ISSN (e): 2250 – 3005 || Volume, 15 || Issue, 9|| Sept. – 2025 ||
International Journal of Computational Engineering Research (IJCER)

Call Drop Rate Prediction in GSM Mobile Networks Using the Hierarchical Temporal Memory: Case Study Of 3 Nigerian GSM Networks

Collins Iyaminapu Iyoloma[1], Nkechinyere Eyidia[2], Tamunotonye Sotonye Ibanibo[3].
[1 &3] Dept. of Electrical Engineering, Rivers State University, Port Harcourt, Nigeria.
[2] Dept. of Computer Engineering, Rivers State University, Port Harcourt, Nigeria.

Abstract
This research study presents a machine intelligence approach to call drop prediction using an emerging neural network called the Hierarchical Temporal Memory (HTM). The proposed HTM approach is applied to a case study call drop data from three GSM mobile operators – the Airtel, Glo and MTN networks in Nigeria. The results using the HTM approach showed that the best performance can be achieved considering classification accuracy frequency for the Glo network data of about 75%. In general, an average classification accuracy of about 57% is achievable by the HTM. Thus, the HTM is a promising candidate for call drop analysis.

Keywords: *Call drop, GSM, machine intelligence, prediction*

Date of Submission: 25-09-2025 Date of acceptance: 05-10-2025

I. Introduction

The growth of the telecommunication industry in Nigeria has witnessed tremendous growth in about fourteen 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.

When GSM services were launched in the country in 2001, as shown in figure 1.1, total teledensity was at 0.4%, with a total of 400,000 subscriptions for both fixed and mobile lines. In 2014, total number of subscription for fixed and mobile lines in Nigeria is in excess of 139.1 million with an estimated teledensity of 99.39% (NCC, 2014).There has been a continuous growth since 2001 as regards to total number of active voice subscribers and the teledensity.

This growth is born out of the desire of Nigerians to key into the values that can be derived from mobile telephony. Government revenue base has increased as result of tax and license fee collected from the Mobile Network Operators and operators likewise has made huge profit through the selling of SIM cards, Recharge card, data etc. As revolutionary as GSM may seem to be, many problems bedevil the sector, among whichare:

i. Call setup failure
ii. Inter-Network connectivity
iii. Network congestion
iv. call drop
v. Distorted signals

All these factors contribute to the poor quality of services rendered by GSM operators in the country (Adegoke et al., 2008).

Several Telecommunication companies in Nigeria are yet to attend to their mobile Subscribers frequent call drop (A situation where mobile call is terminated unexpectedly without the intention of any of the callers).There has been several call drops complains by the subscribers. Call drop impact on the Quality of service experience by the subscribers. There are several factors that can lead to call drop which could be; network failure, poor signal quality, low network coverage and interference. Poor network coverage is generally believed to be the major cause of call drop in Rural Area as well as electricity, while network congestion and network failure as result of inadequate network infrastructures are the common factors that lead to call drop in Urban Area.

In this research paper, an emerging machine intelligence neural technique called the Hierarchical Temporal Memory (HTM) is proposed to predict call drop rate in Nigerian GSM networks.

II. Related Studies

While network availability has grown, this has not been matched by quality of service. It is not enough to have purchase SIM card at inexpensive priceand low cost bandwidth, efficiency and accessibility of telecoms and service should be paramount. Therefore there is need for network operators to do more on quality of service especially in meeting the set KPIs thereby increasing subscribers' satisfaction.

Rex (2015) investigated the QoS of Nigeria GSM using Call drop rate and Hanover success rate as key KPI. Erlang B probability was use to highlight the service quality base on the number of channels available at any given moment. The result of the research showed that the service quality with respect to call drop in Nigeria is inadequate. It was recommended that further enhancement is urgently needed since the telecoms operators are far from providing a good service to their subscribers.

Joseph and Kingsley (2014) adopted some KPIs(drop call rate, outage call rate and call setup success) to examine GoS and QoS performance of mobile network bases on a cell-cluster. It was concluded after network optimization there was improvement in the network performance and thereby significantly increased the customer satisfactions.

Joseph et al., (2013) considered propagation environment in relation to network performance using Erlang-B Formula. Four major state where selected in the research (Abuja, Lagos, Kaduna and Port Harcourt).Also KPIs like traffic intensity, call duration, channel availability and utilization where used. The results showed that there was variation in the KPIs in the different regions.

Abu (2012) explored the GSM Coverage in Nigeria and its impact on the Economic Welfare of Citizensusing regression analysis to analyze the data collected, recommends that Government should intensify and improve regulations through the Nigerian Communication Commission to protect and safeguard the interest of subscribers in Nigeria.

Idigo et al (2012) researched the QoS of Visafone Mobile network using Call Setup Success Ratio(CSSR), Traffic Channel Congestion(TCH), and Call Drop Ratio (CDR) as the essential KPIs, iManager M2000was used to pull CSSR, CDR and TCH Congestion Ratio measurements for the period of the study.Descriptive and inferential statistics were used to study the collated data and the data were analyzed using plotted graphs. The result showed that Traffic Channel Congestion Ratio and Call Drop Ratio during busy hour were below 2% and Call Setup Success Ratio was above or equal 98%.

Regarding the Performance evaluation of GSM, Adegoke et al., (2008) using call set up and drop call as KPI, stated that all the network performed fairly well in call set up but poorly in respect to dropped calls. It was indicated that the performance of GSM operators in the country is still a far cry from the expectations of the subscribers.

Hence, having considered all the past related works, it was concluded that several KPI has been applied to improve network performance and thereby enhancing customer satisfaction. Rex (2015) research showed that the service quality with respect to call drop in Nigeria is inadequate. It was recommended that further enhancement is urgently needed since the telecoms operators are far from providing a good service to their subscribers.

So far, there has not been any machine intelligent model design and implementation to advice telecommunication operators on the causes of call drop as a result of porting from one network to another with respect to partial feature mapping and sparse learning. This research will critically look into this.

III.Materials and Methods

The materials employed are based on open source data obtained from Popoola and others (Popoola et al., 2018). This data (Table 1) is used in the simulations for generating the results provided in a later section (Section 4). The data presents the Dropped Call Rate (DCR) obtained from three Mobile operators (AIRTEL, MTN and GLOBACOM). The utilized dataset features extracted for analysis basically include two key fields: The month field and the corresponding DCR for that month. These data (DCR field data) are in continuous form i.e. they change over time.This feature reduction operation makes it more challenging for machine learning neural prediction techniques to solve. It also conforms to the real time processing paradigm of smaller feature set and higher reliability. Simulations are performed using the MATLAB® software tool.

Table.1 Dataset of Dropped Call Rate (Source: Popoola et al., 2018)

s/n	Month	Operator	DCR	Operator	DCR	Operator	DCR
1	12	Airtel	0.70	glo	0.52	mtn	0.58
2	11	Airtel	0.71	glo	0.50	mtn	0.49

3	10	Airtel	0.73	glo	0.54	mtn	0.63
4	9	Airtel	0.78	glo	0.50	mtn	0.65
5	8	Airtel	0.86	glo	0.49	mtn	0.64
6	7	Airtel	0.76	glo	0.55	mtn	0.68
7	6	Airtel	0.77	glo	0.55	mtn	0.55
8	5	Airtel	0.76	glo	0.57	mtn	0.50
9	4	Airtel	0.69	glo	0.54	mtn	0.45
10	3	Airtel	0.65	glo	0.57	mtn	0.50
11	2	Airtel	0.69	glo	0.50	mtn	0.71
12	1	Airtel	0.65	glo	0.50	mtn	0.67
13	12	Airtel	0.63	glo	0.60	mtn	0.82
14	11	Airtel	0.62	glo	0.41	mtn	0.82
15	10	Airtel	0.70	glo	0.46	mtn	0.72
16	9	Airtel	0.75	glo	0.53	mtn	0.78
17	8	Airtel	0.71	glo	0.55	mtn	0.76
18	7	Airtel	0.74	glo	0.41	mtn	0.72
19	6	Airtel	0.75	glo	0.40	mtn	0.72
20	5	Airtel	0.72	glo	0.53	mtn	0.93
21	4	Airtel	0.69	glo	0.48	mtn	0.85
22	3	Airtel	0.79	glo	0.87	mtn	0.50
23	2	Airtel	0.84	glo	0.46	mtn	0.90
24	1	Airtel	0.82	glo	0.50	mtn	1.02
25	12	Airtel	0.73	glo	0.86	mtn	0.72
26	11	Airtel	0.75	glo	0.96	mtn	0.78
27	10	Airtel	0.79	glo	0.91	mtn	1.23
28	9	Airtel	0.82	glo	0.81	mtn	1.16
29	8	Airtel	0.85	glo	0.78	mtn	1.22
30	7	Airtel	0.82	glo	0.81	mtn	1.23
31	6	Airtel	0.80	glo	0.85	mtn	1.30
32	5	Airtel	0.74	glo	0.78	mtn	1.33
33	4	Airtel	0.67	glo	1.43	mtn	1.43
34	3	Airtel	0.60	glo	0.83	mtn	1.19
35	2	Airtel	0.71	glo	0.85	mtn	1.29
36	1	Airtel	0.84	glo	1.19	mtn	1.21

The proposed method employed is based on HTM which follows from the Cortical Learning Algorithm (CLA).CLA is an unsupervised learning algorithm that is able to make more intelligent prediction in a lesser time and has been shown to be very promising with good predictive and online classification capabilities (Osegi, 2021; Osegi & Jumbo, 2021).

The proposed systems architecture for call-drop predictions is given in Figure 1. It consists of four key units (sub-systems) including the Load Data Unit (LDU), Encoder Unit (EU), Spatial Pooler Unit (SPU), and a Temporal Pooler Unit (TPU).

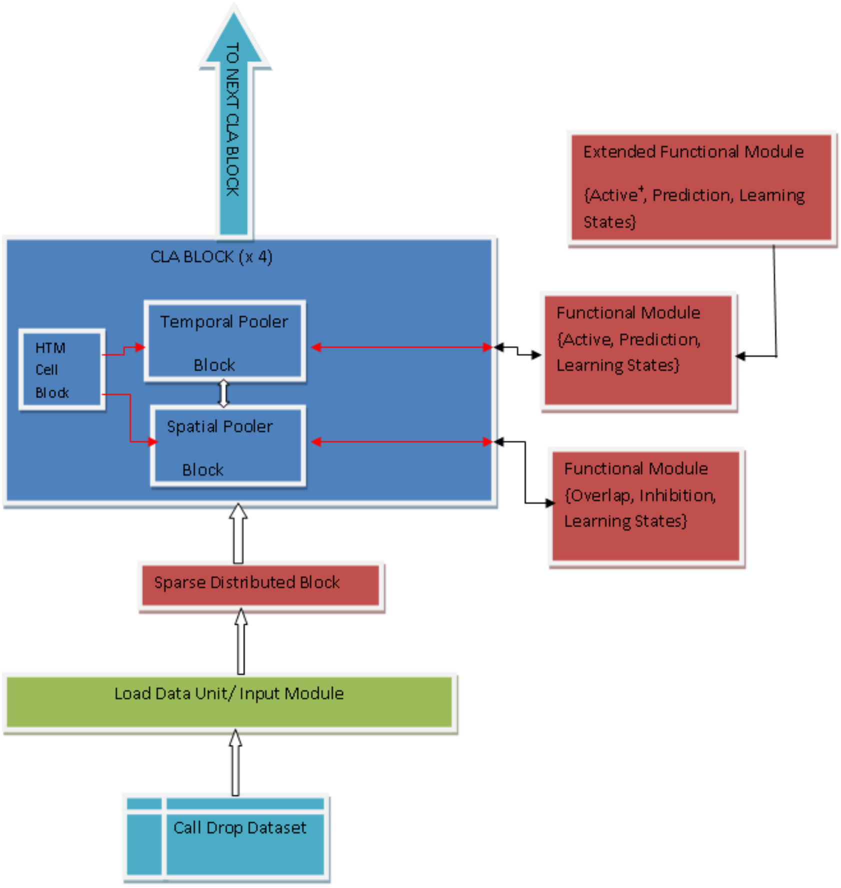

Figure 1: Architecture of the Proposed System

Load Data Unit: The Load Data Unit (LDU) serves as container for accessing the call-drop dataset. In the present design, the LDU uses a text file for easy retrieval and data storage.
Encoder Unit: An Encoder Unit (EU) is used for transforming the call-drop dataset into a sparse distributed representation (SDR). This is typically a scalar encoder; though other types of encoders are possible, a scalar encoder is more appropriate for the time series, due to lower data processing cost. The EU specifically encodes the inputs into binary data.
Spatial Pooler Unit: The Spatial Pooler Unit (SPU) generates a sequence of sparse distributed representations (SDRs) under the influence of the cortical synapses. The HTM, which is based on the Cortical Learning Algorithms (CLA) uses a similarity metric referred to as "overlap" (Ahmad and Hawkins, 2015) for evaluating the SDR match formulations in the HTM. Overlap is computed as:

$$overl(x, y) \equiv x \cdot y \qquad (1)$$

Where x and y are two binary SDRs.
For a match to be realized, the overlap score must be greater than a threshold as:

$$match(x, y) \equiv overlap(x, y) \geq \theta \qquad (2)$$

Temporal Pooler Unit: The Temporal Pooler Unit (TPU) performs temporal processing on the SDR sequence generated in the SPU. In the HTM, this process is handled using the "union principle" described in Ahmad and Hawkins (2015) and also uses the overlap evaluation metric. This principle allows a previous representation to be compared with a current one in order to determine the next set of predictions; if a match is found to be above a certain threshold, the current prediction becomes active and is predicted at the next time step; otherwise it remains inactive. The predictive state in a HTM learning cortical network at time step t is typically computed as suggested in (Cui et al., 2016):

$$\pi_{ij}^{t} = \begin{cases} 1 & if\ \exists_d \ \|\widetilde{D}_{ij}^{d} \circ \mathrm{A}^t\|_1 > \theta \\ 0 & otherwise \end{cases} \qquad (3)$$

where,

$\widetilde{D}_{ij}^{d}$ = an M×N binary matrix representing the permanence of a connected synapse

d = a cortical segment

i, j = cell and column states

A^{t} = an M×N binary matrix denoting the activation state of the cortical network

θ = the cortical segment activation threshold

N = number of cortical columns

M = number of neurons (cortical cells) per column

A system flow of the SP algorithm is as shown in figure 2.

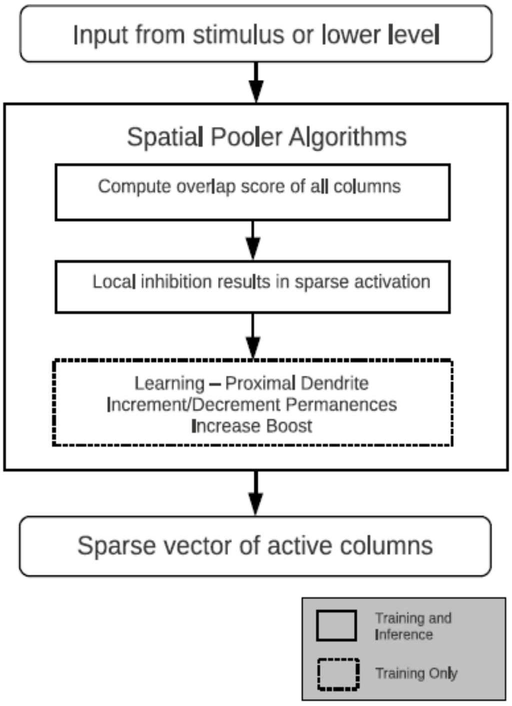

Figure 2: Overview of Spatial Pooling (Price,2011).

IV.Results and Discussions

The experimental results considering the proposed HTM based on CLA are presented and discussed in this section. The data as provided in Table 1 (see Section 3) has been re-engineered as shown in Tables 2 - 4for Airtel, Glo, and Mtn GSM networks respectively; this is in order to facilitate analysis using the HTM-CLA software program developed by Osegi (Osegi, 2021).

Table.2 Derived Dataset of Dropped Call Rate (DCR) for Airtel – T_h = 0.7

s/n	**Month**	**Encoded DCR state**
1	a	1
2	b	2
3	c	2
4	d	2
5	e	2
6	f	2
7	g	2
8	h	2

9	i	1
10	j	1
11	k	1
12	l	1
13	a	1
14	b	1
15	c	1
16	d	2
17	e	2
18	f	2
19	g	2
20	h	2
21	i	1
22	j	2
23	k	2
24	l	2
25	a	2
26	b	2
27	c	2
28	d	2
29	e	2
30	f	2
31	g	2
32	h	2
33	i	1
34	j	1
35	k	2
36	l	2

Table.3 Derived Dataset of Dropped Call Rate (DCR) for Glo – $T_h = 0.7$

s/n	Month	Encoded DCR State
1	a	1
2	b	1
3	c	1
4	d	1
5	e	1
6	f	1
7	g	1
8	h	1
9	i	1
10	j	1
11	k	1
12	l	1
13	a	1
14	b	1

15	c	1
16	d	1
17	e	1
18	f	1
19	g	1
20	h	1
21	i	1
22	j	2
23	k	1
24	l	1
25	a	2
26	b	2
27	c	2
28	d	2
29	e	2
30	f	2
31	g	2
32	h	2
33	i	2
34	j	2
35	k	2
36	l	2

Table.4 Derived Dataset of Dropped Call Rate (DCR) for Mtn – T_h = 0.7

s/n	Month	Encoded DCR State
1	a	1
2	b	2
3	c	2
4	d	2
5	e	2
6	f	2
7	g	2
8	h	2
9	i	1
10	j	1
11	k	1
12	l	1
13	a	1
14	b	1
15	c	1
16	d	2
17	e	2
18	f	2
19	g	2
20	h	2

21	i	1
22	j	2
23	k	2
24	l	2
25	a	2
26	b	2
27	c	2
28	d	2
29	e	2
30	f	2
31	g	2
32	h	2
33	i	1
34	j	1
35	k	2
36	l	2

The Month attributes for the considered mobile networks are reformatted to conform to suitable alphabetic codes in the ASCII character set. The numericdate field factors are correctly encoded asmonths attribute (features) in the ASCII set. Thus, 12 for Decemberelement is encoded as ASCII character "a" and 11 for November is encoded as "b" etc. In the same vein, the other months say October, September etc., are all encoded as such.

The DCR values are also encoded to a class based state i.e. a two-state representation. This achieved by using a threshold factor, T_h such that the DCR values greater than this value will trigger a 2- for dropped or anomalous call and 1 – for stable states.

4.1. Simulation Results and Discussions

Results of tests have been tabulated in Table 5 using the specified HTM-CLA network parameters (see Appendix A).

The results show simulation reports after several runs of HTM/CLA system. In the performed experiments, the task is to continually predict the DCR class level state at the next time step given a history of the DCR class values of the previous time steps. For the experiments on each mobile operator data, 80% of the data as defined in Tables 2 to 4 are used for online training. The remaining 20% are used for predictions; for these percentages of data, the class label is unknown to the HTM-CLA system.

Prediction classification accuracies (CA) are read and recorded for each run and the average computed.The results show good prediction performance of the HTM/CLA for mtn and glo networks but not so impressive performance for the Airtel network.

Table.5 Simulation tests with prediction accuracies for each HTM/CLA run

Trial No.	**HTM-CLA CA_{airtel} (%)**	**HTM-CLA CA_{glo} (%)**	**HTM-CLA CA_{mtn} (%)**
1	66.67	72.22	63.89
2	63.89	63.89	58.33
3	33.33	63.89	55.56
4	47.22	63.89	33.33
5	58.33	63.89	61.11
6	50.00	63.89	58.33
7	58.33	72.22	50.00
8	55.56	63.89	55.56
9	33.33	63.89	52.78
10	33.34	63.89	72.22

avg:	50.00	**65.56**	56.11

From the results in Table 5, the average prediction performance is about 57.2%. On the average, the best predicted performance is obatined from the glo network data (in bold) and as can also be observed the maximum CAs can be obtained from both the glo and mtn network data. In Figure 3 is shown the comparative prediction response using data of the various considered networks. As can be clearly seen, data obtained from Glo network gave the best possible results in terms of the classification frequency. A maximum CA of about 75% is also achievable by the Glo network.

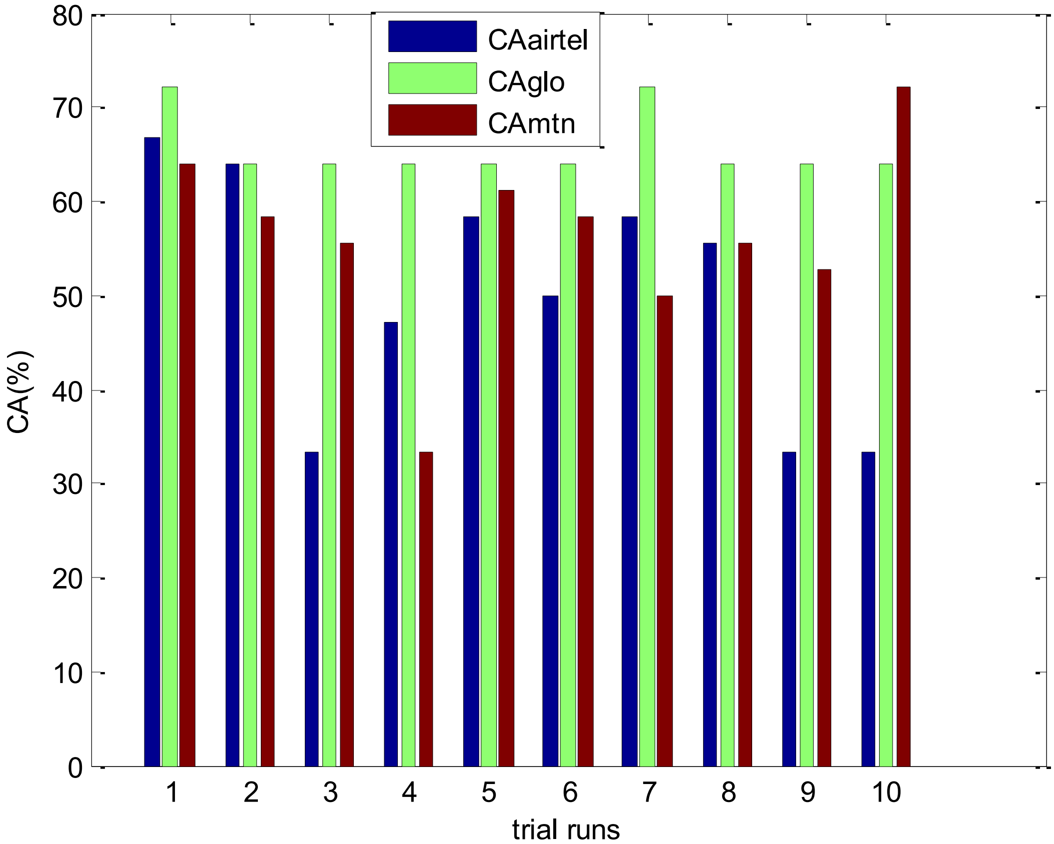

Figure 3: Prediction Response of the HTM-CLA on call drop data of various networks.

V.Conclusions

In this research paper, an emerging machine intelligence artificial neural network technique called Hierarchical Temporal Memory (HTM) based on the Cortical Learning Algorithms (CLA) has been proposed for call drop rate prediction. The system applies the principles of neo-cortical learning to make online predictions on a given communication network dataset.Practically, the performance of HTM-CLA for predicting call drop for the airtel network was not so impressive but it still fared reasonably well for the other communication networks (glo and mtn).

HTM-CLA is a robust artificial neural network strategyas it does not require separate training and test datasets but rather learns continually on the input train. Thus, it is more proactive thanconventional artificial neural networks for problems that require timely interventions like call drop analysis.

In conclusion, CLA holds great promises as a future neural network model if properly planned and re-engineered. Using functional object-oriented approach, the ideas of neuroscience and biology, simple logical reasoning blocks and complex data structures can lead to better neural models of the brain. Thus, it is desirable that existing neural networks exploits the potentials of this promising new artificial neural technology.

References

[1]. Adegoke A.S, I.T. Babalola, and W.A. Balogun (2008).Performance Evaluation of GSM Mobile System in Nigeria, the Pacific Journal of Science and Technology, 9(2), 436-441.

[2]. Ahmad, S., & Hawkins, J. (2015). Properties of sparse distributed representations and their application to hierarchical temporal memory. *arXiv preprint arXiv:1503.07469*.
[3]. Cui, Y., Ahmad, S., & Hawkins, J. (2016). Continuous online sequence learning with an unsupervised neural network model. *Neural computation*, *28*(11), 2474-2504.
[4]. Idigo V.E., A.C.O.Azubogu, C.O.Ohaneme and K.A.Akpado(2012).Real-Time Accessments of Qos of Mobile Cellular Networks in Nigeria, International Journal of Engineering Inventions,1(6),64-68.
[5]. Joseph M. Mom, Nathaniel S. Tarkaa and Cosmas I. Ani (2013).The Effects of Propagation Environment on Cellular Network Performance, American Journal of Engineering Research, 2(9), 31-36.
[6]. Joseph and Kingsley (2014).A Practical Optimization Method to Improve QoS and GoS-based key Performance indicators in GSM Network Cell Cluster Environment, International Journal of Wireless & Mobile Networks,6(5),93 - 107.
[7]. E.N. Osegi. (2021). https://doi.org/10.24433/CO.3936064.v1
[8]. Osegi, E. N., & Jumbo, E. F. (2021). Comparative analysis of credit card fraud detection in Simulated Annealing trained Artificial Neural Network and Hierarchical Temporal Memory. *Machine Learning with Applications*, *6*, 100080.
[9]. Popoola, S. I., Atayero, A. A., Arausi, O. D., & Matthews, V. O. (2018). Path loss dataset for modeling radio wave propagation in smart campus environment. Data in brief, 17, 1062-1073.
[10]. Price, R. W. (2011). Hierarchical temporal memory cortical learning algorithm for pattern recognition on multi-core architectures.
[11]. Rex Ndubuisi Ali (2015), Handoff and Drop Call Probability: A Case Study of Nigeria's Global System for Mobile Communications (GSM) Sector, Scholars Journal of Engineering and Technology,3(2A),166-169.
[12]. Nigerian Communications Commission (2014). 2014 year end subscriber/Network data report for Telecommunications Operating companies in Nigeria. Retrieved from: http://www.2.ncc.gov.ng/index.php/docman-main/industry-statistics/research-reports/656-2014-year-end-subscriber-network-data-report-for-telecommunications-operating-companies-in-nigeria/file4

Appendix A. HTM-CLA Parameters

TABLE A.1:KEY DEFAULT HTM-CLA SYSTEM PARAMETERS

Parameter Number	**Parameter Name**	**Parameter Description**
1.	Initial Permanence	0.21
2.	Connected Permanence	0.50
3.	Permanence Increment	0.10
4.	Permanence Decrement	0.01
5.	Number of Columns	256
6.	Stimulus threshold	10
7.	Boost factor	1.1