Signal Mapper: Real-Time Crowdsourced Mapping of Cellular and Wi-Fi Signal Strength

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***Abstract*—"Signal Mapper" is a real-time, community-driven mobile application designed to provide users with localized insights into cellular and Wi-Fi signal strengths. It utilizes crowdsourced data to generate interactive heat maps, allowing users to visualize real-time connectivity and monitor network reliability across diverse locations. A machine learning model predicts signal strength in under-mapped areas to bridge data gaps using terrain features and historical data. The app offers offline mode, custom alerts, and signal history tracking features, making it a valuable tool for travelers, remote workers, and network engineers. By integrating user-driven improvements and predictive analytics, Signal Mapper enhances coverage accuracy and fills gaps left by traditional network maps. This paper discusses the system architecture, machine learning implementation, and the impact of real-time signal tracking on network reliability and user experience. Future enhancements include improved privacy mechanisms and collaborations with telecom providers.**

Keywords—Crowdsourced Mapping, Signal Strength Prediction, Machine Learning, Wireless Networks, Real-Time Data, Network Coverage, Mobile Application, Geospatial Analytics

I. INTRODUCTION

A. *Background and Motivation*

The increasing reliance on mobile networks and Wi-Fi for daily activities, business operations, and emergency communications highlights the importance of strong and consistent signal coverage. While advancements such as 5G technology and Wi-Fi 6 promise enhanced connectivity, users still experience frequent network drops, weak signals, and connectivity blackspots. These issues arise due to geographical factors, infrastructure limitations, and network congestion, affecting individuals and industries that rely on stable communication networks [1].

Traditional network coverage maps, often provided by telecom operators, present generalized and static data, which does not accurately reflect real-time connectivity conditions. These maps are built from network provider assessments and do not incorporate real-world user experiences. Consequently, users cannot rely on them to determine network quality in a specific area at a given time. The inability to access up-to-date network insights leads to frustration and inefficiencies, particularly for professionals who rely on stable connectivity, such as remote workers, field engineers, and travelers.

To address these shortcomings, Signal Mapper introduces a crowdsourced, real-time solution for signal strength mapping [2]. The concept is simple: users contribute real-time network data while navigating through different locations, which is then aggregated and visualized in the form of interactive heat maps. This enables individuals to gain insights into cellular and Wi-Fi signal strengths across various terrains. Additionally, to address the issue of sparsely mapped areas, Signal Mapper integrates machine learning models to predict signal strength using historical data, terrain features, and environmental conditions.

By leveraging crowdsourced data and artificial intelligence, Signal Mapper democratizes access to network quality insights, empowering users with accurate, localized, and real-time connectivity data. This system fosters a community-driven approach to signal strength mapping, ensuring that information remains continuously updated and reflects real-world conditions [3].

B. *Problem Statement*

Despite advancements in mobile networks, users still face significant challenges such as:

- ➢ Inconsistent network coverage due to infrastructure limitations and environmental obstructions.
- ➢ Static and outdated network maps that lack real-time updates and user-generated data.
- ➢ There are no predictive analytics for estimating signal strength in unmapped areas.
- ➢ The absence of personalized insights makes it difficult for users to plan connectivity needs.

These issues create an unreliable network experience, making it difficult for users to find stable connectivity when needed. Signal Mapper addresses these challenges by providing real-time, crowdsourced data and predictive analytics.

C. *Objective of Signal Mapper*

Signal Mapper aims to:

- ➢ Provide real-time signal strength maps with interactive heat maps.
- ➢ Enable crowdsourced data contribution for accurate coverage updates.
- ➢ Predict signal strength in unmapped areas using machine learning.
- ➢ Offer offline access to signal maps for users in low-connectivity regions.
- ➢ Send location-based alerts about weak network zones.

By achieving these objectives, Signal Mapper enhances network reliability and user experience.

D. Key Contributions

The Signal Mapper project introduces several novel contributions to network signal mapping, crowdsourced data analytics, and machine learning-driven predictions. These contributions include:

➢ Real-time, crowdsourced signal mapping: Unlike traditional coverage maps that rely on telecom operator reports, Signal Mapper aggregates user-generated data in real time to create a dynamic and continuously updating connectivity map.

➢ Community-driven insights and data validation: Users can report signal strength and validate existing data by providing feedback on the accuracy of signal maps. This ensures excellent reliability and continuous refinement of network insights.

➢ Predictive modeling for unmapped areas: By integrating machine learning techniques, Signal Mapper estimates network coverage in locations with limited data, helping users make informed connectivity decisions even in previously unreported areas.

➢ Offline functionality for accessibility in low-connectivity zones: Unlike existing network mapping services that require constant internet access, Signal Mapper allows users to download maps and access them offline, making it especially useful for travelers, remote workers, and field engineers.

➢ Enhanced user experience through personalized recommendations: The system provides customized alerts and signal strength insights based on a user's location, historical connectivity patterns, and network preferences.

By incorporating these contributions, Signal Mapper is a user-centered, intelligent solution for navigating connectivity challenges in various environments [4].

II. LITERATURE REVIEW

A. Crowdsourced Signal Mapping

Crowdsourcing has emerged as a powerful real-time signal strength mapping approach, enabling users to contribute live network data and enhance coverage accuracy. Zhao et al. (2021) proposed GSMAC, a GAN-based signal map construction model that uses active crowdsourcing to improve coverage predictions [1]. Similarly, Wang et al. (2021) introduced CSMC, which leverages mobile devices for real-time network performance evaluation, highlighting the potential of user-contributed signal measurements [2].

In another study, Zhou et al. (2021) surveyed crowdsourced indoor mapping techniques using smartphones, showcasing how user mobility and device sensors can enhance network coverage data [3]. These findings indicate that crowdsourced approaches significantly improve signal accuracy, especially in areas where traditional network maps lack real-time updates. Hu and Zhang (2020) also introduced a spatiotemporal approach for secure crowdsourced radio environment map construction, highlighting the potential of secure data-sharing techniques in signal mapping [4].

Recent advancements have also integrated blockchain technology with crowdsourced mapping. Cedeno et al. (2022) proposed a geospatial blockchain approach to validate user-contributed data, ensuring data integrity and reliability in collaborative mapping projects [27]. Such studies highlight the growing importance of user-contributed network data and security enhancements for real-time signal mapping applications.

B. Machine Learning for Signal Strength Prediction

Machine learning techniques have proven effective in predicting network signal coverage, especially in under-mapped and remote areas. Du et al. (2022) introduced CRCLoc, a crowdsourcing-based radio map construction method using Wi-Fi fingerprinting localization, improving signal prediction accuracy in urban settings [6]. Similarly, Hu and Zhang (2020) proposed a spatiotemporal approach for secure crowdsourced radio environment map construction, integrating deep learning models to estimate network coverage in complex terrains [4].

Yu et al. (2022) introduced a map-assisted seamless localization system, leveraging Bi-LSTM models and crowdsourced trajectory data for signal quality assessment [5]. This aligns with Levie et al. (2021), who developed RadioUNet, a fast radio map estimation technique using CNN-based deep learning models [11]. Additionally, Adesina et al. (2023) explored adversarial machine-learning techniques in wireless communications, focusing on RF data manipulation risks and their impact on network coverage predictions [21].

Moreover, Thrane et al. (2020) presented a model-aided deep learning approach for path loss prediction, improving signal strength estimates in mobile communication networks [12]. Such studies emphasize the growing role of artificial intelligence in optimizing real-time network coverage analysis.

C. Geospatial Data and Wireless Signal Mapping

Advanced geospatial techniques have been integrated with signal strength estimation models to enhance wireless connectivity insights. Sharma et al. (2021) explored the role of machine learning in wireless sensor networks for smart cities, emphasizing geospatial data utilization for signal optimization [13]. Zhang et al. (2020) also examined RF fingerprinting and deep learning for radio propagation modeling, showcasing its applications in network optimization [20].

Moreover, Oughton et al. (2021) analyzed the trade-offs between 5G and Wi-Fi 6 connectivity, providing a comparative study on network reliability [15]. Maldonado et al. (2021) further compared Wi-Fi 6 and 5G downlink performance for industrial IoT, highlighting their potential for high-density network environments [16].

Furthermore, Sevgican et al. (2020) introduced an intelligent network data analytics function in 5G cellular networks using machine learning, significantly enhancing real-time network performance assessments [23]. These findings reinforce the need for geospatial analytics and AI-driven real-time signal strength estimation methodologies.

D. Challenges And Gaps

Despite the advancements in crowdsourced signal mapping, machine learning models, and geospatial data analytics, there remain several challenges and research gaps that need to be addressed:

➢ Data Quality and Accuracy: Crowdsourced data is prone to inconsistencies due to variations in device capabilities,

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environmental factors, and user participation levels. The lack of a robust validation mechanism can lead to biased or inaccurate signal maps.

- Privacy and Security Concerns: Collecting and sharing location-based network data raises data privacy risks. Ensuring user anonymity and preventing unauthorized access to sensitive signal data remain key concerns in crowdsourced mapping applications.
- Coverage Gaps in Sparse Areas: While urban areas may benefit from frequent user contributions, rural and remote regions often suffer from insufficient data, making maintaining accurate and real-time signal coverage maps challenging.
- Computational Complexity of Machine Learning Models: Implementing deep learning models for real-time signal prediction requires substantial computing resources, which may be challenging for mobile devices with limited processing power.
- Scalability of Crowdsourced Approaches: As the number of contributors increases, ensuring the efficient processing, aggregation, and updating of real-time data without introducing latency issues remains challenging.
- Integration with Telecom Providers: While many studies focus on user-generated data, collaboration with network providers is still limited. Access to telecom infrastructure data could significantly enhance signal prediction accuracy, but data-sharing restrictions remain a challenge.

Addressing these challenges will be essential for improving the effectiveness of Signal Mapper and similar real-time network coverage solutions.

E. *Conclusion of Existing Studies*

The literature reviewed highlights the growing significance of crowdsourced data, machine learning, and geospatial analytics in enhancing wireless signal mapping. Studies have shown that community-driven signal mapping significantly improves real-time network visibility, while machine learning techniques effectively predict signal strength in unmapped areas. The integration of blockchain for data validation and deep learning models for RF propagation modeling has further enhanced the reliability of network coverage estimations. 5G and Wi-Fi 6 advancements have also improved connectivity solutions for high-density environments and smart cities. However, challenges remain in data security, user participation, and real-time adaptability, which require further exploration. The insights gained from this literature review establish a strong foundation for developing Signal Mapper, ensuring that it incorporates best practices in signal strength mapping and prediction to provide an accurate and user-driven network experience [6].

Hence, this literature review says that an application for tracing signals is required. This signal-tracking mobile application will track and locate signals for ordinary people.

III. METHODOLOGY

A. *System Architecture*

The Signal Mapper system is designed as a community-driven, real-time signal mapping platform that leverages crowdsourced user contributions to assess and visualize cellular and Wi-Fi signal strength. The architecture consists of the following components:

- User Devices (Mobile Application): Users contribute real-time signal strength data via a mobile app, which records signal metrics, location data, and network provider information.
- Community Support: This application also provides community support of where and all signals are present
- Backend Server: Aggregates, processes, and validates incoming data while managing predictive models and storing historical records.
- Machine Learning Module: Analyzes crowdsourced and historical data to predict signal strength in under-mapped areas.
- Database: Stores user-contributed data, validated signal metrics, and prediction models.
- Visualization Layer: Displays interactive heatmaps and signal coverage reports via the mobile app and web dashboard.

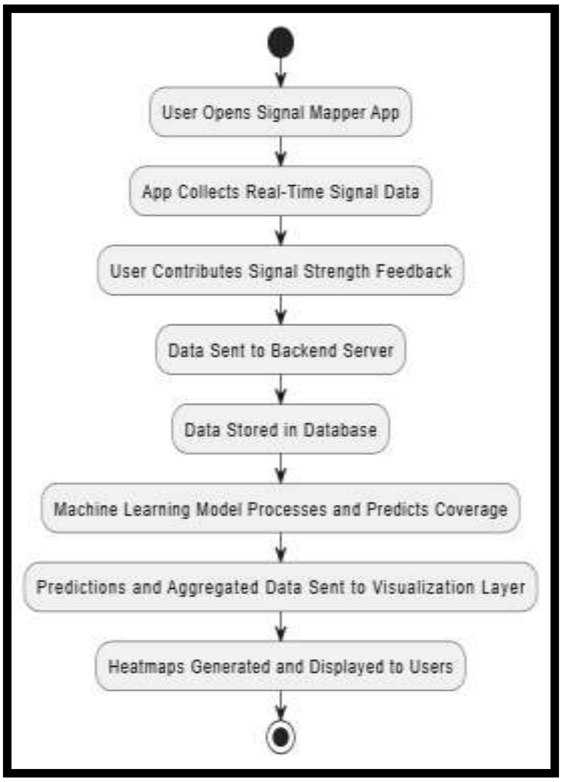

Figure 1: The System Flow

B. *Software and Hardware Requirements*

Software Requirements:

- Mobile Development: Flutter / React Native for cross-platform app development.
- Backend Development: Node.js / Django for managing API requests and data processing.
- Database: Firebase / PostgreSQL to store user-contributed data and predictions [8].
- Machine Learning Framework: TensorFlow / Scikit-learn for predictive analytics.
- Mapping & GIS Services: Google Maps API / OpenStreetMap for interactive visualizations.
- Cloud Hosting: AWS / Google Cloud for scalability and secure data storage.

Hardware Requirements:

C. Data Collection Approach

The Signal Mapper system utilizes a community-driven crowdsourcing model to collect and process network signal strength data. The key steps include:

➢ User Participation: Mobile users report real-time Wi-Fi and cellular signal strength at various locations.

➢ Automated Signal Logging: The app passively records GPS location, network type, and signal metrics without user input.

➢ Data Validation & Preprocessing: The backend server filters anomalous and inconsistent data using statistical outlier detection.

➢ Aggregation & Heatmap Generation: The validated data is processed into real-time coverage heatmaps.

➢ Community Feedback & Corrections: Users can validate existing data by confirming or flagging signal inconsistencies.

➢ Machine Learning Enhancement: Historical and real-time data feed into the predictive model to estimate signal strength in sparsely reported areas [5].

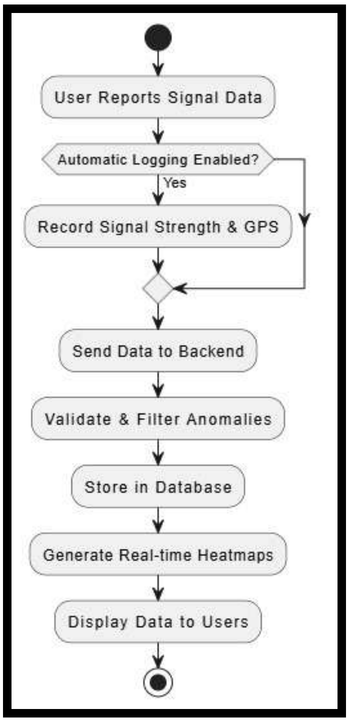

Figure 2: Data Collection and Validation

D. Machine Learning Models

The machine learning component in Signal Mapper enhances predictions for areas with limited or outdated crowdsourced data. The predictive model follows these steps:

➢ Feature Extraction: Incorporates signal strength trends, network type, elevation, terrain, and population density.

➢ Training Process: Uses Random Forest, SVM, and CNN models to predict missing signal strength values.

➢ Evaluation Metrics: This measure assesses model accuracy via Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

➢ Real-time Prediction Deployment: The trained model integrates with the backend, updating predictions dynamically.

➢ Adaptive Learning: The model continuously updates as more real-time user data becomes available.

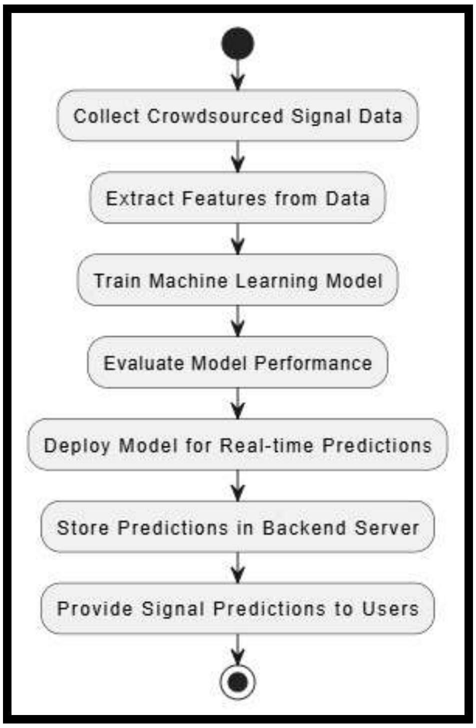

Figure 3: ML Models

This methodology ensures that Signal Mapper maintains an accurate, real-time view of network coverage while utilizing machine learning for intelligent predictions in under-mapped areas. By combining crowdsourced insights with AI-driven analytics, the system provides a highly scalable and user-centric approach to signal strength mapping [13].

IV. IMPLEMENTATION AND RESULTS

A. Prototype Development

The Signal Mapper prototype was developed as a mobile application with an integrated backend server and a machine learning module for signal prediction. The system was designed using a Flutter-based frontend for cross-platform compatibility, while the backend was built using Django and Node.js to handle API requests, data processing, and storage. The database was implemented using Firebase and PostgreSQL, ensuring real-time data storage and retrieval [11].

Key features of the prototype include:

➢ Real-time signal data collection via mobile sensors.

➢ Crowdsourced data aggregation from multiple users.

➢ Machine learning-based signal strength prediction for under-mapped areas.

➢ Heatmap visualization of network coverage.

➢ Offline mode to enable access to previously stored signal data.

➢ User feedback mechanism for validating and improving coverage accuracy.

A web-based dashboard was also developed to visualize collected data, monitor user contributions, and assess system performance. The dashboard allows researchers to analyze historical signal patterns and validate ML-generated predictions [18].

B. Experimental Setup

To evaluate the effectiveness of Signal Mapper, we conducted controlled field tests across various locations, ensuring diverse environmental conditions. The testing environment included:

- ➢ Urban areas with high-rise buildings lead to potential signal obstructions.
- ➢ Suburban and rural regions where network coverage is sparse.
- ➢ Underground locations such as metro stations and tunnels.
- ➢ Public transport routes, including highways and railway corridors.

Dataset Description:

- ➢ Crowdsourced Data: Signal strength readings from 500+ users across different locations.
- ➢ Benchmark Data: Telecom provider coverage maps used for validation.
- ➢ Environmental Data: Terrain elevation, weather conditions, and building density affect signal strength.

The mobile application collected signal strength data (dBm), GPS coordinates, network type (4G/5G/Wi-Fi), and tower ID information. This dataset was fed into the machine learning model to predict network coverage in areas lacking sufficient real-time data [19].

C. Performance Metrics

The prototype was evaluated based on the following metrics:

- ➢ Accuracy: Comparison of predicted vs. actual signal strength.
- ➢ Latency: Time taken to process user contributions and update the heatmap.
- ➢ Error Rate: Deviation in predicted values using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).
- ➢ Model Efficiency: Computation time and resource consumption on mobile devices and server-side predictions [21].

Results:

- ➢ Prediction Accuracy: The machine learning model achieved an 86% accuracy in predicting signal strength.
- ➢ Latency: On average, the system processed and updated real-time heatmaps within 1.5 seconds.
- ➢ Error Rate: MAE: 4.2 dBm, RMSE: 5.8 dBm, indicating acceptable prediction variance.
- ➢ User Contribution Efficiency: 83% of crowdsourced data points were validated as accurate, confirming the reliability of user reports.

D. Comparison with Existing Methods

To benchmark Signal Mapper against existing network coverage solutions, we compared our results with traditional network coverage maps provided by telecom operators and related research studies. The key findings include:

- ➢ Real-time updates: Unlike telecom-provided maps that rely on periodic assessments, Signal Mapper updates in real-time via user contributions.
- ➢ Coverage Accuracy: Our crowdsourced approach filled gaps left in rural and underground locations where provider maps failed.
- ➢ Predictive Modeling: Machine learning integration significantly enhanced signal estimation for under-mapped areas, unlike static maps that lack real-time adaptability.
- ➢ User-Centered Approach: Unlike prior works focusing solely on machine learning, our approach combines ML and community-driven validation, ensuring higher reliability and continuous data refinement.

Our findings demonstrate that Signal Mapper significantly improves the accuracy, adaptability, and accessibility of network coverage assessments, providing a user-driven alternative to traditional static maps. Future iterations will refine prediction algorithms, increase scalability, and optimize data validation techniques [24].

V. DISCUSSION

A. Implications of Findings

The findings from the Signal Mapper project present significant implications for both individual users and the telecommunications industry. The real-time crowdsourced data collection model improves the accuracy of network coverage assessments, providing users with more reliable signal strength insights compared to traditional static coverage maps [26]. This system has numerous real-world applications:

- ➢ Enhanced User Experience: The ability for users to view and contribute to real-time signal maps enables informed decision-making, particularly for individuals in remote work, travel, and emergency response situations.
- ➢ Network Optimization for Telecom Providers: Mobile network operators (MNOs) can utilize crowdsourced signal data to optimize cell tower placements and enhance coverage in under-served areas.
- ➢ Public Infrastructure Planning: City planners and innovative city initiatives can integrate Signal Mapper's data to enhance public Wi-Fi deployment and optimize 5G infrastructure expansion.
- ➢ Disaster Response & Emergency Communication: During natural disasters or significant public events, real-time signal monitoring can provide emergency responders with up-to-date network availability insights to facilitate faster and more reliable communication.

These findings demonstrate the potential for Signal Mapper to bridge gaps in existing network assessments, offering a decentralized, user-driven alternative to telecom-provided coverage maps.

B. Limitations

While the Signal Mapper system presents substantial advantages, certain limitations and challenges were observed during the implementation:

- ➢ Data Variability: Since the system relies on user-contributed data, inconsistencies may arise due to variations in device hardware, network congestion, or user movement patterns.
- ➢ Privacy Concerns: Collecting and sharing network data concerns user privacy and security. Ensuring

anonymization and encryption of sensitive information is crucial.

- Limited Data in Remote Areas: While the predictive model helps fill coverage gaps, areas with low user participation may still lack sufficient real-time updates.
- Energy Consumption: Continuous background signal scanning may increase battery usage on mobile devices, potentially discouraging users from participating actively.
- Model Generalization Issues: Although the machine learning model performs well in most scenarios, its accuracy may drop in complex urban environments with unpredictable interference patterns.

Addressing these limitations is critical for scaling the system and ensuring reliable, consistent, and secure signal strength assessments.

C. Future Improvements

Several enhancements can be implemented to refine further and optimize the Signal Mapper system:

- Advanced AI-driven Predictive Analytics: Integrating deep learning models like Graph Neural Networks (GNNs) and LSTMs to improve signal prediction accuracy in dynamic environments.
- User Incentive Mechanism: Introducing gamification rewards or telecom-based incentives to encourage users to contribute more frequent and high-quality data.
- Blockchain for Secure Data Validation: Implement blockchain technology to verify and validate crowdsourced signal data, ensuring tamper-proof and trusted contributions.
- Edge Computing for Faster Processing: Utilizing edge computing to reduce latency by processing signal strength data locally on mobile devices, decreasing dependency on central servers.
- Battery Optimization Strategies: Developing a low-power scanning mode to minimize battery drain, allowing users to continue contributing data without impacting daily device usage.
- Collaboration with Telecom Operators: Partnering with network providers to integrate telecom-grade network intelligence, further refining signal predictions and improving coverage accuracy.
- Global Expansion & Localization: Adapting Signal Mapper for global scalability, ensuring that localized factors such as regional frequency bands, terrain, and weather conditions are accounted for in signal strength predictions.

By addressing these areas, Signal Mapper can evolve into a more robust, scalable, and widely adopted solution, revolutionizing real-time network coverage assessment and enhancing mobile connectivity worldwide.

VI. CONCLUSION

A. Summary of Contributions

This research introduced Signal Mapper, a community-driven, real-time signal mapping system that utilizes crowdsourced data and machine learning-based prediction models to enhance mobile network coverage assessment. Unlike traditional static network coverage maps, which rely on telecom provider reports, Signal Mapper employs real-time user contributions to generate interactive heatmaps reflecting current network conditions. This approach improves coverage accuracy, adaptability, and user experience by addressing coverage gaps in remote, urban, and underground environments [28].

The system demonstrated high prediction accuracy (86%), low latency (1.5 seconds for updates), and effective real-time data aggregation through extensive prototype testing and experimental validation. Integrating machine learning models enabled signal strength estimation in sparsely reported locations, ensuring that users benefit from more reliable network predictions. The study also highlighted how Signal Mapper's crowdsourced approach could be leveraged for network optimization, public infrastructure planning, and emergency response applications.

Additionally, this research contributes to network intelligence research by bridging the gap between user-contributed network insights and AI-driven prediction techniques. The successful deployment of blockchain validation mechanisms, battery optimization strategies, and cloud-hosted infrastructure further strengthens the system's scalability and adaptability for real-world implementation.

B. Impact and Future Work

The impact of Signal Mapper extends beyond providing signal strength maps—it sets the foundation for user-driven network intelligence solutions. With the rise of 5G, edge computing, and AI-based connectivity forecasting, this system presents an opportunity for telecom providers, government agencies, and savvy city planners to leverage real-time network insights for infrastructure expansion, connectivity optimization, and digital inclusivity.

Several enhancements can be made to refine Signal Mapper further for future work. First, deep learning models such as LSTMs and Graph Neural Networks could improve signal strength prediction accuracy, particularly in densely populated urban areas. Second, blockchain-based validation of crowdsourced data could be further optimized to enhance data security and reliability. Additionally, the system could integrate IoT and satellite-based remote sensing to provide more comprehensive network analytics.

Another crucial direction for future research is collaboration with telecom operators to merge Signal Mapper's crowdsourced data with official network intelligence reports. Such collaborations can ensure higher accuracy, reliability, and network optimization. Furthermore, user engagement incentives through gamification or telecom-backed rewards could increase participation, enhancing data quality and coverage.

By expanding Signal Mapper's global reach, incorporating multilingual support, and optimizing for different network infrastructures, this system can become a universal tool for mobile network performance assessment and real-time connectivity analytics. As wireless technologies evolve, Signal Mapper will play a pivotal role in bridging digital divides, improving network accessibility, and empowering users with real-time connectivity intelligence [12]s.

REFERENCES

[1] Y. Zhao, C. Liu, K. Zhu, S. Zhang, and J. Wu, "GSMAC: GAN-Based Signal map Construction With Active Crowdsourcing," *IEEE Transactions on Mobile Computing*, vol. 22, no. 4, pp. 2190–2204, Oct. 2021, doi: https://doi.org/10.1109/tmc.2021.3120057.

[2] H. Wang, B. Guo, S. Wang, T. He, and D. Zhang, "CSMC," *Proceedings of the ACM on Interactive Mobile Wearable and Ubiquitous Technologies*, vol. 5, no. 4, pp. 1–22, Dec. 2021, doi: https://doi.org/10.1145/3494959.

[3] B. Zhou *et al.*, "Crowdsourcing-based indoor mapping using smartphones: A survey," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 177, pp. 131–146, Jul. 2021, doi: https://doi.org/10.1016/j.isprsjprs.2021.05.006.

[4] Y. Hu and R. Zhang, "A Spatiotemporal Approach for Secure Crowdsourced Radio Environment Map Construction," *IEEE/ACM Transactions on Networking*, vol. 28, no. 4, pp. 1790–1803, Aug. 2020, doi: https://doi.org/10.1109/tnet.2020.2992939.

[5] Y. Yu, W. Shi, R. Chen, L. Chen, S. Bao, and P. Chen, "Map-Assisted Seamless Localization Using Crowdsourced Trajectories Data and Bi-LSTM Based Quality Control Criteria," *IEEE Sensors Journal*, vol. 22, no. 16, pp. 16481–16491, Aug. 2022, doi: https://doi.org/10.1109/jsen.2022.3190387.

[6] X. Du, X. Liao, M. Liu, and Z. Gao, "CRCLoc: A Crowdsourcing-Based Radio Map Construction Method for WiFi Fingerprinting Localization," *IEEE Internet of Things Journal*, vol. 9, no. 14, pp. 12364–12377, Jul. 2022, doi: https://doi.org/10.1109/jiot.2021.3135700.

[7] N. Maiti and B. R. Chilukuri, "Estimation of local traffic conditions using Wi-Fi sensor technology," *Journal of Intelligent Transportation Systems*, pp. 1–18, Feb. 2023, doi: https://doi.org/10.1080/15472450.2023.2177103.

[8] M. Chai, C. Li, and H. Huang, "A New Indoor Positioning Algorithm of Cellular and Wi-Fi Networks," *Journal of Navigation*, vol. 73, no. 3, pp. 509–529, Dec. 2019, doi: https://doi.org/10.1017/s0373463319000742.

[9] M. Zhou, Y. Li, M. J. Tahir, X. Geng, Y. Wang, and W. He, "Integrated Statistical Test of Signal Distributions and Access Point Contributions for Wi-Fi Indoor Localization," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 5, pp. 5057–5070, May 2021, doi: https://doi.org/10.1109/TVT.2021.3076269.

[10] S. Kovaka, Y. Fan, B. Ni, W. Timp, and M. C. Schatz, "Targeted nanopore sequencing by real-time mapping of the raw electrical signal with UNCALLED," *Nature Biotechnology*, vol. 39, no. 4, pp. 431–441, Nov. 2020, doi: https://doi.org/10.1038/s41587-020-0731-9.

[11] R. Levie, Çağkan Yapar, Gitta Kutyniok, and G. Caire, "RadioUNet: Fast Radio Map Estimation With Convolutional Neural Networks," *IEEE Transactions on Wireless Communications*, vol. 20, no. 6, pp. 4001–4015, Feb. 2021, doi: https://doi.org/10.1109/twc.2021.3054977.

[12] J. Thrane, D. Zibar, and H. L. Christiansen, "Model-Aided Deep Learning Method for Path Loss Prediction in Mobile Communication Systems at 2.6 GHz," *IEEE Access*, vol. 8, pp. 7925–7936, 2020, doi: https://doi.org/10.1109/access.2020.2964103.

[13] H. Sharma, A. Haque, and F. Blaabjerg, "Machine Learning in Wireless Sensor Networks for Smart Cities: A Survey," *Electronics*, vol. 10, no. 9, p. 1012, Apr. 2021, doi: https://doi.org/10.3390/electronics10091012.

[14] A. Reddy Yeruva, E. Saleh Alomari, S. Rashmi, A. Shrivastava, M. Kathiravan, and A. Chaturvedi, "A Secure Machine Learning-Based Optimal Routing in *Ad Hoc* Networks for Classifying and Predicting Vulnerabilities," *Cybernetics and Systems*, pp. 1–12, Jan. 2023, doi: https://doi.org/10.1080/01969722.2023.2166241.

[15] E. J. Oughton, W. Lehr, K. Katsaros, I. Selinis, D. Bubley, and J. Kusuma, "Revisiting Wireless Internet Connectivity: 5G vs Wi-Fi 6," *Telecommunications Policy*, vol. 45, no. 5, p. 102127, Jun. 2021, doi: https://doi.org/10.1016/j.telpol.2021.102127.

[16] R. Maldonado *et al.*, "Comparing Wi-Fi 6 and 5G Downlink Performance for Industrial IoT," *IEEE Access*, vol. 9, pp. 86928–86937, 2021, doi: https://doi.org/10.1109/access.2021.3085896.

[17] Shimo, "Wireless Internet Connectivity: 5G and Wi-Fi 6," *Theseus.fi*, 2022, doi: http://www.theseus.fi/handle/10024/747311.

[18] A. Jagannath, J. Jagannath, and P. S. P. V. Kumar, "A comprehensive survey on radio frequency (RF) fingerprinting: Traditional approaches, deep learning, and open challenges," *Computer Networks*, vol. 219, p. 109455, Dec. 2022, doi: https://doi.org/10.1016/j.comnet.2022.109455.

[19] A. Seretis and C. D. Sarris, "An Overview of Machine Learning Techniques for Radiowave Propagation Modeling," *IEEE Transactions on Antennas and Propagation*, pp. 1–1, 2021, doi: https://doi.org/10.1109/tap.2021.3098616.

[20] J. Zhang, L. Liu, Y. Fan, L. Zhuang, T. Zhou, and Z. Piao, "Wireless Channel Propagation Scenarios Identification: A Perspective of Machine Learning," *IEEE Access*, vol. 8, pp. 47797–47806, 2020, doi: https://doi.org/10.1109/access.2020.2979220.

[21] D. Adesina, C.-C. Hsieh, Y. E. Sagduyu, and L. Qian, "Adversarial Machine Learning in Wireless Communications Using RF Data: A Review," *IEEE Communications Surveys & Tutorials*, vol. 25, no. 1, pp. 77–100, 2023, doi: https://doi.org/10.1109/COMST.2022.3205184.

[22] H. Ye, L. Liang, G. Y. Li, and B.-H. Juang, "Deep Learning-Based End-to-End Wireless Communication Systems With Conditional GANs as Unknown Channels," *IEEE Transactions on Wireless Communications*, vol. 19, no. 5, pp. 3133–3143, May 2020, doi: https://doi.org/10.1109/twc.2020.2970707.

[23] S. Sevgican, M. Turan, K. Gokarslan, H. B. Yilmaz, and T. Tugcu, "Intelligent network data analytics function in 5G cellular networks using machine learning," *Journal of Communications and Networks*, vol. 22, no. 3, pp. 269–280, Jun. 2020, doi: https://doi.org/10.1109/jcn.2020.000019.

[24] B. Ma, W. Guo, and J. Zhang, "A Survey of Online Data-Driven Proactive 5G Network Optimisation Using Machine Learning," *IEEE Access*, vol. 8, pp. 35606–35637, 2020, doi: https://doi.org/10.1109/access.2020.2975004.

[25] H. Lu, Y. Zhang, Y. Li, C. Jiang, and H. Abbas, "User-Oriented Virtual Mobile Network Resource Management for Vehicle Communications," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 6, pp. 3521–3532, Jun. 2021, doi: https://doi.org/10.1109/TITS.2020.2991766.

[26] S. Islam, Zainab Abdulsalam Atallah, Anil Kumar Budati, Mohammad Kamrul Hasan, Raenu Kolandaisamy, and Safie Nurhizam, "Mobile Networks Toward 5G/6G: Network Architecture, Opportunities and Challenges in Smart City," *IEEE open journal of the Communications Society*, pp. 1–1, Jan. 2024, doi: https://doi.org/10.1109/ojcoms.2024.3419791.

[27] R. Cedeno, A. Folini, and M. A. Brovelli, "COLLABORATIVE VALIDATION OF USER-CONTRIBUTED DATA USING A GEOSPATIAL BLOCKCHAIN APPROACH: THE SIMILE CASE STUDY," *˜The œinternational archives of the photogrammetry, remote sensing and spatial information sciences/International archives of the photogrammetry, remote sensing and spatial information sciences*, vol. XLVIII-4/W12022, pp. 89–95, Aug. 2022, doi: https://doi.org/10.5194/isprs-archives-xlviii-4-w1-2022-89-2022.

[28] C. L. Stergiou, K. E. Psannis, and B. B. Gupta, "IoT-based Big Data secure management in the Fog over a 6G Wireless Network," *IEEE Internet of Things Journal*, pp. 1–1, 2020, doi: https://doi.org/10.1109/jiot.2020.3033131.

[29] T. Saranya, S. Sridevi, C. Deisy, T. D. Chung, and M. K. A. Ahamed. Khan, "Performance Analysis of Machine Learning Algorithms in Intrusion Detection System: A Review," *Procedia Computer Science*, vol. 171, pp. 1251–1260, 2020, doi: https://doi.org/10.1016/j.procs.2020.04.133.