Adaptive Discriminant Quadratic Boosting Classification Based Radix Hash Data Storage for Context Aware Cloud IoT Services

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ABSTRACT
Internet-of-Things (IoT) promises to give services to the users through connecting physical things using Internet. The conventional context aware system collects the data from users and stores it in cloud server. But, accuracy of classifying collected data using existing method was poor to store the user data with lower space complexity and to respond the user needed services with minimal time. In order to solve the above drawbacks, an Adaptive Discriminant Quadratic Boosting Classification based Radix Hash Cloud Data Storage (ADQBC-RHCDS) Model is proposed. The ADQBC-RHCDS Model is designed for providing the context aware IoT services to the cloud users with minimal response time and space complexity. In ADQBC-RHCDS model, Internet-of-Things (IoT) afford the services to the end cloud users by connecting an entity (i.e., person, place, or object) with sensors through Internet. Context Aware IoT helps to monitor and gather the information from users. After collecting the information, it is forwarded to the cloud server. Followed by, the cloud server classifies the collected information by designing Adaptive Discriminant Quadratic Boosting Ensemble Classifier (ADQBEC). After that, the classified data gets stored in the Radix Hash Tree Based Secured Cloud Data Storage (RHT-SCDS) for easy data access. Radix Hash Tree is a search tree used to store a set of data. Whenever the cloud user needs to access the data (i.e. insert or delete data), user sends the request to the cloud server. Then, cloud server provides the required services to the cloud user with minimal response time. Experimental evaluation of ADQBC-RHCDS model is carried out on factors such as classification accuracy, space complexity, and response time. The experimental result shows that the ADQBC-RHCDS model is able to reduce the space complexity and response time of context aware IoT services to the cloud users when compared to state-of-the-art works.
Keywords: Adaptive Discriminant Analysis, Cloud Users, Hash Value, Internet-of-Things, Quadratic Boosting, Radix Hash Tree, Strong Classifier

I. INTRODUCTION

In cloud computing, context-aware system gives needed services to users through the Internet of things (IoT) environment where context data are collected from a huge number of sensors, and this context data are part of the context-awareness services provided to the users. The Internet of Things (IoT) is a vision in which each device connected with computing technology to commune with one another through the Internet. The IoT devices operate as a significant role in enhancing quality of life in different applications for example smart living, transportation, education, agriculture, industry etc. Because of the technological improvement of the mobile devices, a novel application domain has emerged, called context-aware computing, in which the system can make use of environmental information from gathered sensor data and respond accordingly without need of any user involvement.

Internet-of-Things (IoT) afford the services to the cloud users by means of connecting an entity with sensors using Internet. Context Aware IoT helps to monitor and collect the relevant context information to the users where relevance is based on the user task. After gathering the information, it is transmitted to the cloud server. Then, the cloud server (CS) categorizes the collected information based on the context. Few research works have been designed for classifying the collected data. However, classification performance was poor and minimizing the response time and space complexity of context aware cloud IoT service provisioning was not solved. In order to addresses this limitation, ADQBC-RHCDS Model is proposed in this research work.

A lightweight context-aware IoT service architecture (LISA) was designed in [1] to render IoT push services in an efficient manner with a minimal space and time complexity. But, classifying the collected data was remained open issue in order to attain better context aware cloud IoT service provisioning. A new Hierarchical Cloud Computing Architecture was introduced in [2] for context-aware IoT services. However, space complexity during IoT service rendering process was more.

An end-to-end energy model was introduced in [3] for Edge Cloud-based IoT platforms. But, the energy efficiency of cloud infrastructures was not improved for small-sized data centers to limit IoT on global energy consumption. But, time and space complexity was not considered. A resource-aware virtual machine migration technique was introduced in [4] where sudden change in sensing environment was examined through clustering the servers. However, the energy efficiency of the cloud data center was not improved.

Constrained Application Protocol (CoAP) was designed in [5] to obtain connected to each other through the Internet. But, prototype of system was not developed for commercial deployment using CoAP. A novel framework was introduced in [6] for accomplishing cloud-based context-aware internet of things services in smart cities with a minimal time. However, scalability of this framework was lower.

A new framework was presented in [7] for rendering efficient context-aware trust-based personalized services with higher accuracy using internet of things. However, response time was not reduced. The context aware service discovery architecture was designed in [8] to analyze and understands the context based on the submitted users request and affords the users with the relevant information and services. But, the amount of memory space taken for storing user data was higher.

Context-aware and self-adaptive security management model was developed in [9] for rendering IoT-Based eHealth services. However, secured data storage was not obtained. A decentralized semantics-based service discovery framework was employed in [10] to efficiently find trustworthy services depend on requester's quality of service demands and changing context necessities. But, the amount of time utilized to respond the user requested services was more.

In order to addresses the above mentioned conventional issues, ADQBC-RHCDS Model is introduced in this research work. The main contribution of ADQBC-RHCDS Model is described in below.

- ✓ To increases the classification performance of context aware cloud IoT service provisioning with a minimal false positive rate when compared to conventional works, Adaptive Discriminant Quadratic Boosting Ensemble Classifier (ADQBEC) is designed in ADQBC-RHCDS Model. On the contrary to traditional works, ADQBEC measures quadratic loss for k number of weak ADA classification results and consequently combines all the results together to identify strong classifier. Hence, ADQBEC provides higher classification accuracy to give better context aware cloud IoT services as compared to existing works.

- ✓ To minimize the space complexity and response time of context aware cloud IoT service rendering when compared to state-of-the-art works, Radix Hash Tree Based Secured Cloud Data Storage (RHT-SCDS) is proposed in ADQBC-RHCDS Model. RHT-SCDS is a type of binary tree that allows very quick searching and also support insertion, deletion operations. Insertion adds a new data to the radix hash tree data structure and thereby diminishes the amount of data stored. Deletion eliminates a hash value from the radix hash tree data structure. From that, RHT-SCDS obtains minimal space complexity and lower amount of time to respond to demanded services of cloud users when compared to traditional works.

The rest of the paper is formulated as follows; In Section 2, ADQBC-RHCDS Model is explained with help of architecture diagram. In Section 3, experimental settings are described and the performance result of ADQBC-RHCDS Model is discussed in Section 4. Section 5 portrays the related works. Section 6 depicts the conclusion of the paper.

II. ADAPTIVE DISCRIMINANT QUADRATIC BOOSTING CLASSIFICATION BASED RADIX HASH CLOUD DATA STORAGE MODEL

The Adaptive Discriminant Quadratic Boosting Classification based Radix Hash Cloud Data Storage (ADQBC-RHCDS) Model is introduced with aiming at enhancing the performance of context aware IoT services in cloud environment through classification. On the contrary to conventional works, ADQBC-RHCDS Model is developed by combining Adaptive Discriminant Quadratic Boosting Ensemble Classifier (ADQBEC) and Radix Hash Tree Based Secured Cloud Data Storage (RHT-SCDS). To enhance the classification performance of collected data with a minimal false positive rate, ADQBEC algorithm is proposed in ADQBC-RHCDS Model using quadratic boosting ensemble technique. In addition to that, RHT-SCDS is a space-efficient data structure for storing set of classified user data on cloud server and where data access is very speedy. Therefore, ADQBC-RHCDS Model minimizes space complexity and response time during context aware IoT service provisioning when compared to existing works. The architecture diagram of proposed ADQBC-RHCDS Model is depicted in below Figure 1.

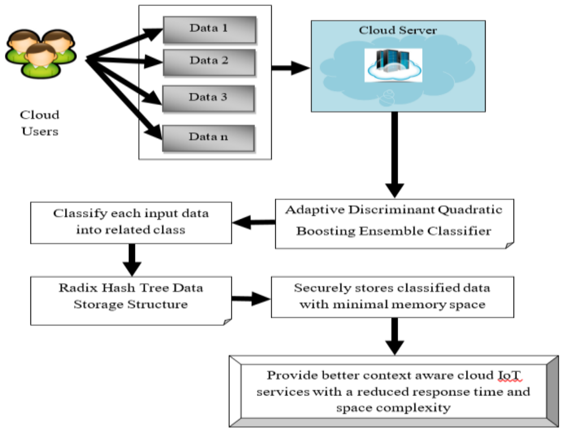

Figure 1 Architecture Diagram of ADQBC-RHCDS Model for Context Aware Cloud IoT Services

Figure 1 shows architecture diagram of ADQBC-RHCDS Model to get enhanced context aware IoT services provisioning performance in cloud environment. As depicted in the above figure, ADQBC-RHCDS model, initially monitor and collect the relevant context data from different users. After collecting the information, it is send to the cloud server. Then, the cloud server (CS) categorizes the collected information. To accurately classify gathered data, ADQBC-RHCDS Model applies Adaptive Discriminant Quadratic Boosting Ensemble Classifier on the contrary to conventional works. After classification process, ADQBC-RHCDS model securely stores classified data with minimal amount of memory space with help of Radix Hash Tree Based Secured Cloud Data Storage (RHT-SCDS). Therefore, ADQBC-RHCDS model provides better context aware IoT services rendering performance in terms of classification accuracy, response time and space complexity. The detailed processes of ADQBC-RHCDS model is shown in below subsections.

A. Adaptive Discriminant Quadratic Boosting Ensemble Classifier

In ADQBC-RHCDS Model, cloud server classifies each collected data of users in cloud environment based on the context by designing a new Adaptive Discriminant Quadratic Boosting Ensemble Classifier (ADQBEC). On the contrary to traditional works, ADQBEC is proposed by applying quadratic boosting concepts in adaptive discriminant classifier. The proposed ADQBEC operates through designing a number of intermediate learners (i.e. weak classifier) on combined linear and quadratic terms. In ADQBEC algorithm, a training data (i.e., information collected from cloud user) is considered as an input for the weak learner (i.e., Adaptive Discriminant Analysis (ADA)). A class label gets repeatedly updated in each round. The quadratic boosting algorithm converges under condition where the given base learner reduces the error during classification. From that,ADQBEC algorithm increases the classification performance in order to accurately categories collected data of users in cloud environment with a minimal time complexity. The process involved in ADQBEC algorithm is demonstrated in below Figure 2.

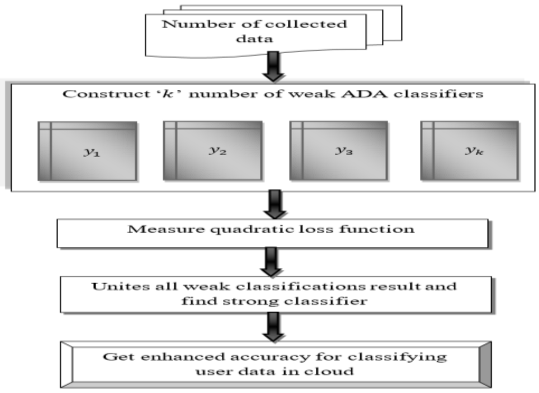

Figure 2 Block Diagram of Adaptive Discriminant Quadratic Boosting Ensemble Classifier

Figure 2 depicts the flow processes of ADQBEC algorithm to minimize the error rate of data classification during context aware IoT cloud services. As presented in the above figure, ADQBEC algorithm initially gets number of collected data from cloud user as input. Subsequently, ADQBEC algorithm generates 'k' number of weak ADA classifier result for each collected data from user in cloud environment. The weak ADA classification process is carried out in two steps. In the first step, weak ADA classifier finds similar data (referred to as neighbors). For each discovered similar data, then weak ADA classifier determines a weight. In the second step, the within-class scatter matrix of the 'i^{th}' data is calculated via a linear combination of the within-class scatter matrix of the chosen neighbors in the first step with help of the linear weights. Let us consider an input collected data are represented as'$\{d_1, d_2, .., d_n\}$'. The weak ADA classifier at first finds k nearest neighbors for each input collected data 'd_i' of cloud users with help of Euclidean distance measurement using below mathematical expression,

$$D(d_i, d_j) = \sqrt{\sum_{i=1}^{n}(d_i, d_j)^2} \quad (1)$$

By using the above mathematical expression (1), base ADA classifier discovers k nearest neighbor for each input data. After determining the finds k nearest neighbors, weight is assigned for each collected data. Subsequently, intra-class scatter matrix is mathematically measured for each data 'd_i' using below,

$$\sum_{\alpha} = \sum_{i=1}^{n}(d_i - \mu_i)(d_i - \mu_i)^T \quad (2)$$

From the above mathematical formula (2), 'μ_i' indicates sample mean of the 'k^{th}'class. Followed by inter-class scatter matrix for each collected data 'd_i' is mathematically computed as follows,

$$\sum_{\beta} = \sum_{k=1}^{n} k(\mu_i - \omega)(\mu_i - \omega)' \quad (3)$$

From the above mathematical equation (3), 'k' represents the number of training samples in each class in which 'm' denotes the number of classes and 'μ_i' refers to the mean for each class. Here, 'ω' indicates total mean which is mathematically determined using below formulation,

$$\omega = \frac{1}{n}\sum_{k=1}^{n} K_{I_i}\mu_i \qquad (4)$$

Then, weak ADA classifier apply the linear discriminant analysis in order to increases ratio of the determinant of the inter-class scatter matrix of the projected data to the intra-class scatter matrix of the projected data using below expression,

$$S(\phi) = arg \max_{\phi} \frac{\phi^T \Sigma_\beta \phi}{\phi^T \Sigma_\alpha \phi} \qquad (5)$$

From the above mathematical formula (5), '$S(\phi)$' denotes class separability function where 'ϕ' represents linear transformation. By using the above process, weak ADA classifie
r categorizes each input data 'd_i' into a corresponding class 'C_i'. However, classification accuracy of weak ADA classifier was not adequate to attain better context aware IoT cloud service provisioning. To enhance the classification performance with a minimal false positive rate, ADQBEC algorithm is designed in ADQBC-RHCDS Model using quadratic boosting ensemble technique. The ADQBEC algorithm initially obtains 'k' number of weak ADA classifier result for each collected data. Subsequently, the ADQBEC algorithm computes the training error for each weak ADA classifier result with the aid of quadratic loss function. In ADQBEC algorithm, quadratic loss function determines how accurate a predictive model (i.e. weak ADA classifier).

Quadratic loss function is calculated by taking the dissimilarity between the predicted result and the actual result. From that, quadratic error between the actual and predicted output is mathematically calculated using below expression,

$$Q_e = \sum_i \left(y_a\,(d_i) - y_p\,(d_i)\right)^2 \qquad (6)$$

From the above mathematical representation (6), 'Q_e' signifies a quadratic loss function of the weak ADA classifier whereas '$y_a\,(d_i)$' denotes the actual output and '$y_p\,(d_i)$' represents a predicted output. After that, all weak ADA classifier results are combined with help of below mathematical formulation,

$$z = \sum_{i=1}^{k} y_i\,(d_i) \qquad (7)$$

From the above mathematical formulation (7), 'z' represents the result of strong classifier and '$y_i\,(d_i)$' denotes a result of weak ADA classifier. After combining the weak classifiers result, the proposed ADQBEC algorithm determines the weak ADA classifier with a minimal quadratic loss function as a strong classifier to exactly classify each collected data using below

$$z = \arg min\, Q_e\,(y_i\,(d_i) \qquad (8)$$

From the above mathematical equation (8), '$\arg min$' help to find the strong classifier with a lower quadratic loss function. By using the above mathematical formula, ADQBEC algorithm correctly classifies each collected data into a consequent class with lower time utilization. From that, ADQBEC algorithm significantly performs data classification with a lower false positive rate during context aware IoT service provisioning in cloud environment.

The algorithmic process of ADQBEC algorithm is explained in below,

// **Adaptive Discriminant Quadratic Boosting Ensemble Classifier Algorithm**
Input: Collected Data‘$\{\boldsymbol{d_1}, \boldsymbol{d_2}, .., \boldsymbol{d_n}\}$’
Output: higher classification accuracy for providingcontext aware cloud IoT service
Step 1: Begin
Step 2: For each collected data ‘$\boldsymbol{d_i}$’
// Weak ADA classifier
Step 3: Measure distance between data using (1)
Step 4: Discover k nearest neighbors
Step 5: Computeintra-class scatter matrix using (2)
Step 6: Determineinter-class scatter matrix using (3)
Step 7: Classify data into a related class using (5)
Step 8: End For
// Apply Quadratic Boosting
Step 9: Obtain ‘$\boldsymbol{k}$’ number of weak ADA classifier result
Step 10: Measure Quadratic loss function using (6)
Step 11: Ensembles all weak ADA classifier results using (7)
Step 12: Discover strong classifier using (8)
Step 13: Accuratelyclassify data into a corresponding class
Step 14: End For
Step 15:End

Algorithm 1 Adaptive Discriminant Quadratic Boosting Ensemble Classifier

Algorithm 1 shows the step by step processes of ADQBEC algorithm to get enhanced classification accuracy for context aware cloud IoT service rendering. As demonstrated in above algorithmic steps, ADQBEC algorithm at the beginning obtains ‘k’ number of weak ADA classifier result for each collected data from different users in cloud. Next, ADQBEC algorithm estimates quadratic loss function for each obtained weak ADA classifier result. Consequently, ADQBEC algorithm unites results of all weak ADA classifier together and thereby designs weak ADA classifier with minimal quadratic loss function as strong classifier. Finally, strong classifier in ADQBEC algorithm precisely classifies all the input collected data gathered from diverse users in cloud environment with a lower time when compared to state-of-the-art works. As a result, proposed ADQBC-RHCDS Model gives higher classification accuracy and minimal response time to render the required services to cloud users when compared to conventional works.

B.Radix Hash Tree Based Secured Cloud Data Storage

After completing the classification process, ADQBC-RHCDS Model designs Radix Hash Tree Based Secured Cloud Data Storage (RHT-SCDS) algorithm in order to securely store the classified data of users on cloud server with a lower space complexity. The propsoed RHT-SCDS is a tree data structure that is utilized to store a set of data by generating a hash value. Besides to that, RHT-SCDS is a compact Prefix tree and also a space-efficient representation for storing set of classified user data on cloud server in which searching is very fast with minimum time complexity of O (n). Here ‘n’ is the length of data stored on it memory. The RHT-SCDS is easy to understand as a space-optimized tree in which each node with only one child is combined with its child. The result is that every internal node of RHT-SCDS contains at least two children. The block diagram of RHT-SCDS algorithm is presented in below Figure 3.

Figure 3 presents the process involved inRHT-SCDS algorithm for achieving secured cloud data stroage with a lower space complexity during context aware cloud IoT service provisioning process. As depicted in the above figure, RHT-SCDS takes number of classified data as input which are indicated as ‘$D_i = D_1, D_2, \dots D_n$’. The RHT-SCDS is proposed with aiming at enhancing cloud data storage performance with higher security and minimal space complexity. The RHT-SCDS initially builds the radix hash tree with a number of nodes to store classified data with help of below mathematical expression,

$$RHT \rightarrow \{\varphi_1, \varphi_2, \dots \varphi_n\} \quad (9)$$

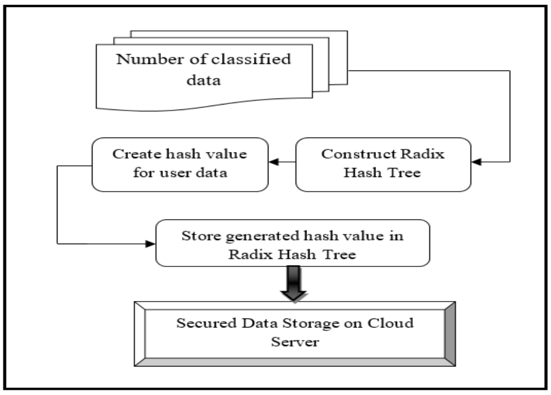

Figure 3 Flow Processes of Radix Hash Tree Based Secured Cloud Data Storage

From the above mathematical formula (9), ‘φ_n’ point outs the number of nodes constructed in radix hash tree data structure. After designing the radix hash tree, RHT-SCDS stores classified data of cloud users in the form of hash value with help of insertion operation in order to decreases space complexity involved during context aware cloud IoT service provisioning process. For each input

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classified data of cloud user 'D_i', then RHT-SCDS generate hash value using below mathematical equation,

$$Hash\ value \rightarrow H(D_i) \tag{10}$$

From the above mathematical expression (10), ' $H(D_i)$' refers to the generated hash value of input classified data 'D_i'. The RHT-SCDS generates distinctive hash value for each input classified data. Subsequently, RHT-SCDS stores hash values of classified user data in it radix hash tree using below mathematical representation,

$$Ins\ (H(D_i)) \rightarrow RHT(\varphi_i) \tag{11}$$

By using the above mathematical formulation (11), RHT-SCDS stores all the input classified data from cloud users with a lower amount of memory and higher security. Here, 'ins' denotes insertion operation which supports for RHT-SCDS to store hash values of data whereas '$RHT(\varphi_i)$' represents nodes of radix hash tree. The proposed RHT-SCDS also supports delete operation where it efficiently removes the stored data on cloud server. From that data deletion operation from radix hash tree data structure is mathematically performed using below,

$$Del\ (H(D_i)) \rightarrow RHT(\varphi_i) \tag{12}$$

From the above mathematical equation (12), 'del' refers to the deletion operation which help for RHT-SCDS to delete hash value of input data '$H(D_i)$' that stored on radix hash tree data structure '$RHT(\varphi_i)$'. Through performing an insertion and deletion process with a minimal time, the proposed RHT-SCDS provides required services to cloud users with lower response time when compared to conventional works.

The algorithmic processes of RHT-SCDS are explained in below.

// Radix Hash Tree Based Secured Cloud Data Storage Algorithm
Input: Number Of classified User Data '$D_i = D_1, D_2, \dots D_n$'
Output: Reduce space complexity and response time of context aware cloud IoT service provisioning
Step 1: **Begin**
Step 2: Design Radix Hash Tree using (9)
Step 3:For each classified user data 'D_i'
Step 4: Create hash value using (10)
Step 5: Store hash value of 'D_i'in Radix

Hash Tree structure using (11)
Step 6: **If** user want to delete data stored on cloud server**, then**
Step 7: Remove hash value of data using (12)
Step 8: **End If**
Step 9: **End for**
Step 10:End

Algorithm 2 Radix Hash Tree Based Secured Cloud Data Storage

Algorithm 2 shows the step by step processes of RHT-SCDS. By using the above algorithmic processes of RHT-SCDS, ADQBC-RHCDS Model effectively accomplish insertion and deletion operations in order to securely save the classified data collected from different users in cloud environment using IoT with a minimal time complexity. From that, ADQBC-RHCDS Model provides the needed context aware cloud IoT services with reduced space complexity and response time when compared to conventional works.

III. EXPERIMENTAL SETTINGS

In order to estimate the performance of proposed, ADQBC-RHCDS Model is implemented in Java Launguage using CloudSim simulator with help of Amazon EC2 Dataset. By using Amazon EC2 Dataset, data are collected from cloud users to store and access data at anytime from anywhere through the internet of things. The ADQBC-RHCDS Model considers different number of data and user requests from Amazon EC2 Dataset to perform experimental process. The effectiveness of ADQBC-RHCDS Model is determined in terms of classification accuracy, response time and space complexity. The perfomance of ADQBC-RHCDS Model is compared with two conventional methods namely Lightweight context-aware IoT service architecture namely (LISA) [1] and Hierarchical Cloud Computing Architecture (HCCA) [2].

IV. RESULT

In this section, the comparative result analysis of ADQBC-RHCDS Model is discussed. The experimental result of ADQBC-RHCDS Model is compared with Lightweight context-aware IoT service architecture namely (LISA) [1] and Hierarchical Cloud Computing Architecture (HCCA) [2] respectively using below metrics with the help of tables and graphs.

A. Measure of Classification Accuracy

In ADQBC-RHCDS Model, Classification Accuracy '(CA)' is determined as the ratio of number of collected data that are correctly classified to the total number of collected data considered for experimetnal process. The mathematical formula for measuring classification accuracy is shown in below,

$$CA = \frac{n_e}{n} * 100 \qquad (13)$$

From the above mathematical formula (13), classification accuracy is evaluated with respect to a diverse number of collected data from users in cloud. Here, 'n_e' indicates the number of collected data exactly classified and 'n' denotes the total number of collected data. The classification accuracy is determined in terms of percentages (%).

Sample Calculation:

- **ProposedADQBC-RHCDS:** number of collected data that are correctly classified is 21 and the total number of the collected data is 25. Then classification accuracy is obtained as follows,

$$CA = \frac{21}{25} * 100 = 84\%$$

- **Existing LISA:** number of collected data properly classified is 18 and the total number of collected data is 25. Then classification accuracy is estimated as follows,

$$CA = \frac{18}{25} * 100 = 72\ \%$$

- **Existing HCCA:** number of collected data accurately classified is 16 and the total number of collected data is 25. Then classification accuracy is formulated as follows,

$$CA = \frac{16}{25} * 100 = 64\%$$

The experimental result analysis of classification accuracy obtained during the processes of context aware cloud IoT service provisioning using three methods namely proposed ADQBC-RHCDS Model and conventionalLISA [1] and HCCA [2] is demonstrated in below Table 1.

Table 1 Tabulation for Classification Accuracy

Number of collected data (n)	Classification Accuracy (%)		
	ADQBC-RHCDS	LISA	HCCA
25	84	72	64
50	88	78	74
75	93	77	75
100	92	79	77
125	94	76	74
150	94	79	76
175	97	83	81
200	93	81	79
225	96	87	84
250	97	88	86

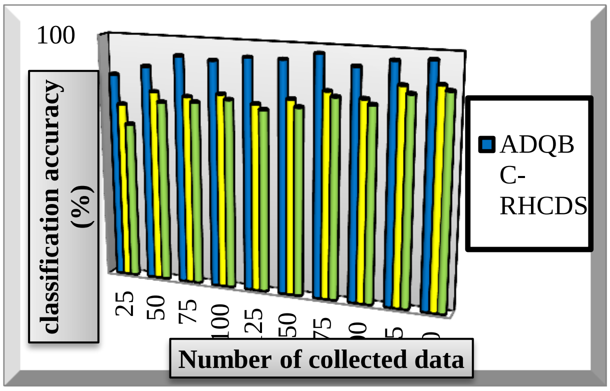

Figure 4 Measurement of Classification Accuracy versus Number of Collected Data

Figure 4 portrays impact of classification accuracy result based on diverse number of collected data in the range of 25-250 using three methods namely proposed ADQBC-RHCDS Model and state-of-the-artLISA [1] and HCCA [2]. As demonstrated in the above graphical figure, proposed ADQBC-RHCDS Model attains enhanced accuracy in order to perfectly classify each collected data into a correlated class with increasing number of collected data as input as compared to existing LISA [1] and HCCA [2]. This is owing to application of Adaptive Discriminant Quadratic Boosting Ensemble Classifier (ADQBEC) in proposed ADQBC-RHCDS Model on the contrary to conventional works.

By using ADQBEC algorithmic steps, proposed ADQBC-RHCDS Model initially gets 'k' number of weak ADA classifier output for all the collected data from dissimilar users in cloud environment. Subsequently, ADQBC-RHCDS Model evaluates quadratic loss function for each weak ADA classifier output. Then, ADQBC-RHCDS Model aggregates output of all weak ADA classifier together and thereby find outs weak ADA classifier with lower quadratic loss function as strong classifier. By using discovered strong classifier output, then ADQBC-RHCDS Model efficiently categories each data collected from cloud users into corresponding class. Thus, proposed ADQBC-RHCDS Model improves the ratio of number of collected data that are correctly classified as compared to other existing works [1] and [2]. As a result, proposed ADQBC-RHCDS Model increases the classification accuracy of context aware cloud IoT service rendering by 16 % and 21 % when compared to LISA [1] and HCCA [2] respectively.

B. Performance Result of Response Time

InADQBC-RHCDS Model, Response Time (RT) determines the amount of time utilized to respond the required services to cloud users from the cloud server. The response time is mathematically measured using below,

$$RT = n * Time(RSR) \tag{14}$$

From equation (14), the response time is calculated with respect to different of user request (n) for giving better context aware cloud IoT services whereas '$Time(RSR)$' indicates the time taken forresponding one user request. The response time is evaluated in terms of milliseconds (ms).

Sample Calculation:

- **Proposed ADQBC-RHCDS:** time used to respond the user requested services is 1.4 ms and the total number of the user request is 10. Then response time is obtained as follows,

$$RT = 1.4 * 10 = 14\, ms$$

- **Existing LISA:** time employed to respond the user demanded service is 1.7 ms and the total number of user the request is 10. Then response time is computed as follows,

$$RT = 1.7 * 10 = 17\, ms$$

- **Existing HCCA:** time consumed to respond the user requested services is 2.2 ms and the total number of user request is 10. Then response time is acquired as follows,

$$RT = 2.2 * 10 = 22\, ms$$

The comparative result analysis of response time acquired during the processes of context aware cloud IoT service rendering using three methods namely proposed ADQBC-RHCDS Model and existingLISA [1] and HCCA [2] is presented in below Table 2.

Table 2 Tabulation for Response Time

Number of user requests (n)	Response Time (ms)		
	ADQBC-RHCDS	LISA	HCCA
10	14	17	22
20	16	19	23
30	19	22	25
40	23	27	31
50	26	29	32
60	30	34	37
70	34	36	39
80	35	38	42
90	38	42	46
100	40	43	47

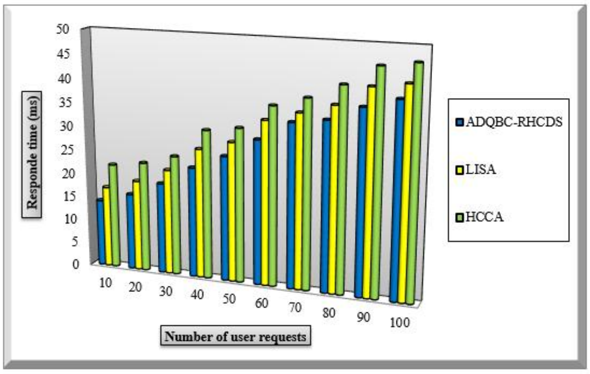

Figure 5 Measurement of Response Time versus Number of User Requests

Figure 5 shows impact of response time with respect to varied number of user requests in the range of 10-100 using three methods namely proposed ADQBC-RHCDS Model and existing LISA [1] and HCCA [2]. As presented in the above graphical representation, proposed ADQBC-RHCDS Model achives lower response time with increasing number of user requests as input as compared to conventional LISA [1] and HCCA [2]. This is due to application of Adaptive Discriminant Quadratic

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Boosting Ensemble Classifier (ADQBEC) and Radix Hash Tree Based Secured Cloud Data Storage (RHT-SCDS) algorithm in proposed ADQBC-RHCDS Model on the contrary to state-of-the-art works. With help of ADQBEC algorithmic concepts, proposed ADQBC-RHCDS Model identifies strong classifier in order to effectively classify each data collected from cloud users into consequent class with a minimal amount of time complexity.

Besides with the application of RHT-SCDS algorithm concepts, ADQBC-RHCDS Model securely stores all the collected data on cloud server with a lower amount of time. Further, RHT-SCDS algorithm supports for ADQBC-RHCDS Model to quickly access the user data stored on cloud server and thereby it reduces the time needed to render the requested services to users in cloud environment using IoT through insertion and deletion operation. Hence, proposed ADQBC-RHCDS Model reduces the amount of time utilized to respond the required services to cloud users from the cloud server when compared to other traditional works [1] and [2]. As a result, proposed ADQBC-RHCDS Model minimizes the response time of context aware cloud IoT service rendering by 11 % and 22 % when compared to LISA [1] and HCCA [2] respectively.

C. Performance Result of Space Complexity

In ADQBC-RHCDS Model, Space Complexity (SC) determines the amount of memory space utilized to store the classified data of users in the cloud server. The space complexity is mathematically calculated using below,

$$SC = n * Memory(SSU) \qquad (15)$$

From equation (15), space complexity involved during the context aware IoT cloud services is measured with respect to different numbers of cloud data 'n'. Here, '$Memory(SSU)$' denotes the memory space employed for storing single user data. The space complexity is estimated in terms of megabytes (MB).

Sample calculation:

- Proposed ADQBC-RHCDS: the memory space taken for storing single user data is 0.46 MB and the total number of user data is 25. Then space complexity level is calculated as follows,

$$SC = 25 * 0.46 = 23\ MB$$

- Existing LISA: memory space employed for storing single user data is 0.52 MB and the total number of data is 25. Then space complexity level is measured as follows,

$$SC = 25 * 0.52 = 26\ MB$$

- Existing HCCA: memory space used for storing single user data is 0.62 MB and the total number of data is 25. Then space complexity level is obtained as follows,

$$SC = 25 * 0.62 = 31\ MB$$

The tabulation result analysis of space complexity involved during the processes of context aware cloud IoT service provisioning using three methods namely proposed ADQBC-RHCDS Model and traditionalLISA [1] and HCCA [2] is depicted in below Table 3.

Table 3 Tabulation for Space Complexity

Number of User Data (n)	Space Complexity (MB)		
	ADQBC-RHCDS	LISA	HCCA
25	23	26	31
50	28	32	37
75	36	39	44
100	40	44	50
125	48	46	55
150	51	54	60
175	48	53	57
200	51	55	60
225	54	59	65
250	57	62	67

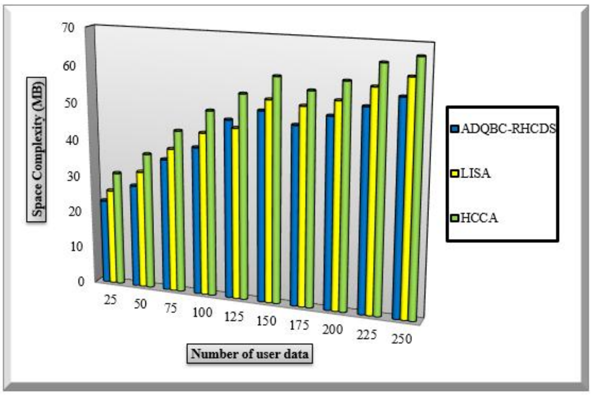

Figure 6 Measurement of Space Complexity versus Number of User Data

Figure 6 shows impact of space complexity with respect to varied number of user data in the range of 250-250 using three methods namely proposed ADQBC-RHCDS Model and existing LISA [1] and HCCA [2]. As presented in the above graphical representation, proposed ADQBC-RHCDS Model achives lower space complexity with increasing number of user data as input as compared to conventional LISA [1] and HCCA [2]. This is due to application of Radix Hash Tree Based Secured Cloud Data Storage (RHT-SCDS) algorithm in proposed ADQBC-RHCDS Model on the contrary to state-of-the-art works.

By using the RHT-SCDS algorithmic steps, proposed ADQBC-RHCDS Model efficiently index the classified data of users on cloud server. Simultaneously, RHT-SCDS algorithmis very space efficient and also addresses the issues of excessive worst-case space utilization through adaptively selecting compact and efficient data structures for internal nodes. Therefore, proposed ADQBC-RHCDS Model decreases the amount of memory space utilized to store the classified data of users in the cloud server when compared to other conventional works [1] and [2]. Thus, proposed ADQBC-RHCDS Model reduces the space complexity of context aware cloud IoT service provisioning by 8 % and 18 % when compared to LISA [1] and HCCA [2] respectively.

V. LITERATURE SURVEY

Adaptive and scalable trust management was carried out in [11] to give different service IoT systems with a lower computational complexity. ICON (IoT-based CONtext-aware) framework was employed in [12] for context-aware IoT applications for example smart home, further ICON leverages fog-based IoT middleware to carry out context-aware processing.

IOT Based HealthCare Remote Monitoring and Context-aware Appointment System was presented in [13] for protecting an individual's data and to get quickly treatment. Conceptual framework was introduced in [14] for performing cloud-based context-aware services. A novel service selection and recommendation model (SSRM) was presented in [15] in which user similarity is evaluated depends on user context information and interest. Semantic-based discovery service was implemented in [16] to solve resource requests requirement problem in IoT.

A review of different model designed for discovering objects and services in context-aware IoT environments was analyzed in [17]. A survey of various context aware computing models developed for The Internet of Things was presented in [18]. A novel multitier fog computing architecture was introduced in [19] for increasing IoT service provisioning performance. Context-aware cloud robotics (CACR) was presented in [20] to get better energy efficiency and to minimize cost.

VI. CONCLUSION

The ADQBC-RHCDS Model is designed with the goal of attaining improved context aware cloud IoT service provisioning performance via data classification and minimizing space complexity and response time. The goal of ADQBC-RHCDS Model is obtained with the assists of Adaptive Discriminant Quadratic Boosting Ensemble Classifier (ADQBEC) and Radix Hash Tree Based Secured Cloud Data Storage (RHT-SCDS). The proposed ADQBC-RHCDS Model enhances the ratio of number of collected data that are correctly classified as compared to other existing works. Also, proposed ADQBC-RHCDS Model minimizes the amount of time utilized to respond the required services to cloud users from the cloud server when compared to other traditional works. Furthermore, proposed ADQBC-RHCDS Model reduces the amount of memory space utilized to store the classified data of users in the cloud server when compared to other conventional works. The performance of ADQBC-RHCDS Model is estimated in terms of classification accuracy, response time and space complexity and compared with two conventional works. The experimental result illustrates that the proposed ADQBC-RHCDS Model gives better context aware cloud IoT service with minimization of response time and space complexity when compared to state-of-the-art works.

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