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Research Article

Machine Learning-Based Prediction of Optimal Neighbour Cells for LTE Handover in Dense Urban Areas: A Case Study from San Francisco

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Abstract:

The demand for uninterrupted and high-speed mobile data continues to grow, driven by the rapid expansion of IoT systems, communication applications, social media platforms, and the increasing number of mobile users. The handover mechanism plays a critical role in maintaining uninterrupted service during user mobility, and indirectly affects data throughput by influencing the device's Reference Signal Received Power (RSRP) levels. In LTE systems—which remain widely used globally—the handover process is vital for ensuring service quality, and its significance is expected to increase further with the densification of base stations in upcoming 5G and 6G technologies. In this study, we utilize a dense LTE drive test dataset to first estimate the device's distance to the base station and the geographical locations of base stations. These estimates, combined with parameters such as serving and neighbour cell identities and DL EARFCNs from seven different cells, are then used to develop an efficient machine learning–based handover prediction model. To evaluate and compare the performance of the Random Forest and XGBoost algorithms, multi-class classification metrics including precision, recall, and F1-score were utilized. The results demonstrate that Random Forest model can effectively identify the optimal target cell without the need for traditional, complex handover algorithms. The XGBoost algorithm gave much lower handover performance rates and F1-score compared to Random Forest.

1. Introduction

The rising demand for multimedia applications, along with the rapid growth of technologies like IoT, autonomous vehicles, and machine-to-machine communication—which require high-speed data transmission on both uplink and downlink—has made it necessary to continually upgrade existing mobile networks. To enhance service quality, 3GPP introduced Long-Term Evolution (LTE). In response to the surge in mobile data demand, LTE-Advanced (LTE-A) and 4G standards were developed in Release 10, with ongoing improvements in performance[1]. However, as 4G LTE systems—still the most widely used globally—struggle to keep up, next-generation networks like 5G and beyond have begun to take their place[2]. With the arrival of 5G technology, we've seen significant improvements in data speeds, reduced latency, and enhanced energy efficiency. Offering high service quality, 5G can operate using smaller base stations compared to LTE systems. However, because it relies on higher frequency bands, more base stations—and consequently more inter-cell handovers—are required to achieve the same coverage area as LTE. Because of the smaller cell coverage in 5G, user equipment (UE) must perform more frequent handovers in certain scenarios. This increase leads to several handover-related challenges that are now recognized as key performance indicators (KPIs). A high number of unnecessary handovers can negatively impact throughput, which in turn reduces Quality of Service (QoS) and user satisfaction[3]. For this reason, preventing unnecessary handovers is important for user satisfaction and energy efficiency for both LTE and 5G and beyond systems. When a correct handover occurs, the device connects to a base station with stronger RSRP values, resulting in lower ping values, increased data speed and energy efficiency. As seen in Figure 1 above, with the handover mechanism, the base station to which the UE is connected changes due to

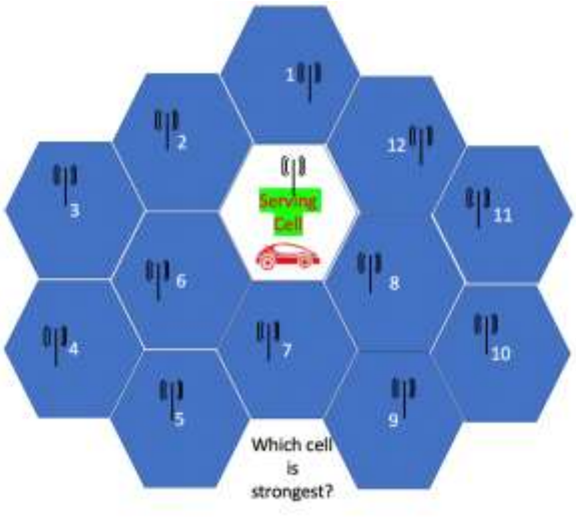

Figure 1. *Handover process*

reasons such as the user moving or the radio signal quality decreasing in the location. The aim is to provide the user with a continuous and high-quality connection. As handover is critical for enhancing performance and reducing radio link failures, it has been extensively studied. Although there are many different handover algorithms, the handover mechanism is usually done using the parameters serving cell RSRP, neighbour cell RSRP, RSRQ, RSSI, UE velocity, and cell identity in classical computations, time series algorithms or machine learning[4-6]. However, traditional rule-based mechanisms often fail to adapt to the dynamic and heterogeneous nature of dense urban environments[7]. The handover process can occur not only between mobile phones and base stations, but also between base stations and unmanned aerial vehicles, satellites and UEs. However, since 4G, 5G and beyond 5G systems are used intensively, research has focused on this direction[8-12].

Shaeya and his research group have worked on handover algorithms for wireless networked drones for 5G and 6G technology and have reported in their studies that machine learning based handover management systems are a more effective way than traditional methods such as MANETS, VANETs, and IEEE 802.11[8].

Khan et al focuses on the management of handover systems on 5G and dense heterogeneous networks. Different approaches such as machine learning, deep learning, software defined network (SDN), augmented reality, and optimized load balancing are compared for future technology 5G systems[13]. Chabira and her team are exploring and analysing AI-driven smart handover and load balancing strategies within smart city scenarios for ultra-dense 5G and upcoming 6G networks[9].

In addition, many studies have been conducted on the handover management algorithm to increase energy efficiency by reducing power consumption in LTE systems[14,15]. Maiwada and his research group have studied the energy efficiency in LTE-A and 5G systems and claim to have created a handover algorithm that is 85% efficient. Ju-Hung Jon et al achieved energy efficiency of up to 40.5% and Avka et all worked on an algorithm that allows 45.29% less handover[16,17].

2. Material and Methods

2.1 Data Collection, Filtering and Binning Process

In the initial phase of the study, data was collected over a 7-day period using a vehicle equipped with a PC-tell scanner in the San Francisco, CA area. The dataset was first filtered to exclude entries with missing values in key parameters such as RSRP, serving and neighbour cell IDs, and location coordinates. Any row or column with missing values in any of the 30 parameters was removed to ensure the integrity of the data used in the algorithm. Additionally, several LTE sublayer parameters deemed irrelevant to the handover analysis were eliminated to streamline processing before the data binning phase.

Data binning, a common technique used to mitigate the impact of minor measurement fluctuations on signal degradation, involves grouping data points within specific intervals and replacing them with their average values. This approach clusters the data into smaller segments—referred to as splits—effectively reducing noise and smoothing out abrupt changes, though at the cost of some resolution[18].

Moreover, this method helps neutralize the impact of vehicle speed during the data collection process. Since RF scanners collect a fixed number of measurements over a set time and route, higher vehicle speeds result in fewer samples, while slower speeds or stops yield more data points. This inconsistency can skew machine learning predictions, especially when excessive measurements are captured near intersections or traffic signs. To address this, the dataset was spatially segmented into 5 m × 5 m geographic grids following feature extraction, with each grid cell representing the average of all features and parameters within that area.

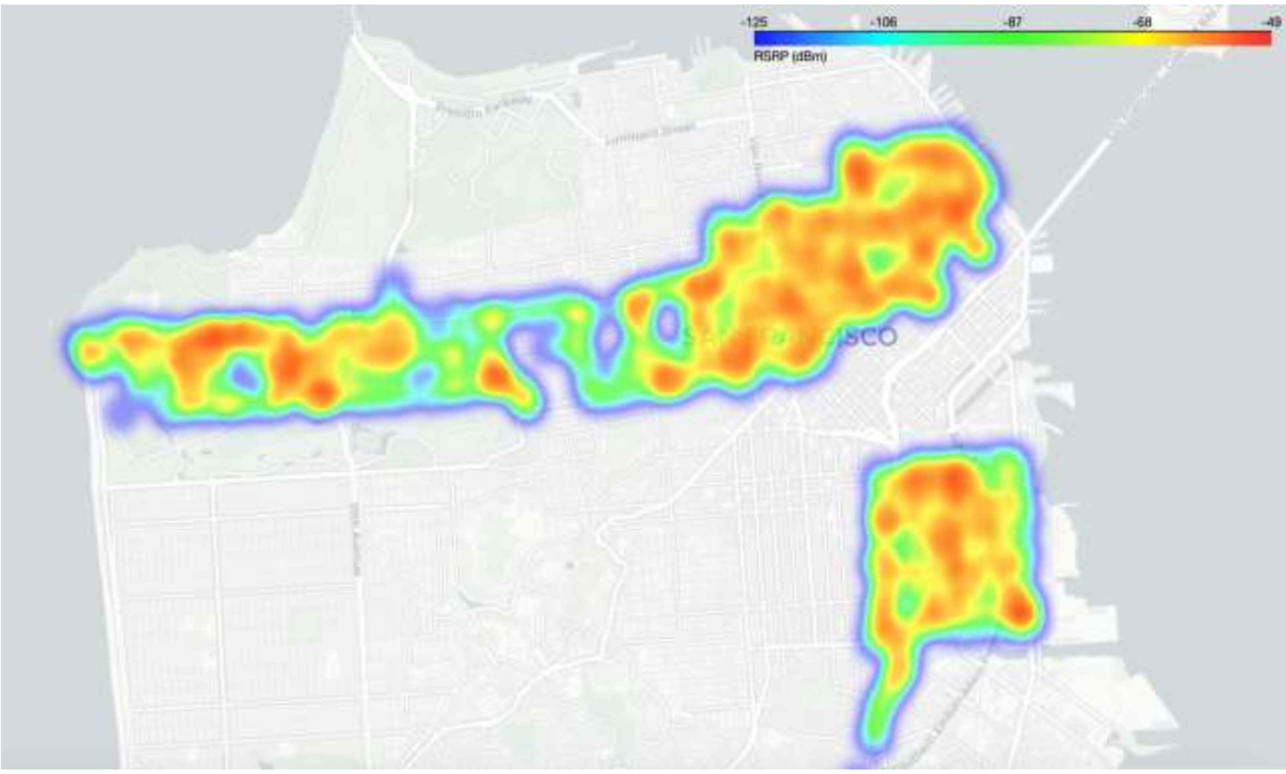

Figure 2. *RSRP heat map on the filtered and binned data*

Figure 2 shows the heat map of RSRP values on the map using data obtained from drive test results and filtered. The number of data after filtering and binning is approximately 4 million with 30 column of LTE sublayer parameters.

2.2 Estimation of Base Stations' Location and Distances

In this stage, a machine learning based model was developed using XGBoost regression and Random Forest regression to estimate the geographical latitude and longitude coordinates and the distance to the serving base station based on the 20 strongest RSRP measurements collected during the driving tests. The latitude and longitude values of the base station were determined with two different regression algorithms depending on the power level of the RSRP values, using the device's RSRP value, the serving cell identity, and the neighboring cells' RSRP values and cell IDs, and the neighboring RSRP value and cell ID, and then the distance was calculated with the help of the haversine formula. Known base station locations were used to train and evaluate the model at a rate of 80%-20%. The Random Forest regressor outperformed the XGBoost model in terms of both location estimation and classification metrics. The trained model results were used in the handover analysis in the next stages and used as an auxiliary parameter to increase our accuracy rate.

The base station location information was estimated by taking the 20 highest RSRP values shown in red in Figure 3 and the corresponding latitude and longitude values with the help of XGBoost and Random Forest regressors depending on the magnitude of the RSRP value. Then, using the Haversine formula (as presented in Equation 1), the distance between the device and the estimated base station location is calculated and incorporated into the dataset as an additional parameter.

$$Haversine\ formula\ for\ distance\ d = 2R\sin^{-1}\left(\sqrt{\sin^2\left(\frac{\text{lat2}-\text{lat1}}{2}\right)} + \sin^2\left(\frac{lon2-lon1}{2}\right)\cos(\text{lat1})\cos(\text{lat2})\right) \quad (1)$$

where R is the radius of the earth (6371 km), d is the distance between two points, lat_1, lat_2 latitude of the two points, and lon_1, lon_2 is the longitude of the points respectively. Figure 4 shows the locations of the base stations predicted with the Random Forest regressor method, which gives more accurate results than the XGBoost method, on the map.

3. Results and Discussions

An optimal handover selection algorithm was developed using XGBoost and random forest regressor to improve decision making in ultra-dense cellular networks. Using key LTE sublayer parameters such as Serving Cell RSRP, Neighbor Cell RSRP, and EARFCN values collected from drive test data, The model was trained to accurately predict the most suitable target cell for handover

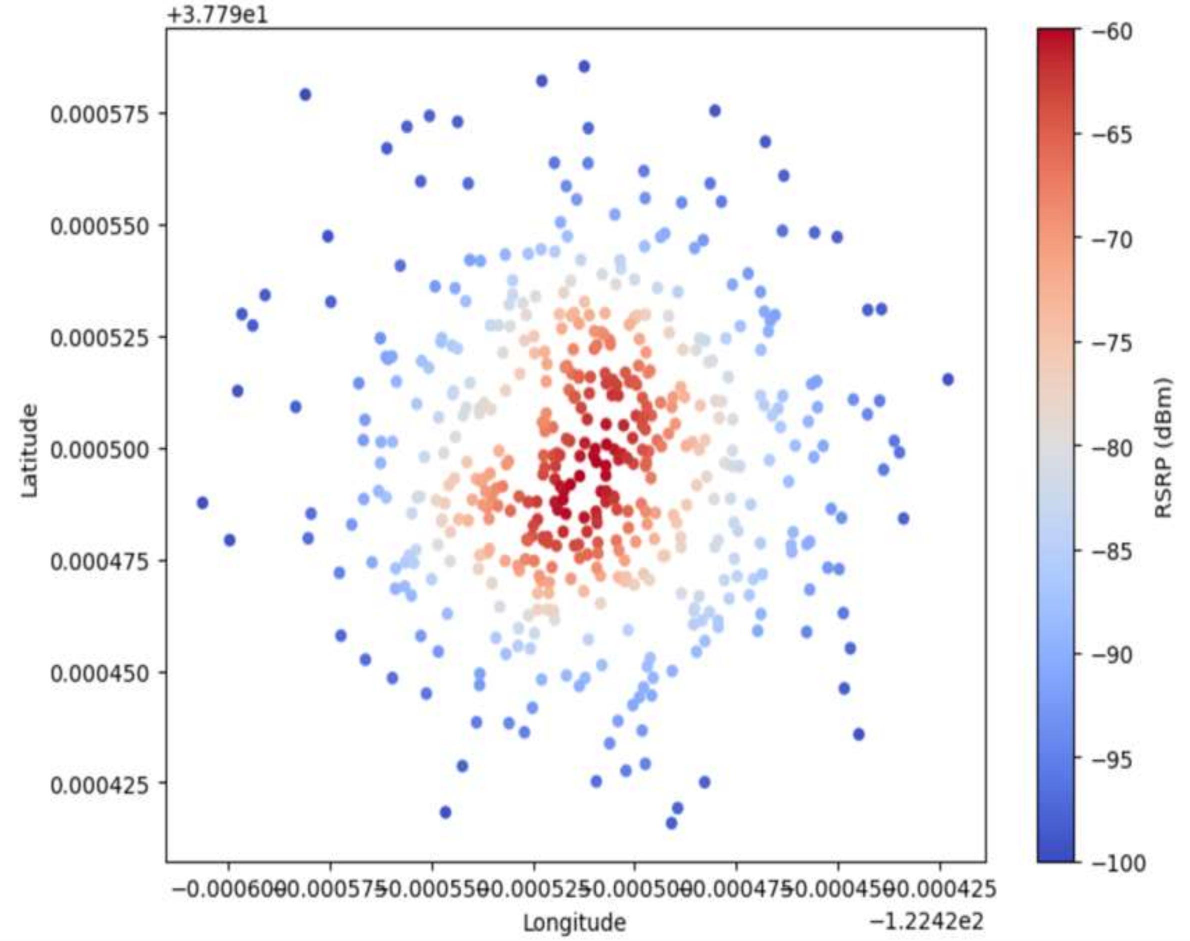

Figure 3. *Representative RSRP heat map for base stations' latitude and longitude value estimation.*

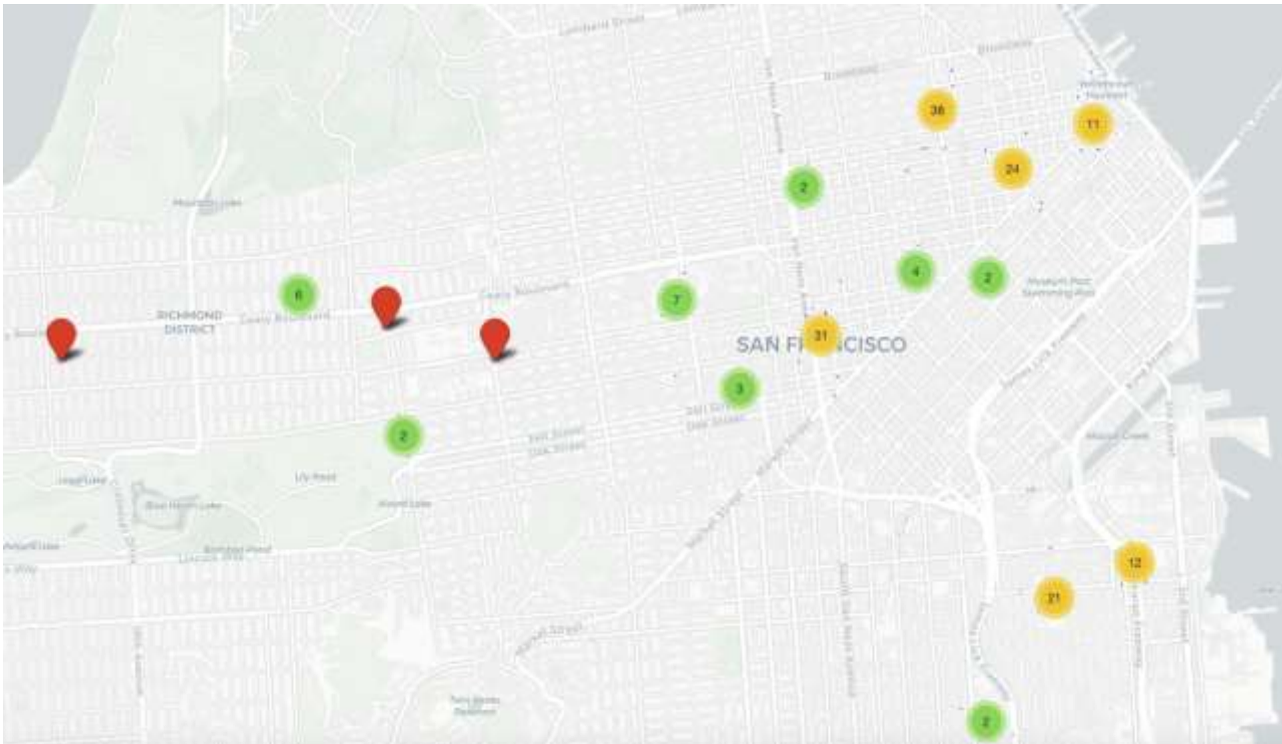

Figure 4. *Estimated base station locations by Random Forest Regressor*

decisions. The model not only took into account signal strength differences, but also incorporated complex feature interactions into the learning algorithm, resulting in improved handover reliability and reduced radio link failures. This data-driven approach provides a scalable and adaptable solution for intelligent handover management, which is critical for maintaining quality of service in 5G and beyond networks, as well as in LTE systems. While the Random Forest regressor estimate for the base station distance has an average error rate of 10m, this value was found to be 685m for the XGBoost algorithm. While recall, accuracy and f1 score were 0.98, 0.88 and 0.88 for the Random Forest algorithm, these values remained at 0.32, 0.16 and 0.21 for the XGBoost model, respectively.

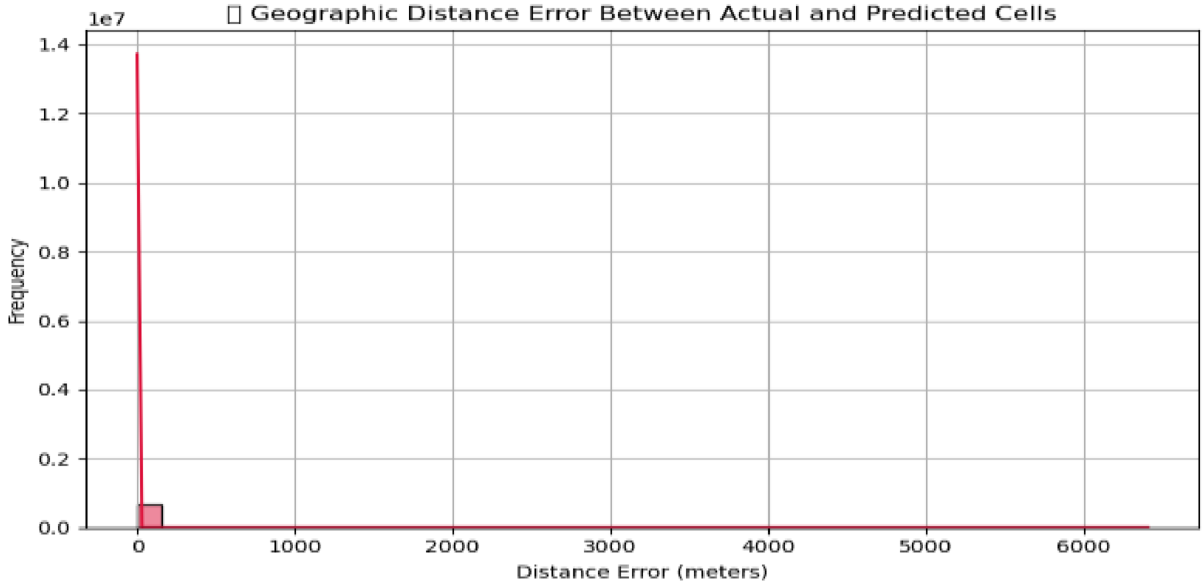

Figure 5. *Random Forest Regressor base station distance Error*

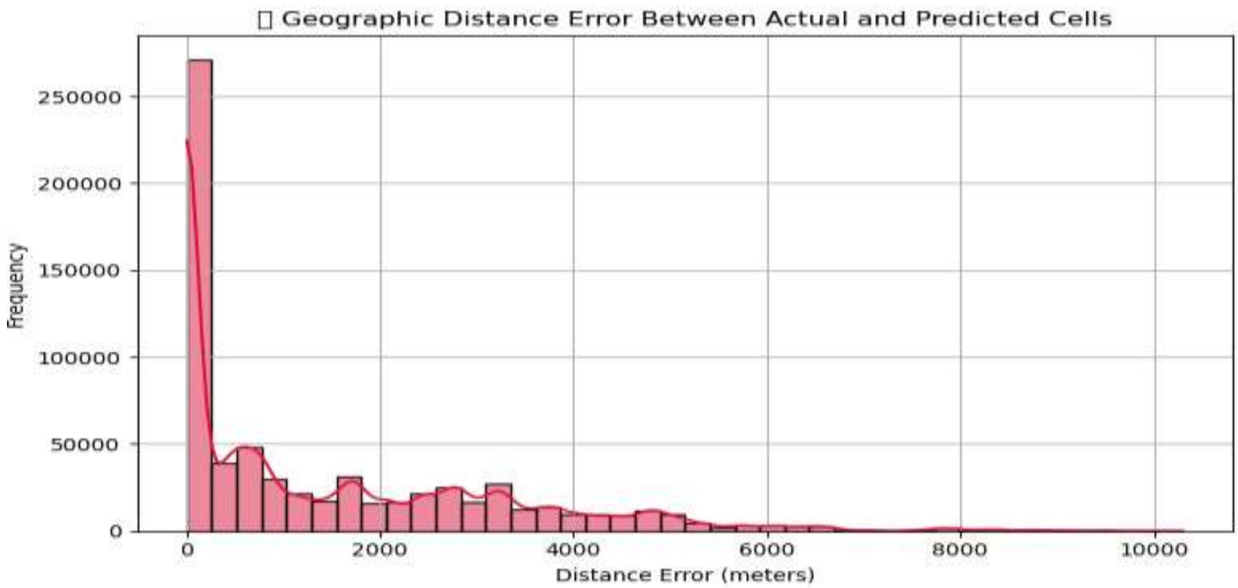

Figure 6. *XGBoost Regressor base station distance error*

Figures 5 and 6 show the error rates of two different regressor methods in predicting the base station location. As can be easily seen from the figures, the Random Forest model outperforms the XGBoost model in location prediction.

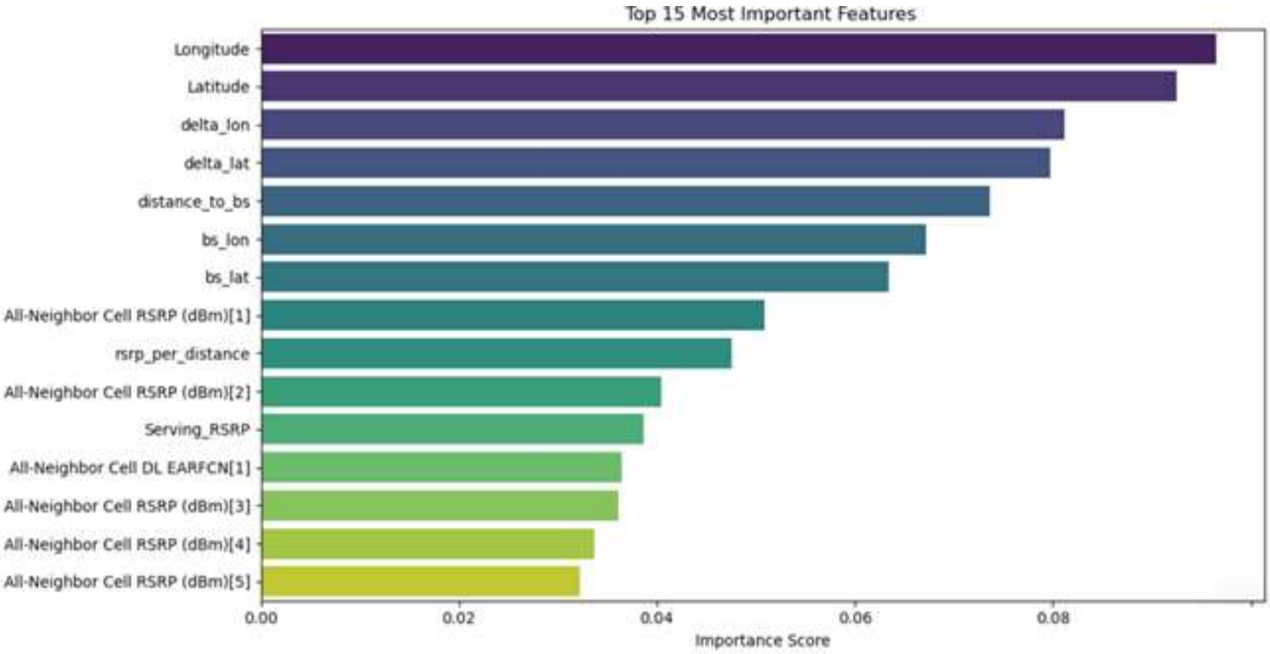

Figure 7. *Random Forest Regressor Handover Performance most important parameters*

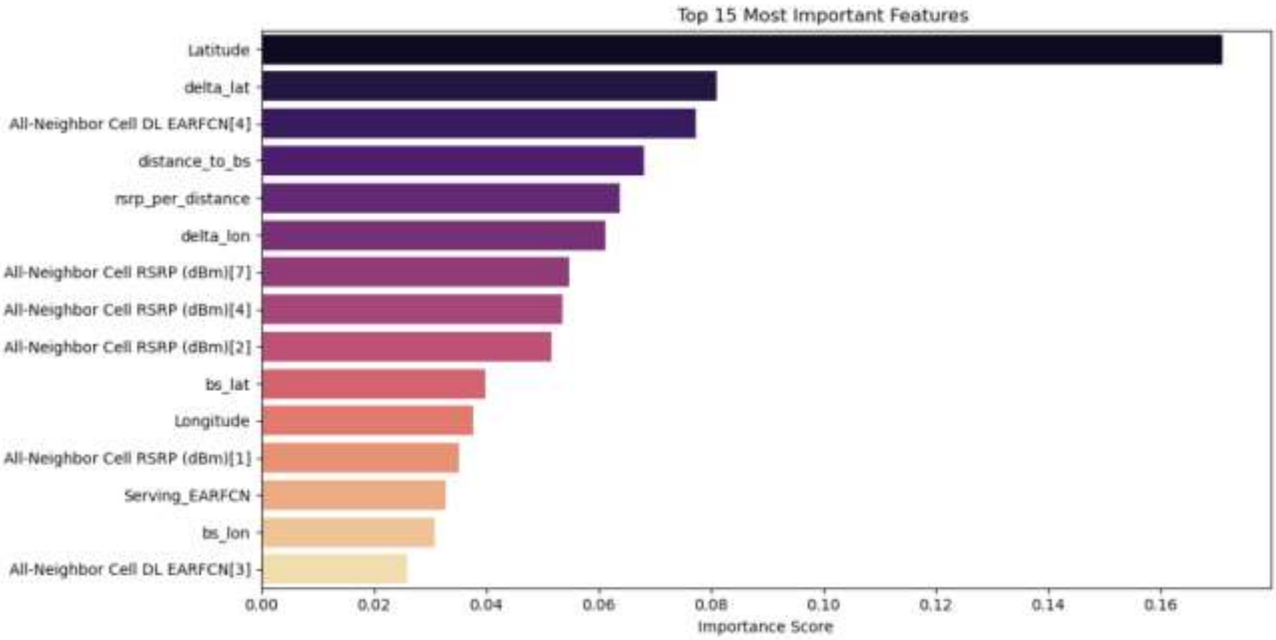

Figure 8. *XGBoost Regressor Handover Performance most important parameters*

Figures 7 and 8 show the 15 most important parameters used in prediction for Random Forest and XGBoost regressors, respectively.

4. Conclusions

In this study, two machine learning models based on Random Forest and XGBoost, which can be used for 4G and possibly 5G mobile networks, are used for handover estimation and the results of the two models are compared. In the study, a 7-day drive test data taken from San Francisco, CA is used. After various filtering and binning processes are performed on the data collected by performing the drive test, the number of parameters to be used in the handover analysis is increased by determining the base station distance. With the system redesigned on the Python platform, 30 LTE sublayer parameters and base station distance data are used in two different models to compare the handover performances. As a result, while the Random Forest regressor achieved an average error of approximately 10 meters in estimating the distance to the base station, the XGBoost algorithm yielded a significantly higher average error of 685 meters. In terms of classification performance, the Random Forest model achieved a recall of 0.98, accuracy of 0.88, and an F1 score of 0.88, whereas the XGBoost model's corresponding metrics were substantially lower, with a recall of 0.32, accuracy of 0.16, and an F1 score of 0.21.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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