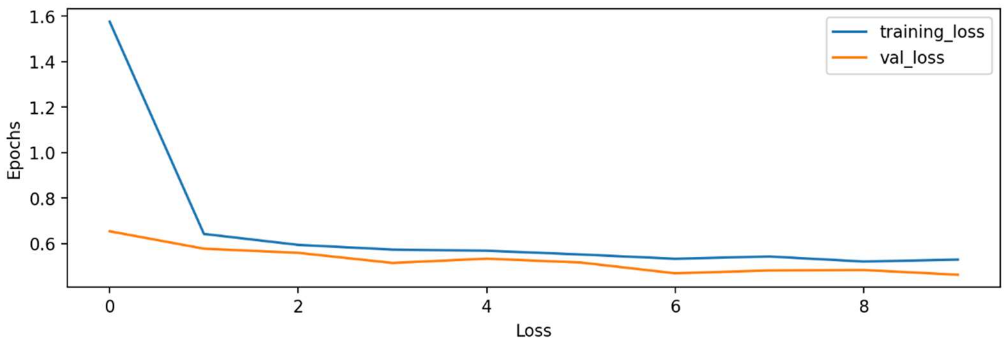
3

There was no case of overfitting in the model because it did not perform better on training set than on test set. As shown below.

Training set:



Test set:



:

	loss	accuracy	val_loss	val_accuracy
0	2.127839	0.553043	0.728358	0.606855
1	0.671018	0.636522	0.622417	0.663306
2	0.629430	0.660870	0.601172	0.709677
3	0.610823	0.671304	0.596101	0.693548
4	0.587572	0.706087	0.563689	0.715726
5	0.577548	0.706087	0.552478	0.719758
6	0.568450	0.722609	0.511076	0.756048
7	0.566247	0.724348	0.547831	0.756048
8	0.546301	0.724348	0.560721	0.737903
9	0.546097	0.746957	0.526201	0.760081

Training Set.

	loss	accuracy	val_loss	val_accuracy
0	1.576163	0.537391	0.654402	0.627016
1	0.642751	0.642609	0.577824	0.735887
2	0.594603	0.698261	0.559583	0.758065
3	0.573903	0.710435	0.515136	0.752016
4	0.568801	0.705217	0.533902	0.752016
5	0.552342	0.735652	0.517016	0.762097
6	0.533529	0.759130	0.469435	0.766129
7	0.543413	0.732174	0.482040	0.786290
8	0.521397	0.762609	0.483994	0.770161
9	0.529668	0.751304	0.463285	0.794355

Test Set

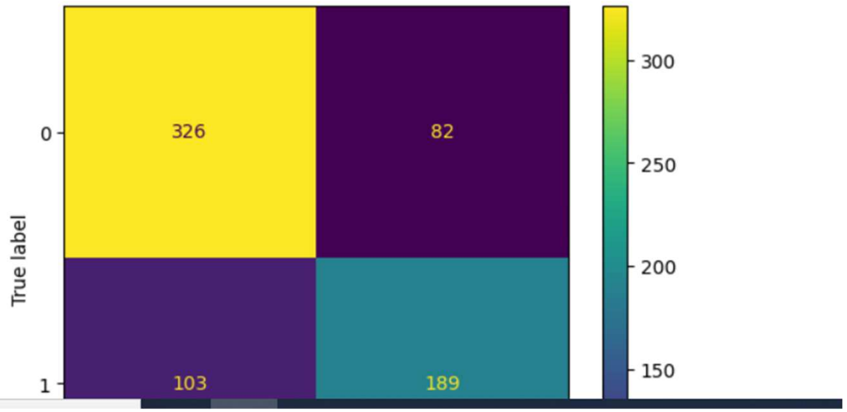
Confusion matrix caught my attention. It is one of the best performance metrics because it gives a better and comprehensive idea of any model's performance more than classification accuracy as shown below.

```
print(classification_report(true_labels, pred))
```

```
              precision    recall  f1-score   support

         0.0       0.76      0.80      0.78       408
         1.0       0.70      0.65      0.67       292

    accuracy                           0.74       700
   macro avg       0.73      0.72      0.73       700
weighted avg       0.73      0.74      0.73       700
```

```
cm  = confusion_matrix(true_labels, pred)
ax = ConfusionMatrixDisplay(cm)

ax.plot()
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x27aa38df160>
```



COMPONENT 4

ABSTRACT

This presents some ethical challenges being faced in AI systems and possible steps to address these concerns prompting unreasonable actions, bias, discrimination, autonomy, opacity and information privacy.

INTRODUCTION

Ethics simply means the moral guidelines that influence people's way of reasoning, attitudes, behaviours within a given entity. This plays a significant role in the manner of approaches, interactions and content-driven decisions on daily basis. Ethics is an assembly of principles which cut across life patterns, human's rights, responsibilities and moral obligations in multidisciplinary dimensions.

ETHICAL CHALLENGES IN ARTIFICIAL INTELLIGENCE

Artificial Intelligent systems often refer to rational packs that are autonomous and quite adaptive. In the sense that they tend to perform multiple tasks in complex domain without any regular guidance by the user. They equally improve their performances via percept sequence learning which happens synchronously. With the recent breakthroughs in artificial intelligence which were driven by improved hardware. There have been some ethical concerns that are associated with the applications of artificial intelligence. Some of them could emanate from poorly designed models, biased propositions, projects from a defective data and poor inclusivity from the designers and intended users. These factors pose a lot of risks to the ever-growing populations, users and especially the processed data (model mostly).

Unreasonable Actions – Many of computer set of commands, rules and data sourcing algorithms depend on knowledge that are interdependent within the dataset. This correspondence based on unlimited quantity of processed information are always acceptable without establishing a causality. This poses a problem because spurious correlations are being observed more than the genuine causal learning. There was an example, of a model designed to speculate client's outcomes in clinical settings. This relied solely on quantifiable data inputs. (e.g., vital signs and past success records of modified treatments), while neglecting emotional factors which can have a good impact on patient fitness. Thus, compromise the accuracy of the algorithmic prediction (Buchmann, Paßmann et al 2019).

Bias – In the real sense of mind, as humans there is this belief that automated human decisions are justified by alleged unbiased systems. This is unrealistic because Artificial intelligent systems make biased decisions. An intelligent agent's performance measures only reflect the designer's intent and probably demands of the intended users. In Amazon it was found out that an algorithm used to train a model for selecting top employees for top positions was biased against females. (Angelo B. 2015).

Discrimination – Due to some obvious multiple biases in AI systems perceived over time, some persons might feel discriminated. Stigmatisation can come in once their autonomy and participation are neglected. This was illustrated during non-representative data sampling in US healthcare where the trained AI system performed unfairly for underrepresented population. According to research, an algorithm used on more 200 million people in US hospitals to predict extra care assistance favoured the whites heavily only. Further investigation showed that the black race was not even a variable in the algorithm (Shin T. 2019).

Autonomy – Heavily loaded processed information and conclusions from AI models could be a threat to autonomy. Content customization by AI systems could be quite challenging because it could mean development of multiple-choice architectures which differ within a sample. AI digs into the dataset attributes and human decision details by filtering. Based on this approach, several contents and information are provided by profiling or sampling within a given population. Therefore, reducing the varieties of information by either deleting irrelevant or contradictory comments based on the user's directives. Provided that information diversity remains critical for autonomy, content customization construes a problem. Example there could be poor guidance from Healthcare AI systems when there is no prior understanding of the basis for their routine care activities. The patients will also face similar dilemma about decisions regarding their care.

Opacity – This happens when the sources of information especially inputs to a given AI system is not comprehensible. Though these inputs are not obviously accessible to observers or pretentious parties. Due to the complexity of codes, multidimensional data and logic sequence which makes the AI systems incomprehensible; transparency is limited. In February 1991 (First Gulf War), an Iraqi missile hit the US base of Dhahran, murdered American soldiers. Information shown that the base's antiballistic system failed to launch because of a computer bug. After every hour, the internal clock deflected by milliseconds, which had a huge impact on the system.

Information Privacy and Group Privacy – In AI systems the notions of Privacy and consent could be transformed via embedded algorithms. Information privacy which deals with the extent an individual control his information, legal rights to data and efforts made by third parties to obtain the given information. It also covers the unauthorized access, use and availability of data contents. This can be quite complex due to couple of socio-techno risks involved, a security concern. This occurs when there is abuse of technology that is used to store and process data. For example, taking a company universal serial bus home which has confidential data. Technology can also be used in ways that are not consistent with ethical principles thus, posing another treat which possibly can lead to data privacy violation.

ACTIONS TAKEN TO ADDRESS SOME OF THE ETHICAL CHALLENGES

AI has contributed enormously to the development of several smart worlds in diverse disciplines**.** It is very necessary and inevitable to address the numerous challenges associated with ethics in AI system in order to unleash its potentials. While providing limitless services to humanity without posing threats and unfair treatment to man. This can be achieved by ensuring informed consent to use data, enforcing data safety and transparency, promoting fairness in algorithms and biases and considering data privacy with attentiveness.

Active collaboration between the stakeholder and end user groups will douse some rippling effects from unjustified actions and bias in AI system. Still on addressing dilemma on opacity and discrimination, developing policies suitable for promoting racial recognition, enhancing moral values, adjusting priorities across economic, political, cultural backgrounds, gender inclusivity and education systems will be a brilliant achievement. Thus, such steps will allow people to advance in the race with AI systems.

It is recommended that AI designs should be made on value impact which must be clear, shared and context-oriented ensuring that model decisions are developed explicitly in the procedures and object (Dignum 2017). For autonomy there is need in a design stance, to accommodate shared awareness via responsible autonomy. This ensures interactive intervention within a given system.

Big companies must be regulated in order to minimize and monitor disparate impacts on their products. Documentation should be encouraged on the approaches and efforts towards reducing unfairness in algorithms.

Conclusion

This document has examined some challenges raised by Artificial intelligent systems with respect to ethics and human values. These were driven by some misguided, inconclusive evidence and unfair outcomes which gave rise to unjustified actions, bias, discrimination and privacy mostly encountered in Artificial intelligent systems.

Some recommendations have been highlighted as possible solutions to mitigating ethical challenges. These include transparency, informed consent to use data, safety and resilience, moral responsibility, improved policies, enforce diverse and inclusive programmes, bottom-top and top-bottom collaborations between end users and stakeholders.

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