EXTRACTION OF STORY-COLLAPSED BUILDINGS BY THE 2016 KUMAMOTO EARTHQUAKE USING DEEP LEARNING

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Abstract

This study addresses building collapse in Mashiki Town, Kumamoto Prefecture, due to the 2016 Kumamoto Earthquake. In the 1995 Kobe Earthquake, many lives were lost due to the collapse of buildings. In order to reduce human casualties, it is important to accurately estimate the collapse or severe damage and to promote countermeasures to prevent especially story-collapse of buildings. However, there are not enough studies on the development of fragility functions to estimate story-collapse. In this study, we developed a method for identifying story-collapsed buildings using deep learning models (CNN) from a large number of photographic images taken during the damage investigation by Mashiki Town government and created a set of data necessary for developing fragility function.

In Mashiki Town, the field investigation was carried out by the local government to issue disaster-victim certificates. This investigation was conducted in accordance with the guideline of the unified loss evaluation method issued by the Cabinet Office of Japan using the support system for livelihood rebuilding of disaster victims. This system also recorded photographic images of damaged buildings taken by investigators.

In this paper, firstly, two building experts visually classified some external images of buildings to identify story-collapsed buildings. The story-collapse is defined as Damage Grade D5 using a damage pattern chart. Secondly, using the set of images classified by the experts as an analysis data, a “story-collapse classification model” using CNN was developed that can classify external images as story-collapsed with high accuracy. In addition, an “external appearance classification model” was developed to remove unnecessary images except for external appearance such as interior of buildings using another CNN with separately created data. Thirdly, images of the remaining investigated buildings that were not visually classified by the experts were mechanically classified using these two models. Finally, processing confirmation of images by visual observation, we have developed a method for accurately distinguishing story-collapsed buildings from all the investigated buildings in Mashiki Town. Also, a dataset of story-collapsed buildings was created by combining with the building location information, and their spatial distribution was visualized.

It was confirmed that the developed extraction method can be implemented in a very short time, and the number of visual confirmation processes can be greatly reduced. In the future, a fragility function for story-collapsed buildings will be developed using this dataset.

Keywords: Story-collapsed building, Photographs of damaged buildings, CNN, the 2016 Kumamoto Earthquake

1. Introduction

This paper describes the results of an investigation concerning the damage caused by the 2016 Kumamoto earthquake on story-collapsed buildings in Mashiki Town, Kumamoto Prefecture, Japan. Out of the 50 people who lost their lives as a direct cause of the 2016 Kumamoto earthquake, 38 died under collapsed houses or tumbled furniture; among them, 33 died due to the complete or partial collapse of their homes (i.e., in which the entire floor collapsed) [1].

In order to minimize casualties, it is important to accurately identify buildings at high risk of typical collapses (i.e., story-collapse damages) and promote countermeasures to prevent their collapses. Story-collapse damages can be evaluated by determining a fragility function, which can be derived from the relationship between the seismic motion and building damage. A story-collapse fragility function was proposed after the 1995 Kobe earthquake [2]; however, not many disasters involving story-collapse damage have occurred since the Kobe earthquake and new functions have not been developed further in Japan.

During the 2016 Kumamoto earthquake, Mashiki Town was suffered from two earthquakes (both of Level 7 on the Japanese seismic intensity scale) that caused a large amount of damage to buildings and directly caused the deaths of 20 people. The authors of this paper have already published reports on the building damage that occurred within Mashiki Town and presented fragility functions based on those data [3]. Those documents, however, did not contain the information on story-collapse. The photographs of damage situation can effectively be used to identify story-collapsed buildings and develop appropriate fragility functions [4]. The local government of Mashiki Town conducted a field investigation, during which it gathered a large number of images. Deep learning has been reported as an effective method for the mechanical categorization of large numbers of images, even in the case of photographs depicting building damage [5, 6].

In this study, we applied a deep-learning convolutional neural network (CNN) to identify story-collapsed buildings from a large number of photographic images captured during the investigation by the Mashiki Town government; then, we created a dataset of story-collapsed buildings in order to develop a fragility function. Fig.1 shows the process followed to extract the story-collapsed buildings.

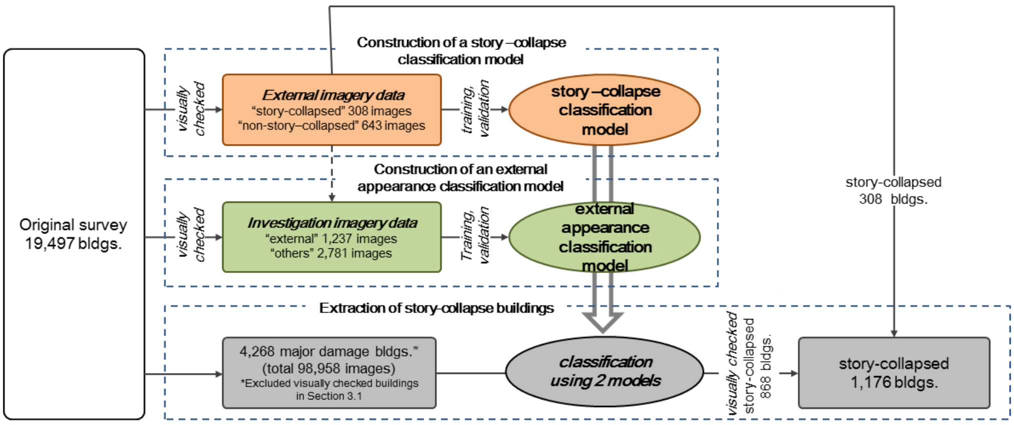


Fig. 1 – Process followed to extract the story-collapsed buildings

2. Data

A series of field investigations were conducted by the local government in Mashiki Town, Kumamoto Prefecture, in order to collect data for the issue of disaster-victim certificates. The support system for livelihood rebuilding of disaster victims [7] was applied to conduct this investigation, according to the "Operational guideline for damage assessment of residential buildings in disasters" (issued by the Cabinet Office of Japan) [8]: each building was assigned to a damage class shown in Table 1 (i.e., major damage, moderate+ damage, moderate- damage, minor damage, or no damage). If a building was classified as major damage, the type of collapse (i.e., story-collapsed or not) was further determined by each investigator. The photographs taken by each investigator and the location information (i.e., longitude and latitude) relative to the damaged buildings were also recorded.

This study was based on data collected through 19,497 survey sheets, which were conducted between April 30 and October 24, 2016. These data include: the investigation number, the damage class, information on the type of collapse (i.e., story-collapsed or not), photographic images, and location information, by each investigation.

3. Construction of a Story-collapse Classification Model

Two experts visually checked the external images of some buildings to whether they suffered from story-collapse or not. The external images which were judged similarly by the experts were used to train and validate the CNN; then, a "story-collapse classification model" was built to classify all the external images as either "story-collapsed" or "non-story-collapsed." Notably, the external images discussed here included also rubble or vacant lots that appeared after the removal of damaged buildings.

3.1 Extraction of the external imagery data

Of the original 19,497 survey sheets, we extracted 1,000: 500 out of the 1,243 sheets during which the occurrence of story-collapse was verified by each investigator, and 500 out of the 18,254 sheets during which the occurrence of story-collapse was not verified by the investigators. This extraction performed randomly, and a stratified sample was taken from the investigations in which investigators did not determine whether story-collapse occurred or not, in order to maintain the ratio of each damage class. Then, a single external image was visually extracted for each surveyed building, for a total of 1,000.

Two experts visually checked these 1,000 external images in order to determine the eventual occurrence of story-collapse: a chart by Okada and Takai [9] was used to define the damage grade caused by the story-collapses (i.e., Damage Grade D5), shown in Table 1. Table 2 provides a breakdown of the data obtained from 951 external images (those judged in the same way by the two experts). The remaining 49 images represented cases in which story-collapse could not be determined: the two experts reached different conclusions or were both unable to identify whether story-collapse occurred. Images for which the experts provided contrasting results included those in which it was difficult to determine the collapse of a given building story, and cases where it was difficult to determine whether an image depicted a site after a damaged building had been removed.

Table 1 – Earthquake loss evaluation classes of buildings by local governments in Japan and schematic images of other damage classification methods (Source: Yamazaki et al. [3])

Current Damage (Loss) Class	Former Damage (Loss) Class	Loss Ratio (r), Damage Index	EMS-98	Okada & Takai (2000)
Major	Major	$r \geq 60\%$	G4  G5 	D4  D5 
		$50\% \leq r < 60\%$	G3 	D3 
Moderate +	Moderate	$40\% \leq r < 50\%$		
Moderate –		$20\% \leq r < 40\%$	G2 	D2 
Minor	Minor	$0\% < r < 20\%$	G1 	D1 
No	No	$r = 0\%$	(G0)	D0

story-collapse
=D5

Table 2 – Number of images visually inspected for story-collapse in external imagery data

		visually checked by experts		Total
		story-collapsed	non-story-collapsed	
type of collapse by investigator	story-collapsed	299	165	464
	non-story-collapsed	9	478	487
Total		308	643	951

3.2 CNN structure, training, and validation

The external imagery data (951 images) built in Section 3.1 were used as an analysis data to train and validate the CNN; then, we built a model to accurately classify the external images into two classes (i.e., "story-collapsed" and "non-story-collapsed"). These operations were conducted based on a Python deep learning library called Keras [14] and using TensorFlow as backend.

In building the model, transfer learning was performed by fine-tuning the trained CNN. This use of fine-tuning has been reported to build classification models that are more accurate than approaches that do not use a trained CNN, or that use a trained CNN simply as a feature extractor [10]. After exploring several CNNs, model structures, and training methods, we decided to use ResNet50 [13] trained with ImageNet [11, 12] as our trained CNN. In order to perform fine-tuning, we used global average pooling to create a fully connected layer and a softmax function to create an output layer (used to classify images as either "story-collapsed" or "non-story-collapsed"). And we deleted existing fully connected layer and output layer, and bound them to newly created layers. The structure of the resulting CNN is shown in Fig.2.

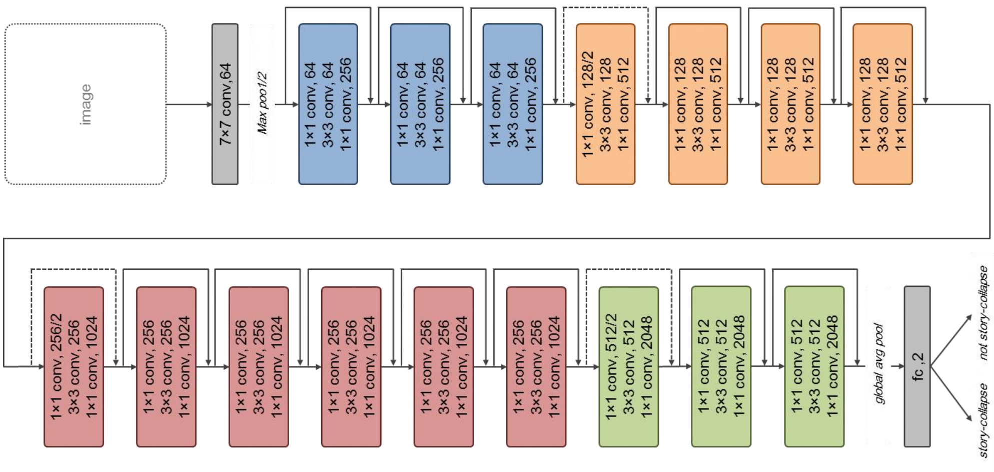
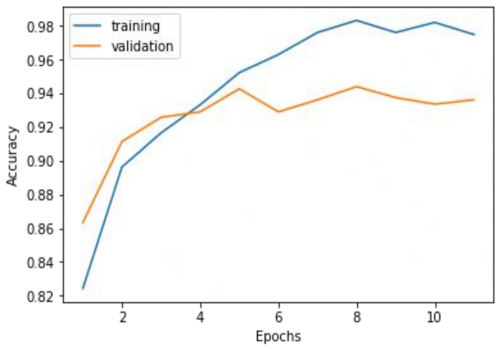


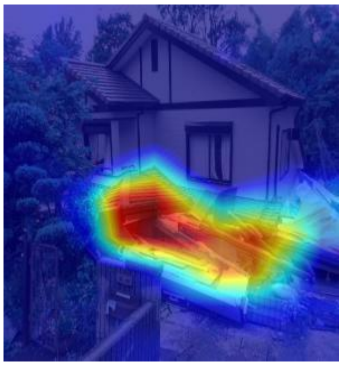
Fig. 2 – Structure of the CNN

The analysis data were split at a 9:1 ratio: 855 pieces of training data and 96 pieces of validation data. In splitting the data, the class ratio between "story-collapsed" and "non-story-collapsed" was retained by employing a stratified splitting method. Fig.3(a) shows the results of the model training. Notably, the weights were updated in all CNN layers during the model training. We conducted an augmentation process during the data training and searched for hyper parameters to increase its accuracy. The blue and orange lines show the accuracy obtained when the training data and validation data were used as input data, respectively. We confirmed that the lines converged within 11 epochs, so we stopped training and then used the CNN with that weight set as our story-collapse classification model. We then used this story-collapse classification model to predict classification classes for validation data, and got an accuracy of approximately 94%.

Grad-CAM [15] is widely used to visualize areas that could serve as a basis for CNN to determine classifications. Fig.3(b) shows an example of the use of Grad-CAM to overlay a heat map over an image classified by the story-collapse classification model as depicting story-collapse. The area highlighting a collapsed story is thought to be a basis for the classification.



(a) Changes in the accuracy of the model during the training process



(b) Example of visualization obtained using Grad-CAM

Fig. 3 – Training and validation of the story-collapse classification model

4. Construction of an External Appearance Classification Model

Our story-collapse classification model was able to accurately classify the images as depicting “story-collapsed” or “non-story-collapsed” buildings. However, many photographic images taken by the investigators did not depict the outside of buildings, but rather internal views of buildings and other elements. Therefore, we decided to build a separate model to extract only the external images. First, we visually checked the photographic images of some buildings to determine whether they represented external images or not; then, we used them to train and validate the CNN. Finally, we built an "external appearance classification model" to classify the photographic images as either "external" or "others".

4.1 Extraction of the investigation imagery data

Of the 19,497 surveyed buildings, we randomly extracted 100 buildings which were found to be major damage. Survey data that were extracted in Section 3.1 were excluded, along with those in which it could not be determined whether buildings suffered story-collapse or not. The 3,067 images of the extracted surveys were visually checked by an expert, who then separated them between “external” (286) and “others” (2,781). A total of 4,018 images (including 951 external image data mentioned in Section 3.1) were hence used as investigation image data for further analyses. Table 3 shows a breakdown of the data.

Table 3 – Number of images visually examined and categorized as “external” or “others” in investigation imagery data

	visually checked by experts		Total
	external	others	
Judged by investigator as major damage	286	2,781	3,067
External imagery data in Section 3.1	951	0	951
Total	1,237	2,781	4,018

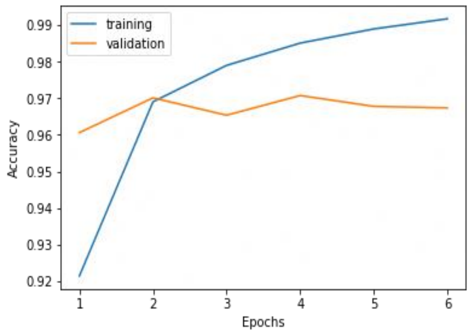
4.2 CNN structure, training, and validation

We used the investigation imagery data (a total of 4,018 images) presented in Section 4.1 to train and validate the CNN, and then built a model to classify each image (as "external" or "others"). As described in

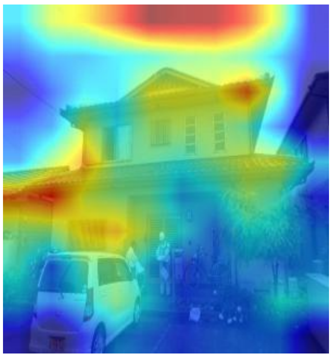
Section 3.2, we used ResNet50 trained with ImageNet as the CNN and performed a transfer learning through fine-tuning. We created a new fully connected layer and an output layer, and then built the CNN (see its structure in Fig.2).

The analysis data were split at a 9:1 ratio (between 3,616 pieces of training data and 402 pieces of validation data). In splitting the data, a stratified splitting method was employed so to retain the desired class ratio between the two classes of images "external" and "others". Fig.4(a) shows the results of using those data to train the model. For the model training, we followed three steps similar to those described in Section 3.2: 1) we updated the weights in all the CNN's layers, 2) we applied an augmentation process to the training data, and 3) we searched for hyper parameters that could increase the accuracy of the model. The blue and orange lines in Fig.5(a) show, respectively, the accuracy obtained when the training and validation data were used as input data. The line of validation data, which is the orange line, converged within six epochs; after that, we stopped the training and used the CNN with the correspondent weight set as our external appearance classification model. This model was then used to predict the classes of the validation data, reaching an accuracy of ~ 97%.

Similarly as shown in Section 3.2, Grad-CAM was applied to visualize areas (i.e., sky or showing the entire external appearance of a building) that could serve as a basis for CNN to classify the images (Fig.4(b)).



(a) Changes in the accuracy of the model during the training process



(b) Example of visualization obtained using Grad-CAM

Fig. 4 – Training and validation of the external appearance classification model

5. Extraction of Story-collapse Buildings

Story-collapsed buildings were extracted from investigations in which the investigator determined that the building was major damage, and the experts did not visually identify whether story-collapse occurred or not in Section 3.1. This final extraction was made using the two models described in Sections 3 and 4, followed by a visual inspection performed by an expert. Survey data including damage classes other than "major damage" were excluded from extraction, since they likely did not include story-collapsed buildings. In fact, the images in which buildings were classified as "moderate+ damage," "moderate- damage," "minor damage," or "no damage" were not included in the images visually identified story-collapse by experts in Section 3.1.

5.1 Construction of the classification method

The story-collapse and external appearance classification models were hence used to mechanically classify 98,958 photographic images (obtained from the 4,268 surveyed buildings) in which the buildings were determined to be major damage. Subsequently, we extracted 1,365 buildings in which at least one image was classified as depicting the state of a story-collapse. Additionally, we extracted 113 survey data that did not include any external images (as determined by the external appearance classification model). An expert visually examined the photographic images of all these surveys (a total of 1,478) and extracted 868 story-collapsed buildings.

The model-based image extraction and classification were both performed by computer. This allowed a particularly quick extraction of photographic images for visual confirmation, from a large amount of original data collected in the field investigations.

The 868 buildings extracted as explained above were combined with other 308 buildings (story-collapsed buildings extracted from the 308 images in the external imagery dataset; see Section 3.1), for a total of 1,176 buildings.

5.2 Validation of the classification accuracy

We attached the longitude and latitude representing the location information of each investigation site based on the investigation number to these 1,176 buildings, and created a final dataset of story-collapsed buildings. Fig.5 shows the spatial distribution of the survey sites: red points, that show our dataset, were concentrated in the areas where collapsed, crumbled, and crushed buildings were also concentrated in the previous reports [16, 17].

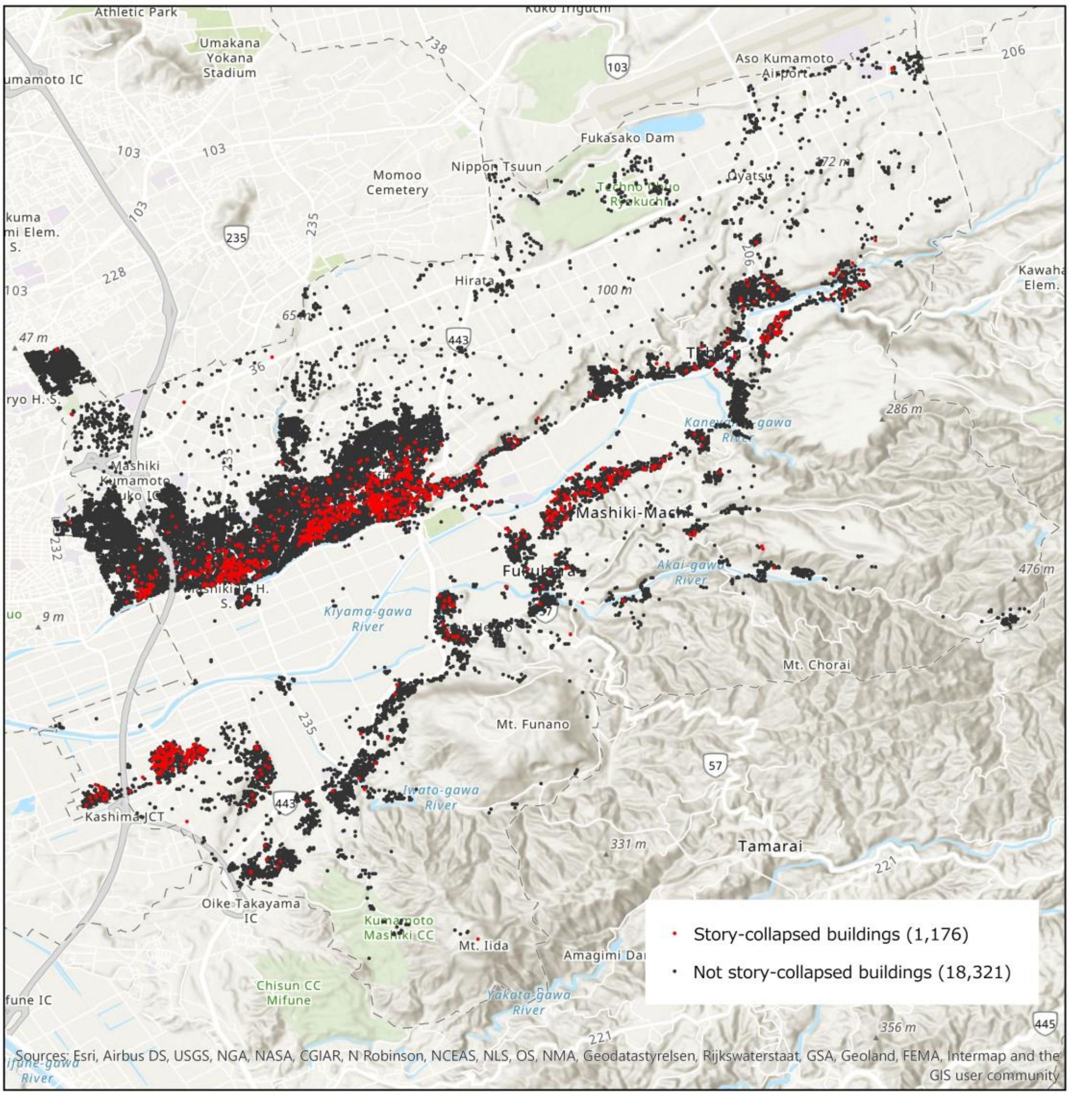


Fig. 5 – Spatial distribution of the extracted story-collapsed buildings

6. Conclusion

In this study, we developed models applying a CNN and trained them using photographic images collected during local government investigations. In this way, we successfully developed a method for the accurate identification of story-collapsed buildings in Mashiki Town. The proposed identification method can be implemented quickly, reducing significantly the amount of time dedicated to visually inspecting photographs of damaged buildings. Interestingly, the data points corresponding to story-collapsed buildings were concentrated in the areas that suffered particularly heavy damage, demonstrating the accuracy of our extraction method. In the future, we plan to use the obtained dataset to build a story-collapse fragility function.

7. Acknowledgements

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9. References

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