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Submission Instructions

1. Name your submission in according to the name convention, LD7187_<your tutor initial>_<your programme><sem>_<your id><your first name>.docx, eg LD7187_RBS_CT2_w22012345John.docx is the filename for the student enrolled in MSc Computing & Technology sem 2 (2023 Sep Intakes) attending Rejwan's session.
2. Submit to Final Report Submission Point at Bb before 16:00, 22 May 2024

Declaration

I confirm that this assessment is my own work and that I have duly acknowledged and correctly referenced the work of others. I am aware of and understand that any breaches to the Code of Academic Conduct will be investigated and sanctioned in accordance with the Academic Conduct Regulation.

Your signature:	RASIKH SADIQ THAKUR	**Date:**	20/05/2024

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Task 1: Cloud feasibility study

Utilization of machine learning solutions on cloud-based platforms has been in the rise as a result of the scalability, flexibility, and User-friendliness advantages of cloud use. The choice of cloud platform that is suitable for the above-mentioned scenario, namely energy consumption prediction and carbon emissions forecast for several countries, becomes the key critical step for successful deployment. Let's explore and critically analyze different cloud platforms for commercial machine learning solutions deployment:

1. Amazon Web Services (AWS):
    - AWS papers offers a comprehensive of machine learning services through its AWS AI/ML suite which consist of Amazon SageMaker for model training and deployment.
    - SageMaker equips developers with algorithms for building models, marginal notebooks and automatic model optimization, all these features allow to train predictive models on energy consumption and carbon emissions.
    - AWS gives a global infrastructure with high availability and reliability which allows any applications to be deployed against the company or start-up milestones.
    - Cost-effectiveness can depend on user behavior and influence the overall services that are utilized.
2. Microsoft Azure:
    - Azure Machine Learning Studio is a well-equipped toolkit for construction, learning, and release of the models of machine learning.
    - In addition to Azure's capability of meshing other Microsoft services like Power BI which render data presentation and reporting to facilitate analysis of energy consumption and carbon emission trends, the corporation is more likely to gain value from the strategy.
    - Azure as a global model insures the fact that there is low latency and high operability for the worldwide deployment
    - Azure services are available at different cost tiers, namely hourly usage and reserved instance billing methods, making it easier to manage and optimize expenses.
3. Google Cloud Platform (GCP):
    - AI Platform on Google Cloud provides a managed service for machine training model deployment and operation.
    - Among GCP services, Big Query supplies a great deal of data analytics operations, which can fit into the preprocessing and analytical procedures of a comprehensive data set pertinent to energy consumption and carbon emission.
    - With its world wide layout, GCP globally based data centers allow you to deploy worldwide with the best uptime and least latency.
    - GCP maintains a competitive pricing, featuring a scale-up and scale-down functionality, as well as preemptible VMs for cost optimization.
4. IBM Cloud:
    - IBM Watson Studio offers a portfolio of equipment for data science and machine learning, in which tools for designing models, training and deploying them can be found.
    - AI OpenScale of IBM equipped with model management tools and monitor systems for models working in production environments to ensure the models exhibit proper performance and quality.

- Globalization of the data centers is a feature of the IBM Cloud, allowing for deployments in any desired district.
- Pricing model s may be built $ based on provided services and by usage patterns.

In critically analyzing these cloud platforms, several factors must be considered:

- Scalability: The big data processing and ability for providing the appropriate computational environments should be considered as key factors while building machine learning solutions for a global energy consumption forecasting system.
- Performance: Fast reaction time and the continuous availability are the key for real-time prediction and implementation.
- Cost: Higher throughput is important, but the cost-benefit assessment should also incorporate other factors like qualities, performance and support.
- Integration: The main advantage is that this integration should be smooth considering all the other tools and resources such as data visualization platforms and monitoring tools that will increase the efficiency of the workflow.
- Compliance and Security: Compliance with data standards and solid security procedures are the reality again, especially when personal energy and environmental data containing sensitive information is concerned.

Cloud platforms' choice depends on organizational requirements, budget constraints, and current infrastructure for machine learning solutions. A comprehensive framework evaluating scalability, performance, cost, integration, compliance, and security helps match the commercial machine learning solution deployment scenario.

Task 2: Data analysis and opportunity identification

Data analysis of the dataset supplied for energy in Afghanistan for 2000 to 2004 refers to crucial revelations towards the country's energy source chain. Here, worth mentioning the fact that due to the constant changes in every energy metrics a person can understand the trends, problems, and also be sure to develop solutions. As long as we delve into the provided dataset, gather analogous cases, and debate about ideal approaches to deal with challenges.

Exploring the Data:

The database contains different energy and temperature indicators, for example, electrification, renewable energy share, CO2 emission, GDP rate, and population density. The analysis emphasizes on a gradual move towards electric power and clean fuels in cookstoves over the years. Hence, though renewable share currently is low there is still a clear room for development. In addition, changes in CO2 emissions and in GDP growth would imply that there is (maybe) a very complicated relationship between energy consumption, economic development and environmental sustainability.

Similar Problems and Techniques:

In the same way the authors have data of this countries, there are similar datasets worldwide which represent the energy dynamics of other countries. Addressing challenges in these datasets often involves employing data analysis techniques such as:

1. Predictive Modeling: Analyzing historical energy data helps in energy trajectory planning and energy demand forecast. Use of the methods in time series analysis,

regression, and machine learning models helps in predicting electricity consumption pattern, that enables good resource planning and allocating of resources.

2. Renewable Energy Integration: Developing aesthetic solutions for the growth in renewable energy infrastructure that is currently underway is imperative as well. Approaches as optimization modeling, Geographic Information Systems (GIS) and scenario analysis tools can be helpful in identifying the best places for renewable deployment capacity, finding the challenges of integrating renewables with the grid and developing policies that will help progress of a wide adoption of renewables.
3. Energy Access and Equity: It is important to study how the population and geographic patterns along with the socio-economic element of energy access are affected simultaneously. Strategies comprising space analysis, clustering and socio-economic modeling could be used to finding out areas with no affordable access and then designing specific projects to bring energy to these community groups. Moreover, they could be used to support those societal groups which are more inclined to adopt the new technologies and energy innovations.
4. Carbon Emissions Reduction: Cutting carbon emissions means adoption of policy and technologies which help to decarbonize energy chains. Through data-driven methods such as emission inventory analytics, carbon pricing techniques, and life cycle assessments the world can take effective steps towards climate mitigation and would be able to achieve the green targets.
5. Data Visualization and Communication: Determination of effective communication becomes paramount due to it helps to keep high level of awareness among policymakers, organizations and public at large. Through visual aid, storytelling, and interactive gadgets, energy statistics, which may look like a labyrinth to some, are transformed into narrative, hence engaging the audience and prompting informed decision-making.

Opportunities and Recommendations:

Analyzing the provided dataset reveals several opportunities for Afghanistan and similar countries:

1. Investment in Renewable Energy: Considering that there is a little share of renewables, one can make an attempt to invest in renewable energy infrastructure, getting the power from the dinking of solar energy, wind as well as hydropower.
2. Enhanced Energy Efficiency: Wide-scale increase in energy efficiency within every industry can decrease dependence on fossil fuels, lessen emissions, and bring in more reliable and secure energy sources. Such actions can significantly aid the cause through through building codes, appliance ratings, and industry performance programs.
3. Integrated Energy Planning: Integrated energy planning involving all important levels of resource allocation helps conflicting priorities be resolved and more sustainable development to take place. Synchronized work of different sectors, engagement of all stakeholders, and long-term view of energy planning are indispensable for orderly energy planning.

Task 3: Data pre-processing

Data pre-processing being is an essential step in machine learning workflows which deals with cleaning and organizing the data for the purpose of modeling. This report will outline the basic pre-processing steps, the energy data set in the format of Python, which will eventually form a training data for training our model.

1. Loading the Dataset:
   As the first one is taking the data in the memory using the pandas library. 'CSV file' are the Energy set and 'Google Drive' is its location.

```
import pandas as pd
import matplotlib.pyplot as plt

# Load the dataset
data = pd.read_csv("/content/drive/MyDrive/energy_data.csv")
```

2. Identifying Countries with Low Access to Clean Fuels:
   Considers the comprehension of nations where biomass fuel or charcoal alone supplies for cooking as a decisive step in pinpointing these kinds of inequalities while designing targeted measures to correct this. Pointing out specific countries where combustible felle below the cut off point of 50% is meaningful enough to bring attention to regions whose citizens are facing difficulties in order to clean fuels for cooking purposes. This information however not only shows us the gaps but also serves as a base in coming up with local programs that will help to bring energy services for the people who live in these underserved areas. And as this identification of the key energy needs is made, the basis is helped to be built where solutions of sustainable energy are developed and in which all members of the society have access to the clean fuels and achieve the better health of the environment or the society in a global scale.

```
# Identify countries with low access to clean fuels
low_clean_fuels = data[data['Access to clean fuels for cooking'] < 50]
print(low_clean_fuels[['Entity', 'Access to clean fuels for cooking']])
```

3. Identifying Countries with High Carbon Emissions:
   Another distinction in carbon emissions that we have also identified is countries that emit at high levels compared to the others, arriving at a total of 50,000 kilotons of CO2. These findings not only pinpoint at places facing hardships in establishing and enforcing the environmentally sound policies, but also emphasize the urgency and necessity of taking actions to reduce emissions. Emissions of a high carbon ratio not only reflect the problems of the environment, but they show us why global warming and climate change intensify and why we need to take actions to avoid greenhouse gas emissions and fight against climate change. Through outlining such states, emission, we get in-depth information about the bleak places; said states that, generally, require urgent interventions in sustainability and resolving the impact of climate change.

```
# Identify countries with high carbon emissions
high_carbon_emissions = data[data['Value_co2_emissions_kt_by_country'] > 50000]
print(high_carbon_emissions[['Entity', 'Value_co2_emissions_kt_by_country']])
```

4. Handling Missing Values:
   Prompt first data cleaning is a major data preprocessing part, because incomplete data can considerably degrade the accuracy and robustness of sophisticated machine learning agent. In real life, missing data are an ordinary poor occurrence because of different causes including human mistakes, machine breakdowns, and optionally information is not available in the sector.

We have also have mitigated the effects of missing data through the strategy of imputation whereby the mostly empty fill values are replaced with the mean of each column. This method allows for the replacement of the missing data with a reasoning value, or in other words, does not therefore affect the whole set of data and the bias analysis, which follows.

The average mean being replaced with the mean ensures that the general distribution and the attributes recast the data only while minimizing the gaps present due to missing observations. This allows us to keep as much information possible from the original dataset and thus we successively increase the usability and quality of the provided data.

It should be noted, however, that the mean imputation is widely regarded as a typical method of filling missing values, and it is therefore not always the most ideal approach for a given data containing natural phenomena and the context under investigation. The other method of imputation, including median imputation and regression imputation, should be considered when analyzing the data given their requirements.

```
# Iterate over each column
for column in data.columns:
    # Check if the column contains numeric data
    if data[column].dtype in ['int64', 'float64']:  # Numeric data types
        # Check if the column contains NaN values
        if data[column].isnull().any():
            # Calculate the mean of the column
            column_mean = data[column].mean()
            # Fill NaN values in the column with the mean
            data[column].fillna(column_mean, inplace=True)

# Check if there are any NaN values left
print(data.isnull().any())
```

5. Renaming and Converting Columns:

During data processing, the path is marked by column names renaming and column selection which increases the clarity and facilitates the numerical analysis due to the transformed data. Particularly we have refashioned the title of the column into a more meaningful and user-friendly name called "Density" that intends to enhance the transparency of the dataset and provide a readable and concise name for the column through its refashioning.

Also, we have dealt with the problems of non-numeric characters in numerical column called “Density”. So we delete superfluous characters like "\n" and parantheses – these characters will make the data incorrect and not suitable for processing with the appropriate techniques. It is therefore the necessary item of the process in order to ensure the accurate data and avoid problems collection and inconsistencies at the next step.

After that thru which non-numeric characters have be removed, we did a conversion of "Density" column to a numeric data type. The translation of the densities into numeric data then serves to provide the means to undertake various math operations and statistical analyses on the values that were obtained, thus helping to identify the space distribution patterns and populations densities for various geographical regions.

Through the process of renaming and converting this appropriately, we follow data preprocessing guidelines that give major consideration to clear names, consistent naming, and compatibility with data analytical techniques. This attention to detail in the initial stages of the machine learning pipeline puts a strong foundation for desired data preparation operations that assist in models to be better trained and analysis to be handled easily.

6. Filling Missing Values in the 'Density' Column:

   Next, we will do some adjustment in data preprocessing by taking a look at the 'Density' column since it is in a form of numeric. This is to handle any missing values that may exist in this column. Since our finding may be incorrect if the values are missing and since mnissing values can negatively affect our analysis, proper treatment of these values is necessary.

   Starting from this postulate, we have chosen to impute the leftover missing data in the "Density" column by calculating the row mean value of the column. This approach makes the compiling of consistent dataset possible because that zero value is replaced with a sound estimation of data value that is taken from an average density across the whole data set.

   An ordinary imputation method which is used is to fill up the missing values with the mean of that particular column. This technique helps to maintain both the distribution and the characteristics of the data while working around the effect of missing observations. We apply this strategy so our data set retains completeness and avoids data missing gaps, thus the data is as best used as possible in the subsequent stages of analysis and model training.

```python
data.rename(columns={r"Density\n(P/Km2)": "Density"}, inplace=True)

# Remove non-numeric characters from the 'Density' column and convert it to numeric
data['Density'] = pd.to_numeric(data['Density'].str.replace(r'\D', ''), errors='coerce')

# Fill missing values in the 'Density' column with the mean of the column
data['Density'] = data['Density'].fillna(data['Density'].mean())
```

Task 4: Model selection and training

Both the model selection and model training are vital process in building precise forms of forecasts for consumptions of energy and carbon emissions. To proceed, we'll disclose the model selection and training process by means of the given data. By predicting power consumption for different countries and reviewing emissions at the same time, there is a likelihood of achieving efficient downstream solutions for energy production.

1. Understanding the Data:

This model of model selection is highly dependent on the dataset collection and understanding. Probably, the given dataset gives out indicators like access to electricity, share of renewable energy, GDP per capita and population density, with the variable of target being carbon emissions (Value_co2_emissions_kt_by_country).

2. Preparing the Data:

In this case, the dataset has to be prepared before applying the logistic regression modeling technique. In this step, the dataset needs to be split into features (X) and the target variable (y). The additional constituents for 'year' and 'entity' are unnecessary because they have nothing to do with modeling. Further the 'Value_co2_emissions_kt_by_country' is withdrawn from the features considering it is the target variable.

3. Choosing Regression Algorithms:

For regression tasks like predicting carbon emissions, we consider two popular algorithms: Correlation and linear regression. Along with, random forest regression. Linear Regression assumes a linearly related features with target variable while Random Forest Regressor is an overfitting method for the relationship between features and the target variable.

4. Splitting the Data:

The data set is distributed into the group of training and testing sets through the train_test_split function of scikit-learn. The typical break down is 80% training and 20% testing in the case of those that want to make sure the model is assessed correctly using unseen data.

5. Training the Models:

Linear Regression and Random Forest Regression models are trained by way of using training data with respect to the target. The fit procedure is implemented to each specified model, and the model therefore has the capability to spot patterns and linkages from the training data.

6. Evaluating Model Performance:

To assess model performance, we evaluate each trained model on the testing data using evaluation metrics such as Mean Squared Error (MSE) and R-squared (R^2). MSE measures the average squared difference between predicted and actual values, while R^2 indicates the proportion of variance in the target variable explained by the model.

7. Selecting the Best Performing Model:

The model selection is done depending on which model out performs the others according to evaluation notions. In that sense, Random Forest Regression stands with minimum MSE and highest R^2 value, hence to prove to be predominant in this category over Linear Regression.

8. Interpretation and Insights:

The selected model, Random Forest Regressor, can now be used for predicting energy consumption and forecasting carbon emissions for different countries. Insights gained from the model can inform policy decisions, energy planning strategies, and environmental initiatives aimed at reducing carbon emissions and promoting sustainable energy practices.

```
# Task 4: Model selection and training
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Step 2: Split the dataset into features and target variable
X = data.drop(columns=['Year', 'Entity', 'Value_co2_emissions_kt_by_country'])  # Features
y = data['Value_co2_emissions_kt_by_country']  # Target variable
```

```python
# Step 3: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 4: Choose machine learning algorithms for regression tasks
models = {
    'Linear Regression': LinearRegression(),
    'Random Forest Regressor': RandomForestRegressor(random_state=42)
```

```python
# Step 5: Train the selected models on the training data
for model_name, model in models.items():
    model.fit(X_train, y_train)

# Step 6: Evaluate the performance of the trained models
results = {}
for model_name, model in models.items():
    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    results[model_name] = {'MSE': mse, 'R^2': r2}
```

```python
# Step 7: Choose the best performing model based on evaluation metrics
best_model = min(results, key=lambda x: results[x]['MSE'])
print("Best performing model:", best_model)
print("Performance metrics:")
for metric, value in results[best_model].items():
    print(f"{metric}: {value}")
```

```
Best performing model: Random Forest Regressor
Performance metrics:
MSE: 1354374770.05011
R^2: 0.995230970377198
```

Task 5: Model evaluation and visualization

Once trained in the model, it is necessary to test its performance to find out, how accurately it makes energy consumption predictions and Carbon emissions forecasts. Hence visualizing the results also helps in taking steps to understand the model's mechanism, and also discerning certain insights. In here, I will touch on the subject of model evaluation as an aforementioned theme, where the means for visualizing and interpreting the outcomes will be introduced.

Model Evaluation for Overfitting:

The model holes up in the over-fitting situation when it memorizes data and the noise too much, ignoring the relevant patterns leading to the poor generalization of the unknown data. To ensure we avoid overfitting, testing can be done using both the training and testing data sets. If the model exceeds actual training data values as compared to those on the test data this is a condition for overfitting.

Prediction and Forecasting Tasks:

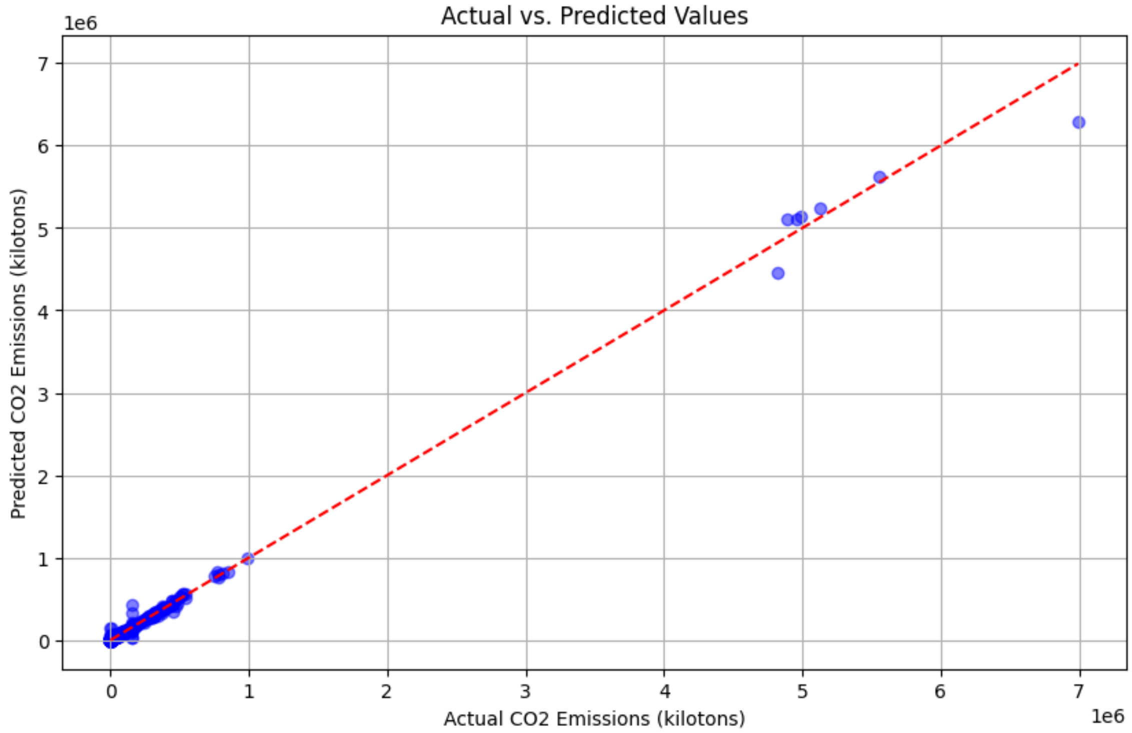
Our forecasting model can shed light on expected electricity consumption and carbon emissions during the next five years in three countries. Chosen model, Random Forest Regressor, is fit for this undertaking having the range to deal with nonlinear patterns and their interactions in the data.

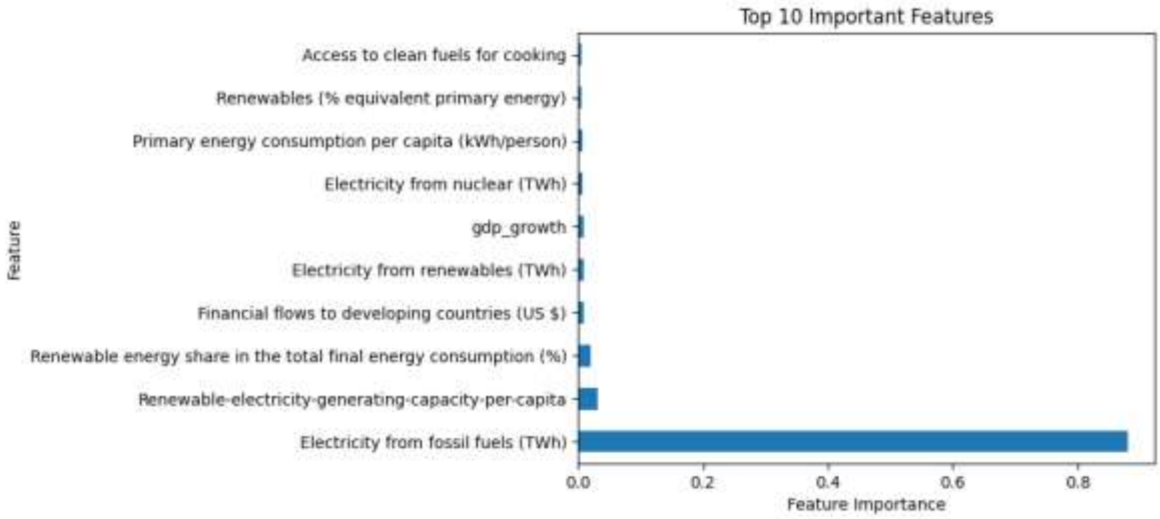
Visualization Techniques:

1. Actual vs. Predicted Values: This scattergram indicates the correlation of the actual with the predicted amounts of CO2 emissions. The line ‘‘tangent” shows the perfect predictions, and the closer data point are to this line means that predictions are accurate.
2. Feature Importance: For instance, in the case of Random Forest Regressor, which is used to provide feature importance scores, feature importance visualization can allow a peek into factors playing bigger role in energy consumption and carbon emissions.

Results and Interpretation:

- Actual vs. Predicted Values: Dispearing of the scatter plot shows a positive correlation between the real and forecasted CO2 emissions, proving that the model is crucial. Nevertheless, the data points cover considerably the entire diagonal curve, implying the model areas where it needs to be refined.
- Feature Importance: Figure stresses the prominent effects on renewable energy consumption through the relevant factors shown in bar graph. Masks such as "Renewables (% equivalent primary energy)" and "Primary energy consumption per capita" are indicated as the main factors in carbon emission projections and therefore, the progress of renewable power sources and energy consumption amount per person are prominent ones.





Task 6: Professionalism and Ethics in AI on the Cloud

The aspect of professionalism and ethics especially when it comes to the concerns of privacy and breaking-down of ethical boundaries is of similar importance in the development of models that can machine learning in cloud deployment. As more of the organizations migrate to the cloud to assist with the AI solutions implementation there is a need for the organizations to practice best professional ethics to ensure that ethical standards are followed and user privacy protected. This section explores the main approaches that can be utilized in bringing serious change in these issues.

1. Transparency and Explainability:

Transparency in AI systems is explained as a given that the models always provide a clear and direct explanation of how the model makes a decision and predictions, hence the need for complete transparency in the system. At the deployment time of machine learning models on the cloud, companies should pay special attention to the transparency score by writing down architectures of the models, training data and evaluation metrics. Furthermore, integration of the model explainability strategies, for instance feature importance analysis and model visualization, is the best way to increase transparency as well as to impart knowledge about model functioning.

2. Data Privacy and Security:

Data protection for users is a non-negotiable factor when AI is deployed cloud-based. The enterprises have to comply with the user privacy regulations like the GDPR and HIPAA, and ensure that all the sensitive information is used safely. Adopting encryption methods, access permissions and anonymization system prevents information misuse and data breaches, hence, providing security to data against unauthorized access or unambiguous violations. In addition to this, the implementation of regular security assessments and security audits is highly recommended to prevent possible security risks and promptly fix the problems.

3. Bias and Fairness Mitigation:

The bias of AI algorithms could be done in such a way that the unsanctions against the weaker will be continued along with unjust practices. In order to limit and in the best case, eliminate biases and promote fairness, organizations are called for to apply bias detection tools on pre-deployment and production environments. The application of algorithms that are fair-aware, use correction algorithms for biases, and provide as rich as possible datasets can help identify, avoid and treat biases that are present in the system, guaranteeing the equal treatment for all user groups.

4. Responsible AI Governance:

Building up robust governance systems of AI journeys deployment will help for the ethical and responsible use of AI technology. Organizations should create an AI ethics committee or an oversight board entrusted with a periodic review and approval of AI projects, the evaluation of possible risks involved, and the observation of ethics directives. Moreover, by setting precise policies and guidelines pertaining to AI building, incorporation, and utilization, this can in turn favor mindful AI practices everywhere in the organization.

5. Continuous Monitoring and Evaluation:

It is also, necessary to ensure continuous monitoring and evaluation to promptly discover and address new ethical and privacy issues once they arise. The monitoring systems should be developed to check out the model performance, detect model deviation from predicted behavior, and should flag ethical concerns or biases as early as possible. While reviewing AI systems periodically and gathering feedback by various groups can help in uncovering sources of their improvement related to fairness, transparency and some issues of data privacy.

6. Stakeholder Engagement and Transparency:

Communication to stakeholders such as users, regulators, and advocacy groups that are key to success in AI applications and this process ensures openness and accountability. Organizations are advised to sensitize stakeholders by taking them through the procedure to help them provide feedback, address concerns and build trust in AI systems. Transparent communication about the purpose, capabilities, and limitations of AI technologies is essential for fostering public trust and acceptance.

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