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Federated-Reinforcement Learning-Assisted IoT Consumers System for Kidney Disease Images

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***Abstract*—The number of people with kidney disease rises every day for many reasons. Many existing machine-learning-enabled mechanisms for processing kidney disease suffer from long delays and consume much more resources during processing. In this paper, the study shows how federated and reinforcement learning schemes can be used to develop the best delay scheme. The scheme must optimize both the internal and external states of reinforcement learning and the federated learning fog cloud network. This work presents the Adaptive Federated Reinforcement Learning-Enabled System (AFRLS) for Internet of Things (IoT) consumers' kidney disease image processing. The main relationship between IoT consumers and kidney image is that the data is collected from different IoT consumer sources, such as ultrasound and X-rays in healthcare clinics. In healthcare applications, kidney urinary tasks reduce the time it takes to preprocess federated learning datasets for training and testing and run them on different fog and cloud nodes. AFRLS decides the scheduling on other nodes and improves constraints based on the decision tree. Based on the simulation results, AFRLS is a new strategy that reduces the time tasks need to be delayed compared to other machine learning methods used in fog cloud networks. The AFRLS improved the delay among nodes by 55%, the delay among internal states by 40%, and the training and testing delay by 51%.**

***Index Terms*—Federated Learning, Reinforcement Learning, Fog, Cloud, Kidney Disease Prediction, Medical Images.**

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I. Introduction

The kidney is a vital human body component responsible for maintaining fluid balance [1]. It regulates fluid and minerals throughout the body by filtering them from the blood [2]. Additionally, the kidney eliminates waste products, toxins, and other unnecessary substances while functioning normally within the human body [3]. The human kidneys play a crucial role, particularly in cases where the ureter is impaired and not functioning correctly. If the kidneys fail to work, it can severely impact the immune system and lead to acute renal failure [4]. To address challenging situations related to kidney disease, various manual methods like dialysis and transplantation are used for treatment and control [5]. Kidney tests involve collecting different images from multiple laboratories and offloading them to servers for further processing and scheduling within the designated system.

Several studies [6]–[10] recently have focused on applying federated learning and reinforcement learning to address kidney disease prediction, scheduling, and resource-constrained problems. These algorithms aim to optimize various objectives, including kidney disease prediction, scheduling, and resource utilization in kidney-related applications. During the processing of these algorithms, different states, actions, and transitions are considered, with both continuous and discrete status. They are widely used for collecting kidney images and scheduling them on fog and cloud nodes to achieve different objectives, such as disease prediction, minimizing time, and reducing resource consumption. The classification of kidney disease images is formulated as a Markov decision problem (MDP), where the problem is divided into different states, actions, transitions, and factors [11].

The study investigated and reviewed a comprehensive collection of recent studies [1]–[20] focused on the execution of kidney disease tasks in fog cloud networks. These studies

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employed reinforcement learning techniques, including A3C, SARSA, DDPG, and q-learning, to optimize the processing time, energy consumption, and accuracy of kidney disease prediction. The federated learning paradigm facilitated training and testing models on different nodes, with the aggregated node responsible for the overall kidney disease analysis. Additionally, convolutional neural network (CNN) based models, such as ResNet, LeNet, and Relu function, were employed to extract relevant features from kidney images based on the specific objectives of the system [21], [22].

Research Questions:

However, despite numerous studies proposing various reinforcement and federated learning schemes, several challenges persist in the current systems for kidney disease processing in fog cloud networks. (i) Existing studies have primarily focused on predicting kidney disease, neglecting the system's performance in processing delays. (ii) These studies have solely concentrated on a single objective, such as prediction. However, modern kidney disease clinics are highly complex and necessitate the optimization of multiple objectives within the distributed fog cloud network. (iii) Reinforcement learning schemes are time and resource-consuming, while federated learning introduces longer delays during the processing of kidney disease applications.

Proposed Work:

We introduce the Adaptive Federated Reinforcement Learning Scheme (AFRLS), comprising preprocessing and adaptive scheduling schemes for kidney image processing. The objective is to minimize pre-processing and execution delays during training, testing, and task execution in fog and cloud networks. However, existing studies suffered from different delays. These studies [1]–[20] and [23] only focused on kidney image prediction such as dialysis rather than executed all images with minimum delays. The study considers the heterogeneity of fog cloud resources, which can be flexibly scaled up or down to prevent resource leakage in the system. We trained 20,000 kidney images on local fog nodes and offloaded them to the centralized decision-maker node for the final decision. The training and testing models are regularly updated and improved at designated nodes with different time intervals. Our research offers the following contributions to the addressed problem.

- We introduce the AFRLS algorithm methodology, which includes preprocessing and adaptive scheduling schemes for kidney data application tasks. The objective is to minimize delays in pre-processing and task execution during training, testing, and execution in fog and cloud networks.
- The work presents a delay-optimized preprocessing scheme for training and testing various kidney tasks, specifically focusing on inflammation-related data.
- We propose an adaptive scheduling scheme that ensures the timely execution of tasks while meeting their respective deadlines and delay requirements.
- We introduce a simulator that demonstrates the practical implementation of the problem under consideration, incorporates its constraints, and analyzes the obtained results.

The paper consists of different sections. In section 2, we discussed the related works. Section 3, the study proposed the reinforcement federated learning system. Section 4, the study presents the AFRLS Algorithm Schemes and their solution in different steps. Section 5 shows the implementation and result analysis of the methods. Section 6 is the conclusion part of the study.

II. Related Work

Recently, many studies have suggested different schemes to deal with kidney diseases in fog cloud networks. This study [1] suggested an Internet of Medical Things (IoMT) cyborg framework based on federated learning and reinforcement learning. The objective was to schedule all kidney images with features on different states-assisted edge and cloud nodes. The clinical healthcare scheduling on fog and cloud based on electronic consumers improves healthcare application performances as presented by this study [2]. The scalable edge nodes and cloud computing-assisted ECG Signal Super-resolution Framework for remote cardiac applications with offloading and scheduling-assisted systems are presented in this work [3]. These studies [1]–[3] focus on remote healthcare solutions based on fog cloud networks and train their healthcare data based on federated reinforcement learning and heuristics. High dietary inflammatory risk of chronic kidney disease based method suggested in this work [4]. This practical approach was implemented and developed in Iran laboratories. Chinese research laboratories presented the chronic kidney tissue damage system in [5].

The fuzzy decision-based task scheduling based on federated learning presented by this work [6]. The goal was to execute all kidney images based on their given quality of services (QoS) in the system. These studies implemented different kidney disease images in the fog and cloud laboratories. However, this work focused on kidney disease prediction in the network. Many machine learning schemes [6]–[10] suggested to train and test the kidney data on the different nodes.

The different diseases enabled kidney disease prediction in COVID-19, which was investigated in [11]. This study presented federated learning where other trained models are deployed at the different layers and offloaded the trained models to the aggregated node. These methods [12]–[20] of reinforcement learning A3C, SARSA, DDPG, and q-learning widely implemented to achieve the different objectives such as energy, time, prediction, delay, and execution. The convolutional neural network (CNN) based models (ResNet, LeNet, and Relu function) [21], [22] are presented to extract the features of kidney images based on their objectives in the system.

However, all studies [1]–[20] suggested the different reinforcement and federated learning-based schemes. However, many challenges still exist in current frameworks for the kidney disease process in the fog cloud networks. All existing studies only focus on kidney disease prediction. However, the system performance regarding processing delays has yet to be addressed in these studies. These studies only focused on a single objective (e.g., prediction). However, current kidney

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disease clinics are very complex and require optimization of multiple objectives in the distributed fog cloud network. Reinforcement learning schemes are time and resource-consuming, and federated learning incurs longer delays during processing in the system. These studies [23]–[29] suggested image processing techniques to process the medical data with their constraints. However, these methods consume much more time and resources when executing images with their constraints.

III. Efficient Federated-Reinforcement Learning System

We present an Efficient Federated-Reinforcement Learning system for decreasing a delay of Kidney disease prediction based on medical Images as shown in Figure 1. The main advantage of combining federated reinforcement learning is to train the diversity of kidney image datasets from different clinical nodes for decisions in aggregated nodes. We use a convolutional neural network (CNN) scheme to get kidney image features for processing. The input is taken at the different nodes, such as fog nodes, for training and testing models. All the local fog nodes shared their models with the aggregated node for further decision-making. The decision tree scheme will decide the prediction and execution on the nodes in the system, as shown in Figure 1. We exploited the kidney image data generated by IoT consumer sources, such as ultrasound scanning and computer technologies. Therefore, our system only focuses on federated reinforcement learning methods rather than data generation.

In the proposed architecture 1, we exploited combined federated reinforcement learning, which consumes fewer resources and has fewer delays as compared to existing approaches. During the dataset training and offloaded in the architecture, we reduced resource consumption on different computing nodes, such as fog and cloud nodes. We divided the kidney images dataset among different nodes for training with certain features and shared it with the aggregated node for decision, and that decision was shared with the local fog nodes for further training and validation. In this way, we can reduce the resource consumption to train a huge dataset on a single node. We can reduce the different delays, such as computation, communication, offloading, and scheduling, In federated reinforcement learning while dividing the kidney image workload among nodes and reducing overall delays in architecture.

A. Problem Formulation

The study assumed the kidney tasks, represented by $\{v = 1, \ldots, V\}$. Each task is autonomous and has different attributes. For instance, v_{img} is the set of images of task v, whereas v_{status} shows task status, $v_{deadline}$ shows deadline. The models with the different features were trained on fog nodes for the kidney images. Therefore, all images must be converted into numeric values. Therefore, all tasks have different image matrixes in the kidney disease workloads.

We assume heterogeneous computing nodes in the resource network, e.g., $\{k = 1, \ldots, K\}$. All computing nodes, such as fog and cloud, are distinct in the network. We assumed that each node is the agent that makes the decision and processes the image data in the system. Each fog node k has a particular speed ζ_k and resources ϵ_k, which is easily scaled up and down at the runtime in the system. In this study, we are using full offloading, where laboratories offload their kidney task images to the particular fog node that is implemented at the hospital for processing.

The study makes the binary decision, where the laboratories have the option for the offloading or not, and determined in the following way.

$$x_{v_{img},\sim K} = \begin{cases} x_{v_{img}} = 1, & Offload \\ x_{v_{img}}, & No-Offload \end{cases} \tag{1}$$

Equation (1) shows that if the available resources are sufficient and do not exist, then offloading will be $x_{v_{img}} = 0$. Otherwise, it will be $x_{v_{img}} = 1$. The study makes the binary decision of whether the laboratories have an option for offloading as follows.

$$y_{v_{img}} = \begin{cases} x_{v_{img}} \sim 1, & Accept \\ x_{v_{img}} \sim 0, & Not-Accept \end{cases} \tag{2}$$

Equation (1) shows that if the available resources can execute workload at the offload, they will accept the workload, e.g., $y_{v_{img}} = 1$. Otherwise, it will wait till the resource gets free, e.g., $y_{v_{img}} = 0$.

$$Off_v^e = \sum_{v=1}^{V} \frac{w_i}{bw_k} + \frac{w_i}{bw_k} \times y_{v,k} \times x_{v,k}. \tag{3}$$

Equation (3) determines the offloading time in the system. Each node determined the training and testing model based on the ResNet method as follows.

$$C_v^e = \sum_{v=K}^{I} \sum_{d=1}^{d\in D} \sum_{k=1}^{k\in K} \sum_{flm=1}^{flm\in FLM} \frac{w_i}{bw_k} + \frac{w_i}{bw_k} \times y_{v,k} \times x_{v,\sim k\in K}. \tag{4}$$

Equation (4) calculates the computation time of the models on the computational nodes.

$$Training_v^e = \sum_{image=1}^{v} \sum_{k=1}^{K} \sum_{flm=1}^{FLM} flm1 \leftarrow \frac{d}{\zeta_k} \times \epsilon_k - ratio_k. \tag{5}$$

Equation (5) calculates the local training time based on the federated learning scheme and their weights shared to the centralized aggregated node.

$$F_v^e = \sum_{v=1}^{V} \sum_{k=1}^{K} \frac{v_{image}}{\zeta_k} \times \epsilon_k - ratio_k. \tag{6}$$

Equation (6) calculates the processing time of images on the different computational nodes.

$$Total = off_v^e + c_v^e + Training_v^e + F_v^e, \quad \forall v = 1, \ldots V. \tag{7}$$

Equation (7) calculates the overall delays for all kidney images. The objectives of the study are to optimize both internal and external states of reinforcement learning and the federated learning fog cloud network to process the kidney image with different delays as shown in equation (7). All states are local federated learning nodes where different datasets are

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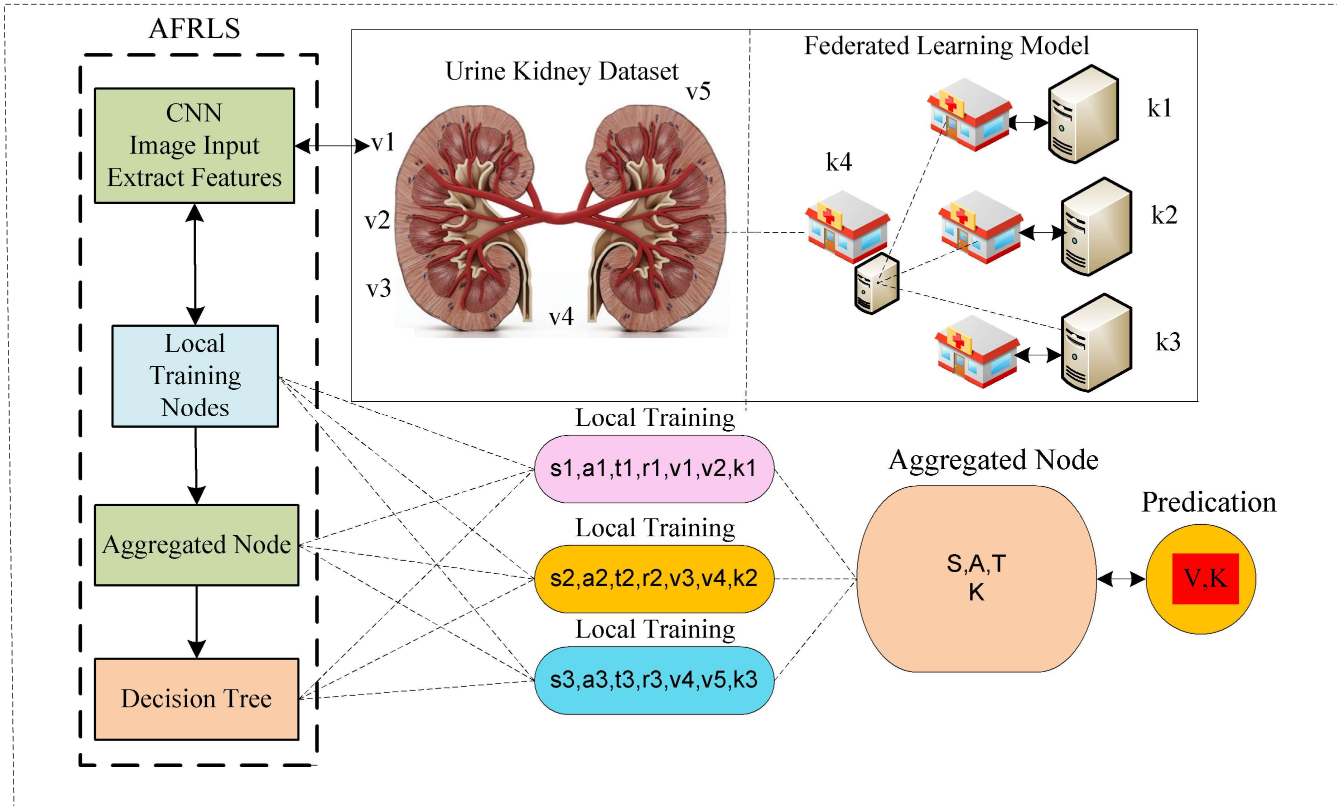

Fig. 1: Federated-Reinforcement Learning-Assisted System for IoT Consumers Kidney Disease Images.

trained to minimize the overall delays for kidney processing images.

$$\min \sum_{dt=1}^{DT} Total. \tag{8}$$

Equation (8) optimized the objective function based on the decision tree method [25].
Subject to

$$\sum_{v}^{v=1\in V} \sum_{k}^{k=1\in K} v_{image} \le \epsilon_k. \tag{9}$$

Equation (9) pre-calculated that all computing nodes have sufficient resources to train and process the kidney images in the network.

$$\sum_{v=1}^{V} \sum_{k=1}^{K} v_{image} \le v_d. \tag{10}$$

Equation (10) ensured that during processing and scheduling, the kidney tasks must be executed before their given deadlines.

$$\sum_{v}^{v=1\in V} v_{image} \leftarrow k. \tag{11}$$

Equation (11) shows the assignment of each task must be allocated to one particular node.

$$\sum_{k}^{k=1\in K,M} w_i \leftarrow k. \tag{12}$$

Equation (12) shows that one node can not schedule the same task on different nodes.

IV. Proposed AFRLS Algorithm Schemes

The study devises the AFRLS, which consists of different components. We consider the centralized aggregated node, where different nodes have trained and tested models based on the CNN ResNET method. Each federated learning-enabled local node consisted of ResNet 50 layers, where different images are trained on the distinct node. Furthermore, these distinct such as fog and cloud, shared their model with the designated aggregated for processing in in the network. We assume that the method has S states, A actions, R rewards, T timestamp and decision TR, ERtrail, and error attributes. Each distinct state having following attributes: $s = (s1, a1, t, tr, rr, r, v, k, v)$. The main objective is to minimize the total time of kidney images (e.g., tasks) and maximize the commutative rewards.

A. AFRLS Algorithm Framework

In this session, we present the AFRLS algorithm frameworks that consist of different phases. Furthermore, we show the entire process in Algorithm 1 that has different schemes for kidney image execution based on their requirements. We assume the ResNet method consisted of 50 layers in image feature extraction in the network. There are two different states in the network. The external states (e.g., $s1, a1, r1, flm1, k1$) are federated learning nodes where each state is assumed as

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the single fog node and connected to the aggregated node for further processing based on decision tree [25] as shown in Figure 2. At the same time, each fog node has its own internal states where each kidney task is executed among different states(e.g., Internal States $s1, a1, r1, v1, k1$) as shown in Figure 2.

Algorithm 1: Proposed AFRLS Algorithmic Framework

Input : $\{K, V, Image, FLM$
Output: $\min Total$;
begin
  for *($flm \sim 1$ to FLM)* **do**
    Call Pre-trained Model Scheme;
    $v_{image} \in V \leftarrow flm \sim FLM$;
    Call local nodes for training;
    $V \leftarrow K$;
    call aggregate node for decision;
    $v_{image} \in V \leftarrow FLM \sim K$;
  Based on decision improved $Total \sim V$;

AFRLS divided the datasets among different fog nodes for training datasets locally, where we minimized pre-processing time and offloaded all trained datasets to the aggregated node for decision, as shown in Figure 2. The study determined the decision tree scheme based on total delays in decisions for all tasks. The study designed the classifier to predict the optimal delays, deadlines, and resource efficiency based on Gini and entropy criteria. The criterion entropy is determined based on supervised learning, where delays and other criteria are labeled at the time of decision. In the decision, there are many dependent variables such as deadline, resources and training, and processing time to the total delay for all tasks. We assume DT is the random decision taken by the algorithm in the following way.

$$dt \sim v = \sum_{dt=1}^{DT} S, A, R, T, ER, TR \sim Total. \tag{13}$$

Equation (13) shows the pair-wise gini impurity with the attributes and objective in the network. We implemented the federated reinforcement learning schemes on each node, for instance, states $S, A, R, T, ER, TR, V, k \in K$ along with weights. Each node optimized the different criteria based on a given deadline, resource, and total delays for all tasks in the network. The study determined the entropy for the considered in the following ways.

$$\begin{aligned} H(Total) = \sum_{k=1}^{K} S, A, R, T, ER, TR \\ \sim dt \sim k \in weights \sim yes \leftrightarrow no = 1, 0. \end{aligned} \tag{14}$$

Equation (14) determines the entropy for the objective function in the network.

We define the all steps of Algorithm 2 in the following way.

- All the nodes are trained and tested in the kidney images as shown in steps 1-5.

Algorithm 2: Federated Reinforcement Learning Scheme

Input : $\{flm \sim FLM, k \sim K, W, V, D, S\}$;
1 **begin**
2   $K[k = 1 \in K]$ Aggregated nodes;
3   k fog node;
4   $batch \sim v_{image} \sim V$ Batch size of tasks;
5   $w \sim W$ Weights of fog nodes layers;
6   **foreach** *(v_{image}, K, FLM, S)* **do**
7   Pre-calculated different federated weights;
8     $k \leftarrow v_{image} = \{k \leftarrow v_{image} \leftarrow \epsilon_k, \zeta_k$;
9   Post-calculated sum of all nodes batch on relu-function;
10     $k \leftarrow V_{image}[v_{image}, batch, k, flm, d, s] = LF(v_{image}, batch, k, flm, d, s)$;
11   Offloaded local trained and tested model based on equation (4);
12   Trained all local nodes based on equation (5);
13   Federated internal and external states are updated;
14     $k \leftarrow V_{image}[v_{image}, batch, k, flm, d]$ shared to the $k1, k2, k3 \sim s1, s2, s3$;
15   Determine the decision tree based gini impurity based on equation (13);
16   Determine the decision tree-based entropy based on equation (14);
17   End Internal States;
18 End External States;

- The decision tree properties such as gini impurity and entropy determined the optimal objectives of the tasks in the system based on different criteria such as deadline, resource, and total delays for all tasks as defined in steps 6-13.
- All the states determined the trial and error (ERR and TR) based on given criteria in the system as shown in 14.
- All the tasks are offloaded to the different nodes and meet their execution, as shown in steps 15-17.

B. Q-Learning Enabled Adaptive Scheduling and Searching Based on Decision Tree

The study presents the decision tree scheme-based adaptive scheduling based on q-learning within AFRLS in different states. In the initial state, the given constrained criteria, such as deadline, total delay, and node resources, are optimized and monitored parallel at different nodes, as shown in Figure 3. The updated weights of all nodes are shared with the aggregated node to optimize the total delay of tasks and meet the deadline and resource requirements in the system. The study combines the decision tree, reinforcement learning, and federated learning schemes to handle the dynamic and adaptive scheduling issues based on different constraints. We present an Algorithm 3 scheme in which all tasks are executed under their given requirements without any loss of their generosity

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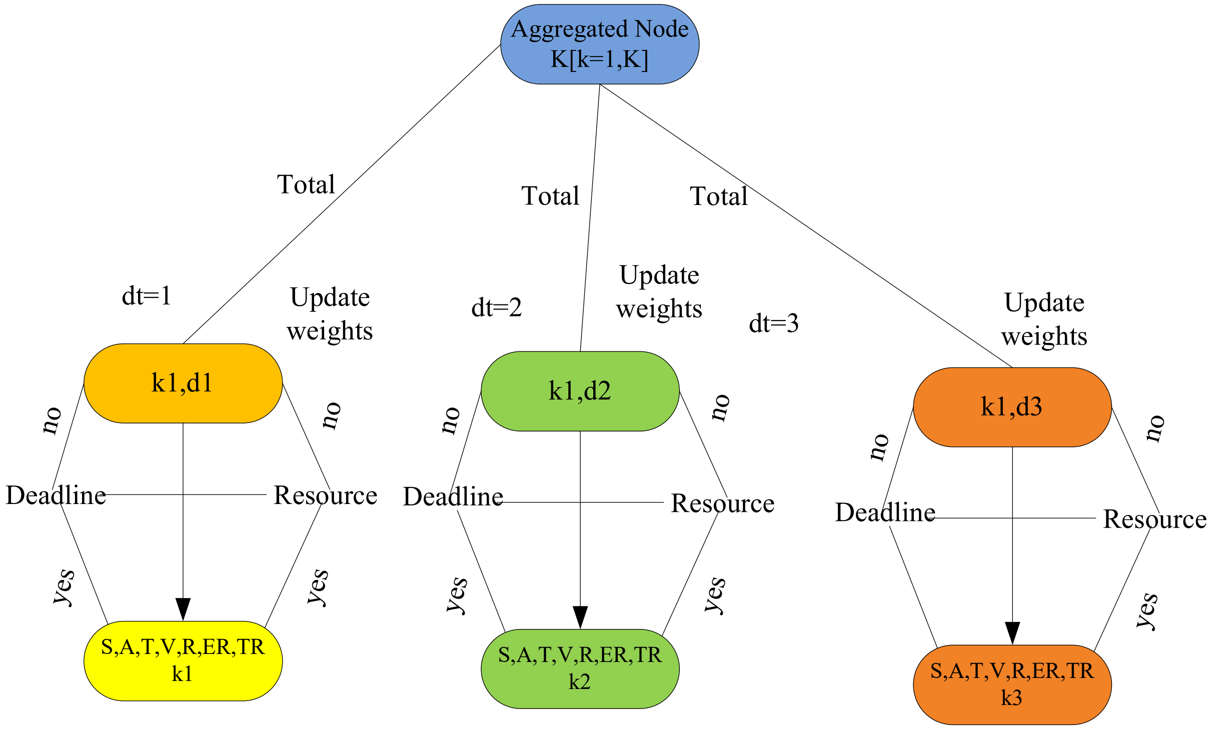

Fig. 2: Decision Tree Based Reinforcement Learning in Federated Learning Fog Cloud Nodes To Minimize the pre-processing time.

in the network. It can be observed that deadlines and resources greatly impact decisions and degrade the overall performance of kidney image processing in architecture.

We suggest that Q-Learning enables adaptive scheduling and searching based on a decision tree work to schedule the kidney images on different heterogeneous nodes for execution. The Q-learning is model-free, where federated learning connects different states in reinforcement learning on different fog cloud nodes. Figure 3 shows the Q-learning adaptive scheduling on heterogeneous nodes based on different criteria such as deadline, resources, and training weights and shared to the aggregated nodes as shown in Figure 3.

Algorithm 3 determines the optimal decision related to the deadline of tasks, total delays, and efficient resource utilization of the nodes during processing training and testing the model in the system. Each node trained and tested the model based on a decentralized, federated learning scheme and offloaded the trained model with the updated weights to the aggregated nodes for further actions. Each node trained and tested the model for all tasks in different states, such as in the probability function. The probability function has initial objective results such as λ' for all tasks, and after the transition states, the objective function must be optimized to the total function, e.g., $\lambda \sim Total$ for all tasks. Algorithm 3 has the following steps.

- Algorithm 3 determines optimal decision tree result based on obtained the objective function of all tasks based on given criteria resource, deadline, and total delay as defined in steps 1-5.

Algorithm 3: Q-Learning Enabled Adaptive Scheduling and Searching Based on Decision Tree and Reinforcement Federated Learning

Input : $\{flm \sim FLM, k \sim K, W, V, D, S\}$;
1 **begin**
2 Call decision Tree $dt \sim S, A, T, V, R, ER, TR, k1$;
3 **if** $(H(Total) == yes)$ **then**
4 Determine the initial objective function of the tasks by λ';
5 **if** *(deadline, Total, resources==yes)* **then**
6 $K[k = 1, K] \sim flm1, \ldots FLM$;
7 $\lambda^* = Total \sim S, A, T, V, R, ER, TR, K1, d1$;
8 Determines the weights $W \leftarrow \lambda^*$;
9 **if** *ERR& TR=0* **then**
10 Reschedule $\lambda^* = Total \sim S, A, T, V, R, ER, TR, K1, d1$;
11 End Scheduling;
12 End Training;
13 End Main

- Each federated learning-enabled node needs to update the trained and tested model weights to the aggregated for the optimal and accurate final scheduling as defined in steps 6-8.
- The trained models should be free from errors (ERR),

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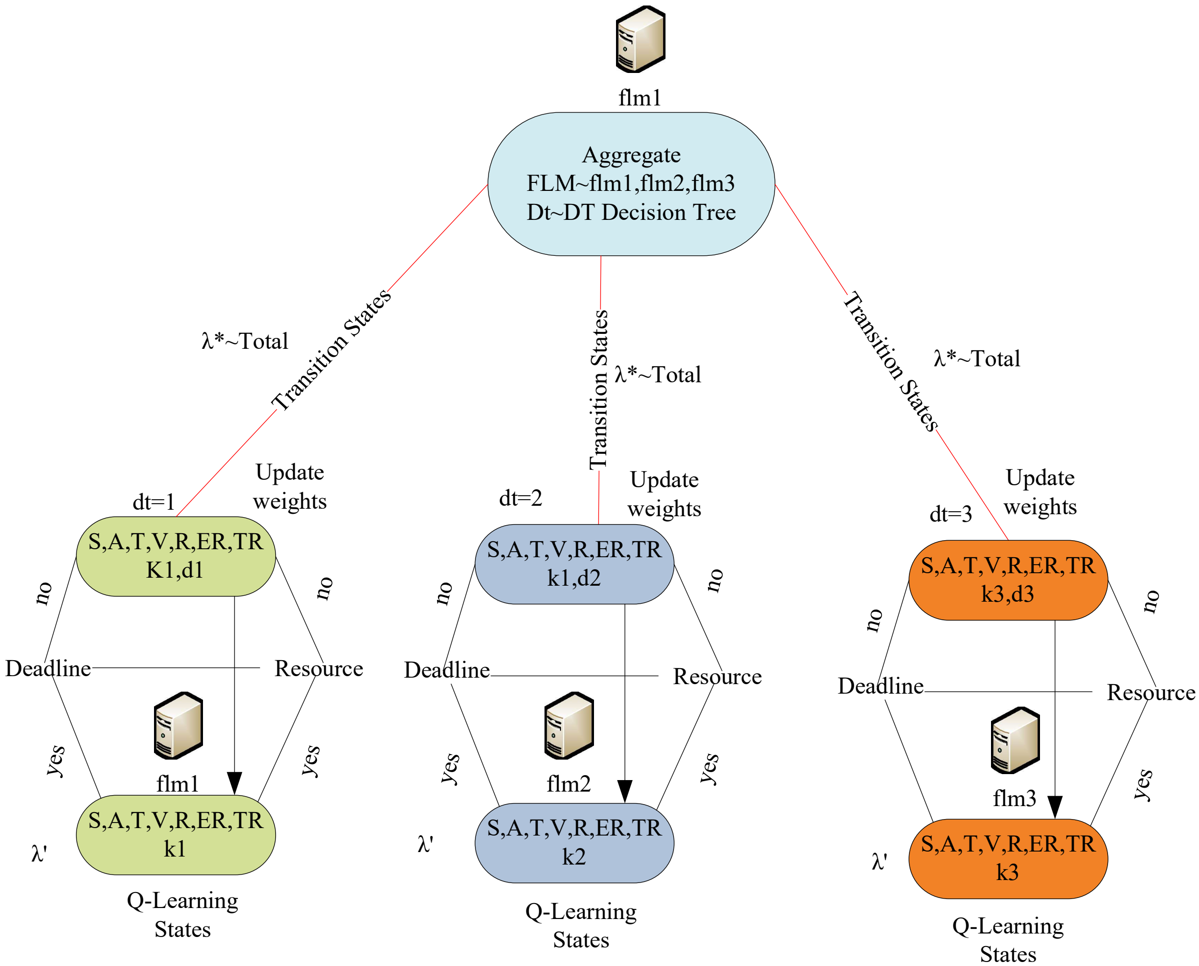

Fig. 3: Q-Learning Enabled Adaptive Scheduling and Searching Based on Decision Tree.

and Trials (TR) returns 1 instead of zero and should have an objective function λ^* for all tasks as defined in steps 9-12.

V. Experimental Setup and Result Analysis

In this session, the study designed the complete Federated Reinforcement Learning Enabled Scheme for Kidney Healthcare Image Tasks system for the experimental purpose. The study implemented the different fog nodes with their configurations in the simulation environment. We defined all configuration parameters such as languages, states, weights, nodes and others are defined with their values. All the simulation parameters are defined in Table I.

Table II shows the dataset of the kidney images.

A. Real World Implementation of AFRLS for Kidney Images

We designed a simulator that works in the real world to experiment with kidney images. The total number of kidney images is 25,000 trained and tested in the system, as shown in Table II. There are 400 features in the kidney dataset, as shown here: https://github.com/ABDULLAH-RAZA/Kidney-Disease-Data-Scheme. It is somehow similar to this dataset [24] as exploited in the kidney image processing model. In the simulator, we assumed each fog node worked as local clinics, where kidney image datasets are trained and offloaded to the

TABLE I: Experiment Configuration

Parameter	Description
Development-Tool	Python, YAML
Kidney Images and Tasks	25000$\sim$ 50000
$States \sim S$	1-100$\in$ K
$Action \sim A$	1-100$\in$ K
$Reward \sim R$	$1 \sim 100$
$Error \sim ER$	$0.01 \sim 0.20$
$Trial \sim TR$	$1 \sim 50$
λ	$50 \sim 300$
Rounds	$1 \sim 1000$
k=1	CPU 5000 GB Storage, High Computing Speed i7
$k = 2$	CPU 15000 GB Storage, High Computing Speed i7
$k = 3$	CPU 25000 GB Storage, High Computing Speed i7
$k = 4$	CPU 35000 GB Storage, High Computing Speed i7

TABLE II: Kidney Images Training and Testing

v_{image1}	v_{image2}	v_{image3}
Uretar	Kidney	Urine
8(GB)	4 (GB)	6 (GB)
$flm1(ms)$	flm2 (ms)	flm3 (ms)
20,000 22,000 25,000	15000 18000 2000	15000 18000 23000

central hospital for final decision. We consider the different resources such as mobile, fog, and cloud networks. AFRLS offers scalable and generalized resources for healthcare image-processing tasks beyond kidney disease. We used the adaptive scheduler, where resources are estimated before scheduling and offloading in our work. Therefore, except mobile nodes, all fog and cloud nodes are scalable at the runtime according to workload size in our system, as shown in Figure 1.

B. Results Analysis Based on Statistics Method

We conducted the experiments for kidney images on heterogeneous computing nodes based on different statistical methods, such as multi-variance ANOVA and dependent variables. The ANOVA set the variables as dependent such as higher resources and execution time and deadlines. The ANOVA method determines the execution of kidney images based on total delays, as shown in equation (7). In this part, the study implemented the different federated and reinforcement learning schemes, e.g., federated learning policy (FLP) and reinforcement federated learning scheme (RFLS) [1], [3], [5], [7], [9], [11], [12], [15], [18]. The study suggested the AFRLS algorithm approach to solve the kidney disease problem. We compare the main finding of the proposed scheme AFRLS and discuss the key findings from the simulation results, particularly in terms of the reduction in time tasks need to be delayed compared to other reinforcement learning methods in fog cloud networks [1], [3], [5], [7], [9], [11], [12], [15], [18]. Figure 4 analyzes the obtained performances of kidney

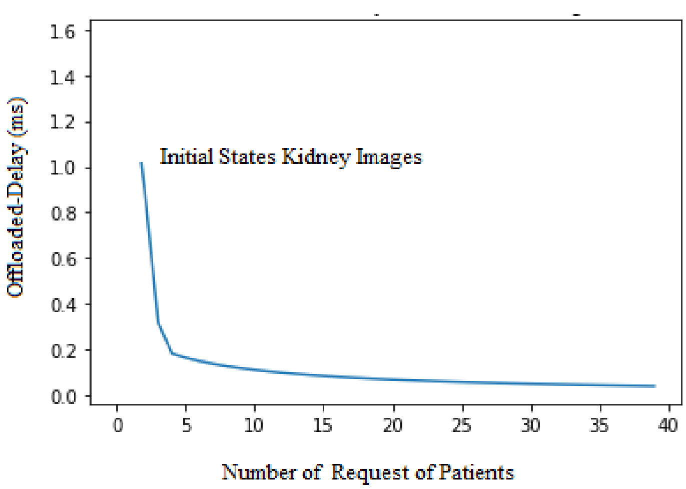

Fig. 4: Initial State Delay In Internal States.

images based on different schemes from input to processes on the different nodes. The offloading among internal images between states could be improved when they are different states are autonomous and share data among states. Therefore, the states are autonomous and learn from each other based on generated rewards obtained from the state, action, and reward on the tasks in the particular node. Figure 4 shows the reward factor could be improved after optimizing the internal states among federated learning nodes during the process in the system. The study conducted kidney image research on 15 patients with different features in the system. Figure 5 shows

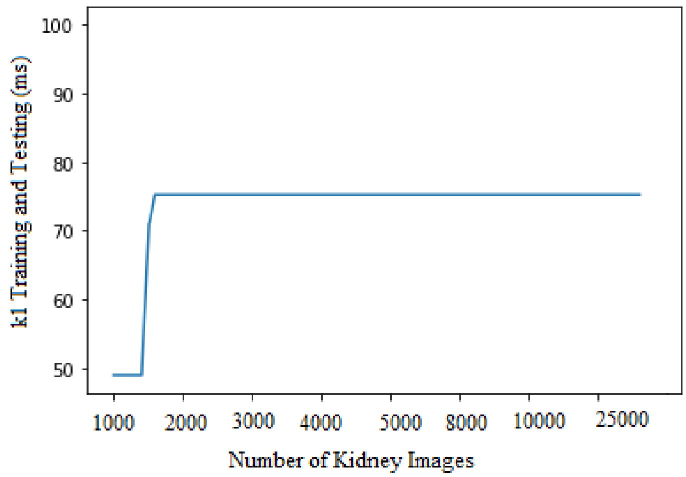

Fig. 5: External States Performance Among Nodes.

the performance of the kidney images from input to processes on the different nodes. The offloading among internal images between states could be improved when they are different states are autonomous and share data among states. Therefore, the states are autonomous and learn from each other based on generated rewards obtained from the state, action, and reward on the tasks in the particular node. Figure 5 shows the reward factor could be improved after optimizing the internal states among federated learning nodes during the process in the system. The study conducted kidney image research on 15 patients with the different features of kidney images. Figure 5 illustrates the obtained optimal results of the 20,000 kidney diseases based on different schemes in the network. It can be observed that, the proposal method obtained the optimal results as compared to existing methods in terms of objective function for all tasks. Figure 6 shows the performance of the kidney images from input to processes on the different nodes. The offloading among internal images between states could be improved when they are different states are autonomous and share data among states. Therefore, the states are autonomous and learn from each other based on generated rewards obtained from the state, action, and reward on the tasks in the particular node. Figure 6 shows the reward factor could be improved after optimizing the internal states among federated learning nodes during the process in the system. The study conducted kidney image research on 15 patients with different features in the system. Figure 6 shows the performances of external states among nodes and obtaining the optimal results on the given 20,000 kidney disease images in the system. Figure 7 shows the execution delay performance of the kidney images

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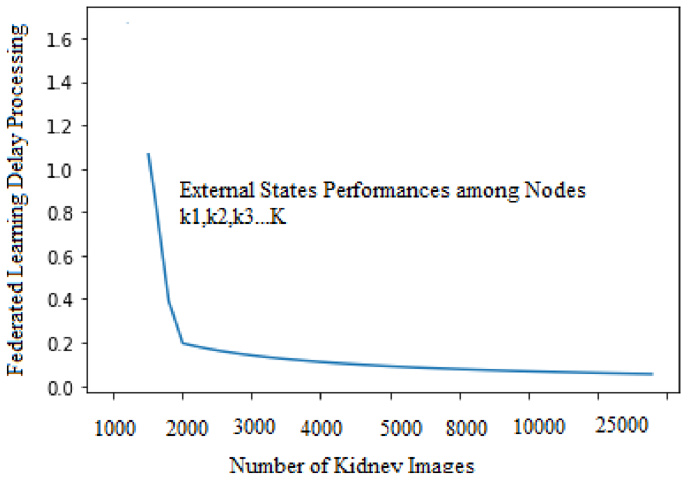

Fig. 6: External States Performance Among Local Training and Testing Performance.

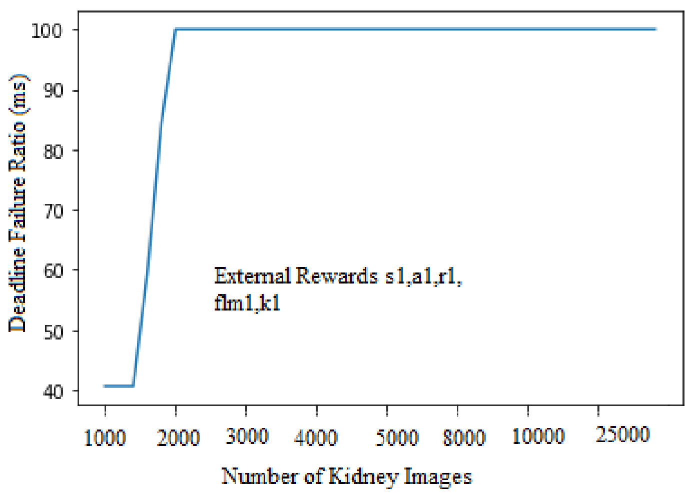

Fig. 7: External States Performance Among Aggregated and Updated Nodes.

from input to processes on the different nodes. The offloading among external images between states could be improved when they are different states are autonomous and share data among states. Therefore, the states are autonomous and learn from each other based on generated rewards obtained from the state, action, and reward on the tasks in the particular node. Figure 7 shows the reward factor could be improved after optimizing the internal states among federated learning nodes during the process in the system. The study conducted kidney image research on 15 patients with different features in the system. Figure 7 shows the performances of external states among nodes and obtaining the optimal results on the given 25,000 kidney disease images in the system. It seems that, during training and testing in different nodes, the processing time is much larger as compared to the pre-set deadline on the given tasks. Therefore, the failure of the ratio of deadline failure increased in the system. It is necessary to optimize different constraints on the given kidney images in the system. Figure 8 shows the execution delay performance of the kidney

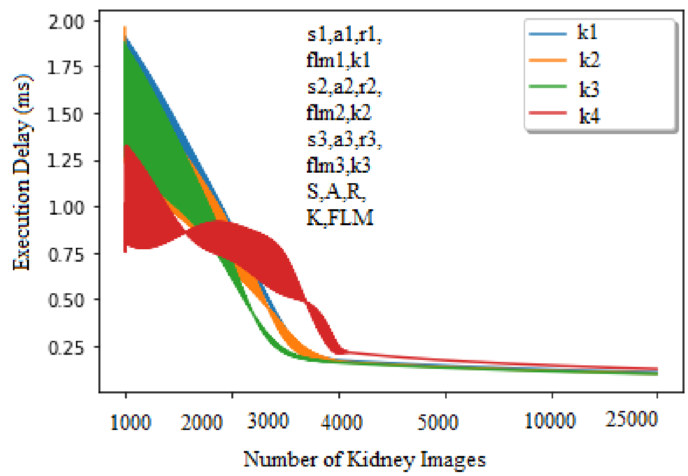

Fig. 8: Initial State Mobile Agent Performance.

images from input to processes on the different nodes. The offloading among external images between states could be improved when they are different states are autonomous and share data among states. Therefore, the states are autonomous and learn from each other based on generated rewards obtained from the state, action, and reward on the tasks in the particular node. Figure 8 shows the execution delay on the images and optimizes the reward factor among external federated learning nodes during the process in the system. Figure 8 shows the performances of external states among nodes and obtaining the optimal results on the given 25,000 kidney disease images in the system. It seems that, during training and testing in different nodes, the processing time is much larger as compared to the pre-set deadline on the given tasks. Therefore, the failure of the ratio of deadline failure increased in the system. It is necessary to optimize different constraints on the given kidney images in the system. Figure 9 execution delays

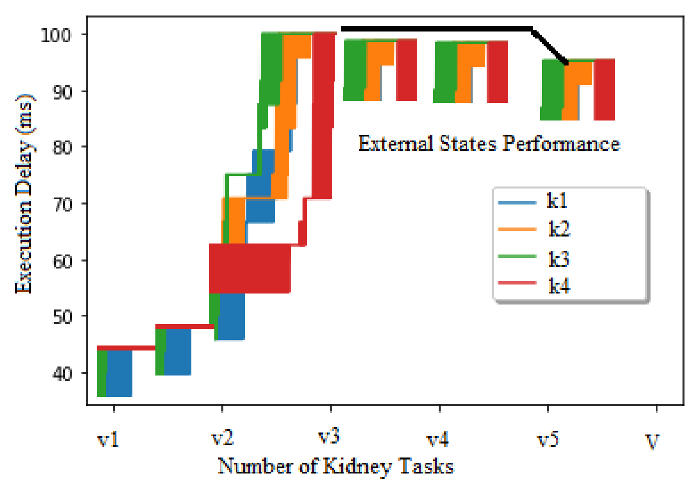

Fig. 9: Initial State Mobile Agent Performance.

kidney images from input to processes on the different nodes. The offloading among internal images between states could be improved when they are different states are autonomous and share data among states. Therefore, the states are autonomous and learn from each other based on generated rewards obtained

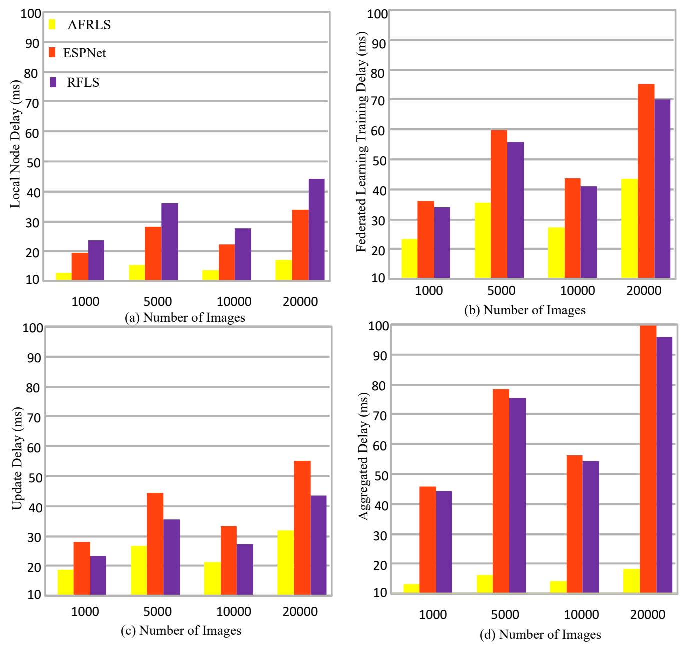

Fig. 10: Delay Performances of All Nodes.

from the state, action, and reward on the tasks in the particular node. Figure 9 shows the reward factor could be improved after optimizing the internal states among federated learning nodes during the process in the system. The study conducted kidney image research on different patients with different features in the system. Figure 9 shows the performances of external states among nodes and obtaining the optimal results on the given 25,000 kidney disease images in the system. It seems that, during training and testing in different nodes, the processing time is much larger as compared to the pre-set deadline on the given tasks. Therefore, the failure of the ratio of deadline failure increased in the system. It is necessary to optimize different constraints on the given kidney images in the system. We added the references [23]–[29] to evaluate the performance of proposed methods for kidney images. The studies exploited the ESPNet method to process the images on nodes. Figure 10 (a,b,c,d) shows the performance of different delays local fog Node Delay (ms), federated Learning Training Delay (ms), Update Delay (ms), and aggregated Delay (ms). The study executed 20,000 kidney images and optimized their system performances on the different nodes. Figure 10 (a,b,c,d) shows that AFRLS outperformed all existing schemes such as ESPNet and RFLS. The main reason is that existing studies only focused on single rewards. However, the proposed work optimizes different rewards among internal and external states. Figure 10 shows the execution delays, prediction, and decision tree performance of the kidney images from input to processes on the different nodes. The offloading among external images between states could be improved based on QoS constraints in the system. Figure 10 shows the reward factor could be improved after optimizing the internal states among federated learning nodes during the process in the system. The study conducted kidney image research on different patients with different features in the system. Figure 10 shows the performances of external states among nodes and obtaining the optimal results on the given 25,000 kidney disease images in the system. It seems that, during training and testing in different nodes, the processing time is much larger as compared to the pre-set deadline on the given tasks. Therefore, the failure of the ratio of deadline failure increased in the system. It is necessary to optimize different constraints on the given kidney images in the system.

VI. Conclusion

The study discussed the optimal results obtained by different machine learning schemes to consider kidney disease images in the system. In this paper, the study showed how federated and reinforcement learning schemes can be used to come up with the best delay scheme. The scheme must optimize both the internal and external states of reinforcement learning and the federated learning fog cloud network. This work presented the Adaptive Federated Reinforcement Learning Scheme (AFRLS). In healthcare applications, kidney image tasks reduce the time it takes to preprocess federated learning datasets for training and testing and run them on different fog and cloud nodes. AFRLS decides the scheduling on different nodes and improves constraints based on the decision tree. Based on the simulation results, AFRLS is a new strategy that, compared to other machine learning methods used in fog cloud networks, reduces the time tasks need to be delayed. The AFRLS improved the delay among nodes by 55%, delay among internal states by 40%, and training and testing delay by 51%, as shown in the simulation results.

In future work, the study will suggest a blockchain-secure, decentralised system for digital healthcare applications. The main constraints will be security, resources, and delays for the tasks on the different mobile fog and cloud networks.

Conflicts of Interest

The authors declare that there is no conflict of interest.

Data Availability

For the considered problem, we exploited the kidney dataset which is a collection of different image data. The total number of kidney images is 25,000 trained and tested in the system, as shown in Table II. There are 400 features in the kidney dataset, as shown here: https://github.com/ABDULLAH-RAZA/Kidney-Disease-Data-Scheme.

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