An Artificial Intelligence-based Handover Triggering and Management Mechanism for 5G Ultra-dense Networks to Improve Handover Authentication

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Abstract — The emergence of 5G ultra-dense networks has gained considerable attention, as solutions of this kind enable rapid and intelligent device connectivity, thus ushering in a new era of high-speed communications. Nevertheless, the process of managing mobility across varying inter-frequency strategies increases interference and complexity. The development of a reliable handover algorithm is crucial for high-quality service, especially in ultra-dense networks with small cells. However, frequent handovers, ping-pong effects, and load-balancing issues arise due to the random and dense deployment of small cells. Additionally, ensuring secure and smooth handover authentication is critical, due to an increased risk of frequent transitions of users across different networks. In such a context, this research focuses on triggering handovers and managing 5G mobile networks, all while protecting sensitive data. We introduce an artificial intelligence-based approach aimed at improving handover initiation and management processes, leveraging Boruta random forest optimization (BRFO) to fine-tune handover margins and identify optimal trigger points for handovers. In addition, an impulsive graph neural network (IGNN) is utilized as a decision framework to predict and minimize unnecessary handovers, thus improving stability in small cell environments. Simulation results demonstrate that the proposed methodology significantly enhances handover management, strengthens authentication, and effectively mitigates a variety of attacks in 5G ultra-dense networks.

Keywords — authentication, communication security, handover, mobility management

1. Introduction

Ultra-dense networks (UDNs) have emerged as an innovation in 5G wireless communication [1]. By deploying a large number of small cells within a confined area, UDNs achieve significantly higher node density compared to traditional cellular networks [2]. They are engineered to meet the ever-growing demand for high data rates, ubiquitous connectivity, and ultra-low latency, challenges that conventional macrocell infrastructures struggle to address.

UDNs enhance network capabilities by improving coverage, boosting capacity, and ensuring better spectral efficiency through small cell deployments. This strategy provides seamless connectivity and a superior user experience in dense urban environments, indoor settings, and high-traffic hotspots [3].

Moreover, UDNs integrate advanced technologies, such as mmWave communication, massive MIMO, and network densification to realize heterogeneous network architectures [4]. These advances are fundamental to supporting the newly emerging ultra-reliable low-latency communication (URLLC) services required by IoT, autonomous driving, AR, and VR applications [5]. UDNs offer improved flexibility, scalability and cost-efficiency compared to macro cell-based designs [5], optimizing spectrum usage and dynamic resource allocation, while simultaneously reducing construction and operational burdens [6].

Advances in wireless technologies and growing user demands have driven a significant evolution in mobile network handover (HO) mechanisms [7]. Initially, user handover decisions required manual intervention, which became impractical with the proliferation of mobile devices [8]. Automated HO systems were, therefore, introduced to facilitate seamless connectivity. In 2G (GSM) and 3G (UMTS) systems, network-controlled HO strategies became standard, leveraging signal strength, quality indicators, and mobility patterns to optimize HO decisions [9]. These automated techniques greatly improved service reliability and efficiency [10].

The arrival of 4G LTE further improved HO by introducing fast handover protocols that reduced latency and packet loss through proactive link establishment and network load balancing [11]. These improvements significantly improved mobile user experiences by enabling high-speed seamless connectivity [12].

In 5G, mobility management becomes even more critical, as URLLC, mMTC, and eMBB services demand different specialized handover mechanisms [13]. Technologies such as beamforming, flexible spectrum sharing, and network slicing help meet these demands by optimizing HO performance and reducing latencies [14]. As 5G deployments expand, handover protocols must ensure persistent connectivity and service continuity in diverse use cases.

Artificial intelligence (AI) has become a transformative force in improving 5G network performance [15]. Machine learning, deep learning, and natural language processing empower 5G networks with autonomous intelligence, enabling dynamic optimization and real-time decision-making. AI algorithms analyze massive datasets from network operations to detect trends, predict anomalies, and improve performance [16].

In dense 5G environments, AI facilitates dynamic network management, optimizing resource allocation, handover management, load balancing, and network slicing [17]. AI-driven automation reduces operating costs, improves service reliability, and accelerates service deployment [18].

Furthermore, AI enables predictive analytics and proactive maintenance by identifying potential failure points and mitigating risks before service interruptions occur [19]. It also plays a crucial role in fortifying the security of 5G networks. AI-based security solutions monitor traffic patterns, detect anomalies in real time, and respond proactively to cybersecurity threats [20]. These capabilities are essential for protecting sensitive information and critical infrastructures in next-generation networks against increasingly sophisticated cyberattacks.

In this work, we propose an AI-driven framework to enhance the efficiency, reliability, and security of handover triggering and management mechanisms, particularly emphasizing the improvement of handover authentication within 5G UDNs.

Optimizing handover triggering points is crucial in a mobile network to ensure efficient and seamless transitions between base stations (BSs), minimizing service interruptions, and maintaining optimal connectivity for users. The handover process in mobile networks is typically initiated based on certain trigger conditions, such as signal strength, speed of movement, and network load.

Below is a summary of the strategies we relied upon to optimize handover trigger points:

1) Handover optimization using Boruta random forest optimization (BRFO). We employ the BRFO algorithm to fine-tune handover parameters by dynamically adjusting the handover boundaries. This technique calculates the optimal conditions for initiating handovers, ensuring smooth transitions between base stations ,while significantly minimizing connection interruptions. The integration of BRFO allows for adaptive optimization of the handover process, thus improving overall network continuity and user experience.
2) Reinforcement learning (RL) is used to continuously optimize handover triggers by rewarding the system for successful handovers (i.e. minimizing ping-pong effects and service interruptions) and penalizing failed handovers. Over time, the system learns the optimal handover trigger points for different scenarios.
3) Impulsive graph neural network (IGNN) for intelligent handover decision making. We utilize an IGNN model as a sophisticated decision-making tool to analyze network states and user mobility behaviors. This model predicts the need for handovers with a high degree of accuracy, effectively reducing unnecessary handovers within small cell networks. By optimizing handover decisions, IGNN contributes to improved network efficiency, better resource allocation, and enhances the overall user experience.

The remainder of this paper is organized as follows. In Section 2, a review of the existing literature related to handover triggering and management in 5G UDNs is presented. Section 3 elaborates on the detailed operational workflow of the proposed system, focusing on BRFO-based handover optimization and IGNN-driven decision-making. Section 4 presents the simulation results and compares the performance of the proposed approach with existing methods, while Section 5 concludes the paper by providing final remarks and summarizing future research directions.

2. Literature Review

A review of the literature on handover triggering and management in 5G UDNs offers specific insights into the research conducted, methodologies adopted and challenges faced. It begins with an overview of the principles and architectures, highlighting such characteristics as low cell density and increased interference. Next, it examines previous studies on handover optimization, including signal strength-based and load balancing algorithms, as well as emerging AI and machine learning approaches.

Additionally, the review discusses security aspects, covering authentication protocols and encryption techniques. It also addresses challenges (as shown in Tab. 1), such as handover latency and interference mitigation, which are crucial for identifying research gaps and areas for improvement.

In [21], the authors discuss improved mobile broadband and extremely low dormancy communications that are supported by such technologies as 5G new radio and beyond. Due to the large number of mobile devices, it is important to manage high mobility in dense networks and constantly alter the time-to-trigger (TTT) and the hysteresis margin. The study suggests a mechanism for 5G and beyond that is based on online learning (learning-based intelligent mobility management – LIM2), to address these issues. For target cell selection, it uses SARSA-based reinforcement learning. For TTT and hysteresis adaptation, it uses the ε-greedy strategy. This method shows promise as a means of improving mobility management and keeping advanced wireless networks connected without any interruptions.

The authors of [22] discuss the difficulties in managing hand-offs in 5G mobile wireless networks that rely on UDN designs. Frequent turnover opportunities for user equipment in UDNs, which are defined by a large number of mmWave BSs, add complexity to the networks. Traditional handover plans simplify things too much, which results in more handovers than necessary and leads to poorer service quality. To address these problems, the authors of the study proposed a new transfer method known as FLDHDT. This technique relies on fuzzy logic to adapt the handover parameters, such as the handover margin (HOM) and TTT depending on the strength of the signal and the horizontal speed of the user equipment's move-

Tab. 1. Research gap summary.

Ref.	Methodology	Technique	Findings	Research gap
[21]	Mobility management in 5G	Adaptive time-to-trigger and hysteresis margin	Number of handovers and throughput	Misallocation of resources and overuse of electricity
[22]	Adaptive handover decision in UDNs	Fuzzy logic and time to trigger	Throughput and ping-pong ratio	Load balancing and inter-cell meddling have not been measured
[23]	MADM handover in 5G in UDNs	Fuzzy logic and MADM	Number of handovers and ping-pong handover	Lack of high-speed situations and ICI tests
[24]	ML protocol for secure 5G handovers	Burrows–Abadi–Needham (BAN) logic	Handover rate by 94.4%	The mobility of 5G UD HetNets needs to be clarified
[25]	Handover authentication mechanism in 5G HetNets	DHan_Auth and Conv_SLSTM	Attack detection accuracy 98.9832	This structure is vulnerable to DDoS outbreaks
[26]	Handover authentication in 5G HetNets	Fuzzy logic and key management	Latency and spatial complexity	Procedure flops to certify user discretion because of insecure channels
[27]	Hysteresis region authenticated handover for 5G HetNets	Artificial neural network and fuzzy logic (ANN-FL)	Handover success rate and communication overheads	A high number of needless handovers may occur in small cell networks at high speed
[28]	Secure handover protocol for 5G	ANN-FL	Handover success rate and handover failure rate	It is not appropriate for executing handovers in high-speed scenarios
[29]	Handover triggering estimation LTE-A/5G	Interval type II fuzzy logic system	Ping-pong handovers	Due to the restricted incidence choice, the recycling of incidence in 5G leads to co-channel interference
[30]	Proactive decision making for handover management 5G	Proactive decision making (PDM) and polynomial regression	Handover ping-pong, handover failure	The number of handovers would increase if MT travels at a high rate of speed

ment. By performing simulations and comparing them with traditional methods, the suggested plan is assessed. The results show that FLDHDT is effective in improving handover efficiency for 5G UDNs, compared to previous approaches. It reduces the number of handovers, lowers the ping-pong ratio, and overall system throughput.

Article [23] presents a new handover strategy to guarantee excellent service in UDNs and to reduce the impact of the aforementioned problems. The technique efficiently triggers handovers and transitions connections to nearby base stations by combining fuzzy logic with multiple-attribute decision algorithms (MADM). Fuzzy system membership functions are refined by subtraction grouping with past information available within the scheme, which improves performance. By reducing the frequency of handoffs, mitigating the impact of ping-pong, and maintaining high levels of service quality, the experimental results show that the suggested strategy outperforms traditional methods.

[24] introduces a machine learning-based handover authentication mechanism to tackle security, privacy, and efficiency issues. The protocol shows strong mutual authentication, protection of session keys, and resistance to several attacks in the course of a formal security analysis using the Burrows-Abadi-Needham (BAN) logic. It also guarantees user anonymity, mutual authentication, and complete confidentiality of key ciphers, according to informal security assessments. Compared to the enhanced 5G identification and key agreement (5G AKA) protocol, the simulation results show better performance metrics. It significantly improves the efficiency of handover signaling and achieves a staggering 94.4% drop-in turnover rate.

A deep learning-based handover authentication system is presented in [25] to solve these issues and enhance user experience. Using the 5G handover-authentication and key agreement (5G AKA) protocol, only data belonging to non-malicious users are authenticated once they have been classified using convolution-stacked long short-term memory (Conv_SLSTM) networks. Encryption and decryption are handled by the authentication process using extended elliptic curve cryptography (Ex_ECC). An evaluation of the model's performance on the Python platform shows that it improves handover processes and resists network attacks with a classification precision of 98.98% and a handover delay of 11.8 s for 200 nodes.

The authors of [26] suggested a solution that relies on fuzzy logic for key and handover management to improve the performance of cloud handover control and identification mechanisms in 5G networks. The goal of the fuzzy logic model is to reduce delays and maximize network efficiency by minimizing handovers and optimizing the selection of the target cell using several factors. The results showed that the model is capable of reducing latency, validating authentication threats, and handling geographic complexity, all of which are important concerns in the management and deployment of 5G networks.

To close the gap, 3GPP has included authenticating and key exchange protocols in its 16th release (3GPP R16). Privacy- and security-related standards applicable to 5G networks are quite high and, although there is a certain number of security protocols described in the literature, many of them are either ineffective or fail to meet these standards. A protocol that simultaneously prioritizes efficiency, security, and privacy is proposed in [27]. In order to ensure user devices, source gNB, and target gNB identification and session key establishment during handover, an intelligent model is created and deployed for target cell prediction using artificial neural networks and fuzzy logic.

Paper [28] presents an ANN-FL protocol that prioritizes security and service quality to solve the problems and meet the changing needs of 5G and beyond (B5G) networks. Simulation results show that thanks to reducing ping-pong handovers by 24.1%, increasing the success rate of handovers by 27.1%, and reducing the failure rate of handovers by 27.3%, the pro-

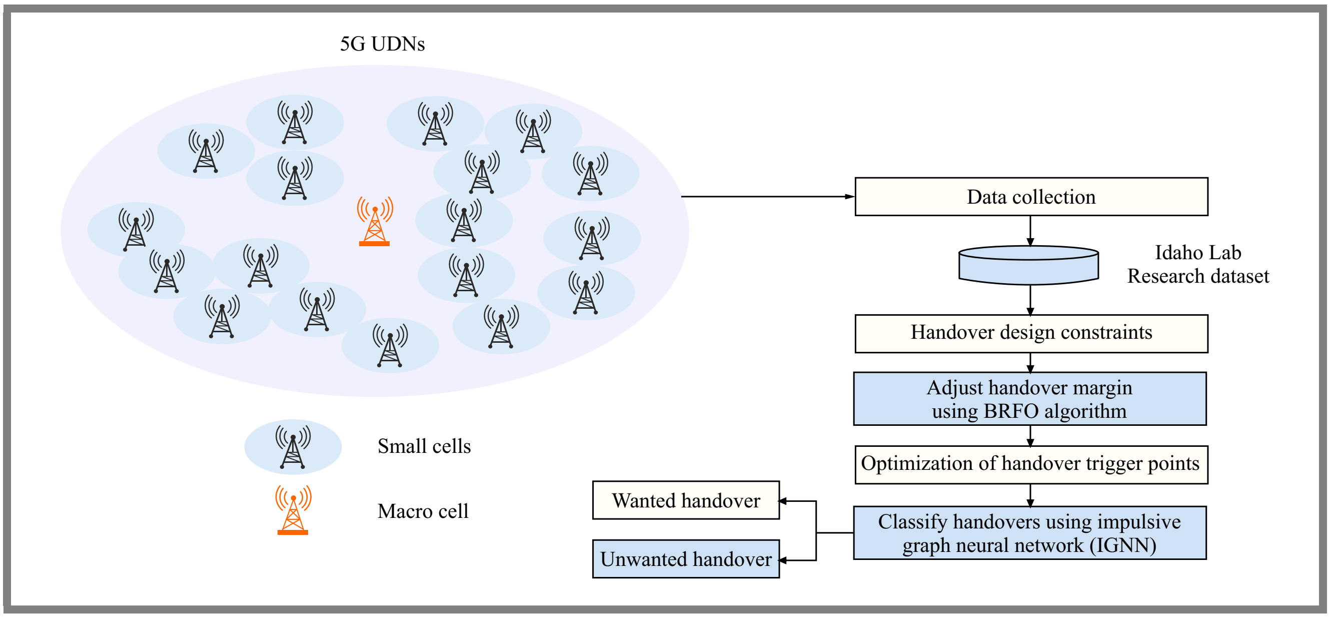

Fig. 1. Handover triggering and management mechanism for 5G UDNs using AI techniques.

tocol is robust against various attacks and effectively improves security and performance in 5G and B5G environments.

The authors of [29] present a new method to estimate the radio link quality (RLQ) of the serving and nearby cells, and then use fuzzy logic to trigger handover procedures. The system uses a simple fuzzy logic system for the prediction of RLQ and a second-order regressors for RLQ prediction. For handover trigger decisions, it uses a cascade fuzzy logic system and successfully mitigates ping-pong, premature, or delayed handovers. Simulation findings show that by using solely information on the quality of the radio connection, handover performance is significantly improved by 50% in high-speed situations, with the ns-3 LTE module. Significantly, the approach solves important 5G network management problems while remaining easy to implement and not being constrained by UE velocity, making it suitable for a wide range of applications, such as UAVs and IoT devices.

In [30], a suitable handover management strategy is proposed to solve mobility-related problems. Its primary objective is to investigate the impact of the handover control parameter on the operation of 5G networks through proactive decision-making in the cell selection process. The method was tested in 5G HetNet simulations to establish its impact on improving mobility management in these networks. The tests included measuring handover attempts, ping-pong transfers, handover mistakes, radio link mistakes, and transfer delays.

Several research challenges have been identified in the literature [21]–[31], including issues related to mobility management, handover optimization, and secure authentication mechanisms. Traditional handover algorithms may not be sufficient for the dynamic nature of ultra-dense networks, leading to problems such as handover latency, ping-pong effects, and load balancing concerns. Therefore, an efficient handover algorithm that optimizes handover triggers and minimizes the amount of unnecessary handover operations.

Additionally, as users move across multiple networks in 5G environments, robust handover authentication solutions are needed to protect against potential security threats.

Despite the progress made in network architecture design, significant challenges remain in ensuring both effective and secure handover authentications, especially in scenarios where pairing is unnecessary. Existing HO authentication protocols, such as identity-based cryptographic techniques, might not fully satisfy the rigorous security requirements of 5G networks, particularly during inter-operator handovers in smaller network regions. Furthermore, the decision-making processes during HO execution in 5G networks are complex, leading to architectural adjustments that may be economically inefficient. The computational burden of HO authentication protocols also poses challenges in meeting the stringent delay demands of 5G networks.

3. Methodology

The proposed mechanism for HO triggering and management in 5G UDNs, illustrated in Fig. 1, utilizes AI-driven techniques. Data from a 5G network are collected and stored within the Idaho Lab Research dataset. Handover constraints are addressed by dynamically adjusting the handover margin through the Boruta random forest optimization (BRFO) algorithm, which refines the handover trigger points. Finally, IGNN is used to classify and differentiate between legitimate and unnecessary handovers.

3.1. Handover Optimization

To minimize HO-related issues in 5G networks, particularly in ultra-dense environments with small cells, optimization of the handover margin is essential. The handover margin sets the threshold signal strength difference required to trigger a handover decision. An effective adjustment of this margin is capable of reducing unnecessary handovers and mitigating ping-pong effects, i.e. scenarios in which users frequently switch between adjacent base stations.

In the presented approach, we use BRFO [31] to fine-tune the handover margin. BRFO merges the Boruta feature selection algorithm and the random forest algorithm, leveraging their strengths to pinpoint the most influential features in order to optimize handover performance. By iteratively assessing significance of the HO margin in conjunction with other influencing factors, such as signal strength, interference, and user mobility, BRFO calculates the optimal HO trigger points.

The mean minimization accuracy or variant number of the randomization value for every input p_s, together with the matching shadier input p_s^b for the total number of trees is:

$$mda = \frac{1}{M_{tree}} \cdot \sum_{a=1}^{a_{tree}} \frac{\sum_{s \in ooN} H\big(q_s = F(p_s)\big) - \sum_{s \in ooN} H\big(q_s = F(p_s^b)\big)}{\big|OON\big|} , \tag{1}$$

$H(\cdot)$ represents the indicator function, whereas OON refers to the predicted error of every sample used for training, calculated using bootstrap aggregation. Calculation of W scores is performed in the following manner:

$$W - score = \frac{mda}{sd} . \tag{2}$$

Let us compute the highest W score in the shadow characteristics by using the standard deviation sd of exact losses. The predictor applies a normalization technique to the data set, scaling the values from 0 to 1 to minimize the impact of extreme values.

$$\alpha_{norm} = \frac{\alpha - \varepsilon_{min}}{\alpha_{max} - \alpha_{min}} . \tag{3}$$

As a result, current input P_s, memory cell output i_{s-1} from the earlier time step $s-1$, and bias terms bf are used to calculate the activation values of forgetting gate ft at time step t. All activation values are divided by the sigmoid function between 0 (totally forget) and 1 (totally recall):

$$F_s = \text{sigmoid}(Z_{F,p}\, P_s + Z_{F,i}\, P_{s-1} + n_F) . \tag{4}$$

Also, the second step defines the LSTM cover to be included in grid cell positions t_s. This job involves two actions [32]. First, we calculate applicant values that can be added to cell positions. Second, the input gate activation values are calculated as:

$$t_s = \tan i(Z_{t,p}\, p_s + Z_{t,i}\, i_{s-1} + n_t) , \tag{5}$$

$$h_s = \text{sigmoid}(Z_{h,p}\, p_s + Z_{h,i}\, i_{s-1} + n_h) . \tag{6}$$

In the third stage, the Hadamard product is defined by creating new cell locations t_s based on the outcomes of the preceding processes:

$$t_s = F_s\, ot_{s-1} + h_s\, oT_s . \tag{7}$$

Output i_s of the reminiscence cells is computed as the subsequent function, in the following manner:

$$o_s = \text{sigmoid}(Z_{0,p}\, p_s + Z_{0,i}\, i_{s-1} + n_0) , \tag{8}$$

$$i_s = o_s \tan i(t_s) . \tag{9}$$

At this stage, the system processes input s at each time point as defined by Eqs. (1)-(9). The output of each gate is obtained by a logic function and a non-linear alteration of the contribution. The following describes the link between input and outcome.

$$R(s) = \sigma_j\big(Z_R\, p(s) + u_R\, i(s-1) + n_R\big) , \tag{10}$$

$$w(s) = \sigma_j\big(Z_w\, p(s) + u_w\, i(s-1) + n_w\big) , \tag{11}$$

$$i(s) = \big(1 - w(s)\big)\, o(s-1) + w(s)\, o\, \hat{i}(s) , \tag{12}$$

$$\hat{i}(s) = \sigma_i\big(Z_i\, p(s) + u_i\, R(s)\, o\, i(s-1)\big) + n_i , \tag{13}$$

where $w(s)$ is the apprise gate trajectory, $R(s)$ is the rearrange gate trajectory, with Z and u being stricture metrics and vector, respectively. σ_j is a sigmoid purpose and σ_i is referred to as a hyperbolic angle.

Algorithm 1 describes the process of optimizing HO using BRFO.

3.2. Handover Decision Model

The HO decision model plays a crucial role in managing handovers within small cell networks, where users' frequent mobility creates numerous handover opportunities. This model helps determine the optimal moments for handovers, ensuring

Algorithm 1 Handover optimization using BRFO

Input: HO design constraints, margin, trigger point
Output: HO optimization parameters
Start

```
Init. population P_s^b with candidate HO configurations
for each solution s ∈ P do
    if the input P_s^b for the total amount of trees then
        Randomly generate P_s^b
    end if
    if P_s^b is defined then
        Compute W score using Eq. (2)
        Normalize the predictor of data set between
         0 and 1 by Eq. (3)
    end if
end for
for each input P_s^b do
    Compute input gate activation values from Eq. (5)
    Formulate input-output relationship by Eq. (10)
    Find the fitness F_s value
    if better value F_s is found then
        Update final value F_s
    end if
end for
```

End

that only necessary handovers occur. By effectively predicting unwanted handovers, the model reduces ping-pong effects and prevents excessive amounts of handover attempts, leading to a more efficient network.

An IGNN is used as the decision-making mechanism [35], [36]. IGNNs are specialized neural networks designed for processing graph-structured data, making them particularly suitable for network optimization and decision-making tasks. In HO management, IGNN analyzes key network parameters and mobility patterns to assess the probability of unwanted handovers. By learning from historical data on handovers and network performance, IGNN identifies patterns that suggest unwanted handovers, allowing it to make more accurate decisions. Let us consider a scenario where B represents a set of interconnected neural networks, each comprising identical types of networks, with both linear and quadratic components at each node of the B-dimensional system. The differential equation defining this network is described as follows:

$$\begin{aligned}\dot{p}_h &= -D_1\, p_h(a) + D_2\, p_h(y\,a) + N_1 F_1\big(p_h(a)\big)\\ &\quad + N_2 F_2\big(p_h(y\,a)\big),\ a \geqslant a_0\,.\end{aligned} \tag{14}$$

The state lattice of the h-th brain framework at a given time demonstrates the postpone importance and $1-y$ is ordinarily alluded to as the beginning significance and relative deferral:

$$\begin{aligned}&F_R\big(p_h(a)\big) =\\ &\big[F_{R1}\big(p_h(a)\big), F_{R2}\big(p_h(a)\big), \ldots, F_{Rb}\big(p_h(a)\big)\big]^S,\quad R = 1,2\,.\end{aligned} \tag{15}$$

The ensuing straight-coupled differential capability depicts the fluctuating activities of interconnected brain organizations:

$$\begin{aligned}&\dot{p}_h(a) = -D_1\, p_h(a) + D_2\, p_h(y\,a) + N_1 F_1\big(p_h(a)\big)\\ &+N_2 F_2\big(p_h(y\,a)\big) + d \sum_{g=1, g\neq h}^{R} m_{hg}\Gamma\big(p_g(a) - p_h(a)\big)\,,\end{aligned} \tag{16}$$

where d is the strength of connection m_{hg} and Γ is a remotely associated unequivocal positive network between two vertices h and g. It is defined as follows, when node g and node h are connected:

$$\text{if } g \neq h \text{ then }\ m_{hg} > 0\,. \tag{17}$$

otherwise

$$m_{hg} = 0\ ,\ \ m_{hg} = -\sum_{g=1,\, g\neq h}^{B} m_{hg}\,.$$

The state of the linking $p_g(a) - p_h(a)$ is linked and nodes g and h vary due to excitement at a specific time a_K. Therefore, the neural networks associated with the stimuli can be obtained in the following form:

$$\begin{cases}\dot{p}_h(a) = -D_1\, p_h(a) + D_2\, p_h(y\,a) + N_1 F_1\big(p_h(a)\big)\\ +N_2 F_2\big(p_h(y\,a)\big) + d \sum\limits_{g=1,\, g\neq h}^{B} m_{hg}\,\Gamma\big(p_g(a)\big),\quad a \neq a_K\\ p_g(a_K^+) - p_h(a_K^+) = j_K\,\big(p_g(a_k^-) - p_h(a_k^-)\big),\quad m_{hg} > 0\end{cases} \tag{18}$$

where $\varsigma = \{a_1, a_2, a_3 \ldots\}$ is a rash series nutritious, $a_{K-1} < a_K$ represents the number of careless occurrences of the impulsive sequence ζ during the interlude (t, a) and j_K indicates the impulsive signal's gain. This is the Laplacian matrix of the compliance system topology. The impulsive sequence ζ a V-asymptotic regular S_{asy}^V impetuous period is:

$$\lim_{K\to\infty}\big(V(a_{K+1} - V(a_K)\big) = a_{asy}^V\,. \tag{19}$$

Let $\overline{m}$, $\overline{n}$, and q be real numbers, and let b be greater than 0. Let y be a real number between 0 and 1. Recognize that the given explanation serves as an explanation.

$$\begin{cases}\dot{p}(a) = \overline{m}\, p(a) + \overline{n}\, p(y\,a),\ \ a \geqslant a_0,\ a \neq a_k\\ p(a_K^+) = j_K\, p(a_k^-)\end{cases}. \tag{20}$$

Assuming that $p(a)$ is greater than zero, let $x(a)$ be a non-negative functional defined on interval $[, +\infty)$ that satisfies:

$$\begin{cases}\dot{x}(a) \leqslant \overline{m}\, p(a) + \overline{n}\, p(y\,a), a \geqslant a_0,\ a \neq a_k\\ x(a_K^+) \leqslant j_K\, p(a_k^-)\end{cases}. \tag{21}$$

Given that 0 is less than $x(a)$ and $x(a)$ is less than $p(a)$ for any s in interval [,], for all values of s greater than or equal to a certain value, $x(a)$ is less than or equal to $p(a)$. Therefore, for $p(a)$ $x(a)$ with $0 < x(a) < p(a)$ for $s \in [\ ,\ ]$:

$$x(a) < p(a),\ \text{for all}\ \ a \geqslant a_0\,. \tag{22}$$

where $S > 0$, such that set:

$$W = \{a \in (a_0, a) : x(a) \geqslant p(a)\},\ \ x(a^*) = p(a^*)\,.$$

and

$$x(a) < p(a)\}, x(a^*) \geqslant p(a^*)\,. \tag{23}$$

We compute the optimal threshold condition as follows:

$$\dot{x}(a) = \overline{m}\, x(a^*) + \overline{n}\, x(y\,a^*)\,. \tag{24}$$

We compute the maximum and minimum range of threshold condition $x(a^*) = p(a^*)$ and $x(y\,a^*) = p(y\,a^*)$, which generates the following set of conditions.

$$\begin{aligned}&0 \leqslant \dot{x}(a^*) - \dot{p}(a^*)\\ &\quad\leqslant \big(\overline{m}\, x(a^*) + \overline{n}\, x(y\,a^*)\big) - \big(\overline{m}\, x(a^*) + \overline{n}\, x(y\,a^*)\big)\\ &\quad= \overline{n}\, x(y\,a^*) - p(y\,a^*)\\ &\quad< 0\end{aligned}. \tag{25}$$

Worldwide μ-dependability model follows the Dasey $< \infty$ condition and S condition with drive-related brain networks when coordinated upgrades or non-synchronized improvements occur during the motivation span. In this way, drive-associated brain organizations can be reworked in the Kronecker item structure:

$$\begin{cases}\dot{p}(a) & = -(H_B \otimes D_1)p(a) + (H_B \otimes D_2)p(y\,a)\\ & +(H_B \otimes N_1)f_1\big(p(a)\big) + (H_B \otimes N_2)f_2\big(p(y\,a)\big)\\ & +d(M \otimes \Gamma)\,p(a), a \neq a_K,\ K \in B\\ & \\ & p_g(a_K^+) - p_h(a_K^+) = j_K\big(p_g(a_K^-)\big),\\ & \text{for}\ (h, g)\ \text{satisfying}\ m_{hg} > 0\,.\end{cases} \tag{26}$$

In this case, the network topology exhibits robust connectivity, indicating that the Laplacian connected matrix A remains unchanged. Algorithm 2 outlines the operational procedure of the HO decision model employing IGNN.

Algorithm 2 Handover decision model using IGNN

Input: Number of small cells and macro cells, threshold condition
Output: Handover decision wanted and unwanted
Start

```
Initialize the random population
if the network is initialized then
    Describe it using the Eq. (14)
end if
if i = 0 then set j = 1
end if
while condition is true do
    if the system study state then
        unwary arrangement ζ is as given in Eq. (19)
    else if p(s) is valid then
        Recognize it as solution to Eq. (20)
    end if
    if a non-negative function χ(a) exists on [y_s0, +∞) then
        Ensure it satisfies Eq. (21)
        x(a) < p(a) for all s ∈ [a_0, a_1],
    else Revise
    end if
end while
```

End

4. Results and Discussion

In the next step, a comparative analysis between the proposed HO triggering and management mechanism and existing approaches is conducted. Performance is validated using the Idaho Laboratory Research dataset. The proposed handover trigger and management mechanism is implemented on the Google Colab platform using Python.

We compare the results of the BRFO+IGNN mechanism with those obtained using existing solutions, including conventional Event A3, FLDH [37] and FLDHDT [22]. Furthermore, the results of the handover authentication of the BRFO+IGNN mechanism are compared with existing mechanisms, such as transport layer security (TLS), fuzzy systems, fuzzy transport layer security (F-TLS) and convolutional SLSTM (CLSTM) [25].

For the handover decision-making process, we compare the performance of the BRFO+IGNN mechanism with several benchmark models, including random forest (RF), decision tree (DT), naive Bayes (NB), linear regression (LR), support vector machine (SVM) and XGBoost.

4.1. Simulation Setup

The data set utilized in this study includes both normal and attack data generated within a simulated setting. Data was gathered from an Internet connected Linux machine running a 5G core network with open-source 5G core software. The network traffic on the 5G core machine limits was captured via Wireshark.

Tab. 2. Simulation setup.

Parameter	Value
Network size	1000 × 1000 m
Number of evolved nodes	3
Number of users	100–500
Amount of pieces of user equipment	5
Mobility model	2D random walk
Speed of user equipment	2–20 m/s
Power of evolved nodes	43 dBm
Power of next generation nodes	23 dBm
Frequency of evolved nodes	2.4 GHz
Frequency of next generation nodes	28 GHz
Packet inter-arrival time	20 ms
Packet size	1000 bytes
Bandwidth of evolved nodes	20 Mbps
Bandwidth of next generation nodes	100 Mbps
Simulation time	100 s

Normal data are categorized into two groups: one involving a single-user equipment simulation and the other involving two user equipment simulations. Malicious data consist of ten distinct attacks, classified into three primary categories: reconnaissance, denial of service (DoS), and network reconfiguration.

Reconfiguration attacks include unified data management, get all network functions, get user data, automatic redirect with a timer, and random data dump. Network reconfiguration attacks are divided into false access and mobility management function insert and delete attacks, as well as random access and mobility management function insert and delete attacks.

The DoS category includes the crash network repository function attack. The data set, covering a total of 50 000 records, is divided using the following proportions: 80% for training and 20% for testing. Data are exported in the CSV format and are used in the proposed research. The analysis considers such attributes as time, source, destination, protocol, length, sequence amounts, acknowledgment amounts, window size, length, timestamp echo reply field, and timestamp value field.

Table 2 presents the parameters used in the simulation setup, which define the characteristics of the simulated network environment necessary to evaluate the proposed mechanisms and algorithms. Together, these parameters create a realistic simulated environment that allows to effectively evaluate the proposed solutions.

Tab. 3. Comparative analysis of proposed and existing HO mechanisms.

Handover mechanism	Number of users				
	100	200	300	400	500
Number of handovers					
Event A3	693	821	1004	1158	1321
FLDH	570	698	881	1035	1198
FLDHDT	447	575	758	912	1075
BRFO+IGNN	324	452	635	789	952
Ping-pong ratio [%]					
Event A3	8.34	8.76	9.09	9.26	9.47
FLDH	5.97	6.40	6.72	6.89	7.11
FLDHDT	3.60	4.03	4.35	4.52	4.74
BRFO+IGNN	1.23	1.66	1.98	2.15	2.37
System throughput [Mbps]					
Event A3	93.72	155.96	242.86	355.83	459.63
FLDH	146.88	209.13	296.02	408.99	512.79
FLDHDT	200.05	262.29	349.19	462.16	565.96
BRFO+IGNN	253.21	315.46	402.35	515.33	619.12

4.2. Comparison

Table 3 presents a comparative evaluation of the proposed HO mechanism against the existing approaches. Figure 2 illustrates the number of handovers corresponding to the varying number of users in different HO mechanisms. The data reveal distinct patterns in handovers as the number of users increases from 100 to 500. Event A3 shows a steady rise in handovers, experiencing a 90.7% increase from 693 at 100 users to 1321 at 500 users. Similarly, FLDH shows a continuous increase, with a 70.2% rise from 570 to 1198 HO. FLDHDT follows a similar trend, showing a significant 139.3% increase from 447 to 1075 handovers.

On the contrary, BRFO + IGNN shows a decreasing trend in HOs as the number of users grows, although the change still reflects a 66.7% drop from 324 to 952 handovers. Event A3, FLDH, and FLDHDT handover mechanisms show a positive relationship between user count and HOs, with increases ranging from 90.7% to 139.3%. However, BRFO + IGNN shows a negative correlation, with a decrease in HOs by 66.7% despite a growing user base.

These results suggest varying levels of efficiency and scalability across the mechanisms, underlining the need to select the most suitable approach based on specific network conditions and user requirements.

Figure 3 illustrates the ping-pong ratio across various user numbers for different HO mechanisms. As the number of users increases from 100 to 500, noticeable differences in the ping-pong ratios are observed among the mechanisms. Event A3 shows a consistent upward trend, with the ratio rising from 13.1% to 13.9%. Similarly, FLDH shows a steady increase in the ping-pong ratio, as it climbs from 18.7% to 19.0%. FLDHDT follows a similar pattern, with values ranging from 24.4% to 31.5%.

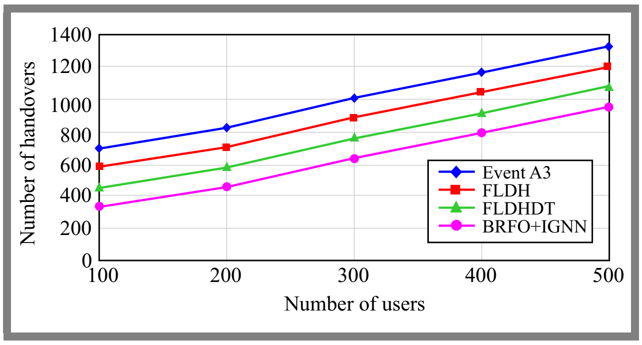

Fig. 2. Handovers against the number of users.

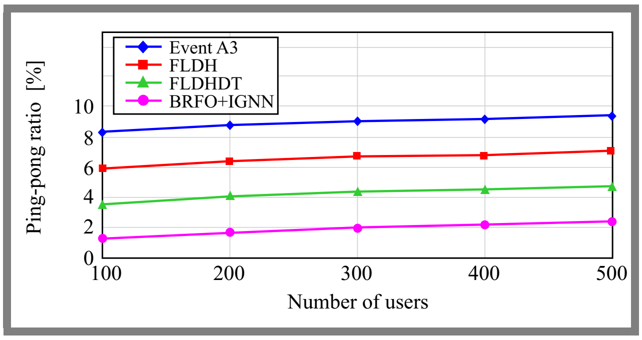

Fig. 3. Ping-pong ratio against the number of users.

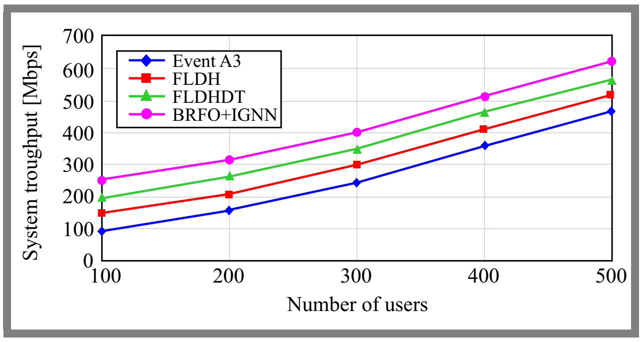

Fig. 4. System throughput against the number of users.

On the contrary, RFO + IGNN reveals an opposite trend, where the ping-pong ratio decreases as the number of users increases. However, the change still varies, with increases from 91.7% to 91.1% within the user range. In general, Event A3, FLDH and FLDHDT exhibit a positive correlation between the number of users and the ping-pong ratio, increasing from 13.1% to 31.5%.

On the other hand, BRFO+IGNN demonstrates a negative correlation, even with increases of 91.1% to 91.7%. These results highlight the differing scalability and performance of HO mechanisms, stressing the importance of selecting the most suitable mechanism based on the specific network demands and user conditions.

Figure 4 presents the system throughput across different HO mechanisms as the number of users increases. As the user count increases from 100 to 500, distinct patterns in system throughput may be observed for each HO mechanism. Event A3 shows a steady increase in throughput, with improvements ranging from 390.1% to 391.8% over the user range. Similarly, FLDH shows a gradual rise in throughput, ranging from

Tab. 4. Comparative analysis of proposed and existing HO authentication mechanisms

HO authentication mechanism	Number of users				
	100	200	300	400	500
Authentication latency [s]					
TLS	8.52	14.32	20.15	25.64	31.25
Fuzzy	7.12	12.02	18.64	21.46	28.56
F-TLS	5.07	10.35	15.64	18.25	25.03
CLSTM	4.23	8.12	9.94	15.35	21.48
BRFO+IGNN	3.53	5.12	7.54	13.32	18.78
Number of unsuccessful handover authentications					
TLS	24	53	105	185	231
Fuzzy	21	46	101	142	195
F-TLS	18	40	98	120	174
CLSTM	14	35	75	85	152
BRFO+IGNN	8	24	55	62	112
Handover delay [ms]					
TLS	18.18	19.60	21.14	23.57	27.15
Fuzzy	14.52	15.95	17.49	19.92	23.50
F-TLS	10.87	12.29	13.83	16.27	19.84
CLSTM	7.22	8.64	10.18	12.61	16.19
BRFO+IGNN	3.56	4.99	6.52	8.96	12.53
Packet loss rate [%]					
TLS	14.40	14.48	14.60	14.67	14.77
Fuzzy	10.84	10.92	11.04	11.11	11.21
F-TLS	7.28	7.36	7.48	7.55	7.65
CLSTM	3.71	3.80	3.92	3.99	4.09
BRFO+IGNN	0.15	0.23	0.36	0.42	0.53

249.6% to 249.8%. FLDHDT follows a similar trend, with increases between 182.9% and 183.5%.

On the contrary, BRFO + IGNN shows a consistent increase in system throughput as the number of users increases, but the rate of change is smaller, fluctuating between 144.4% and 144.7%. Both Event A3, FLDH, and FLDHDT show a positive relationship between system throughput and the number of users, with increases varying from 182.9% to 391.8%.

BRFO+IGNN also exhibits a positive trend, but with smaller increases, ranging from 144.4% to 144.7%. These observations highlight the different efficiencies and scalability of the HO mechanisms, underlining the importance of selecting the appropriate method depending on network needs and user scenarios.

4.3. Comparison of HO Authentication

Table 4 presents a comparison of the proposed HO authentication method with existing solutions. Figure 5 illustrates the authentication latency as the number of users changes for various HO authentication techniques. As the user count rises from 100 to 500, noticeable trends appear in authentication latency across the different methods. TLS authentication

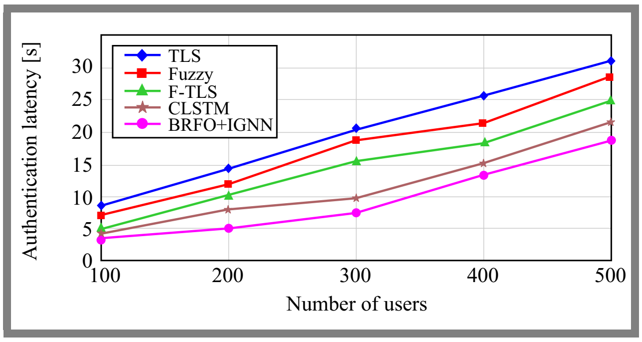

Fig. 5. Authentication latency against the number of users.

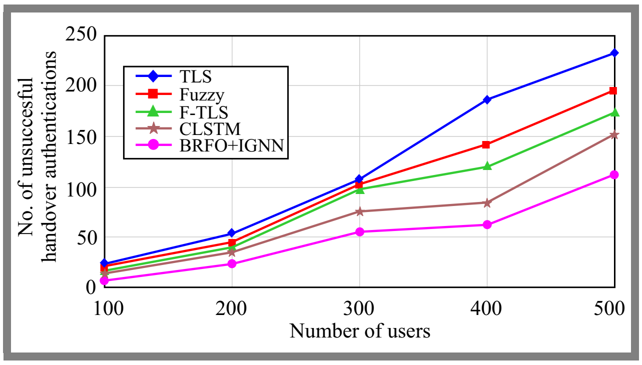

Fig. 6. Amount of unsuccessful handover authentications against the number of users.

shows a steady increase in latency, with an improvement between 52% and 59% across the user range. Likewise, fuzzy authentication displays a gradual increase in latency, with an improvement between 35.23% and 40.12%.

In contrast, F-TLS authentication shows a reduction in latency as user numbers grow, with improvements ranging from 53.7% to 53.8%. CLSTM authentication also reveals an improvement in latency as the number of users increases, ranging from 61.6% to 61.5%. BRFO+IGNN authentication consistently improves latency even as the number of users increases, with an improvement from 46.9% to 46.8%. Both TLS and fuzzy authentication mechanisms exhibit a direct correlation between the number of users and authentication latency, with improvements from 62.6% to 70.125%.

However, the F-TLS, CLSTM, and BRFO+IGNN authentication methods show an inverse correlation, with enhancements ranging from 46.8% to 61.8%. These results highlight the varying performance and scalability of each authentication method, emphasizing the need to choose the most suitable method according to specific security demands and user conditions.

Figure 6 illustrates the number of unsuccessful handover authentications, as the number of users varies between different HO authentication methods. As the number of users increases from 100 to 500, trends in unsuccessful HO authentications for each mechanism become apparent. TLS authentication shows a steady increase in unsuccessful handovers, with a rate ranging from 12.54% to 15.12% as the number of users increases. Similarly, the fuzzy authentication method also experiences a gradual increase, with rates ranging from 25.24% to 28.62%. On the contrary, F-TLS authentication shows fluc-

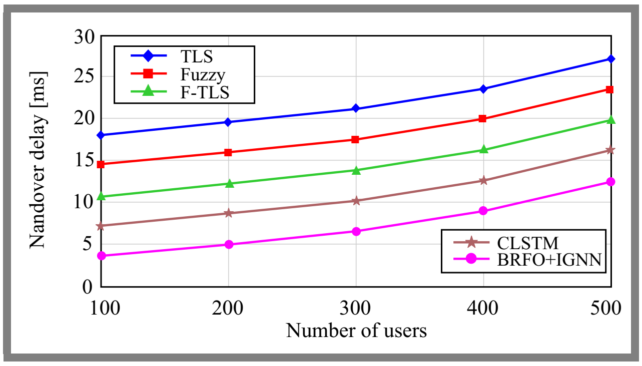

Fig. 7. Handover delay against the number of users.

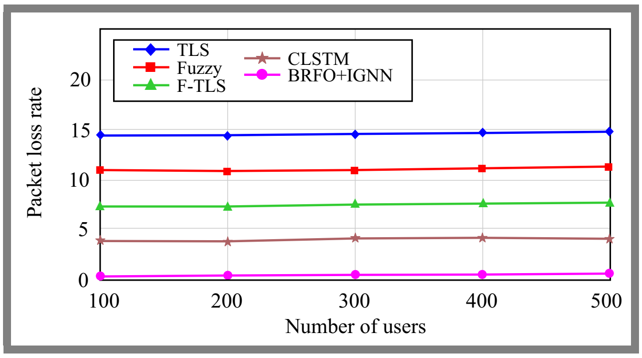

Fig. 8. Packet loss rate against the number of users.

tuating patterns, although there is a general increase, with rates varying from 32.15% to 36.53%. The CLSTM method follows a comparable trend, with its unsuccessful HO ratio ranging from 11.25% to 15.63%.

The BRFO+IGNN method also shows a continuous increase in unsuccessful handovers, even as the user count grows. Across all authentication methods (TLS, Fuzzy, F-TLS, CLSTM and BRFO+IGNN), there is a positive correlation between the number of users and the rate of unsuccessful HO authentications, with enhancements ranging from 23.51% to 28.62%. These results highlight the importance of evaluating the scalability and reliability of authentication mechanisms, stressing the need to address potential security vulnerabilities and optimize performance in different user contexts and security requirements.

Figure 7 illustrates the HO delay in relation to the varying user counts for different handover authentication methods. As the user count increases from 100 to 500, distinct trends are observed across the mechanisms. TLS authentication shows a gradual increase in the delay in HO, with improvements varying between 49.8% and 49.3%. Fuzzy authentication displays a steady increase in delay, with enhancements between 61.9% and 61.9%.

In contrast, F-TLS authentication reveals a reduction in delay as user numbers grow, with improvements ranging from 33.7% to 33.8%. CLSTM also shows a decrease in the delay with user count, with enhancements between 55.7% and 55.6%. BRFO + IGNN consistently reduces delay as the user count increases, with improvements ranging from 71.3% to 71.1%. TLS and fuzzy mechanisms exhibit a positive relationship between user numbers and HO delay, with enhancements of 49.3% to 61.9%. On the other hand, F-TLS, CLSTM, and BRFO+IGNN demonstrate a negative relationship, with enhancements ranging from 33.7% to 71.3%.

These results underscore the importance of optimizing HO mechanisms to reduce delays and improve network performance based on specific user requirements.

Figure 8 illustrates the packet loss rate as a function of the number of users for various HO authentication mechanisms. As the number of users increases from 100 to 500, different trends are observed in the packet loss rate. TLS authentication shows a steady increase in packet loss, with improvements ranging from 2.6% to 2.6% across the user range. Similarly, fuzzy authentication demonstrates a gradual increase in packet loss, with improvements varying from 3.4% to 3.4%, while the F-TLS authentication method exhibits a reduction in packet loss as the number of users grows, with improvements ranging from 1.3% to 1.3%.

The CLSTM authentication method also shows a decrease in packet loss in the user range, with improvements of 5.4% to 5.3%. BRFO + IGNN authentication consistently reduces the packet loss rate, even as the number of users increases, with improvements from 98.7% to 98.7%. TLS and fuzzy methods show a positive correlation between the number of users and packet loss, with improvements ranging from 2.6% to 3.4%.

On the other hand, the F-TLS, CLSTM and BRFO+IGNN methods demonstrate a negative correlation, with enhancements varying from 1.3% to 98.7%. These results highlight the critical need to fine-tune authentication mechanisms to reduce packet loss and improve network stability, tailored to specific user scenarios and requirements.

Tab. 5. Comparative analysis of the proposed and benchmark HO authentication mechanisms [%].

HO decision model	Accuracy	Precision	Recall	F-measure
RF	54.66	53.24	53.67	53.46
DT	61.64	60.23	60.66	60.44
NB	68.63	67.21	67.64	67.43
LR	75.61	74.20	74.63	74.41
SVM	82.60	81.18	81.61	81.40
XGBoost	89.58	88.17	88.60	88.38
BRFO+IGNN	96.57	95.15	95.58	95.37

4.4. Comparison of HO Decision Making Mechanisms

Table 5 presents a comparison of the results between the proposed and existing HO decision-making mechanisms. BRFO+IGNN consistently surpasses the benchmark models in all performance metrics, demonstrating higher accuracy, precision, recall, and F-measure values. Among the benchmark models, RF shows the poorest performance, with accuracy, precision, recall, and F-measure values of 54.65%, 53.24%, 53.67% and 53.46%, respectively. DT and NB models exhibit moderate performance, with improvements in all metrics over RF. LR and SVM models show further performance gains, surpassing DT and NB in all metrics. The XGBoost mod-

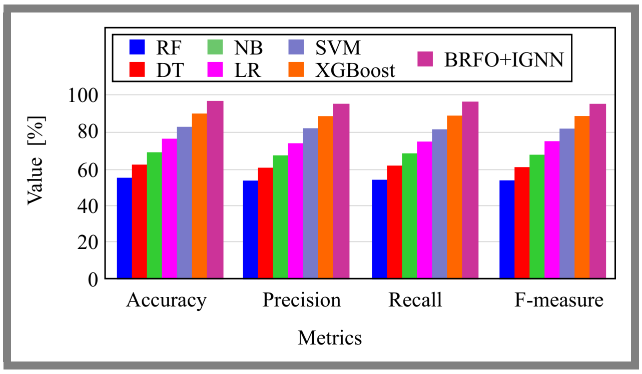

Fig. 9. Comparison of proposed and benchmark HO authentication mechanisms.

el, a gradient boosting algorithm, demonstrates even better performance, outperforming LR and SVM on all metrics.

However, the proposed BRFO+IGNN stands out, achieving an impressive accuracy of 96.57%, a precision of 95.15%, a recall of 95.58%, and an F-measure of 95.37%.

Compared to the top-performing benchmark model (XGBoost), BRFO+IGNN shows significant improvements in all areas, confirming its effectiveness in handover decision making (Fig. 9). This analysis highlights the superior performance, suggesting it has strong potential for practical deployment, enhancing both network reliability and performance.

5. Conclusions

This paper proposes a method that uses artificial intelligence (AI) techniques to improve handover triggering and management in wireless networks, specifically focusing on HO authentication. The approach applies Boruta random forest optimization (BRFO) to fine-tune the handover parameters, allowing to calculate optimal HO trigger points by adjusting the handover margins in order to strengthen supporting reliable authentication during vertical handovers. Additionally, an IGNN acts as the decision-making entity, predicting unwanted handovers and minimizing unnecessary handover events in small cell networks.

Performance of the proposed model is evaluated through simulation experiments which demonstrate its effectiveness in optimizing handover processes, authentication, and defense against potential attacks in 5G ultra-dense networks (UDNs).

The results show that BRFO + IGNN outperforms existing methods such as Event A3, FLDH, and FLDHDT in several key metrics.

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