RAMCO INSTITUTE OF TECHNOLOGY

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DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

INNOVATIVE TEACHING PLAN

Year/Semester/Section: II/IV/B **Date: 27.3.2025**

Topic : Machine Learning Life Cycle **CO Coherency: CO1**

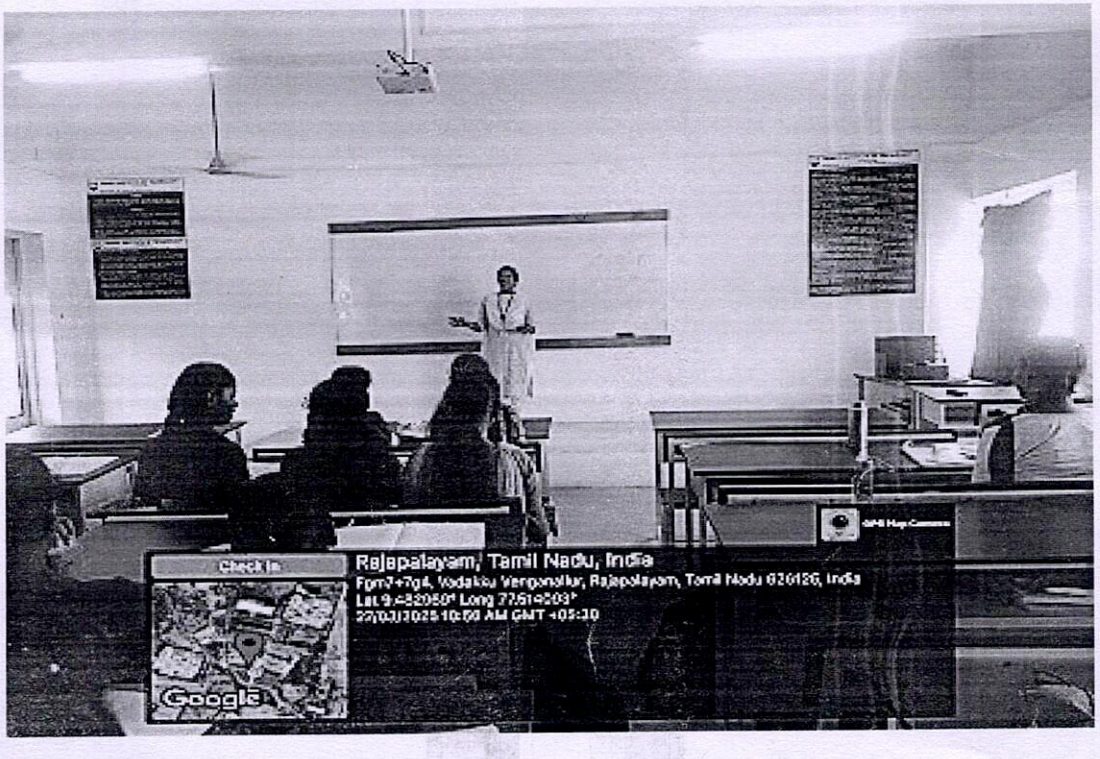
Duration : 45 minutes

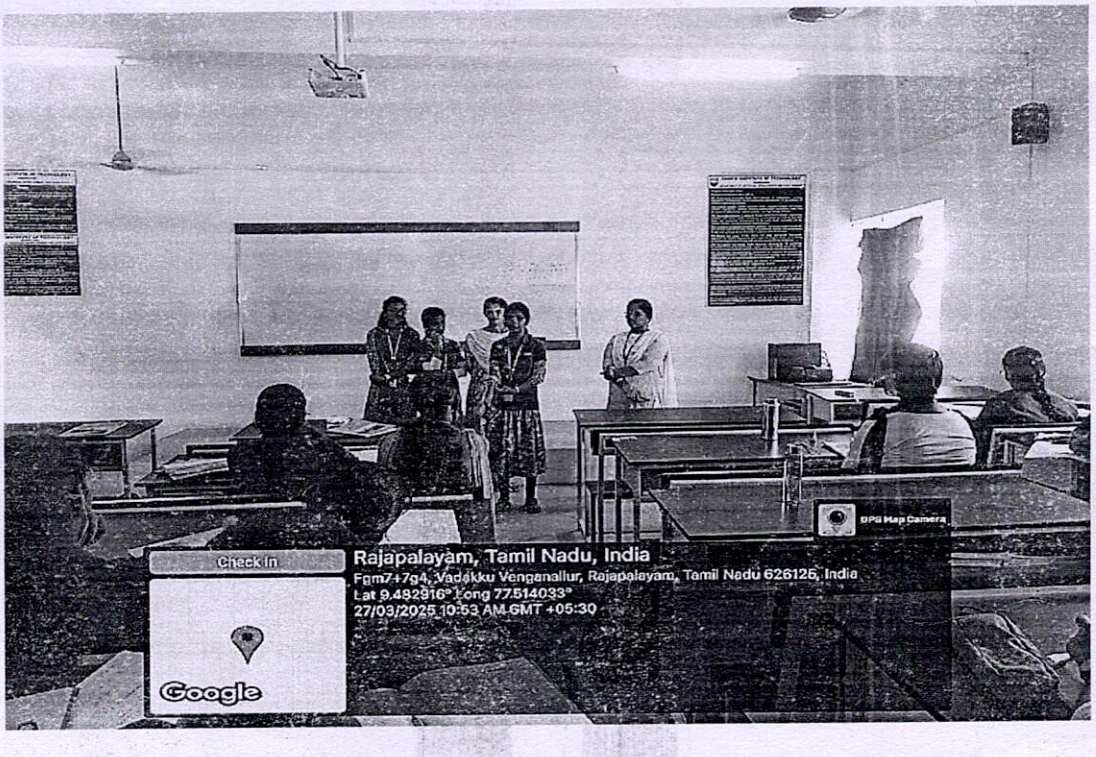
Role play is an interactive teaching method where students act out roles in a specific scenario or context to enhance learning. It encourages active participation and helps students understand concepts by experiencing them in a practical way.

Introduction : Course The instructor instructs the necessity of another topic and the introduction of the students, who are assigned different roles to play the machine learning life cycle

ML Phase	Student Name
S Aswitha	Planning
A Athithya	Data Preparation
R Divya Dharsini	Model Engineering
G Harsini	Model Evaluation
G Vennila	Model Deployment
E Dhanalakshmi	Monitoring and Maintenance

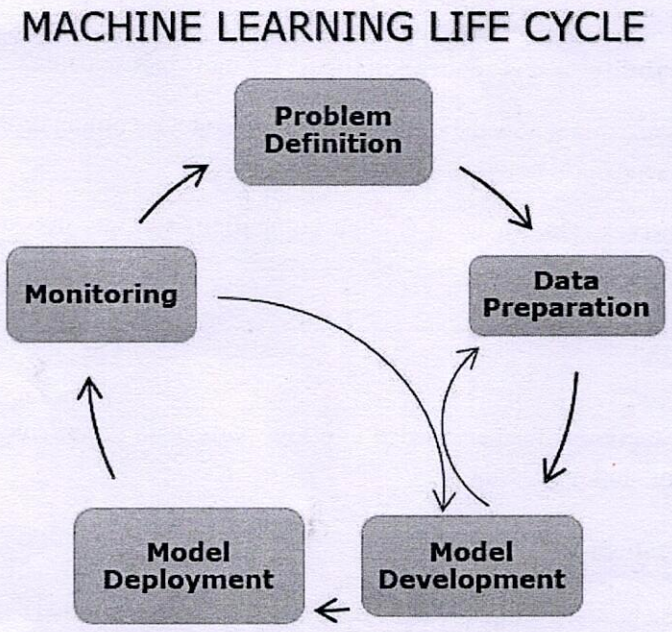
The photograph depicts the roles played by II Year B Section Girls





The 6 steps in a standard machine learning life cycle:

1. Planning
2. Data Preparation
3. Model Engineering
4. Model Evaluation
5. Model Deployment
6. Monitoring and Maintenance



Each phase in the machine learning cycle follows a **quality assurance** framework for constant improvement and maintenance by strictly following requirements and constraints..

1. Planning

The planning phase involves assessing the scope, success metric, and feasibility of the ML application. We need to understand the business and how to use **machine learning** to improve the current process. For example: do we require machine learning? Can we achieve similar requests with simple programming?

We also need to understand the cost-benefit analysis and how We will ship the solution in multiple phases. Furthermore, We need to define clear and measurable success metrics for business, machine learning models (Accuracy, F1 score, AUC), and economic (key performance indicators).

Finally, We need to create a feasibility report.

It will consist of the information about:

- **Availability of the data**: Do we have enough data available to train the model? Can we get a constant supply of new and updated data? Can we use synthetic data to reduce the cost?
- **Applicability**: Will this solution solve the problem or improve the current process? Can we even use machine learning to solve this issue?
- **Legal constraints**: Do we have permission from the local government to implement this solution? Are we following an ethical way of collecting the data? What will be the impact of this application on society?
- **Robustness and scalability**: is this application robust enough? Is it scalable?
- **Explainability**: Can we explain how the machine learning model is coming up with the results? Can we explain the deep neural networks' inner workings?
- **Availability of resources**: Do we have enough computing, storage, network, and human resources? Do we have qualified professionals?

2. Data Preparation

The data preparation section is further divided into four parts: data procurement and labeling, cleaning, management, and processing.

Data collection and labeling

We need first to decide how we will collect the data by gathering the internal data, open-source, buying it from the vendors, or generating synthetic data. Each method has pros and cons, and in some cases, we get the data from all four methodologies.

After collection, we need to label the data. Buying cleaned and labeled data is not feasible for all companies, and We may also need to make changes to the data selection during the development process. The data collection and labeling require most of the company resources: money, time, professionals, subject matter experts, and legal agreements.

Data Cleaning

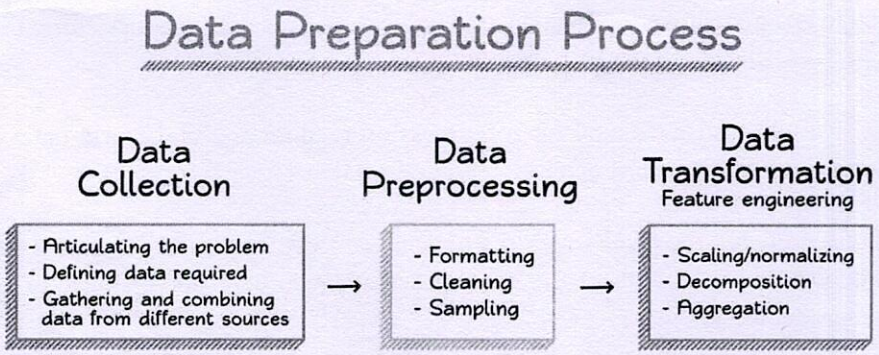
Next, we will clean the data by imputing missing values, analyzing wrong-labeled data, removing outliers, and reducing the noise. We will create a data pipeline to automate this process and perform data quality verification.

Data processing

The data processing stage involves feature selection, dealing with imbalanced classes, feature engineering, data augmentation, and normalizing and scaling the data. For reproducibility, we will store and version the metadata, data modeling, transformation pipelines, and feature stores.

Data management

Finally, we will figure out data storage solutions, data versioning for reproducibility, storing metadata, and creating ETL pipelines. This part will ensure a constant data stream for model training.



3. Model Engineering

In this phase, we will be using all the information from the planning phase to build and train a machine learning model. For example: tracking model metrics, ensuring scalability and robustness, and optimizing storage and compute resources.

1. Build effective model architecture by doing extensive research.
2. Defining model metrics.
3. Training and validating the model on the training and validation dataset.
4. Tracking experiments, metadata, features, code changes, and machine learning pipelines.
5. Performing model compression and ensembling.
6. Interpreting the results by incorporating domain knowledge experts.

We will be focusing on model architecture, code quality, machine learning experiments, model training, and ensembling.

The features, hyperparameters, ML experiments, model architecture, development environment, and metadata are stored and versioned for reproducibility.

4. Model Evaluation

Now that we have finalized the version of the model, it is time to test various metrics. Why? So that we can ensure that our model is ready for production.

We will first test our model on a test dataset and make sure we involve subject matter experts to identify the error in the predictions.

We also need to ensure that we follow industrial, ethical, and legal frameworks for building AI solutions.

Furthermore, we will test our model for robustness on random and real-world data. Making sure that the model inferences fast enough to bring the value.

Finally, we will compare the results with the planned success metrics and decide on whether to deploy the model or not. In this phase, every process is recorded and versioned to maintain quality and reproducibility.

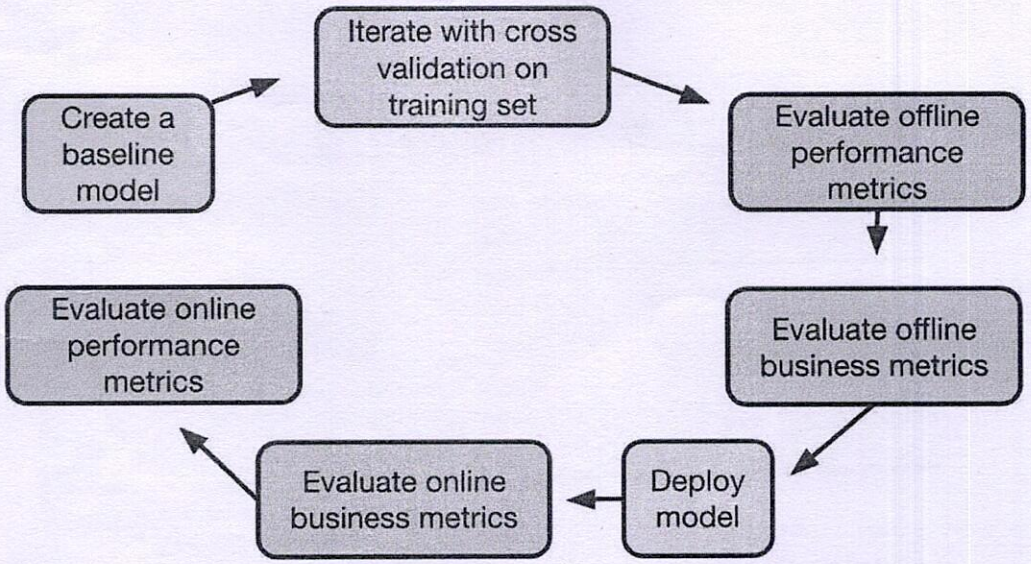
5. Model Deployment

In this phase, we deploy machine learning models to the current system. For example: introducing automatic warehouse labeling using the shape of the product. We will be deploying a computer vision model into the current system, which will use the images from the camera to print the labels.

Generally, the models can be deployed on the cloud and local server, web browser, package as software, and edge device. After that, We can use API, web app, plugins, or dashboard to access the predictions.

In the deployment process, we define the inference hardware. We need to make sure we have enough RAM, storage, and computing power to produce fast results. After that, we will evaluate the model performance in production using A/B testing, ensuring user acceptability.

The deployment strategy is important. We need to make sure that the changes are seamless and that they have improved the user experience. Moreover, a project manager should prepare a disaster management plan. It should include a fallback strategy, constant monitoring, anomaly detection, and minimizing losses.



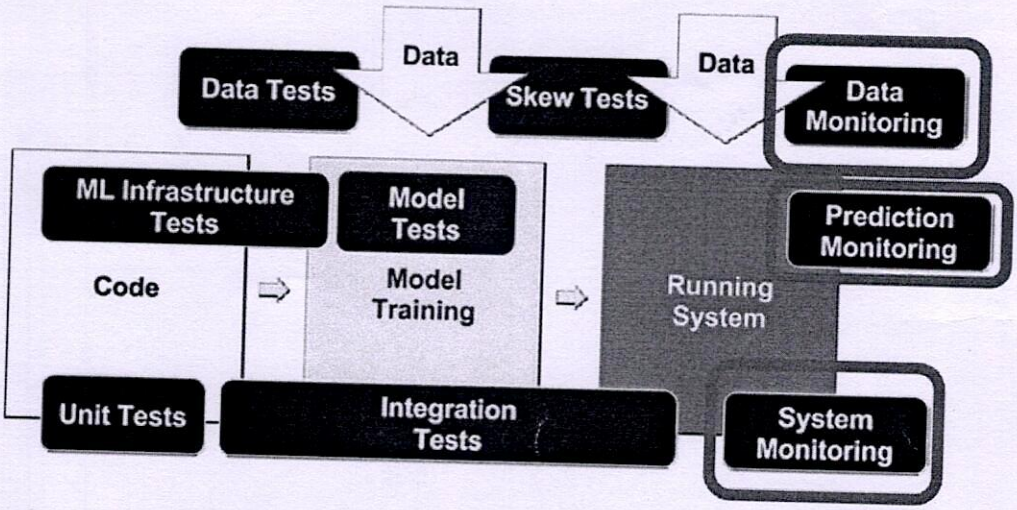
6. Monitoring and Maintenance

After deploying the model to production we need to constantly monitor and improve the system. We will be monitoring model metrics, hardware and software performance, and customer satisfaction.

The monitoring is done completely automatically, and the professionals are notified about the anomalies, reduced model and system performance, and bad customer reviews.

After we get a reduced performance alert, we will assess the issues and try to train the model on new data or make changes to model architectures. It is a continuous process.

In rare cases, we have to revamp the complete machine learning life cycle to improve the data processing and model training techniques, update new software and hardware, and introduce a new framework for continuous integration.



Outcome of the method:

In this article,students have learned about machine learning project planning based on requirements and constraints, data collection and labeling, model engineering, model evaluation, model deployment, and monitoring and maintenance. Apart from that,students have learned various ways to maintain quality, reproduce the results, and debug the process in case of failure. Students confidently ask questions and engage in discussions with their peers without hesitation. Student teachers also enjoy their teaching practice without any fear.

Feed Back Questions

Did you find the role play engaging?

○ Yes ○ No

Did Your Classmates effectively communicate their role?

○ Yes ○ No

Did you feel the role play demonstrated the intended skills or concepts?

○ Yes ○ No

Do you want to participate in forthcoming innovative learning practices?

○ Yes ○ No

Is there any difficulty level of understanding the concept?

○ Yes ○ No

Faculty In-charge

16/4/25

16/4

HOD

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Department of Artificial Intelligence and Data Science

Academic Year 2024 – 2025 (Even Semester)

Degree, Semester & Branch: BTech/IV/AD-B Section

Course Code & Title: AL 3451- Machine Learning

Name of the Faculty member (s): Dr.R.M.Rajeshwari

Innovative Practice Description

- **Unit / Topic: Unit -I/ Machine Learning Life Cycle**
- **Course Outcome:** CO1
- **Topic Learning Outcome:** TLO2
- **Activity Chosen: Role Play Method**
- **Justification:**
  - Role play in the machine learning life cycle helps simulate real-world scenarios, enabling stakeholders to understand and validate the model's behavior from different user perspectives. It enhances communication between technical and non-technical teams, ensuring that requirements are accurately captured. This method also supports ethical considerations by anticipating user reactions and potential biases.
- **Time Allotted for the Activity:** 45 minutes
- **Details of the Implementation:**

Implementing the machine learning (ML) lifecycle using the role play method involves simulating real-world interactions at each stage to enhance understanding and decision-making. During **problem definition**, team members take on roles such as business owners, data scientists, end users, and regulators to align on goals, constraints, and success metrics. In the **data collection** phase, data engineers, subject matter experts, and user advocates simulate sourcing data while addressing privacy and bias concerns. For **data preparation**, data scientists and analysts discuss issues like missing values or outliers, considering their impact on fairness and usability. When **building the model**, roles such as business owners and domain experts help evaluate trade-offs between model accuracy and interpretability. In the **model evaluation** stage, stakeholders like end users and compliance officers explore how different metrics affect real-world outcomes, particularly in high-stakes scenarios. During **deployment**, DevOps engineers, support staff, and users simulate the model's real-time application, ensuring robust error handling and a smooth user experience. Finally, the **monitoring and maintenance** phase involves ML engineers and privacy officers simulating the response to model drift or failures, helping to establish a sustainable feedback loop.

This method fosters cross-functional collaboration, surfaces ethical concerns early, and ensures that technical decisions are grounded in real-world context.

- **CO – PO / PSO mapping:**

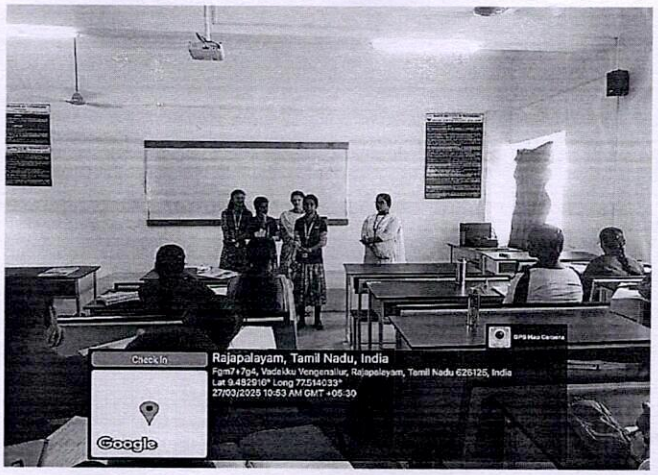
CO	PO3	PO4	PSO 1
CO1	3	3	3

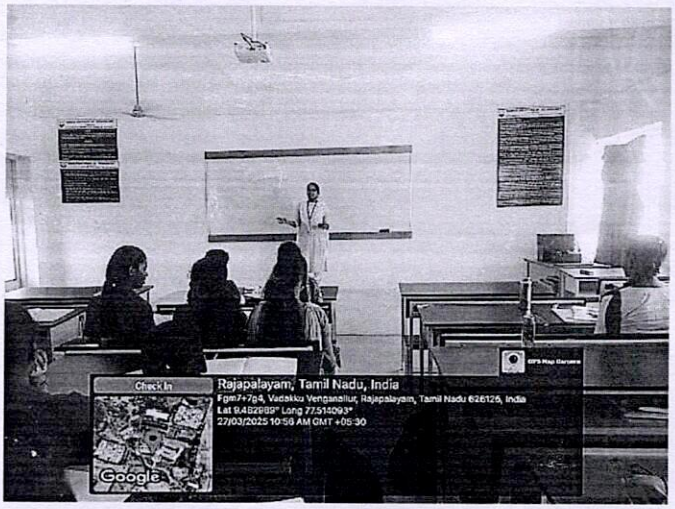
(1 – Low 2 – Moderate 3 – High)

- **PO / PSO mapped:**

Innovative practice	PO3	PO4	PSO1
	3	3	3
Justification for correlation			
PO3	PO3 emphasizes designing models to solve real-world problems, which aligns with the role play method by simulating practical scenarios throughout the ML lifecycle. This approach helps students understand user needs, ethical concerns, and deployment challenges. It enhances their ability to build effective, user-centric predictive models.		
PO4	PO4 focuses on applying research-based knowledge to validate the effectiveness and performance of ML algorithms. The role play method supports this by simulating model evaluation through multiple perspectives, such as end users and compliance officers, allowing students to test and validate algorithms in real-world scenarios. This helps them critically assess the performance of ML models, ensuring they are effective, practical, and aligned with user needs and ethical standards.		
PSO1	PSO1 focuses on creating ML models with minimized bias and variance errors. The role play method aids this by involving diverse stakeholders, such as data scientists, business owners, and end users, in the model-building and evaluation stages. This collaborative approach helps identify and address potential biases in data, model selection, and predictions, leading to more balanced and generalizable models with reduced bias and variance errors.		

- **Images / Screenshot of the practice:**





- **Reflective Critique:**
  - ***Feedback of practice from students and other stakeholders:***

From a student's perspective, the role play method in the machine learning lifecycle is highly engaging and insightful. It helps bridge the gap between theoretical knowledge and real-world application by allowing students to actively simulate scenarios from multiple viewpoints. This method enhances their understanding of the complexities involved in model building, including data preparation, ethical concerns, and user needs. It also promotes critical thinking, collaboration, and problem-solving, providing a holistic learning experience that goes beyond just building models to understanding how they impact real-world problems. Overall, it feels more practical and connected to the challenges they'll face in the field.

  - ***Benefit of the practice:*** (E.g.: Outcome attainment would have increased due to innovative practice over conventional practice)

- The role play method enhances learning by providing a hands-on, interactive approach to the machine learning lifecycle, allowing students to understand real-world challenges from multiple perspectives. It promotes collaboration, critical thinking, and communication between technical and non-technical stakeholders. Additionally, it helps identify potential biases, ethical issues, and user concerns early, leading to more effective and user-centric ML models.

❖ ***Challenges faced in implementation:***

- Challenges faced during the implementation of the role play method include coordinating active participation from all students, as some may feel hesitant or lack confidence in taking on roles. It can also be time-consuming to design realistic scenarios and ensure they align with learning objectives. Additionally, assessing student performance in role play sessions can be subjective without clear rubrics, and technical depth might be compromised if the focus shifts too much toward soft skills.

❖ **References:**

- https://towardsdatascience.com/
- https://www.coursera.org/
- https://learn.microsoft.com/en-us/training/modules/ml-model-lifecycle/

2/7/25

Signature of Faculty Member

Dr.D.M.Rajeshwari

2/7/3

HOD

Dr.M.Kaliappan