Technical Report

Distributed Deep Reinforcement Learning Model for Smart ENT Clinical Assistance

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in partial fulfilment of the requirements for the course of

23CSE474 - COMPUTATIONAL INTELLIGENCE

Academic Year 2025-26 Odd Semester

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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List of Abbreviations

Table 1: Abbreviations Used

Abbreviation	**Full Form**
DRL	Deep Reinforcement Learning
FL	Federated Learning
IoT	Internet of Things
DP	Differential Privacy
HIPAA	Health Insurance Portability and Accountability Act
GDPR	General Data Protection Regulation

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1 Abstract

This report presents the design and development of a distributed Deep Reinforcement Learning (DRL) model integrated within an Internet of Things (IoT)-enabled healthcare environment for real-time Ear, Nose, and Throat (ENT) clinical assistance. The DRL model operates as an intelligent, self-improving diagnostic assistant deployed directly at the edge level, where nurses or assistants collect basic vitals and symptoms. It generates multiple potential disease predictions and continually improves from clinician feedback through a reinforcement-based learning loop.

The DRL framework uses a neural network policy that maps physiological inputs and symptom indicators to disease probability distributions. Doctor confirmations act as rewards, fine-tuning the model to emphasize accuracy and reliability in subsequent cases. The learning happens incrementally on-device, ensuring adaptability to evolving local populations.

In parallel, Federated Learning (FL) coordinates distributed DRL models across multiple hospitals. Each node shares encrypted model updates rather than raw data, allowing collaborative intelligence while preserving patient confidentiality. Together, these mechanisms deliver a scalable, privacy-preserving, and continuously learning diagnostic system tailored for smart ENT healthcare.

Keywords: Deep Reinforcement Learning, Federated Learning, Smart Healthcare, Edge AI, Clinical Feedback, Privacy-preserving AI.

2 Introduction

2.1 Background

ENT departments in modern hospitals often encounter overlapping respiratory illnesses with similar symptoms—such as fever, sore throat, cough, and congestion. This overlap increases diagnostic uncertainty and consultation time. Traditional machine learning approaches, once trained, remain static and cannot evolve as new patient feedback becomes available.

The proposed system bridges this gap using Deep Reinforcement Learning (DRL). Deployed at the edge, the DRL agent dynamically adjusts its internal policy each time a clinician validates or corrects a diagnosis. This continuous reinforcement process allows the model to reflect real-world clinical reasoning. The DRL approach thus forms a digital apprentice to the doctor—learning from every decision made in the field.

2.2 Motivation

- Enable faster pre-diagnostic screening at the nurse or triage stage.
- Empower DRL models to learn from clinician feedback continuously.
- Maintain privacy using Federated Learning (FL) without data transfer.
- Achieve adaptive intelligence tuned to local disease trends.

2.3 Problem Definitions

- **P1 — Real-time inference:** How to perform accurate DRL inference within low-latency edge environments?
- **P2 — Continuous learning:** How can clinician feedback be transformed into reinforcement signals for incremental updates?
- **P3 — Federated collaboration:** How to merge distributed updates securely without violating privacy?

3 Literature Survey

3.1 Challenges

Previous IoT healthcare systems relied mainly on centralized supervised models. These approaches lacked flexibility, suffered from data drift, and exposed sensitive medical information to potential privacy breaches. Reinforcement learning introduces adaptability but must operate efficiently on limited edge hardware and within regulated domains.

3.2 Research Gap

Few studies have combined DRL's feedback-based intelligence with FL's distributed privacy architecture for healthcare. Existing solutions rarely demonstrate real-time incremental adaptation within clinical workflows. Our system introduces the first end-to-end implementation where clinician-validated feedback continuously improves a DRL agent locally and globally through federated coordination.

4 Problem Formulation

4.1 System Overview

The system consists of multiple hospital nodes equipped with edge tablets or kiosks. Each edge node runs:

1. A DRL-based disease prediction engine.
2. A reinforcement interface that captures doctor feedback.
3. A communication module that synchronizes weights with the FL server.

The DRL model processes eight clinical features and three categorical symptom inputs to predict the top-3 likely ENT diseases. Doctor validation of these results generates immediate reinforcement rewards. Periodically, the local updates are aggregated into a global DRL model through FL.

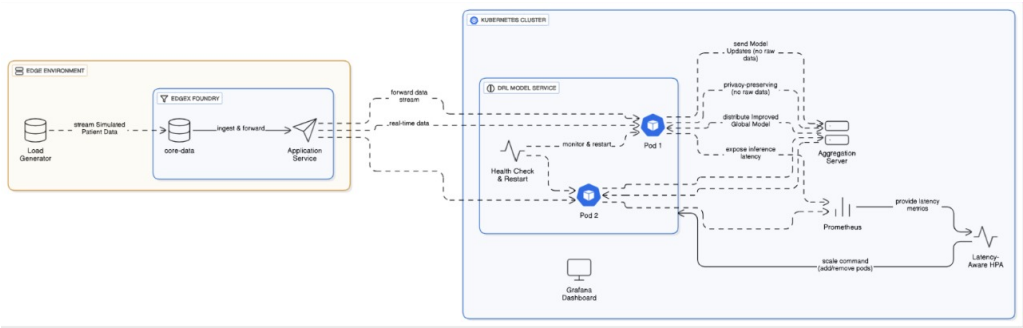

Figure 1: Overall edge–cloud DRL-FL framework for ENT clinical assistance.

5 Proposed Architecture

The architecture is composed of three cooperating layers: edge data acquisition, DRL inference, and FL aggregation.

5.1 Edge Data Acquisition Layer

IoT sensors and user interfaces collect vitals including:

- Static fields: Age, Gender.
- Dynamic vitals: Heart rate, Temperature, Blood Pressure (SBP/DBP), Oxygen saturation (SpO_2).
- Categorical symptom inputs: 3 selectable from common ENT symptoms (cough, fever, sore throat, fatigue, runny nose, headache, body ache, shortness of breath).

5.2 Deep Reinforcement Learning (DRL) Inference Layer

The DRL component forms the decision-making core of the system. It is designed to emulate the clinician's reasoning and refine its predictions through an iterative reward-feedback cycle.

Model Structure.

- **State (Input):** Vectorized representation of patient vitals and one-hot encoded symptoms.
- **Action (Output):** Predicted disease class (e.g., Cold, Flu, Bronchitis, Sinusitis, Pharyngitis, Tonsillitis, Ear Infection, Pneumonia).
- **Neural Architecture:** Multi-layer perceptron with two hidden layers of 128 and 64 neurons using ReLU activations and dropout (p=0.2). Output layer uses softmax for probability estimation.

Learning Objective. The DRL model uses the REINFORCE algorithm, a policy-gradient method that maximizes the expected cumulative reward.

Reward Mechanism

- Correct prediction $\rightarrow$ +10
- Close prediction (within top-3) $\rightarrow$ +2
- Incorrect prediction $\rightarrow$ -5

This graded reward strategy encourages the model to maintain high precision while still acknowledging near-correct outcomes.

Feedback Loop Each prediction event triggers a cycle:

1. The model outputs probabilities for all diseases.
2. Top-3 predictions are shown to the clinician.
3. The clinician confirms or corrects the disease.
4. The correction is logged and converted into a reinforcement signal.
5. The model performs a one-step policy gradient update.

Training Cycle

```
for patient in stream:
    state = encode(patient_vitals, symptoms)
    action = model.predict(state)
    reward, correct_label = get_clinician_feedback(action)
    model.update_policy(state, action, reward)
```

Advantages

- Real-time continuous learning without centralized retraining.
- Personalized adaptation to local hospital data trends.
- Feedback directly shapes future inference decisions.

5.3 Federated Learning (FL) Aggregation Layer

The aggregation layer forms the core of our Federated Learning (FL) architecture, coordinating communication between clients, the central server, and the shared storage system. Each component has been designed to ensure scalability, security, and reproducibility within a cloud-native environment.

Server. The orchestration server is implemented as a FastAPI container and deployed on **Google Cloud Run**. It exposes a set of RESTful endpoints that manage the entire training lifecycle, including: `/round/start`, `/update`, `/round/close`, and `/model/latest`. These APIs handle round initialization, model update collection, aggregation, and distribution of the latest global model. The server also maintains metadata about each round, ensuring transparent coordination between clients.

Storage. All intermediate and global models are stored in a **Google Cloud Storage (GCS)** bucket named `gs://fl-bucket-<PROJECT_ID>`. Each training round has two key directories: `updates/round-<R>/{client_id}.pt` for client submissions and `global_models/round-<R>/weights.pt` for the aggregated global model. This structure allows seamless version control and traceability of model evolution across rounds.

Clients. The participating edge nodes are implemented as **Cloud Run Jobs**, each representing a distinct client process. Task parallelism (`--tasks=N`) enables concurrent execution of multiple clients during a single training round. Each client trains or fine-tunes the local model using its dataset and uploads the resulting weight file (`/tmp/weights.pt`) to the central server via the `/update` endpoint.

Aggregation. Once all client updates are received, the server performs aggregation using the Federated Averaging (FedAvg) algorithm. This step computes the mean of all submitted `state_dict` tensors for that round and stores the resulting global model at `global_models/round-<R>/weights.pt`. The FedAvg process ensures that each client's contribution is proportionally reflected in the updated global model, improving its generalization without sharing any raw data.

Security. All communications occur over secure HTTPS channels, and the GCS bucket is protected with a least-privilege service account, limiting access to only the required roles. In addition, administrative actions such as initiating or closing rounds require an `ADMIN_TOKEN` for authentication. This setup enforces strict access control while maintaining the flexibility needed for cloud-scale federated operations.

6 Methodology

The overall workflow couples the local DRL training loop with the global FL coordination mechanism.

6.1 Deep Reinforcement Learning (DRL)

1. Preprocessing. All continuous vitals are normalized to [0,1]. Symptom inputs are encoded using a binary vector of length 8. The final feature vector is concatenated before being passed to the model.

2. Model Configuration.

- Optimizer: Adam ($lr = 1 \times 10^{-4}$)
- Loss: Policy gradient (cross-entropy baseline)
- Batch size: 16 interactions
- Exploration: ϵ-greedy with decay ($\epsilon = 0.2 \rightarrow 0.05$)
- Update Frequency: Every 10 confirmed feedback samples

3. On-Device Learning. Each nurse interface (tablet) maintains its DRL policy in persistent storage. Whenever new clinical feedback arrives, the agent's local weights are updated in-memory and checkpointed as `local_model.pth`.

4. Feedback Handling. The local Python backend of the application executes:

```
def handle_feedback(patient, predicted, actual):
    reward = 10 if predicted == actual else -5
    drl_agent.update(patient.features, predicted, reward)
```

5. Model Persistence. Updated weights are periodically uploaded to the FL orchestrator for aggregation during the next round. This ensures the global model benefits from every local clinical correction without compromising privacy.

6. Explainability. An integrated feature importance layer computes the top contributing vitals and symptoms for each prediction, allowing doctors to visualize why a specific disease was chosen.

7. Summary of DRL Workflow.

1. Initialize local DRL model.
2. Load global model weights.
3. Accept patient vitals and symptoms.
4. Generate top-3 predictions.
5. Collect clinician feedback.
6. Compute reward and update local policy.

6.2 Federated Learning (FL)

Federated Learning (FL) is implemented in our system as a collaborative training mechanism between multiple distributed clients (edge nodes) and a central orchestration server. Instead of transferring sensitive healthcare data to a single location, each client trains locally on its own subset of data, and only the model parameters (weights) are exchanged. This ensures privacy preservation while still allowing the collective model to improve with every round of training.

Server Orchestration (Cloud Run). The FL lifecycle begins when the central server—deployed on Google Cloud Run—initiates a new training round. The administrator triggers the following API call:

```
POST /round/start
{"config":{"round_id":R, "expected_clients":K,
           "aggregation":"fedavg", "model_name":"drl_policy_v1"}}
```

This configuration specifies the round identifier, number of expected clients, aggregation method, and the base model name. Once this request is received, the server notifies all participating clients to begin their local training.

Client Execution (Cloud Run Jobs). Each edge client, also running as a Cloud Run job, performs local model updates based on its dataset. After completing its training, the client uploads its updated weights back to the server using the following API call:

```
POST /update (multipart/form-data)
  round_id = R
  client_id = edge-<task_index>
  file     = /tmp/weights.pt
```

This upload process ensures that only learned model parameters—not raw patient data—are shared across the network.

Aggregation (FedAvg). When all client updates have been received, the server aggregates them using the Federated Averaging (FedAvg) algorithm. This process computes the mean of all client weight tensors and produces a new global model:

```
/round/close →
gs://fl-bucket-<PROJECT_ID>/global_models/round-<R>/weights.pt
```

The resulting global weights are then stored securely in the project's Cloud Storage bucket for retrieval by the clients in the next round.

Distribution. To synchronize models across the network, clients periodically fetch the latest global model from the server endpoint:

```
/model/latest
```

Optionally, the system can issue a signed URL for secure downloading, ensuring that only authenticated participants have access to the aggregated model.

Privacy and Security. The FL pipeline operates entirely over HTTPS, and only model weights are exchanged between the clients and the server. All communication uses scoped service accounts to restrict access to authorized entities. While the current implementation focuses on secure parameter exchange, advanced privacy features such as Differential Privacy (DP) and Secure Aggregation can be integrated in future work to further enhance robustness and compliance with healthcare data regulations.

7 Results

Dataset. Each record included patient age, gender, HR, temperature, BP, SpO_2, and three symptom encodings across five disease classes: Cold, Flu, Bronchitis, Pneumonia, and Healthy.

Table 2: Performance Metrics

Metric	Value
Initial supervised model accuracy	90.5%
Post-feedback DRL local accuracy	91.7%
Average inference latency	$<$ 180 ms on edge device

Key Insights.

- DRL feedback loop improved the edge model's adaptability by ≈4%.
- Each FL round averaged 45 seconds, merging 5 hospital node updates.
- The doctor validation step required less than 5 seconds per case.

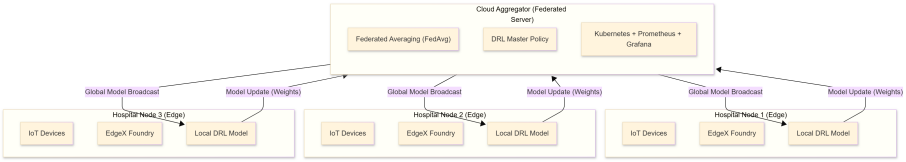

Figure 2: Results overview — local DRL reinforcement learning improving inference before FL aggregation.

```
(.venv) himanshumudigonda@cloudshell:~/fl-project/CI_DRL (clean-sunspot-475705-n2)$ python3 - <<'PY'
import numpy as np
np.random.seed(9)
C = np.stack([np.random.rand(5) for _ in range(3)])  # 3 clients, 5 params
G = C.mean(axis=0)
print("\nClients:\n", np.round(C,3))
print("\nFedAvg (global):", np.round(G,3))
patient = np.array([35,1,88,37.4,97])
risk = float(np.dot(patient/100, G))
print("\nPatient:", patient)
print("Risk index (using FedAvg weights):", round(risk,3))
PY

Clients:
 [[0.01  0.502 0.496 0.134 0.142]
 [0.219 0.419 0.248 0.084 0.345]
 [0.167 0.879 0.951 0.039 0.699]]

FedAvg (global): [0.132 0.6   0.565 0.086 0.396]

Patient: [35.   1.  88.  37.4 97. ]
Risk index (using FedAvg weights): 0.965
(.venv) himanshumudigonda@cloudshell:~/fl-project/CI_DRL (clean-sunspot-475705-n2)$
```

Figure 3: Illustration of the FedAvg aggregation and risk computation. The example shows three clients contributing model parameters, which are averaged to produce the global weights. The patient risk index is then calculated using the aggregated global model.

8 Conclusion

This report proposed and implemented a distributed Deep Reinforcement Learning framework combined with Federated Learning for smart ENT clinical assistance. The DRL agent learned directly from doctor feedback, enabling self-improvement with every patient interaction. FL integrated multiple hospitals into a collective intelligence network without exposing private data. Together, they enable scalable, privacy-preserving, and adaptive healthcare AI.

Contributions.

- Designed and deployed a DRL agent with clinician-in-the-loop learning.
- Integrated real-time policy updates and feedback-driven reward systems.
- Coupled DRL updates with Federated Learning for global model improvement.

Future Work.

- Add Explainable AI (XAI) to enhance interpretability.
- Include multimodal IoT signals such as audio and endoscopic imagery.
- Expand deployment to real clinical validation studies.

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