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# A Lightweight Web-Based Signal Strength Monitoring System for Community-Based 4G

Azita Laily Yusof*, Muhammad Farhan Kamil, Ahmad Zaki Aiman Abdul Rashid, Norsuzila Ya'acob, and Nani Fadzlina Naim

***Abstract*—The rapid advancement of fourth-generation (4G) and fifth-generation (5G) wireless communication networks has increased the demand for reliable and accessible mobile connectivity within community environments. However, signal degradation and weak network coverage remain significant challenges that may affect communication quality, internet accessibility, and digital inclusion. Conventional drive-test and signal monitoring solutions are often costly, complex, and inaccessible for public use. Therefore, this paper presents the development of a lightweight web-based system for real-time monitoring and visualization of cellular signal strength using a Python-based architecture integrated with interactive web mapping technologies. The proposed system utilizes drive-test data collected through GNetTrackSuite Lite, where the generated Keyhole Markup Language (KML) files are converted into Global Positioning Exchange (GPX) format for processing and visualization. The system was developed using Python, Tkinter, Pandas, Leaflet, and OpenStreetMap to provide an interactive graphical user interface (GUI) capable of visualizing Received Signal Strength Indicator (RSSI), Reference Signal Received Power (RSRP), and Reference Signal Received Quality (RSRQ) along User Equipment (UE) trajectories. A normalization-based classification method was implemented to categorize signal quality into good, medium, and poor coverage conditions represented using green, yellow, and red indicators, respectively. The developed system enables users to identify weak coverage zones and obtain data-driven insights regarding network performance within community areas. Drive-testing activities were conducted in Seksyen 7, Shah Alam, Selangor, Malaysia, to demonstrate the functionality of the proposed framework. The results show that the developed system successfully provides an accessible, low-cost, and user-friendly platform for signal strength visualization and local connectivity assessment. The proposed framework contributes toward community applications and supports inclusive digital access by enabling users to better understand network coverage conditions for communication and daily digital activities.**

***Index Terms*—4G, 5G, Community, Drive Test Python, GPX, RSRP, RSRQ, RSSI, Signal Strength Visualization**

## I. Introduction

The rapid evolution of wireless communication technologies has significantly transformed modern digital society through the deployment of fourth-generation (4G) and fifth-generation (5G) mobile networks.

According to the Global System for Mobile Communications Association (GSMA), global mobile internet users exceeded 5.6 billion in 2024 [1], representing more than 69% of the world population, while 5G connections are projected to surpass 5.5 billion by 2030 [2]. The increasing dependency on mobile communication services for education, healthcare, transportation, community services, online business, and social interaction has intensified the demand for reliable, high-speed, and stable wireless connectivity. In Malaysia, the implementation of the Jalinan Digital Negara (JENDELA) initiative and nationwide 5G deployment has accelerated digital transformation efforts to improve broadband accessibility and network quality across urban and suburban communities [3]. Nevertheless, despite the rapid deployment of 4G and 5G infrastructures, network signal degradation and weak coverage zones remain critical challenges, particularly in residential and densely populated urban areas.

Signal quality and coverage inconsistency may significantly affect user Quality of Experience (QoE), resulting in reduced data throughput, unstable communication links, increased latency, interrupted voice calls, and poor internet accessibility. Several studies reported that signal attenuation caused by buildings, obstacles, terrain conditions [4], user mobility [5], and network congestion [6] can substantially degrade cellular network performance. In practical environments, Received Signal Strength Indicator (RSSI), Reference Signal Received Power (RSRP), and Reference Signal Received Quality (RSRQ) are among the most important parameters used to evaluate cellular signal quality and communication reliability in 4G and 5G networks. Table I shows the signal range for RSRP, RSRQ, and RSSI based on 3GPP TS 36.133 [7] for 4G and 3GPP TS 38.133 [8] for 5G.

Poor RSRP values below −156 dBm and degraded RSRQ values below −43 dB are commonly associated with unstable connectivity and reduced network performance, particularly in indoor and community-based environments. Consequently, continuous monitoring and visualization of these signal parameters are essential to support network optimization and improve public awareness of local network connectivity.

Conventional signal monitoring and drive-test solutions are commonly implemented using specialized commercial equipment and professional software tools such as Keysight's NEMO Handy [9] which are often expensive, complex, and inaccessible to ordinary users and local communities. Moreover, existing approaches [10] generally focus on

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Azita Laily Yusof, Muhammad Farhan Kamil, Ahmad Zaki Aiman, Norsuzila Ya'acob, and Nani Fadzlina Naim are with the Faculty of Electrical Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia.

*Corresponding author
Email address: azita968@uitm.edu.my

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technical network analysis rather than providing accessible visualization platforms that support community applications and digital equity initiatives. Although several mobile applications are available for signal measurement collection, many lack integrated visualization frameworks capable of transforming raw drive-test data into intuitive and interactive geographical representations. Therefore, there is a need for a resource-efficient, cost-effective, and user-friendly signal monitoring framework capable of visualizing network quality information in real-world community environments.

TABLE I. 4G & 5G SIGNAL STRENGTH RANGE BASED ON 3GPP [7][8]

| Signal Strength | Good | Bad |
|---|---|---|
| | **4G** | |
| RSRP (CSI-RSRP) | -44 dBm | -140 dBm |
| RSRQ | - 50 dBm | -118 dBm |
| RSSI | -25 dBm | -100 dBm |
| | **5G** | |
| RSRP (SS-RSRP L3) | -31 dBm | -156 dBm |
| RSRP (SS-RSRP L1 & CSI-RSRP) | -44 dBm | -140 dBm |
| RSRQ (SS-RSRQ) | 20 dB | -43 dB |
| RSSI (CLI-RSSI) | -25 dBm | -100 dBm |

To address these challenges, this paper presents the development of a web-based system for monitoring and visualization of cellular signal strength using a Python-based architecture integrated with interactive mapping technologies. The proposed system utilizes drive-test measurements collected using GNetTrackSuite Lite through smartphones operating in 4G and 5G environments. The collected data, exported in Keyhole Markup Language (KML) format, are converted into Global Positioning Exchange (GPX) format for compatibility with the developed system. The graphical user interface (GUI) was developed using Python Tkinter, while signal visualization was implemented using Leaflet and OpenStreetMap technologies. The proposed framework enables users to upload GPX files, select the desired signal parameter, and generate interactive browser-based maps displaying signal strength distribution along User Equipment (UE) trajectories.

In the proposed system, RSSI, RSRP, and RSRQ measurements are categorized using a normalization-based classification method that dynamically identifies good, medium, and poor signal conditions represented by green, yellow, and red indicators, respectively. This approach allows users to rapidly identify weak coverage zones and obtain data-driven insights regarding network quality within community areas. Drive-testing activities were conducted in Seksyen 7, Shah Alam, Selangor, Malaysia, to evaluate the functionality and practicality of the developed framework in a real-world environment.

The main contributions of this paper are summarized as follows:

1) A Python-based signal monitoring and visualization framework that are efficiently resourced for 4G and 5G community network assessment is developed.
2) An integrated workflow combining GNetTrackSuite Lite, KML-to-GPX conversion, Tkinter GUI processing, and Leaflet-based interactive mapping is proposed.
3) A normalization-based signal classification approach for visual identification of good, medium, and poor coverage zones is implemented.
4) An accessible and cost-effective community-centric visualization platform that supports digital accessibility and connectivity awareness is presented.
5) An interactive web-based mapping mechanism capable of visualizing RSSI, RSRP, and RSRQ distributions along UE trajectories is developed using OpenStreetMap technologies.

The remainder of this paper is organized as follows. Section 2 presents the related works on signal monitoring and visualization systems. Section 3 describes the methodology and system architecture of the proposed framework. Section 4 discusses the implementation and visualization results obtained from the drive-testing activities. Finally, Section 5 concludes the paper and presents recommendations for future work.

## II. RELATED WORKS

### *A. Existing Cellular Signal Monitoring and Drive-Test Systems*

Cellular signal monitoring and drive-test analysis are important processes in evaluating the performance and reliability of fourth-generation (4G) and fifth-generation (5G) wireless communication networks. Conventional drive-test approaches are commonly performed using specialized hardware and proprietary software platforms such as TEMS Investigation and TEMS Discovery to collect network measurements including Received Signal Strength Indicator (RSSI), Reference Signal Received Power (RSRP), and Reference Signal Received Quality (RSRQ). These parameters are widely utilized to assess signal coverage, communication quality, throughput performance, and network reliability in operational environments.

Despite their effectiveness, previous studies identified several major limitations associated with existing drive-test visualization systems. One of the most significant limitations is the high operational cost of traditional drive-testing approaches. Existing systems require expensive measurement equipment, proprietary software licenses, skilled personnel, and extensive field-testing activities, making them inaccessible for ordinary users, local communities, and small-scale organizations [11]–[13]. In addition, manual walk-test and drive-test procedures are highly labor-intensive and time-consuming, particularly for large-scale urban coverage analysis [14].

Another limitation involves scalability and accessibility. Existing monitoring frameworks are primarily designed for telecommunication operators and researchers rather than community-driven applications [11], [13], [14]. The heavy reliance on proprietary infrastructures and commercial software environments limits public participation in network performance monitoring and reduces accessibility for smaller

organizations [12], [14]. Consequently, community users have limited access to practical and low-cost tools capable of visualizing and understanding local network conditions.

Several studies also reported inadequate support for real-time and crowd-sourced signal collection frameworks. Although prototype systems such as the "Tattle" framework attempted to leverage User Equipment (UE) for real-time reporting and crowd-sourced monitoring, these approaches are still limited in deployment and practical adoption [14]. The absence of community-driven data acquisition systems restricts the ability to collect large-scale and geographically diverse signal datasets [14], [15].

Furthermore, 5G networks are highly sensitive to environmental and contextual conditions such as physical obstructions, urban structures, network load, and interference [12], [16]. Existing prediction and monitoring systems often struggle to accurately represent these environmental variations, resulting in discrepancies between simulated and actual coverage performance [12], [17]. Coverage holes and signal degradation issues continue to exist even when advanced simulation tools are utilized.

In addition, many current monitoring platforms depend heavily on proprietary infrastructures and closed-source software tools such as MATLAB 5G Communication Toolbox and TEMS Discovery [12], [18]. This dependency increases implementation costs and reduces flexibility for educational, research, and community applications. Although several recent studies explored portable and low-cost monitoring approaches for specific environments such as industrial and factory settings, these systems are not generalized for broader 4G and 5G community coverage analysis [19]. Therefore, the development of efficient, modular, portable, and low-cost monitoring systems remains an important research challenge.

### *B. Wireless Signal Visualization and Geographic Mapping Technologies*

Interactive signal visualization frameworks have become increasingly important for analyzing spatial signal distributions and network coverage behavior in wireless communication systems. Geographic Information System (GIS)-based technologies, interactive web mapping platforms, and trajectory visualization frameworks are widely utilized to represent signal measurements geographically. These visualization approaches assist researchers and network operators in identifying weak coverage regions and understanding signal behavior in urban and residential environments.

However, current wireless signal visualization frameworks still exhibit several technical and practical limitations. One major limitation is the lack of automation and real-time responsiveness in signal acquisition and visualization workflows. Several existing systems require offline processing, manual data preparation, and periodic calibration procedures before signal information can be visualized effectively [20], [21]. Such limitations reduce flexibility and responsiveness in community environments where dynamic and on-demand monitoring capabilities are required.

Moreover, several previous studies reported that real-time visualization support remains limited in existing frameworks because many systems depend on offline analysis methodologies [22], [23]. These limitations reduce usability for applications requiring rapid identification of weak coverage zones and immediate network assessment.

Another important issue involves poor geographic integration and limited support for geographically contextualized monitoring. Although several systems incorporated geospatial visualization technologies, many frameworks still lack seamless integration between wireless signal data and real-time Geographic Information Systems (GIS) mapping platforms [24], [25]. Existing mapping systems are also constrained by hardware limitations and scalability challenges, particularly when processing high-resolution or large-scale geographical datasets [24].

In addition, many existing visualization platforms prioritize technical signal representation rather than intuitive and user-friendly interface design [21], [26]. This creates accessibility barriers for non-technical users and limits the effectiveness of these systems in applications. Although platforms such as Visawin demonstrated improvements in user operability and extensibility, their integration with modern wireless technologies and diverse signal metrics remains limited [21].

Signal reliability and visualization accuracy also remain major concerns in current frameworks. Previous studies reported that RSSI measurements are highly affected by multipath fading, temporal signal variation, interference, and environmental dynamics, leading to inconsistent visualization results [27], [28]. Although advanced approaches such as Channel State Information (CSI)-based analysis provide improved accuracy, these methods are not widely implemented in practical community-oriented monitoring systems [28].

Furthermore, scalability and interoperability limitations continue to affect existing frameworks. Several visualization systems struggle to support large-scale deployments such as city-wide monitoring environments [26], [29]. Existing architectures also demonstrate limited interoperability across multiple wireless technologies and signal parameters, reducing their applicability in inclusive 4G and 5G monitoring environments [29]. Therefore, there remains a strong need for scalable, interactive, user-friendly, and geographically integrated signal visualization systems that are suitable and community friendly.

### *C. Smartphone-Based Drive-Test Data, GPX/KML Processing, and Interactive Mapping*

Recent advancements in smartphone technologies have enabled mobile devices to perform signal monitoring and drive-testing activities without requiring expensive professional equipment. Smartphone-based applications such as GNetTrackSuite Lite are capable of collecting RSSI, RSRP, RSRQ, and Global Navigation Satellite System (GNSS) information simultaneously during mobility activities. This capability introduces significant opportunities for developing low-cost and community-accessible signal monitoring systems.

Several studies explored smartphone-based geospatial applications involving GNSS positioning, environmental

sensing, and trajectory analysis [30]-[34]. However, existing literature provides limited discussion regarding the integration of smartphone-generated drive-test data with GPX/KML geospatial processing for cellular network visualization applications.

Previous studies involving smartphone-based GNSS positioning also reported several technical challenges related to noisy observations, environmental effects, and measurement inaccuracies [30]–[32]. These limitations may affect the reliability and accuracy of cellular coverage visualization systems when relying solely on smartphone-generated measurements. As a result, robust data processing and integration mechanisms are necessary to improve geospatial signal analysis reliability.

Although some studies demonstrated near real-time processing capabilities for geospatial monitoring applications [33], there is still very limited evidence regarding the integration of real-time drive-test data processing with web-based interactive mapping frameworks specifically designed for cellular coverage analysis. Existing web-based geospatial platforms are generally developed for infrastructure monitoring [35] or disaster management applications [36] rather than wireless communication visualization.

Furthermore, current studies do not adequately address scalable and automated workflows capable of processing large-scale drive-test datasets for community-wide signal coverage analysis [31]. The integration between smartphone-generated KML data, GPX trajectory processing, Python-based graphical interfaces, and browser-based interactive mapping technologies remains insufficiently explored in the context of wireless communication monitoring.

### *D. Research Gaps and Motivation*

Based on the reviewed literature, several significant research gaps can be identified. First, existing cellular signal monitoring and drive-test visualization systems remain highly dependent on expensive proprietary tools, specialized hardware, and labor-intensive measurement procedures [11]–[14]. These limitations reduce accessibility and prevent widespread adoption within communities and educational environments.

Second, current visualization frameworks lack integrated, streamlined, and user-friendly architectures capable of combining signal measurement acquisition, geospatial trajectory processing, and interactive mapping visualization within a single platform [20], [21], [24], [25]. Many existing systems still depend heavily on offline processing workflows and complex technical procedures.

Third, previous studies provide limited support for automated and geographically integrated visualization of RSSI, RSRP, and RSRQ measurements using interactive web-based mapping technologies [22]–[26]. Existing platforms also exhibit scalability, interoperability, and usability limitations that reduce their effectiveness for community-centric applications.

Fourth, despite the increasing use of smartphone-based signal monitoring applications, current literature demonstrates limited research regarding the integration of smartphone-generated drive-test data, GPX/KML processing, and web-based interactive visualization for identifying weak cellular coverage zones [30]–[36]. Existing studies also lack resource-efficient frameworks capable of supporting local connectivity analysis and initiatives that promote wider access to digital services.

To further highlight the differences between the proposed framework and representative studies reported in the literature, Table II presents a feature-based comparison of existing cellular signal monitoring and visualization systems. The comparison considers key characteristics including smartphone-based drive testing, visualization capability, GPX/KML processing, interactive web mapping, supported signal parameters, implementation approach, and community accessibility. It demonstrates that while previous studies address specific aspects of cellular signal monitoring, none provides an integrated open-source framework that combines lightweight Python-based implementation, interactive visualization, normalization-based signal classification, and community-oriented deployment within a single platform.

TABLE II. COMPARISON TABLE WITH EXISTING WORKS

| Features | [11] | [14] | [19] | [20] | [21] | Proposed System |
|---|---|---|---|---|---|---|
| Smartphone drive-test | ✓ | ✓ | ✓ | ✗ | ✗ | ✓ |
| Open-source implementation | ✗ | ✓ | ✗ | Partial | Partial | ✓ |
| Python GUI | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ |
| KML → GPX Processing | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ |
| Interactive web map | ✗ | Partial | ✗ | ✓ | ✓ | ✓ |
| Leaflet/OpenStreetMap | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ |
| RSSI visualization | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| RSRP visualization | ✓ | ✗ | ✓ | Partial | ✗ | ✓ |
| RSRQ visualization | ✓ | ✗ | ✓ | Partial | ✗ | ✓ |
| Automatic signal classification | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ |
| Community-oriented application | Partial | ✓ | ✗ | ✗ | ✗ | ✓ |
| Low-cost deployment | Partial | ✓ | Partial | ✗ | ✗ | ✓ |

Therefore, this study proposes a Python-based signal monitoring and visualization framework integrating GNetTrackSuite Lite drive-test measurements, KML-to-GPX geospatial processing, Tkinter graphical user interface development, and Leaflet-based interactive mapping technologies. The proposed system aims to provide a low-cost, scalable, geographically integrated, and user-friendly platform

capable of visualizing RSSI, RSRP, and RSRQ distributions along User Equipment (UE) trajectories within community environments.

In addition, the proposed framework introduces normalization-based signal classification and interactive color-coded visualization to support rapid identification of weak coverage zones and improve local connectivity awareness. By addressing the limitations identified in previous studies, the proposed work contributes toward:

1) Lightweight and cost-effective signal monitoring architectures
2) Community-accessible network visualization systems
3) Integrated GPX/KML geospatial processing workflows
4) Interactive browser-based mapping visualization,
5) Support for community-oriented and digital accessibility applications.
6) Improved accessibility for 4G and 5G network performance analysis.

## III. METHODOLOGY

### *A. Overview of Methodology*

This study proposes a web-based signal monitoring and visualization system for fourth-generation (4G) and fifth-generation (5G) wireless communication networks within community environments. The methodology was designed using a software engineering-oriented approach focusing on modular system development, geospatial data processing, interactive visualization, and user-centered graphical interface implementation.

The proposed framework integrates smartphone-based drive-test data acquisition, Keyhole Markup Language (KML) to Global Positioning Exchange (GPX) data conversion, Python-based graphical user interface (GUI) development, and browser-based interactive mapping visualization. The system architecture emphasizes lightweight implementation, low-cost deployment, usability, scalability, and accessibility for community applications. The overall methodology consists of six major phases which are requirement analysis; system design; drive-test data collection; data processing and conversion; GUI and visualization development; and signal analysis and visualization. The complete workflow of the proposed system is illustrated in Fig. 1.

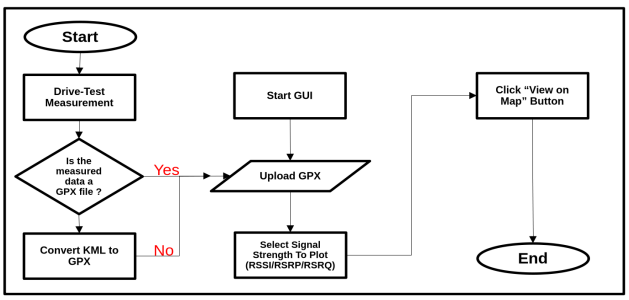


**Fig. 1.** Complete workflow of the proposed system.

### *B. Requirement Analysis*

Requirement analysis was conducted to identify the functional and non-functional requirements [37] of the proposed monitoring system. According to [37], functional requirements refers to services the GUI should provide, how does the GUI act based on given inputs, and what's forbidden for the GUI to produce. While non-functional requirements refers to the GUI constraints. The analysis focused on developing an efficient and user-friendly platform capable of supporting cellular signal visualization for community-based applications.

#### *1) Functional Requirements & Non-Functional Requirements*

The functional requirements of the system are summarized as shown in Table III and the non-functional requirements are shown in Table IV:

TABLE III. FUNCTIONAL REQUIREMENTS [37]

| Functional Requirement | Description |
|---|---|
| File Upload | The system shall allow users to upload GPX files |
| Signal Selection | The system shall support RSSI, RSRP, and RSRQ visualization |
| Interactive Visualization | The system shall display signal trajectories on an interactive map |
| Coverage Classification | The system shall classify signal quality into good, medium, and poor categories |
| Browser Integration | The system shall launch browser-based map visualization automatically |

TABLE IV. NON-FUNCTIONAL REQUIREMENTS [37]

| Non-Functional Requirement | Description |
|---|---|
| Lightweight Architecture | The system should operate without high computational requirements |
| Usability | The GUI should be simple and user-friendly |
| Scalability | The system should support larger GPX datasets |
| Portability | The system should operate on standard desktop environments |
| Accessibility | The system should support end-user applications. |

### *C. System Architecture Design*

The proposed system adopts a hybrid desktop-to-web architecture consisting of five primary modules which are data acquisition, data conversion, GUI processing, signal classification, and interactive visualization. The architecture was designed to ensure modularity, maintainability, scalability, and ease of integration.

#### *1) Data Acquisition Module*

The data acquisition module is responsible for collecting cellular signal measurements using GNetTrackSuite Lite

installed on smartphones. During drive-testing activities, the application records RSSI, RSRP, RSRQ, geographic coordinates and UE trajectory information. The collected data are exported in KML format for further processing.

*2) Data Conversion Module*

The generated KML files are converted into GPX format to improve compatibility with Python-based processing and mapping libraries. GPX was selected because it provides structured geospatial trajectory information suitable for browser-based visualization and trajectory plotting. The conversion process extracts latitute, longitude, timestamp and signal parameters for subsequent visualization and analysis.

*3) GUI Processing Module*

The GUI module was developed using Python Tkinter to provide a desktop-based interface that are efficient in utilizing its resources. The interface allows users to browse GPX files, select signal parameters, initiate visualization processess, and access browser-based interactive maps. The GUI emphasizes simplicity and usability to support both technical and non-technical users.

*4) Signal Classification Module*

The signal classification module performs normalization-based signal categorization for RSSI, RSRP, and RSRQ measurements. The normalization process is defined as (1):

$$\text{Normalized Value} = \frac{(\text{Value} - \text{MinValue})}{(\text{MaxValue} - \text{MinValue})} \quad (1)$$

where *Value* represents the measured signal value, *MinValue* represents the minimum recorded signal, and, *MaxValue* represents the maximum recorded signal. The normalized values are classified into 'Good Signal' in green, 'Medium Signal' in yellow, and 'Poor Signal' in red. The classification thresholds are summarized in Table V.

TABLE V. THRESHOLD CLASSIFICATION

| Normalized Value | Signal Category | Color |
|---|---|---|
| > 0.66 | Good | Green |
| 0.33 – 0.66 | Medium | Yellow |
| < 0.33 | Poor | Red |

*5) Interactive Visualization Module*

The interactive visualization module was implemented by integrating the Leaflet JavaScript library, OpenStreetMap, and Python-based web rendering technologies. The module enables the visualization of user equipment (UE) trajectories, signal strength distributions, and weak coverage areas within the network. Signal measurement points are displayed as color-coded markers according to a normalization-based classification algorithm, thereby providing a clear and interpretable representation of coverage quality.

*D. Drive-Test Data Collection*

Drive-testing activities were conducted in Seksyen 7, Shah Alam, Selangor, Malaysia, representing a community-based urban environment. The drive-test process involved activating GNetTrackSuite Lite on a smartphone, recording cellular network measurements during mobility, collecting RSSI, RSRP, and RSRQ values, and exporting the collected measurements into KML format. The collected datasets contain both signal measurements and geospatial trajectory information for visualization purposes.

*E. Software Development Methodology*

The proposed system was developed using an iterative software development methodology to support incremental enhancement and modular integration which includes requirement identification, GUI design, data processing development, visualization integration, system testing, and performance validation. Python was selected as the primary programming language due to its cross-platform compatibility, extensive library support, and rapid development capability.

The software libraries utilized in this study are summarized in Table VI.

TABLE VI. SOFTWARE LIBRARIES UTILIZED

| Software/Library | Purpose |
|---|---|
| Python | Core programming language |
| Tkinter | GUI development |
| Pandas | Data processing |
| Leaflet | Interactive map visualization |
| OpenStreetMap | Geographic map rendering |
| GPX Parser | Geospatial trajectory processing |

*F. Interactive Visualization Workflow*

The operational workflow of the proposed system is illustrated as follows:

Step 1 *Drive-Test Measurement Collection*
Users collect signal measurements using GNetTrackSuite Lite during drive-testing activities.

Step 2 *KML Export*
The recorded datasets are exported in KML format.

Step 3 *KML-to-GPX Conversion*
The KML file is converted into GPX format for compatibility with the developed system.

Step 4 *GPX Upload*
The user uploads the GPX file through the GUI interface.

Step 5 *Signal Selection*
The user selects one of the available signal parameters (RSRP, RSRQ, RSSI)

Step 6 *Signal Processing*
The system processes the trajectory and signal measurements using normalization-based classification.

Step 7 *Browser-Based Visualization*

The system launches an interactive browser map displaying (UE trajectories, Signal distribution, Weak coverage regions.)

*G. System Testing and Validation*

System testing was conducted to ensure functional correctness, usability, and visualization accuracy of the proposed framework. The testing process focused on successful GPX file loading, correct signal parameter extraction, accurate trajectory plotting, proper signal classification, browser integration functionality, and GUI responsiveness. The proposed framework was also evaluated from a software engineering perspective using several suggested metrics such as processing time, visualization accuracy, system usability, scalability, reliability, and memory efficiency.

The proposed methodology integrates smartphone-based drive-test collection, geospatial data conversion, Python GUI processing, and interactive web visualization into a unified framework that are resource-efficient for local 4G and 5G signal monitoring. The modular software engineering approach improves maintainability, usability, scalability, and accessibility while enabling efficient identification of weak coverage zones using interactive browser-based mapping technologies.

## IV. Results And Discussion

This section presents and discusses the results obtained from the drive-test measurements collected and processed using the developed Signal Strength Monitoring System GUI. The analysis focuses on the visualization and evaluation of cellular signal parameters, namely, Reference Signal Received Power (RSRP), and Reference Signal Received Quality (RSRQ), within the selected community environment. The collected drive-test data were processed through the proposed Python-based framework and visualized using interactive web-based mapping technologies to identify signal strength variations and weak coverage zones along the User Equipment (UE) trajectory. Figure 2 illustrates the developed Signal Strength Monitoring System GUI utilized for GPX file loading, signal selection, and interactive map visualization.

*A. Reference Signal Received Power (RSRP) Analysis*

Fig. 3 illustrates the RSRP distribution along the User Equipment (UE) trajectory collected during the drive-test session in Seksyen 7, Shah Alam, Selangor, Malaysia. The developed Python-based visualization framework successfully mapped the RSRP measurements using interactive Leaflet and OpenStreetMap technologies with normalization-based signal classification. The generated visualization categorized the signal conditions into good, medium, and poor coverage regions represented by green, yellow, and red trajectory markers, respectively. This approach enables efficient geographical visualization of cellular network performance in a community environment.

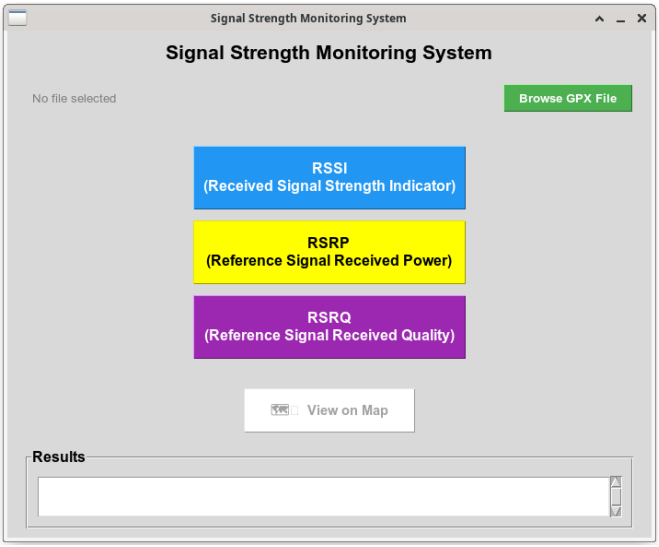


**Fig. 2.** Signal Strength Monitoring System GUI.

Based on the measurement results, the trajectory from Jalan Kristal 7/70 near Jalan Kristal 7/80B and Jalan Kristal 7/81 towards Persiaran Bestari exhibited poor RSRP performance, as shown in Figure 4. Most of the measured RSRP values in this region were below −100.9 dBm, indicating weak cellular coverage conditions. In LTE and 5G communication systems, low RSRP values are commonly associated with higher path loss, shadow fading, non-line-of-sight (NLOS) propagation, and multipath interference caused by surrounding buildings and urban obstructions. These conditions may degrade communication reliability, reduce throughput performance, and increase the probability of radio link instability.

In contrast, the trajectory from Persiaran Bestari towards Jalan Kristal 7/70 and M/7M as shown in Figure 5 demonstrated stronger RSRP performance with measured values greater than or equal to −80.7 dBm, represented by green markers. The improved signal quality indicates more favorable propagation conditions with reduced environmental attenuation and better line-of-sight communication between the UE and serving base station. Overall, the results demonstrate that the proposed monitoring framework is capable of identifying weak coverage zones and providing geographically integrated signal visualization for 4G and 5G network analysis within community environments.

B. Reference Signal Received Quality (RSRQ) Analysis

Figure 6 illustrates the overall RSRQ distribution obtained from the drive-test measurement conducted in Seksyen 7, Shah Alam, Selangor, Malaysia. RSRQ is an important LTE and 5G radio performance parameter that represents signal quality by considering both received signal power and interference conditions within the communication channel. Based on the generated visualization, most of the measured RSRQ values were categorized as medium signal quality, represented by

yellow trajectory markers. Smaller regions of good and poor signal quality were also observed throughout the drive-test route, indicating variations in network quality and interference conditions along the UE trajectory.

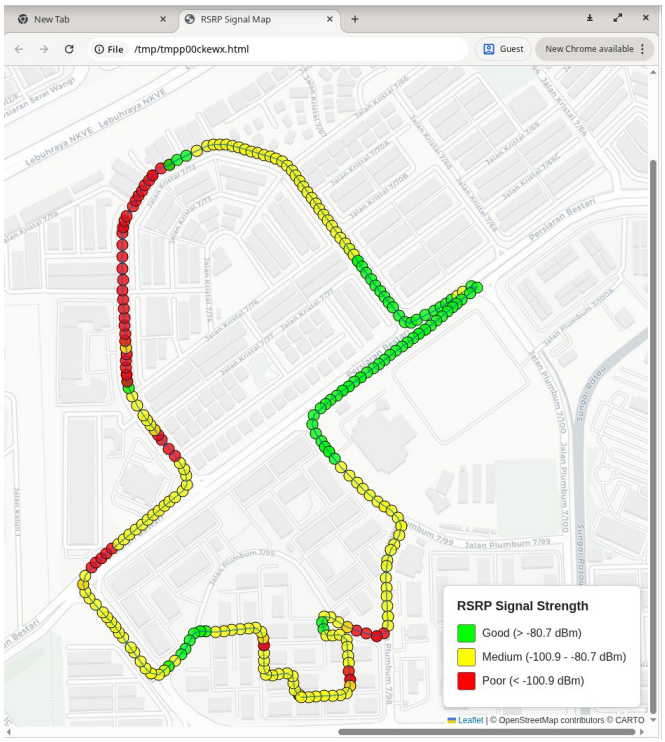


**Fig. 3.** RSRP Signals (Overall)

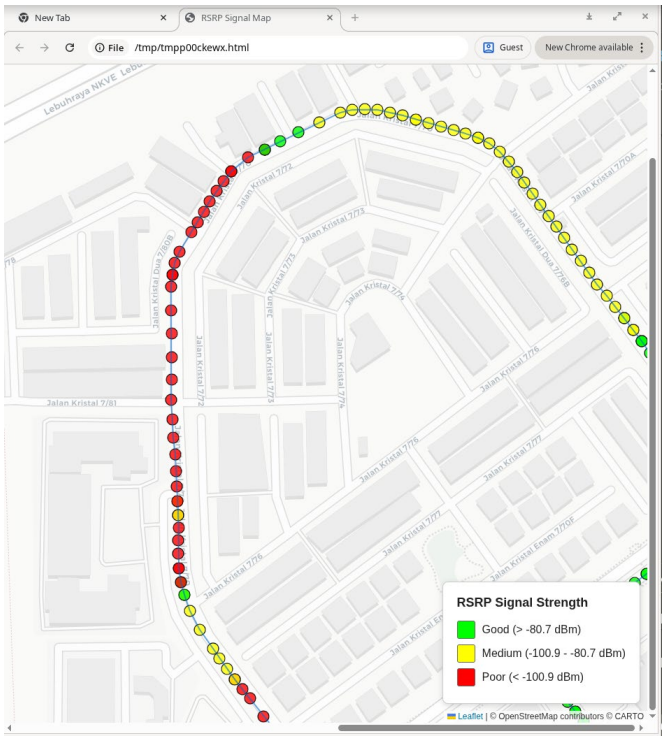


**Fig. 4.** RSRP Signals (Poor Signals)

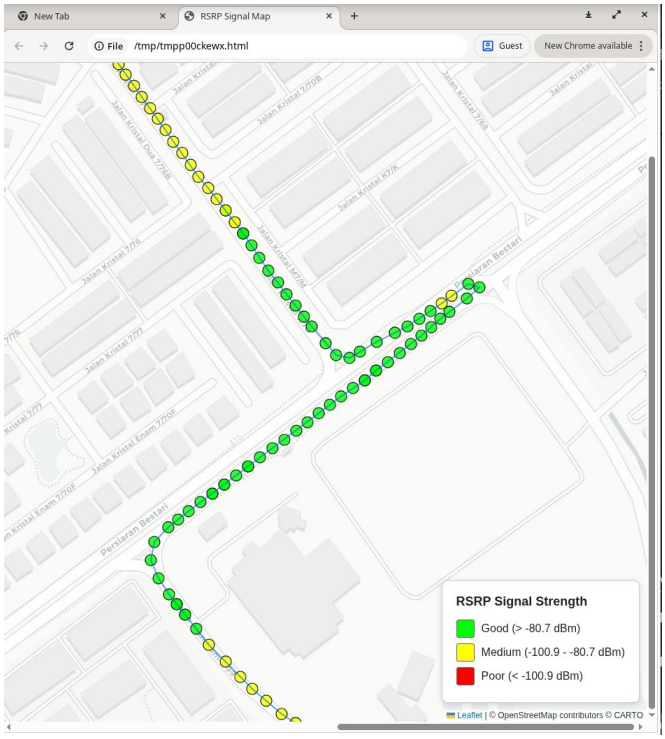


**Fig. 5.** RSRP Signals (Good Signals)

The trajectory from Persiaran Bestari heading towards Jalan Plumbum and Persiaran Permai demonstrated poor RSRQ conditions, as shown in Figure 7. The measured RSRQ values in this region were generally lower than −13.7 dB and represented by red markers. In LTE and 5G systems, poor RSRQ values commonly indicate increased interference levels, network congestion, signal instability, and degraded channel quality. From a telecommunication engineering perspective, the degraded RSRQ performance may be caused by inter-cell interference, surrounding urban structures, and fluctuating radio propagation conditions, which negatively affect communication reliability and Quality of Service (QoS).

In contrast, Figure 8 shows that the trajectory along Persiaran Bestari exhibited good RSRQ performance, represented by green markers with values greater than −10.4 dB. The improved RSRQ conditions indicate better signal quality, lower interference levels, and more stable communication links between the User Equipment (UE) and the serving base station. Overall, the results demonstrate that the proposed visualization framework is capable of identifying variations in signal quality geographically and effectively supporting wireless network monitoring and weak coverage zone analysis within community environments.

C. System Performance Evaluation

To further evaluate the practicality of the proposed framework, a software performance evaluation was conducted in addition to the visualization analysis. The evaluation considered computational efficiency, resource utilization, system responsiveness, and visualization reliability. Specifically, GPX processing time, memory consumption, CPU

utilization, visualization latency, and visualization accuracy were measured to assess the capability of the proposed framework for interactive signal strength monitoring on a standard desktop environment.

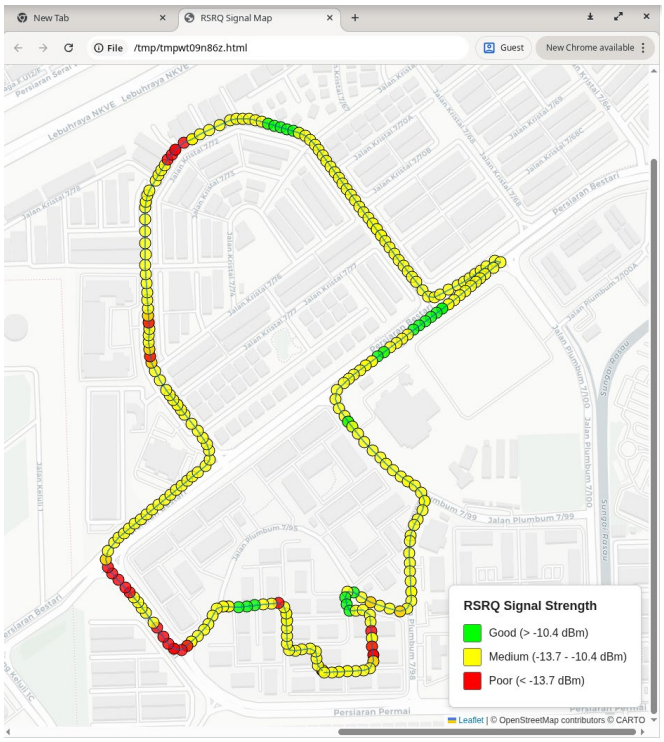


**Fig. 6.** RSRQ Signals.

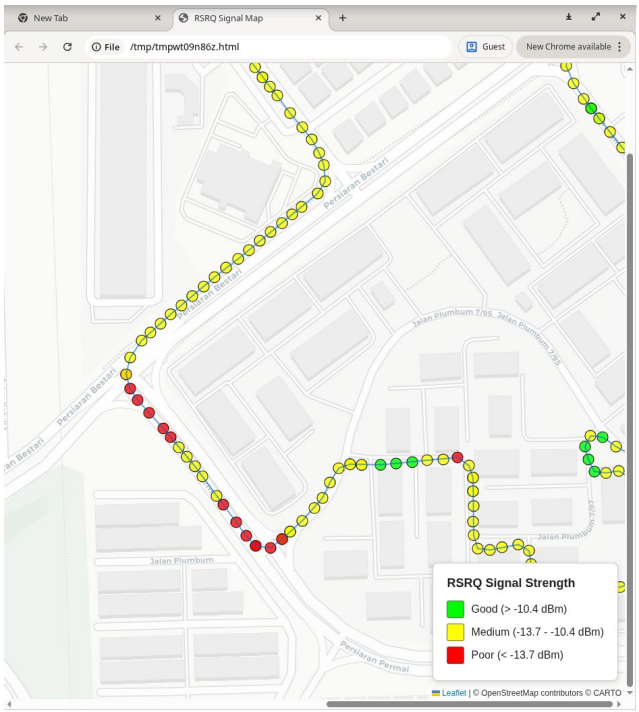


**Fig. 7.** RSRQ Signals (Poor Signal).

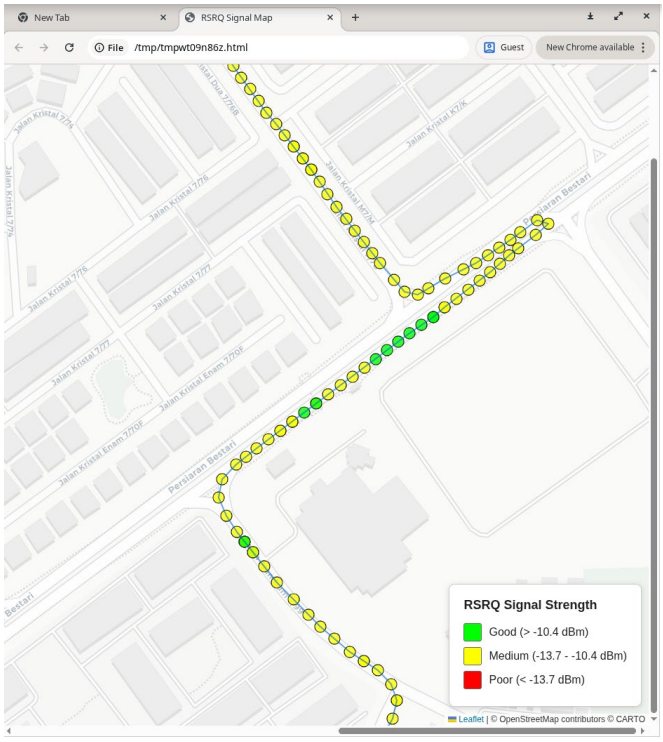


**Fig. 8.** RSRQ Signals (Good Signal).

Table VII summarizes the computational performance of the proposed framework. During the evaluation, the framework processed a GPX dataset containing 291 trajectory points with an average processing time of 2.48 s, demonstrating efficient loading and preparation of the measurement data for visualization. The application required only 1.40 MB of additional memory during processing, while the resident memory size (RSS) remained 42.35 MB, indicating a lightweight memory footprint suitable for execution on ordinary desktop computers. Furthermore, the measured CPU utilization of the application was negligible during the processing stage, while the overall system CPU and memory utilization remained at only 4.9% and 26.2%, respectively, indicating minimal computational overhead.

System responsiveness was evaluated using the average visualization latency, defined as the elapsed time between the user's visualization request and the successful rendering of the interactive map. The proposed framework achieved an average visualization latency of only 0.0194 s across two visualization sessions. This result indicates that the interactive map was rendered almost instantaneously following data processing, thereby providing a responsive user experience suitable for interactive exploration of cellular signal measurements.

The reliability of the visualization process was assessed by comparing the number of successfully displayed signal measurements with the total number of measurements contained in the GPX dataset. The proposed framework successfully processed and visualized all 291 trajectory points, resulting in a visualization accuracy of 100%. No measurement points were discarded due to missing XML elements, empty attribute values, invalid signal measurements, or incorrect

geographical coordinates. These results demonstrate that the developed GPX parsing, signal extraction, and visualization pipeline preserves the integrity of the original drive-test dataset while accurately presenting cellular signal distributions on the interactive map.

TABLE VII . PERFORMANCE EVALUATION OF THE PROPOSED FRAMEWORK

| Performance Metric | Result |
|---|---|
| GPX Dataset Size | 291 trajectory points |
| Average Processing Time | 2.48 s |
| Average Visualization Latency | 0.0194 s |
| Application Memory Usage | 1.40 MB |
| Peak Memory Usage | 0.83 MB |
| Resident Memory (RSS) | 42.35 MB |
| CPU Utilization | 0.0% |
| Overall System CPU Usage | 4.9% |
| Overall System Memory Usage | 26.2% |
| Visualization Accuracy | 100% (291/291) |
| Missing Elements | 0 |
| Invalid Coordinates | 0 |
| Invalid Signal Values | 0 |
| Empty Records | 0 |

D. Discussion on Framework Limitations

Although the proposed framework successfully provides an accessible and lightweight platform for visualizing RSSI, RSRP, and RSRQ measurements using interactive web-based mapping, several limitations should be acknowledged. First, the developed system relies on offline drive-test data collected using GNetTrackSuite Lite and subsequently converted from KML to GPX format. Consequently, the framework is intended for post-processing and visualization rather than real-time cellular network monitoring. Future work may integrate live measurement acquisition through smartphone application programming interfaces (APIs) or cloud-based communication services to enable continuous signal monitoring. Second, the evaluation was conducted using measurements collected within a single community environment in Seksyen 7, Shah Alam, Selangor, Malaysia. Although the case study demonstrates the feasibility of the proposed framework, the performance and usability of the system may vary under different geographical environments, including rural areas, high-density urban regions, indoor scenarios, or highway deployments where propagation characteristics differ significantly. Additional large-scale validation across diverse environments would further improve the generalizability of the proposed approach.

Furthermore, the proposed visualization framework primarily focuses on signal strength and signal quality indicators, namely RSSI, RSRP, and RSRQ. Other important network performance metrics, such as Signal-to-Interference-plus-Noise Ratio (SINR), throughput, latency, packet loss, handover events, and Quality of Experience (QoE), were not incorporated into the current implementation. Integrating these performance indicators would provide a more comprehensive assessment of wireless network performance.

Finally, the normalization-based signal classification adopted in this work provides a simple and computationally efficient mechanism for categorizing signal quality. However, the classification thresholds are derived from the collected dataset and may not always represent optimal thresholds under different network operators, deployment scenarios, or radio environments. Future research could investigate adaptive or machine learning-based classification techniques capable of automatically learning context-aware signal quality thresholds from larger and more diverse datasets.

## V. CONCLUSION

This study presented the development of a lightweight web-based signal monitoring and visualization system for fourth-generation (4G) and fifth-generation (5G) wireless communication networks within community environments. The proposed framework successfully integrated smartphone-based drive-test measurements collected using GNetTrackSuite Lite, KML-to-GPX geospatial processing, Python Tkinter graphical user interface development, and Leaflet-based interactive web mapping technologies. The developed system was capable of visualizing RSSI, RSRP, and RSRQ measurements geographically along User Equipment (UE) trajectories using normalization-based signal classification and color-coded mapping visualization. The implementation demonstrated that low-cost and open-source technologies can effectively support practical wireless coverage analysis without relying on expensive proprietary drive-test infrastructures.

The experimental results obtained from the drive-test conducted in Seksyen 7, Shah Alam, Selangor, Malaysia demonstrated the capability of the proposed framework to identify weak coverage zones and visualize variations in cellular signal performance. The RSRP analysis showed several regions with poor signal strength below −100.9 dBm, particularly around Jalan Kristal 7/70, Jalan Kristal 7/80B, and Jalan Kristal 7/81, while stronger signal conditions were observed along Persiaran Bestari. Similarly, the RSRQ analysis revealed areas affected by degraded signal quality and interference conditions, particularly near Persiaran Permai and Jalan Plumbum. From a telecommunication engineering perspective, these findings indicate the influence of urban obstructions, multipath fading, path loss, and environmental propagation conditions on wireless network performance. Overall, the developed framework successfully provided geographically integrated signal visualization, weak coverage identification, and community-accessible wireless monitoring capabilities for community applications.

For future work, the proposed system can be extended into a fully mobile-based application capable of operating directly on both Android and iOS platforms. The future mobile application may integrate real-time signal acquisition, automated GPX/KML processing, cloud-based data storage, and live

interactive mapping without requiring external desktop processing. Cross-platform development frameworks such as Flutter or React Native can be utilized to support simultaneous Android and iOS deployment while maintaining highly efficient performance and a consistent user experience. In addition, future enhancements may include machine learning-based signal prediction, real-time crowd-sourced data collection, automatic weak coverage detection, multi-user collaborative mapping, and integration with 5G Quality of Service (QoS) analytics. These improvements would further enhance the applicability of the proposed framework for smart city development, initiatives that promote equitable digital access, and next-generation wireless network optimization.

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