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Recommendation Model-Based 5G Network and Cognitive System of Cloud Data with AI Technique in IOMT Applications

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Abstract

Recommender system provides the significant suggestion towards the effective service offers for the vast range of big data. The Internet of Things (IoT) environment exhibits the value added application services to the customer with the provision of the effective collection and processing of information. In the extension of the IoT, Internet of Medical Things (IoMT) is evolved for the patient healthcare monitoring and processing. The data collected from the IoMT are stored and processed with the cognitive system for the data transmission between the users. However, in the conventional system subjected to challenges of processing big data while transmission with the cognitive radio network. In this paper, developed a effective cognitive 5G communication model with the recommender model for the IoMT big data processing. The proposed model is termed as Ranking Strategy Internet of Medical Things (RSIoMT). The proposed RSIoMT model uses the distance vector estimation between the feature variables with the ranking. The proposed RSIoMT model perform the recommender model with the ranking those are matches with the communication devices for improved wireless communication quality. The proposed system recommender model uses the estimation of direct communication link between the IoMT variables in the cognitive radio system. The proposed RSIoMT model evaluates the collected IoMT model data with the consideration of the four different healthcare datasets for the data transmission through cognitive radio network. Through the developed model the performance of the system is evaluated based on the deep learning

	model with the consideration of the collaborative features. The simulation analysis is comparatively examined based on the consideration of the wireless performance. Simulation analysis expressed that the proposed RSIoMT model exhibits the superior performance than the conventional classifier. The comparative analysis expressed that the proposed mode exhibits ~3 – 4% performance improvement over the conventional classifiers. The accuracy of the developed model achieves 99% which is ~3 – 9% higher than the conventional classifier. In terms of the channel performance, the proposed RSIoMT model exhibits the reduced recommender relay selection count of 1 while the other technique achieves the relay value of 13 which implies that proposed model performance is ~4-6% higher than the other techniques.
CC License CC-BY-NC-SA 4.0	***Keywords- Cognitive Radio Network, Internet of Medical Things, deep learning model, ranking, Cloud data, Recommender model***

1. Introduction

On the other hand, Recommendation System (RS) offers an exciting solution to resolve the difficulties present in an e-commerce website. It makes use of the nature and details of the consumer, and product details to find the consumer interests and periodically recommend the products which can buy [1]. Several methods have been presented to design RS, and various practical systems have been profitably realized in diverse business environments. RS finds useful in e-commerce which reflects the particular domain features [2]. RSs act as software agents which derive the preferences or interests of distinct users for goods either implicit or explicit and create recommendation respectively. The system supports the users to enhance decision making quality while searching or purchasing for online product. The RS is intersection of statistics, information filtering, data mining, and machine learning which helps the users to predict a preference else rating for product, service such as books, movies and restaurants and so on [3]. In recognizing the similarities or preferences between user group and users, it acts as a significant role in area of social networking, RS can be classified into five techniques as Content based filtering, Collaborative filtering, Demographic, Knowledge Based and Hybrid Approach [4].

With the recommender system the information are processed and transmitted using the cognitive 5G system. The cognitive system in the radio communication comprises of the different RS model those are categorized into two divisions such as Model based and Memory based. In RSs are defined as software techniques and tools which offer recommendation for items which might be useful to the customer [5]. Numerous roles are given by RSs such as Service provider using the RSor Users make use of the RS for goals and tasks as presented through. The Recommendation System should address five major problems to gather the user data, the technique of knowledge acquisition is used depending on that the profile is build [6]. To demonstrate the profiles as it formulates foundation for distinct users profile, which is easy way. Generally, a recommendation list will be created depending upon the user preference, item feature, user-item previous interaction, and extra details like temporal and spatial data. DL model is an interesting topic to address the recommendation process. In recent years, DL models have gained significant attention in several application areas namely object detection, computer vision, etc [7]. Both academicians and industrialists have begun to employ DL models in several application areas owing to their ability in solving several complicated tasks over the classical models. Presently, the DL model has revolutionized the recommendation architectures intensely and brought several chances for improving the performance of the RS. DL can capture the non-linear and non-trivial user-item relationship and allow the codification of complex abstraction as data representation in the higher layers [8].

Additionally, it hooks the complex relationship in the data itself, from plentiful reachable data sources like contextual, textual, and visual information. Different ways are available to design the DL models for RS. The NNs can be trained for the prediction of rating or interaction concerning the product or user attribute [9]. The DL models can be used for predicting the succeeding action depending upon the past data and content. Another way of using the DL model is to predict the next items in a sequence of views or purchases. The incorporation of images can be considerably enhanced to recommend as many clients users decide mostly depending upon visual information and text description can be sometimes not very accurate or misleading. Deep Learning comes under the domain of Machine Learning. The conventional definition of DL is that it will learn the representation of deep, i.e., it learns various stages of representation and data abstraction [10]. Because of practical causes, it assumes any kind of differentiable architectural model as 'DL' and it will optimize a differentiable objective function by the use of a modified version of Stochastic Gradient Descent (SGD). Neural architectures showed great achievement in the processes of unsupervised as well as supervised learning. Here, distinct models are defined. Earlier to exploring the information related to the advancements of DL, it is essential to comprehend the motivation behind the application of DL models for RS [11].

It is apparent that diverse RS has been presented in the recent years for processing the big data. At present, the using IoMT the information about patients are collected and processed for the big data processing. In this case, it is simple to raise a question of the requirement of numerous distinct architectural 20 models. Along the same tangent, it could be reasonable of providing a neat explanation of the benefits of every presented architecture and in what way it can be useful. A fascinating feature of neural architectures is that it can be differentiable in a dedicated way it offers proper inductive bias based on the input data type. When the intrinsic arrangement of the model is exploited, then the DNN can find useful. For example, CNN as well as RNN make use of the inherent features of the vision [12]. Likewise, the chronological structure of session or click-logs is mainly appropriate for the inductive bias offered by the convolution model. Furthermore, DNN is complex in the way that it has many parts of neural systems and can be integrated to an individual differentiable function and undergo training in a dedicated way. A main benefit is that it deals with content based RS [13]. It is predictable that if the user or products are modelled in web where multi-modal data is ordinary. At this point, the classical alternate will become mainly less striking and therefore, the RS could not perceive the benefits of joint representation learning. The development in the domain of RS is highly linked to the recent advancements in relevant modality [14]. For instance, for processing the review comments, preprocessing become mandatory where recent DL models has the ability to process textual data on their own.

Contribution and Organization of Paper:

This paper proposed a RSIoMT model for the effective processing of the information using the IoMT devices. With the implementation of the IoMT data transmission using cognitive network is evaluated with the deep learning model. The specific contribution of the paper is presented as follows:

1.To process the features of the big data model those are collected from the IoMT system. The data for analysis is collected from the four different datasets such as diabetes, cardiac, hepatitis and lung.

2. Based on the collected data the recommender model estimates the features in the data set those are processed and stored with the collaborative based deep learning model.

3. The data for processing is transmitted over the network based on the query from the different datasets with the cognitive 5G communication environment. The cognitive system uses the distance vector estimation based on the iteration computation along with the ranking.

4. Simulation analysis expressed that the proposed RSIoMT model achieves the higher accuracy of the 99% which is significantly higher than the conventional classifiers. In case of the recommender model the system achieves the effective energy efficiency compared with the other techniques.

This paper is organized as follows: In section II provides the existing literature on the deep learning for big data. Section III provides the developed model for the processing through deep learning is presented and section IV provides the simulation datasets and results obtained are presented. Finally, in section V presented a overall conclusion for the proposed RSIoMT.

2. Related Works

When the data given is partial otherwise vague, fuzzy set theory is suitable in the areas in these circumstances, introduced in [15] There is a requirement for a structure which can deal with uncertain situation ignited the fuzzy logic progression. Fuzzy logic is majorly employed for circumstances that are uncertain of the actual language in a broad sense. When from a narrow sense, the concept of many-value logic is known as fuzzy logic which comes under symbolic logic. RS depended fuzzy set theory is demonstrated as follows. To deal with the problems of vagueness in addition to data sparsity within the data of customer and product for telecom services, a hybrid approach is needed [16]. This approach combines the customer based and the product based filtering using fuzzy set method to deal the similarity in fuzzy products. By employing the Movie Lens 100 K dataset which contains 1 lakh rating records from 943 customers for 1682 products, the prediction accuracy of the system is examined. To avoid the problem of sparsity, the authors applied product based collaborative filtering to build a solid customer-product rating matrix. The sparsity rate which is missing is estimated as 94.96% in the dataset. The estimated value lies between 94.64% and 95.59% in [17].

Even though this method is helpful to reduce the cold start issue, the major focus of the authors is overcome the sparsity issue. Due to the ineffectiveness of the customer depend on Top-N recommendation algorithms, this method is less scalable. A method projected in [18] to provide a recommendation which is a personalized one to the business partners for Small and Medium Businesses (SMBs). The analysis of product similarity is merged to develop a relevance based semantic procedure to reduce the issues of sparsity and cold start. Every organization is assumed as a product in addition their own similarities along with the products are determined. The fuzzy linguistic term is obtained by the rating from business customers in addition to the field experts followed by an estimation of resemblance between product-based fuzzy collaborative filtering as well as product-based fuzzy semantic approach. The estimations of the closeness of fuzzy coefficient rates to produce the list of relevant Top-N business and rates that are predicted for the rating of fuzzy set are calculated. When the rates of coverage, precision, recall, and Fmeasure increases, MAE decreases with increase in the level of sparsity. It revealed that the method performed fine when contrast between the algorithms projected in [19]. To various customers who are going through the same area in university digital library, a RS is presented using a fuzzy linguistic system [20]. The tool which offers a general space by allowing several customers as well as resources to operate in a simultaneous manner based on the idea of Google Wave. This method easily deals with the cold start issues of fresh customers. The fresh customers required to describe the profile via choosing a rate two-tuple linguistic to enter into the system. The priorities of a fresh customer is demonstrated by a vector which consequently compare itself to the another vectors to estimate the similarities. The procedure of inserting of a fresh resource is same as the procedure of inserting a new customer. The rates 0.8674, 0.8734, 0.8693 are the average of precision, recall and F-measure correspondingly

In [21], hybrid RS for the workers of technology transfer office is offered and eliminates the cold start problem. To improve the properties of data discovery in a study purpose set and to divide the study resources, fuzzy linguistic modelling is employed. The author used a method as same as employed in [22] to avoid the issue of cold start. The authors used the method of collaborative filtering which uses a closest neighbour algorithm to produce recommendation in order to the priorities of closest neighbours for the fresh customers. But, the constraint of the method is to overcome the confusions in addition to create an internal organization of the customer profile, interaction among the field experts constantly is needed.

Artificial Neural Networks contains a collection of interlinked artificial neurons and a computation design to process the data. From the diverse kinds of ANN, Back Propagation Neural Networks (BPNN) and Feed Forward Networks (FFNN) are widely used. The ANN has the capability of learning, memorizing and also establishing a relation between the input data and also has the capability to model the non-linear dependencies [23].

In [24] have projected a method which offers customized suggesting using the notion that the customer with identical navigation actions with same interest. A BPNN training method is employed for enhancing the accuracy of the RS by the classification of customers into groups with the identical navigation actions. The actions of the customer navigation are additionally investigated by the extraction of navigation patterns suing unsupervised web mining techniques.

3. System Model for Recommender System Cognitive Network

The proposed RSIoMT model comprises the recommender model to process 5G network with big data processing with the IoMT network. The proposed model operates in the recommender model to evaluate the IoMT big data collected with the consideration of the four stages for the processing. The examination is based on the consideration of the four stages such as descriptor for the image, indexing of dataset, similarity measures, and relevant items search. Initially, the proposed RSIoMT model evaluates the dimension of the dataset that is collected from the IoMT. Upon the estimated dimensions of the dataset based on the history of the features of the dataset. The dataset from the IoMT are indexed and the developed model applies the recommender model with the computation of the attribute variables in the medical dataset those are stored in the form of big data. Through the computation of the Euclidean distance, the variables are computed and processed with the squared distance, cosine distance and Chi-squared distance for the big data in the extracted features in the developed RSIoMT.

With the estimated Euclidean distance the features are extracted and processed with the computation of the attributes features in the dataset. Through the estimation of the extracted features the search process is performed in the big data for the computation of the ranking features in the big data for the processing. In the 5G users the query process is applied within the recommender system with computation of the similarity function to compute the feature indexes. In the similarity function estimation features are estimated based on the estimation of the similarity features. The feature extraction in the big data for the IoMT big data is explained in the figure 1.

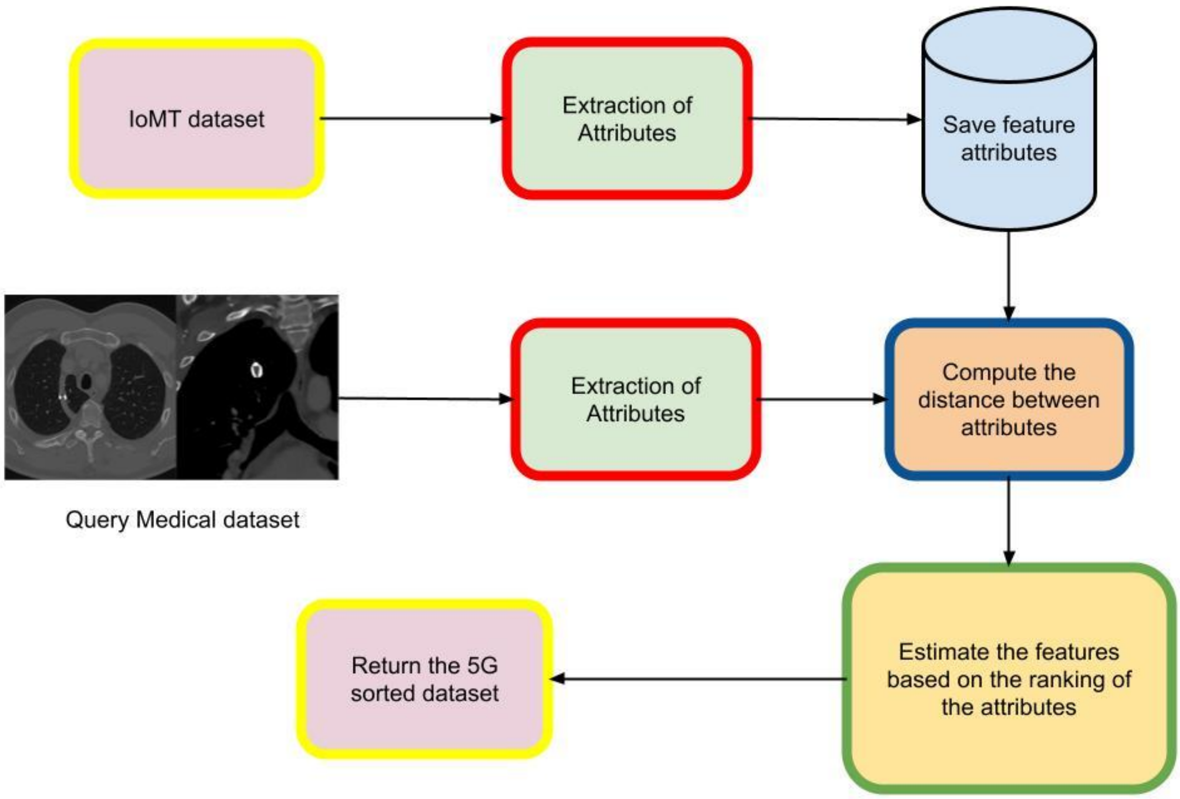

Figure 1: *Overall Flow in the RSIoMT*

With the ranking strategy-based IoMT process the 5G model with the recommender model is designed for the computation of the data transmission link between the users. In figure 2 the 5G recommender model for the acknowledgment of the users in the 5G network is considered for the analysis. Initially, with the estimated features in the IoMT dataset the features are evaluated with the recommender model. The recommender model implemented for the processing is examined for the attributes in the dataset. The features those are extracted are processed and evaluated with the neural network based ranking system. In the figure 2 the 5G network model for the recommender system is presented for the consideration of the direct and multicast link for the data communication in the 5G network for the big data processing.

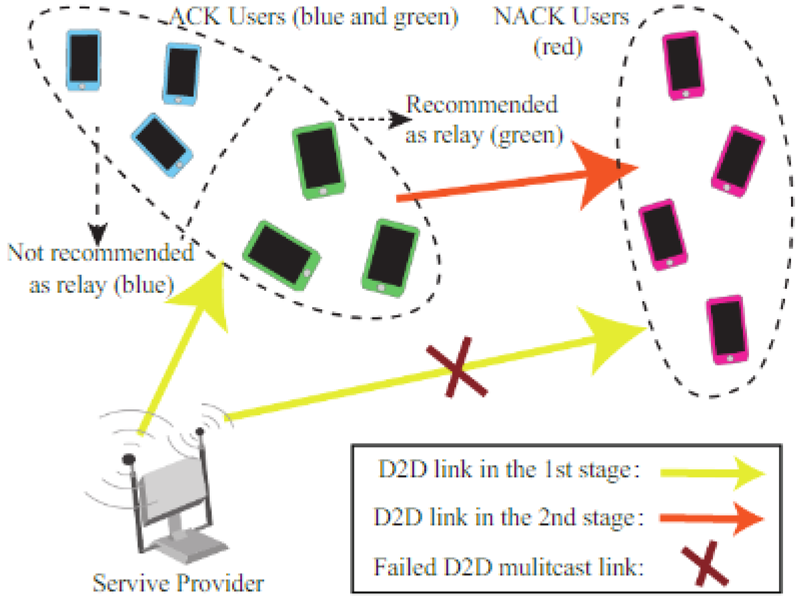

Figure 2: *Communication Link in RSIoMT*

The descriptor of healthcare dataset influence by the different features in the estimation of the variables. In the descriptors the features are processed based on the numerical analysis characterized by the probability density function estimation with the probability theory. In the estimation of the attributes h represents the random variable . The measured quantity of the variable is presented in equation (1)

$$s_a^{(h)} = \int x^{(p)}(x)dx \tag{1}$$

Where $a = 0,1,2 \ldots$ ....considered as the pdf general moment. Evidently,$s_0 = 1$ represented as the mean and variance value with the centralized features. The existence of the moment features guaranteed based on the computation for the boundedness denoted as $s_a^{(h)}$ with the finite value. At same instances, the pdf are compact in the reconstruction precision form based on the moment features. In this scenario, the developed RSIoMT model evaluate the non-redundant and explanation about the features in the dataset. Unfortunately, the momentum in the input data were processed with the missing variable in the big data. The missing variable in the dataset is presented in the equation (2) and (3)

$$s_a^{(h)} = \sum_{k=0}^{a} \binom{a}{k} m_k^n m_{p-k}^{(f)} \tag{2}$$

$$s_a^{(h)} = \sum_{k=0}^{p/a} \binom{a}{2k} \sigma^2 (2k-1).\, s_{a-2k}^{(f)} \tag{3}$$

In the ranking of the big data based on the features evaluate the variable in the dataset with consideration of the momentum features with the extra terms with momentum of h_f with lower multiplied orders based on the power denoted as σ. The momentum features in the RSIoMT model is presented in the equation (4) – (8)

$$s_1^{(g)} = s_1^{(f)} \tag{4}$$

$$s_2^{(g)} = s_2^{(f)} + \sigma^2 \tag{5}$$

$$s_3^{(g)} = s_3^{(f)} + 3\sigma^2 s_1^{(f)} \quad (6)$$

$$s_4^{(g)} = s_4^{(f)} + 6\sigma^2 s_1^{(f)} + 3\sigma^4 \quad (7)$$

$$s_5^{(g)} = s_5^{(f)} + 10\sigma^2 s_3^{(f)} + 15\sigma^2 s_1^{(f)} \quad (8)$$

In the resistance descriptors the parameters are denoted as the σ in the alternative manner the features estimated based on the distance features are represented as in equation (9) and (10)

$$M_p = s_a - \sum_{k=1}^{[\frac{p}{2}]} (2k-1) \binom{p}{2k} I_{p-2ks_2^k} \quad (9)$$

where $M_p$represented as the consistent iterative way for processing as shown in equation (10)

$$M_p = s_a - \sum_{k=1}^{[\frac{p}{2}]} (2k-1) \binom{p}{2k} I_{p-2k}(-m_2)^k \quad (10)$$

In the above equation (10) the integer value is denoted as $p \geq 0$ with the self-sufficeint descriptor. Alternatively, the features random features are computed based on the pre-processing of the big data for the processing with the variance estimation. In the datset features are evaluated based on the consideration of the series sets denoted as $I_p, p = 1,2, \ldots ..$is obtained from the equation (9) for the big data features denoted as except$m_2^{(f)}$. In figure 3 the flow chart of the proposed RSIoMT for the processing big data is presented.

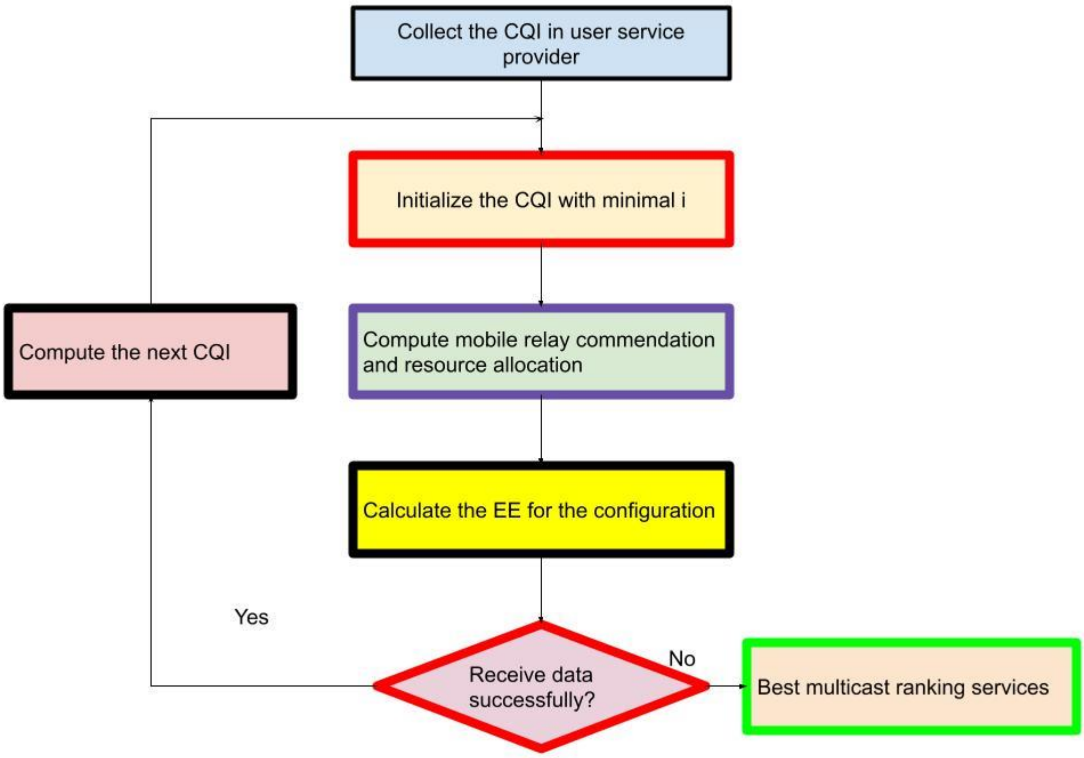

Figure 3: *Flow Chart of the RSIoMT*

Within the internal layer the channel allocation and relay selection is performed to resolve the problem associated with the 5G communication with the three-dimensions optimal matching. The problem in the 5G communication for the recommendation model is performed for the optimal relay and channel resource to evaluate the coordination based interference strategy. The developed model comprises of the combined bidding scheme with the multi-relay retransmission with the NACK strategy in the users. In figure 4 the recommender model for the proposed RSIoMT model in the big data processing and data transmission with the machine leaning mode is presented.

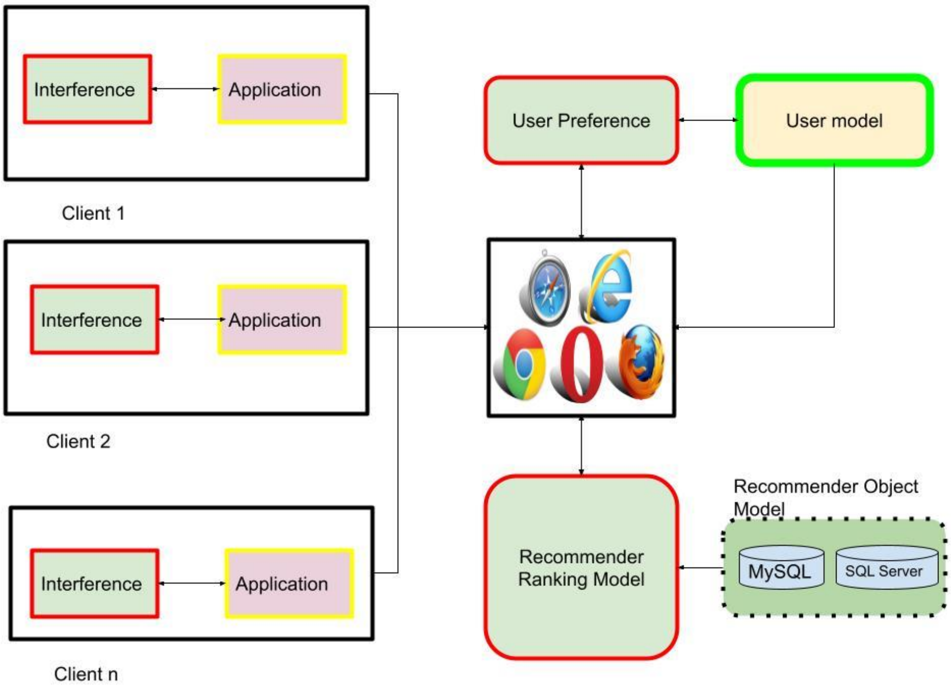

Figure 4: *Mobile Relay Recommendation and Resource Allocation RSIoMT*

The first step in the algorithm uses the ACK users in the rank with the descending order based on the computation of the base station in the distance. At first stage, the developed RSIoMT model comprises of the ACK rank with the arrangement of the users in the descending order based in the distance between the base station. The proposed RSIoMT model comprises of the user ACK with the ranking in the mobile relay base station with the NACK users based on the station location with the reduced interference in the communication link. The computed distance in the mobile relay is defined as the r for the user count k, the interference in the mobile relay r based on the cellular user k for the co-channel communication. The cellular spectrum is computed based on the mobile relay r for the accumulated cellular network user. The computed coordinate matrix for the interference is presented as in equation (11)

$$X - \{x_r | r = 1,2, \ldots \ldots, N\} \tag{11}$$

In the above equation (11) X denoted the one row and column matrix in N users and x_r demonstrated the spectrum shared between the cellular user in the relay r. In this assume that the relay in the each mobile share the cellular user for the available spectrum resources. In the second scenario of the proposed RSIoMT perform the relay selection with the combination of the auction problem with the bidders denoted as J for the NACK users in the N items for the selected relay in the ACK users. The proposed RSIoMT with the NACK users are combined with the service set represented as $V_r(r = 1,2, \ldots \ldots, N)$ for the mobile relay item of the r-th users. The mobile relay user service set is denoted as in equation (12)

$$V = \{v_r | r = 1,2, \ldots \ldots, N\} \tag{12}$$

In the 5G communication with the cloud data collected from the IoMT devices are collected and processed with the CQI level of the EE as presented in the equation (13) – (16)
The utility of this combinatorial auction is the EE at the current CQI level:

$$U = max\ EE \tag{13}$$

$$(i) V_i \cap V_j = \emptyset, i \neq j \quad (14)$$

$$i, j \in \{1,2, \dots \dots N\} \quad (15)$$

$$R_{min,r} \geq R \quad (16)$$

Based in the consideration of the above condition (16) the NACK users are provided with the services those are denoted as the $R_{min,r} = \overbrace{r \in N, V_{r \neq \emptyset}}^{min} R_{r,j}$ for worst relay rate in the two stage process to ensure the rate higher that R for the first state. The proposed RSIoMT model perform the ranking with the estimation of the big data processed with the Artificial intelligence technique. In the algorithm 1 presented the proposed RSIoMT model for the IoMT big data with the recommendation model.

Algorithm 1: RSIoMT Mobile Relay Recommendation Model for the Big Data

Input: CSI (CQI) information, $S, \tilde{s}, R: X$ *and* $V$are initialized into blank set.
Output: EE (Energy efficiency) and V(recommended mobile relay set)
1: Values in set $S$are sorted in descending order with respect to the distance between ACK users and service providers;
2. for r = 1 to N do
3. $x[r] = \overbrace{k \in K}^{\arg max} d_{r,k}$
4. Remove k from K
end for
5. Calculate $R_{r,j}$using set Xand CSI information for each NACK user;
6. for j= 1 to Jdo
7. Find the maximal $R_{r*j}$for NACK user jand put jinto $V_{r*} = V_{r*} \cup \{j\}$
end for
8. $R_{min,r} = min R_{r,j} \in N$and $V_r \neq \varphi$
9. While $R_{min,r} \geq R$ do
10. Initialize $increment = inf$, $R_{temp} = 0, V' = V, V_{temp} = 0$
11. for r= 1 to Nd
12. if $V_r'$is empty, skip
13. Try to remove mobile relay rand find other set $V_{r'}'$ for the user jbelongs to V_r'
14. Calculate the minimal rate $\widetilde{R_{min,r}}$
15. If $\widetilde{R_{min,r}} - R_{min,r} < increment$ then
16. $V' = V_{temp}$
17. $increment = \widetilde{R_{min,r}} - R_{min,r}$
18. $R_{temp} = \widetilde{R_{min,r}}$
19. end if
20. end for
21. if $R_{temp} > R$ then
22. Accept the adjustment $V = V'$
23. $R_{min,r} = R_{temp}$
else
Break
end if
end while
24. Calculate EE using $EE = \frac{R}{\sum_{k=1}^{K} \sum_{r=1}^{N} x_r, P_r + P_s}$

4. Results and Discussion

The proposed RSIoMT model comprises of the IoMT data those are stored in the big data for the processing with the AI technique. The simulation setting for the propsoed RSIoMT is presented as follows. The developed model consists of the cellular network with the radius of 1.5km with consideration of the service provider at the cell center. Every users are intended to offer multicast services those are distributed randomly with the distance for the 5G communication average of 750 meters with the path loss factor of 4. In the service provider the transmit power is increased for the cellular user for the interference source and user for the direct to direct link with the 30dBm, 30dBm and 21dBm, respectively. The power spectral density in the background noise are estimated set as -174dBm. The channel signal bandwidth are computed in the single channel with the frequency of 1KHz. The simulation setting for the proposed RSIoMT model for the estimation is presented in table 1. The simulation setting for the existing the classifier model with the classifier is presented.

Table 1: *Parameter Setting*

Parameter	SVM	NN	DNN	RSIoMT
Probability (Pa)	-	-	-	0.25
Step Scaling Factor (∞)	-	-	-	0.01
No of Iterations	600	600	600	600
Cognitive Constant(C1)	-	-	2	-
Social Constant(C2)	-	-	2	1
Inertia Weight (W)	-	-	-	0.8
Zeta (Diversification)	-	1	-	-
Intensification Factor (Q)	-	-	-	0.5
Seed	2001	-	-	-
Degree	-	-	-	3
Learning Rate	0.0001,0.1	-	-	0.3
Momentum	0.68,0.99	-	-	0.2
Neurons	200	-	-	-
Hidden Layer	-	-	-	3

Through the proposed RSIoMT model for the existing method such as different classifier model such as SVM, NN and DNN model. The performance of the proposed RSIoMT for the consideration of the different parameters such as False Positive Rate (FPR), False Negative Rate (FNR), sensitivity, specificity, accuracy, F- 80 score, Youden Index (Y), Discriminant Power (DP), G-measure, Positive likelihood (P+), Negative likelihood (P-).
With the implementation of the proposed RSIoMT model the deep learning model for collaborative filtering is implemented. The analysis of the model is based on the consideration of the dataset such as diabetes, cardiac, hepatitis and lung diseases. The dataset comprises of the instances 589 minimum and 1823 maximum value as presented in table 2.

Table 2: *Dataset Description*

Dataset	No. of instance	No. of classes	Positive	Negative
Diabetes	636	2	500	136
Cardiac	1811	2	380	1431
Hepatities	839	2	684	155
Lung	585	2	135	450

The recommendation relay comprises of the explicit information service providers. The analysis is based on the information obtained from the physical layer information with the ranking features in the dataset. In the analysis of the proposed RSIoMT mode examine the feature ranking for the extracted variables. In table 3 the recommender model for the classification of the features are presented. The comparison of means and standard deviation for the different datasets are presented in figure 5.

Table 3: *Features in the Dataset*

Feature name	Diabetes		Cardiac		Hepatities		Lung	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Total characters	72.013	47.352	68.049	43.894	58.098	37.408	65.272	42.018
Positive	0	0	0	0	0	0	0	0
Negative	0	0	0	0	0	0	0	0
Neutral	0	0	0	0	0	0	0	0
Positive Exclamation	0.009	0.097	0.015	0.123	0.023	0.149	0.012	0.109
Negative Exclamation	0	0	0	0	0	0	0	0
Negation	0	0	0	0	0	0	0	0
Positive Features	1.459	1.648	1.273	1.623	0.886	1.278	1.246	1.402
Negative Features	0.998	1.441	1.350	1.654	1.031	1.338	0.957	1.362
Neutral Features	0.011	0.104	0.007	0.081	0.027	0.163	0.009	0.109

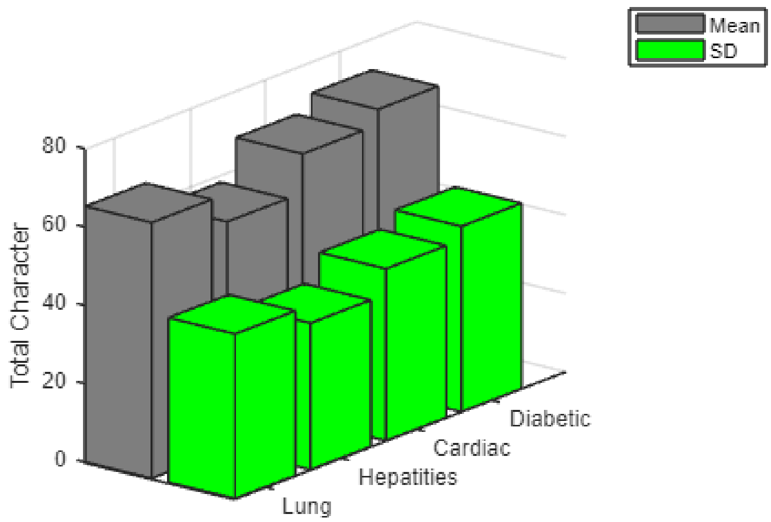

Figure 5: *Comparison of the Mean and SD*

In the table 3 the features those are positive and negative are evaluated for the different dataset based on distribution of the positive and negative features. The random distribution of the positive and negative features the dataset for the consistent variable performance with the proposed RSIoMT with the developed model. The comparative analysis of the dataset incorporates the different features for the estimation of simulation analysis variable for the different dataset such as diabetes, cardiac, hepatitis and lung diseases. From the table 4 – 7 the analysis of the results obtained for the different datasets are presented.

Table 4: *Comparative Analysis of Diabetes Dataset*

Classifier	FPR	FNR	Sens. (%)	Spec. (%)	Accu (%)	F-scor	Y (%)	ρ+ (%)	ρ- (%)	DP

						e (%)				
RSIoMT	2.96	0.99	99.16	98.12	99.38	99.07	96.23	33.41	97.23	5.06
ACO	9.92	1.81	98.18	90.07	96.38	97.68	88.25	9.88	49.53	4.34
PSO	35.89	13.29	86.70	64.10	82.54	89.02	50.80	2.41	4.82	1.90
SVM	45.63	14.63	85.36	54.36	80.34	87.92	39.73	1.87	3.71	1.69
NN	41.28	13.28	86.71	58.71	81.91	88.82	45.43	2.10	4.42	1.85

Table 5: *Comparative Analysis of Cardiac Dataset*

Classifier	**FPR**	**FNR**	**Sens. (%)**	**Spec. (%)**	**Accu (%)**	**F-score (%)**	**Y (%)**	**ρ+ (%)**	**ρ- (%)**	**DP**
RSIoMT	0.35	3.35	97.86	99.43	99.02	97.34	96.29	275.0	29.74	0.35
ACO	0.64	8.84	92.45	99.23	97.34	95.67	90.51	142.2	11.23	0.64
PSO	6.10	19.34	82.56	94.56	92.36	79.93	74.55	13.21	4.85	6.10
SVM	14.57	18.00	83.73	86.73	86.93	66.72	67.41	5.62	4.74	14.57
NN	14.31	16.72	85.92	86.18	87.43	68.34	68.96	5.81	5.12	14.31

Table 6: *Comparative Analysis of Hepatities*

Classifier	**FPR**	**FNR**	**Sens. (%)**	**Spec. (%)**	**Accu (%)**	**F-score (%)**	**Y (%)**	**ρ+ (%)**	**ρ- (%)**	**DP**
RSIoMT	8.12	1.17	98.82	91.87	97.49	98.45	90.69	12.16	77.97	4.84
ACO	13.49	2.07	97.92	86.50	95.70	97.35	84.43	7.25	41.76	4.18
PSO	20.30	3.42	96.57	79.69	92.61	95.23	76.26	4.75	23.25	3.57
SVM	25.11	3.06	96.93	74.88	91.18	94.20	71.82	3.85	24.43	3.66
NN	28.38	6.06	93.93	71.61	87.84	91.82	65.55	3.30	11.80	2.87

Table 7: *Comparative Analysis of Lung*

Classifie	**FPR**	**FNR**	**Sens.**	**Spec**	**Accu**	**F-**	**Y**	**ρ+**	**ρ-**	**DP**

r			(%)	. (%)	(%)	score (%)	(%)	(%)	(%)	
RSIoMT	0.89	6.42	93.57	99.10	97.77	95.27	92.67	15.41	2.98	104.09
ACO	20.37	12.67	87.32	79.62	85.20	89.53	66.95	4.28	6.28	2.07
PSO	4.42	17.29	82.70	95.57	92.64	83.65	78.28	18.69	5.52	1.80
SVM	4.65	13.43	86.56	95.34	93.33	85.60	81.91	18.59	7.09	2.10
NN	5.41	21.83	78.16	94.58	90.59	80.14	72.75	14.42	4.33	1.51

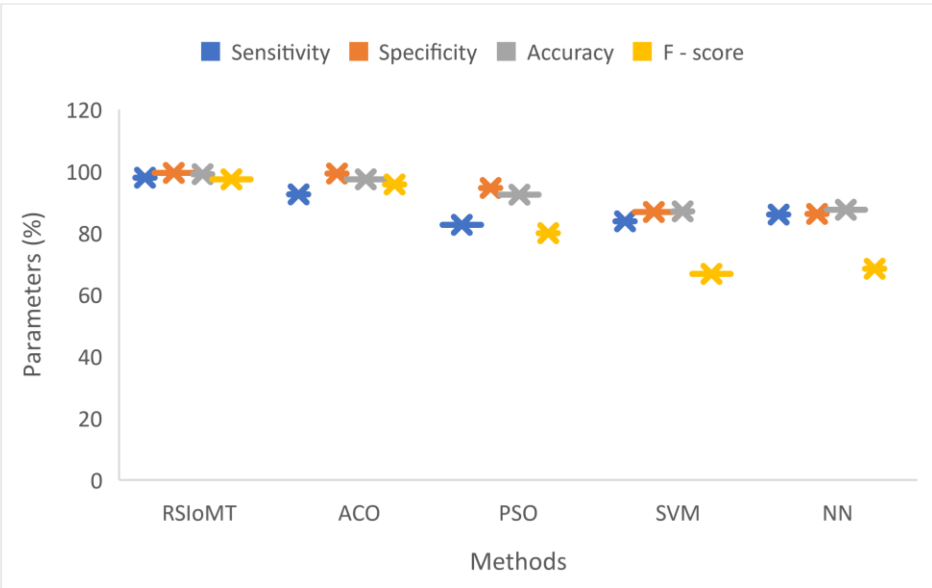

Figure 6: *Comparison of Diabetic Dataset*

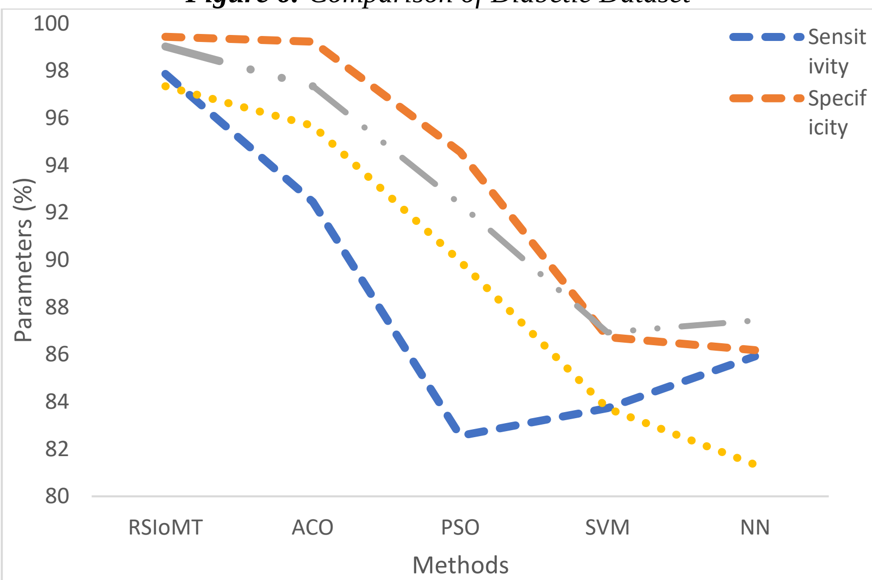

Figure 7: *Comparison for Cardiac Dataset*

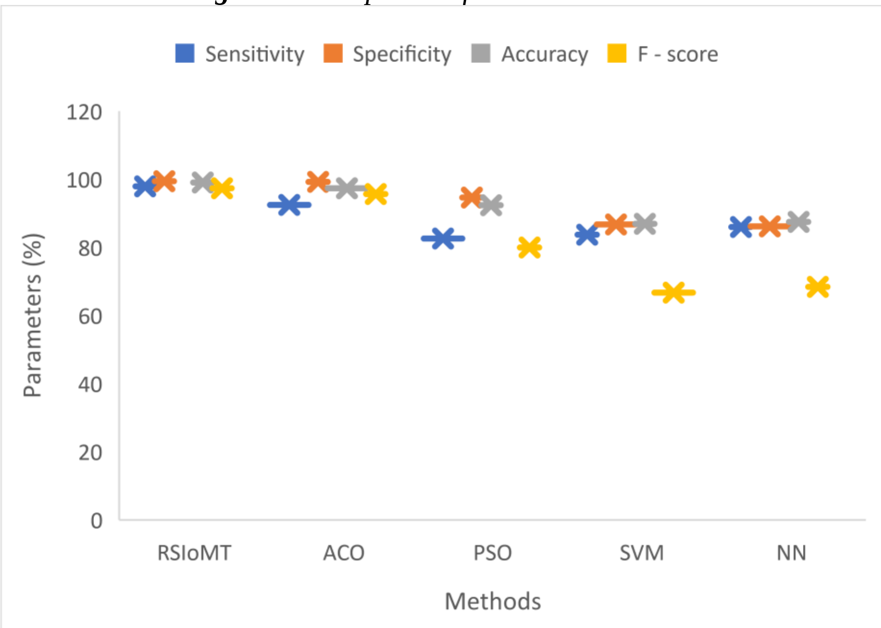

Figure 8: *Comparison of Hepatities dataset*

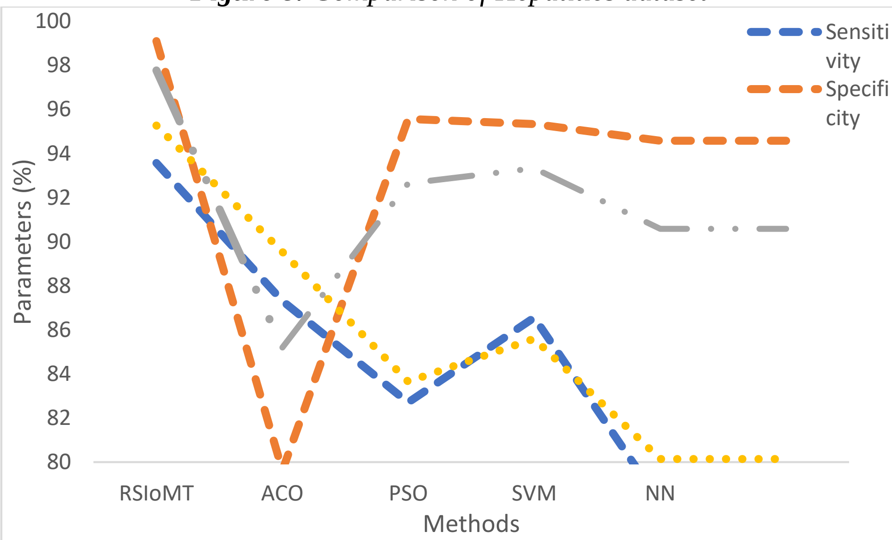

Figure 9: *Comparison of Lung dataset*

The simulation analysis of the different datsets are presented in the comparative analysis with the different technique are presented in figure 6 -9. The comparative analysis expressed that the proposed RSIoMT model achieves the higher accuracy value of 99% which is significantly higher than the ACO, PSO, SVM and NN classifiers. Simualrly, in terms of other parameters also propsoed RSIoMT model achievs the higher performance in terms of sensitivity, specificity and F -score. The simulation analysis of the proposed RSIoMT mode for the big data processing in the 5G network model is evaluated based on the recommender model. Initially, the parameter RSIoMT model performance is evaluated based on the consideration of the different technique such as CMS, SRS and SSI model. The performance of the recommender mode comprises of the 5G cognitive model for the examination of the consideration of the IoMT model with the estimation of configuration through the D2D transmission through muticast approach for the reduced energy consumption for the similar information transmission. In the figure 10 provides the energy efficiency model for the computation of the different technique such as CMS, SPS and SSI mode with the proposed RSIoMT.

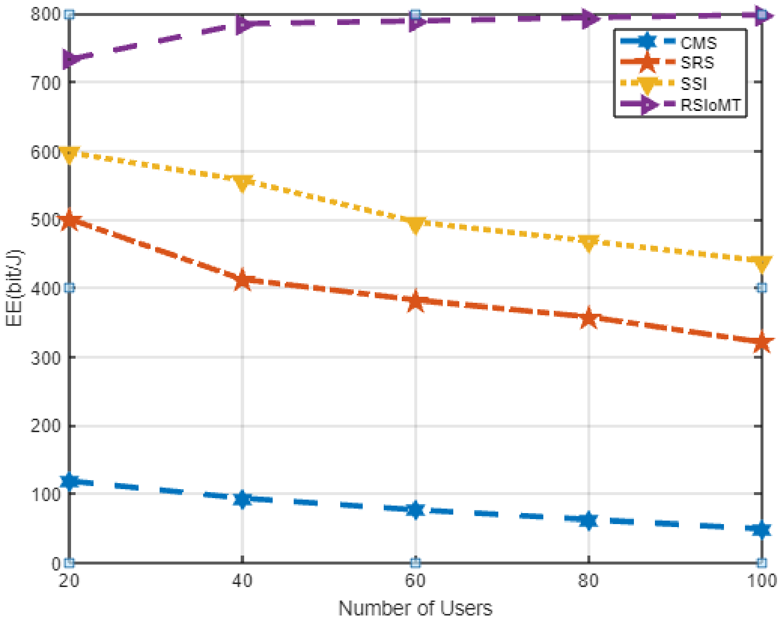

Figure 10: *Comparison of the EE*

In the table 8 the comparative analysis of the proposed RSIoMT model with the existing model is presented.

Table 8: *Comparison of EE in the RSIoMT*

EE(bit/J)				
Users	**CMS**	**SRS**	**SSI**	**RSIoMT**
20	118	500	597	733
40	93	412	557	785
60	76	382	496	789
80	62	358	468	794
100	49	321	439	798

Table 11: *Comparison of Average Data Rate*

Average Data Rate (bps)				
Users	**CMS**	**SRS**	**SSI**	**RSIoMT**
20	197	587	834	896
40	139	433	986	1074
60	109	401	1008	1116
80	78	392	1086	1178
100	48	379	1109	1197

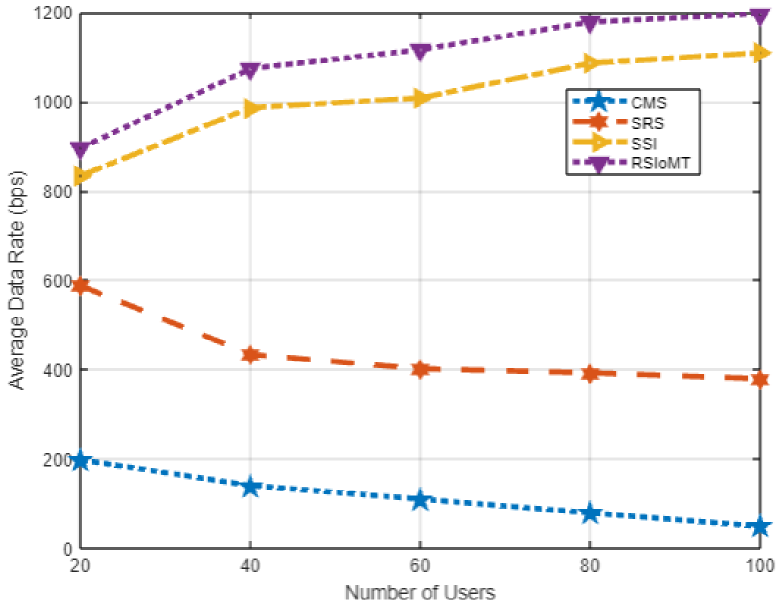

Figure 11: *Comparison of Average Data Rate*

The comparative estimation of the EE value in the proposed RSIoMT with the existing CMS, SRS and SSI model is presented. The evaluated value expressed that the minimal data is transmitted for the higher cosy. The conventional technique CMS, SRS and SSI are not effective for the large scale mobile IoT network. The simulation examination of the developed model expressed that the with increase in number of users the energy efficiency is significantly improved. With the proposed model it is observed that the with increase in number of users the EE is not affected. Through examination it is concluded that the proposed RSIoMT model is effective for the IoMT big data model. In figure 11 the comparative illustration of the average data rate for the proposed RSIoMT model is presented. The comparative analysis expressed that the proposed mode achieves the higher average data rate compared with the other algorithms. In the existing technique the CMS exhibits the worst performance compared with the other techniques. In case of SRS the second stage does not have more NACK those are trapped as the worst case. The RAR technique exhibits the average minimal data rate compared with the SSI. However, the proposed RSIoMT model exhibits the higher data rate for the data transmission in the recommender system. In figure 12 the count of the recommender mobile relay is presented for the different users such as 20, 40, 60, 80 and 100. The comparative analysis of the recommender system with the conventional SSI and SRS are presented in table 12.

Table 12: *Comparison of Mobile relay*

Recommender Mobile Relay				
Users	**CMS**	**SRS**	**SSI**	**RSIoMT**
20	4	5	5	1
40	8	6	4	1
60	11	4	4	2
80	15	4	3	2
100	19	3	3	2

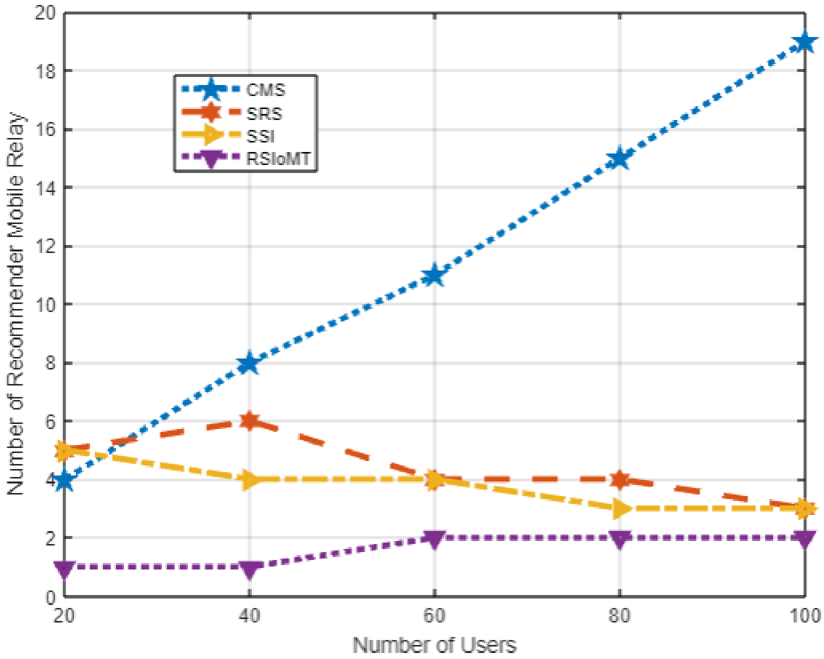

Figure 12: *Comparison of Recommender Relay*

In figure 12 the comparative illustration of the recommender mobile relay for the varying users are presented. The comparative analysis expressed that the with the total number increases for users count the recommender user also increased for the service demand. The designed SSR model is designed based on the consideration of the ACK relay which is sufficient enough to increases the quality of service to the users. With the proposed RSIoMT model the number of users are relatively low compared with the SSI. With the recommender mode the proposed RSIoMT model achieves the cooperative recommendation partner for the minimal mobile relay user for the effective services to the increased data rate. Through the analysis it is observed that proposed model exhibits the effective performance compared with the conventional techniques.

5. Conclusion

Recommender system involved in the processing of the multiple information those are collected in the big data process using the 5G cognitive system. The information about patient are collected and processed using the IoMT devices and stored in the big data. However, the conventional technique fails to develop a effective model to process the 5G cognitive data transmission for the medical data in IoMT. This paper proposed a RSIoMT model to compute the IoMT big data and evaluated with the deep learning model . The proposed RSIoMT model uses the computed distance for processing the information about the healtcare data features in the network. The proposed model uses the ranking based recommender model with the estimation of the distance features. Finally, the recommender system is evaluated with the deep learning model for the classification of the information those collected from the IoMT. The comparative analysis expressed that the proposed RSIoMT model exhibist the improved performance than the existing techniques. In case of classifier model the proposed RSIoMT model achieves the accuracy of 99% for the different datasets, which is significaintly higher than the conventional technique. The performance of the proposed RSIoMT model exhibits the ~3-7% higher performance than the existing techniques. In case of cognitive network the energy efficiency is achieved significantly which achieves the ~6% increased performance.

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