sciendo
www.degruyter.com/view/j/remav

DETECTING ABANDONED HOUSES IN RURAL AREAS USING MULTI-SOURCE DATA

Changro Lee[1]*

[1]*Departament of Real Estate, Kangwon National University, 1 Kangwondaehak-gil, Chuncheon, Gangwon-do, 24341, Republic of Korea, e-mail: spatialstat@naver.com, ORCID: 0000-0002-7727-3168*

* *Corresponding author*

ARTICLE INFO

Keywords:

abandoned houses, rural area, neural network, images, building registry

JEL Classification:

R20, R30

ABSTRACT

Abandoned houses have become a common feature of the local landscapes: the rising number of abandoned houses is a major challenge facing many counties in South Korea. Their presence negatively influences the neighborhood by undermining its aesthetic quality, depreciating the perception of safety in the neighborhood properties, and deepening the fiscal deficit of local financing. The detection of abandoned houses is the first step toward adequate housing management by local governments. This study aims to provide a cost-effective and prompt approach to identifying abandoned houses in rural areas. Multi-source data, that is, images and building registry data are utilized and a multi-input neural network is designed to adopt these heterogeneous datasets. Trained by the two source datasets, the proposed network achieves 86.2% accuracy in classifying abandoned houses, which is an acceptable performance level in administrative practice. The database of abandoned houses identified in this manner is expected to promote effective housing management by governments and ultimately contribute to mitigating vacancies in rural areas.

Citation: Lee, C.(2023). Detecting abandoned houses in rural areas using multi-source data. *Real Estate Management and Valuation, 31*(3), 58-66. https://doi.org/10.2478/remav-2023-0021

1. Introduction

Over the past decade, the number of abandoned houses (AHs) in South Korea has been steadily increasing. In 2020, the total number of AHs nationwide was approximately 1.5 million units, compared to1.1 million units in 2011 (KOSIS, 2022b). AHs exist widely in both metropolitan and rural areas and engender social issues that disturb the quality of neighborhoods and people residing therein. AHs not only encourage crime in the neighborhoods, but also decrease house prices (Mallach, 2018). Additionally, AHs cause local governments to suffer reduced property tax revenues and incur the burden of monitoring and demolishing these dilapidated buildings. All these issues explain why local governments in South Korea have made their best efforts to effectively detect abandoned houses and reuse them creatively, for example as community halls and business incubator centers.

In this study, we attempt to systematically identify AHs. The prompt and cost-effective detection of AHs is the first step in shaping local policies for house abandonment. A county was selected as the study area, and a relevant approach for identifying AHs in the area was provided. The detection performance level ascertained from the proposed approach is presented, and the acceptable level of detection accuracy in local administrations is discussed.

The contribution of this study is twofold. First, in contrast to previous studies that intensively explored urban vacancies, we analyze rural house abandonment. AHs in rural areas may be less noticeable; however, lower visibility does not indicate lesser importance. Second, this study attempts to combine multi-source data to improve the detection accuracy of AHs. Prior studies have tended to depend on a single source dataset such as field survey data or utility data to identify AHs, but we combine heterogeneous datasets for the detection of AHs and demonstrate that this approach enhances detection performance.

The remainder of this paper is organized as follows. Section 2 reviews urban and rural vacancies and existing methods of detection of AHs. Section 3

eISSN: 2300-5289 | © 2023 The Author(s) | Article under the CC BY license

describes the experimental setting, including the study area, datasets used, and the model used to detect AHs. In section 4, we explain the detection performance and implications for local governments. Finally, the study is summarized and the directions for future studies are presented in section 5.

2. Literature review

2.1. Urban vacancy

AHs in cities have been extensively investigated in the context of urban shrinkage. In Europe, most studies have focused on cities in Western Europe, such as Liverpool and Manchester in the UK, attributing the emergence of AHs to low birth rates and economic decay during the 1990s (Rink et al., 2012; Ortiz-Moya, 2015; Döringer et al., 2020). In contrast, in the US, urban vacancy in the Rust Belt has been intensively analyzed: the well-known Rust Belt cities include Detroit, Cleveland and Pittsburgh. These studies attributed the urban decline in these cities to the relocation of the manufacturing industry and suburbanization (Pallagst, 2009; Ghosh et al., 2019; Ganning & Tighe, 2021).

To revitalize shrinking cities, these studies suggest the following strategies for local governments: removing policy barriers to reusing vacant properties, providing tax incentives to encourage housing redevelopment, supporting the demolition of AHs for resale, and reusing vacant lots in a creative manner, such as for community gardens. Overall, it has been argued that AHs in European cities are mainly driven by falling birth rates and economic decline, while urban vacancies in American cities are caused by industrial transformation (Wiechmann & Pallagst, 2012).

Urban vacancy in South Korea has been studied mainly from the perspective of the *doughnut city*. This term is used to describe the growing population on the city periphery and the parallel decline in urban activity in the city center. AHs in doughnut cities, particularly old houses in the city center, are a serious social problem in South Korea, and relevant studies have attributed the rise of doughnut cities to development projects of new towns on the ring road, strict policy barriers limiting revitalization projects of old downtowns, and young people's increasing preference for suburban life (Kim & Nam, 2016; Lee & Joo, 2022; Oh & Kim, 2022). These factors have contributed to an increase in AHs in the cities of South Korea over the past decade.

However, AHs are not confined only to urban areas. Many rural counties also experience serious levels of house abandonment. AHs in the rural areas of South Korea in 2020 amounted to 317,000 units nationwide, increasing by 18% from 269,000 units in 2011 (KOSIS, 2022b). Rural AHs in South Korea are not the result of recreational or seasonal use. They are the direct product of severe depopulation and economic stagnation over the last few decades. In 2020, approximately 4.5 million people resided in rural areas, which is in drastic contrast to the 6.6 million people in the same areas in 1997 (KOSIS, 2022a). Rural abandonment is less visible than urban abandonment; vacant houses are scattered sporadically across the landscape and located remotely in the countryside or hidden deep within the mountains. However, invisibility does not mean that AH problems in rural areas are less severe. Increasing AHs in rural areas cause local governments to experience some hardships more intensely, such as the deepening of local financing deficits and the rising costs of management of dilapidated buildings. Unlike previous studies that focus on urban AHs, this study investigates rural AHs and suggests a relevant approach to detect AHs.

2.2. Detection of abandoned houses

Detecting individual AHs and counting their exact numbers is the first step in local housing policy and regional planning. Although the systematic identification of AHs is critical, it is challenging to detect them in a cost-effective and prompt manner. Several detection methods have been proposed, including field surveys, utility data monitoring, and satellite image analysis. Field surveys, although very accurate and reliable, are resource-intensive and time-consuming. Using utility data such as power, gas, and water is a relatively cost-effective and opportune approach, but data availability is limited owing to personal data protection regulations. Analysis of satellite images, generally via a deep learning-based computer vision algorithm, is a cost-effective method, and the related data are easily available owing to the open data policies of global portal sites. However, a primary concern when using computer vision algorithms is achieving reliable performance.

Field surveys remain the preferred method for identifying vacant properties in the existing literature. Morckel (2014) investigated the probability of housing abandonment in Youngstown, Ohio using field survey data. Yin and Silverman (2015) conducted a fine-grained analysis of the patterns of property

eISSN: 2300-5289 | © 2023 The Author(s) | Article under the CC BY license

abandonment in Buffalo, New York using survey data as well. In both studies, vacant house data were collected and compiled based on windshield surveys (observations made from a moving automobile) and walking surveys (observations made on foot). Field surveys continue to be utilized in the literature to identify abandoned properties, including vacant land properties (Sakamoto et al., 2017; Baba & Hino, 2019).

Abandoned housing manuals commonly recommend the use of utility records of electric, gas, water, and phone services for detecting AHs in neighborhoods (Kelly et al., 2016). Although this option is limited in practice owing to private data protection, Kumagai et al. (2016) obtained water hydrant data from Neyagawa City, Japan, and used the information to estimate housing vacancies.

Because of the increasing availability of satellite and street view images, imagery data[1] have been actively used for identifying AHs since the 2010s (Deng & Ma, 2015; Du et al., 2018; Zou & Wang, 2020). These studies employed a convolutional neural network (CNN), a de facto strand algorithm for image analysis, and demonstrated the ability to detect AHs using CNN. Applications of CNN are rapidly expanding to other similar areas, such as the aesthetic assessment of property appearance (Law et al., 2020) and house valuations (Lee & Park, 2020).

This study bridges the following research gaps. First, only urban vacant houses have so far been intensively investigated in the literature, leaving house abandonment in rural areas less explored. Thus, this study focuses on rural AHs. Second, detecting AHs using single-source data has been a common approach in previous studies, but single data sources, such as field surveys or utility data, have certain limitations, as explained earlier. Integrating a variety of source data has often been suggested as a future study direction to improve AH detection accuracy in the literature (Kang et al., 2018; Zou & Wang, 2021). In this study, two heterogeneous datasets, that is, images and building registry data, were utilized for the detection of AHs.

3. Dataset and a multi-input neural network

3.1. Study area and dataset

Yeongwol-gun was selected for analysis: Yeongwol-gun is a county in Gangwon Province, and one of several deeply distressed counties in South Korea. It has experienced severe depopulation from 58,781 people in 1992 to 37,904 people in 2021, which constitutes a decrease of more than 35% over the last three decades (KOSIS, 2022a). Yeongwol-gun conducted a field survey to manage AHs in its administrative jurisdictions in 2019. The 518 AHs identified in 2019 are used for this analysis. Yeongwol-gun also administers 714 houses as benchmark properties for tax assessments. These are selected from a group of occupied houses in the neighborhood, and are generally considered representative of houses in the neighborhood. Thus, the 714 houses were accepted as a valid control group in this study and taken to represent normal or occupied houses (OHs). In summary, the input data consisted of a total of 1,232 houses (518 AHs plus 714 OHs), and this input had two heterogeneous datasets: metadata and photographs. During the field survey by Yeongwol-gun in 2019, metadata were collected from the county's building registry and photographs were taken by field surveyors employed by Yeongwol-gun in 2019.[2] Figure 1 shows the locations of the AHs and OHs used in this study. There was no significant difference in the locations between the AHs and OHs. The OHs are densely located in the middle of the county, which corresponds to the downtown area of Yeongwol-gun.

Tables 1 and 2 present the descriptive statistics for the AHs and OHs, respectively. The median building and site areas of the AHs are 56.0 m2 and 214.0 m2, respectively. The size of AHs is significantly smaller than that of OHs: the median building and site areas of which are 87.8 m2 and 385.5 m2, respectively. The age of AHs is higher than that of OHs: the median age for AHs and OHs is 38 and 25 years, respectively. The assessed values show a more drastic difference: the median assessed value of AHs is 5,350 USD and the median assessed value of OHs is 34,480 USD, which is more than six times higher than that of AHs. Categorical variables also indicate a significant

[1] Imagery data cover a wide range of data type, including scanned documents, remotely sensed data, and photographs. In this study, the term image mainly refers to photographs of properties.

[2] Metadata are publicly available from the government website (https://www.data.go.kr/data/15044713/openapi.do), and photographs can be provided after receiving permission from the Yeongwol-gun government. Metadata includes the following attributes: house type, road condition, building frame, site area, building area (sum of each floor area), area of 1st floor, number of floors, property age, assessed value, site longitude, and site latitude. These eleven attributes were employed during the neural network training.

difference between AHs and OHs. A typical AH consists of a vehicle-inaccessible site with an irregular shape and a wooden frame building. Conversely, a representative OH comprises a vehicle-accessible site with a trapezoidal shape and a masonry construction building. Because the characteristics of AHs differ significantly from those of OHs, these attribute differences need to be vigorously considered in the identification of AHs. A total of 1,232 houses (518 plus 714 houses) were subsequently split into 985 training and 247 test samples in a random manner for the analysis.

Figure 2 shows example images of AHs and OHs in the study area. As expected, AHs are generally characterized by overgrown vegetation, damaged roofs, and crumbling exterior walls. In contrast, OHs display relatively good maintenance conditions with the roofs and exterior walls appearing neat. These visual features must also be captured efficiently and utilized for the detection of AHs.

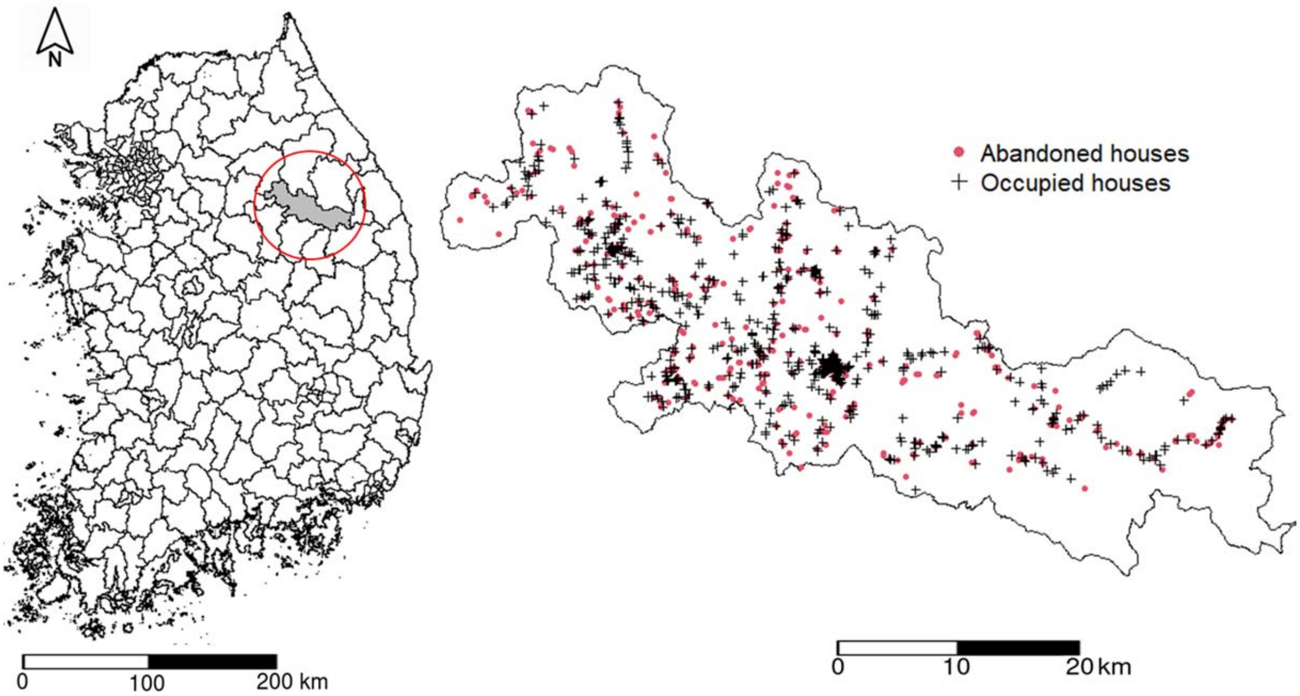

Fig. 1. Locations of AHs and OHs in Yeongwol-gun. *Source*: own study.

Table 1

Descriptive statistics of AHs (n = 518)

	Min.	Median	Mean	Max.
Building area (m^2)	6.8	56.0	66.1	1,059.2
Site area (m^2)	25.0	214.0	309.6	1,081.0
Age (year)	4	38	40	101
Assessed value (USD)	850	5,350	5,720	65,960
Road condition	Vehicle-accessible: 35 (7%), Vehicle-inaccessible: 477 (92%), No road: 6 (1%)			
Site shape	Rectangular: 11 (2%), Trapezoidal: 16 (3%), Irregular: 491 (95%)			
Building Frame	Wooden: 385 (74%), Masonry: 98 (19%), Steel: 23 (4%), Reinforced concrete: 8 (2%), other: 4 (1%)			

Source: own study.

Table 2

Descriptive statistics of OHs (n = 714)

	Min.	Median	Mean	Max.
Building area (m^2)	13.8	87.8	112.9	918.1
Site area (m^2)	48.0	385.5	416.7	1,712.0
Age (year)	2	25	30	98
Assessed value (USD)	2,200	34,480	44,320	622,360

eISSN: 2300-5289 | © 2023 The Author(s) | Article under the CC BY license

Road condition	Vehicle-accessible: 534 (75%), Vehicle-inaccessible: 180 (25%), No road: 0 (0%)
Site shape	Rectangular: 118 (17%), Trapezoidal: 438 (61%), Irregular: 158 (22%)
Building Frame	Wooden: 145 (20%), Masonry: 389 (54%), Steel: 101 (14%), Reinforced concrete: 75 (11%), other: 4 (1%)

Source: own study.

Fig. 2. Example photographs of AHs and OHs in Yeongwol-gun. *Source*: own study.

3.2. Designing a multi-input neural network

Because both metadata and imagery data need to be exploited to detect AHs, a flexible model is required to process multiple datasets jointly. A neural network is an ideal option in such a case because it offers adaptable architectures for a variety of tasks: it can receive mixed inputs such as metadata and photographs, or produce multiple heterogeneous outputs, such as classification results and supplementary sentences explaining the results. Even in a more complex problem, for example, a task required to accept multiple inputs and produce multiple outputs simultaneously, a neural network makes it easy to solve the problem through its flexible architecture, as opposed to using traditional models such as regression analysis, decision trees, and support vector machines.

To receive two heterogeneous inputs, that is, photographs and metadata, two input layers were created, one for photographs and the other for metadata. The output layer should remain a single layer because only one output (classification of houses) is produced. Intermediate dense layers were added between the input and output layers to process the intermediate outputs produced from the previous layers. In summary, a multi-input (and single-output) neural network was designed for the analysis, and Figure 3 depicts the network architecture used in this study. As shown in the figure, one branch consists of a pre-trained CNN to process photographs, and the other branch comprises a dense neural network (DNN) to process metadata, that is, building registry data. ResNet-50 is a residual network (He et al., 2016) that is 50 layers deep; it was adopted as a pre-trained CNN in this study after considering the network size, complexity, and application programming interface convenience. Two dense layers, that is, classifier layers, were added to ResNet-50 to capture information in the new image dataset of the AHs and OHs. The DNN consists of two dense layers to process building registry data. The CNN and DNN components were

eISSN: 2300-5289 | Received 2022-12-02 | Revised 2023-02-22 | Accepted 2023-02-23

concatenated, and an additional dense layer was added to the combined network to capture minor nuances in the datasets. The network is then connected to the final output layer, which classifies the house as abandoned or occupied.

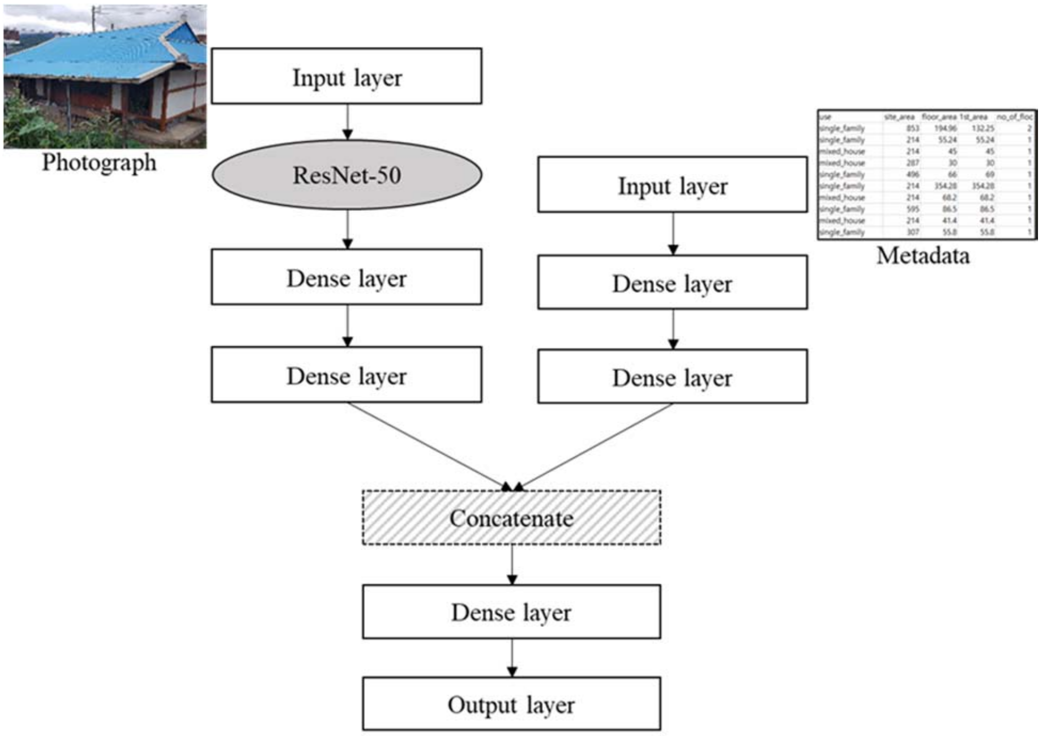

Fig. 3. Architecture of a multi-input neural network. *Source*: own study.

The implementation details are as follows: a root mean squared propagation (RMSProp) optimizer (Mukkamala & Hein, 2017) and Glorot initialization with a uniform distribution were adopted. A low learning rate of 0.0002 was used because part of the network (ResNet-50) was reused in the form of transfer learning. ResNet-50 was set to be untrainable to preserve the previously learned knowledge, and the two dense layers after ResNet-50 were set to be trainable. A rectified linear unit (ReLU) activation function was applied to all layers, except for the last output layer, in which a sigmoid activation function was used. The network was trained for 20 epochs with a batch size of 64. The cross-entropy was selected as the loss function.

4. Results

4.1. Classification accuracy

Table 3 lists the performance information of the proposed neural network. The network resulted in an overall accuracy of 86.2%. It is not easy to provide an objective reference to evaluate this accuracy level because the detection performance of AHs inevitably varies according to geography (urban or rural areas) and data quality (data type, resolution level of images,[3] amount of data). As a minimum guideline, the performance metrics from similar studies are as follows: Deng and Ma (2015) applied a logistic regression model using aerial photographs and a geographical information system and achieved an accuracy of 80.4% on the test dataset in Binghamton, New York. Zou and Wang (2021) employed a neural network by feeding Google Street View images into their model; they reported 78.7% accuracy on the test dataset in Detroit, Michigan. The multi-input neural network adopted in this study achieved better performance than in these previous studies, but a definite conclusion cannot be drawn. The two previous studies detected AHs in urban settings, whereas the current study classified AHs in rural landscapes, which warrants additional analysis.

However, from the perspective of administration in

[3] This study has no problem in photograph quality because the photographs were taken by surveyors in person, and thus the resolution level of them is quite high. In the case that satellite photographs are used, however, a blurry low-resolution photo may not allow researchers/machines to distinguish a subject building from nearby buildings.

eISSN: 2300-5289 | © 2023 The Author(s) | Article under the CC BY license

practice, an accuracy higher than 80% can be considered acceptable. The primary goal of local governments is to identify most AHs in their administrative jurisdictions in a cost-effective manner instead of detecting all AHs without exception, as missing AHs can be identified using complementary methods, such as follow-up field surveys.

Table 3

Network performance on the test dataset

Observed / Predicted	OH	AH	Sum	Accuracy
OH	137	28	165	83.0%
AH	6	76	82	92.7%
Sum	143	104	247	
Accuracy	95.8%	73.1%		**Total: 86.2%**

Source: own study.

4.2. Implications

As explained in Tables 1 and 2, the attributes of AHs are drastically different from those of OHs, making it necessary to employ additional metadata, such as building registries. When implementing a single-input neural network that is only capable of processing image data, the network achieved an overall accuracy of 75.3%. By utilizing both image and metadata, the study achieved 86.2% accuracy, which is a noticeable improvement.

Prior studies have tended to use a single data source, such as utility data or aerial photographs. Local governments also generally depend on single data sources, such as building registry data or field surveys. However, with the advancement of information technology, particularly deep learning algorithms, local governments have been enabled to obtain a variety of datasets with less difficulty and exploit them jointly in the framework of deep learning. House images can be collected from portal sites on a regular basis without any human involvement,[4] and metadata such as building registries or property tax rolls can be retrieved from the database almost instantaneously by local government officials. This changing environment can be a good starting point for local governments to exploit multiple data sources to more effectively detect AHs.

Using the approach proposed in this study, expensive field survey costs can be avoided and long update periods (generally five to ten years) can be shortened. Governments can respond to increasing numbers of AHs in a cost-effective and prompt manner, thereby enabling successful housing management.

5. Conclusions

A rural area was chosen for the analysis, and a neural network was used to identify AHs in a cost-effective manner. To enhance detection performance, multiple data sources, that is, images and building registry data, were exploited, and a two-input neural network was specified accordingly. The results demonstrated an accuracy rate of 86.2%, which is acceptable for administrative purposes.

Unlike many previous studies that have focused on urban vacancies, this study explored rural house abandonment. The results of this study are expected to help administer farming and fishing houses that remain uninhabited for several years. In addition, instead of resorting to a single-source dataset, such as building registry data, we took our analyses is one step further and fully exploited heterogeneous datasets for the effective detection of AHs.

This research needs to be expanded to other geographical settings to generalize the current study findings. The detection method proposed in the study may show different performances depending on localities, such as suburbs close to cities or remote villages in mountain districts. Rural and urban differences in the detection of AHs are also worth investigating in a future study because the different densities of house distribution and heterogeneous house types are expected to generate different challenges. Finally, this study used ResNet-50, a pre-learned network trained on ImageNet (Deng et al., 2009) that mostly involves animals and daily necessities. That is, ResNet-50 is not a CNN tailored for real estate recognition. Fortunately, an image dataset, such as the Places dataset comprising scene photographs (Zhou et al., 2018), has become available now. A network pre-learned by a visual database mainly consisting of real estate photographs should be employed in future research to further improve AH detection performance.

The foremost step in AH management is to identify AHs in a prompt and cost-effective manner. The approach proposed in this study can be applied to local administration with ease. Both house images and building registry data can be collected economically, and a neural network can be designed in a sufficiently flexible manner to adopt heterogeneous datasets. The quality database of AHs accumulated in this way is expected to facilitate housing management by local

[4] For example, representative Korean portals such as Naver and Daum provide various services including e-mail, shopping, aerial photos, and street-view photos.

governments and ultimately contribute to reducing vacancies in rural areas.

Funding Sources

This study was supported by a 2022 Research Grant from Kangwon National University.

References

Baba, H., & Hino, K. (2019). Factors and tendencies of housing abandonment: An analysis of a survey of vacant houses in Kawaguchi City. *Japan Architectural Review, 2*(3), 367–375. https://doi.org/10.1002/2475-8876.12088

Deng, C., & Ma, J. (2015). Viewing urban decay from the sky: A multi-scale analysis of residential vacancy in a shrinking US city. *Landscape and Urban Planning, 141*, 88–99. https://doi.org/10.1016/j.landurbplan.2015.05.002

Deng, J., Dong, W., Socher, R., Li, L.-J., Kai Li., & Li Fei-Fei. (2009). Imagenet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition (pp. 248-255). IEEE. https://doi.org/10.1109/CVPR.2009.5206848

Döringer, S., Uchiyama, Y., Penker, M., & Kohsaka, R. (2020). A meta-analysis of shrinking cities in Europe and Japan. Towards an integrative research agenda. *European Planning Studies, 28*(9), 1693–1712. https://doi.org/10.1080/09654313.2019.1604635

Du, M., Wang, L., Zou, S., & Shi, C. (2018). Modeling the census tract level housing vacancy rate with the Jilin1-03 satellite and other geospatial data. *Remote Sensing (Basel), 10*(12), 1920. https://doi.org/10.3390/rs10121920

Ganning, J. P., & Tighe, J. R. (2021). Moving toward a shared understanding of the US shrinking city. *Journal of Planning Education and Research, 41*(2), 188–201. https://doi.org/10.1177/0739456X18772074

Ghosh, S., Byahut, S., & Masilela, C. (2019). Metropolitan regional scale smart city approaches in a Shrinking city in the American rust belt—case of Pittsburgh, Pennsylvania. In Smart Metropolitan Regional Development, pp. 979–1021. Springer. https://doi.org/10.1007/978-981-10-8588-8_17

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, 770-778.

Kang, J., Körner, M., Wang, Y., Taubenböck, H., & Zhu, X. X. (2018). Building instance classification using street view images. *ISPRS Journal of Photogrammetry and Remote Sensing, 145*, 44–59. https://doi.org/10.1016/j.isprsjprs.2018.02.006

Kelly, J., Gross, A., & Lassar, B. (2016). *Abandoned housing strategies 101*. Vital Neighborhoods Consulting, LLC.

Kim, J. H., & Nam, J. (2016). A study on vacant house distribution and management of urban declining age. *Journal of the Korea Regional Science Association, 32*(1), 105–122.

KOSIS. (2022a). *Population and households*, Korean Statistical Information Service, https://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_1B040A3

KOSIS. (2022b). *Type and volume of vacant houses*. Korean Statistical Information Service, https://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_1JU1512

Kumagai, K., Matsuda, Y., & Ono, Y. (2016). Estimation of housing vacancy distributions: Basic Bayesian approach using utility data. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLI*, 709–713. https://doi.org/10.5194/isprs-archives-XLI-B2-709-2016

Law, S., Seresinhe, C. I., Shen, Y., & Gutierrez-Roig, M. (2020). Street-Frontage-Net: Urban image classification using deep convolutional neural networks. *International Journal of Geographical Information Science, 34*(4), 681–707. https://doi.org/10.1080/13658816.2018.1555832

Lee, C., & Park, K. H. (2020). Using photographs and metadata to estimate house prices in South Korea. Data Technologies and Applications.

Lee, J. E., & Joo, P. J. (2022). A study on changes in spatial characteristics of vacant houses in Sejong City. *Journal of the Korean Urban Management Association, 35*(1), 49–62. https://doi.org/10.36700/KRUMA.2022.3.35.1.49

Mallach, A. (2018). *The empty house next door*. Lincoln Institute of Land Policy.

Morckel, V. C. (2014). Spatial characteristics of housing abandonment. *Applied Geography (Sevenoaks, England), 48*, 8–16. https://doi.org/10.1016/j.apgeog.2014.01.001

Mukkamala, M. C., & Hein, M. (2017). Variants of rmsprop and adagrad with logarithmic regret bounds. In *International conference on machine learning*, 2545-2553. PMLR.

Oh, G. S., & Kim, G. H. (2022). An impact of local industrial structure and population movement on an increase in vacant houses. *Journal of the Korean Urban Management Association, 35*(3), 49–77. https://doi.org/10.36700/KRUMA.2022.9.35.3.49

Ortiz-Moya, F. (2015). Coping with shrinkage: Rebranding post-industrial Manchester. *Sustainable Cities and Society, 15*, 33–41. https://doi.org/10.1016/j.scs.2014.11.004

Pallagst, K. (2009). Shrinking cities in the United States of America. The Future of Shrinking Cities: Problems, Patterns and Strategies of Urban Transformation in a Global Context. University of California.

Rink, D., Haase, A., Grossmann, K., Couch, C., & Cocks, M. (2012). From long-term shrinkage to re-growth? The urban development trajectories of Liverpool and Leipzig. *Built Environment, 38*(2), 162–178. https://doi.org/10.2148/benv.38.2.162

Sakamoto, K., Iida, A., & Yokohari, M. (2017). Spatial Emerging Patterns of Vacant Land in a Japanese City Experiencing Urban Shrinkage A Case Study of Tottori City. *Urban and Regional Planning Review, 4*, 111–128. https://doi.org/10.14398/urpr.4.111

Wiechmann, T., & Pallagst, K. M. (2012). Urban shrinkage in Germany and the USA: A comparison of transformation patterns and local strategies. *International Journal of Urban and Regional Research, 36*(2), 261–280. https://doi.org/10.1111/j.1468-2427.2011.01095.x PMID:22518884

Yin, L., & Silverman, R. M. (2015). Housing abandonment and demolition: Exploring the use of micro-level and multi-year models. *ISPRS International Journal of Geo-Information, 4*(3), 1184–1200. https://doi.org/10.3390/ijgi4031184

Zhou, B., Lapedriza, A., Khosla, A., Oliva, A., & Torralba, A. (2018). Places: A 10 million image database for scene recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 40*(6), 1452–1464. https://doi.org/10.1109/TPAMI.2017.2723009 PMID:28692961

Zou, S., & Wang, L. (2020). Individual vacant house detection in very-high-resolution remote sensing images. *Annals of the Association of American Geographers, 110*(2), 449–461.

Zou, S., & Wang, L. (2021). Detecting individual abandoned houses from google street view: A hierarchical deep learning approach. *ISPRS Journal of Photogrammetry and Remote Sensing, 175*, 298–310. https://doi.org/10.1016/j.isprsjprs.2021.03.020

eISSN: 2300-5289 | © 2023 The Author(s) | Article under the CC BY license