An Intelligent Predictive Model for Call Drop Management

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ABSTRACT

Many factors such as call setup failure, distorted signals and network congestion add to the poor quality of services rendered by GSM (Global System for Mobile Communication) operators. The call drop is more pertinent to customers' satisfaction that is why it is one of the most important key performance indicators (KPI) in measuring customer's satisfaction. This paper describes the procedure for the design and implementation of an intelligent cortical learning model for predicting call drops. The data was obtained from UCL repository which indicates the three major factors that causes call drop. The data was trained with a machine learning approach to determine the threshold value which subsequently was used as an input to the system to determine the quality of network performance. In order to achieve this, six indicators for network performance was used such as network performance is poor and there is a call drop, is excellent, there is no call drop or is fair, call drop may occur. The object oriented analysis and design methodology was used for proper analysis and design of the system, while implementation was done with matlab for simulation and PHP programming language for the application. The results obtained displayed a threshold value 9.24 which is the average value gotten after several training. Again the system was able to determine the quality of network performance in the area of study with predictions for call drops using the aforementioned indicators. The results also as explained has proved a novel approach when compared to the existing systems which only suggested the causes of call drop instead of making predictions. This prediction will encourages customers' confidence in the use of different GSM network and will also increase the business potentials of the operators.

Keywords: Call drop, Cortical Learning Algorithm, Spatial Pooler, Temporal Pooler, active cell, KPI.

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1. BACKGROUND TO THE STUDY

The growth of the telecommunication industry in Nigeria has been tremendous in about fifteen years after its liberalization and regulation by government through the Nigerian Communication Commission (NCC, 2014). The industry growth has been mostly in the voice segment until recently when attention is being paid to data (Adegoke et al., 2008). Mobile communication is now viewed as a necessity and is one of the fastest growing and most demanding technologies. The GSM family of technologies has provided the world with mobile communications since 1991(Bilal et al., 2009). Global System for Mobile communication (GSM) network performance and Quality of Service (QoS) evaluation are the most important steps for the mobile operators (Dinesh and Kaushal, 2016) as the revenue and customer satisfaction are directly related to network quality and its performance. One of the major issues experienced by the subscribers is call drop (Pragyan et al., 2012). Some even port from one network to another hoping to enjoy good quality of service without experiencing any call drop; however, the reverse is the case. This has, therefore, resulted into high level of customer dissatisfaction and complaints. The modern telecommunications network provide a wide range of voice services, therefore, there is an increasing need for evaluating voice quality. It is generally expressed as a Mean Opinion Score (MOS) (ITU-T, 2003). MOS is expressed as a single digit in the range of 1 to 5 where 1 mean bad audio quality and 5 is perceived as excellent audio quality.

Subscribers have experienced several issues arising from the services rendered by the telecommunications operators such as call setup failure, inter-network connectivity, network congestion, and call drop (Dajab et al., 2009). Call drop is the cutting off due to technical causes of the phone calls before the speaking parties had finished their conversational tone and before one of them had hung up (Prashant and Poonam 2016).
This paper is aimed to design and implement an intelligent model for predicting call drop which will assist customers to know if there will be call drops before calls are made.

1.1 Statement Of Problem
Over fifteen years ago, Global System for Mobile Communication (GSM) was introduced into this country. Subscribers have experienced several issues arising from the services rendered by the telecommunications operators in the country. One of the major issues experienced by the subscribers is call drop. Some even port from one network to another hoping to enjoy good quality of service without experiencing any call drop; however, the reverse is the case. This has, therefore, resulted into high level of customer dissatisfaction and complaints

1.2 Objective
The objectives of this study are:
i. To develop a framework to analyze and predict call drops.
ii. To train the proposed dataset using cortical learning algorithm in order to obtain threshold value.

2. METHODOLOGY

The dataset of three major hardware factors that causes call drop in a live network obtained from the UCI repository is depicted in table 1. It was collected for the period of 10 days, the Type-1 fault is when there is a broken High Level Data Link (HDCL) communication between Control and Main Board (CMB) and Frame Unit Control (FUC). Type-2 fault is assigned to Abis Control Link broken alarm while Type-3 is when Power Amplifier (PA) forward power (3db) alarm. These were break down into mean (**U**1), maximum (**U**2), Standard Deviation (**U**3), Variance (**U**4) and Signal Power (**U**5) respectively.

Table 1: Dataset of three major factors that causes call drop.

L1	U1	U2	U3	U4	U5
Type-1	0.97	34	3.11	9.48	13.78
Type-1	1.06	42	1.48	3.53	7.07
Type-1	1.82	13	3.08	9.47	20.80
Type-1	1.41	20	3.28	10.79	25.94
Type-1	0.95	32	3.20	10.24	11.66
Type-1	1.24	51	3.80	14.40	13.00
Type-2	0.59	14	0.93	1.14	0.93
Type-2	0.52	16	1.26	1.61	1.13
Type-2	0.71	17	1.62	2.62	2.12
Type-2	0.67	17	1.22	1.49	1.18
Type-2	0.23	7	0.68	0.46	0.47
Type-2	0.36	13	1.01	1.02	0.53
Type-3	0.51	59	2.08	4.32	4.12
Type-3	0.55	22	1.45	2.09	1.65
Type-3	1.04	21	2.44	6.04	9.61
Type-3	1.17	21	2.14	4.59	6.84
Type-3	0.42	23	1.70	2.65	2.48
Type-3	0.64	10	1.13	1.27	1.96

The architecture of the system consists of Load Data Unit (LDU), Encoder Unit (EU), Spatial Pooler Unit (SPU), Temporal Pooler Unit (TPU) and Call Drop Predicting System (CDPS) as depicted in Figure 1. The Load Data Unit (LDU) serves as container for accessing the call-drop dataset. It uses a text file for easy retrieval and storage of data. The call-drop is transformed into a sparse distributed representation (SDR) using an Encoder Unit (EU). The EU specifically encodes the inputs into binary data using scalar encoder

In scalar encoder the maximum and minimum values was set from the range of bit that can be used. The range of bits goes from 28 to 520 bits. When 28 range of bits was used such as 0000000000000000000000000000, 0.23 and 59 was obtained as minimum and maximum from the dataset. Hence, if the input value is equal to minimum, then the two leftmost bits are turned on as 1100000000000000000000000000. If the value is higher, then skip the first bit and turn on the two following bits as 0110000000000000000000000000. This process continues until the maximum value obtained which is 59 is inputted. This stream of bits is called potential pool in the algorithm and forms a Sparse Distributed Block in which Spatial Pooler can read from. The primary function of Spatial Pooler is to select active column in a bucket which is a collection of active and non-active columns and a column is a collection of cells
The bucket is computed as follow

$$Bucket = \frac{Maxvalue - Minvalue}{n - w + 1}$$ (Ahmad and Hawkins, 2015).

Maxvalue = 59
Minvalue = 0.23
n is the length of the bits = 28
w is the weight which is also a constant = 21

$$Bucket = \frac{59 - 0.23}{28 - 21 + 1} = 7$$

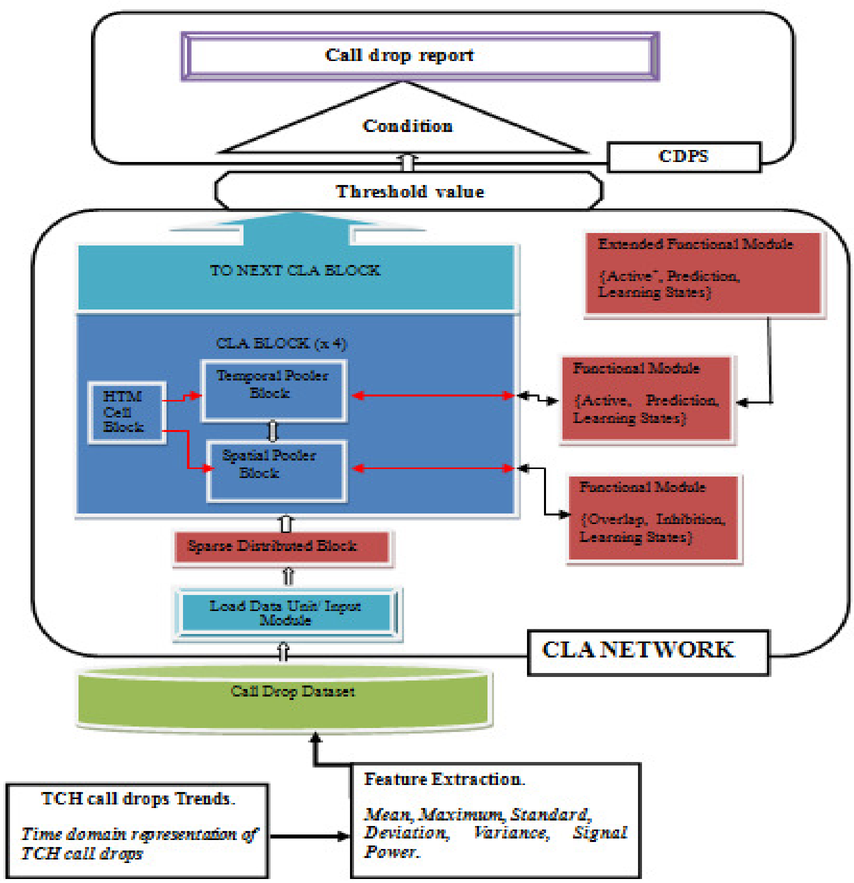

Figure 1: Architecture of the System.

Hence since the number of bucket is equal to seven, then it will be represented in 7 rows and 7 columns:

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Figure 2: A bucket of 7 rows and 7 columns

Figure 2: shows a bucket of 7 rows and 7 columns and each column has 7 cells.

The Spatial Pooler, after reading the sensory input, forms the sparse distributed block, an overlap is computed in order to determine active column. Therefore, to compute overlap, active bit is represented as 1 and inactive is represented as 0. A bit is active 1 if it is active at time t1 and t2

Time t1 = 0110000000000000000000000000
Time t2 = 0011000000000000000000000000
Overlap = 0010000000000000000000000000

A local neighborhood inhibition is performed on the overlap by allowing columns with strong activation inhibit weaker activation columns. This resulted into a sparse of active columns as shown in figure 3, which have 4 active columns and 3 inactive columns. Then, the 4 active columns configured by Spatial Pooler are input into the Temporal Pooling which is the next stage in the architecture.

Active Column	Inactive Column	Active Column	Active Column	Inactive Column	Inactive Column	Active Column
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Figure 3: Output from Spatial Pooling with 4 active column and 3 inactive columns.

Temporal Pooler has three Phases; the summary of each phase is show below where t is the time:
Phase 1: compute the active state, activestate(t), for each cell;
Phase 2: compute the predicted state, predictivestate(t), for each cell; and
Phase 3: update synapses. Numenta (2011).

Phase 1: Check if any cell or cells are in predictive state in current active column due to feed-forward input from a previous time. If yes, all predicting cells will be switched to active. The active cells replace the old input to the system. If there is no other predicting cell; then all cells in the column are turned to active. Moreover, any cell that has dendrite segment that best matches the input at the previous time is picked for learning as in represented below; let X and Y represent active and predictive cells respectively, Time T1

Active Column	Active Column	Active Column	Active Column
0	0	Y	0
X	0	0	Y
0	0	0	0
0	Y	X	X
0	Y	0	0
0	0	0	Y

Figure 4: A bucket showing active and predictive cells at time T1.

At time T1 as shown in Figure 4, the first column has one active cell, second column has two predictive cells, third column has one active and 1 predictive and the forth column has one active and two predictive cells. Hence, all the predictive cells are switched to active cells at Time T2 as shown in Figure 5 since there were predicted at time T1.

Time T 2

Active Column	Active Column	Active Column	Active Column
0	0	X	0
0	0	0	X
0	0	0	0
Y	X	Y	0
Y	X	0	0
0	0	0	X

Figure 5: A bucket showing all the predictive cells switched into active cells at time T2.

Phase 2: However, some cells in any column may enter a predictive state. If this happens then permanence value of the activated dendrite segment associated synapses will be modified. These changes are marked as "temporary". If the cell currently predicted the feed –forward input, then changes in permanent values will either be removed or allowed. In addition to the modifications to the synapses associated with the active segment, the cell's segment that best matches the state of the system at the previous time step is also selected for learning in order to predict sequences further back in time. Using the previous state of the system, the permanent values of its associated synapses are modified and are also marked as 'temporary'. Finally, a vector representing the active and predictive states of all cells in the level becomes the input to the next level in the hierarchy.

Table 2: Value obtained in relation to call drop report.

S/N	**VALUE OBTAINED (T)**	**CALL DROP REPORT**
1	T > 0 and T ≤ 8.67	The network performance is poor and there is a call drop
2	T > 8.67 and T < 9.24	The network performance is good and there is no call drop.
3	T = 9.24	The network performance is excellent. There is no call drop.
4	T > 9.24 and T ≤ 10.02	The network performance is fair. Call drop may occur
5	T > 10.2 and T ≤ 25	The network performance is poor and there is a call drop
6	T > 25	An abnormal value encountered. Kindly re runs experiment.

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Phase 3: The last phase actually carries out learning. Cells which have undertaken learning have pending modifications to the existing dendrite segments and may also have learned new segments. If the cell acceptably predicts feed-forward input, then these pending changes are made permanent and the permanent values of the appropriate synapses are incremented. Otherwise, if the cell ever stops predicting, then these pending changes are empty and the permanent values of the appropriate synapses are decremented. The result is sent to the next section for another set of training in order to obtain a better result. This is repeated four times and then the final training results obtained. This is the threshold value. The value is entered into the Call Drop Predicting System (CDPS) to check for the condition that is applicable to the value obtained as shown in Table 2.

3. EXPERIMENTS AND RESULTS.

These applications have been run and tested successfully.

3.1 Experiment 1

The application is launched as shown in figure 6; an interface will be displayed showing number of iteration which is the number of times in which the training will be repeated and it is set at 20.The Minimum overlap is set at 2 because overlap can only occur when compare to different time say T1 and time Tn. where n could be any number apart from 1.The Permanence is the value associated with synapse which is the connection of a column to the input bits or potential pool and it range from 0.0 to 1.0. It is set at 0.21 which mean when the input bits is below permanence 0.21; it should not response to the input bits. The Desired Local Activity is the number of input bits in which the column can connect to at a time. The Sequence size is the input bits used which is 28.Simulate button was clicked in order to submit the imputed values. The predicted values were read and recorded for each run as shown in Table 3.

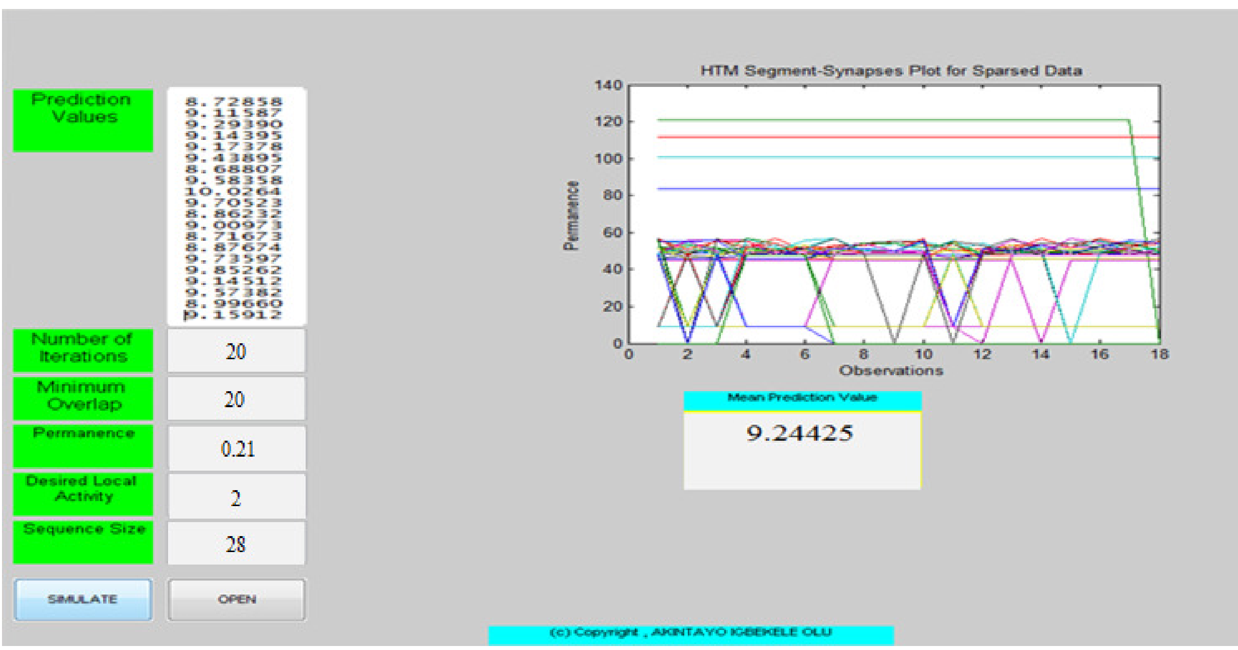

Figure 6: Interface showing input and output after simulation.

Table 3: The result of prediction after simulation.

Run Number	Predicted value
1	8.72858
2	9.11587
3	9.29390
4	9.14395
5	9.17378
6	9.43895
7	8.68807
8	9.58358
9	10.0264
10	9.70523
11	8.86232
12	9.00973
13	8.71673
14	8.87674
15	9.73597
16	9.85262
17	9.14512
18	9.57382
19	8.99660
20	9.15912

3.2 Experiment 2

A test drive was conducted in Rumuodara and Rumuokwurushi to obtain a dataset which was analyzed by term investigator software to obtained values showed in table 3 where RSCP stand for received signal code power which is the power measure on a particular communication channel by the receiver and it is used as an indication of signal strength. It have interval of twenty and the map of the coverage area is show in figure 7. The value obtained is inputted in the predicting application to determine call drop as shown in Figure 8. Location address is the area in which the test result was obtained. Other info tells more about the site. It could be 2G, 3G, 4G sites or combination of the sites. It could also be Colocation or Greenfield site.

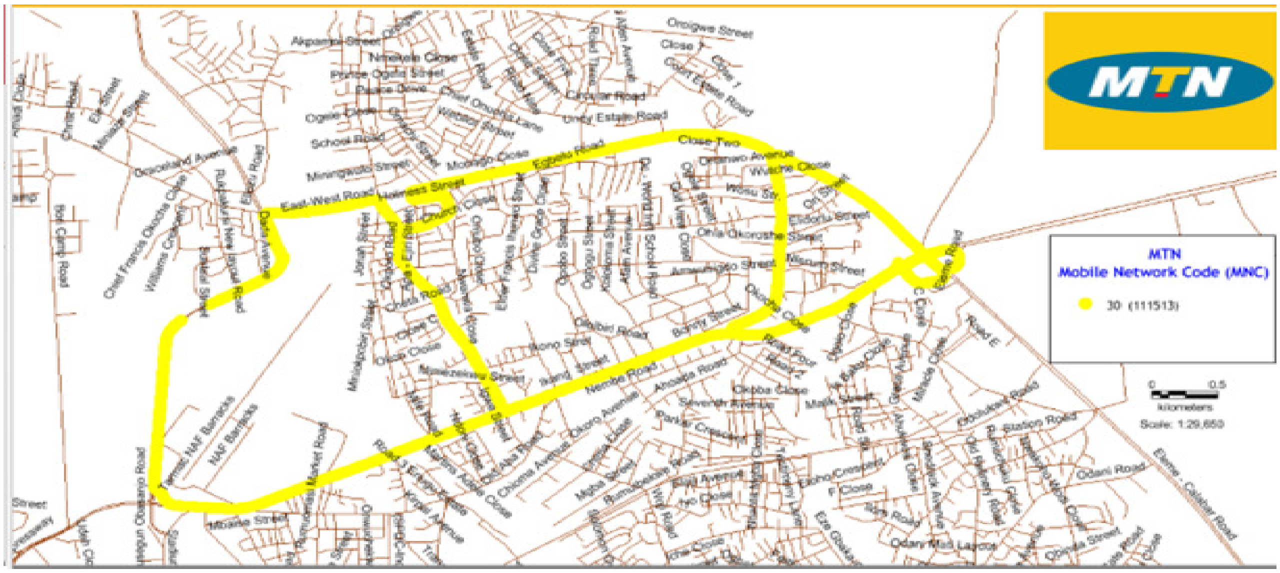

Figure 7: Interface showing coverage area of Rumuodara and Rumuokwurushi

Table 3: Value obtained in Rumuodara and Rumuokwurushi

S/N	Interval	Value Obtained
1	-120 ≤ Rscp < -100	8.82
2	-100 ≤ Rscp < -80	9.59
3	-80 ≤ Rscp < -60	9.24
4	-60 ≤ Rscp < -40	10.50
5	-40 ≤ Rscp < -20	9.52
6	-20 ≤ Rscp < -0	9.23

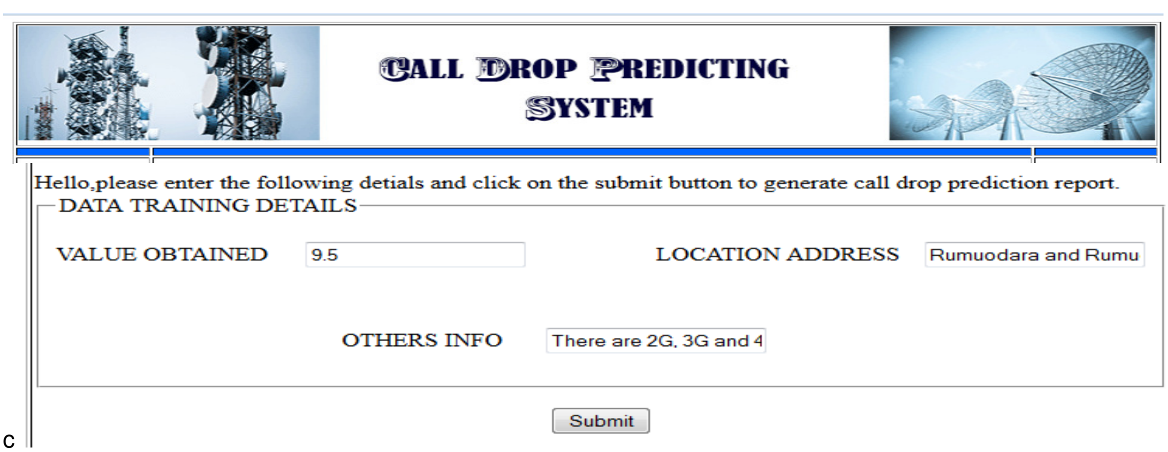

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Figure 8: Interface showing valued obtained and other site details.

4. DISCUSSION OF FINDING

Experiment 1 test results have been presented using the itemized parameters shown in Figure 6. The predicted values are read and recorded for each run. Minimum predicted value is 8.68, which occurred at 7th run while maximum predicted value occurred at 9th run, which is 10.02. The mean predicted value is 9.24. This is the best predicted performance value. This is taken as the threshold value obtained. Figure 9 and Figure 10 shows visualization of HTM synapses of call-drop of original data and sparse Data respectively. It was observed that learning was at peak within permanence range of 45 and 55 for both this therefore confirms that learning in a sparse way does not affect how pattern can be learnt.

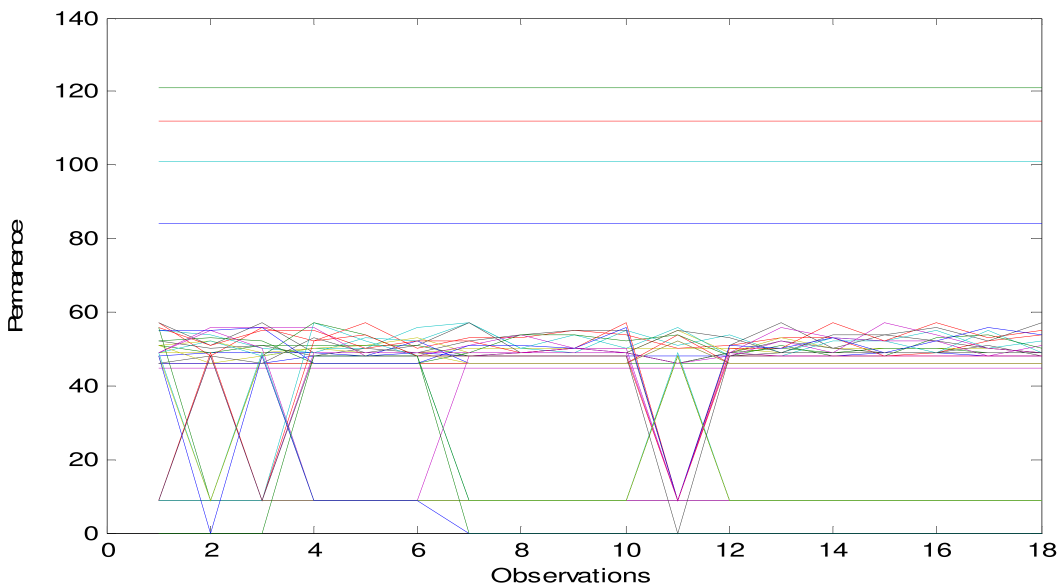

Figure 9: Visualization of HTM Segment Synapses of Call-drop of Original data after simulation

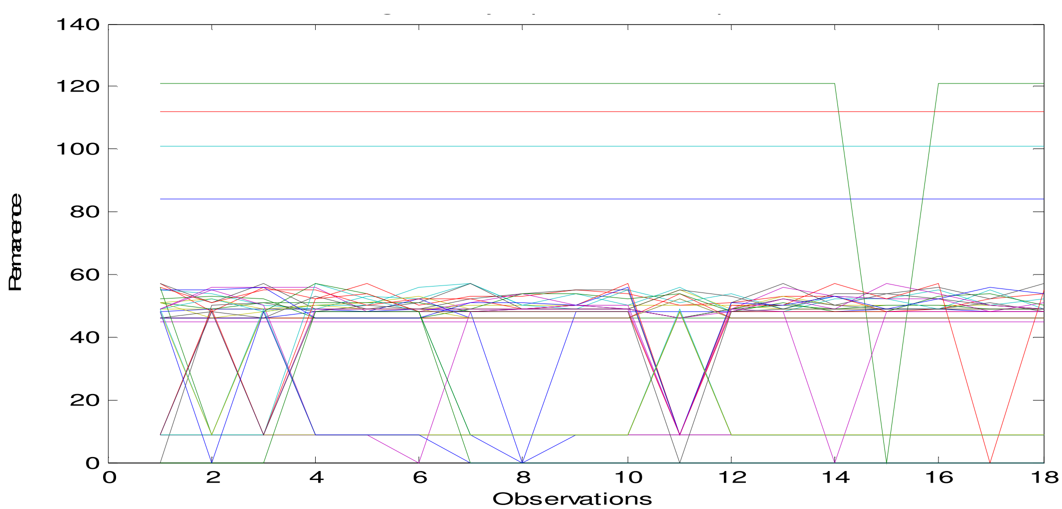

Figure 10: Visualization of Sparse HTM Segment Synapses Plot for sparse Data after simulation.

Experiment 2 determines the network performance as follow: when the first value obtained 8.82 was entered into the system, the display report as shown in Figure 11 indicated that the network performance at Rumuodara and Rumuokwurushi is good and there is no call drop experience by the customer but can be improved. When 9.59 were entered, the display report is the network performance is fair and call drop may occur. Furthermore, as shown in Figure 12 where value obtained 9.24 was entered, the report is network performance is excellent and there is no call drop. The forth value obtained is 10.50 and when this was entered into the system, the report is the network performance is poor and there is call drop. Urgent attention is needed immediately as shown in Figure 13.

It is clear that different values were obtained at different interval around the area. This shows that the network performance varies as a result of variation in the base transmission stations in their area; hence customers at different area within the coverage area are experiencing different network performance. Figure 14 shows the network performance and call drop report, different colour were used to write the criticality of the performance. The sum of the total result obtained is 56.9 and the average is 9.48. This was entered into the system to obtained general performance as shown in figure 15. Therefore, the general network performance at Rumuodara and Rumuokwurushi is fair and call drop may be experience by the user.

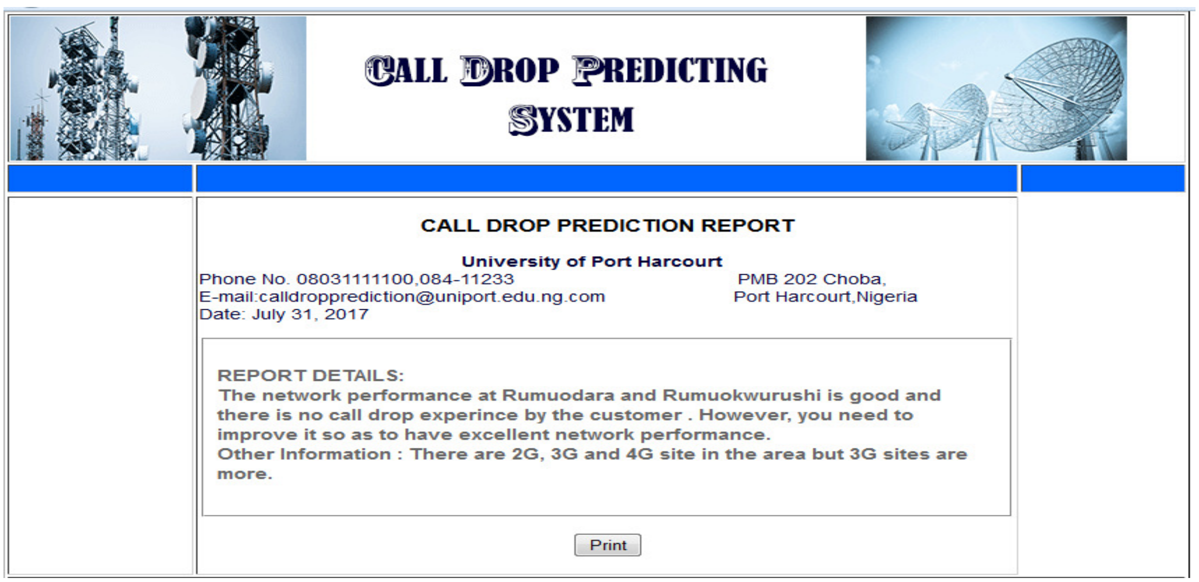

Figure 11: Interface showing report when the valued obtained is 8.82.

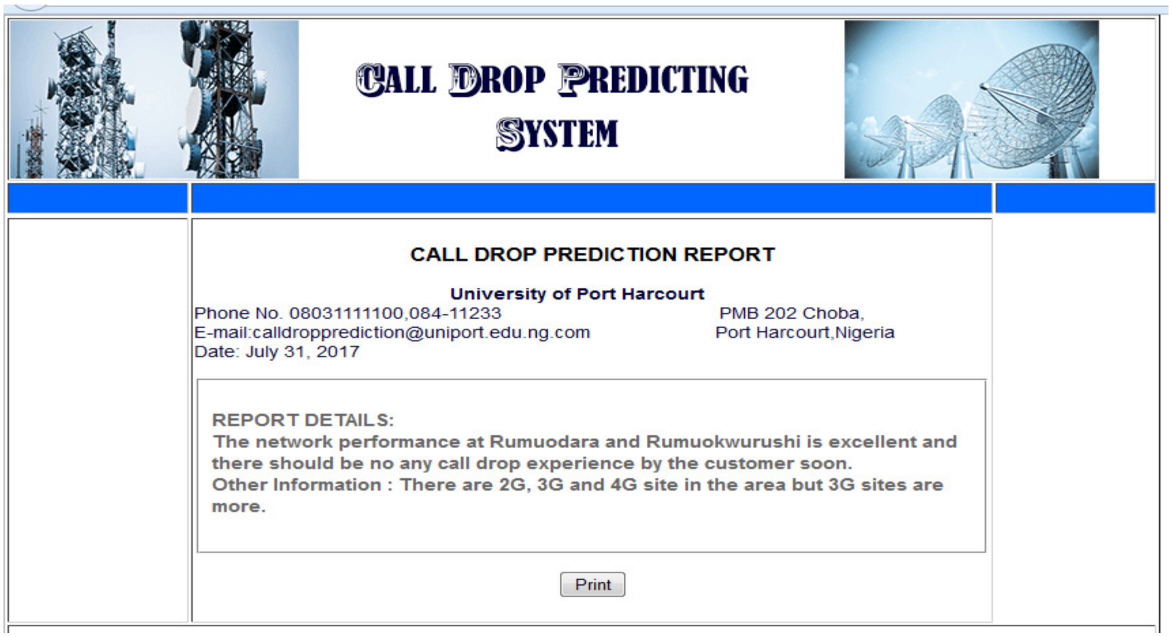

Figure 12: Interface showing report when the valued obtained is equal to 9.24.

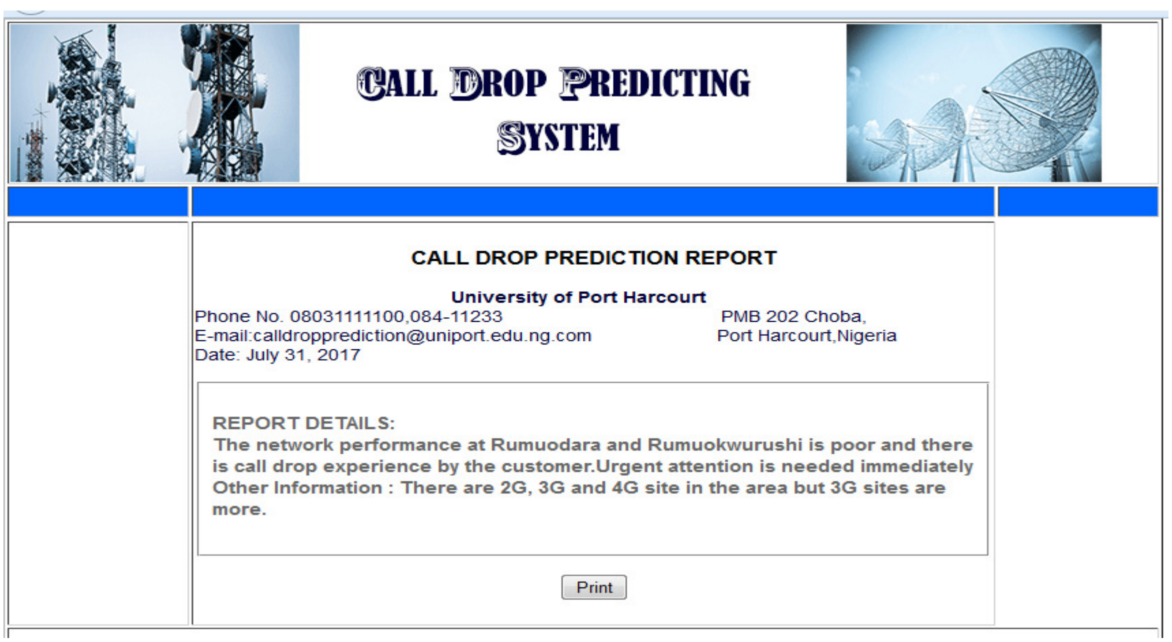

Figure 13: Interface showing report when the valued obtained is equal to 10.50.

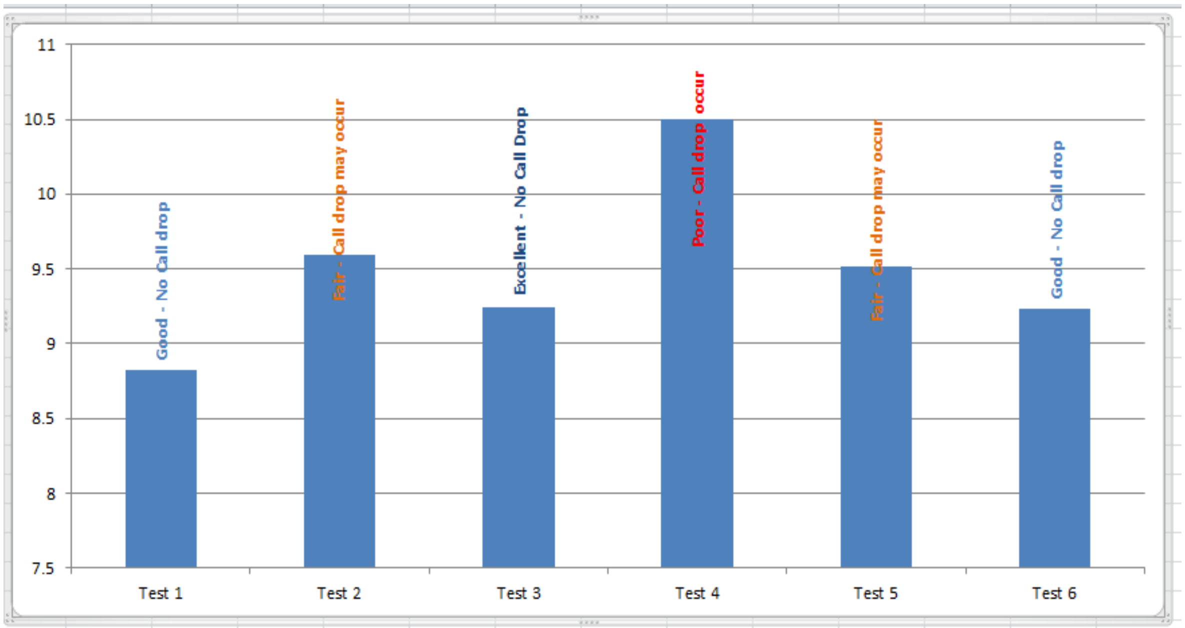

Figure 14: Interface showing network performance and call drop report.

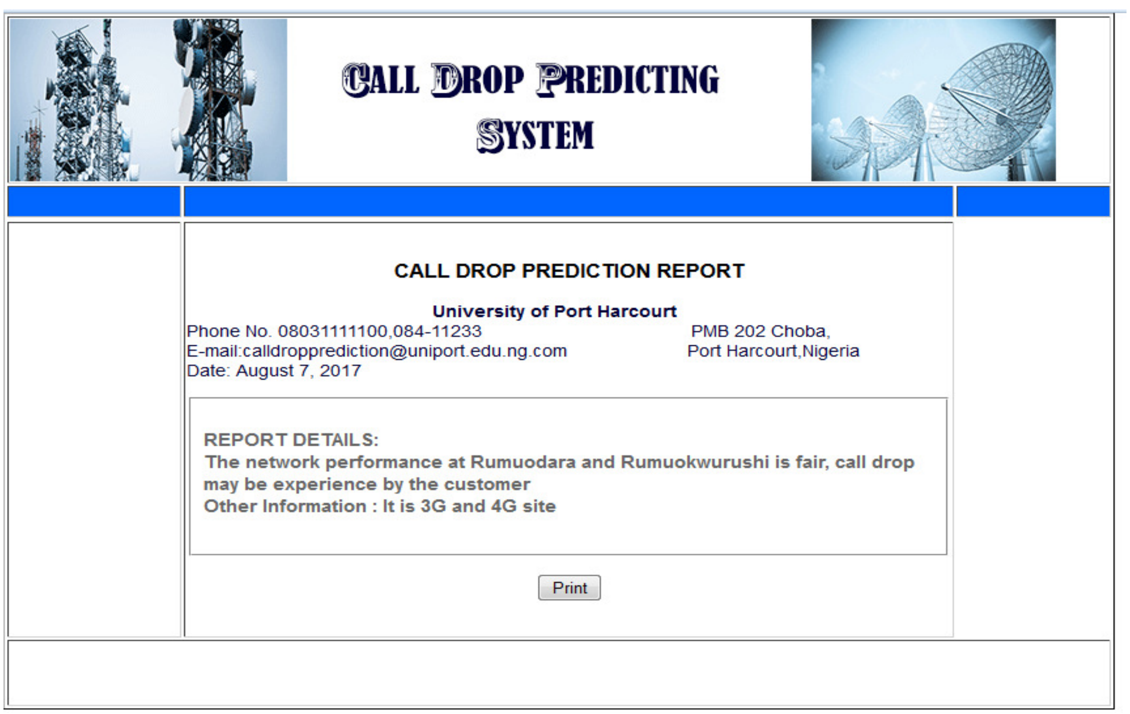

Figure 15: Interface showing general network performance and call drop report at Rumuodara and Rumuokwurushi.

5. CONCLUDING REMARKS

An intelligent cortical learning model for predicting call drops has been design and implementation; training and simulation has been performed on a dataset to obtain a threshold value. This system outsmarts the existing system because it used large training sample to obtained better result as recommended in the existing system and instead of only suggesting the causes of call drop as applicable in the existing system, it was able to predict a call drop in a lesser period. This prediction will encourages customers' confidence in the use of different GSM network and will also increase the business potentials of the operators.

6. CONTRIBUTIONS TO KNOWLEDGE

This research has made the following contributions to knowledge:

1. The study has developed an improved model for predicting call drops.
2. A predictive call drop application was developed in the study.

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