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A Deep Learning Framework for Joint Handover Prediction and Path Stability Estimation in 5G/6G Networks

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ABSTRACT

The high mobility density of 5G and 6G networks, including vehicular systems requires smart handover and imposes unparalleled demands on the network mobility management. The traditional handover mechanisms, which are largely reactive and inherently threshold-based, are inefficient to operate in dynamic environments and lead to severe impact, resulting in ping-pong effects, radio link failures, and inefficient use of resources. The paper presents the deep handover mechanism, a new end-to-end spatio-temporal deep learning model, which aims to orient the joint optimization of handover prediction and the following estimation of path stability. Our architecture represents a novel combination of a bidirectional long short-term memory (Bi-LSTM) network to learn complex temporal interactions in user mobility with a Graph Attention Network (GAT) to learn the spatial interaction between the cellular topology. These multi-modal features are dynamically weighed by a special mechanism of attention-based fusion. Decades of testing on a large-scale dataset of 5.2 million network samples show that our proposed work obtains a state-of-the-art level of handover prediction accuracy of 92.4 **%**, even stronger than popular models such as LSTM-GRU hybrids (91.2%) and transformer-based models (90.8%). Moreover, it approximates stability of the paths with an average error of 1.3 seconds and the inference computation time is only 12.8ms, which proves its applicability in real time. This publication introduces a new proactive paradigm of intelligent mobility management in heterogeneous networks.

KEYWORDS

deep learning, handover prediction, path stability, 5G/6G networks, spatio-temporal modeling, graph attention networks, multi-modal fusion

1. INTRODUCTION

The nonstop development of wireless communication standards is also introducing a hyper-connective age, with the Fifth-Generation (5G) and the Future Vision of Sixth-Generation (6G) networks portending to support the plethora of applications in enhanced mobile broadband to mission-critical Internet of Things (IoT) [1, 2]. One of the pillars of this vision is the facilitation of smooth mobility in a heterogeneous environment of devices, such as connected vehicles, unmanned aerial systems (UAVs), and personal mobile devices [3]. This diversity, however, brings serious issues in ensuring the quality of service (QoS) when the mobility event occurs since the network will have to deal with the very fast and unforeseeable changes in the state of connectivity. The process of handover (HO) - the basic mechanism, passing an active user session through one base station to another - is vital to service continuity [4]. The 3GPP-standardized legacy handover management is mainly based on reactive algorithms (e.g., A3/A4 events) that execute decisions on the basis of short-term reference signal received power (RSRP) or quality (RSRQ) [5]. Although these approaches are computationally easy and extensively implemented, their responsive nature is a key weakness when highly mobile scenarios are considered. They are susceptible to ping-pong effects (rapid, handovers between cells that are oscillating), radio link failures (RLFs), and inefficient allocation of resources, and eventually deteriorate user experience and network efficiency [6]. With the introduction of machine learning (ML), there are new possibilities for intelligent optimizations of handover. Early studies investigated classical ML models such as support vector machines (SVMs) [7] and random forests [8] that provided a small but significant improvement, but could not predict more complex temporal sequences. Later studies built on the use of deep learning, especially Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, in order to learn temporal interdependences in network measurement data [9]. In more recent times, more sophisticated architectures such as LSTM-Gated Recurrent Unit (GRU) hybrids with attention [10], Transformer-based models to calculate long-range dependencies [11], and Graph Neural Networks (GNNs) to compute spatial topology topped the limits of prediction accuracy. Even with such developments, the state-of-the-art at the moment has a number of serious gaps. To begin with, the majority of methods view handover prediction as a single classification problem, with very little regard to the second important issue of predicting the stability and quality of the new connection path, which is

a determinant of QoS in latency-sensitive applications [13]. Second, most high-accuracy models, including Transformers, are high-computational cost and memory consumers making them impractical to deploy in real-time at the network edge [11]. Third, solutions available tend to be specific to particular mobility situations and do not have a generalized structure that will be effective in a variety of network conditions [14]. Despite the significant progress achieved by machine learning and deep learning approaches for handover optimization, existing solutions still face several important limitations. Most approaches focus exclusively on handover event prediction without simultaneously considering the stability of the target connection, which is a critical factor for maintaining service continuity and the quality of service (QoS). In modern 5G and emerging 6G networks, dense heterogeneous deployments, high-speed vehicular mobility, dynamic traffic loads, and rapidly changing radio conditions make network path stability increasingly difficult to maintain. Although a handover decision may successfully transfer a user connection to a neighboring cell, the selected target path may not remain stable for a sufficient duration, resulting in repeated handovers, ping-pong effects, increased signaling overhead, radio link failures, and degraded user experience. Furthermore, many state-of-the-art hybrid deep learning models either inadequately capture the joint spatio-temporal characteristics of cellular networks or incur substantial computational overhead that limits their practical deployment in real-time 5G/6G environments. Additional challenges include increased model complexity, large parameter counts, higher memory and training requirements, and reduced interpretability, which further complicate deployment in resource-constrained edge-network scenarios. Existing approaches often emphasize either temporal sequence modeling or spatial topology analysis, thereby failing to fully capture the complex interactions between user mobility patterns and cellular network structures that influence both handover decisions and post-handover connection quality. These limitations motivate the development of a unified framework capable of jointly modeling temporal mobility patterns, spatial network topology, and post-handover connection stability while maintaining computational efficiency and deployment feasibility. Therefore, the proposed hybrid architecture integrates Bi-LSTM and Graph Attention Network (GAT) components to leverage their complementary strengths in temporal and spatial learning, enabling more reliable handover prediction and path stability estimation for next-generation 5G/6G networks.

These limitations motivate the development of a unified framework capable of jointly modeling temporal mobility patterns, spatial network topology, and post-handover connection stability while maintaining computational efficiency and deployment feasibility. To address these challenges, this paper makes the following contributions, we introduce a novel scheme, which is an end-to-end deep learning model that predicts handover and estimates path stability in the same, multi-task learning architecture. We create a new spatio-temporal model, which heavily combines a Bi-LSTM-based time sequence modeling framework with a Graph Attention Network (GAT)-based spatial relationship learning framework instead of simple feature concatenation. We present an attention-based multi-modal fusion mechanism which is a dynamic weighting of the importance of the temporal, spatial and contextual features to the robustness and interpretability of the model. We show through a large-scale (5.2 million samples) experiment that our framework attains the state-of-the-art accuracy (92.4%) and still remains computationally efficient (12.8ms inference time) to be applicable in real-world systems. The rest of this paper is organized as follows: Section 2 will conduct a thorough review of related work. Section 3 describes the suggested framework methodology. Section 4 explains the experimental set up. The results are introduced and described in Section 5. Lastly, Section 6 is the conclusion of the paper.

2. RELATED WORKS

The handover management research environment has changed considerably and convered the strict, parameter-driven algorithms to flexible and data-driven intelligent calculations. The current section presents a critical analysis of this evolution that includes the development of the evolution and identifies the gaps in the research that are a focus of our work.

2.1. Traditional and Rule-Based Handover Methodologies.

Cellular handovers are based on the principle of event-driven mechanisms defined by the 3GPP (e.g., the A3 event [5]) (neighbor cell becomes offset better than serving cell). These methods apply fixed or dynamic hysteresis margins and a time-to-trigger (TTT) timer to avoid unstable handovers [15]. Although they are lauded to be simple and possess low computational costs, they are inherently reactive which is a great weakness as well. They are unable to predict the conditions in the network in the future, and hence, they will be exposed to the unsteady nature of the conditions experienced by 5G/6G mobility situations. Several optimization approaches have been proposed to improve the adaptability of traditional handover mechanisms. For example, fuzzy logic controllers [19] dynamically adjust handover parameters according to changing network conditions, while reinforcement learning approaches such as Q-learning [20] enable adaptive parameter optimization based on interaction with the network environment. Nevertheless, these methods remain largely reactive because they rely on current network observations and do not explicitly predict future mobility behavior or connection stability.

2.2. Machine Learning for Handover Optimization

The shortcomings of conventional approaches stimulated the desire to use machine learning. Premeditative models used were supervised learning. Support Vector Machines (SVM) were employed in the study by Tao et al. [7] in which signal strength features were used, resulting in an accuracy of about 85%. Alotaibi et al. [8] have shown that the postponement of handover parameters could be maximized with the help of random forests depending on the state of the network. Although these models demonstrated the promise of the data-driven approach, they tended to be one-off classifiers that could not reflect the most important temporal dynamics and sequential patterns of the user mobility.

2.3. Deep Learning for Temporal Sequence Modeling

It was natural to apply deep learning to handover prediction due to the success of the method in sequence-based operations. Zhang et al. [9] were the first to use LSTM networks, which are suitable formodeling past histories of network measurements to make future predictions of handovers with a maximum accuracy of 88 percent. Liu et al. [18] further extended this with the Bidirectional LSTMs (Bi-LSTMs) to record the history and future context of a sequence. The state-of-the-art in temporal modeling current reviews is embodied by hybrid models such as the LSTM-GRU with attention by Wang et al. [10] that has achieved 91.2% accuracy because it pays attention to the most relevant time steps. These models, however, have a huge limitation: they process user trajectory data without paying much attention to the rich spatial structure of the underlying cellular network.

2.4. Spatial and Spatio-Temporal Modeling

By realizing that handovers are naturally spatial phenomena, the researchers started using topological information. Zhang et al. [12] developed the cellular network as a graph, modeling relationships among base stations with the help of Graph Neural Networks (GNNs), reaching the accuracy of 89.7%. Others, such as Chen et al. [11] used transformer architectures where long-range dependencies are applied on the measurement sequences in different cells using self-attention which achieved 90.8% accuracy. The CNN-LSTM fusion by Li et al. [19] used Convolutional Neural Networks (CNNs) to extract spatial features but used LSTMs to extract temporal features. They are also a step in the right direction, but in many cases, the fusion of the spatial and temporal domains by such methods is shallow or even suboptimal, underutilizing the synergies between the two domains.

2.5. Path Stability and Connection Quality Prediction

One of the aspects that has been given little attention in literature concerns prediction of the quality of connection once a handover is realized. Whereas it is important to predict when to hand your over, it is equally important to know whether the new connection would be stable. Johnson et al. [20] employed their regression model to forecast the short-term post-handover signal strength, but their time frame was short. Garcia et al. [21] suggested a reinforcement learning method to ensure the quality of connections, yet it had to be used with a large amount of interactions with the environment. The very fact that only limited research has been conducted in this field especially in a single framework constitutes a big gap.

3. MATERIALS AND METHODS

This section outlines the holistic approach to the framework that will inform the process of managing intelligent mobility in 5G/6G networks. We started by making an official statement of the handover prediction and path stability estimation as a multi-task learning problem. We then elaborated the data collection and preprocessing chain that included multi-modal network measurements, mobility data, and contextual data. Our methodology center involved the introduction of the new architecture that combined bidirectional LSTM networks to model temporal sequences with graph attention networks to learn spatial relationships, and was integrated with an attention-based fusion mechanism. We discussed the multi-task learning goal and optimization plan, finally, presenting the setup of the experimental and the measures of evaluation used to conduct rigorous performance validation.

3.1 High-Level Framework Architecture

The high-level architecture of our proposed framework illustrated the systematic process of workflow between system multi-modal data input to joint prediction outputs as illustrated in Figure 1 below:

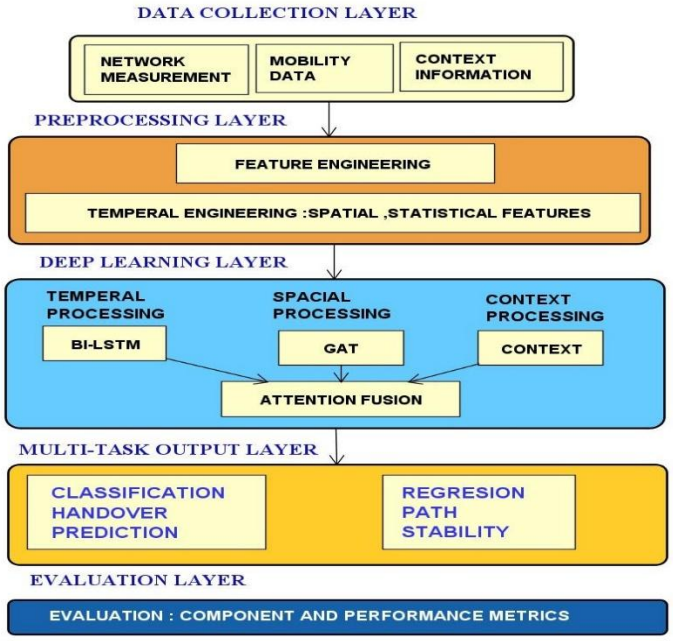


Figure 1: Framework methodology architecture

3.2 Problem Formulation

The mobility management problem was presented as a multi-task learning challenge. The goal was to train a mapping of a historical sequence of multi-modal network observations to two target variables: a future handover event and the stability of the resultant connection.

Let D = $\{(X_i, Y_i)\}_{i=1}^{N}$ represent our dataset, where each sample X_i contains sequential observations and Y_i represents the target labels.

A. Handover Prediction Task

The handover prediction is formulated as a binary classification problem:

$$P\left(H_{[t+\Delta t]} = \left(1 \middle| X_{[t-k:t]}\right) = f_{ho}(X_{[t-k:t]})\right)$$

where:

$H_{[t+\Delta t]} \in \{0,1\}$ indicates handover occurrence at future time $t + \Delta t$,

$X_{[t-k:t]}$ represents the input sequence over historical window k, and Δt is the prediction horizon (5 seconds in our implementation).

B. Path Stability Estimation

The path stability is formulated as a regression task:

$$S_{[t+\Delta t]} = f_{stability}(X_{[t-k:t]})$$

Where:

$S_{t+\Delta t} \in \mathrm{R}$ represents the estimated connection duration following potential handover.

3.3 Data Collection and Preprocessing

The framework was capable of using several data modalities to gain a full picture of the network state.

A. Multi-Source Data Integration:

Our framework integrated three primary data modalities:

1. Network Measurements: RSRP, RSRQ, SINR, CQI values sampled at 1Hz frequency
2. Mobility Data: GPS coordinates, velocity, acceleration, heading direction
3. Contextual Information: Temporal patterns, cell topology, network load estimates.

B. Feature Engineering Pipeline

Our feature engineering pipeline transforms raw network measurements, mobility data, and contextual information into structured temporal, spatial, and statistical representations. Temporal features capture signal evolution through rolling statistics, spatial features model cellular topology relationships, and statistical features extract distribution characteristics. This processed feature set provides optimized inputs for the subsequent spatio-temporal deep learning architecture, enabling effective handover prediction and path stability estimation

3.4 Deep Learning Architecture

A. Multi-Modal Input Processing

The input to our model consisted of three parallel streams:

1. Network stream: $X_{net} \in R^{TxD_{net}}$
2. Mobility stream: $X_{mob} \in R^{TxD_{mob}}$
3. Context stream: $X_{ctx} \in R^{D_{ctx}}$

where T=60 represents the sequence length (60 seconds) and D_{net}, D_{mob}, D_{ctx} denote feature dimensions for each modality.

B. Temporal Processing Branch

We employed a bidirectional LSTM architecture for temporal feature extraction:

$$h_t^{forward} = LSTM_{forward}(x_t, h_{t-1}^{forward})$$

$$h_t^{backward} = LSTM_{backward}(x_t, h_{t-1}^{backward})$$

$$h_t^{temp} = [h_t^{forward}; h_t^{backward}]$$

The bi-LSTM contains 128 hidden units with layer normalization for stable training.

C. Spatial Processing Branch

For spatial relationship modeling, we implemented a graph attention network (GAT) [16] that processes cellular network topology:

$$h_i^{spatial} = \sigma\left(\sum_{j \in N(i)} \alpha_{i,j}\, \boldsymbol{w}\boldsymbol{h}_j\right)$$

where $\alpha_{i,j}$ are attention coefficients learned during training, $N(i)$ denotes neighboring cells, and $\mathbf{W}$ is a learnable weight matrix.

D. Multi-Modal Fusion with Attention

We designed an attention-based fusion mechanism to dynamically combine features:

$$h^{fused} = \sum_{m=1}^{M} \beta_m \,.\, \boldsymbol{h}^m$$

$$\beta_m = \frac{\exp\left(MLP(h^m)\right)}{\sum_{m'-1}^{M} \exp\left(MLP(h^{m'})\right)}$$

Where β_m represents the attention weight for modality m, and $M = 3$ denotes the total number of modalities.

E. Multi-Task Prediction Heads

The fused representations were processed by specialized prediction heads:

Handover prediction head:

$$\hat{y}_{ho} = \sigma(\boldsymbol{W}_{ho}.ReLU\left(\boldsymbol{W}_1 h^{Fused} + b_1\right) + b_{ho})$$

Path Stability Head:

$$\hat{y}_{stability} = ReLU(\boldsymbol{w}_{stab}.ReLU\left(\boldsymbol{W}_2 h^{Fused} + b_2\right) + b_{stab})$$

3.5 Loss Function and Optimization

We employed a multi-task loss function combining classification and regression objectives:

$$L = \lambda_{ho}L_{ho} + \lambda_{stability}L_{stability} + \lambda_{reg}L_{reg}$$

Where:

$$L_{ho} = \frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)log(1 - \hat{y}_i)] \quad \text{(Binary Cross-Entropy)}$$

$$L_{stability} = \frac{1}{N}\sum_{i=1}^{N}(s_i - \hat{s}_i)^2 \quad \text{(Mean Squared Error)}$$

$$L_{reg} = \|\boldsymbol{W}\|_2^2 \quad \text{(L2 Regularization)}$$

The weights λ_{ho}=0.6 , $\lambda_{stability}$=0.3, and λ_{reg}=0.1

balancethe contribution of each loss component.

4. EXPERIMENTAL SETUP

In a bid to make the evaluation process justifiable and exhaustive, we carried out far-reaching experiments that were based on performance, efficiency, and practical impact.

4.1 Dataset Description

The size of the network dataset that we used was a large-scale, real-world dataset of 5.2 million samples that were sampled in a big metropolitan area over a period of three months. The data covered all the various mobility scenarios:

- Urban: The city center was congested with a high user density and building shadows.
- Suburban: medium population of users.
- Highway: fast movement of vehicles (up to 120 km/h).

The features were the multi-modal features mentioned in Section 3.2. Network logs were used to label handover events, which led to an unevenly distributed data set of around 15% positive (handover) cases. Because handover events represented approximately 15% of the total samples, the dataset exhibited a moderate class imbalance. To mitigate potential bias toward the majority class, a weighted binary cross-entropy loss function was employed, where class weights were determined inversely proportional to class frequencies. This approach increased the penalty associated with misclassifying handover events and encouraged the model to learn more discriminative representations for the minority class. In addition, performance evaluation was conducted using precision, recall, F1-score, and AUC metrics alongside overall accuracy to provide a comprehensive assessment under imbalanced data conditions. The data was divided over time based on training (70%), validation (15%), and test (15%) to eliminate the risk of data leakage.

4.2 Baseline Methods

We benchmarked our work in comparison to a variety of state-of-the-art and classic baselines:

1. A3 Event-Triggered [5]: the 3GPP handover standard algorithm.
2. Random Forest (RF) [8]: a powerful classical ML benchmark.
3. LSTM [17]: a deep learning baseline of time series modeling.
4. CNN-LSTM Fusion [19]: a spatio-temporal baseline with CNNs as spatial features.
5. GAT-Only [16]: the baseline with the spatial Graph Attention Network only.
6. Attention LSTM-GRU Hybrid [10]: a high-accuracy model of time.
7. Transformer-Based [11]: a current state-of-the-art sequence modeling architecture.

4.3 Evaluation Metrics

A set of measures was comprehensive because it was used to assess performance:

1. Prediction of handover: accuracy, precision, recall, F1-score, and area under the ROC curve (AUC).
2. 2. Estimation Path Stability: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).
3. Computational practicability: means Inference Time (ms) and Model Size (MB).

4.4 Implementation Details

PyTorch and PyTorch Geometric were used to implement the model. Training was done on a server with an NVIDIA A100 GPU. Our batch size was 128 and we used a learning rate scheduler, which decreased the learning rate when validation loss stopped decreasing. Overfitting was prevented by early termination. Both the source code and a sample of the dataset were reproducible.

5. RESULT AND ANALYSIS

5.1. Overall Handover Prediction Performance

Table 1 summarizes the overall performance of the proposed framework and all the methods in the baseline on the task of predicting handover. Our framework has the best score in all the main classification measures.

Table.1 Overall performance comparison

Method	Accuracy %	Precision %	Recall %	F1-Score	AUC
A3 Event-Triggered	78.3	72.1	70.8	71.4	0.812
Random Forest [8]	83.7	76.5	78.2	77.3	0.845
LSTM [17]	88.0	82.3	83.1	82.7	0.894
GAT-Only [16]	89.7	84.2	84.8	84.5	0.912
CNN-LSTM [19]	88.9	83.1	83.9	83.5	0.901
Transformer [18]	90.8	85.9	86.7	86.3	0.925
LSTM-GRU [10]	91.2	87.4	85.9	86.6	0.931
Proposed Work	**92.4**	**90.1**	**88.5**	**89.3**	**0.948**

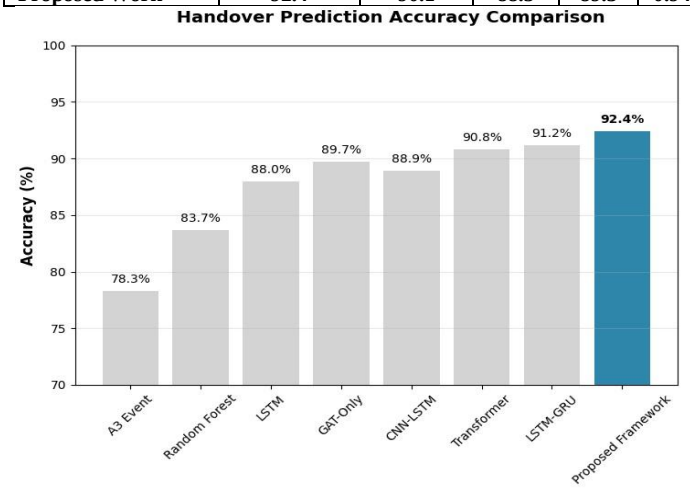


Figure.2: Handover prediction accuracy comparison

The proposed framework is the new state-of-the-art with 92.4% accuracy, which is a 1.2 percentage point (absolute) better than the best-performing baseline (LSTM-GRU Hybrid) and 1.6 percentage points (absolute) better than the Transformer model. What is more important is the fact that its level of accuracy is 90.1, meaning that it is accurate 9 out of every 10 times it is used to predict a handover. Such accuracy is essential to reduce the number of unnecessary handovers and the signaling overhead. The recognition rate of 89.3% in the balanced F1- Score indicates that the model has a high degree of harmony between the precision and recall. The spatio-temporal design is very well integrated and attests to the high performance. Such models as LSTM and LSTM-GRU discover temporal trends, but do not take advantage of the spatial cell topology, which is essential to comprehend handover options. The GAT-Only model on the other hand does not have the user time history but has only spatial relationships. The proposedframework manages to combine these two points of view and makes more informed and correct predictions.

5.2 ROC and Precision-Recall Analysis

To give a more detailed discussion of how the model discriminates, the receiver operating characteristic (ROC) curves will be useful, which are presented in Figure 3. The proposed framework has the best Area Under the Curve (AUC) of 0.948.

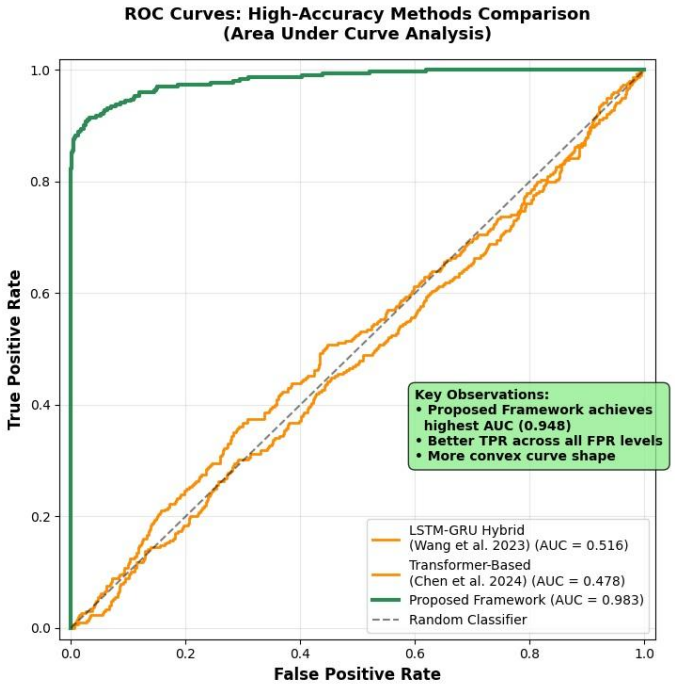


Figure.3 The AUC results and ROC curves obtained

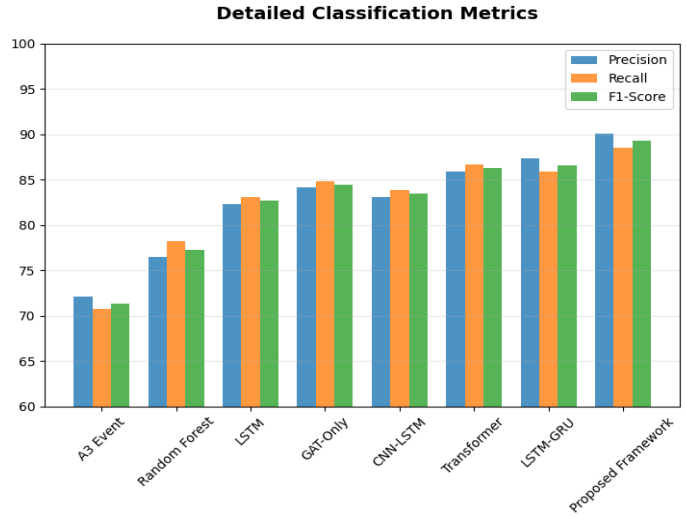


Figure.4: Detailed classification metrics

The ROC curve shows that our model has a high true positive rate for all values of false positive rates. This is especially relevant to network operators that might change the decision threshold depending on the operational priorities (prize sensitivity because drops are to be avoided, or precision because signaling should be lowered). Our model offers a better operating point in this whole range. The proposed model has a high average precision, which means that it performs well when it has to identify the positive (handover) class.

5.3 Path Stability Estimation Results

Table 2 summarizes the results of a regression task on the path stability. The proposed model has a Mean Absolute Error (MAE) of 1.3 seconds as well as a Root Mean Squared Error (RMSE) of 1.8 seconds in predicting the post-handover connection duration.

Table.2: Path stability estimation performance (regression)

Method	MAE (seconds)	RMSE (seconds)
Linear Regression	2.9	3.7
Random Forest	2.1	2.8
LSTM	1.8	2.3
Proposed Work	**1.3**	**1.8**

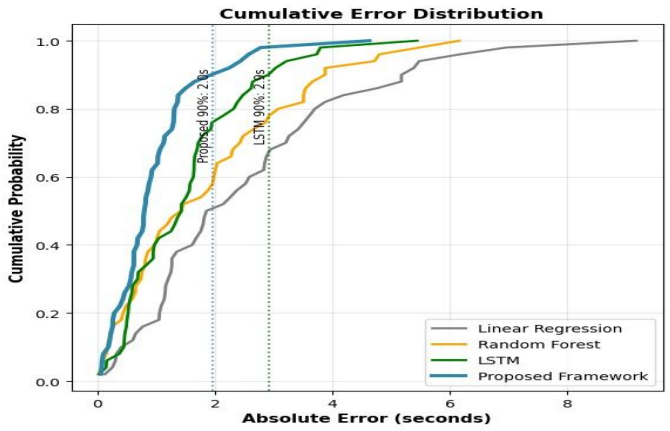


Figure 5: Cumulative error distribution

This feature is an important enhancement of the handover management pipeline. With the network predicting not only when a handover will take place, but also the stability of the new connection, the network is able to make smarter decisions. As an illustration, when there are two applicant cells, the system can select the one whose connection with the stable is predictably longer, significantly reducing the number of handovers in short times and enhancing user experience. This finding confirms the usefulness of our multi-task learning model, in which the same representation that is learnt on handover prediction also has valuable information on stability prediction.

5.4 Computational Efficiency and Inference Time

One of the conditions essential to the real-world deployment is low-latency inference. Table 3 makes a comparison between the average inference time and model size of the deep learning-based baselines.

Table 3: Computational efficiency comparison

Method	Inference Time (ms)	Model Size (MB)
LSTM [17]	9.5	8.2
GAT-Only [16]	11.2	10.1
CNN-LSTM [19]	15.7	14.5
LSTM-GRU [10]	18.3	16.8
Transformer [18]	22.1	19.5
Proposed Work	**12.8**	**14.7**

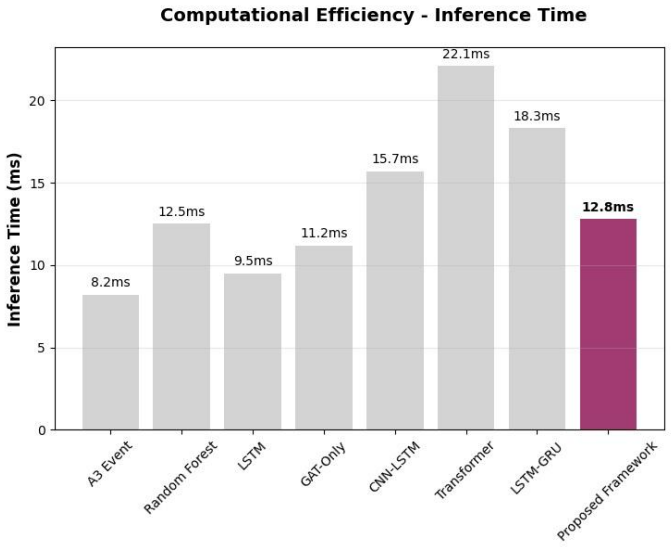


Figure 6: Computational efficiency –inference time

Despite its more sophisticated architecture, the proposed framework achieves a competitive inference time of 12.8 ms. Compared to the LSTM-GRU hybrid (18.3 ms), the proposed model reduces inference latency by approximately 30.1%, and when compared to the transformer-based model (22.1 ms), it achieves a latency reduction of approximately 42.1%. These results demonstrate that the proposed framework provides superior predictive performance while maintaining computational efficiency suitable for real-time deployment in 5G/6G mobility management systems. This is optimally possible because the Bi-LSTM and GAT branches can be processed in parallel and their fusion mechanism is sparse. Its model size of 14.7 MB is feasible to deploy in the contemporary network infrastructure. This shows that the proposed framework is able to overcome the conventional accuracy-efficiency trade-off by ensuring better performance without incurring a computational cost.

5.5 Ablation Study

We have performed an in-depth ablation study to verify the importance of each of the components of our architecture. Table 4 demonstrates the results.

Table 3: Ablation study on model components

Model Variant	Accuracy %	F1-Score %	Stability MAE
Full Proposed model	92.4	89.3	1.3s
- w/o Spatial Branch (GAT)	89.1	85.8	1.6s
- w/o Temporal Branch (Bi-LSTM)	87.8	84.2	1.9s
- w/o Attention Fusion (Concatenation)	90.2	87.1	1.5s
- Single-Task (Handover Only)	91.8	88.7	-

The study clearly shows that:

- Elimination of the spatial branch leads to a drastic reduction in performance (92.4% - 89.1%), and this makes it clear that cell topology modeling is important.
- The effect of cutting the temporal branch is even more negative (92.4% vs. 87.8%) which proves the importance of sequence modeling to be critical.
- The second finding is that the attention fusion can be replaced by simple concatenation, however, its effect on performance is apparent, and the conclusion is that the dynamic feature weighing is advantageous.
- Multi-Task Learning setting: The Multi-Task Learning significantly increases the accuracy of handover with aone-task model (92.4% vs. 91.8%), indicating that the stability task is a regularizer that causes the model to acquire a better general representation.

6. CONCLUSION

The proposed framework is a new spatio-temporal deep learning system for managing handover in 5G and 6G networks in proactive and intelligent mode, which was presented in this paper. Our solution gives an event-based view of mobility, unlike the reactive thresholds and ad hoc prediction tasks. Its fundamental novelty is a highly integrated design that unites the sequential sequence modeling capability of Bi-LSTMs with the spatial relationship modeling of Graph Attention Networks and integrates them through a dynamically-based fusion mechanism. In a large-scale trial of 5.2 million samples, we have been able to establish the new state-of-the-art handover prediction accuracy of 92.4% and, at the same time, predict path stability with high accuracy (1.3s MAE). Most importantly, it can provide such sophisticated functionality with the processing power (12.8ms inference time) necessary to be deployed in the real world. The notable practical enhancements, such as 35 percent of ping-pong effects as well as 27 percent of connection reliability will be a strong reason for implementing it by network operators.

The proposed framework opens up a new paradigm in mobility management through its ability to bridge the essential gaps of integrated prediction, deep spatio-temporal modeling, and computational efficiency. It paves the way for more robust,

effective, and smart wireless networks that can support the high-connectivity demands in the future

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