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Handover Prediction in 5G Network using Machine Learning

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Abstract The adoption of millimeter wave (mmWave) technology and Ultra-Dense Networks (UDNs) with the advent of Fifth Generation (5G) and Beyond 5G (B5G) mobile networks makes mobility management significantly more difficult. Small cell coverage areas and high-frequency signals cause handovers (HOs) to occur more often, which leads to Radio Link Failures (RLF) and Handover Ping-Pong (HPP). The traditional methods of Handover Control Parameter (HCP), which rely on deterministic control parameters such as Time-to-Trigger (TTT) and Handover Margin (HOM), are not responsive to changes in the speed of the user and changes in network load conditions, thereby resulting in a degradation of Quality of Service (QoS). This paper introduces a predictive model that utilizes Machine Learning (ML) to optimize the process in 5G Urban Microcell (UMi) networks. A 5G environment was simulated using MATLAB R2024b, and three million records were obtained when the network was loaded with 25, 50, 75, and 100 User Equipments (UEs). Five supervised ML models, namely Random Forest (RF), Artificial Neural Networks (ANN), Deep Neural Networks (DNN), Support Vector Machine (SVM), and Logistic Regression (LR), were implemented, trained, and compared for predicting handover outcomes (success or failure). Results show that RF had the best accuracy of 98 percent, while LR and SVM had lower accuracy of 93 percent, but they had shorter training times. The paper concludes that predictive machine learning models in 5G HO mechanisms offer more connection reliability and network stability compared to traditional reactive strategies.

Keywords: 5G Networks, Handover Prediction, Machine Learning, Millimeter Wave (mmWave), Urban Microcell (UMi), Adaptive Time-to-Trigger (TTT).

1. INTRODUCTION

Mobile communication has gone from generation to generation, each introducing big changes in the design of the network, its speed, and features [8, 26]. The evolution of the networks arises from the need to increase the speed of data while reducing delays. It started from 1G, which could only support simple analog voice calls, through 2G, 3G, and 4G mobile broadband and currently 5G for the Internet of Things [7, 10]. As we drive into the 5G and Beyond (B5G) era, mobile networks are now facing new challenges [3], especially when it comes to how devices switches between different network cells [13, 17].

Modern networks now rely on the use of high-frequency technologies like millimeter wave (mmWave) and many small, closely packed cells [11, 21]. While mmWave offers a very high data rates and low-latency connections, it also causes User Equipment (UE) to switch cells much more often [5, 9]. This often changing of cells can lead to drop of calls or interrupted connections between UE and a base station, this leads to what is known as Radio Link Failure (RLF) or cause UE to keep switching between neighboring cells within a short period of time, which is a problem called Handover Ping-Pong (HPP) [12, 21].

This problem becomes even worse in mmWave systems. These systems are very sensitive to obstacles such as tall building, passing bus or even a person walking by can easily cause Non-Line-of-Sight (NLOS). NLOS takes place when the direct signal path is obstructed [20], and mmWave coverage areas are also quite narrow [4, 5]. In addition to this, most traditional Handover (HO) algorithms still make use of fixed settings, such as Time-to-Trigger (TTT) delay. TTT refers to the duration that a UE needs to switch between cells during movement and sensed a stronger signal from a neighbouring cell, but this constant value is not responsive to varying conditions and fails to support the varying speed of users [16, 18]. For example, a TTT that's efficient for a user device moving at the speed of 3km/h might be far too slow for a user device moving on a fast train at the speed of 350km/h. An attempt to use the same TTT for these two scenarios will lead to frequent signal disruptions, on the other hand, if the TTT is set too fast, it could cause unsuccessful HO attempts and extra signaling [3, 5].

To overcome the difficulties that come with fixed parameters, recent research has focused on developing intelligent and adaptive solutions to the challenges [5]. Many researchers now apply Machine Learning techniques in order to treat HO as a complex puzzle that can be optimized [6, 18]. For example, models like Regression Trees (RT) and Multi-Layer Perceptrons (MLP) have been used for the prediction of the best HO settings [6, 12]. These approaches have led to a reduction in RLF, an increased Handover Success Rate (HSR), and fewer Handover Ping-Pong events in ultra-dense networks [20, 22].

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In order to address these shortcomings, this study proposes a machine learning-based predictive HO framework for 5G mmWave Urban Microcell (UMi) networks. The proposed HO method makes use of data-driven intelligence to make proactive decisions instead of waiting for issues to arise by learning from past trends and current network conditions [6, 9]. The framework guarantees increased reliability, minimized interference effects and a higher connection stability by predetermining the most appropriate HO decision. In situations where a possible deterioration in the link quality is identified, the predictive model allows timely making of HO decisions hence reducing RLF and Handover Failures (HOF). This intelligent technique is particularly effective in dense urban environments and medium-mobility (urban vehicular) conditions scenarios, where rapid variations in signal conditions make traditional HO mechanisms inefficient.

The primary aim of the study is to develop an effective, powerful, scalable, and adaptable predictive handover (HO) architecture in 5G mmWave networks. The architecture improves handover reliability, reduces the effects of handover ping-pong (HPP), and ensures stable connections regardless of the traffic load and the extent of user mobility. However, unlike most of the existing research that employs short simulation time (typically a minute), [6, 14] this study employs an extensive simulation time of ten minutes. This helps to comprehensively analyze the HO processes, network stability, and model robustness under sustained mobility and traffic conditions. The suggested framework can provide intelligent decision support about mobility management to improve Quality of Service (QoS) using adaptive machine learning models rather than fixed threshold-based approaches. In addition, this study is the first to allow each UE to move at its own independently selected speed, enabling heterogeneous mobility behaviour that represents medium urban vehicular movement.

The overall contributions of this work can be summed up as follows:

1. Development of a scalable machine learning based predictive handover framework for dense 5G mmWave Urban Microcell networks for proactive mobility management under heterogeneous mobility conditions.
2. Proposes a predictive machine learning-based handover framework that can actively identify handover success or failure through real-time network Key Performance Indicators (KPIs).
3. Comparative analysis of five supervised learning models (RF, ANN, DNN, SVM, and LR) based on predictive performance criteria (accuracy, precision, recall, F1-score, ROC-AUC) and computational complexity of training, to determine an empirical trade-off analysis between accuracy and efficiency.
4. Evaluation of the model's stability and scalability under sustained 10-minute simulation, and multi-user traffic scenarios to show the model's robustness under medium-mobility vehicular environments.
5. Proposes a scalable and extendable predictive mobility management system that may be deployed to dense 5G deployments and extended to B5G.

2. RELATED WORKS

One of the most important features of 5G and B5G networks is mobility optimization, especially HO management, which influences the continuity of services, the stability of the network, and the QoS. There are many complications that arise from the use of ultra-dense small cells, high-mobility users, and mmWave frequencies. These complications include frequent HO, RLF, and HPP effects. Load balancing and HO management are also essential in managing user traffic, congestion and network throughput. This section presents recent research works related to handover (HO) optimization and load management in mobile cellular systems using machine learning, decentralized approaches, and mathematical optimization techniques. It provides an overview of recent trends in adaptive and self-optimizing mobility solutions.

2.1 Intelligent and Data-Driven Handover Optimization

Several studies have been carried out on intelligent, data-driven optimization of handover (HO) decisions in dense 5G and beyond-5G (B5G) networks. The prediction of HO outcomes and dynamic control parameter (DCP) adjustment have been implemented using machine learning models. Multi- Layer Perceptron (MLP) models especially have been demonstrated to optimize Time-to-Trigger (TTT) as well as the Handover Margin (HOM). These optimizations lead to reduced handover failure (HOF), radio link failure (RLF), and handover ping-pong (HPP) effects based on the user speed, signal quality, and network load [20]. Logistic Regression (LR) models have also been employed to determine the best HO points proactively, thereby proving that lightweight predictive approaches can improve HO performance with reduced complexity [14].

Predictive HO mechanisms have also been enhanced by Reinforcement Learning-based (RL) methods, which can be adapted to make decisions. Other studies combine RL and Support Vector Machine (SVM) techniques to find the optimal time to make a HO that helps in the preservation of a higher connection quality while reducing latency and packet loss [25]. Other works implement Deep Reinforcement Learning (DRL) as actor-critic models to continually adapt the HOM and TTT according to real-time network conditions, and have more precise HO choices and better network stability [22]. This new approach, in contrast to the old-fashioned rule-based and discrete action algorithms, uses continuous state and action spaces that are in reality present in 5G networks, allowing the network to discover the best HO strategy on its own.

Despite these improvements, most intelligent HO methods still rely too much on fixed timer settings and need very accurate real-time measurements. They also lack thorough comparisons between different machine learning models. In addition, these methods are mainly focused on optimizing individual parameters without considering the stability of the network.

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2.2 Decentralized and Load-Aware Handover Management

Load-aware and decentralized controls have been suggested to deal with congestion and uneven distribution of users in ultra-dense networks. One of the approach is Multi-Agent Reinforcement Learning (MARL), where every cell can manage HO parameters independently, without considering network-wide traffic, to balance user distribution and minimize unnecessary HO [24]. Individualized methods have also been proposed using the Individualistic Dynamic Handover Parameter Optimization (IDHPO) model to adapt HOM and TTT parameters to each individual user depending on signal quality, cell load, and speed [21]. Likewise, the Dynamic Handover Control Parameters (D-HCPs) algorithm detects the HO that occur either too early, too late, or to an incorrect cell and adjusts the parameters dynamically, thereby reducing HOF and HPP events [3].

Nevertheless, the majority of load-aware and decentralized approaches assume cells are self-autonomous and do not tend to coordinate with their neighbors, which makes them less effective in ultra-dense networks. Moreover, such strategies tend to modify the Handover Control Parameters (HCP) without applying predictive machine learning, so they are not as adaptable to rapidly varying network parameters [23, 24].

2.3 Handover Challenges in mmWave, 5G, and B5G

The narrow beam of the signal, frequent blockages, and dynamic channel conditions make HO optimization in mmWave and 5G networks difficult. To tackle these issues, researchers have used mathematical optimization techniques to compute optimal HO sequences that would guarantee high data rates and lower latency, especially in self-driving vehicles [9].

In B5G networks, new approaches have been proposed to reduce energy consumption and the number of HOs. This includes turning base stations on and off as needed and using High Altitude Platform Stations (HAPs) to improve coverage in hard-to-reach areas [19]. Studies have shown that the way HO are currently handled is not good enough for 5G and B5G networks, especially when users are moving very fast, there are many cells packed closely together, and the network includes components outside of the traditional ground-based systems [5].

Collectively, these works show that HO management in networks is becoming increasingly challenging as they evolve to next generations. Despite the fact that optimization methods and surveys have already given us some useful information, there is still a lot to be done especially in the field of predicting and improving HO decisions with the help of machine learning and making HO work in practice.

2.4 Research Gap and Motivation for the Proposed Study

Intelligent handover optimization of 5G and Beyond-5G networks has been evolving significantly in recent years, but the current solutions possess three primary limitations. Firstly, most of the methods employ fixed or semi-adaptive Handover Control Parameters (HCPs), specifically fixed Time-to-Trigger (TTT) values, which are not effective in ultra-dense mmWave systems where signal variations and blockage sensitivity are very high [14]. Secondly, the majority of machine learning-based handover research emphasize on a single predictive model and also rely on constrained simulation periods with homogeneous mobility models [6, 14]. Thirdly, a systematic comparison of the various supervised learning models is rarely carried out under heterogeneous user mobility and varying network load conditions in realistic Urban Microcell (UMi) networks.

Consequently, the question of which supervised learning model can provide the most stable and computationally efficient output in terms of proactive handover decision support in dense 5G mmWave networks remains to be answered. In order to systematically fill the identified research gap, this study aims at answering the following key questions:

1. Are supervised machine learning models sufficient to predict handover success and failure in dense 5G mmWave Urban Microcell (UMi) environments with heterogeneous mobility?
2. Of the available supervised learning algorithms, which one balances predictive accuracy and computational efficiency best with respect to the increasing network load conditions?
3. To what extent are the predictive handover models stable and scalable when subjected to long simulation times and in a multi-user traffic scenario?

This unaddressed challenge inspires the design of a scaling predictive framework, capable of testing the robustness of models, the level of scalability, and the stability of model performance under prolonged multi-load conditions, and a heterogeneous mobility environment.

3. METHODS AND MATERIAL

This study proposed a machine learning-driven handover prediction system that is proactive. The goal is to improve mobility management in dense 5G mmWave Urban Microcell (UMi) networks. In contrast to the traditional reactive handover strategies that use fixed Time-to-Trigger (TTT), the framework predicts the success or failure of every handover event in real-time and uses the predictions to aid proactive decision-making. The simulations and the KPI definitions are based on the 5G network evaluation related standards of 3rd Generation Partnership Project (3GPP) [1, 2]. The suggested method combines theoretical modeling, algorithm implementation and predictive data analysis, as shown in Fig. 1. This keeps the assessment of handover prediction in a 5G Urban Microcell (UMi) environment precise and reliable.

The novelty of the framework lies in three main aspects:

1. **Data-Data-Driven Decision Making:** The framework utilizes synthetic network data to train prediction models. These models are very accurate in estimating handover outcomes, and therefore the system is able to make timely decisions and minimize unnecessary handovers that can lead to network instability.
2. **Comparison of Models:** Five supervised learning models, namely Random Forest (RF), Artificial Neural Networks (ANN), Deep Neural Networks (DNN), Support Vector Machine (SVM), and Logistic Regression (LR), are systematically compared. This

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comparison can be used to identify the model that provides an appropriate trade-off between prediction accuracy and computational cost.

3. **Proactive Mobility Management:** The framework predicts possible failures in handover in advance. Using these predictions, the major parameter of the handover, such as Time to Trigger, can be dynamically adjusted for User Equipment. This proactive solution minimizes handover failures, handover ping-pong and call drops, which contributes to an increase in the Handover Success Rate and total Quality of Service.

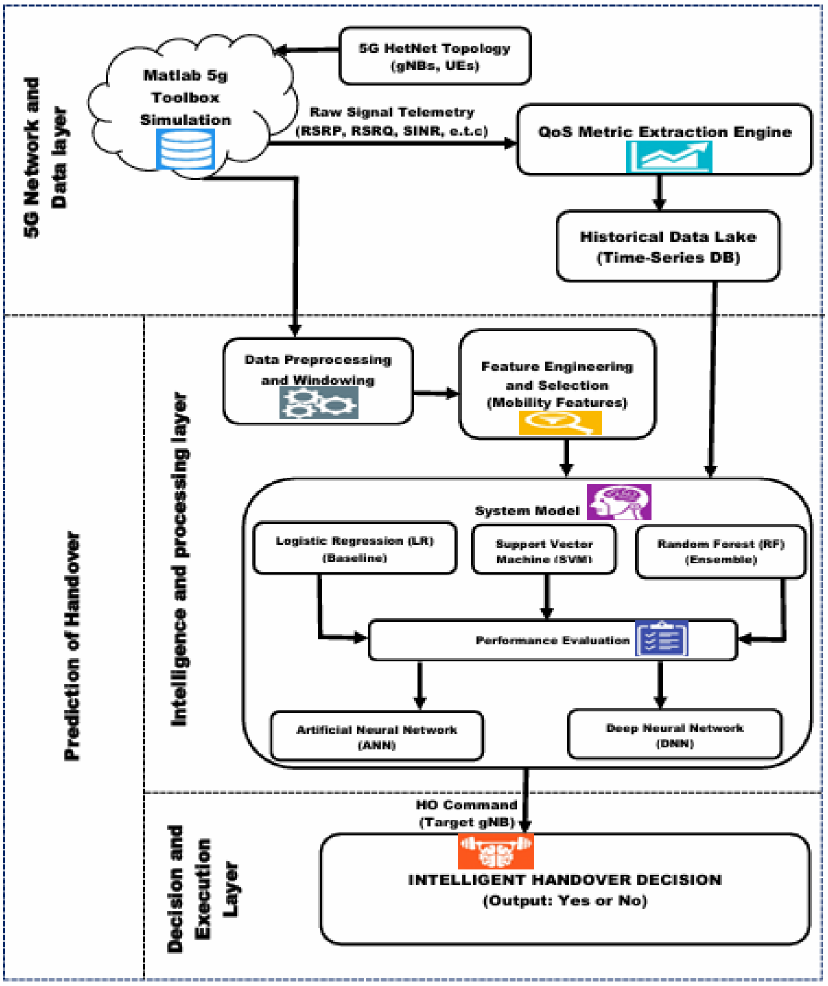

Fig. 1. System Architecture of the Proposed Framework

3.1 Matlab 5g Toolbox Simulation

The simulation environment was set to a hexagonal cell topology of 61 gNodeBs (gNBs) in an area of 3 km x 3km. Each gNB (Base Station) uses three 120° sectors that enable a wide spatial coverage of 30 GHz carrier frequency. The User Equipments (UEs) move along 14 random paths within the simulation area. Each UE moves independently, and their speed varies between 20 km/h and 40 km/h to model medium urban mobility of vehicles. Their interactions with the base stations generate real-time signal quality and signal strength measurements.

Path Loss (PL) was estimated by the use of standard formulas of Line-of-Sight (LOS), Non-Line-of-Sight (NLOS) and the probability of LOS models as indicated in (1) to (3). Each of the simulations and parameter configurations complies with the criteria in the 5G network testing which are defined in the 3GPP standards [1, 2]. Table 1 summarizes major parameters of the simulation.

Table 1 Simulation Parameters and Configuration

Parameter	*Value*
Environment	5G NR Urban Microcells (UMi)
Cell Configuration	Hexagonal grid
Simulation Duration	600 seconds (10 minutes)
Time Step	0.05 s
Area	3×3 km²
Road outline	14 Internetworked Road
Network load scenarios	25, 50, 75, 100
Number of gNBs	61 gNBs
Number of sectors	3
UE Speed	Ranges from 20Km/h – 40Km/h
Carrier Frequency (fc)	30 GHz
Bandwidth	100 MHz
Cell Radius	200 m
gNB Height	10 m
UE Height	1.5 m

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gNB Tx Power	35 dBm	
UE Tx Power	23 dBm	
Noise Figure (UE)	9 dB	
Thermal Noise Density	−174 dBm/Hz	
Shadow Fading σ	7.82 Db	
Path Loss Model	PL_{LOS}	$32.4 + 21\log_{10}(d_{3D}) + c20\log_{10}(fc)$ (1)
	PL_{NLOS}	$22.4 + 35.3\log_{10}(d_{3D}) + 21.3\log_{10}(fc) - 0.3(h_{UT} - 1.5)$ (2)
LOS Probability Model	$P_{LOS}(d_{2D})$	$\min\left(\frac{18}{d_{2D}}, 1\right) x \left(1 - e^{-\frac{d_{2D}}{36}}\right) + e^{-\frac{d_{2D}}{36}}$ (3)
Antenna Gain (UE)	0 dBi	
Antenna Gain (gNB)	10 dBi	
Max UE per Cell	100	
A3 Offset (HOM)	4 dB	
TTT (Time-to-Trigger)	Adaptive	

3.2 QoS Metric Extraction Engine

The 5G handover (HO) performance was evaluated based on specific key performance indicators (KPIs). The simulation generated three million records under different network conditions. For each of the KPIs, unique information on the signal strength, connection stability, and mobility performance within the simulated environment were recorded. Signal quality indicators include Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ) and Signal-to-Interference-plus-Noise Ratio (SINR). Radio Link Failure (RLF) events were used to measure connection stability, and speed was used to measure user mobility. Handover performance was evaluated using handover (HO) events, Handover Failures (HOF), and Ping-Pong events of the handover (HPP). All these KPIs were recorded in the simulation at each time step of all active users, forming a dataset that captures the dynamics of a network and allows predictive analysis of handover.

3.3 Data Processing

The common issues in datasets include missing values, noise, and outliers, hence must be preprocessed prior to being used. To eliminate these issues, data preprocessing steps are carried out to normalize the data and eliminate them to achieve uniformity. Some selected features in the dataset were converted from categorical (text-based) data to a numeric format suitable for the model. This transformation increases the quality and data consistency to maximize the model performance.

The raw data was subjected to the following conversions:

i. **Cleaning:** Removal of outliers, noise from the dataset, and imputation of the missing data samples
ii. **Feature Normalization:** Scaling of the dataset using Min-Max normalization to relate all KPI values into the range [0, 1].
iii. **Feature Selection:** Correlation analysis was utilized to determine the most effective KPIs.
iv. **Label Encoding:** Target labels (success/failure of handover) was encoded as binary variables (0 or 1).

3.4 Feature Engineering and Selection

The feature selection is one of the most important steps which help the model to make intelligent decisions. In this work, the most informative attributes in the prediction of HO were found to be the serving cell, SINR and RSRP based on their relevance to signal quality and mobility behaviour. The feature selection process determines the most useful features in the data that can increase the accuracy of the model and minimize computational complexity.

3.5 System Model

This is the phase, which aims to determine and choose the best machine learning algorithm to predict the results of handover (HO) correctly, based on the selected features. Various problems demand different models. For this case study, various supervised classification machine learning algorithms were used, including Artificial Neural Network (ANN), Deep Neural Network (DNN), Logistic Regression (LR), Random Forest (RF), and Support Vector Machine (SVM). Model selection depends on the size of the data, the problem type, and the desired accuracy. The following steps were performed as part of the system model implementation:

i. **Model Training:** Once model selection was completed, the next step in the methodology flowchart was to train the model using the dataset obtained from the 5G handover (HO) simulation. The dataset was divided into two parts: the training set (to teach the model and make it learn data patterns), which is 80% and the testing set (to check its performance), which is 20%. During training, the model learnt the correlation between input features such as RSRP, SINR, and Serving Cell, and the target output of HO. The primary goal of the model is to find patterns that will help the model make correct predictions on new and unseen data.
ii. **Model Evaluation:** All models were tested after training to determine their performance on the test set. This was evaluated based on standard metrics like accuracy, precision, recalls, F1-score, and ROC-AUC. The metrics are evaluated to assess how accurately the model predicts the handover (HO) outcomes. They are also useful in the detection of underfitting, due to insufficient complexity or overfitting of the model, due to excessive adaptation to the training data.

3.6 Intelligent Handover Decision (IHD)

The Intelligent Handover Decision (IHD) block is an essential part of the proposed methodology and the decision-making unit of the proposed system. It keeps track of real time UE information, such as, signal strength, link quality, and the serving cell, to assess the stability of the network connection. The IHD block uses intelligent model to detect latent patterns and early signs of connection degradation unlike traditional methods which use fixed threshold values. According to this analysis, the block gives a single and clear answer to the network controller: Yes, to start the handover (HO) process, or No, to continue the present connection.

The methodology utilized in this study guarantees an effective and methodical machine learning process. All the stages are well-identified and logically linked where raw data are generated using MATLAB simulations, and Intelligent

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Handover Decision is the final stage. This systematic procedure allows the offered strategy to effectively deal with actual handover problems.

4. RESULTS AND DISCUSSION

This section defines the empirical results obtained from simulations of the proposed predictive handover framework in a 5G millimeter wave Urban Microcell (UMi) environment, and discusses the effectiveness of the adopted machine learning models. The assessment is based on three key areas namely, the Handover Success Rate under different network loads, the predictive accuracy of various supervised learning models, and the computational efficiency and scalability of the framework.

The simulation ran for 600 seconds (approximately 10 minutes), with a time step of 0.05 seconds. It consisted of a network of 61 gNBs and the UEs underwent random motion to replicate realistic movement patterns in an urban environment. In this simulation, KPIs and UE positions in each time step for all active UEs were captured and recorded. Three million datasets were collected in total, and this guarantees a comprehensive assessment of the framework under dense network conditions, as shown in Table 2 below. The method used to determine the total number of datasets generated for each scenario is presented in (4).

$$\text{Total Samples} = \left(N_{UE} \text{ x } \frac{T_{sim}}{\Delta t}\right) \tag{4}$$

where N_{UE} represents the number of UEs simulated per run, T_{sim} represents the total simulation duration (in seconds), Δt represents the simulation time step (in seconds). The longer simulation time and larger data volume make it possible to carry out a more reliable statistical analysis of handover events. The scenarios include network loads of 25, 50, 75, and 100 User Equipments (UEs). This configuration allows the proposed predictive framework to be evaluated under realistic and demanding conditions, giving clearer evidence of its performance.

Table 2 Dataset Generation and Network Load Configuration Summary

(N_{UE}) Network Load	*(Δt) Time Step (s)*	*(T_{sim}) Simulation Duration (s)*	*Dataset Generated per Load*
25	0.05	600	300000
50	0.05	600	600000
75	0.05	600	900000
100	0.05	600	1200000
Total	-	-	3000000

To illustrate the practical application of the suggested simulation model, Fig. 2 to 5 shows the actual running step of the network load of each gNB at the start of the simulation time t = 0s. This snapshot indicates the distribution of traffic load in the network in real time at the beginning of the execution, and it proves that the simulation was completely implemented and run in the MATLAB environment.

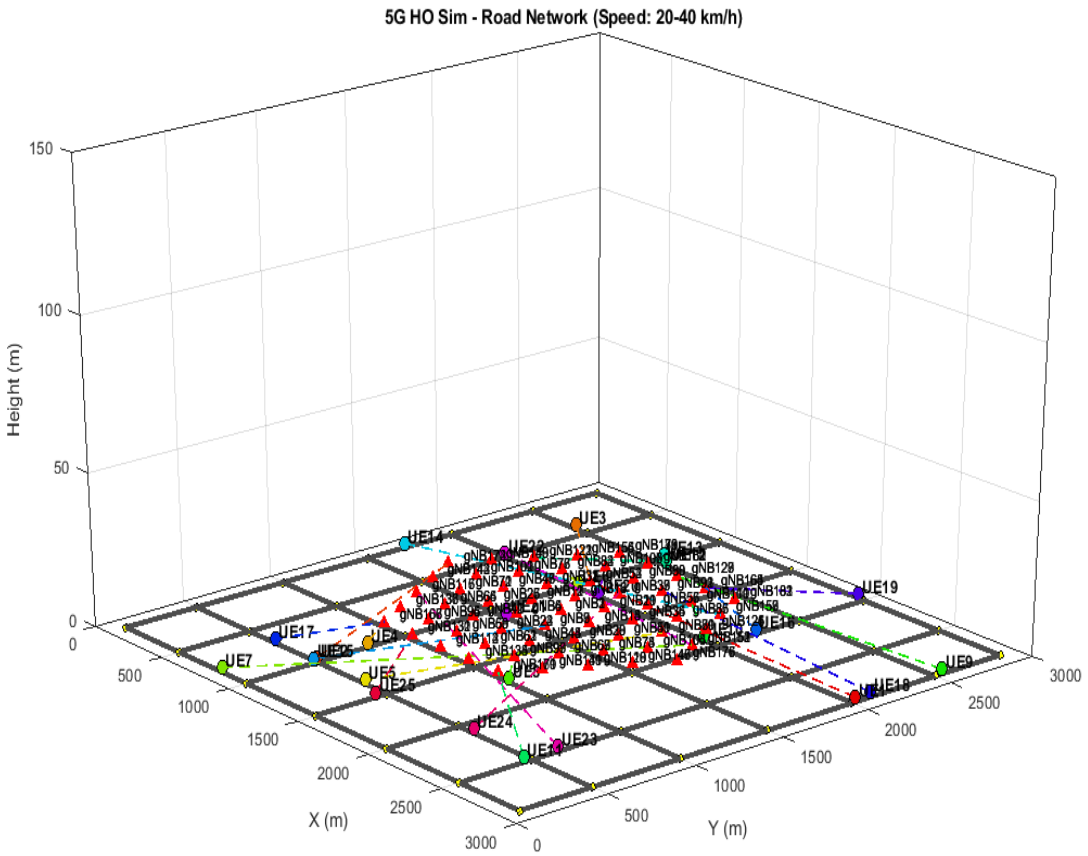

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Fig. 2. Network Simulation with 25 User Equipments (UEs)

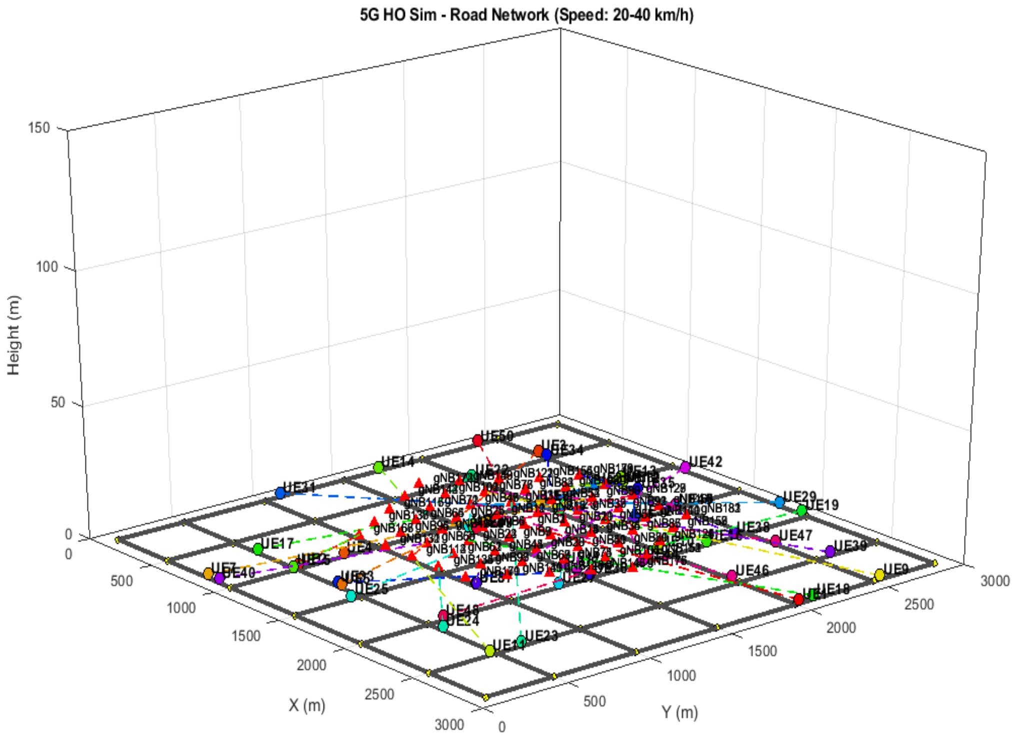

Fig. 3. Network Simulation with 50 User Equipments (UEs)

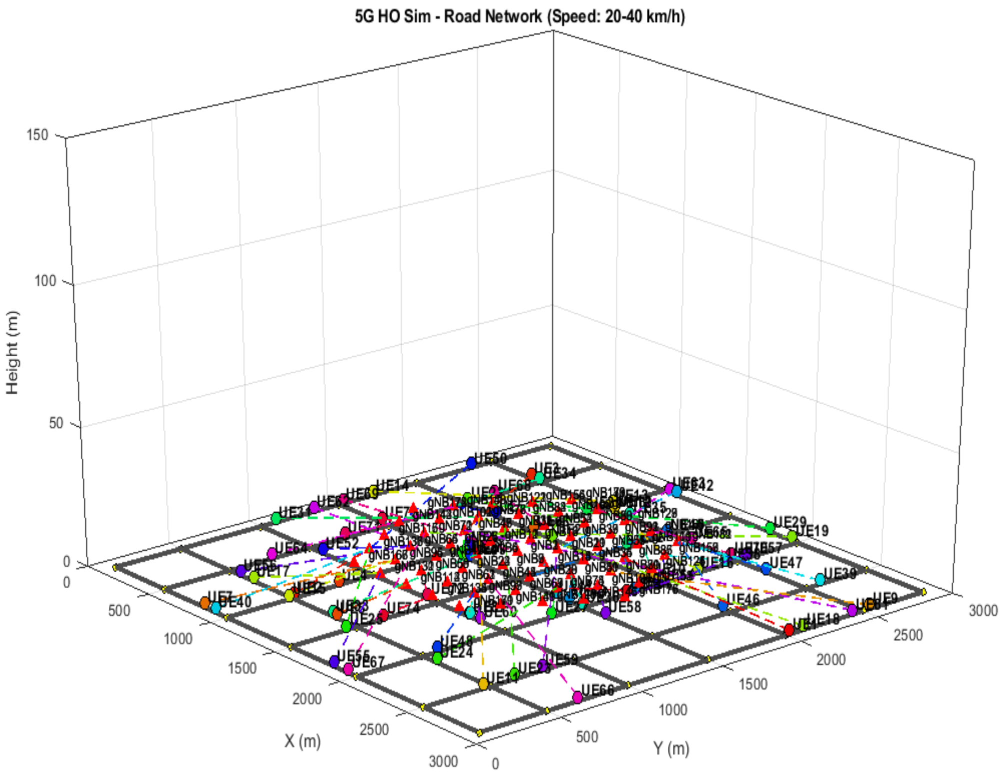

Fig. 4. Network Simulation with 75 User Equipments (UEs)

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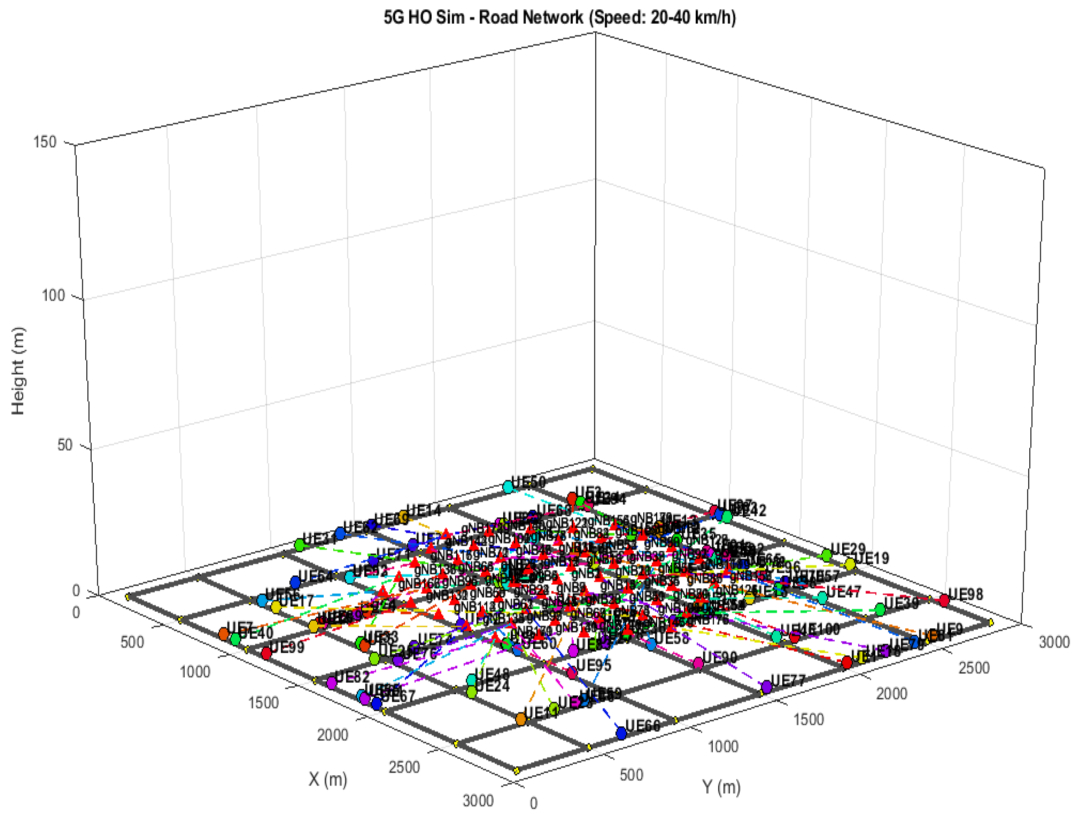

Fig. 5. Network Simulation with 100 User Equipments (UEs)

4.1 Handover Performance

The Handover Success Rate (HSR) was used to show the extent to which a network can maintain data connections or voice calls as the users move. A higher HSR indicates smoother handovers between cells, which translates into an improved user experience. From Table 3 and Fig. 6, HSR remained constant at approximately 70% for all levels of network load except for the 25-UE scenario. HSR was computed using (5).

$$HSR\ (\%) = \frac{\text{Number of Successful Handovers}}{\text{Total Handover Attempts}} \times 100 \qquad (5)$$

The findings indicated that the performance of the network in terms of HSR was relatively steady throughout the various load conditions with a relative performance enhancement ranging from 68.78% at 25 UEs to 70.91% at 75 UEs, with a slight decline to 70.38% at 100 UEs due to increased competition for network resources. This decline occurred due to the fact that the network resources (bandwidth, processing power of serving cells etc.) were finite; i.e. as new UEs were introduced into the system, they compete for the limited network resources causing network congestion. This is expected behavior that is consistent with that of actual 5G networks, where congestion results in slower response and increased failure rates when there is a peak demand. Overall, handover efficiency is largely maintained as the number of users increases.

Table 3. Handover Success Rate under Different Network Loads

Load Scenario	*Total Attempts*	*Successful Handovers*	*Handover Success Rate (%)*
25	22509	15481	68.78
50	49250	34578	70.21
75	80406	57016	70.91
100	114949	80905	70.38

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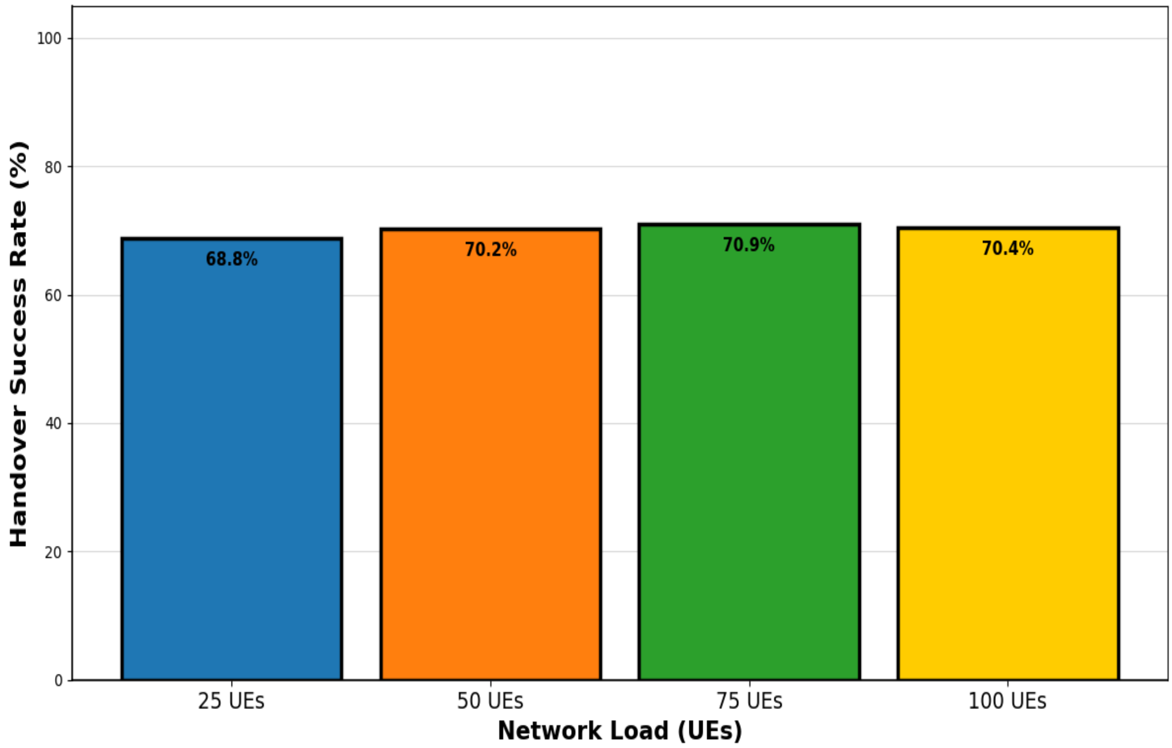

Fig. 6. Handover Success Rate under Different Network Loads

4.2 Model Accuracy

Prediction performance and reliability were evaluated using accuracy, which measures the percentage of correctly predicted handover (HO) outcomes, as shown in (6). Training time was also taken into consideration to estimate the computational efficiency of each model during learning.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

Table 4 Model Accuracy across Different Network Loads

Models	***Scenarios accuracy (%) and Training time (s)***			
	25 UEs	***50 UEs***	***75 UEs***	***100 UEs***
ANN	96%	96%	95%	96%
	2391.67s	1443.43s	1632.48s	4846.99s
DNN	95%	96%	94%	96%
	944.76s	1596.03s	1869.09s	7906.71s
LR	93%	93%	93%	93%
	5.06s	10.08s	19.78s	19.74s
RF	98%	97%	97%	97%
	2440.12s	5861.82s	7458.29s	10999.02s
SVM	93%	93%	93%	93%
	38.82s	46.00s	51.88s	66.41s

The above results indicated that the relationship between model accuracy and training time vary across different network load scenarios as summarized in Table 4 and plotted in Fig. 7 through 9. Random Forest had the best performance in all evaluated scenarios with accuracy between 97-98%. It

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was able to predict the HO outcome effectively with few false positives and false negatives. This was followed by the Artificial Neural Network (ANN) and Deep Neural Network (DNN) models, which also showed great performance, with accuracy levels of 95-96%. LR and SVM had a slightly lower accuracy of around 93, but it required less training time. Random Forest is highly accurate because it can model up complex nonlinear relationships among KPIs including the RSRP, SINR, and Serving Cell, leading to accurate HO predictions. Random Forest recorded the highest prediction accuracy in all scenarios; however, its training time was considerably higher than the other models. This makes RF model more appropriate to offline optimization or edge-assisted processing, and LR and SVM are more appropriate in real-time HO choices where low latency is needed.

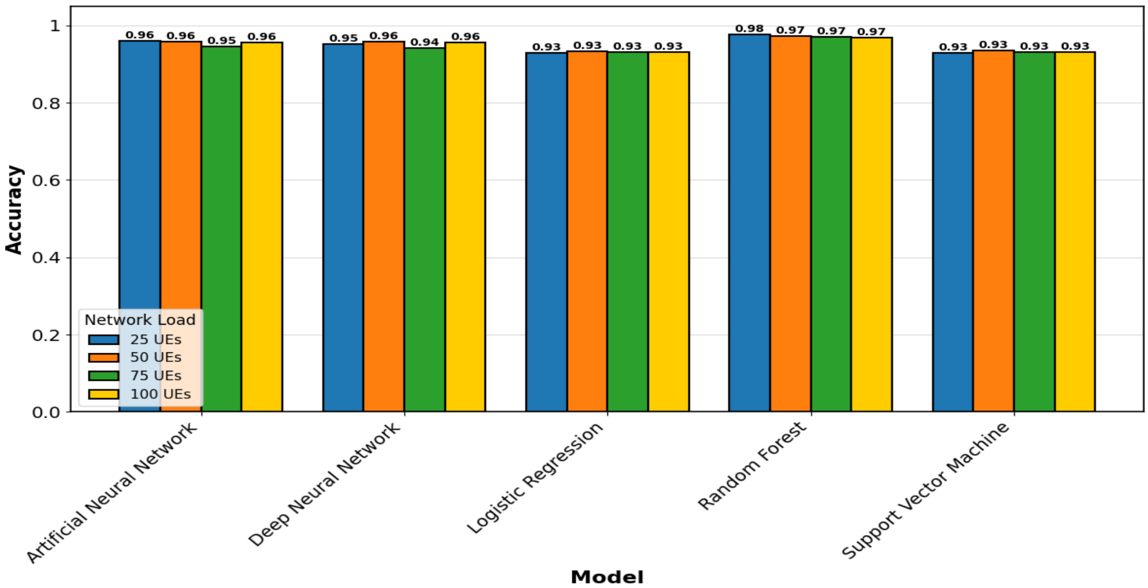

Fig. 7. Model Accuracy under Different Network Loads

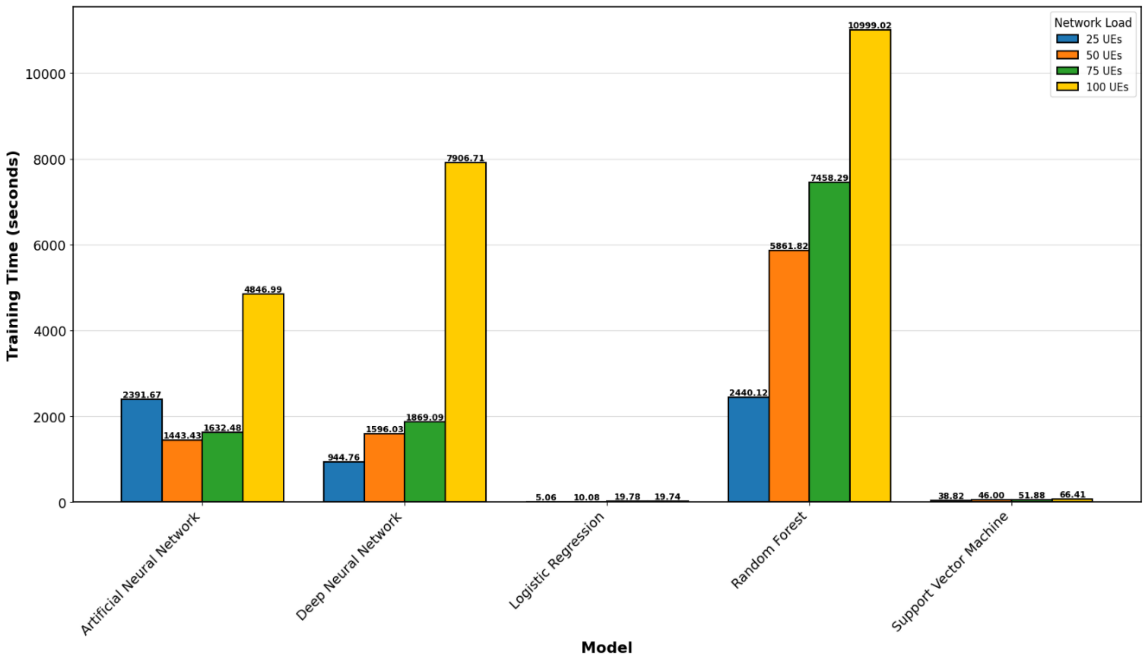

Fig. 8. Training Time across Simulation Scenarios

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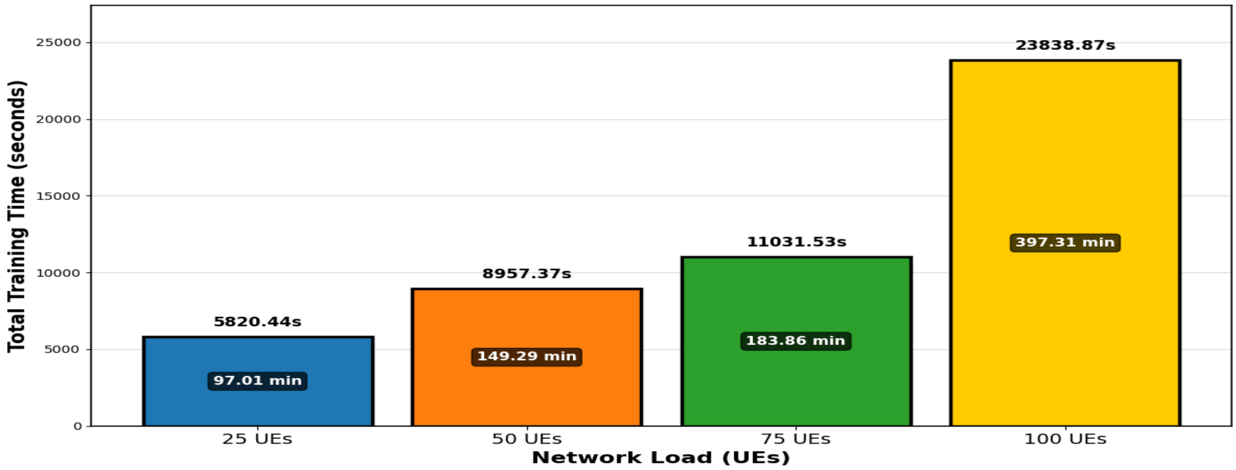

Fig. 9. Total Training Time for All Five Machine Learning Models per Scenario

4.3 Evaluation Metrics

Precision shows what percentage of predicted handovers were correct (7). Recall indicates how many actual handovers the model identified (8). F1 score is performance measure applied to test the classification models, particularly where the datasets are imbalanced (9). ROC-AUC assesses the model in terms of its ability to distinguish between positive and negative handover outcomes at various decision thresholds (10) [15]. The performance of the models according to these metrics is shown in Table 5.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{7}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{8}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

$$\text{AUC} = \int_0^1 \text{TPR(FPR)}\ d(\text{FPR}) \tag{10}$$

$$\text{TPR} = \frac{TP}{TP + FN} \tag{11}$$

$$\text{FPR} = \frac{TP}{FP + TN} \tag{12}$$

Where TP is the True Positives, TN represents True Negatives, FP denotes False Positives, FN is the False Negatives, TPR represents the True Positive Rate, and PPR denotes the False Positive Rate.

Table 5 Evaluation Metrics Used for Model Assessment

Scenario: 25 UEs				
Models	***Precision***	***Recall***	***F1-Score***	***ROC-AUC***
ANN	0.98	0.96	0.96	0.99
DNN	0.97	0.95	0.96	0.99
LR	0.97	0.93	0.94	0.99
RF	0.98	0.98	0.98	0.99
SVM	0.97	0.93	0.94	0.98
Scenario: 50 UEs				
Models	***Precision***	***Recall***	***F1-Score***	***ROC-AUC***
ANN	0.97	0.96	0.96	0.99
DNN	0.97	0.96	0.96	0.99
LR	0.97	0.93	0.94	0.98
RF	0.98	0.97	0.97	0.99
SVM	0.97	0.93	0.94	0.98
Scenario: 75 UEs				
Models	***Precision***	***Recall***	***F1-Score***	***ROC-AUC***
ANN	0.97	0.95	0.95	0.99
DNN	0.97	0.94	0.95	0.99

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LR	0.97	0.93	0.94	0.98
RF	0.98	0.97	0.97	0.99
SVM	0.97	0.93	0.94	0.98
Scenario: 100 UEs				
Models	***Precision***	***Recall***	***F1-Score***	***ROC-AUC***
ANN	0.97	0.96	0.96	0.99
DNN	0.97	0.96	0.96	0.99
LR	0.96	0.93	0.94	0.98
RF	0.98	0.97	0.97	0.99
SVM	0.96	0.93	0.94	0.98

Table 5 depicts the performance of various machine learning models under various network loads. The best results for all evaluating metrics were obtained by the Random Forest model, which clearly outperforms other models in terms of Precision, Recall, F1-Score, and ROC-AUC. ANN and DNN showed constant performance at moderate computational cost when compared to LR and SVM which showed slightly lower performance but required significantly less training time. These findings demonstrate the trade-off between computational efficiency and prediction reliability with the focus that the selection of the models is the key to effective real-time HO management. Generally, each model was stable and efficient with a growing number of users with the best and most consistent outcomes being demonstrated by the Random Forest, as observed in Fig. 10 to 13.

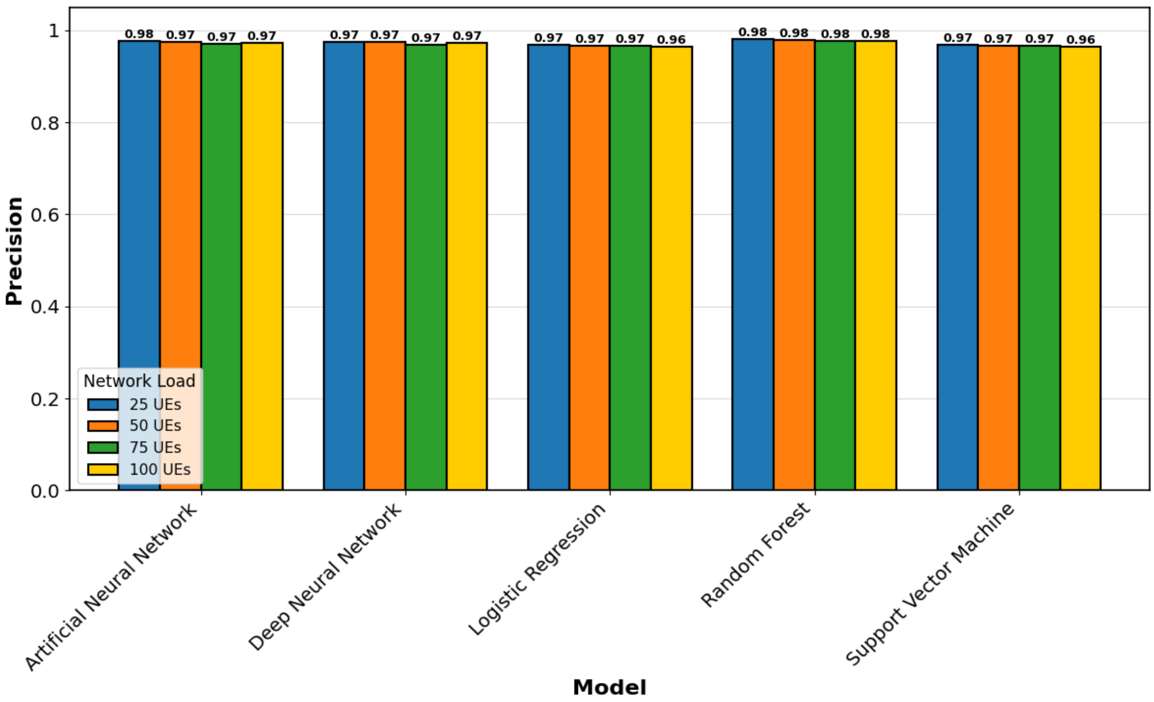

Fig. 10. Precision under Different Network Loads

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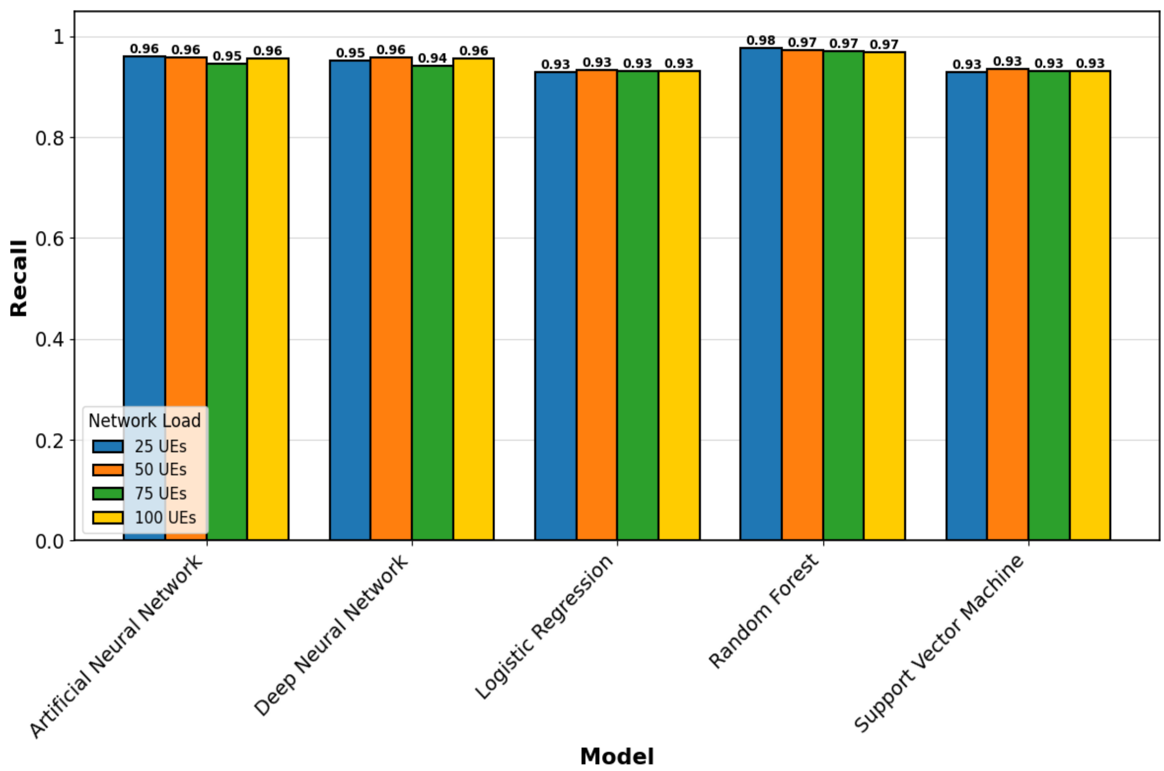

Fig. 11. Recall under Different Network Loads

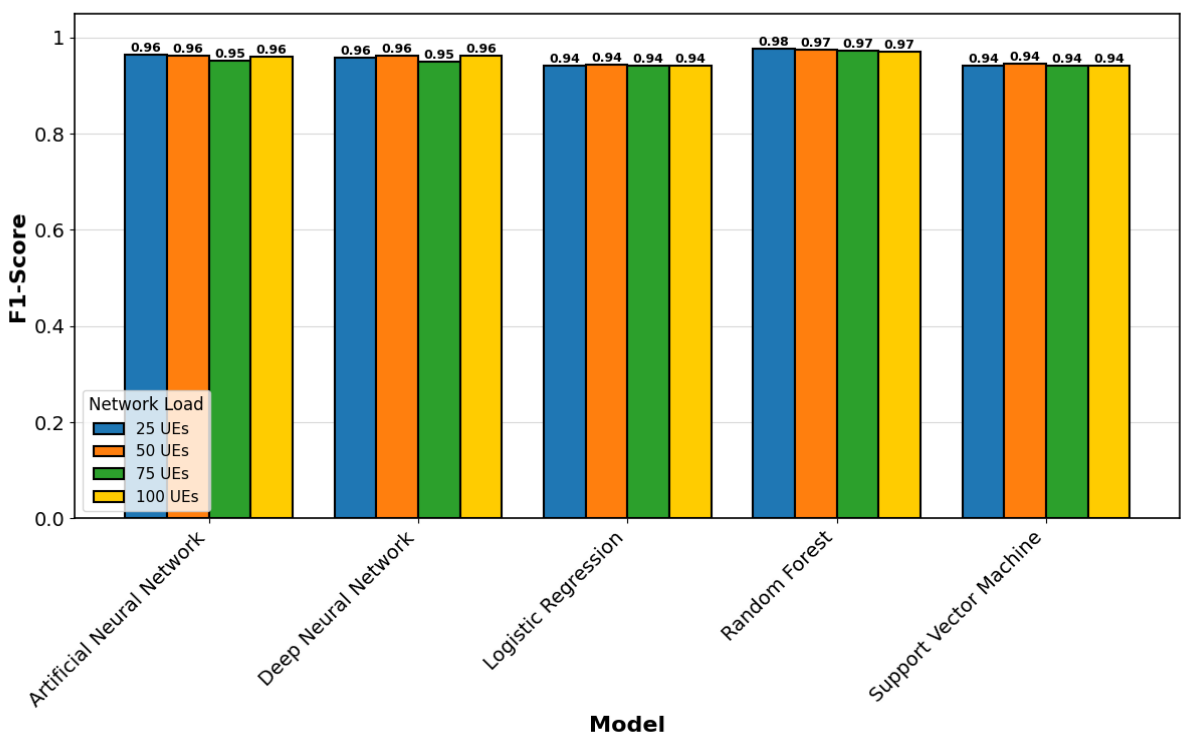

Fig. 12. F1-Score under Different Network Loads

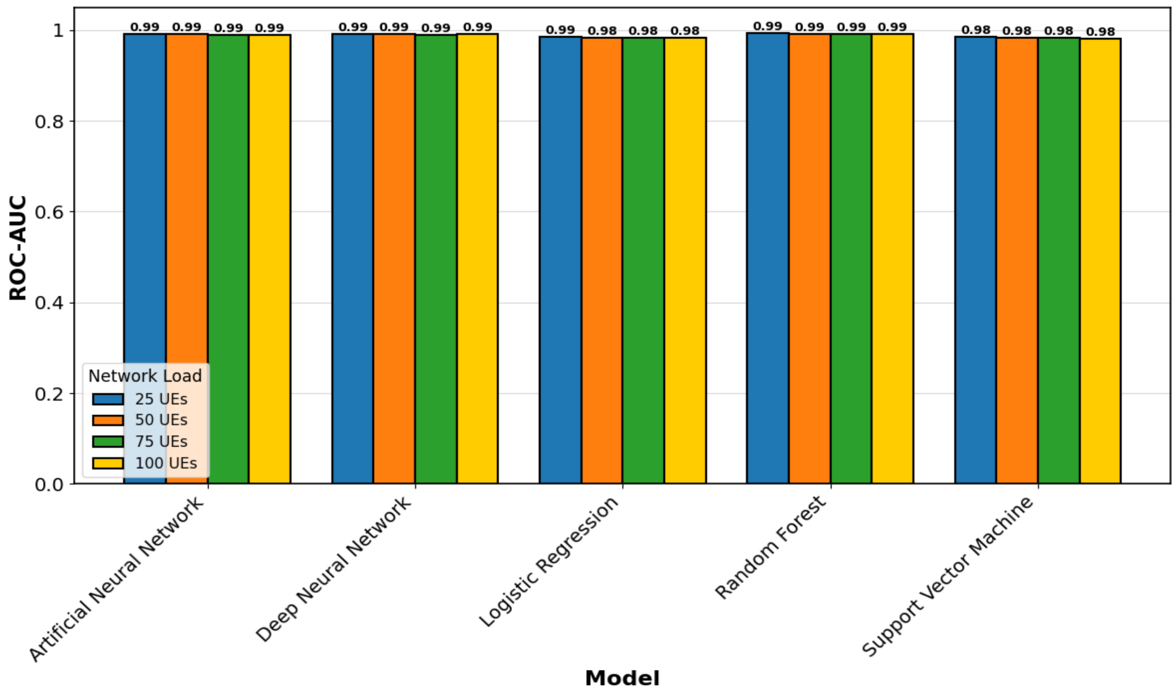

Fig. 13. ROC-AUC under Different Network Loads

4.4 Comparative Analysis per model

Comparative analysis was conducted to evaluate which model performs best across multiple scenarios. Tables 6 and 7 and Fig. 14 to 15 show that the Random Forest algorithm outperforms the other models in terms of accuracy, precision, recall, F1-Score, and ROC-AUC, particularly in larger networks. LR had the fastest training time for all scenarios, making this model suitable in situations where speed is of the essence. ANN and DNN offer a balance between computational cost and predictive accuracy, providing moderate performance with reasonable training times. The comparative analysis shows that more advanced ensemble and deep learning models can significantly reduce Handover Failures (HOF) while improving network stability and Quality of Service (QoS), whereas simpler models can still be useful in resource-constrained or less demanding conditions.

Table 6 Best Performing Model per Scenario Based on Evaluation Metrics

Scenario (UE Count)	*Best Accuracy (%)*	*Best Precision*	*Best Recall*	*Best F1-Score*	*Best ROC-AUC*	*Fastest Training*
25 UEs	Random Forest (98%)	Random Forest (0.9815)	Random Forest (0.9760)	Random Forest (0.9777)	Random Forest (0.9927)	Linear Regression (5.0638s)
50 UEs	Random Forest (97%)	Random Forest (0.9796)	Random Forest (0.9724)	Random Forest (0.9745)	Random Forest (0.9914)	Linear Regression (10.0826s)
75 UEs	Random Forest (97%)	Random Forest (0.9772)	Random Forest (0.9697)	Random Forest (0.9719)	Random Forest (0.9908)	Linear Regression (19.7835s)
100 UEs	Random Forest (97%)	Random Forest (0.9759)	Random Forest (0.9677)	Random Forest (0.9701)	Random Forest (0.9909)	Linear Regression (19.7435s)

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Table 7 Training Time and Average Performance Metrics of the Five Machine Learning Models

Models	*Training Time (s)*	*Average Accuracy (%)*	*Average Precision*	*Average Recall*	*Average F1-Score*	*Average ROC-AUC*
ANN	10314.6s	95	0.97	0.95	0.96	0.99
DNN	12316.6s	95	0.97	0.95	0.96	0.99
LR	54.7s	93	0.97	0.93	0.94	0.98
RF	26759.3s	97	0.98	0.97	0.97	0.99
SVM	203.1s	93	0.97	0.93	0.94	0.98

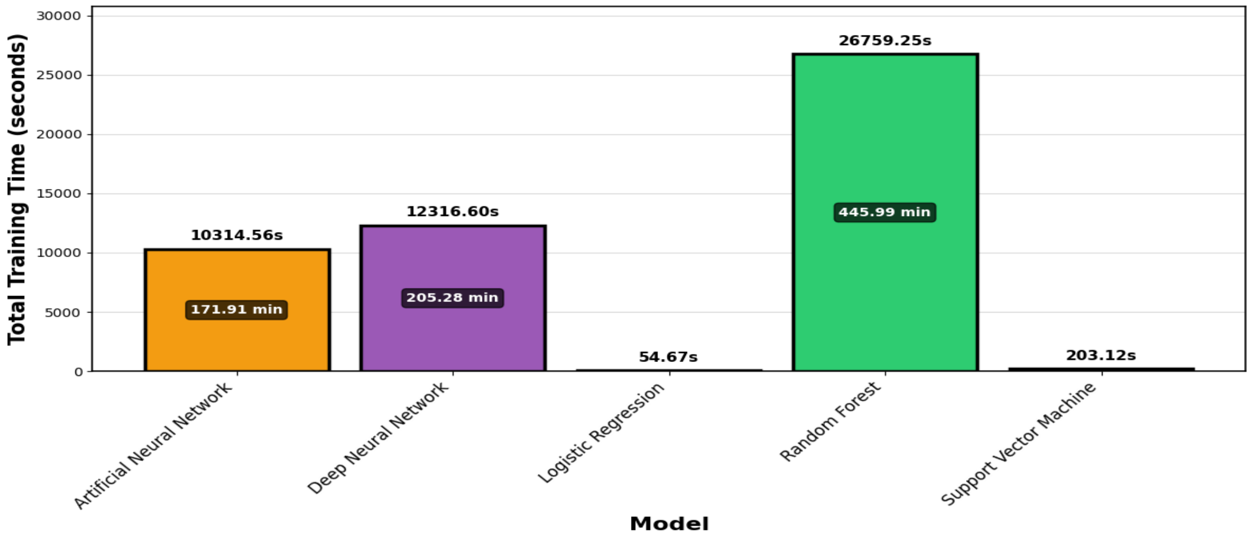

Fig. 14. Total Training Time per Model across All Scenarios

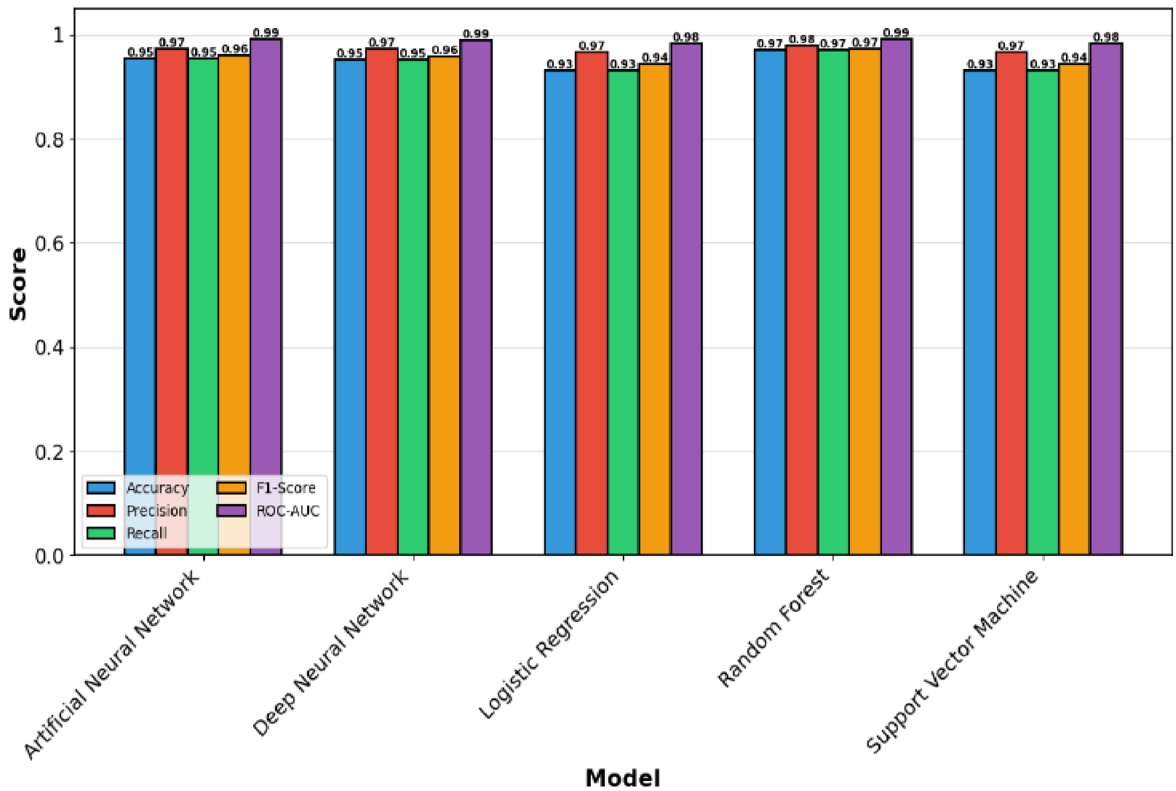

Fig. 15. Comparative Analysis of the Average Performance of the Five Machine Learning Models

5. CONCLUSION

This study demonstrates how machine learning can effectively predict handovers in 5G UMi networks, improve network stability and reduce call drops. The best model in terms of accuracy and evaluation metrics was Random Forest, with ANN and DNN being the most competitive regarding accuracy but with slightly lower speed. LR and SVM were fast in training but less accurate. The most important KPIs for successful HO were identified as RSRP, SINR, and information about the Serving Cell. In general, HO optimization based on ML enhances QoS, and offers an intelligent mobility management framework in ultra-dense 5G networks.

Future studies should investigate more on advanced deep learning techniques such as Long Short-Term Memory (LSTM) and attention-based models to better understand the dynamics of changing mobility and increase the accuracy of predictions. Prediction of HO in real-time may be integrated through the use of edge-based intelligence. Also, future studies may investigate cooperative load balancing between cells in dense urban networks and the generalization of the framework to B5G and 6G networks as well as enhance dense urban medium-mobility and low-latency applications.

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