UJEAS

UNIZIK JOURNAL OF ENGINEERING AND APPLIED SCIENCES

UNIZIK Journal of Engineering and Applied Sciences 6(4), December (2026), 4105-4113
Journal homepage: https://journals.unizik.edu.ng/index.php/ujeas
PRINT ISSN: 2992-4383 || ONLINE ISSN: 2992-4391

Design and Implementation of Handoff Decision Making Algorithm using Machine Learning Technique

Umoren, Emmanuel Ekikere[1*]

Department of Electrical and Electronic Engineering, University of Uyo, Uyo, Nigeria.

Udofia, Kufre Michael

Department of Electrical and Electronic Engineering, University of Uyo, Uyo, Nigeria.

Ogungbemi, Emmanuel Oluropo

Department of Electrical and Electronic Engineering, University of Uyo, Uyo, Nigeria.

Obot, Akaninyene Bernard

Department of Electrical and Electronic Engineering, University of Uyo, Uyo, Nigeria.

Corresponding Author's E-mail:* ***emmanuel.umoren14@gmail.com*

Abstract

This paper focuses on the design and implementation of handoff decision making algorithm using machine learning technique. In wireless communication, mobile operators and their subscribers always experience dropped calls as a result of technical error in handover process which affects the quality of service (QoS) in the network. The technique employed used decision tree, random forest, gradient boosting and multi-layer perceptron as machine learning models which were trained to learn patterns that map feature space to handoff decisions. The results obtained indicates that at low mobility band, the decision tree produced 99.22%, 98.12%, 98.29% and 98.20% as an evaluation metrics for accuracy, precision, recall and F1-score. Also, at medium mobility band, the gradient boosting produced 97.91%, 95.38%, 94.92% and 95.14% for accuracy, precision, recall and F1-score. Again, at high mobility band, the multi-layer perceptron gave 99.49%, 98.44%, 99.49% and 98.96% for the same evaluation metrics. This shows that at different mobility band, the values of the evaluation metric vary depending on the type of mobility band. The machine learning technique is recommended for the applications of handoff decision algorithm and future generations of network.

Keywords: Wireless communication, Quality of service, Handoff decision, Machine learning technique

1. Introduction

Handover is a procedure of changing the frequency of the channel, scattering code and period space when moving from one cell to another cell during conservation. This can be initiated when the quality of the recent calls reduces below the expected value of the threshold signal in the network. The technology of handover procedure normally grant access to the continuity of customers call with good quality of calls conservation in the network (Muhammad *et al.,* 2023).

The benefits derived from the fifth generation (5G) technology guarantee significant changes in the affected communication by empowering faster data, low latency and improved connectivity in the network. However, inaccurate signal measurement always led to a problem due to the high millimeter wave rate and the required bandwidth wanted to increase the capacity of the system (Kasim *et al.,* 2020).

The development of artificial intelligence (AI) inspires system for enlightening the performance of the fifth-generation network. Artificial intelligence processes require huge datasets during network processes to forecast and find ways to recover the presentation of the network (Rajesh *et al.,* 2025).
Machine learning is a computerized system that abstracts information from data by revealing concealed designs. The application of these methods for huge measure information has increased the importance in mobile plans. The machine learning procedure lies on choosing suitable system including supervised and unsupervised learning (Chiputa *et al.,* 2022).

In recent technology, one challenge in mobile network is as a result of handover management, which refers to the procedure of shifting continuing message gathering from one transmitting session to another when the user transfers between exposure zones. This task becomes more challenging in heterogeneous networks due to fluctuating network traffic caused by real-time and widespread applications (Ahmadi *et al.,* 2020).
Umukoro *et al.,* (2024) investigated the mobility movement in cellular network across different radio access technologies. The method used was a self-optimizing fuzzy logic-based vertical handover model which act as an intelligent handover decision. Several handover decision factors were considered in this research and user mobility are used as fuzzy inputs. The result obtained reduces unnecessary vertical handover and ping-pong effects.
Odo and Ezeonye, (2022) analyzed the performance of inter-cell vertical handoff in 4G LTE network. The method used employs scientific approach for calculating call setup success rate (CSSR) and handover success rate (HOSR) using Microsoft excel and benchmarking with the NCC KPI's. The results obtained shows that cells LG0002F, LG0006A, LG0007A and LG0007B were able to achieved NCC guidance of ninety-eight percent for CSSR while LG0002D, LG0002E, LG0003B and LG0006A was able to accomplished the NCC recommended guidance of ninety-eight percent for HOSR.

Divakaran *et al.,* (2023) discussed on the enhancement mechanisms in 5G heterogeneous wireless network. The technique used evaluates relevant input parameters, develop fuzzy rule and the effectiveness of the network using MATLAB simulation tools. The results obtained shows that at 50gNB, the fuzzy handover had an average latency of 2.2 seconds while authentication handover average latency was 2.5 seconds. Also, at 150gNB, the fuzzy handover had a latency of 2.9 seconds and authentication handover latency of 4.7 seconds.
Sajjad *et al.* 2021 presented a robust and well-organized technique design for the improvement in heterogeneous networks. The method used involves a pipe-line approach which consist of selection of handover decision parameters, simulation model and assessment parameter to enhance the network model. The results indicates that the signal interference values range from -5 to 43dBs when the mobile users were moving from one transmitting unit to another.

Previous studies implemented by Kasim *et al.,* 2020, Sajjad *et al.* 2021, Odo and Ezeonye (2022), Divakaran *et al.,* (2023) and Umukoro *et al.,* (2024) engrossed their works on mobility management, enhancement mechanisms in 5G heterogeneous cellular networks and vertical handoff in 4G LTE network. Their works did not extend to the machine learning techniques that has the capacity to produce low ping-pong rate which reduces signaling overhead and optimize the network performance of cellular networks.

1.1 Horizontal and Vertical Handoff

In order to enhance the performance and reduce unnecessary handoff like ping-pong effect, prediction techniques are used based on user mobility patterns. As wireless networks (Wi-Fi, LTE) evolved, the handoff decision algorithms had to consider multiple technologies in heterogeneous networks which lead to the development of vertical handoff (Abdulkarem and Lukman, 2021).
Handoff mechanism consists of four diverse phases, namely handoff process, network collection, handoff commencement, handoff decision making and these are categorized into horizontal and vertical handoff. Horizontal handoff refers to a system implemented between two links with similar technology while vertical handoff also refers to the handoff which occur between systems that are not similar in technology. Again, there are two classes of vertical handoff due to their part of coverage. These are upward handoff and downward handoff. Upward handoff normally occurs when a mobile station switches from minor exposure zone to great exposure link. Downward handoff takes place when a mobile station switches from the great exposure to the minor exposure link. (Satapathy and Mahapatro, 2021). Figure 1 shows the diagram of a horizontal and vertical handoff.

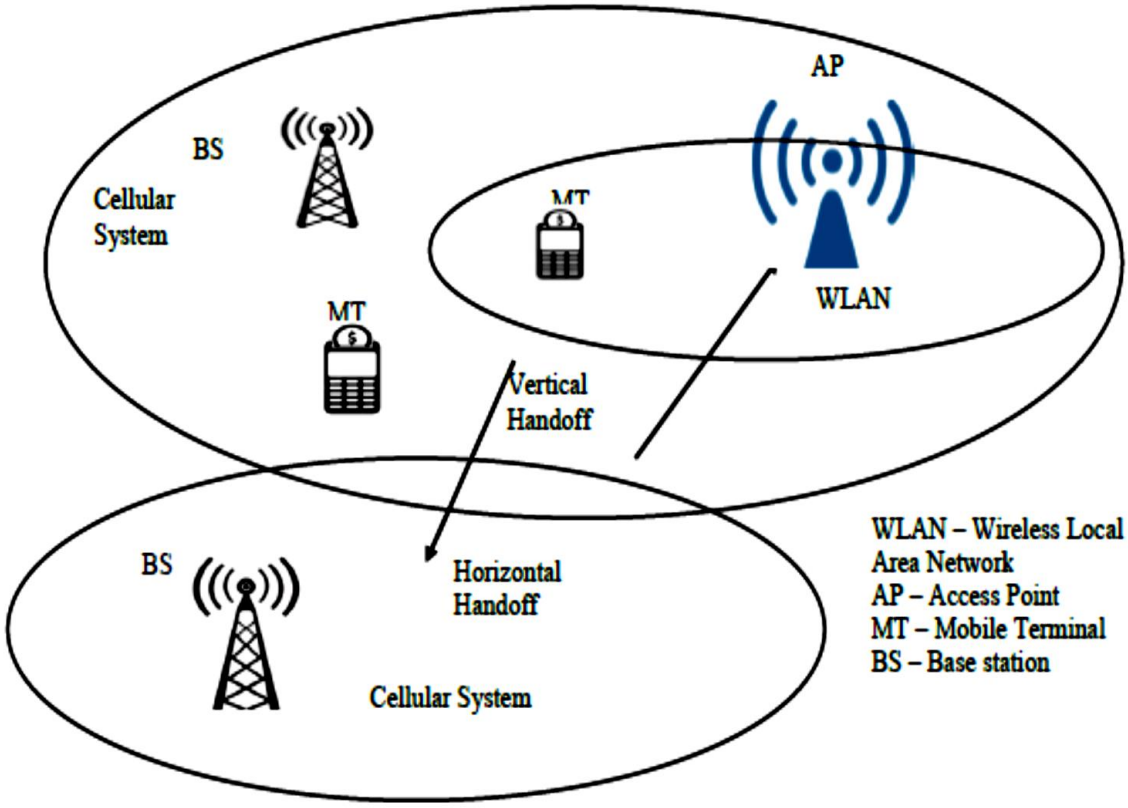

Figure 1: Diagram of a horizontal and vertical handoff

2.0 Materials and methods

The materials needed for the design of handoff decision making algorithm comprise of both hardware and software materials. The hardware materials are computer workstation with adequate random-access memory, central processing unit and graphics processing unit for developing and training of the machine learning models. Python was used as the primary programming language. MATLAB and Google Colab were used as supporting software

2.1 method

The technique used involves four machine models, namely decision tree, random forest, gradient boosting and multi-layer perception. The machine models were trained and the conventional handoff algorithms like RSS, SINR and hysteresis was also implemented as baseline for comparison with the machine learning models.

Heterogeneous dataset of about 200,000 samples was generated which contains eighteen (18) engineering features based on handoff requirements. In order to achieve high reliability and accurate outcome in handoff, eighty percent (80%) of the data acquired was used for training, ten percent (10%) for testing and ten percent (10%) for validation. The performance evaluation for the models in the handoff decision was computed using evaluation metrics, like accuracy, precision, recall and F1-score. Statistical evaluation was conducted to ensure that the model handles dataset fluctuations and also meets with the operation criteria by using bootstrap confidence intervals in order to achieve high reliability of accuracy. The design simulator for the handoff algorithm in heterogeneous network is presented in Figure 2. This simulator represents a multi-tier communication environment which compose of interconnected macro cells, small cells, femto cells, user equipment and the core network. The macro cell (MC) provides a wide area coverage with high transmission power, small cell (SC) was deployed to reduce congestion and improve signal quality, femto cell (FC) extend network coverage indoors, user equipment (UE) represents when the mobile users move across the network zones and the core network (CN) consists of entities that manages authentication, resource allocation, mobility management and handoff execution.

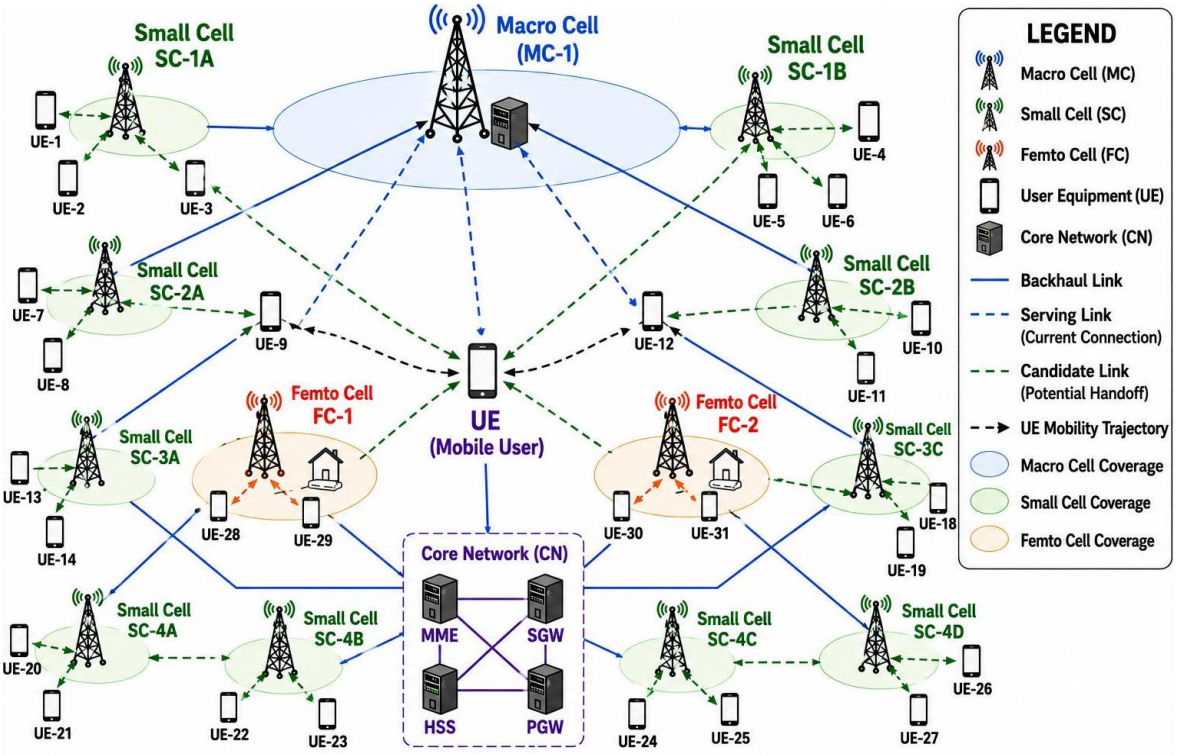

Figure 2: Design simulator for the handoff algorithm in heterogenous network

2.2 Training of machine learning models for handoff algorithm

The machine models used in this research work are presented in this section:

2.2.1 Decision Tree

A decision tree model is a controlled machine technique widely used for arrangement and regression tasks. This model is organized in a hierarchy manner which comprise of several nodes of different specifications. The tree depth comprised of different values of 0, 1, 2, and 3. 0 is the stay connected to the serving cell, 1 is the handoff to neighbour one, 2 is the handoff to neighbour two and 3 is the best available target. The function of the internal node is to examine the features of the datasets while the leaf node signifies the expected category. Decision tree-based handoff models used multiple network and user interrelated metrics (Priyanka *et al.*, (2023). A decision tree partitions the input space that minimize node impurity as shown in Equation 1.

$$G_m(t) = \sum p_i(n|t)\left(1 - p_i(n|t)\right) \quad (1)$$

Where $G_m(t)$ is the Gini impurity and $p_i(n|t)$ represent model probability of class nth at node t.

2.2.2 Random Forest

Random Forest is a collective algorithm that builds numerous decision trees and combine their expectations through common voting. This technique operates by building a crowd of decision tree throughout the period of training for the classification of the final output (Wenshyang *et al.*, 2022). This model provides feature importance and improves on the accuracy and stability. A random forest aggregates tree is as shown in Equation 2.

$$y_n = M_k(b_1(x_i), b_2(x_i), b_h(x_i)) \quad (2)$$

The y_n represent final output, M_k denotes the modal classifiers, x_i is the input data and b_h is the base learner.

2.2.3 Gradient Boosting

This model is efficient in handling complex non-linear relationship and always work with mixed data types. The gradient boosting model improves handoff decision system by combining multiple weak decision model obtained from past handoff outcomes (Satapathy and Mahapatro, 2021). Gradient boosting normally updates the model by adding weak learners that follow the negative gradient of the loss as given in Equation 3.

$$M_{f(x_0)} = M_{f-1}(x_0) + vh_n(x_0) \quad (3)$$

$M_{f(x_0)}$ defines the current model, M_{f-1} is the previous model, x_0 is the input data, v defines the training outcome and h_n signifies the base learning model.

2.2.4 Multi - Layer Perceptron (MLP)

This is artificial neural network technique which make use of intelligent handoff decision making algorithm in heterogeneous networks (Umukoro *et al.*, 2024). The multi-layer perceptron has an input, output, hidden layer, weighted sum and an activation function. The pre-activation function value of the multi-layer perceptron is given in Equation 4.

$$Z = Tk + c - a = \text{activation}(k) \quad (4)$$

where Z is the pre − activation value, T represent weights parameters, c is a constant added to the weighted sum, k represents data input value and a is final output of the neuron.

3.0 Result and Discussion

Table 1 presents the simulated results of the machine models and conventional algorithms using evaluation metrics like accuracy, precision, recall and F-1 score. At low, medium and high mobility band, the results of the machine models are almost the same values while the results of the conventional algorithms have different values for the same mobility band.

Table 1: Results of the machine learning models and conventional algorithms using evaluation metrics

S/N	Mobility Band	Method	Accuracy	Precision	Recall	F1- Score
1.	Low	Decision Tree	0.992241	0.981234	0.982968	0.982086
2.	Low	Random Forest	0.995639	0.990124	0.989684	0.989881
3.	Low	Gradient Boosting	0.977355	0.950841	0.944062	0.947144
4.	Low	MLP	0.995489	0.984355	0.995700	0.989974
5.	Low	RSS	0.780555	0.586718	0.680160	0.605586
6.	Low	SINR	0.690214	0.557596	0.897785	0.611659
7.	Low	Hysteresis	0.717040	0.526332	0.845924	0.597717
8.	Medium	Decision Tree	0.992739	0.981463	0.984577	0.983008
9.	Medium	Random Forest	0.995896	0.989279	0.991674	0.990466
10.	Medium	Gradient Boosting	0.979148	0.953889	0.949270	0.951402
11.	Medium	MLP	0.995550	0.984297	0.995654	0.989922
12.	Medium	RSS	0.781707	0.587757	0.680540	0.606933
13.	Medium	SINR	0.690120	0.559088	0.898118	0.612455
14.	Medium	Hysteresis	0.718940	0.527274	0.846276	0.599228
15.	High	Decision Tree	0.991929	0.984789	0.981345	0.983057
16.	High	Random Forest	0.994992	0.992928	0.986388	0.989615
17.	High	Gradient Boosting	0.973322	0.960518	0.928294	0.943057
18.	High	MLP	0.994982	0.984428	0.994964	0.989650
19.	High	RSS	0.787623	0.614822	0.681115	0.630688
20.	High	SINR	0.709414	0.581458	0.900305	0.642839
21.	High	Hysteresis	0.720858	0.543792	0.828860	0.614016

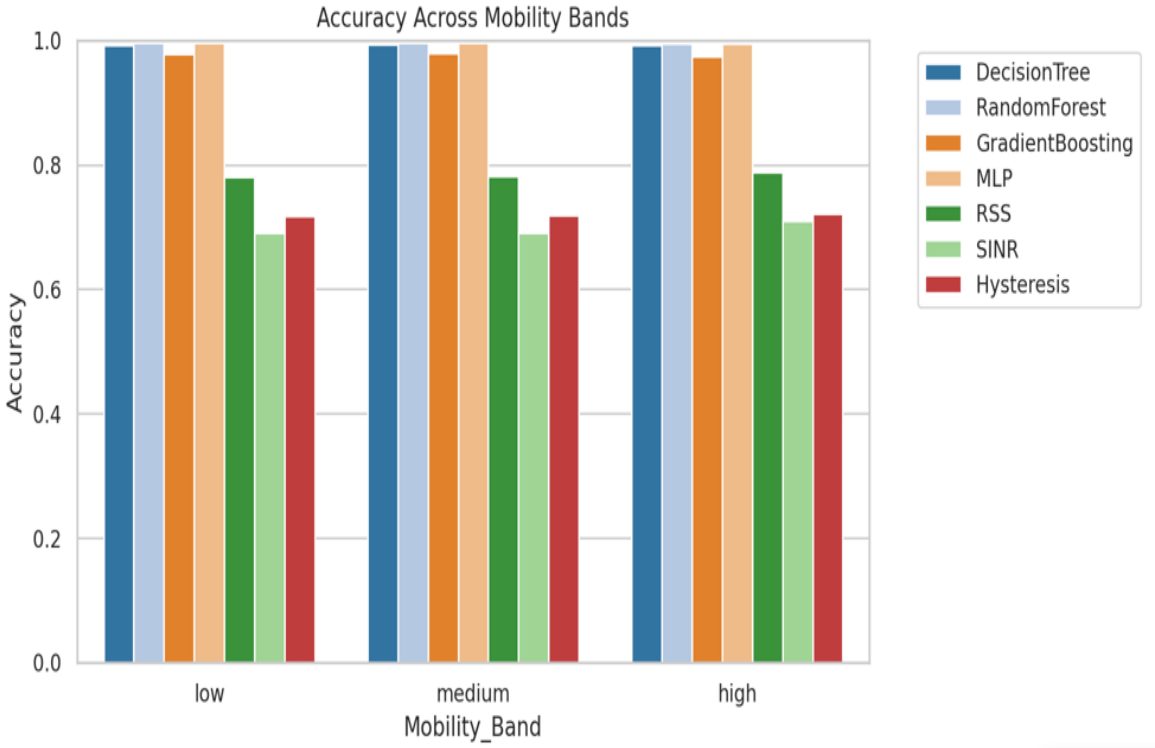

Figure 3: Plot of bar chart showing accuracy against mobility band

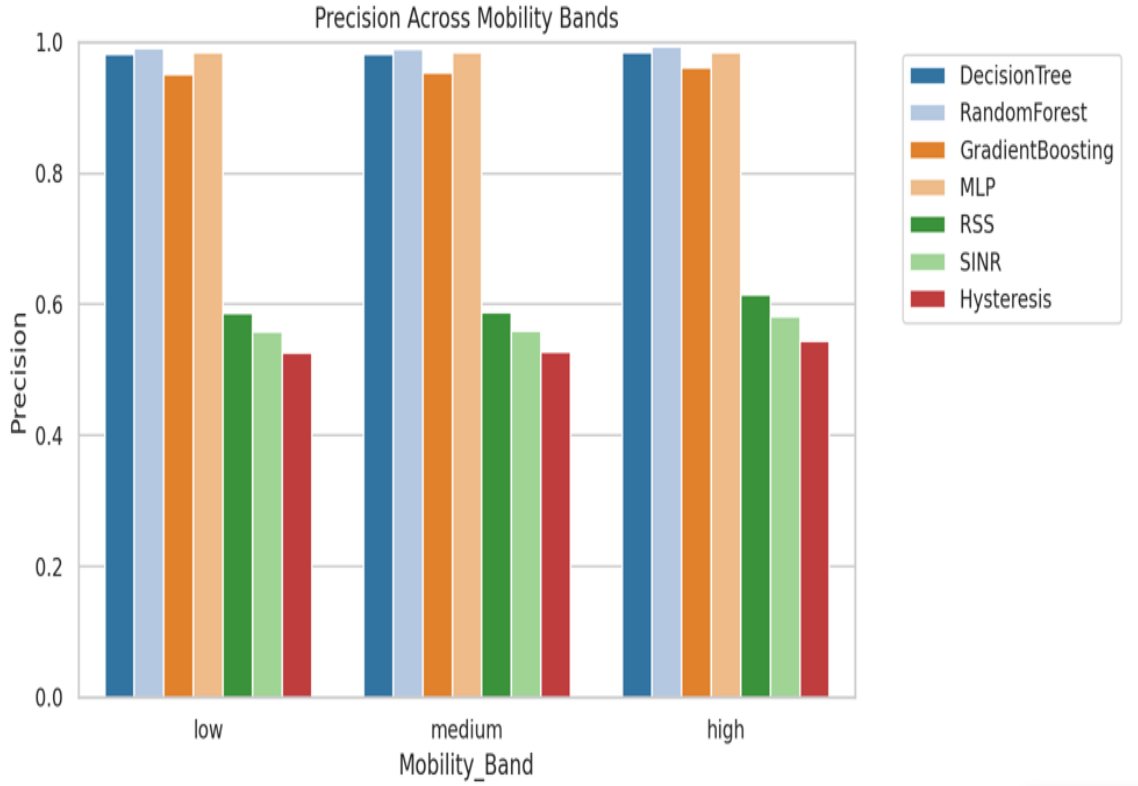

Figure 4: Plot of bar chart indicating precision against mobility band

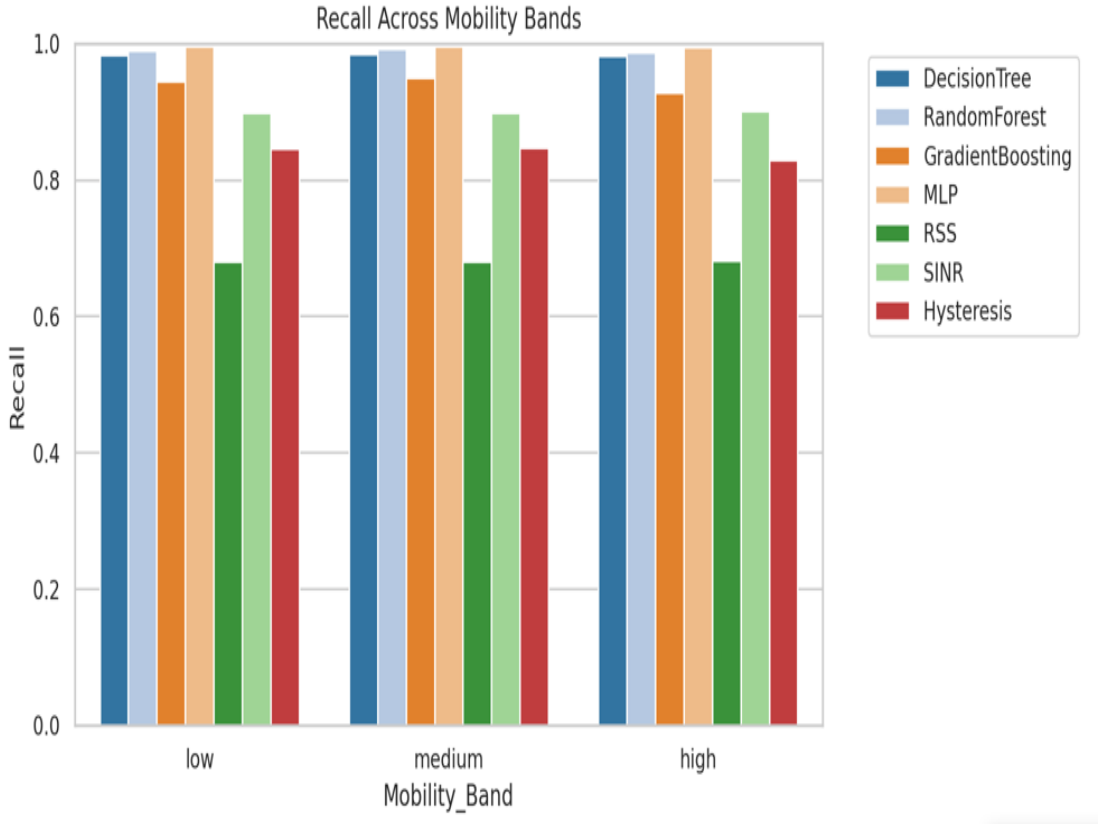

Figure 5: Plot of bar chart showing recall against mobility band

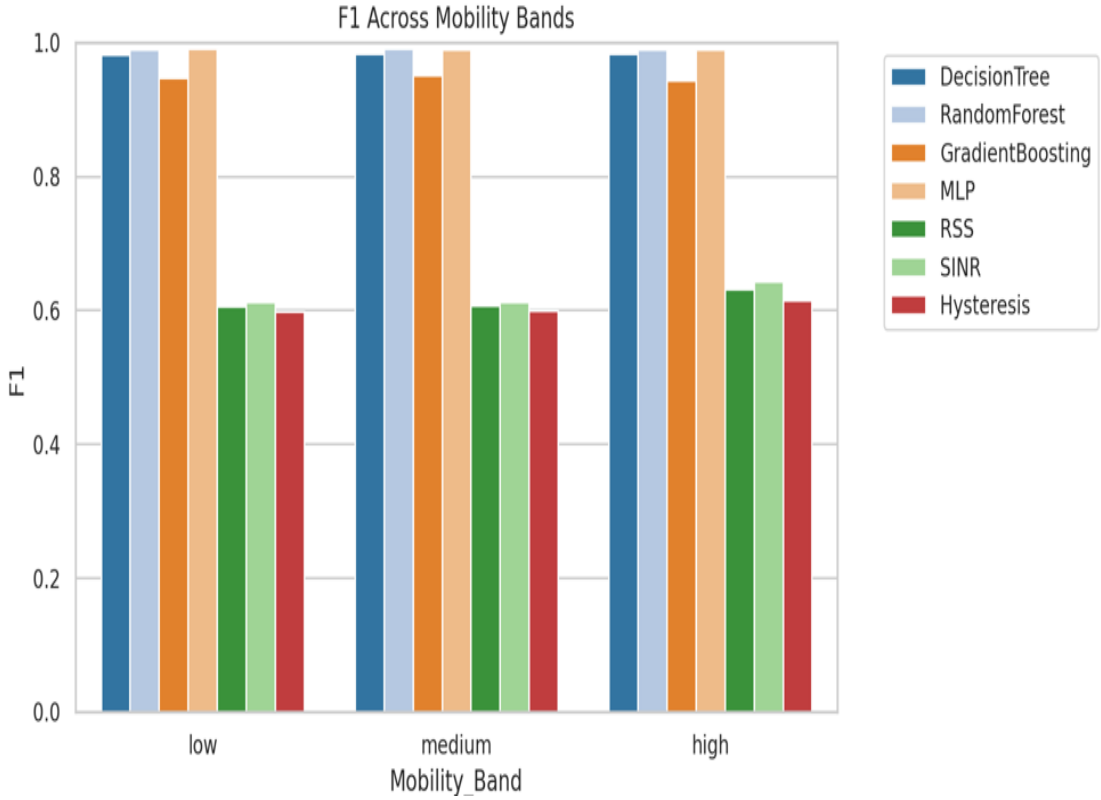

Figure 6: Plot of bar chart indicating F-1 Score against mobility band

The results shown in Figure 3 indicated that at low mobility band, the multi-layer perceptron had a higher value of 99% for accuracy and SINR produced a lower value of 69% for accuracy. Also, the results shown in Figure 4 showed that at medium mobility band, the random forest produced higher value of 99% for precision and hysteresis

had a lower value of 52% for precision, and when this was compared with Muhammad *et al.*, (2023), the de-fuzzified weights of the network parameter of the packet loss for the control gave 18.83% and 14.75% for video. At high mobility band in Figure 5, the multi-layer perceptron acquired a higher value of 98% for recall and RSS had a lower value of 68% for recall. The results shown in figure 6 indicated that at low mobility band, the multi-layer perceptron had a higher value of 99% for F1-score and hysteresis had a lower value of 59% for F1-score. However, at high mobility band, the machine learning models maintain approximately 99% of accuracy and 98% in F1-score. When this was compared with Priyanka *et al.*, (2023), different network selection models provided a high ping-pong rate of 30% for neural network and 21% for multiple attribute decision making (MADM). Again, the conventional algorithms like RSS and hysteresis degrades under high mobility for recall and F-1 score since their methods depend heavily on instantaneous thresholds checks which become less reliable at higher speeds.

4.0. Conclusion

This study examined the design and implementation of handoff decision making algorithm that can reduce needless handovers and improve the quality of service. In cellular network, application of machine learning in handover mechanism mandated from the actualization that cellular networks consist of mass producers of data that always address the issues of failure in handovers. The future technologies like 5G/6G are advancing better than the previous technologies with regards to low latency and high speed of data.

The parameter measurements in handoff decision algorithms requires extra time in selecting best cell demands especially when consideration are given to multiple characteristics at the time handover is about to start. Network selection is important when entering programs across diverse networks when traffic occurred as a result of reactive components.

The machine learning models produced better results across all classification metrics than the conventional algorithms. It also depicts that the proposed machine model is stable and stronger across all mobility ranges. The contribution to knowledge is that this study provides a novel approach with suitable machine learning algorithms that predicts the best handover decision that identify anomalies and effect correction in the network.

5.0 Recommendation

It is recommended that other software programming language like Julia, C++, fuzzy logic other than machine learning technique should be used to design and model handoff decision making algorithms in order to compare the result obtained from it with that of the machine model.

Acknowledgements

The authors wish to acknowledge the contributions of the laboratory staff of the Department of Electrical and Electronic Engineering, University of Uyo, Uyo, Nigeria toward the success of this research work.

References

Abdulkarem, B. A. and Lukman, A. (2021). Design and development of handover simulator model in 5G cellular network. International Journal of Electrical and Computer Engineering, 11(4), 1–16.

Ahmadi, K., Miralavy, S. P. and Ghassemian, M. (2020). Software-defined networking to improve handover in mobile edge networks. International Journal of Communications Systems, 33(14), 1 – 13.

Chiputa, M., Zhang, M., Ali, M. N. Chong, H. J., and Kumar, A. (2022). Enhancing handover for 5GmmWave mobile Networks using jump Markov Linear System and deep reinforcement learning, Sensors, 22(3), 746 – 754.

Divakaran J., Arvind, C. and Srihari, K. (2023). Fuzzy logic-based handover authentication in 5G telecommunication heterogeneous networks. Computer Systems Science and Engineering, 46(1), 1142 – 1153.

Kasim, A. N., Shayea, I. and Khan, A. (2020). Evolutionary paths towards mobility management in 5G heterogeneous networks. IEEE Microwave Theory and Technique in wireless Communications (MTTW), 1, 24 – 29.

Muhammad W. K., Umar, S. K., Muhammad, M. S. and Nasir, R. (2023). Multi-criteria handoff decision making algorithm for seamless mobility in heterogeneous wireless networks. Journal of Communications, 18(3), 164 -171.

Odo, G. O., and Ezeonye, C. S. (2022). Analysis and evaluation of inter-cell vertical handoff for 4G networks using NCC key performance indicators. Journal of Engineering and Applied Science, 20(1): 767 – 774.

Priyanka, A., Gauthamarayathirumal, P. and Chandrasekar, C. (2023). Machine learning algorithms in proactive decision making for handover management from 5G and beyond 5G. Egyptian Informatics Journal, 24, 1 – 10.

Rajesh, P., Vijayalakshmi, A. and Ebenezer, A. B. (2025). An artificial intelligence-based handover triggering and management mechanism for 5G ultra-dense networks to improve handover authentication. Journal of Telecommunications and Information Technology, 2, 9 – 20.

Sajjad, A. K., Ibraheem, S., Mustafa, E. and Ayman, A. E. (2021). An Improved Handover Decision Algorithm for 5G Heterogeneous Networks. IEEE International Conference on Communication, held at Kuala Lumpur, Malaysia, from 7th – 9th May 2021, 530p.

Satapathy, P. and Mahapatro, J. (2021). Energy-Efficient Vertical Handover in Heterogeneous Networks. In proceedings IEEE International IOT Electron Mechatronics Conference, held at Canada, from 12th – 14th June 2021, 109p.

Umukoro A., Joseph, M. A. and Ogwu, A. (2024). A self - optimizing fuzzy logic model for managing vertical handover in heterogeneous mobile cellular networks. Journal of Systematic, Evaluation and Diversity Engineering, 5(5), 1-16.

Wenshyang, H., Tengyu C., Yanjing, W. and Minghua, C. (2022). Adaptive handover decision using fuzzy logic for 5G ultra-dense networks. Multidisciplinary Digital Publishing Institute, 11(3278), 1 – 15.