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RESEARCH ARTICLE

IoT based energy aware local approximated MapReduce fuzzy clustering for smart healthcare data transmission

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Abstract

Big data is a collection of large amounts used to store and to process for future use. Internet of things (IoT) technology is used in smart homes and smart healthcare. IoT has limited resources like processing capability and supplied energy. Many researchers carried out their research on resource-optimized data clustering in bigdata environments. However, the computational complexity and energy consumption were not reduced by existing techniques. Therefore, the IoT-based energy aware local approximated fuzzy MapReduce clustering (IoT-EALAFMRC) method is introduced. The main objective of the IoT-EALAFMRC method is to perform an efficient priority-based data transmission in a smart healthcare environment. Initially, IoT devices are used to collect a large number of patient data in different locations at the same time. During data transmission, there is a chance of traffic occurrence. In order to reduce the traffic occurrence rate during the data transmission to the physician (i.e., doctor), EALAF- MRC is used with map and reduce function to group the patient data into normal constrained data or emergency constrained data based on physical health condition with higher clustering accuracy. The IoT-EALAFMRC method performs the cluster assignment based on neighborhood relationships among data. After clustering of patient data, the data is sent to the physician with minimum time consumption. By minimizing the traffic, the retransmission of patient data is reduced. This in turn, helps to reduce energy consumption. Experimental evaluation is carried out using the IoT-EALAFMRC method on factors such as energy consumption, clustering accuracy and execution time for different numbers of patient data.

Keywords: Big data, Local approximated fuzzy clustering, Physical health condition, Smart healthcare, Internet of things.

Introduction

Big data technology is to provide high-quality of data processing and data analysis. Smart healthcare is a new technology with wearable devices, IoT and mobile internet to access information and to connect people in an intelligent manner. A cognitive data transmission method (CDTM) was introduced (Arun Kumar, M, *et al*., 2019) to monitor and transmit healthcare data. However, the clustering accuracy was not improved by using CDTM. An interference aware energy efficient transmission protocol (IEETP) was designed (Kashif, M, *et al*.,2020) for smart cities. RLMDS algorithm and computing QoS in medical information systems was designed (Amit, C, *et al*.,2021) in fog computing. Distributed hierarchical data fusion architecture was designed (Rustem, *et al*., 2019) to attain timely and accurate results. The designed architecture allowed the decision-making processes at different levels.

An IoT-based COVID-19 detection and monitoring system was introduced (Mirza, S, *et al*., 2022) with semi-automated tracing capability. A hybrid OCC/BLE system was designed (Moh Khalid M, *et al*., 2019) to guarantee efficient remote transmission. The patch gathered the ECG data consistent with the patient's health condition to minimize power consumption. An asynchronously operating data transmission was carried out (Susumu, T., *et al*., 2021) with a fixed number of data transmissions. Narrowband internet of things (NB-IoT) was used (Thitapa, A., *et al*., 2020) to transmit the data for service quality development. Healthcare data transmission was employed to connect the bluetooth into healthcare instruments for data communication.

A secure and scalable healthcare data transmission

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framework was introduced in IoT (Eshrag, S,. *et al.,* 2022). K-nearest neighbor (KNN) imputation was carried out for dimensionality reduction. An integrated low-powered IoT blockchain platform was designed (Tarek, A,. *et al*., 2021) for healthcare applications to store EHRs. Blockchain ethereum comprises web and mobile applications for securing access to health information. Enhanced LSTM for heart disease prediction in IoT-enabled smart healthcare systems (Olivia C, J., *et al*., 2024).

The issues identified from literature are lesser clustering accuracy, higher clustering time, higher error rate, higher computational cost, higher computational complexity and so on. An IoT based energy aware local approximated fuzzy MapReduce clustering (IoT-EALAFMRC) Method is introduced.

The contribution of IoT-EALAFMRC method is to perform efficient priority-based data transmission in a smart healthcare environment. IoT devices are used to collect a large number of patient data in different locations at the same time. In order to reduce the traffic occurrence rate during the data transmission to the physician, energy aware local approximated fuzzy MapReduce clustering is used with the map and reduce function to group the patient data into normal constrained data or emergency constrained data based on physical health condition. The IoT-EALAFMRC method performs the cluster assignment based on neighborhood relationships among data. After that, the data is transmitted to the physician with minimum time consumption. Through minimizing the traffic, the retransmission of patient data is reduced. Improvement of data analysis and protection using novel privacy-preserving methods for big data application (Mohamed, V,. *et al.,*2024).

The structure of the paper is given as. Section 2 reviews the different clustering methods for healthcare data transmission. In section 3, the proposed EALAFMRC method is described with an architecture diagram. The experimental settings and comparative results analysis of the EALAFMRC method is explained in section 4 and 5. Section 6 concludes the paper.

Related Works

A multi-agent system (MAS) with deep learning-based privacy-preserving data transmission (BDL-PPDT) scheme was introduced (Kuruva, K., *et al*.,2022) for clustered IIoT environment. An EPPDA scheme was introduced (Faris A, A., *et al.,*2021) with authentication for IoT-based healthcare applications. EPPDA employed homomorphic encryption to protect data privacy. A hybrid security model was designed (Mohamed G., *et al*., 2018) for providing the text data in medical images. The designed model combined 2D discrete wavelet transform with a hybrid encryption scheme.

A data collection and secure transmission scheme was introduced (Ata Ullah, M., *et al*., 2021). Taxonomy was introduced to attain secure, efficient and reliable data collection with minimal computational cost and compression ratio. A secure and scalable healthcare data transmission framework was designed (Eshrag, S., *et al*., 2022) with IoT based on an optimized routing protocol. Asynchronously operating data transmission was carried out with a fixed number of data transmissions on trees. A machine learning method was introduced (Angela, J., *et al*.,2022) to examine health data metrics to address the trade-off issue. Levenberg-Marquardt algorithm was employed to enhance the accuracy. A self-driven dual reinforcement model with meta-heuristic framework to conquer the IoT-based clustering to enhance agriculture production (Muruganandam C, M., *et al*., 2024).

A discrete event simulation (DES)-based model was introduced (Reinaldo, Y., *et al*., 2020) for entities by discrete events to assist health systems. Exploring real-time patient monitoring and data analytics with IoT-based smart healthcare monitoring (Nilesh M, K., *et al*., 2023). The designed model classified health-related topics for medical data transmission. A secure and privacy-preserving data transmission scheme was introduced (Huijie, T., *et al*., 2021) for healthcare. A healthcare system (HES) framework was introduced (Haiping, T., *et al*., 2017) to gather medical data from WBANs through the gateway. Improved steganography for IoT network node data security promotes secure data transmission using generative adversarial networks (Prabhu. R, A., *et al*., 2023).

Methodology

A smart healthcare system is used to monitor the health condition of the patient. The IoT-EALAFMRC method is introduced to improve the clustering efficiency of big data analytics with a minimum error rate. The IoT-EALAFMRC method is introduced with the application of the local approximated fuzzy clustering process and MapReduce process. IoT-EALAFMRC method used a local approximated clustering process to cluster data effectively. In IoT-EALAFMRC method, the local approximated fuzzy clustering process used the neighborhood relationship between the data for grouping similar data in clusters. IoT-EALAFMRC method used the mapreduce function for minimizing the irrelevant data on clusters for efficient big data analytics. The overall architecture diagram of the IoT-EALAFMRC method is illustrated in Figure 1.

Figure 1 explains the architecture diagram of the IoT-EALAFMRC method to cluster the data from big dataset. As illustrated in Figure 1, the healthcare data is collected from the patients at different locations with the help of IoT devices. IoT-EALAFMRC method used local approximated fuzzy clustering to perform the cluster formation where data grouping is based on the correlation among neighborhood data. The IoT-EALAFMRC method is used to obtain improved clustering accuracy for efficient big data analysis. Then, the IoT-EALAFMRC method used MapReduce function to

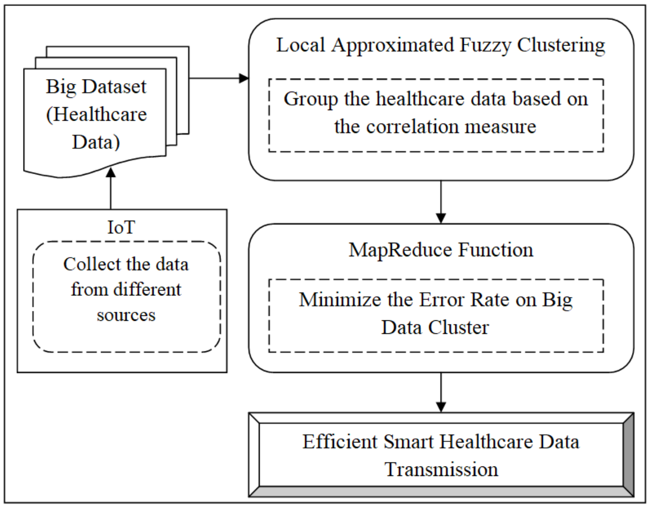

Figure 1: Architecture diagram of IoT-EALAFMRC method

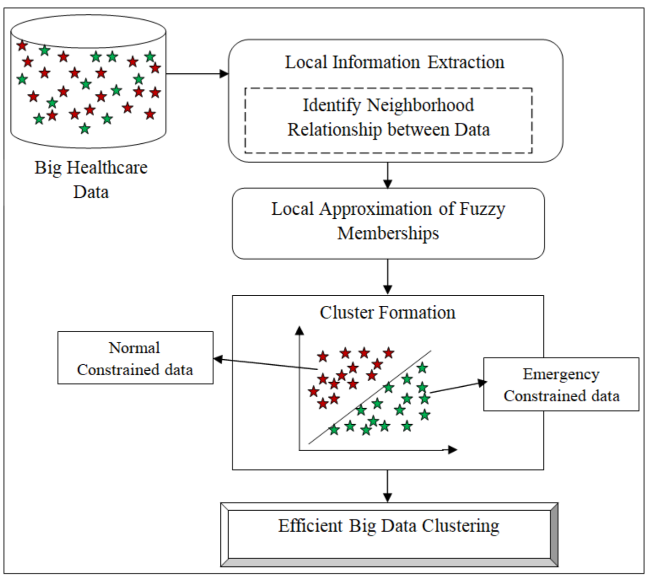

Figure 2: Processes of LATFC algorithm for big data clustering

reduce the error rate of big data clustering by removing the irrelevant data on clusters. The elaborate processes of the IoT-EALAFMRC method are illustrated in the subsections.

Local Approximated Fuzzy Clustering

The local approximated tanimoto fuzzy clustering (LATFC) algorithm is used to improve the clustering accuracy with minimum time complexity. LATFC algorithm executes cluster assignment depending on the neighborhood relationship among the data. LATFC algorithm used the Tanimoto index to find the neighborhood relationship between data. LATFC algorithm automatically determines the number of clusters. The LATFC algorithm has three steps such as, local information extraction, local approximation of fuzzy membership and cluster formation. The process of LATFC algorithm is illustrated in Figure 2.

Figure 2 illustrates the process involved in the LATFC algorithm to improve the big data clustering performance. LATFC algorithm performs the local information extraction and the neighborhood relationship between data is computed with the help of Tanimoto correlation. LATFC algorithm is used to categorize the healthcare data into two classes, normal constrained and emergency constrained, based on energy availability. This helps the LATFC algorithm to form two different clusters with higher clustering accuracy and lesser time complexity for efficient big data clustering.

Local information extraction

In local information extraction, correlation (i.e. similarity) between every data pair is determined and nearest neighbors are identified. The correlation value helps LATFC algorithm to determine the weights for the local approximation of fuzzy memberships. The Tanimoto index in the LATFC algorithm identifies how closely two data pairs get matched. Let us consider the big healthcare dataset 'DS' with a large amount of data. 'N' symbolizes the total number of healthcare data in a big dataset. The LATFC algorithm used determines the Tanimoto index (TI) for each healthcare data 'DS' in a big dataset. It is formulated as,

$$TI = \frac{\sum PD_{test} PD_{train}}{\sqrt{\sum PD_{test}^{2}} + \sqrt{\sum PD_{train}^{2}} - \sum PD_{test} PD_{train}} \quad (1)$$

From equation (1), 'PD_{test}' denotes the testing patient data. 'PD_{train}' symbolizes the training patient data. The output of TI ranges between '-1' and '1'. The value of TI' 1 ' represents the positive correlation between two patient data. '-1' symbolizes the negative correlation between two patient data. .

Local approximation of fuzzy memberships

In the LATFC algorithm, each patient data 'PD' is interrelated with the membership vector '$x(PD)$'. Each patient data.'$x_i(PD)$ ' denotes the membership degree of 'PD' in cluster 'i'. The local approximation of fuzzy membership is formulated as,

$$PD: x(PD) = (x_1(PD), x_2(PD), \ldots.. x_M(PD)) \quad (2)$$

$$0 \leq x_i(PD) \leq 1;\ \sum_{i=1}^{M} x_i(PD) = 1 \quad (3)$$

From (2) and (3), '$|\cdots|$' denotes the number of patient data. The membership vector value of each patient data varies between '0' and '1'. The membership vector value denotes how much percentage patient data belongs to the cluster. LATFC algorithm describes the membership vector for each patient data in a big healthcare dataset. The vector of one patient data. 'PD_i' is approximated through nearest neighbors'PD_j' memberships and it is formulated as,

$$x(PD_i) \approx \sum_{PD_j \in KNN(PD_i)} w_{PD_i PD_j} x(PD_j) \quad (4)$$

From (4), '$KNN(PD_i)$' symbolizes the K-nearest neighbor of patient data. '$w_{PD_i PD_j}$' symbolizes the weight that each neighbor contributes to an approximation of fuzzy membership to that neighbor. The neighbors with higher correlation values have higher weights in the LATFC algorithm. The neighborhood relationships are determined for all data to limit the fuzzy memberships.

Cluster formation form fuzzy memberships

After computing the fuzzy memberships for each healthcare data in a big dataset, cluster formation is carried out. Similar types of healthcare data are clustered by assigning each data to a cluster with the highest membership degree. One data is clustered into more than one cluster with a high membership score for multiple clusters. The algorithmic process of local approximated Tanimoto fuzzy clustering is shown as,

```
// Local Approximated Tanimoto Fuzzy Clustering
    Input: Big Dataset (i.e. Healthcare Dataset)
    Output: Improved Clustering Accuracy and Reduced Time Consumption
    Begin
      For each healthcare data 'PD_i'
            Measure tanimoto correlation between neighborhood data
            Classify data based on correlation value
            Perform local approximation of fuzzy memberships
            Cluster similar type of healthcare data based on fuzzy memberships
      End For
    End
```

Algorithm 1 Local Approximated Tanimoto Fuzzy Clustering

Algorithm 1 illustrates the LATFC process to perform big data clustering. LATFC significantly groups the healthcare data into different clusters with higher accuracy and lesser time consumption. In this way, the IoT-EALAFMRC method uses the LATFC algorithm to achieve higher clustering accuracy and minimal time complexity for big data analytics.

MapReduce Phase

MapReduce function is introduced in the IoT-EALAFMRC method reduces the error rate of big data clustering. All healthcare data is processed in the form of key/value pairs. The MapReduce function comprises two main phases, namely, map and reduce phases. The map function is used in every input key/value pair and creates the output key/value pairs. In the reduce phase, all intermediate results are clustered by keys to achieve the final result. The process of the Mapreduce function is illustrated in Figure 3.

Figure 3 illustrates the block diagram of the Mapreduce function. Let us consider that cluster with similar kind of patient data '$C_i = \{PD_1, PD_2, .. PD_m\}$'. '$m$' symbolizes the number of training patient data in clusters. Let '$C_i = (PD_i, y)$' be a collection of training patient data in which 'PD_i' symbolizes the input patient data and 'y' symbolizes the corresponding output. The map phase considers one data pair and generates a list of pairs in different domains.

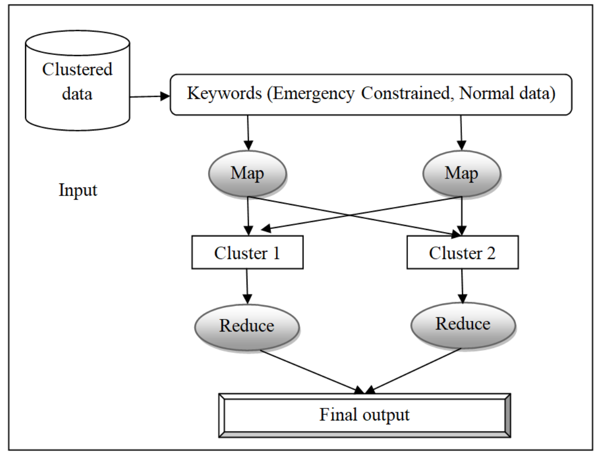

Figure 3: Processes of MapReduce function

The reduce function produces the final cluster result. The algorithmic process of MapReduce function is given as,

```
// MapReduce Algorithm
    Input: Clustered Data
    Output: Lessen Error Rate of Big Data Clustering
    1: Begin
    2:    For each clustered patient data 'PD_i'
    3:        Mapping of data into appropriate clusters
    4:        Reduce phase generates the final result
    5:        Perform efficient data transmission
    6:    End for
    7:End
```

Algorithm 2 MapReduce for Big Data Analytics

Algorithm 2 illustrates the step-by-step process of MapReduce to minimize the error rate involved in big data clustering. With help of the above algorithmic process, IoT-EALAFMRC method effectively decreases the error rate of clustering for efficient big data analytics.

Experimental Settings

The proposed IoT-EALAFMRC method is implemented in JAVA language. The performance of the proposed method is computed using the COVID-19 in India dataset. The URL of the dataset is https://www.kaggle.com/imdevskp/covid19-corona-virus-india-dataset. This dataset includes information collected from day-to-day state-wise number of cases, raw patient data, day-by-day nation-level numbers, state-level latest numbers, district-level latest numbers, day-by-day number of tests, and latest state-level statistics obtained from COVID-19 India dataset. Experimental evaluation is carried out on certain parameters like execution time, clustering accuracy and energy consumption for different number of patient data.

Discussion

In this section, the analysis of the results for three different parameters, execution time, clustering accuracy and energy consumption for efficient data transmission, is discussed. The comparison is carried out with the IoT-EALAFMRC method and existing methods, cognitive data transmission method (CDTM) [1] and interference aware energy efficient transmission protocol (IEETP) [2] using COVID-19 India dataset from Kaggle.

Impact on Clustering Accuracy

Clustering accuracy is the ratio of number of patient data that are correctly grouped to the total number of data points. It is formulated as,

$$CA = \frac{Number\ of\ patient\ data\ that\ are\ correctly\ clustered}{N} * 100 \quad (1)$$

From (1), the clustering accuracy is computed. 'N' symbolizes the number of patient data.

Table 1 explains the performance results of clustering accuracy of three techniques with respect to the different number of patient data in the range 100 to 1000. In order to prove the clustering accuracy of the proposed IoT-EALAFMRC method, the comparison is carried out with existing methods such as the cognitive data transmission method (CDTM) [1] and IEETP [2]. During the result analysis, the number of patient data is considered to be 700. The clustering accuracy of the IoT-EALAFMRC method is 88%. Similarly, the clustering accuracy of CDTM [1] and IEETP [2] is 77 and 84%. Ten results of clustering accuracy are obtained. The diagrammatic representation of clustering accuracy is illustrated in Figure 4.

Figure 4 illustrates the performance result of clustering accuracy along with different numbers of patient data. With increasing the number of patient data, the clustering accuracy increases or decreases correspondingly in all three techniques. Clustering accuracy using the IoT-EALAFMRC method is higher than in other existing works. This is because of energy aware local approximated fuzzy MapReduce clustering in IoT-EALAFMRC method. Map and reduce function in the proposed method groups the patient data based on a physical health condition. IoT-EALAFMRC method carried out the cluster assignment based on neighborhood relationships among patient data to increase the clustering accuracy. Consequently, the IoT-EALAFMRC method increases the clustering accuracy by 14 and 6% when compared to CDTM [1] and IEETP [2], respectively.

Impact on Energy Consumption

Energy consumption is the product of a number of patient data and the amount of energy utilized by one patient's data. It is measured in terms of joules (J). It is calculated as,

$$EC = N * Energy\ consumed\ by\ one\ patient\ data \quad (2)$$

From (2), the energy consumption is determined.

Table 2 explains the performance results of energy consumption of three techniques with respect to the number of patient data in the range 100 to 1000. The energy consumption of the proposed IoT-EALAFMRC method is lesser when compared to existing methods such as the cognitive data transmission method (CDTM) [1] and interference aware energy efficient transmission protocol (IEETP) [2]. During the result analysis, the number of patient data is considered to 500. The clustering accuracy of the IoT-EALAFMRC method is 23 J. Similarly, the clustering accuracy of CDTM [1] and IEETP [2] is 41 J and 31 J. Ten results of energy consumption

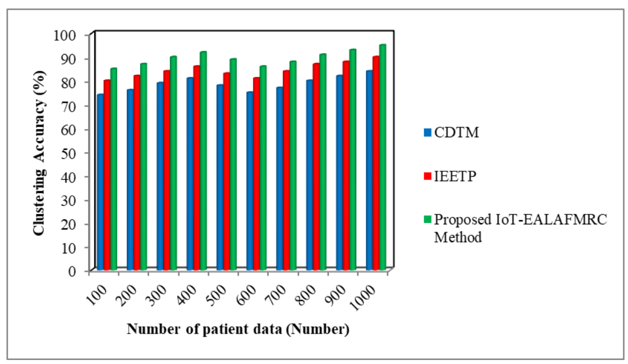

Figure 4: Measurement of Clustering Accuracy

Table 1: Tabulation of clustering accuracy

Number of patient data (Number)	*Clustering accuracy (%)*		
	CDTM	*IEETP*	*Proposed IoT-EALAFMRC method*
100	74	80	85
200	76	82	87
300	79	84	90
400	81	86	92
500	78	83	89
600	75	81	86
700	77	84	88
800	80	87	91
900	82	88	93
1000	84	90	95

Table 2: Tabulation of Energy Consumption

Number of patient data (Number)	*Energy consumption (J)*		
	CDTM	*IEETP*	*Proposed IoT-EALAFMRC method*
100	29	21	14
200	32	23	16
300	35	25	19
400	38	28	21
500	41	31	23
600	43	34	25
700	46	37	28
800	48	39	30
900	51	40	32
1000	53	42	35

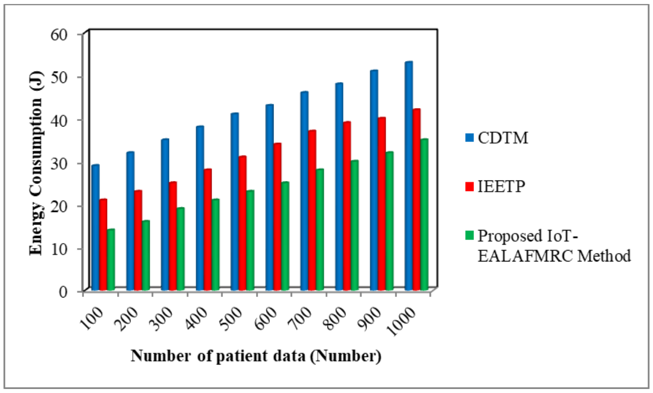

Figure 5: Measurement of energy consumption

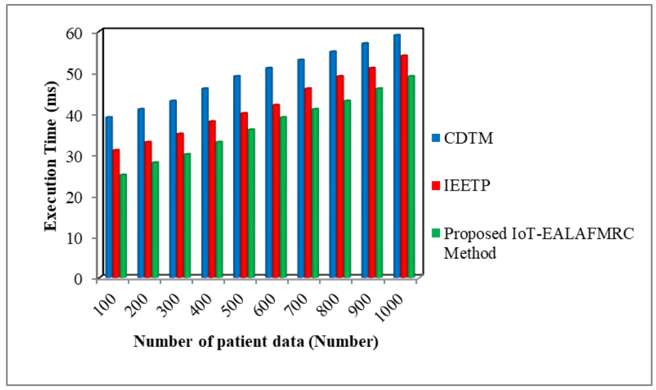

Figure 6: Measurement of execution time

are obtained. The diagrammatic representation of energy consumption is illustrated in Figure 5.

Figure 5 illustrates the performance result of energy consumption along with different numbers of patient data. With increasing the number of patient data for accomplishing experimental evaluation, the energy consumption is also increased in all three techniques. But comparatively, energy consumption using the IoT-EALAFMRC method is lower than other existing works. This is because of using energy-aware local approximated fuzzy mapreduce clustering in IoT-EALAFMRC method. Map and reduce function in the proposed method groups the patient data based on a physical health condition. IoT-EALAFMRC method carried out the cluster assignment based on neighborhood relationships among patient data. After data clustering, the data is sent to the physician with minimum energy consumption. Therefore, the IoT-EALAFMRC method reduces energy consumption by 43 and 25% when compared to CDTM [1] and IEETP [2], respectively.

Impact on Execution Time

Execution time is defined as the product of a number of patient data and the amount of time consumed by one patient data for data transmission. It is measured in terms of milliseconds (ms). It is determined as,

$$ET = N * Time\ consumed\ by\ one\ patient\ data\ for\ data\ transmission \quad (3)$$

From (3), the execution time is calculated. When the execution time is less, the method is said to be more efficient.

Table 3 explains the performance results of the execution time of three techniques with respect to the number of patient data in the range 100 to 1000. The execution time of the proposed IoT-EALAFMRC method is lesser when compared to existing methods such as the cognitive data transmission method (CDTM) [1] and interference aware energy efficient transmission protocol (IEETP) [2]. During the result analysis, the number of patient data is considered to 200. The clustering accuracy of the IoT-EALAFMRC method is 28 ms. Similarly, the clustering accuracy of CDTM [1] and IEETP [2] is 41 and 33 ms. Ten results of execution time are obtained. The diagrammatic representation of execution time is illustrated in Figure 6.

Table 3: Tabulation of execution time

Number of patient data (Number)	*Execution time (ms)*		
	CDTM	*IEETP*	*Proposed IoT-EALAFMRC method*
100	39	31	25
200	41	33	28
300	43	35	30
400	46	38	33
500	49	40	36
600	51	42	39
700	53	46	41
800	55	49	43
900	57	51	46
1000	59	54	49

Figure 6 illustrates the performance result of execution time along with different numbers of patient data. With increasing the number of patient data for accomplishing experimental evaluation, the execution time is also improved using all three techniques. But comparatively, execution time using the IoT-EALAFMRC Method is lower than other existing works. This is owing to the application of energy aware local approximated fuzzy MapReduce clustering in IoT-EALAFMRC method. The designed method used map and reduce function to group the patient data into normal constrained data or emergency constrained data based on a physical health condition. The IoT-EALAFMRC method performs the cluster assignment based on neighborhood relationships among data. After patient data clustering, the data is sent to the physician with minimum time consumption. Therefore, the IoT-EALAFMRC method reduces the execution time by 26 and 12 % when compared to CDTM [1] and IEETP [2], respectively.

Conclusion

A new data transmission method called the IoT-EALAFMRC method performs an efficient priority-based data transmission in a smart healthcare environment. IoT devices collect a large number of patient data in different locations. Energy aware local approximated fuzzy MapReduce clustering uses map and reduce function to group the patient data into normal constrained data or emergency constrained data based on physical health condition with higher clustering accuracy. IoT-EALAFMRC method performs cluster assignment based on neighborhood relationships among data. With minimal traffic, retransmission of patient data gets reduced. This in turn, helps to reduce energy consumption. Experimental analysis is conducted with Java language through performance metrics such as clustering accuracy, execution time and energy consumption. The performance analysis demonstrates that the IoT-EALAFMRC method outperforms well in terms of higher clustering accuracy with lesser energy consumption and execution time when compared to conventional techniques.

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