東京都大田区における空家の特徴に関する基礎的分析

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Basic Analysis of Characteristics of Vacant Houses in Ota Ward, Tokyo

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With the number of vacant houses increasing nationwide, municipalities need to understand the characteristics of vacant houses with particular problems to take effective measures. As a part of collaborative research with Ota Ward, Tokyo, we analyzed the characteristics of vacant houses with various problems based on Ota Ward's vacant houses database. First, we used random forest regression analysis to clarify the influence of various geographic attributes on the vacant house density in each area. Then we used LIFULL HOME'S dataset as a control group and analyzed the characteristics of facade images of individual vacant houses by using VGG16 and Grad-CAM visualization. In this way, we found some fundamental features that can help detect potential vacant houses.

Keywords: 空家 (vacant house), 地域特性 (regional characteristics), 物件属性 (property Attributes), ランダムフォレスト (random forest), コンピュータビジョン (computer vision)

1. Introduction

1.1. Background

Vacant houses increasing in Japan are likely to cause damage to the surrounding neighborhood by collapsing and falling, which increase the fire risk, and hurt the living environment. Local municipalities have carried out plans to promote comprehensive measures against vacant houses and ensure a safe and secure living environment. For example, the improvement plan carried out by Ota Ward has emphasized managing proper management and a series of renovations and autonomous disintegration (Ota Ward Vacant Housing Promotion Plan, 2016). The dataset of vacant houses Ota Ward currently collates includes reports of building conditions from concerning residents, as well as images of buildings and geographical locations collected manually by the municipality.

The public data is not fully utilized despite its richness. By exploring ways to make effective use of these data, a less labor-intensive method of identifying vacant houses is expected.

1.2. Literature Review

Many existing studies focus on the correlation between vacant house distribution and geographic attributes. Nishiura et al. (2017) used the population elderly rate and steepness to predict the rate of vacant houses, and Kitajima et al. (2019) researched on correlation between vacant houses occurence and road average width, the distance to the nearest railway station, and areas zoned for use. Despite the abundance of data, the public data previous studies have used are limited.

Other studies have focused on the impact of building attributes on the occurrence of vacant houses. Akiyama et al. (2019) used building registration information in Kagoshima City to construct a model for predicting vacant houses at individual building level.

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Kagoshima city provides extremely detailed information on buildings contributed to high accuracy in prediction, however the researcher has taken little account of geography in their study.

The development of convolutional neural networks has helped in identifying facade features of vacant houses. Fujii et al. (2022) applied deep metric learning and transfer learning to specified vacant houses（特定空家）and get a classification accuracy of 99.6% using VGG16. Specified vacant houses refer to those severely damaged and seriously affect the surrounding landscape, no previous studies have focused on identifying exterior features of general vacant houses.

Geographic attributes, building attributes and building facade images are publicly available, but in previous vacant housing researched few have effectively combined them for vacant house prediction.

Using data provided by the municipalities and national public data to explore vacant housing characteristics from these three aspects together, a more accurate identification of vacant houses is expected.

1.3. Research Objective

This study aims to identify vacant houses in Ota Ward from geographic attributes, building attributes, and building images, find patterns in the distribution of vacant houses, and the appearance characteristics of individual vacant buildings.

2. Methodology

2.1. Pre-processing of data given by Ota Ward

There are estimated 48,450 vacant houses in Ota Ward (Ministry of Internal Affairs and Communications, 2018), while the vacant housing point data collected by Ota Ward Architectural Adjustment Section based on residents' reports totaled 724 houses in 2021, Fig 1 demonstrates their geographic distribution. As shown in Fig 2, Ota Ward has provided the following information in the framework of a joint research project: (1) the geographical location of the each registered vacant houses with building attributes(built years, structure, building area), (2) separate excel files of each vacant house including building images. The above information does not include the building owner's personal data.

For (1) the geographical location information, we did geocoding for each vacant house with Google Maps API. Then we adjusted vacant house points' location in ArcGIS pro to ensure they fell within the right building of the Building Condition Survey of Tokyo Metropolitan Government Urban Planning GIS data. Building

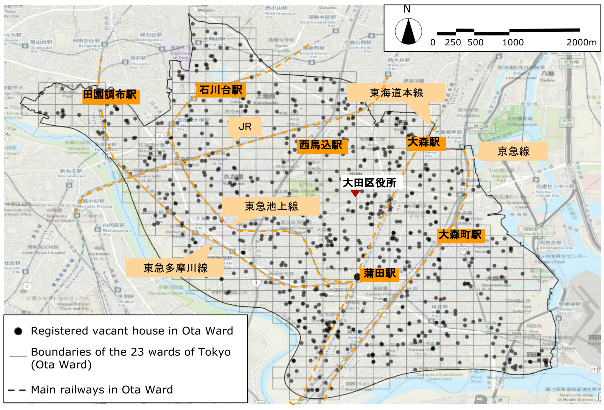

Fig 1 Geographical Distribution of registered vacant houses in Ota Ward

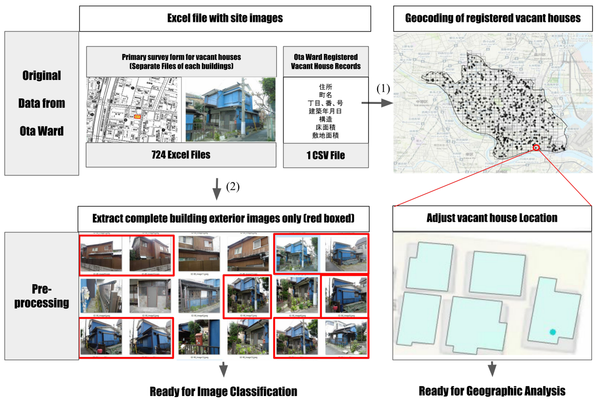

Fig 2 Processing of data given by Ota Ward

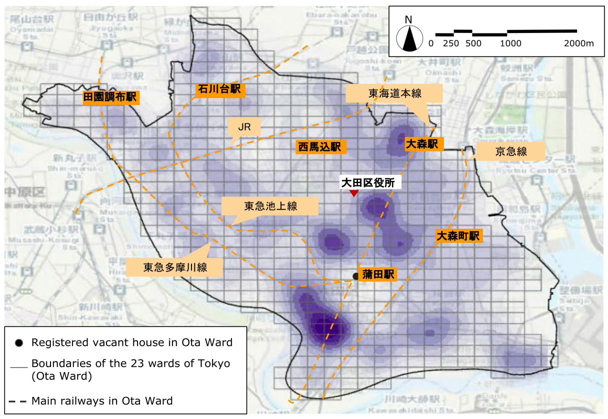

Fig 3 Kernel Density of vacant houses in Ota Ward

Condition Survey of Tokyo Metropolitan Government Urban Planning GIS data in 2016 has attributes of building usage and stucture hazard level, through spatial join, we added these attributes to the vacant house points.

Due to the small ratio the registered vacant houses take up in actual vacant houses numbers (approx. 1.5%), Kernel density map of vacant houses in Ota Ward is generated based on the point data of vacant houses (Fig 3).

For (2) separate excel files of each individual vacant houses, we extracted all building images into one folder. The photos that don't cover the whole building, taken too far from the building are manually deleted from the images dataset for vacant house identification. 4,216 exterior images of the whole building were extracted.

In this way, we have set up the geocoding map data and building exterior images of registered vacant houses in Ota Ward.

2.2. Data collection of geographical attributes

With reference to the selection of geographical characteristics of what can lead to the occurence of vacan houses in the relevant literature, we collected data in four broad categories: population, regional facilities, regional hazard level, and regional building characteristics.

Based on the smallest area unit of national census data, we divided Ota ward into 250m grids. As shown in Fig.3, each grid is given the collected potential influencing geographic attributes. For catalog population and hazard level, we get the data of each grid directly from Ministry of Internal Affairs and Communications (MIAC) and Ministry of Land, Infrastructure, Transport and Tourism (MLIT); for catalog regional facilities and regional building attributes, we calculated and summarized the GIS data of each attribute in each 250m grid by spatial join.

2.3. Vacant house density estimation model

To explore the relationship between geographic characteristics and the distribution of vacant houses, We used random forest for regression analysis. The kernel density values of vacant houses in each 250m grid are used as the dependent variable, and the various types of geographic data in Table 1 are used as independent variables. Based on the best combination of parameters from the GridSearchCV simulation, we set the number of estimators to 300, and the max depth to 6. Test data took up 30% of all 556 grids.

Table 1 Geographic Attributes of Ota Ward

Catalog	Content	Data source	Data type	Year
Population	Population size	Ministry of Internal Affairs and Communications	▲	2010, 2015
	Population growth			
	Elderly rate			
Regional facilities	Middle schools	Ministry of Land, Infrastructure, Transport and Tourism		2015
	Healthcare facilities			2015
	Bus stops			2010
	Railway stations			2020
Hazard level	Overall hazard level	Ministry of Internal Affairs and Communications	▲	2015
	Fire hazard level			
	Building collapse hazard level			
	elevation	Ministry of Land, Infrastructure, Transport and Tourism		2009
	Degree of slope			
	Landslide Hazard Risk Level			2020
	Assumed storm surge inundation area			2020
	Ratio of Wood building area	Tokyo Metropolitan Government Building Status		2016
Regional Building Attributes	Count of Buildings			
	Average building area			
	Average Total Floor Area			
	Densely populated wood-frame housing area	Tokyo Metropolitan Government Disaster-Resistant City Development Promotion Plan(H28)		2016
	area zoned for use	Ministry of Land, Infrastructure, Transport and Tourism		2019
	Overall road length	Zmap Town Ⅱ by zenrin Corporation		2018
	Road width			

Note: "▲"in Data type represents that open sources provide the data information of the potential influencing factor in each 250m grid, they only require join field with each 250m mesh; " " in Data type represents that the factor is distributed in overall Ota ward, the number of each 250m mesh needs to be calculated by spatial join.

Table 2 Parameters used in transfer learning

Parameters	Data
Batch Size	4
Epoches	50
Learning Rate	0.0002
Optimization function	SGD

2.4. Models for determining vacant buildings using

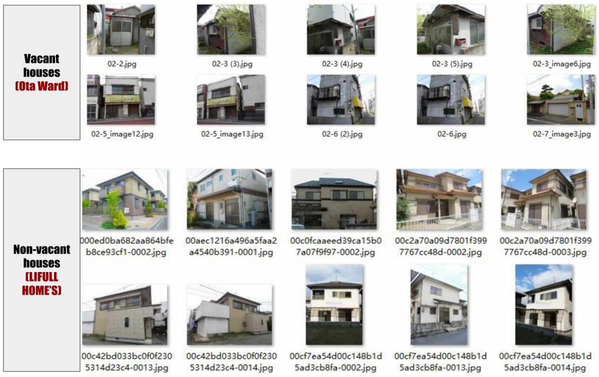

Fig 4 Image dataset for vacant house identification

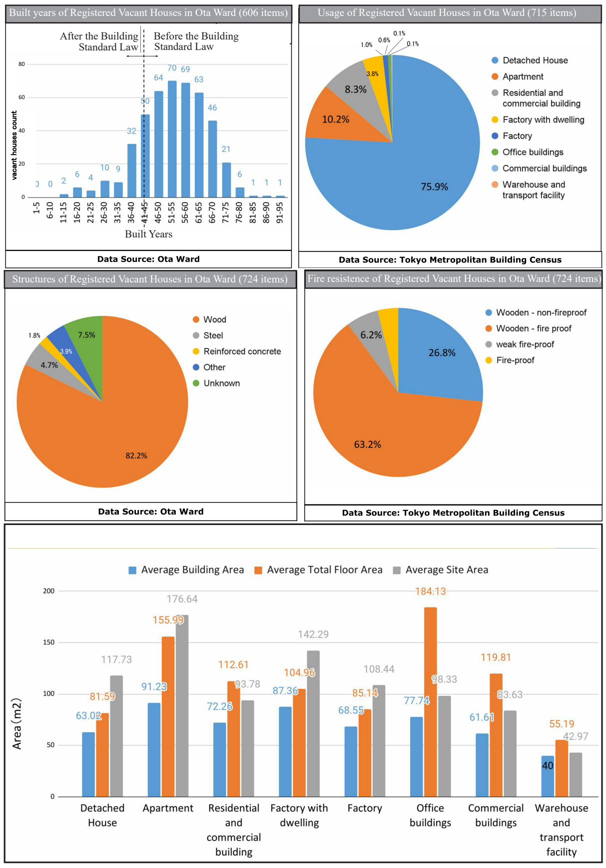

Fig 5 Building attributes of registered vacant houses in Ota Ward

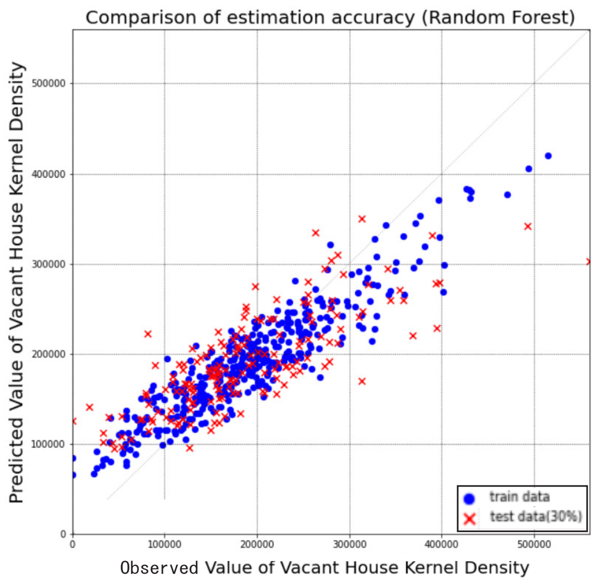

Fig 6 Relationship between estimated value and observed value of vacant house kernel density in each 250m grid

building facade images

We conducted transfer learning using VGG16 backbone (Simonyan, 2015). The number of classes of last output layer was set to 2. Parameters in our learning model are listed in Table 2.

To confirm whether the model was looking for different building characteristics in both classes during identification or not, we used Grad-CAM to visualize the prediction result.

Corresponding to building exterior images given by Ota Ward, we need to prepare some non-vacant house images for image classification. The National Institute of Informatics provides LIFULL HOME'S Dataset to researchers, which was offered by LIFULL Co., Ltd. for promoting research in informatics and the related fields. As a part of the data LIFULL HOME'S provided, Snapshot Data of Rentals updated in September 2015 contains rental house information published online such as on-site pictures, their location, size and use.

For the control group of vacant houses, we tried to minimize the effect of irrelevant variables on the experimental results. We only selected detached houses from LIFULL HOME'S in Tokyo, and compressed the vacant house images to the same resolution, format and size as the LIFULL HOME'S images to ensure the machine learning with a similar amount of information about the images in the two categories obtained.

3. Results

3.1. Building attributes of vacant houses

Based on the building attributes provided by Ota

Ward and Tokyo Metropolitan Government Building status, we summarized the building attributes of vacant houses in Ota Ward in 2021, as shown in Fig 5.

Among the registered vacant houses in Ota Ward, over 85% are built before the building Standards Law. 79.5% of the buildings are detached houses, and over 90% are of residential usage. As for the building structure, 82% of the vacant houses are of wooden structure, and only 10.1% of the vacant houses are fire-resistant buildings.

3.2. Geographical analysis results

3.2.1. Prediction Result of 250m grids in Ota Ward

Through the random forest model, we compared the estimated value and the observed value of vacant house kernel density in each 250m grid. As showed in Fig 6, the test dataset has the prediction accuracy has reached 80.3% for training data and 58.5% for test data.

3.2.2. Variance Importances of geographic indexes

Variable importances of each geographical attribute obtained from the above random forest model are shown in Fig 7, which suggests how much influence one attribute has on the distribution of vacant houses.

As shown in Fig 7, there are 5 geographical attributes with variable importance above 5%: the count of all buildings (10.45%), the area of densely populated wood-built residential areas (10.19%), overall hazard level (7.50%), fire hazard level (7.33%) and building collapse hazard level (5.35%). Each attribute from above is related to the building density of one area thus has High correlation with one another.

Among the top 10 attributes that contribute most to the distribution of vacant houses, 4 are from the catalog of Hazard level and 6 are from the catalog of regional building attributes. These two catalogs also have greater average variable importance value (2.37%, 2.37%) than catalog of population (1.52%) and Regional facilities (1.51%).

3.3. Evaluation of vacant house identification model

Through transfer learning with VGG16, we obtained a vacant house identification model with an accuracy of 98.1%. As shown in Fig 8, out of 862 vacant house

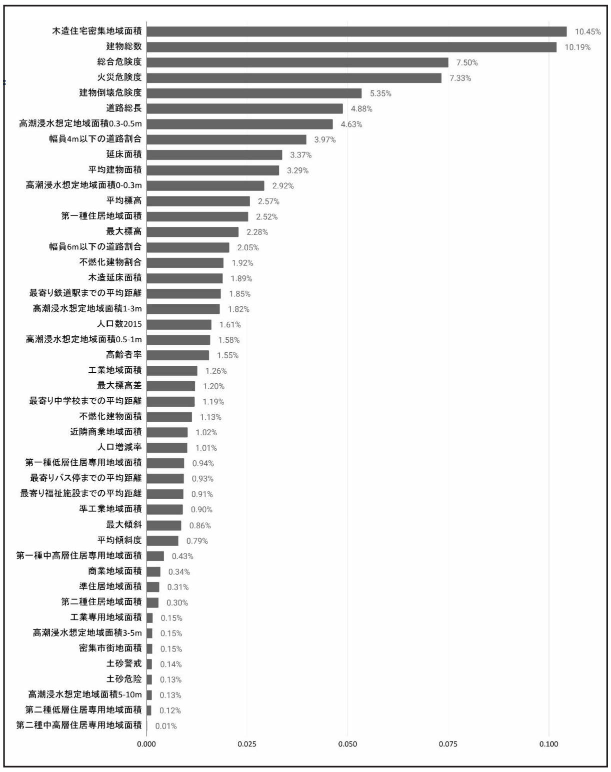

Fig 7 Variable Importance of geographic indexes

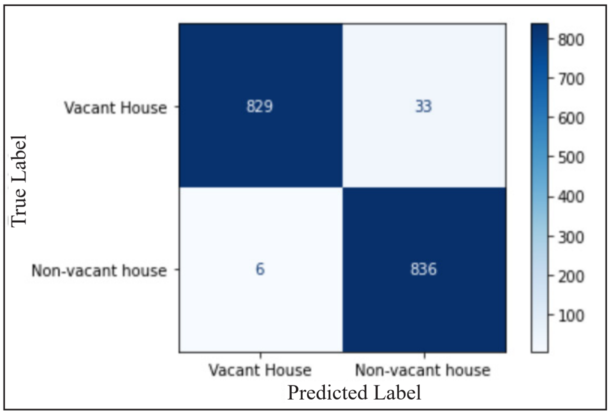

Fig 8 Confusion matrix for test data using vacant house identification model

Fig 9 Grad-CAM attention in building opening parts

images and 842 non-vacant house images, only 33 vacant house images and 6 non-vacant house images were predicted to the wrong class.

We visualized the images with the correct prediction results using layer block5_conv3 in VGG16, examples of visualization by Grad-CAM are shown from Fig 9 to Fig 13.

Images in the two categories are both getting high attention for building opening parts such as doors, windows, and balconies in their visualization results (Fig 9). Most of the predictions focused on one or more building opening parts. Some predictions focused on the condition of the entire wall, as shown in the Fig 10, with flat walls in non-vacant houses and walls covered with greenery in vacant houses receiving similarly high levels of attention.

In vacant house images, large areas of greenery around the house (Fig 11) or collapsed and damaged structures (Fig 12) received high attention.

Finally, the structural relationship between the roof and the body of the house received high attention in a few predictions (Fig 13), the exact discriminatory mechanism remains to be confirmed.

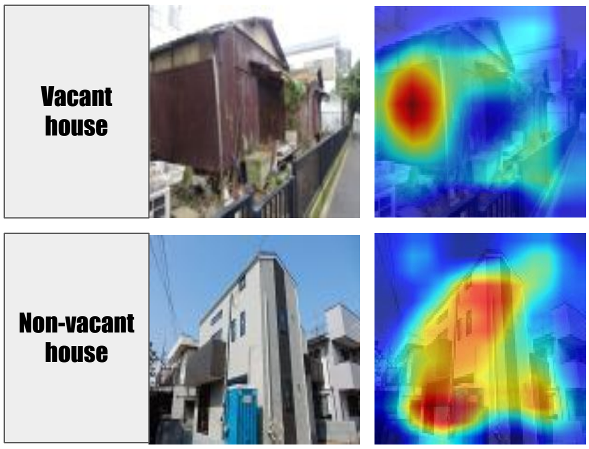

Fig 10 Grad-CAM attention on the entire wall

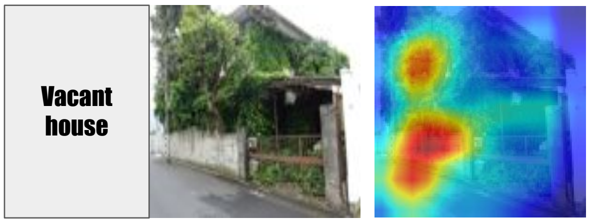

Fig 11 Grad-CAM attention on the greenary

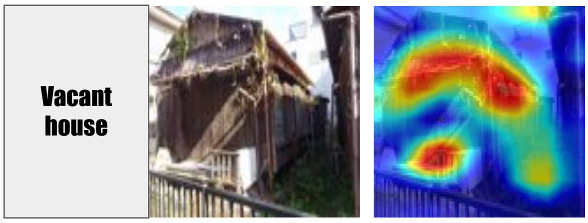

Fig 12 Grad-CAM attention on damaged structures

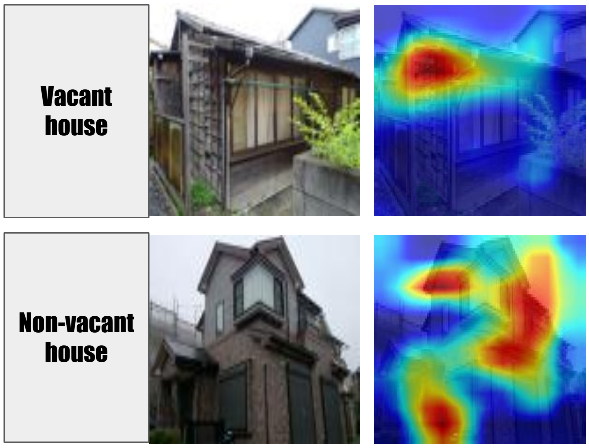

Fig 13 Grad-CAM attention on structures of the building

4. Conclusion

In this paper, we first conducted the geographical analysis to find the correlation between geographic attributes and distribution of vacant houses in Ota ward, As shown in the result, the influence each geographic attribute has on the distribution of vacant houses in Ota Ward can be quantified.

Next we conducted Image classification to find the appearance characteristics of individual vacant buildings. By using building facade images from Ota Ward and LIFULL HOME'S dataset, we obtained an identification model with a considerable accuracy, and acquired some hints on what distinguish vacant houses from non-vacant houses by Grad-CAM visualization.

In the future, we will focus on the prediction of each individual building, using this study as a basis for a new prediction model with valid geographic characteristics and image feature information for each building.

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