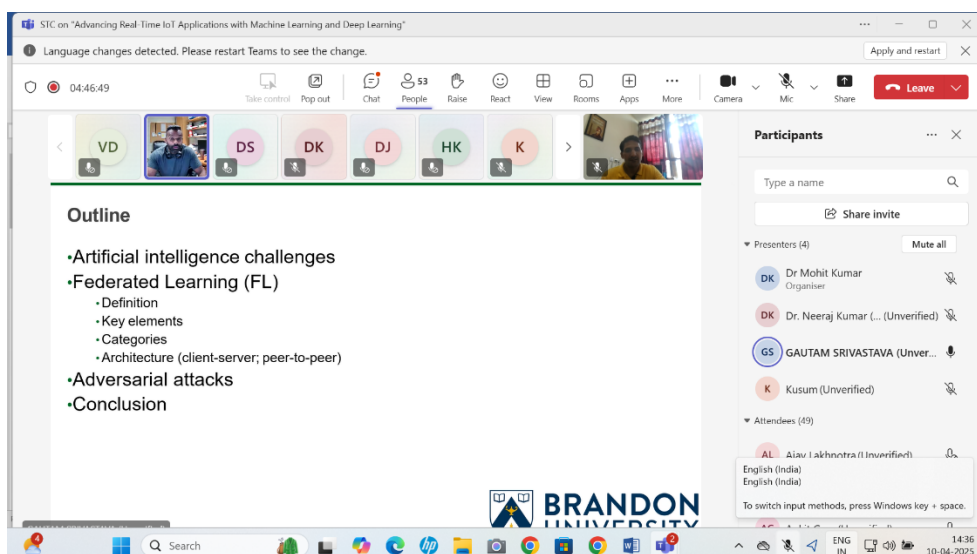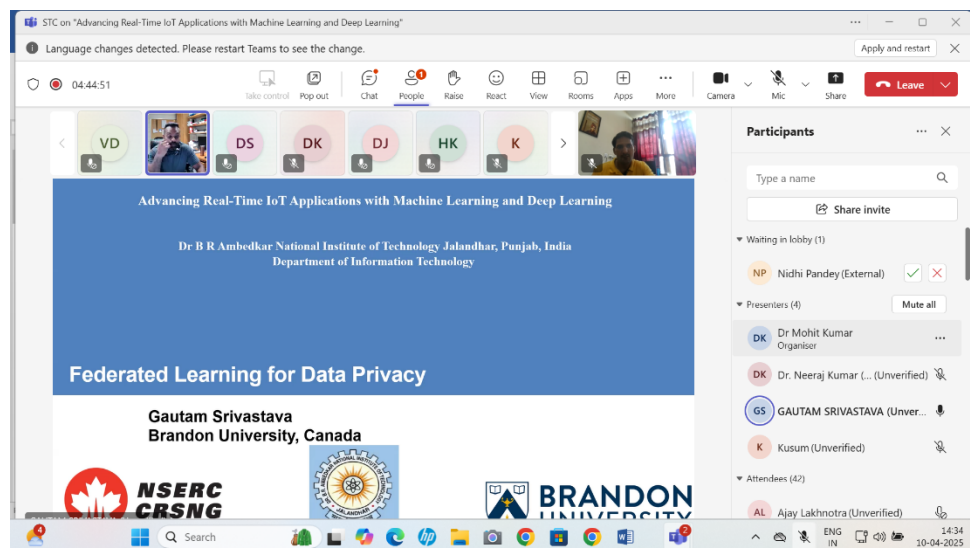**Report for conducting Short-Term Course on "Advancing Real-Time IoT Applications with Machine Learning and Deep Learning" from 10 -14 April, 2025**

Online Short Term Program on **"Advancing Real-Time IoT Applications with Machine Learning and Deep Learning"** was organized by the Department of **Information Technology during on 10th – 14th April 2025.** The Short-Term Course was successfully conducted with active participation from faculty, research scholars, and industry professionals. The program provided a comprehensive platform for participants to explore the integration of IoT with cutting-edge AI technologies, focusing on real-time data processing, predictive analytics, and intelligent automation. Through a blend of expert lectures, hands-on sessions, and interactive discussions, attendees gained valuable insights into deploying ML and DL techniques for practical IoT use cases across domains such as healthcare, smart cities, and industrial automation. The course featured distinguished speakers from academia and industry who shared emerging trends, challenges, and solutions in this rapidly evolving field. Participants expressed strong appreciation for the depth of content, clarity of instruction, and practical relevance of the sessions. The event not only strengthened foundational understanding but also sparked collaborative ideas for future research and innovation in AI-driven IoT systems. 138 no. of participants have registered for the workshop and collection was Rs. 46850 (Including GST).

Federated Learning. Definition – Rounds of Learning

- It is an iterative learning process composed of the following steps:

1. Each client i trains its LLM_i on its local training data D^t and it updates the parameters of the LLM_i, θ^t.

2. The clients send their updated parameters θ^t to the server.

3. The server computes the global parameters θ^t by aggregating the local parameters $\{\theta_1^t, \theta_2^t, ..., \theta_n^t\}$ of all the LLM using an specific federated aggregation operator Δ, formally
$$\theta^t = \Delta(\theta_1^t, \theta_2^t, ..., \theta_n^t).$$

4. After the aggregation, the LLM are updated with the aggregated parameters:
$$\theta_i^{t+1} \leftarrow \theta^t, \forall i \in \{1, ..., n\}$$

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Traditional Approaches to Solve MLC – PT Methods

Second-order methods:

✓ Another possibility is to consider every possible subset of labels as a single class and transform the problem into a multi-class problem. It is known as **Label Powerset (LP)** method.

✓ It requires 2^b number of classifiers to be trained.

Advantages:
✓ Simplicity

Disadvantages:
✓ With a large number of labels, handling 2^b number of classifiers is quite difficult.

✓ Another problem is that all the combinations may not be present in the dataset, so it is biased towards the subset of labels present in the dataset; hence, if a subset is not present in the training dataset, it cannot be predicted.

✓ Also, the number of instances related to a subset may be very less, and it may induce an imbalance problem as well.

	Y		
	Labels		
L_1	L_2	...	L_b
y_{11}	y_{21}	...	y_{1b}
y_{21}	y_{22}	...	y_{2b}
.	.		.
.	.		.
.	.		.
y_{s1}	y_{s2}	...	y_{sb}

Power set:
$\{\{L_1\}, ... \{L_b\}, \{L_1, L_2\}, ... \{L_1, L_b\}, ... \{L_1, L_2, L_3\}, ... \{L_1, L_2, L_b\}, ..., \{L_1, L_2, L_3, L_4\}, ... \{L_1, L_2, ..., L_b\}\}$

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ABV-Indian Institute of Information Technology and Management-Gwalior

P K Singh (Unverified)