ORIGINAL ARTICLE

Providing Universal Health Care Access to Filipinos Region-wide using Back Propagation and Recurrent Neural Networks for Finding Optimal Locations to Place Rural Health Unit Facilities in the Philippines

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ABSTRACT

Background and Objective. Access to healthcare remains a challenge in most areas in the Philippines. Fifty-three percent (53%) of the Philippine population do not have access to a rural health unit (RHU) within a 30-minute travel time. As a response, the Department of Health (DOH) needs to construct an additional 2400 RHUs by 2025. This paper uses the Philippine Health Facility Development Plan 2020-2040 (PHFDP) as a reference to present a solution for locating sites for RHU placement in under-served areas using neural networks to meet the 30-minute travel time by maximizing population accessibility.

Methods. RHU accessibility was measured using geographic attributes as inputs to a back propagation neural network (BPNN) and a recurrent neural network (RNN): (1) land coverage and hazard data, representing geographical limitations; (2) population density and distribution, indicating demand for healthcare services; and (3) infrastructure-related features, such as road networks, points of interest, and the locations of existing RHUs, which influence healthcare accessibility. The models were trained to identify underserved areas and were implemented on a nationwide scale, excluding NCR, to locate candidate areas to increase population access to the new RHUs. The models were validated using a healthcare facility accessibility index (HCFAI) to assess RHU coverage improvement.

Results. The BPNN showed stronger generalization across regions, achieving 79.1% average accuracy in distinguishing low from high accessible areas on Region 1 and identifying 1668 out of 3305 locations in the region as candidate sites. The RNN, better capturing unique regional characteristics, required separate training: 77.2% average accuracy on Region 1, identifying 1593 candidate sites. Our findings suggest expanding the use of land improves population access to healthcare facilities. Both models found more than the needed number of RHUs by 2040. The BPNN was more consistent than RNN to improve a region's overall accessibility by increasing the HCFAI. The BPNN can increase population access to an RHU from 2.5-98.5% from its original population with access to an RHU.

Conclusion. The study demonstrates the usage of geographic attributes and neural networks to improve healthcare accessibility. The BPNN and RNN are adequate algorithms to find under-served areas and candidate sites for RHU construction to maximize population accessibility. The HCFAI metric validates the locations to highlight which neural network maximizes more of the region's population. The study contributes to ongoing efforts to improve healthcare infrastructure and accessibility, offering data-driven recommendations for RHU locations.

Keywords: health services accessibility, data science, access to primary care, Philippines, public facilities, recurrent neural network, back propagation neural network, site selection, optimization

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INTRODUCTION

Healthcare Facilities Inaccessibility and System in the Philippines

Access to healthcare remains a challenge in the Philippines due to insufficient health infrastructure to accommodate the growing population.[1] The country is an archipelago of 7,641 islands, making it difficult to reach geographically isolated and disadvantaged locations in need of rural health units (RHUs).[2] This presents geographical challenges for remote areas to meet standards of the Philippine Health Facility Development Plan 2020-2040 (PHFDP) compared to developed areas in terms of disparities in health accessibility.[3] This study applies the proposed solution to all regions in the Philippines, excluding the National Capital Region (NCR). The PHFDP was established to align with the Universal Health Care Act of 2019 (UHC) to provide healthcare to Filipinos.[4,5] Primary care facilities (PCFs) provide primary health services which support first-contact, accessible, continuous, comprehensive and coordinated person-focused care.[1,6] RHU is a type of PCF that supports consultations and laboratory tests to name a few.[1] As of 2019, the country has 3012 PCFs and aims for 6013 by 2040 (99.6% increase). Additional RHUs are achieved through site selection, identifying optimal locations to maximize healthcare access.[7-10] The study hypothesizes adding RHUs improves primary healthcare access in underserved areas to meet the 30-minute travel time. Using back propagation neural network (BPNN) and recurrent neural network (RNN) to optimize PCF locations, highlights how machine learning (ML) contributes to increasing accessibility and reducing healthcare disparities by providing actionable insights for policy makers, precise planning, and resource allocation. This study was conducted by a multidisciplinary team with expertise in ML, data analysis, and public health. The researchers have backgrounds in computer science, geographic information systems (GIS), and ML, ensuring a well-rounded technical approach in addressing healthcare accessibility challenges.

Related Work

Access to healthcare in the Philippines is limited, with both health workers and patients facing challenges such as inadequate resources in public hospitals.[1,11,12] The country implements various health policies, including the United Nations' third Sustainable Development Goal (SDG) for health and well-being, and the UHC framework developed by the World Health Organization (WHO).[13] The PHFDP aims to expand healthcare access by adding PCFs, which serve as the entry point into the healthcare system.[1] The study supports PHFDP's goals through increasing RHU access. As an example, one study proposes utilizing common models to address the facility location problem (e.g., cooperative covering maximal models) by locating optimal locations for PCFs in Antipolo City in Region 4-A due to scarce application of model implementation in the Philippines for underserved areas.[10] It builds on the idea performed in Antipolo City by applying ML methods on a regional scale. Unlike traditional models, which rely on mathematical formulations and struggle with complex, non-linear relationships, BPNN and RNN models adapt and improve with new data and automate the site selection process.

The PHFDP provides a map of the current distribution of RHUs with a percentage of population access and the number of facilities needed per region by 2040 represented by near-accurate coordinates supplied by a geocoding Python library, since not all RHU coordinates are publicly available. This study aims to contribute to the improvement of healthcare infrastructure by identifying optimal locations for RHUs. Using a geographic map of the Philippines, the objective is to strategically distribute RHUs in areas with populations that have limited access to healthcare services. The BPNN enhances efficiency of big data calculations and broadens the scope of site selection. BPNNs have shown to be effective in determining optimal locations for retail stores, hotels, and supermarkets, outperforming traditional regression models in multi-factor problems.[7,9] They provide higher accuracy than other methods like SVRs, random forest, and root mean square error. Similarly, RNNs have been applied in geographic contexts, such as urban route planning, where it effectively predicts optimal paths using spatial data.[14] Its adaptability to static and dynamic environments highlights its potential for identifying optimal routes. BPNNs reduce prediction errors through gradient descent, while RNNs use internal memory to process past inputs.[14,15] The study aims to contribute to the existing literature pool of health accessibility studies done in the Philippines for expanding the methods used in these studies within the healthcare context.

MATERIALS AND METHODS

RHU site selection is traditionally manual. Our ML approach automates this process, integrating geographic and population demographic data for systematic, scalable and precise planning. The dataset describes area accessibility through geospatial factors by combining: roads, points of interest (POIs), RHUs, land coverage, population density, and hazards (flood, drought, rain intensity). This data forms a 1.65 km^2 hexagonal grid (30-minute travel time) with parameters influencing a healthcare facility accessibility index (HCFAI) ranging from 0 to 1. HCFAI, developed for this study, uses the geospatial factors to measure population coverage to an RHU, with high values indicating better coverage. The PHFDP outlines strategies for healthcare infrastructure expansion but does not include a standardized metric for measuring population accessibility to healthcare facilities. It only has the PCF formula to determine the projected needs. The team developed a custom accessibility metric (HCFAI)[1] that integrates the PCF formula with geographic and demographic factors, incorporating travel distance and existing healthcare facility distribution. This metric allows for a data-driven assessment of underserved areas and optimal RHU placement. Using k-means clustering, areas are classified as high-access (1) or low-access (0), prioritizing low-access zones for modeling. For conciseness, Region 1 is presented as a sample in Figures 1 and 2, and Figures 3 and 4 to illustrate geospatial mapping of the RHU sites. The same methodology was applied to other regions, but they are not displayed due to image scaling constraints. The maps highlight roads, RHUs, POIs, and population density for Region 1, omitting some factors for clarity (Figure 5).

The dataset was normalized and up-sampled using SMOTE library to address the imbalance between low and high-accessible areas, ensuring unbiased training for the models. The up-sampled dataset, both models were trained using 10-fold cross-validation to obtain a version model with the highest accuracy. Table 1 is the architecture of the models. The researchers implemented a BPNN and RNN using Python 3.9, PyTorch 2.6.0 with CUDA 12.4 support, PyCaret, Pandas, scikit-learn, and QGIS for spatial data processing, and the code can be made available upon request to ensure replicability.

Each area is equally represented by ensuring complete documentation of factors, preventing model bias. The models were trained with 10-fold cross-validation, selecting the highest accuracy fold to identify regional candidate sites for RHUs. BPNNs generalized across regions while RNNs required retraining per region due to dependence on regional historical data. Candidate sites identified are potential locations addressing low-access areas. The HCFAI of the region was recalculated to validate the BPNN and RNN models.

RESULTS

Model Training and Testing

The BPNN (batch size 64) outperforms the RNN (batch size 128) in precision for low-access areas (0.97 vs. 0.83) and recall for high-access areas (0.98 vs. 0.85). BPNNs achieve higher overall accuracy (0.78 vs. 0.77) and MCC (0.622 vs. 0.552), RNNs show more balanced recall across classes. BPNNs have a higher F1-score for class 1 (0.81 vs. 0.79), while the RNN slightly outperforms in class 0 (0.76 vs. 0.75). Metrics are detailed in Tables 2 and 3.

Model Application and Validation: Searching for Candidate Sites

The trained BPNN (Figure 3) identified 1,668 candidate sites in Region 1 (50.5% of the land area), while the RNN (Figure 4) identified 1,417 sites (42.9%). The legend for the symbology is on Figure 6. The RNN models trained on regional data identified more low accessible areas in the region.

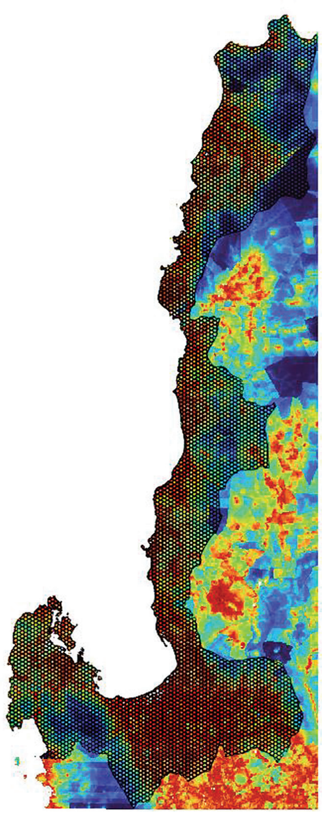

Figure 1. Population density map of Region 1.

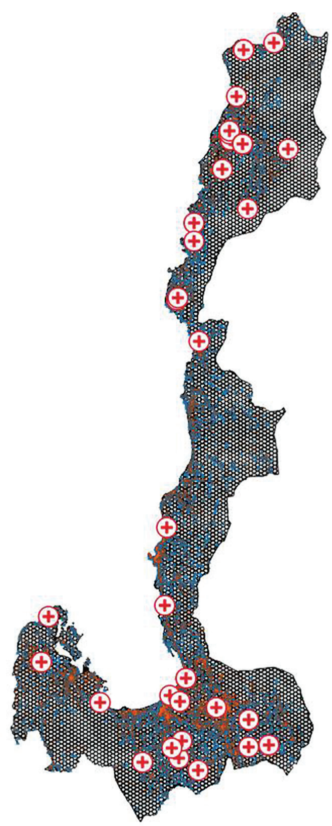

Figure 2. Geographical features of Region 1.

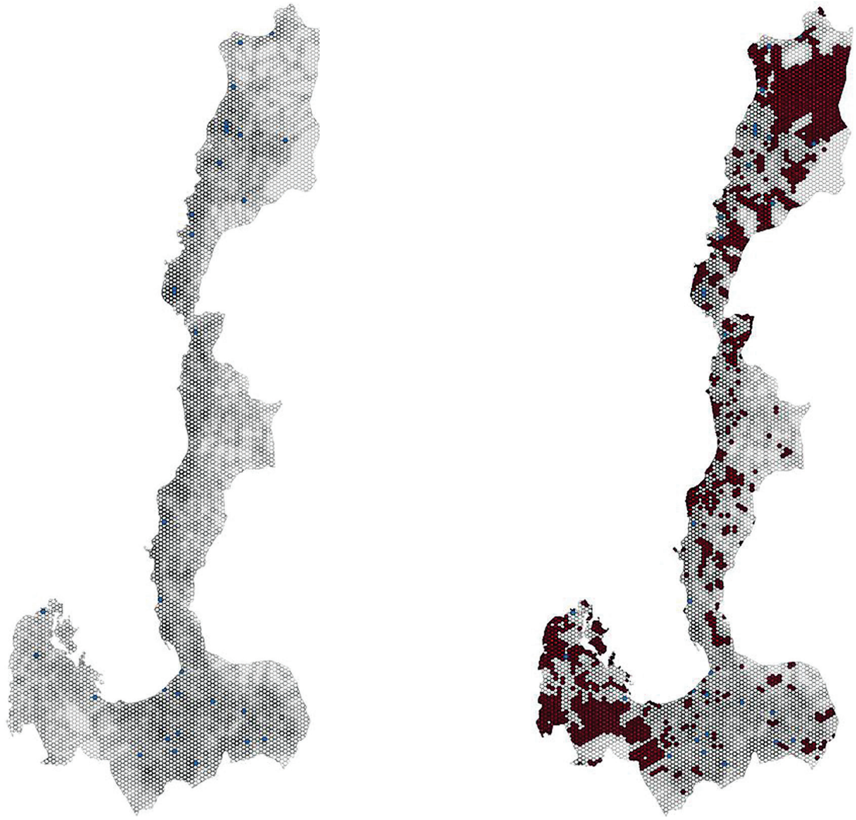

Figure 3. BPNN: Region 1 existing (left) and candidate sites alongside existing RHU locations (right).

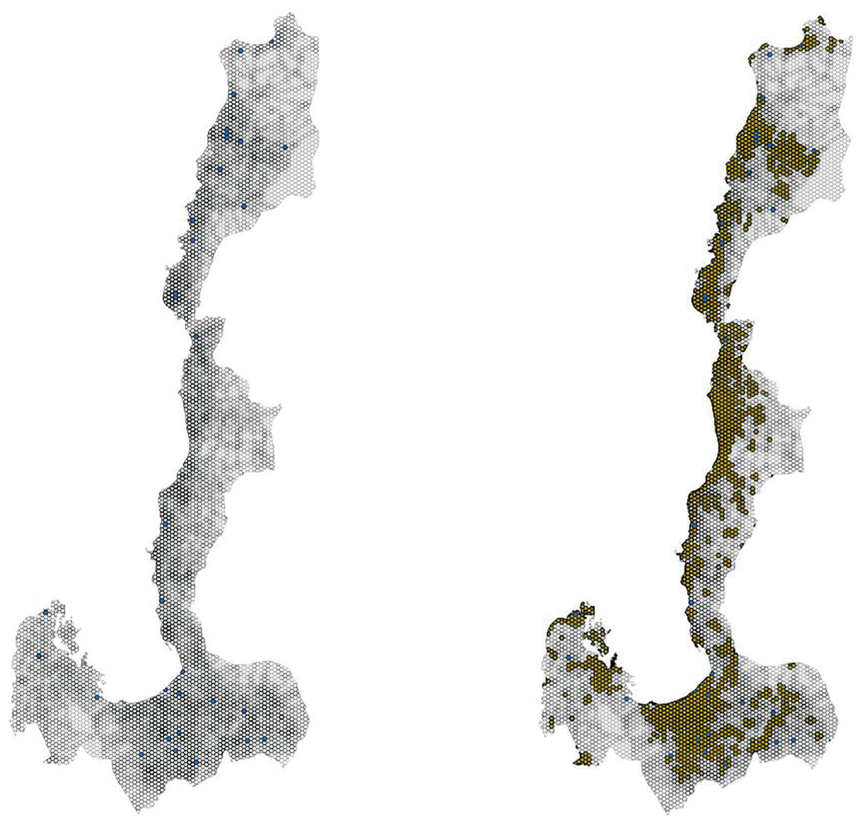

Figure 4. RNN: Region 1 existing (left) and candidate sites alongside existing RHU locations (right).

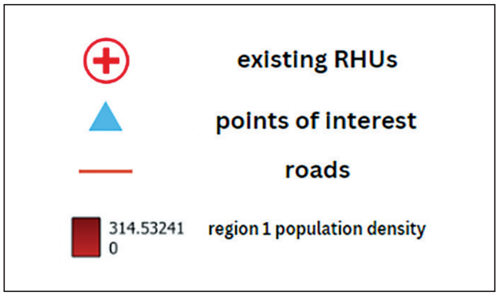

Figure 5. Geographical and population density legend maps.

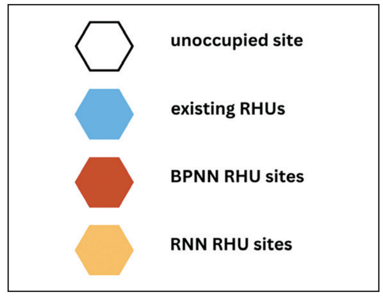

Figure 6. Legend for candidate and existing sites.

The BPNN consistently increased the overall HCFAI of each region. For instance, regions with 76-100% of its population classified having no access saw at least an 8% increase in HCFAI: MIMAROPA (increased by 17.5%), BARMM (23.4%), and Region 5 (8.82%) if RHU were to be put up (Figure 7). The population benefits with the HCFAI increase. Figure 8 covers how much more of the population gain access if RHUs were to be placed in all the candidate sites. Regions 5 and 10 have the greatest population coverage increase at 91.8% and 98.5%, respectively.

DISCUSSION

Model Application and Validation: Candidate Site Search

Tables 2 and 3 show the BPNN is better at identifying low-access areas with lower recall for low-access areas. It is unable to correctly identify low-access areas (61%) unlike the way it correctly identifies high-access areas (98%). The effects are reflected in Figures 3 and 4 where the candidate sites are alongside the existing RHU sites. The models classified similar areas as low accessible with the RNN having a more distributed set of sites while the BPNN found sites in clusters (noticeably dense in north and south of the region). Both models agree on some locations, but different site selections indicate that each model interprets healthcare accessibility uniquely. BPNNs find RHU sites more densely (e.g., urban areas) while RNNs distribute RHUs evenly, regardless of population density.

RNN exceeds BPNN in classifying more than half of the total area during model application as candidate sites (Figure 9). RNN provides more options for RHU placement and suggests flexibility or inclusion in its classification criteria. This may indicate improved pattern recognition in spatial data or greater sensitivity to key factors influencing site suitability. As a result, decision-makers would have more site options when planning RHU placements, potentially improving accessibility and service coverage. In Region 2, it classified 8824 of 9407 (93.8%) of the region as a potential RHU site. Figure 7 shows BPNN outperformed the RNN in terms of HCFAI increase in each region. It was higher than the original HCFAI value of the region. BPNN's ability to generalize without retraining makes it cost-effective, as it can be used across regions without additional computation. The RNN, requiring retraining for each region varied in performance, and at times, would be lower than the original HCFAI value (Region 13 and BARMM).

Although RNN identified more candidate sites (Figure 9), these locations were not always most optimal in terms of increasing HCFAI. Retraining RNNs for each region adds computational complexity and may lead to inconsistencies in performance across different areas. The factors influenced models' site predictions. Areas with high population density and no nearby RHU, and locations near POIs (e.g., schools,

Table 1. BPNN and RNN Model Training Architecture

	Number of Layers	Batch Size	Number of Epochs	Activation Function	Optimizer
BPNN	6	16,32,64,128	250	Sigmoid	SGD
RNN	6	16,32,64,128	250	Tanh	Adam

Table 2. BPNN Evaluation for Region 1 Training

Metric	Precision	Recall	F1-score	Support
Class 0	0.97	0.61	0.75	1033
Class 1	0.70	0.98	0.81	944
Macro Average	0.83	0.79	0.78	1977
Weighted Average	0.84	0.78	0.78	1977
F1	0.7470308788598575			
MCC	0.6224087961220331			
Accuracy	0.78			

Table 3. RNN Evaluation for Region 1 Training

Metric	Precision	Recall	F1-score	Support
Class 0	0.83	0.70	0.76	1000
Class 1	0.73	0.85	0.79	977
Macro Average	0.78	0.77	0.77	1977
Weighted Average	0.78	0.77	0.77	1977
F1	0.7559652928416486			
MCC	0.5524367788813155			
Accuracy	0.77			

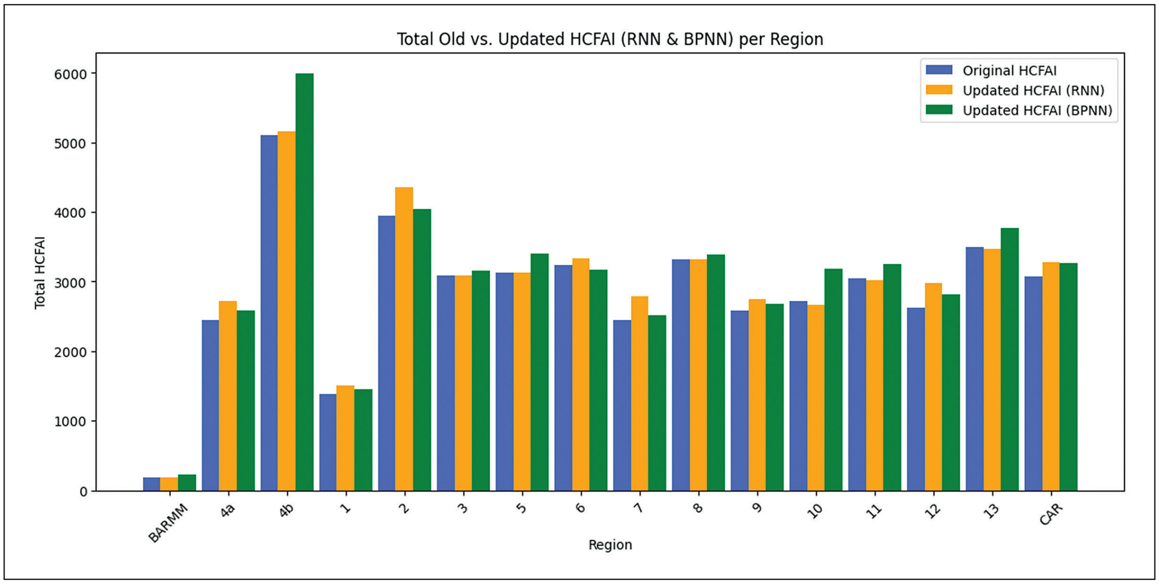

Figure 7. Original vs. updated HCFAI of each region recalculated after applying the BPNN and RNN.

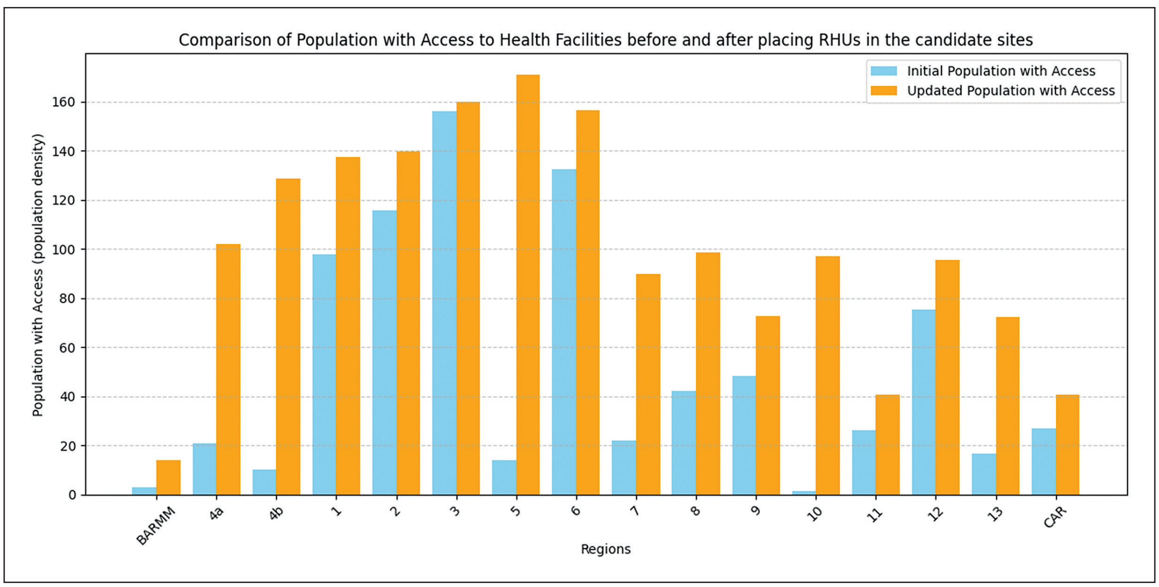

Figure 8. Initial vs. updated population access to an RHU if a facility were to be placed in all candidate sites.

markets), are prioritized. Overall, the BPNN performs better than the RNN due to its consistent performance, as shown in Figures 7 and 9. It is cost-effective, simple, and fast to use if policy makers and local government units (LGUs) were to plan their healthcare infrastructure.

Impact on Philippine Healthcare Accessibility

The results highlight healthcare inaccessibility across the regions, revealing that despite numerous potential RHU sites, access remains uneven. Figures 7-9 can help guide policy makers to see how many Filipinos in different areas could reach universal healthcare status. The results expand population coverage accessibility to PCFs, especially those who do not meet the 30-minute travel time requirement. Placing RHUs in candidate sites reduces high inaccessibility in regions. For instance, areas where 76-100% of the population lack facility access. Regions classified with high levels of population inaccessibility, Region 5, MIMAROPA, and BARMM, at least half (or nearly half) the total area was identified as a potential RHU site and increased population coverage.[1] The HCFAI was a significant metric to demonstrate a greater population can benefit if granted access to RHUs. The maps generated above could aid LGUs or health policy makers in planning for RHU construction and what key areas to prioritize based on the population coverage requiring one.

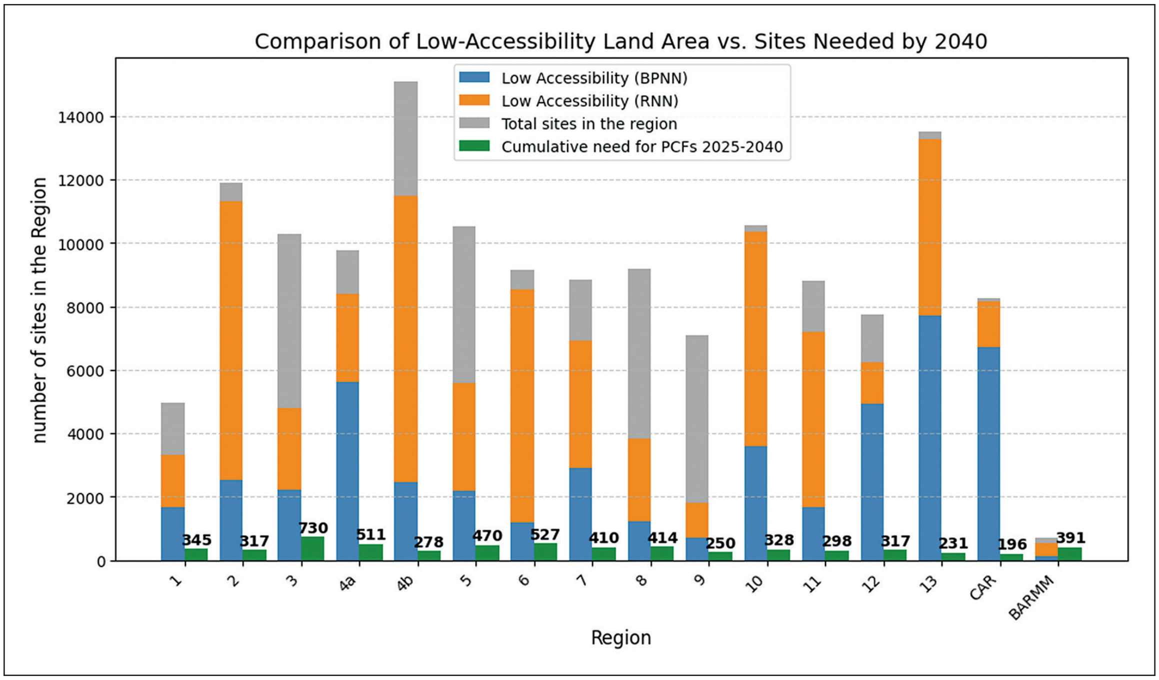

Figure 9. Cumulative need for RHUs by 2040 vs. the number of sites generated by the RNN and BPNN.

For patients, the proposed solution would increase access to healthcare by ensuring a balanced distribution of facilities nationwide, including in remote areas far from major cities to be within 30 minutes from their homes. For health providers, the models offer valuable insights to make well-informed, data-driven decisions to improve healthcare infrastructure. The models suggest optimal locations based on population needs, enabling more targeted resource allocation. Figure 8 gives policy makers an idea of the effects of the number of RHUs constructed in a given area to how much of the population would gain access. This could be a starting point of how policy makers could prioritize RHU construction based on which population needs it most. The PHFDP could also benefit from having the population access coverage metric alongside the target number of RHUs needed by 2040. The findings demonstrate the potential for digitizing healthcare planning, for the DOH, LGUs, and local policy makers. The HCFAI serves as a basis for assessing healthcare accessibility, enabling data-driven decision-making, and improving equitable distribution of health services. By including this metric and integrating the results with PHFDP, we contribute to evidence-based decision-making and planning healthcare infrastructure, ultimately improving equitable healthcare access for Filipinos.

Limitations

A geo-location API was used to identify RHU coordinates from the list of RHUs in the DOH's database. Future research can complete the current list of coordinates. Moreover, different hazards (outside of flooding, drought, and rain intensity), like volcanic eruptions and earthquakes, were not included in the study due to data availability and accessibility. A key limitation is the absence of a standardized accessibility metric within the PHFDP. While our proposed metric provides a structured approach to evaluating healthcare access, future research should explore validation with empirical data, stakeholder consultations, and integration with national health planning frameworks. Another factor not accounted for is land ownership, as publicly available datasets do not typically include this information. While the models identify optimal RHU locations based on accessibility and geographic factors, the feasibility of constructing facilities in these areas may be influenced by land availability, ownership disputes, or zoning restrictions. Future studies could incorporate land ownership data, if available, to enhance the practical applicability of site selection recommendations. Furthermore, the paper could be improved by scaling its results on a municipality-level, instead of a regional-level, as RHUs are locally managed.

CONCLUSION

The study developed BPNN and RNNs using geospatial features to identify optimal RHU locations. The models adapt to local contexts, aiding strategic resource allocation and healthcare planning, making these scalable across regionally. The BPNN is preferred for planning the health infrastructure because it is able to locate candidate sites for RHUs while increasing population's access to RHUs. It is able to generalize across regions without retraining makes it practical for large-scale implementation. Findings contribute to public health research, providing a metric for accessibility to take into account when considering population. This provides actionable insights for health officials to effectively plan around the existing health infrastructure to improve accessibility in underserved areas. Though not yet used by Filipino policy makers, the methods provide a foundation for digitizing healthcare accessibility planning.

Statement of Authorship

All authors certified fulfillment of ICMJE authorship criteria.

Author Disclosure

All authors declared no conflicts of interest.

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