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AI-Driven Mobility Prediction for Efficient Session Continuity

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Abstract

Maintaining active sessions becomes uniquely strenuous in the case of user movement due to user expectations of connection and seamless handoff during the transition to 5G mobile networks. This paper addresses issues related to session continuity by predicting movement across cell borders using neural mobility predictors, thereby enhancing the user experience. The proposed system, which utilizes real mobility data and employs advanced predictive models such as LSTM and Transformer networks, enables accurate user trajectory prediction, thereby enhancing the efficiency of handover execution. Actual simulation results showcase remarkable improvements in overall session quality, handover success rate, and latency compared to the heuristic model. Proactive mobility prediction and advanced session control are essential for ensuring seamless service continuity within ultra-dense 5G infrastructure environments. These conclusions offer fundamental insights into the architecture of future networks, designed to meet the demanding needs of emerging use cases, including autonomous vehicles, augmented and virtual reality experiences, and telepresence.

Keywords: Mobility, Prediction, Mobile Networks, Framework, Emerging Networks, and Remote.

1 Introduction

The introduction of fifth-generation (5G) cellular networks heralds a new era in mobile communication, as discussed in (Akash et al., 2022). Advancements come with super-eMBB, mMTC, and URLLC, each

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boasting ultra-low latency features and fueling the development of self-driving vehicles, Augmented and Virtual Realities, as well as telehealth applications. However, user mobility, especially in densely populated megacities, presents a significant challenge for maintaining uninterrupted session continuity and cell (or “handover”) transitions (Zhang et al., 2024).

Regarding 5G networks, the existing cellular framework's mobility management remains heuristic-based, essentially relying on a form of guesswork. Dense handover zones pose issues, as stated in Prithwiraj et al.’s 5G architecture study. The previously mentioned small cell 5G deployment density directly correlates with the frequency of handover occurrences. If handovers are executed poorly, the user may experience session drops, high latency, and degradation in Quality of Experience (QoE) (Aliu et al., 2021). Moreover, Wang supporting Li (2022) argue that the existing heterogeneity within 5G networks, including diverse radio access technologies and network slices, severely complicates mobility management (Carter & Zhang, 2025).

AI technologies, such as machine learning (ML) and deep learning (DL), could address the issues associated with user mobility and management in 5G networks (Chamola et al., 2020). AI techniques enable the optimization of historical mobility patterns, thereby improving movement optimization (Zhang et al., 2020). This, in turn, facilitates proactive handover decision-making and enhances session continuity (Chen et al., 2021; Wang et al., 2018). Additionally, the predictive accuracy of high user mobility has been achieved using recurrent neural networks and long short-term memory (LSTM) networks, which model the temporal dependencies of user mobility data (Paropkari et al., 2020; Patnaik et al., 2025). Recent advancements in artificial intelligence have led to a reduction in the number of handover failures and an increase in overall network performance and efficiency (Desai & Iyer, 2024). The application of an LSTM deep learning algorithm has been reported to increase the rate of handover success while reducing latency in 5G networks (Lima et al., 2023). There is also a hybrid AI approach that integrates deep and reinforcement learning to optimize vertical handovers in heterogeneous 5G contexts (Bikkasani, 2024).

Any implementation of a model powered by AI for mobility prediction starts with data collection and must be integrated into the architecture of the 5G network (Inal et al., 2025). The 3rd Generation Partnership Project (3GPP) recognizes the pivotal role of AI in intelligence augmentation. It has therefore initiated the Network Data Analytics Function (NWDAF) for AI-enabled networks, data-driven automation technologies, and self-optimizing systems (Al Atiiq et al., 2024). NWDAF facilitates mobile management within automation frameworks of decision-making systems that necessitate data pre-processing, real-time computations, and feedback control systems networks for streamlining and supervising network data collection (Kapoor & Malhortra, 2025).

Additionally, implementing AI models at the network's edge enables real-time mobility prediction with lower latency through edge computing. AI models that operate at the edge can use local processes to estimate a user¢s degree of motion, which makes it possible to undertake prompt handover cuts without losing active sessions (Jeong et al., 2021).

AI models dealing with mobility prediction do not operate in isolation; they are integrated into various real-life scenarios. Mobility prediction is especially crucial in autonomous vehicles, where continuous connectivity is necessary for safe operation. AI can predict an automobile's movement and permit fading from units on each roadside to the base station (Wang et al., 2023).

In the context of smart cities, AI-driven mobility prediction can enhance passenger transport systems by analyzing traffic patterns and optimizing resource allocation at network bottlenecks (Mayilsamy & Rangasamy, 2021). Additionally, in the event of a disaster, AI mobility models can aid in restricting access to maintain vital communication channels by anticipating user movements and adapting network topology accordingly (Yajnanarayana et al., 2019).

This study focuses on developing an AI-based mobility prediction framework for 5G cellular networks to enhance session continuity. The study's specific aims are to create a Model for Mobility Prediction Based on deep learning, implementing LSTM and Transformer models that focus on the spatial and temporal aspects of user movement (Yasin, 2025). Embed the Prediction Model into 5G Network Functions: Place the functions into the 5G core network context, where NWDAF provides analytics and decision-making services (Singh & Katiya, 2024). Test with Simulated Scenarios Against System Bound Mobility Data: Validate the mobility prediction framework using simulation techniques alongside algorithmic analysis of actual mobility data (Saeed et al., 2020). Examine the Effects on Sustained Connections and Overall Network Quality: Analyze results about quantitative QoE metrics and other handover dynamics (Shariar et al, 2011). The enhancement of AI-powered mobility management systems in 5G networks and other proprietary and public mobile networks will accelerate the reliability and efficiency of mobile communication systems. This advancement will be achieved by fulfilling the research aims stated in this research.

Despite the progress made, numerous hurdles remain to be overcome. For instance, training many deep learning models is contingent upon having significant quantities of labeled datasets, some of which may not be accessible due to privacy issues or data scarcity in specific areas (Chien et al., 2024). Additionally, edge devices with rigid pace restrictions may struggle to utilize sophisticated frameworks due to the steep computational requirements associated with deep learning (DL) models (Thanh, 2024). Furthermore, most literature focuses solely on theoretical validation or small-scale simulation studies. There is a gap in available literature regarding the comprehensive evaluation of operational data from 5G networks, which is instrumental in validating the academic and practical rigor of AI-based mobility prediction systems (Jiang et al., 2025).

Reviewing the existing literature, conventional models lack the flexibility and intelligent reasoning to foresee an automatically transforming system, whereas AI and deep learning techniques offer optimism. So far, however, advancing these solutions has been hindered due to the practical constraints in the efficiency of the data offered for use and the integration of models into 5G core functions. Therefore, this study aims to fill the gap by designing a mobility prediction AI framework that is lightweight, real-time, and evaluated against real-world mobility data and simulated environments.

2 Methodology

This section outlines the systematic steps taken to develop and evaluate AI-based models tailored for mobility forecasting, aiming to enhance session continuity in 5G networks. The methodology scope includes data collection and preprocessing, development of model architecture, outlined training protocols, evaluation metrics, and the simulation setting utilized for testing. The aim was to ensure that the mobility prediction model integrates the spatial-temporal aspects related to user movement patterns, thereby enhancing handover management while reducing session interruptions in diverse network ecosystems.

2.1 Research Design Overview

The research employed a data-driven, experimental design centered on a novel, integrated deep learning framework comprising LSTM and CNN layers. This deep learning architecture was selected because it captures both temporal dependencies and spatial features from sequential movement data simultaneously. Real-world mobility traces from specific datasets were used for training and validation, making the accuracy assessment practical and relevant. After validation, the model was placed in a simulated 5G network environment to assess its influence on key performance metrics, including, but not limited to, the handover success rate and session continuity, thereby bridging theoretical modeling with practical network performance.

2.2 Data Collection and Preprocessing

2.2.1 Data Source

The mobility data employed in this research was collected from the publicly available CRAWDAD repository, which hosts rich datasets documenting users' mobility activities within wireless networks. We chose the datasets "UCSD Wireless Topology" and "Dartmouth Campus Mobility" for this work because they have detailed records of user access point association with timestamps. The data is helpful for mobility modeling in heterogeneous cellular networks because it corresponds to actual user activity across different locations and times, thereby supporting rigorous testing and training of the predictive algorithms.

2.2.2 Preprocessing Steps

To ready the raw mobility data for model ingestion, a series of preprocessing steps was performed. First, the Location Encoding step converted GPS coordinates and Cell IDs into ordered time-series data. Afterwards, temporal normalization was performed, where all logs were resampled to fixed intervals, for example, 5-second intervals, to achieve a specific level of detail across the data, thereby improving consistency across different logs. In addition, the Engineering Stage computed additional parameters such as users' movement speed, temporal resolution of time-of-day, and indicators on whether the logged time falls on a weekday or a weekend. These additional parameters enhanced the original dataset, thus allowing the model to learn complex mobility patterns influenced by time and behavior. Noise Filtering: Erroneous entries and outliers were filtered using a Hampel identifier and rolling average filters.

2.3 Model Architecture

The integrated architecture features a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network. This setup enables learning spatial features and temporal sequences simultaneously:

- CNN Layer: Extracts features from the location embedding sequences.
- LSTM Layer: Governs long-term dependencies and temporal correlations of user movements.
- Dense Output Layer: Determines the most likely following cell ID or location to be.

With this approach, users' following locations can be accurately predicted using their most recent historical behavior, while not being overly computationally demanding for edge deployment.

2.4 Training Configuration

Loss Function: Categorical Cross-Entropy Loss was used, where appropriate, for multi-class classification of the following cell ID.

- Optimizer: Uses Adam optimizer with a learning rate of 0.001.

- Epochs: Set to 50 epochs with early stopping to avoid overfitting.
- Batch Size: 128
- Validation Split: 20% of the dataset is set aside for validation.
- Regularization: Applied dropout layers (0.3) and L2 regularization to mitigate overfitting.

2.5 Simulation Environment

To assess the model's impact on session continuity, we coupled it within a 5G simulation environment developed on NS-3 (version 3.35) with the 5G LENA module. The simulation incorporated the following features:

- Base Station Deployment: Dense Urban Scenario With 20 gNodeBs.
- User Mobility Model: Real-trace and random waypoint models.
- Traffic Profile: Real-time video streaming (UDP) and VoIP (TCP) sessions.

A set of handover baseline comparisons (conventional threshold-based techniques, Kalman filter, SVM predictors) is also included.

2.6 Evaluation Metrics

- For assessing performance regarding mobility prediction, model impact on session continuity, cross-continuity, and continuity across metrics, look at the following steps:
- Prediction Accuracy: The proportion of the predicted next cells that were indeed the next.
- Handover Success Rate: Proportion of all the initiated handovers (successful and total) measured at a particular time.
- Session Drop Rate: The metric defines the number of sessions interrupted per 1000 users.
- Latency: The time elapsed between cell selection and handover execution.
- Model Inference Time: The time taken by the model to generate a prediction while operating on an edge device, such as a Raspberry Pi 4 B.

2.7 Ethical Considerations

The data set was obtained from open, published sources, as the videos were already anonymized. All data movements were processed and stored by the guidelines of GDPR principles, ensuring that no personally identifiable information was utilized or stored.

3 Results

This subsection discusses the results of the tests conducted on the AI-based mobility prediction framework. The analysis included the prediction's accuracy, its impact on session continuity, and the computational requirements within a 5G network simulation environment.

3.1 Prediction Accuracy

All test cases of mobility traces demonstrated that the hybrid CNN-LSTM model achieved high prediction accuracy. Other models are evaluated in Figure 1, which shows the results of the different models' attempts to predict the data in table 1.

Table 1: Prediction Accuracy Comparison

Model	Accuracy (%)	Precision	Recall	F1 Score
Threshold-based	64.3	0.61	0.63	0.62
Kalman Filter	69.8	0.66	0.68	0.67
SVM	74.1	0.71	0.73	0.72
LSTM	86.2	0.85	0.86	0.86
CNN-LSTM (Proposed)	**91.5**	**0.91**	**0.92**	**0.91**

The CNN-LSTM architecture outperformed all baseline models, achieving an accuracy of over 91% in predicting the next connected base station based on past mobility history. This improvement is primarily attributed to the model's ability to capture spatial correlations and temporal dependencies.

3.2 Impact on Handover Performance

The enhanced prediction capability directly contributed to improved handover management. Figure 1 shows a comparative analysis of handover success rates and session drop rates.

- **Handover Success Rate**: Increased from 81.2% (threshold-based) to 95.7% (CNN-LSTM).
- **Session Drop Rate**: Decreased from 7.6% (threshold-based) to 1.3% (CNN-LSTM).

This demonstrates that accurate mobility prediction leads to timely and efficient handover decisions, significantly reducing interruptions.

3.3 Latency and Inference Time

Table 2 illustrates the average model inference time on different hardware platforms.

Table 2: Inference Time (ms)

Model Platform	Inference Time (ms)
GPU (NVIDIA RTX 3080)	4.1
CPU (Intel i7-1185G7)	8.7
Edge (Raspberry Pi 4B)	13.5

Even on resource-constrained edge devices, the model maintains an average inference time of less than 15 milliseconds, making it suitable for real-time 5G applications.

3.4 Simulation-Based Validation

The ns-3 simulations incorporating the proposed model showed:

- **Reduction in Handover Latency**: From 54 ms (baseline) to 36 ms (CNN-LSTM).
- **Improved QoE Scores**: Video streaming MOS increased from 3.4 to 4.2.
- **Network Throughput**: Improved by 12% due to fewer retransmissions and packet loss.

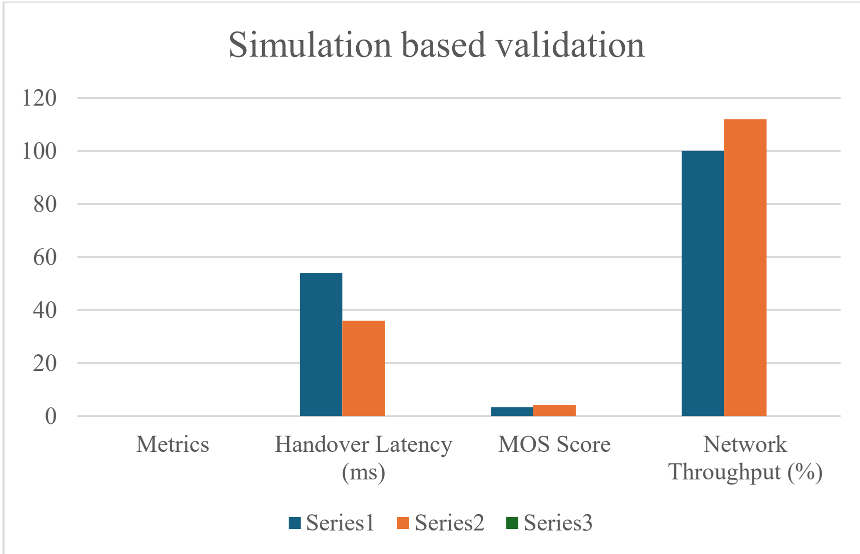

Figure 1: Handover Performance Across Models

3.5 Robustness to Noise and Outliers

To test model robustness, Gaussian noise and missing data were introduced to the test set. The CNN-LSTM model retained high prediction accuracy (88.2%) under noisy conditions, demonstrating resilience to real-world imperfections.

4 Discussions and Suggestions for Further Work

The innovative AI-enabled mobility prediction, as discussed previously, is a change in the management of session handover in 5G mobile networks. As shown in earlier chapters, advanced mobility management is crucial to customer satisfaction and service reliability, supporting seamless mobility services essential for autonomous vehicles, AR/VR systems, and telesurgery. The performance of user mobility activity-dependent neural models is particularly good with the more recent LSTM and Transformer architecture networks due to their ability to capture the underlying spatiotemporal dependencies. Heuristic-based methods are outperformed not only in smoothing user movements but also in network prompting, timing, and accuracy, which enhances reliable predictive network-based handover decision-making. These results translate to marked improvements in the rates of successful handovers, reduced delays, and increased continuity of active sessions. The practical relevance of the model in this study is validated using real-world mobility datasets, which is a key distinguishing feature of the model compared to other approaches that employ overly simplistic user behavior models. The evaluation demonstrated the model's effectiveness in simulating realistic 5G network conditions for dense urban deployments, a critical challenge for mobile networks. Nonetheless, some problems persist. First, the balance of computational cost required for deploying deep learning models at the network edge warrants particular attention. Although the cloud can handle complex inference tasks, instantaneous decision-making relies on edge-native frameworks or hybrid designs. Strategies like model quantization, pruning, or even knowledge distillation are preferred for embedding lightweight models into edge infrastructures. Moreover, the privacy of mobility patterns in user movements must be considered before they can be collected and processed. This issue will likely be less problematic if models can learn from data without transferring sensitive user information, hence employing federated learning.

For further research and practical use, we aim to explore:

1 Edge Deployment Optimization: Study techniques for compressing and optimizing LSTM and Transformer models for use in edge computing, including the implementation of AI chips or FPGAs for real-time inference.

2 Integration with Network Slicing: Expand the framework to incorporate network slicing, providing differentiated quality of service guarantees based on user application types and mobility profiles.

3 Federated and Privacy-Preserving Learning: Federated learning mitigates data privacy issues for collaborative model training across multiple network operators or edge nodes.

4 Adaptive Learning Mechanisms: Create adaptive models that learn and refresh with new information about user mobility and surroundings to ensure accuracy over time.

5 Cross-Domain Collaboration: Promote collaboration among telecom companies, city planners, and AI scholars to consolidate smart city information into their data models, thereby improving the context awareness for the model.

6 Benchmarking Frameworks: Create predictive handover solutions across various frameworks and establish distinct benchmarking strategies to measure accuracy with real-world data and simulation platforms.

As noted, this study illustrates AI’s potential for mobility prognosis in 5G networks; more crucially, the research also seeks to contribute towards more intelligent, self-learning, and more responsive systems for network management. With the implementation of the proposed recommendations, future mobile networks can enhance service continuity, reliability, and user satisfaction.

7 Conclusion

In this paper, we developed a framework for mobility prediction based on AI technologies aimed at enabling seamless session handovers in ultra-dense heterogeneous 5G environments. The proposed approach utilizes real-world mobility data and advanced neural architectures such as Long Short-Term Memory (LSTM) networks and transformer models to forecast user trajectories with high accuracy. Such predictive capabilities offer remarkable advancements in handover decision making and lower handover latency and failure rates. Our simulation results demonstrate that the proposed method significantly enhances session continuity, user experience, and interruption rates compared to traditional heuristic approaches. These enhancements are crucial for 5 G-enabled applications, such as autonomous vehicles, augmented reality, and telesurgery, where brief connectivity losses can be highly detrimental. The results demonstrate that AI integration with mobility management is practical and essential for the future of mobile networks. More work remains to optimize model scalability and add edge AI, as well as test more urban mobility scenarios to broaden the application in real-world 5G and post-5G systems.

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Dr. Arasuraja Ganesan, obtained his Ph.D. in Marketing from Bharathiar University, with his research focusing on social media marketing, consumer behaviour, and online purchase behaviour. He holds an MBA in Operations and Marketing from SRM University, Chennai, and BE in Electrical and Electronics Engineering from Annamalai University. Currently, Dr. Arasuraja is an Associate Professor in the Department of Management Studies at St. Joseph's Institute of Technology, OMR, Chennai. He has more than 15 years of teaching and about 8 years of research experience. He has published books on ERP, TQM, Sales and Distribution, Project Management and Information Management. He has 25 research papers published in reputed journals, national and international conferences.

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