Regression Reinforced Logistic Gaussian Deep Belief classifier for IOT based Prana Healing Distributional Services

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Abstract- The Internet of Things (IoT) is a recently appearing phrase for contemporary generation of the Internet that permits interpretation between similar devices. IoT behaves as an assistant in healthcare and plays an exceptionally foremost part in broad extents of medicinal assistances distinguishing applications. Through finding out the pattern of frameworks that are noticed, the nature of the disease can be anticipated. From a technical point of view, IoT is attaining a swiftly heightening attention in many domain applications, specifically in healthcare. Meanwhile, IoT-based Pranic Healing has been extensively applied to establish the efficacy of short term energy healing on patients suffering from Diabetic Foot Ulcers for ubiquitous health monitoring. In this paper, an IoT Cloud-based Pranic Healing healthcare monitoring method called Regression Reinforced Logistic Gaussian Deep Belief Neural Classifier (RR-LGDBNC) is proposed to continuously acquire cloud user request services and allocate virtual machines via cloud service providers in a timely and accurate manner. First, with the details of the participants provided as input, an appropriation of requested cloud user service is made by the cloud service provider employing Logistic Gaussian-based Convolutional Deep Belief Neural Classifier model. Next, Dynamic Regression and Reinforced Virtual Machine Allocation are applied to the requested services for allocating the virtual machine with less migration. The evaluation for RR-LGDBNC method is experimented on the traces of the COMPDIAM-DFU patient details for gaining optimal appropriation and allocation of virtual machines to the respective cloud user via cloud service provider. Our experiment results show that the proposed method has the potentialities to minimize the response time and improve both accuracy and sensitivity even in the case of increase in the number of migrations when compared to the state-of-the-art methods.

Keywords – Internet of Things, Diabetic Foot Ulcer, Logistic Gaussian Convolutional Deep Belief, Neural Classifier

I. INTRODUCTION

The Internet of Things (IoT) has metamorphosed from being an interdependence of embedded computing devices to an interrelationship of smart sensor devices. However, when applied to the smart healthcare framework, it directs to certain open issues, essentially low storage and limited processing capacity. Meantime, cloud computing provides speedy processing and immense storage potentiality. Hence, there arise the requirements of IoT cloud homogenization to get on with tremendously challenging smart healthcare services. A machine learning-based health care monitoring in Internet of Things (IoT) environment was designed in [1]. In this work, an IoT-based student healthcare monitoring was proposed to examine the essential signs and recognize biological and behavioral alternates via smart healthcare technologies. All the data acquired from the sensors were initially stored and then transferred to cloud space for the purpose of remote health monitoring. In this model, with the aid of IoT devices, essential data were obtained and machine learning methods were employed for recognizing the anticipated risks of student's physiological and behavioral changes. Though better accuracy was attained using deep learning, the response time involved in decision making process remained unaddressed. To address this issue, in this work, Logistic Gaussian-based Convolutional Deep Belief Neural Classifier is presented that with the aid of sub-sampling splits the features and extracts the most typical features, therefore minimizing the response time involved in classification. A cognitive healthcare framework was proposed in [2] that acquired the Internet of Things (IoT) cloud technologies. This framework utilized smart sensors for communications between users and deep learning technique for making decision making in an intelligent fashion within the smart city angle. With the assistance of cognitive and smart framework patient monitoring was performed in a precise and timely manner for real time application at affordable cost. The EEG pathology classification employing deep learning achieved better accuracy. However, the frequency of migration involved during the classification during patient monitoring was not considered, therefore compromising the rate of sensitivity. To address this issue, in this work, Dynamic Regression and Reinforced Virtual Machine Allocation is designed that based on the overload time function, optimal virtual machine allocation is done.

1.1 Contributing remarks

The key contributions of this paper are:

- Proposed a novel method for development of reinforced and convoluted deep belief network classifier for IoT distributional cloud services on prana healing
- Developed a Logistic Gaussian-based Convolutional Deep Belief Neural Classifier model using Logistic Regression and Convolution function for appropriation of cloud user requests
- Deployed Dynamic Regression and Reinforced Virtual Machine Allocation model for optimal virtual machine scheduling
- Demonstrated and analyzed the cloud service rendering deployment in terms of various performance metrics like accuracy, sensitivity and response time for different cloud user requests

1.2 Organization of the paper

The rest of the paper is organized as follows. Section 2 presents the related work of existing IoT cloud based healthcare frameworks. Proposed method is presented in Section 3 along with its design and implementation in detail. Section 4 describes the experimental setup and presents the results of both qualitative and quantitative analysis in detail. Section 5 presents concluding remarks.

II. RELATED WORKS

The magnitude and structure of the world population has remodeled over the last couple of decades, and these tendencies are predicted to continue. Such demographic tendencies have notable inferences for almost all areas of the society, specifically in health and healthcare. Due to this, the mortality rate has been reduced and increasing the life expectancy dramatically. However, this necessitates considerable refinement in both the healthcare service and the living environment because of the reason that older people usually require more healthcare than their younger counterparts.

A comprehensive survey in IoT-based healthcare was proposed in [3] ensuring security and privacy aspects. On the other side, remote health monitoring is receiving a considerable attention in the recent few years and therefore recognizing daily chores have become a promising solution. Due to this, Internet of Things (IoT) is gaining a rapidly growing attention and specifically in personalized healthcare.

In [4], a wearable IoT cloud based healthcare monitoring was proposed for quick view of real time data. The crucial restriction being posed in the recent years is the limited scalability in these cloud environments and hence incompetence to regale to the prerequisites of centralized Internet of Things (IoT) based computing framework. A novel method called, HealthFog for combining ensemble deep for real-life application of automatic Heart Disease analysis was proposed in [5]. With this, prediction accuracy was said to be improved.

In the present smart generation, academic professionals have identified that IoT has elevated potentiality for data transfer in healthcare domain in a critical manner. Moreover, with the combination of IoT features into medical devices also minimizes the overall cost and response time in smart healthcare system.

In [6], a smart healthcare system for patients was proposed with the objective of minimizing the communication latency using blockchain and cryptographic methods. Certain challenges and opportunities involving IoT for smart healthcare were investigated in [7]. In addition to improve the quality of healthcare services, yet another outline of monitoring of patient health based on IoT was presented in [8].

The world is surfacing issues like irregular medical resource dissemination, the increasing chronic diseases and therefore the elevated medical expenses. Integrating the state-of-the-art information technology into the healthcare structure will heavily avoid the problems. In [9], big health application system based on the health Internet of Things was proposed. A review of IoT-based distributed healthcare system was presented in [10]. Yet another review of the inception of IoT in healthcare was proposed in [11], along with the complexities of several aspects influencing its current standing and also provided mechanisms for an optimal roadmap of IoT in healthcare.

One of the many domain areas enhanced by the pervasive perception of IoT technologies is the healthcare that is utilized in assisting the healthcare core functions. In this manner, conventional hospitals are transformed into next-generation smart digital environments significantly making utilization of interconnected sensor and data scheduling techniques. Patient’s basis health signs were monitored intermittently using smart healthcare in IoT [12]. However, less focus was made on the reaction time. To address this issue, a complex event processing technology adopting hierarchical data fusion was presented in [13].

Real time data are highly required as far as time sensitive healthcare data are concerned. Conventional cloud servers do not accomplish the minimum latency requirements of healthcare IoT devices and end users [14]. To address this issue, an integration of analytical and hybrid fuzzy-based reinforcement learning algorithm was proposed in [15] with the purpose of minimizing high latency between healthcare IoTs, end-users, and cloud servers in an extensive fashion.

Yet another advanced technique based on event triggering for improving the accuracy with minimum response time was presented in [16]. But, smart healthcare for online diagnosis necessitates patients to share their physiological information and with the lack of efficient security measures, as the information being sensitive are said to be misused by malicious users. A security enforcement framework employing Software Defined Networking was proposed in [17].

The changeover of traditional healthcare framework to a data driven and patient-centric healthcare 4.0 has instituted a sensible transposition in the health statistics. In [18], Cloud of Things architecture and platforms focusing on the energy aspect was presented in detailed. A Deep Learning based Internet of Health framework was proposed in [19] to improve the accuracy rate. An ensemble deep learning method for automatic heart disease analysis was presented in [20]. High level activity patterns were extracted by utilizing Markov model with four states, therefore improving the accuracy involved in continuous monitoring.

Although reasonable work has been master minded, this work ensures accuracy, sensitivity and minimum response time via reinforced deep belief network and convolution method with the aid of regression function for optimal scheduling. In the next section, we provide the proposed Regression Reinforced Logistic Gaussian Deep Belief Neural Classifier (RR-LGDBNC) method.

III. REGRESSION REINFORCED LOGISTIC GAUSSIAN DEEP BELIEF NEURAL CLASSIFIER

The sensing network is contemplated to be the cornerstone of the IoT-Cloud framework, whose principal responsibility is to acquire patient health-related information and transmitting these data via wireless channel to IoT-Cloud. The sensed data are then directed to the IoT-Cloud for further processing. In our work, computational efficient optimal allocation of the cloud user request services (i.e., patient requests) are performed via virtual machine (i.e., pranic healers) by the cloud service provider (i.e., schedulers) in an accurate manner. This objective is achieved in our work by employing two different models. They are appropriation of required cloud user services by the cloud service provider using Logistic Gaussian-based Convolutional Deep Belief Neural Classifier model and assignment or scheduling of the virtual machine to the respective cloud users by employing Dynamic Regression and Reinforced Virtual Machine Allocation model. Figure 1 shows the block diagram of the proposed method.

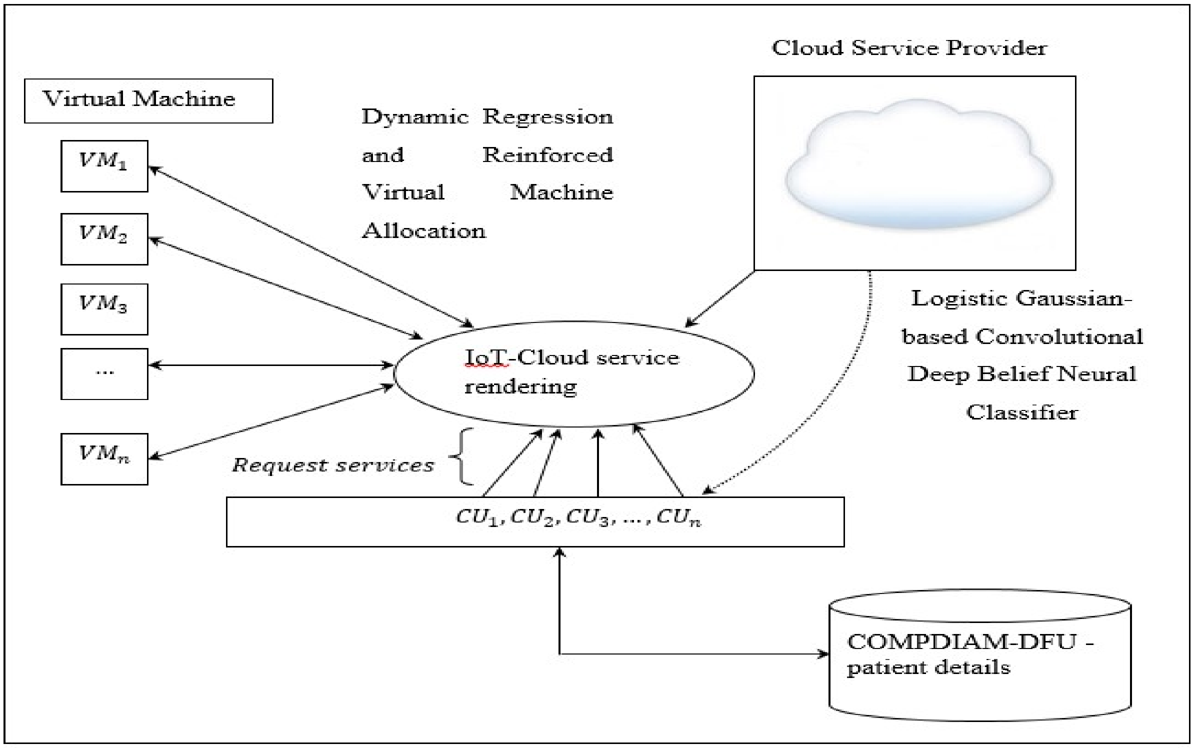

Figure 1 Block diagram of Regression Reinforced Logistic Gaussian Deep Belief Neural Classifier (RR-LGDBNC)

As illustrated in the above figure, with the details of the participants provided as input employing the COMPDIAM-DFU -patient details, the objective remains in scheduling cloud user's service requests with the respective virtual machine with minimum response time and false positive rate in a precise manner via cloud service provider. This is said to be achieved using two different steps. First, Logistic Gaussian-based Convolutional Deep Belief Neural Classifier model is designed that appropriates the requested cloud user services with the respected cloud service providers in a timely manner. Next, a Dynamic Regression and Reinforced Virtual Machine Allocation are proposed to schedule the virtual machine to the respective cloud user in an optimal manner even in case of large number of migrations.

3.1 System model

Let us consider a scenario with 'n' cloud user 'CU' (i.e., patient), requesting for the required services from the 'n' scheduler 'CSP' (i.e., cloud service provider), where each cloud service provider allocates a virtual machine 'VM' (i.e., pranic healers) to the requested users in an optimal fashion. The cloud system model as shown in figure 2 given below is employed in our work.

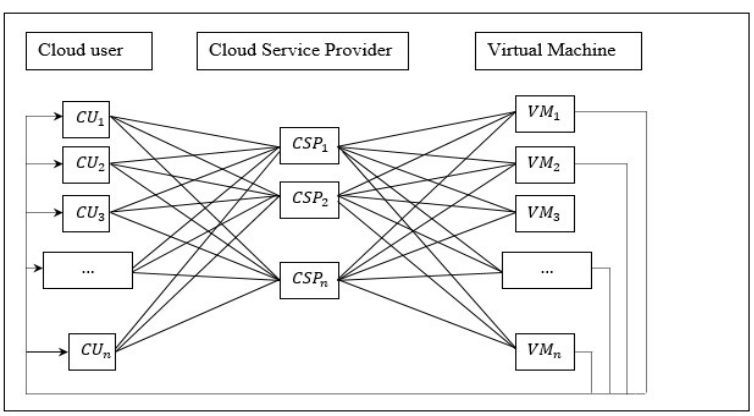

Figure 2 System model of IoT-Cloud based Healthcare Monitoring framework

3.2. Logistic Gaussian-based Convolutional Deep Belief Neural Classifier

The Internet of Things (IoT) is the inter-relationship of incomparable embedded computing devices within the prevailing Internet framework. Generally, IoT is anticipated to provide state-of-the-art connectivity of devices that goes far behind machine-to-machine communications (M2M). The integration of these aspects has boosted the feasibility of employing a sensor network comprising of a large number of intelligent sensors, permitting the data collection, processing, and allocation, gathered in a variety of frameworks. In this section, appropriation of cloud user request is made by the cloud service provider employing Logistic Gaussian-based Convolutional Deep Belief Neural Classifier model. Figure 3 shows the block diagram of Logistic Gaussian-based Convolutional Deep Belief Neural Classifier model.

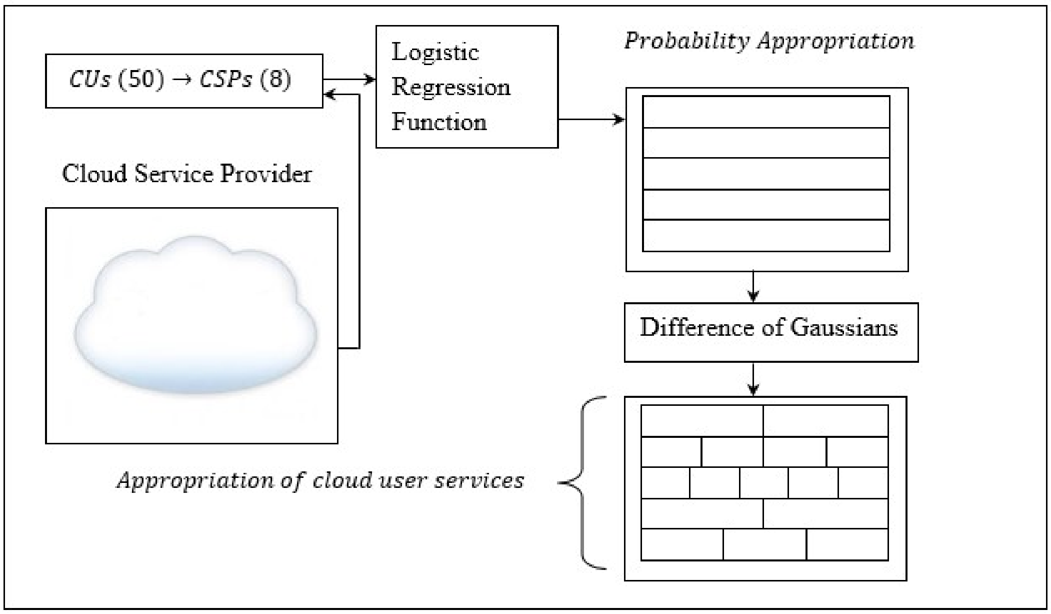

Figure 3 Block diagram of Logistic Gaussian-based Convolutional Deep Belief Neural Classifier

As shown in the above figure, the input layer in the proposed method is utilized to preprocess the data (i.e., provided by the cloud user or the patient) while inputting the raw data (i.e., energy healing on patients suffering from Diabetic Foot Ulcers) into the neural network. The process of preprocessing is principally the raw data as a vector and normalizing it in order to shoot up the speed during training process. The function form with 'CU' representing the input is mathematically expressed as given below.

$$f(CU) = \begin{cases} 0, if\ CU < 0 \\ CU, if\ CU \geq 0 \end{cases} \quad (1)$$

As a subsampling process, the pooling is utilized to partition the features (i.e., the association between the cloud user and cloud service provider) and extract the most typical features, that can significantly minimize the output feature scale, thus minimizing the parameters or features 'F^k' essential for overall processing. This is mathematically expressed as given below.

$$S_G = \sum_k W_k^T F^k = \sum_k W_k^T f_k(CU, CSP) \quad (2)$$

From the above equation (2), for a group 'G' the input to the softmax at spatial element '$f_k(CU, CSP)$' represents the activation for respective '(CU, CSP)' in the 'kth' feature map. With this a feature map is generated based on the set of weighted filters '$W_k^T f_k$' respectively. Now, the training set comprises of a label sample '$\{(CU^1, CSP^1), (CU^2, CSP^2), \ldots, (CU^n, CSP^n)\}$', where the label value '$CSP = 0,1\ or\ 2$' for '50' different cloud users. We assume that the logistic regression function is as follows

$$h_\theta(CU) = \frac{1}{1+e^{-\theta^T CU}} \tag{3}$$

From the above equation (3), 'θ' represent the model parameter (i.e., the details of the participants). Then, for a given training sample 'CU' with 'n' groups, the appropriation probability of state 'i' is '$Prob(CSP = i|CU)$' and the output of the regression function are mathematically expressed as given below.

$$h_\theta(CU) = \begin{bmatrix} Prob(CSP = 1|CU;\theta) \\ Prob(CSP = 2|CU;\theta) \\ Prob(CSP = 3|CU;\theta) \\ \dots \dots \\ Prob(CSP = n|CU;\theta) \end{bmatrix} = \frac{1}{\sum_{j=1}^{n} e^{CU\theta_j}} \begin{bmatrix} CU\theta_1 \\ CU\theta_2 \\ CU\theta_3 \\ \dots \\ CU\theta_n \end{bmatrix} \tag{4}$$

From the above equation (4), '$\theta_1, \theta_2, \theta_3, \dots, \theta_n$' represents the model parameters with the process of normalization being performed using '$\frac{1}{\sum_{j=1}^{n} e^{CU\theta_j}}$'. Followed by which points of interest are detected by means of Difference of Gaussians (DoG) that occurs at multiple scales.

$$C(CU, CSP, k\sigma) = C(CU, CSP, s_i\sigma) - C(CU, CSP, s_j\sigma) \tag{5}$$

From the above equation (5), '$C(CU, CSP, s\sigma)$' represent the convolution of original participant details '$f(CU, CSP)$' with noise '$N(CU, CSP, s\sigma)$' at scale '$s\sigma$' respectively. This is mathematically expressed as given below.

$$C(CU, CSP, s\sigma) = N(CU, CSP, s\sigma) * f(CU, CSP) \tag{6}$$

From the above equation (6), a Difference of Gaussians between scales '$s_i\sigma$' and '$s_j\sigma$' denotes the difference of the noisy data at scales '$s_i\sigma$' and '$s_j\sigma$' respectively. The pseudo code representation of Logistic Gaussian-based Convolutional Deep Belief Neural Classifier is given below.

Input: Cloud Users '$CU = CU_1, CU_2, \dots, CU_n$', Cloud Service Providers '$CSP = CSP_1, CSP_2, \dots, CSP_n$', Virtual Machines '$VM = VM_1, VM_2, \dots, VM_n$'
Output: Optimal allocation of cloud service providers
1: **Initialize** model parameter 'θ' 2: **Begin** 3: **For** each Cloud Users 'CU' with Cloud Service Providers 'CSP' and Virtual Machines 'VM' 4: Form feature map based on spatial element using (2) 5: **For** each model parameter 'θ' 6: Evaluate logistic regression function using (3) 7: Evaluate appropriation probability of state 'i' using (4) 8: **End for** 9: Evaluate Difference of Gaussians (DoG) that occurs at multiple scales using (5) 10: **Return** (optimal appropriation of CSPs) 11: **End for** 12: **End**

Algorithm 1 Logistic Gaussian-based Convolutional Deep Belief Neural Classifier

According to the Logistic Gaussian-based Convolutional Deep Belief Neural Classifier, the objective of the algorithm remains in appropriating the cloud user requests to the cloud service providers with minimum time and false positive rate. This objective is said to be achieved by means of two different functions. First, an appropriation probability is measured separately with which optimal cloud service providers are said to be grouped, therefore minimizing the overall time involved. Next, with the aid of Difference of Gaussians function, optimal appropriate is said to be ensured, therefore minimizing the false positive rate involved.

3.3 Dynamic Regression and Reinforced Virtual Machine Allocation

With the appropriation of cloud user service requests made by the cloud service provider, optimal and dynamic scheduling of virtual machine to the cloud user is made by employing Dynamic Reinforced Virtual Machine Allocation model. In our Dynamic Regression and Reinforced Virtual Machine Allocation model, the cloud server schedules virtual machine to respective cloud user in an optimal and dynamic manner with switching between virtual machine in case of overloading.

In case of virtual machine being overloaded the cloud service provider applies the overload time to determine if a virtual machine is over-utilized or not and accordingly allocation is made. Also by applying dynamic reinforced model migration between over-utilized and under- utilized virtual machine, the accuracy is said to be improved. Also, a Randomized Markov Regression function is introduced that solves the issues related to optimizing the average time between VM migrations by employing overload time to the conventional Reinforced Machine Learning. Hence, it is called as the Dynamic Regression and Reinforced Virtual Machine Allocation model. Figure 4 shows the block diagram of Dynamic Regression and Reinforced Virtual Machine Allocation model.

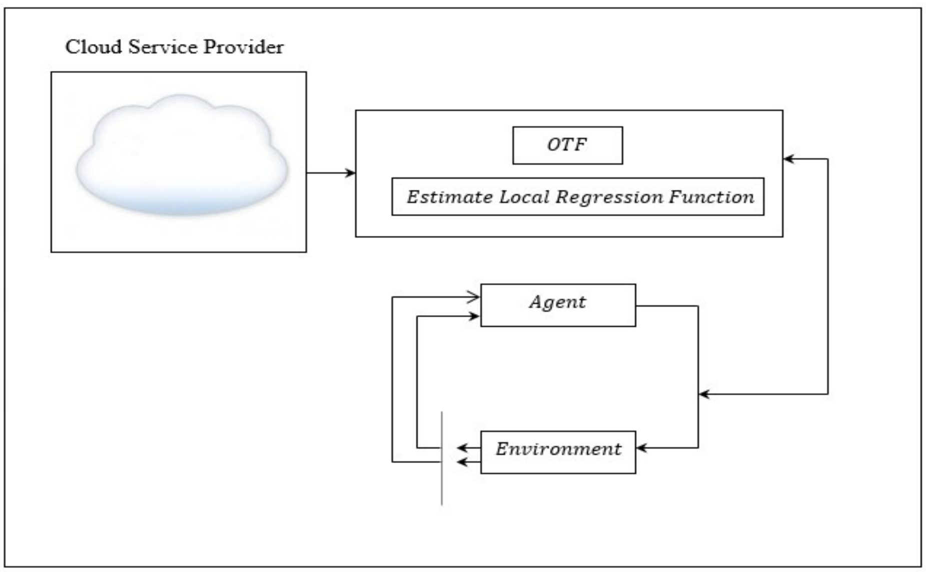

Figure 4 Block diagram of Dynamic Regression and Reinforced Virtual Machine Allocation model

As illustrated in the above figure, with the consideration of IoT cloud data center framework, 'n' virtual machines serve as resources for the cloud users and each virtual machine is formulated as an element of state 's' and therefore the state set of IoT cloud data center framework is '$S = \{s_1, s_2, \dots, s_n\}$' accounting all virtual machines. Each state 'S_i' for time 't' represent the state of the candidate cloud user where '$i = 1,2, \dots, n$'.

Reinforcement Learning allows an agent (i.e. cloud service provider) to learn optimal behavior (i.e. optimal allocation of virtual machine) via continual experiment interactions with its environment (i.e. cloud computing framework) at distinct time intervals 't' without any previous expertise. The agent (i.e. cloud service provider) acquires a reward based on the action (i.e. allocation of virtual machine to respective cloud user) determined.

$$OT = \frac{VMt_o(VMUti_t)}{VMt_a} \quad (7)$$

From the above equation (7), the overload time 'OT' is measured based on the time during which the virtual machine has been overloaded 'VMt_o', CPU utilization threshold differentiating between non-overload and overload states of the virtual machine '$VMUti_t$' and the total time during which the virtual machine has been active 'VMt_a' respectively. With the overload time, a local regression is applied for smooth switch over and is mathematically expressed as given below.

$$OT(VMt_o, VMt_a) = \frac{t_{mig} + VMt_o}{t_{mig} + VMt_a} \tag{8}$$

From the above equation (8), the regression function is evaluated using the migration time 't_{mig}', time during which the virtual machine has been overloaded 'VMt_o' and the total time the virtual machine is active 'VMt_a'. Let us consider a reward function 'Rew' as defined by the Randomized Markov function with a tuple '$(S, A, Prob, Rew, \alpha)$', where '$S$' represents the state (i.e., total number of cloud users and virtual machines), 'A' the actions (i.e., the allocation of cloud users with the respective virtual machines), then the '$Prob$' denoting the transition probability matrix with the adoption of regression function is mathematically expressed as given below.

$$Prob^a_{s,s'} = OT\ [Prob_{Rew}(S_{t+1} = s' \mid S_t = s, A_t = a)] \tag{9}$$

Based on the results of state transition probability matrix from state 's' to 's'' obtained as in above equation (9), the reward function 'Rew' with a discount factor of 'α' is mathematically expressed as given below.

$$Rew^{OT}_x = OT\ [Prob_{Rew}(R_{t+1} = r | S_t = s, A_t = a)] \tag{10}$$

From the above equation (10), the regressive reward value 'Rew^{OT}_x' is estimated for action 'A_t', when performing a transition '$s \rightarrow s'$' utilizing the state transition probability matrix '$Prob^a_{s,s'}$', with '$a_t \in A$', '$r_t \in R$' and '$s_t \in S$'. The reward value for each virtual machine is updated according to the regression function value. Then, the '$Prob_{Rew}$' is mathematically expressed as given below.

$$Prob_{Rew}(s', r | s, a) = argmax\ [OT(VMt_o, VMt_a)][Prob(s_{t+1} = s', r_{t+1} = r \mid s_t = s, a_t = a)] \tag{11}$$

From the above equation (11), lower being the results of the regression function value higher is the probability of the virtual machine being assigned with the respective cloud user by the cloud service provider. The pseudo code representation of Dynamic Regression and Reinforced Virtual Machine Allocation is given below.

Input: Cloud Users '$CU = CU_1, CU_2, \dots, CU_n$', Cloud Service Providers '$CSP = CSP_1, CSP_2, \dots, CSP_n$', Virtual Machines '$VM = VM_1, VM_2, \dots, VM_n$'
Output: Minimum Migration Virtual Machine allocation
1: **Initialize** time 't', discount factor 'α' 2: **Begin** 3: **For** each Cloud Users 'CU' with Cloud Service Providers 'CSP' and Virtual Machines 'VM' 4: Evaluate overload time using (7) 5: Evaluate regression function using (8) 6: Evaluate regressive transition probability matrix using (9) 7: Evaluate regressive reward function using (10) 8: Measure probability of reward function using (11) 9: **Return** (virtual machine)

End for

End

Algorithm 2 Dynamic Regression and Reinforced Virtual Machine Allocation

The objective of the above Dynamic Regression and Reinforced Virtual Machine Allocation algorithm remains in returning the virtual machine with minimum migration to the respective cloud user by the cloud service provider. This is achieved by means of first evaluating the over load time and then retrieving the regressive, probability of reward function. With this, the sensitivity and accuracy is said to be improved even with higher migration rate.

IV.EXPERIMENTAL SETUP

In this section, the experimental settings of the proposed Regression Reinforced Logistic Gaussian Deep Belief Neural Classifier (RR-LGDBNC) are implemented in CloudSim simulator via Java platform. The RR-LGDBNC method is simulated in a cloud area of size with 500 cloud user requests placed in cloud service rending. The simulation of RR-LGDBNC method for several instances with respect to varied number of cloud users for evaluating proposed performance is presented in this section. The performance of RR-LGDBNC method is measured in terms of accuracy, sensitivity and response time. The result of RR-LGDBNC method is compared with existing machine learning-based health care monitoring [1] and Cognitive Smart Healthcare [2].

4.1 Case Scenario

In this section, the case scenario of Regression Reinforced Logistic Gaussian Deep Belief Neural Classifier (RR-LGDBNC) using the COMPDIAM-DFU dataset consisting of the details of the participants and the results of the pilot project was carried out to establish the efficiency of short term Energy (Pranic) Healing on patients suffering from Diabetic Foot Ulcers. Simulations for case analysis were conducted with the aid of 50 different cloud users and an average of 8 cloud service providers. Figure 5 shows the implementation scenario of Energy (Pranic) Healing on patients suffering from Diabetic Foot Ulcers.

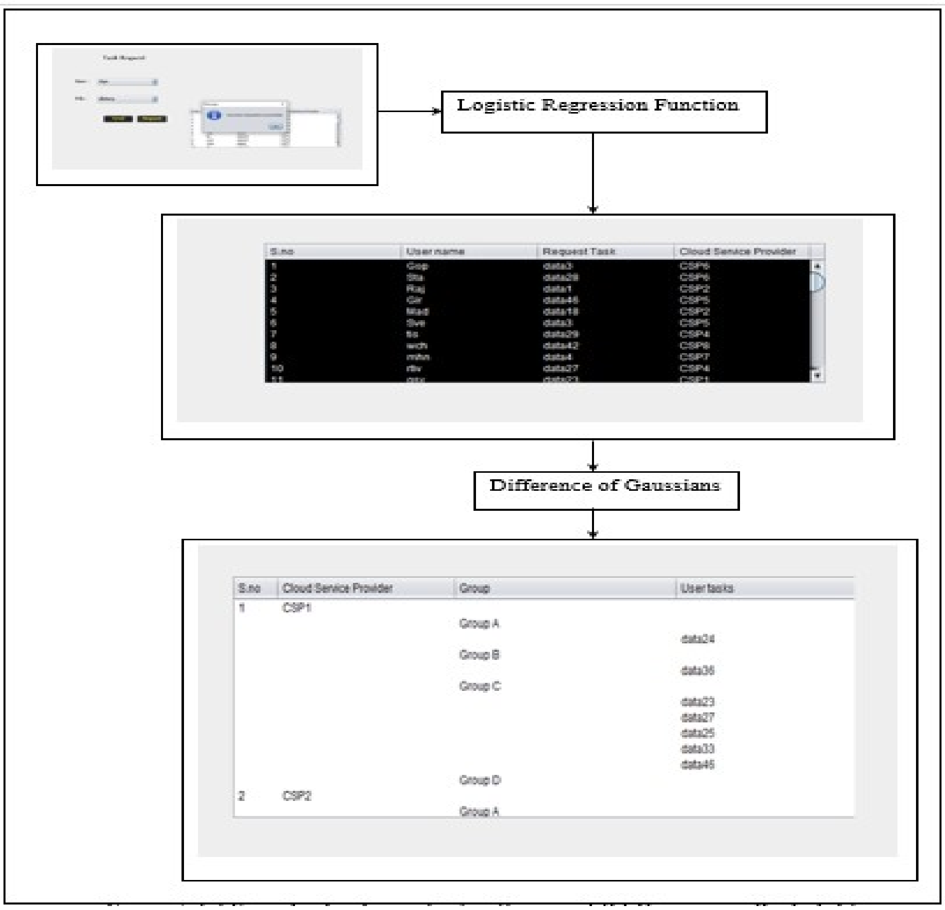

Figure 5 (a) Sample cloud user (patient) request (b) Regression Probability Appropriation (c) Similarity Appropriation

As shown in the above figure, with 50 cloud user request services placed in the IoT cloud environment and 8 cloud service providers for scheduling, first, Logistic Gaussian-based Convolutional Deep Belief Neural Classifier model is applied to appropriate required cloud user services requests to the virtual machine via cloud service provider as in figure 5 (a). As shown above, a Logistic Regression Function is applied for performing initial probability appropriation. Here, each cloud user request is appropriated via 8 cloud service providers (i.e., '6', '5', '7', '8', '4', '9', '5', '6') respectively as in figure 5 (b).

Followed by which, difference of Gaussians is applied to finally, appropriate cloud user services according to similar functions as in figure 5 (c). Figure 6 given below shows the optimal virtual machine allocation by the cloud service provider for each cloud user requests using Dynamic Regression and Reinforced Virtual Machine Allocation.

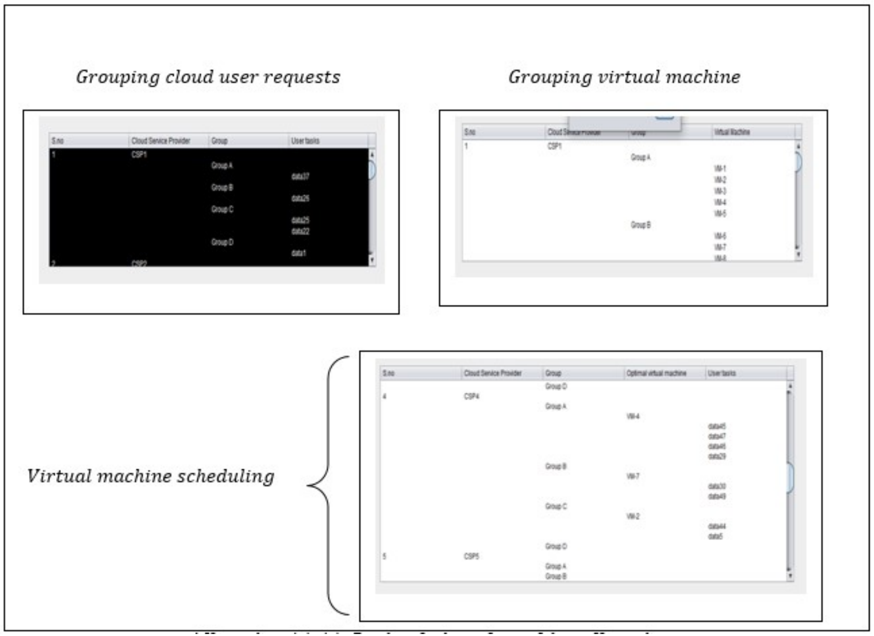

Figure 6. Allocation (a) (c) Optimal virtual machine allocation

As shown in the above figure 6 (a), first, cloud user requests are placed in to four different groups (i.e., '$Group\ A$', '$Group\ B$', '$Group\ C$' and '$Group\ D$') according to their services requested. This is performed by first applying the regression function to evaluate the overload at each virtual machine and accordingly grouping is performed based on similar service requests. Next, the virtual machines are grouped (as in figure 6 (b)) according to their availability taking into consideration the time and functions being performed by employing probability matrix. Finally, the actual optimal scheduling of the virtual machine by the cloud service provider using the argmax function results is shown in figure 6 (c).

V. RESULTS AND DISCUSSIONS

5.1 Analysis of Accuracy

Appropriate scheduling of cloud users with the respective virtual machine by the cloud service providers result in the optimal allocation in cloud data center. In other words, during scheduling and allocation of virtual machines to the corresponding cloud user requested with the services, accuracy plays the major role for IoT based distributional services. The accuracy is mathematically expressed as given below.

$$A = \sum_{i=1}^{n} \frac{CU_{ac}}{CU_i} * 100 \qquad (12)$$

From the above equation (12), the accuracy 'A' is measured based on the cloud users accurately assigned with the virtual machine 'CU_{ac}' and the total cloud users considered for simulation setup 'CU_i'. It is measured in terms of percentage (%). Table 1 given below shows the accuracy using three different methods.

Table 1- Comparison of accuracy using RR-LGDBNC, machine learning-based health care monitoring [1], Cognitive Smart Healthcare [2]

Cloud users	Accuracy (%)		
	RR-LGDBNC	machine learning-based health care monitoring	Cognitive Smart Healthcare
50	88	84	80
100	86.35	83.55	79.55
150	86	81.25	79.25
200	85.85	80.85	79
250	85	79.55	75.45
300	84.65	79.25	75.25
350	84.15	78	75
400	82.13	77.55	74.35
450	82	76.35	73.55
500	80.15	75	73.15

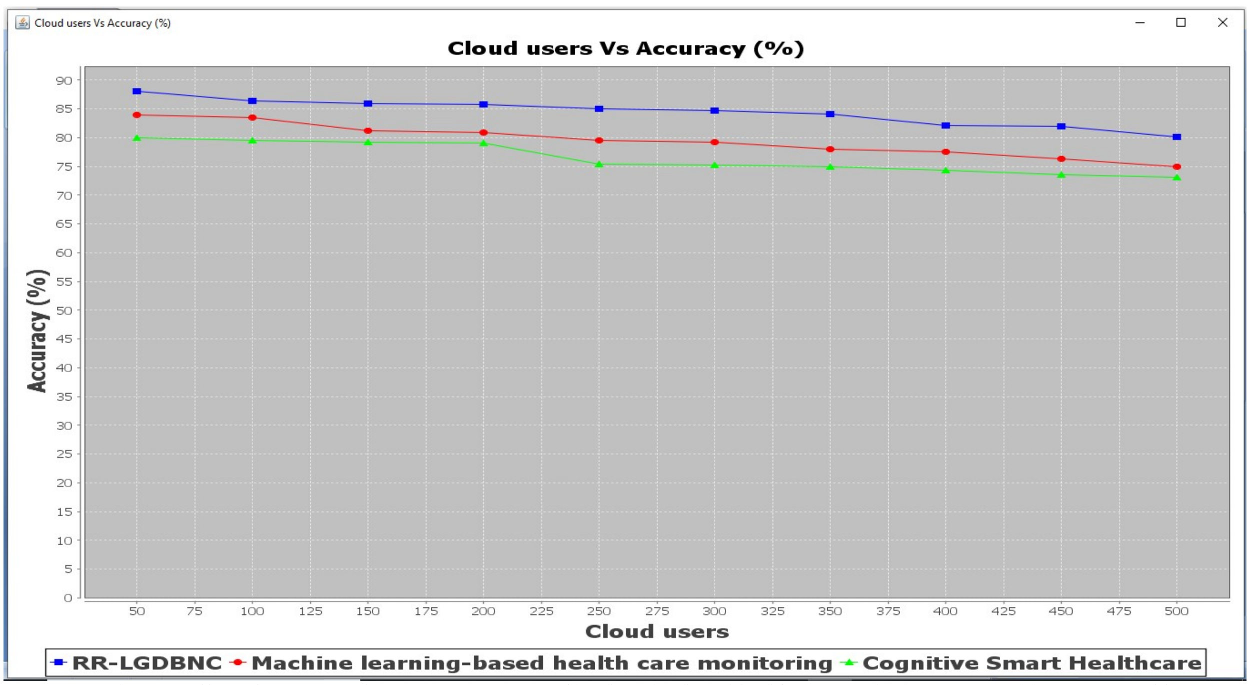

Figure 7 Effect of accuracy using RR-LGDBNC, machine learning-based health care monitoring [1], Cognitive Smart Healthcare [2]

Figure 7 given above shows the accuracy of Classifier for IOT based Prana Healing Distributional Services. From the figure the accuracy is inversely proportional to the number of cloud users or increasing the number of cloud users causes a significant number of cloud user requests being placed in the cloud data center and hence a gradual decrease in the accuracy rate. However, with experiments conducted using '50' different unique cloud user request services placed in IoT cloud environment, '44' cloud users request accurately assigned with the respective virtual machine using RR-LGDBNC, '42' cloud users request accurately assigned with the respective virtual machine using [1] and '40' cloud users request accurately assigned with the respective virtual machine using [2], the accuracy rate was found to be '88%', '84%' and '80%' respectively.

With this the accuracy was found to be better using RR-LGDBNC upon comparison with [1] and [2]. The rationale following the improvement in the accuracy was due to the utilization of local regression function in the Dynamic Regression and Reinforced Virtual Machine Allocation algorithm. By applying this function, the virtual machine with minimum migration rate is returned by the cloud user and scheduled to the respective cloud user in an optimal manner. This in turn increased the accuracy involved in cloud user requests being assigned with the respective virtual machine by cloud service provider using RR-LGDBNC by 6% compared to [1] and 10% compared to [2].

5.2 Analysis of sensitivity

Sensitivity measures the ratio of positives that are correctly identified (i.e. the proportion of those who have some condition (i.e., virtual machine allotted with respective cloud user services request). In other words, for IoT-based prana healing distribution services, sensitivity is a measure of how well a test (i.e., virtual machine scheduling) can identify true positives (i.e., optimal virtual machine allocation). It is the percentage ratio of true positives out of all the samples (i.e., total number of cloud user request services) that have the condition (optimal virtual machine allocation and non-allocation of virtual machine). This is mathematically expressed as given below.

$$Sen = \frac{TP}{TP+FN} \tag{13}$$

From the above equation (13), the sensitivity rate 'Sen', is measured on the basis of the true positive rate 'TP' and the false negative rate 'FN' respectively. It is evaluated in terms of percentage (%).Table 2 given below shows the sensitivity using three different methods.

Table 2 Comparison of sensitivity using RR-LGDBNC, machine learning-based health care monitoring [1], Cognitive Smart Healthcare [2]

Cloud users	**Sensitivity (%)**		
	RR-LGDBNC	machine learning-based health care monitoring	Cognitive Smart Healthcare
50	94	90	86
100	93.85	89.95	85.25
150	91	89.55	85.15
200	90.85	88.15	85
250	90.35	88	84.85
300	90	87.55	84.35
350	89.55	87.35	84
400	89	87	82.15
450	88.65	86.55	82
500	88	86	81.35

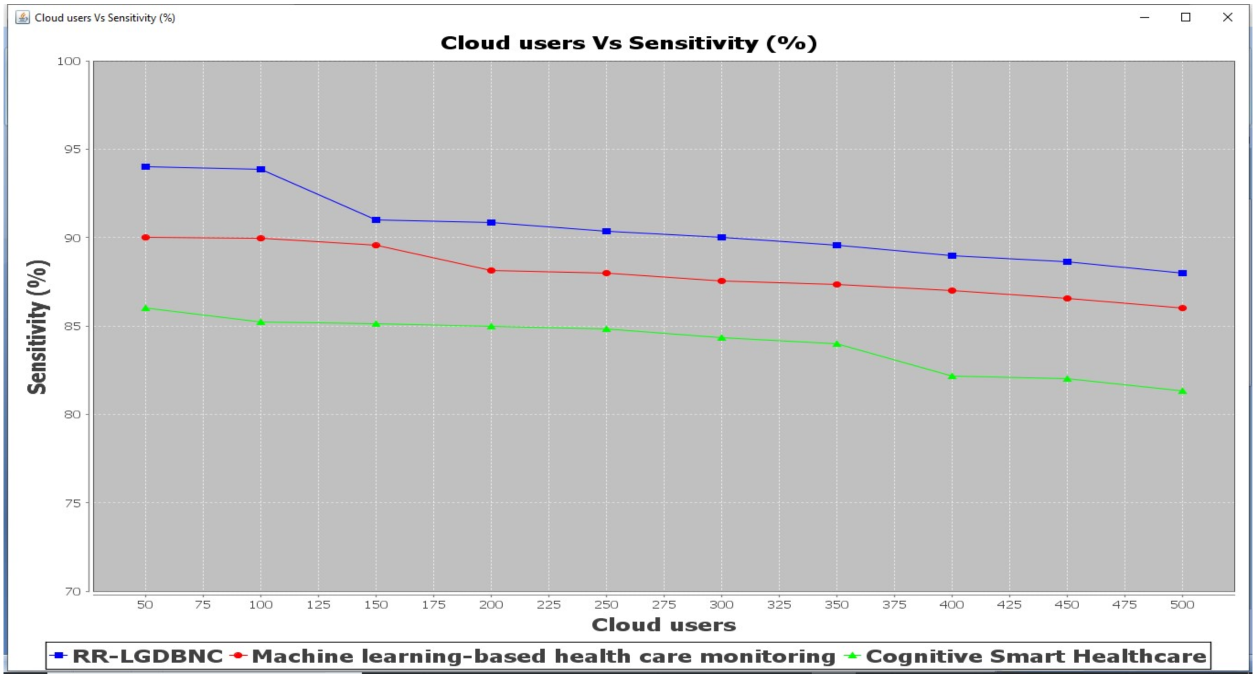

Figure 8 Effect of sensitivity using RR-LGDBNC, machine learning-based health care monitoring [1], Cognitive Smart Healthcare [2]

Figure 8 given above shows the influence of sensitivity rate for 500 different cloud user request services acquired at different time intervals by the cloud service provider for optimal scheduling of virtual machines. From the figure it is inferred that the sensitivity involved in optimal virtual machine scheduling for IoT based pranic healing distributional services reduces with the increase in the number of cloud user requests. This is because by increasing the cloud user services request a small amount of overload is said to take place at the data center while scheduling the virtual machine by the cloud service provider and therefore causes a decrease in the sensitivity rate also.

However, for a simulation of '50' cloud user requests placed in the cloud data center, '47' cloud user requests services were properly being scheduled by the cloud service provider using RR-LGDBNC, '45' cloud user requests services were properly being scheduled using [1] and '43' cloud user requests services were properly being scheduled using [2]. In addition, '3' cloud user requests services were not being scheduled by the cloud service provider using RR-LGDBNC, '5' cloud user requests services were not being scheduled using [1] and '7' cloud user requests services were not being scheduled using [2]. From the results it is inferred that the sensitivity using RR-LGDBNC is comparatively greater than [1] and [2]. The reason behind the improvement is because of the application of Dynamic Regression and Reinforced Virtual Machine Allocation model. With this model, switching between virtual machine in case of overloading is performed in an optimal manner, therefore increasing the accuracy rate using RR-LGDBNC by 3% when compared to [1]. Moreover, by applying the Randomized Markov Regression function, the virtual machine with minimum load is being utilized with the higher probability of scheduling with the respective cloud users request. With this, the sensitivity rate is said to be improved using RR-LGDBNC by 8% compared to [2] respectively.

5.3 Analysis of Response Time

Finally, the time taken to respond by the cloud user for each request is evaluated. In other words, the cloud user requested services have to manage service request allocation under response time. This is mathematically expressed as given below.

$$RT = \sum_{i=1}^{n} CU_i * Time\left[CU\left[request\ services\right]\right] \quad (14)$$

From the above equation (14), the response time 'RT' is measured based on the number of cloud users request services being considered for simulation 'CU_i' and the time consumed in allocating the request services of each cloud user by the cloud service provider '$Time\left[CU\left[request\ services\right]\right]$'. It is measured in terms of milliseconds (ms). Table 3 given below shows the response time using three different methods.

Table 3 Comparison of response time using RR-LGDBNC, machine learning-based health care monitoring [1], Cognitive Smart Healthcare [2]

Cloud users	Response time (ms)		
	RR-LGDBNC	machine learning-based health care monitoring	Cognitive Smart Healthcare
50	2.625	3.0755	4.175
100	3.155	4.135	5.235
150	4.215	6.235	8.145
200	4.835	6.455	8.215
250	5.215	7.135	8.355
300	5.535	7.245	10.235
350	6.155	8.355	11.145
400	8.325	10.145	12.355
450	10.455	12.355	13.455
500	12.355	14.155	15.415

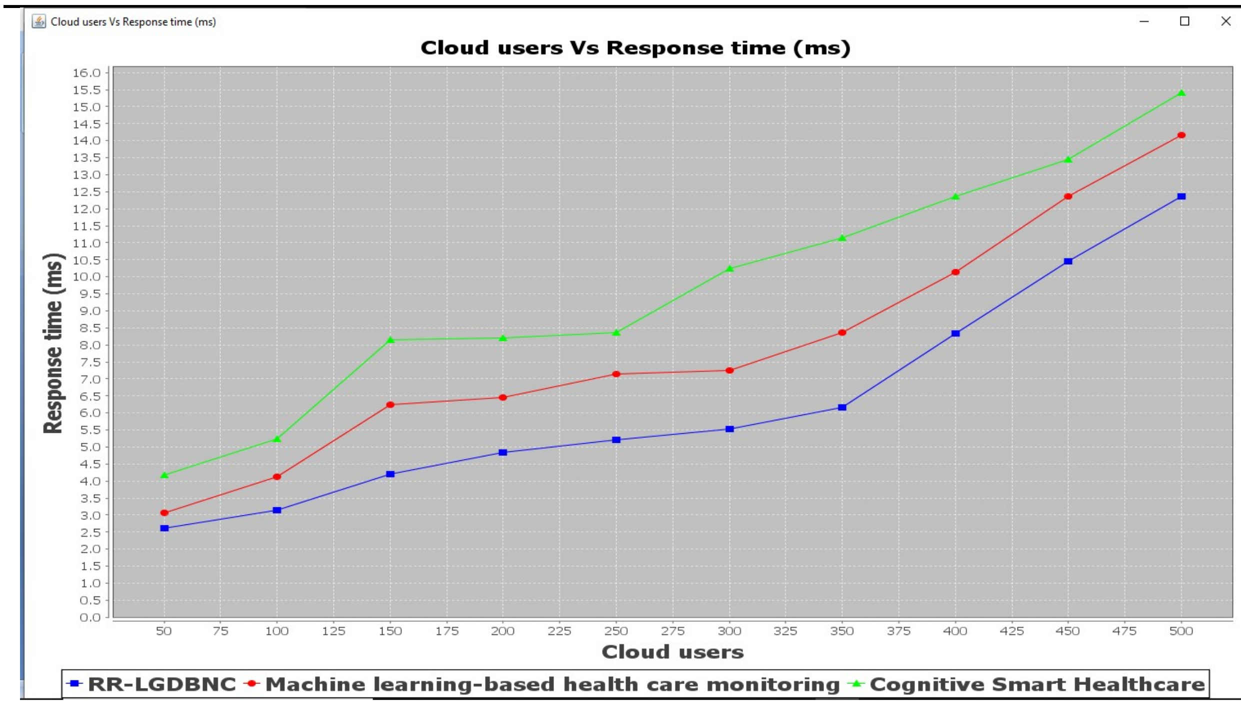

Figure 9 Effect of response time using RR-LGDBNC, machine learning-based health care monitoring [1], Cognitive Smart Healthcare [2]

Figure 9 given above shows the response time for IOT based Pranic Healing Distributional Services. From the figure, x axis refers to the cloud user requests placed in the range of 50 to 500 and y axis refers to the response time measured in terms of milliseconds. From the figure, increasing the number of cloud user requests causes an increase in the rendering of services by the cloud service provider and therefore an increase in the virtual machine scheduling. This is in turn increases the response time also. With '50' cloud user requests for virtual machines, the time consumed in allocating the virtual machine by the cloud user using RR-LGDBNC was found to be '$0.0525ms$', the time consumed in allocating the virtual machine by the cloud user using [1] was found to be '$0.0615ms$' and the time consumed in allocating the virtual machine by the cloud user using [2] was found to be '$0.0835ms$'. With this the overall response time was observed to be '$2.625ms$', '$3.0755ms$' and '$4.175ms$' respectively. The reason behind the reduced response time using RR-LGDBNC was due to the application of Logistic Gaussian-based Convolutional Deep Belief Neural Classifier. By applying this algorithm, an appropriation probability was first estimated separately with which optimal cloud user request services were grouped and then accordingly scheduled with the respective virtual machine by the cloud service provider that in turn minimizes the response time using RR-LGDBNC by 22% compared to [1] and 37% compared to [2] respectively.

VI. CONCLUSION

This paper presents a deep belief neural classifier for IoT based prana healing distributional services using cloud environment. In this paper, first, Logistic Gaussian-based Convolutional Deep Belief Neural Classifier model based on the logistic regression and difference of Gaussians is proposed to reduce the response time involved in scheduling the respective virtual machine to the cloud user requests. Next, Dynamic Regression and Reinforced Virtual Machine Allocation model is proposed to improve accuracy and sensitivity for appropriation and scheduling of cloud user requests in an optimal manner. The efficiency of RR-LGDBNC method is estimated in terms of accuracy, sensitivity and response time compared with state-of-the-art works. The simulation results shows that the RR-LGDBNC method presents better performance with an enhancement of accuracy, sensitivity and minimization of response time for cloud service rendering when compared to the state-of-the-art works.

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