Unleashing the Power of Multi-Source Data for Building Attribute Prediction Based on Deep Learning in Flood Risk Assessment

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ABSTRACT

Knowledge of a structure's physical attributes is critical for analyzing the risks associated with natural disasters such as floods and hurricanes. However, collecting these data over a wide geographical area is a difficult task because it often requires manual labor. Even in Louisiana, which is at considerable risk for flood-related natural disasters, the state government has sparse structure level data about the composition of building type, number of stories, foundation type, foundation height, presence of a basement, and presence of a garage, all of which are significant predictors of flood risk in many flood risk assessment methods. In this study, an automated model is proposed to predict these six attributes by utilizing a data fusion-based methodology. The model extracts feature from a building's Google Street View (GSV) image through a Convolutional Neural Network (CNN) architecture. Likewise, an Artificial Neural Network (ANN) architecture is employed to extract features from community data taken at the census-block-group level. Another ANN is used to extract features from structure-level data obtained through a real estate database. These three feature streams are then fused and processed with a fusion module to predict a building's attributes needed for flood risk assessment. Through this technique, accuracies close to or surpassing 90% are achieved on all five classification tasks. Likewise, the Mean Absolute Error (MAE) for foundation height estimation is small enough to make usable improvements to flood risk estimates over existing data sources and modeling assumptions. Although CNN and ANN models are used in this study, the basic framework can be applied with other machine learning models as well, if features can be extracted from them. Likewise, all the experiments are performed in the context of flood risk assessment in Louisiana. However, the framework can be easily extended to other natural disasters and geographical regions.

INTRODUCTION

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Assessing the resilience of a structure against flood damage entails first surveying its physical attributes – such as foundation type, foundation height, number of stories, building type, presence of basement, and presence of garage – which are then used as parameters in flood risk assessment models. However, manual survey of structural attributes can be tedious, resource intensive, and prone to human error. Recently, some researchers have turned to Artificial Intelligence based methods to automate manual surveys. Almost all these techniques use images or image-related data, either taken at the street level [1, 2] or from satellites [3, 4]. Techniques such as [5] attempt to directly predict vulnerability by combining the two imagery sources. There has also been an effort [2] to incorporate additional information such as the images' metadata to improve performance beyond what would otherwise be possible using images alone, but the additional information is still the property of the images themselves.

In this study, we go beyond images to predict six building attributes necessary for flood risk assessment – foundation type, foundation height, building type, number of stories, presence of basement, presence of garage. Our starting hypothesis is that images are important but insufficient for structural attribute estimation, and that other kinds of data about the structure and the neighborhood where the structure is located might prove equally valuable. We will demonstrate that this is a valid hypothesis using three heterogeneous data sources and a neural network-based data fusion architecture.

PROPOSED METHOD

As stated in Introduction, the preferred type of data for estimating structural attributes is visual. Therefore, in line with the existing literature, GSV images are used as one data source in this study. Unlike existing literature, however, we also employ two additional pieces of information. One of them is information about the census block group (the second smallest administrative division used by the US Census Bureau, typically consisting of 250-550 housing units) in which the structure is located. This is to utilize the correlation between the physical properties of structures that are located near each other as well as between the structural attributes and the information about the neighborhood in which the structure is located. From here on, we will refer to this data as community info. Since the attributes need to be predicted at the structure level, additional structural characteristics are also used. Contrary to block group level data, these are fine-grained and directly characterize the structure, rather than a group of structures. In this study, we refer to these as building info. The specific community info are as follows: population, population density, housing units, median rent, median age, households with a mortgage (%), median number of vehicles, median built year, households, median household size, white-collar workers (%), blue-collar workers (%), housing CPI, housing expenditure, total expenditure, median household income, population with bachelor's degree (%), crime index, air pollution index. Likewise, the building info are: type of owner (individual or company), exterior surface material, area, tax value, perimeter, owner-occupied or rented, number of rooms, number of units, construction frame type.

The high-level overview of the method proposed in this study is illustrated in Fig. 1. The architectural setup consists of four modules: three of them are ANN-based and one CNN based. Two ANN modules are used to extract features from community info and individual info separately, while a CNN is used to extract features from the image. A sample image and its prediction are also demonstrated. The community and individual characteristics were obtained from the US Census Bureau's American community survey and ATTOM Inc., while street-view images were obtained from Google Inc. Although a CNN (MobileNet V2 [6]) is used in this study, it can be replaced by any CNN or Transformer based architecture as deemed suitable. Another ANN then fuses the information contained in the three feature branches and predicts the building attributes. These building attributes go into a flood risk assessment model. After the flood risks of individual buildings have been determined in a region, a flood risk map is generated, which policymakers and homeowners can use for adopting mitigation measures. The possible classes for the different attributes are as follows – foundation type: slab, beam; building type: residential, commercial, mobile; number of stories: single, multi; basement's presence: present, absent; garage's presence: present, absent. As can be seen, predicting these five attributes is a classification problem. Foundation height estimation, however, is a regression problem, where the predictions can theoretically take any numerical value. In this study, the attributes are predicted separately in a single-task learning setup but multi-task learning can be adopted if necessary.

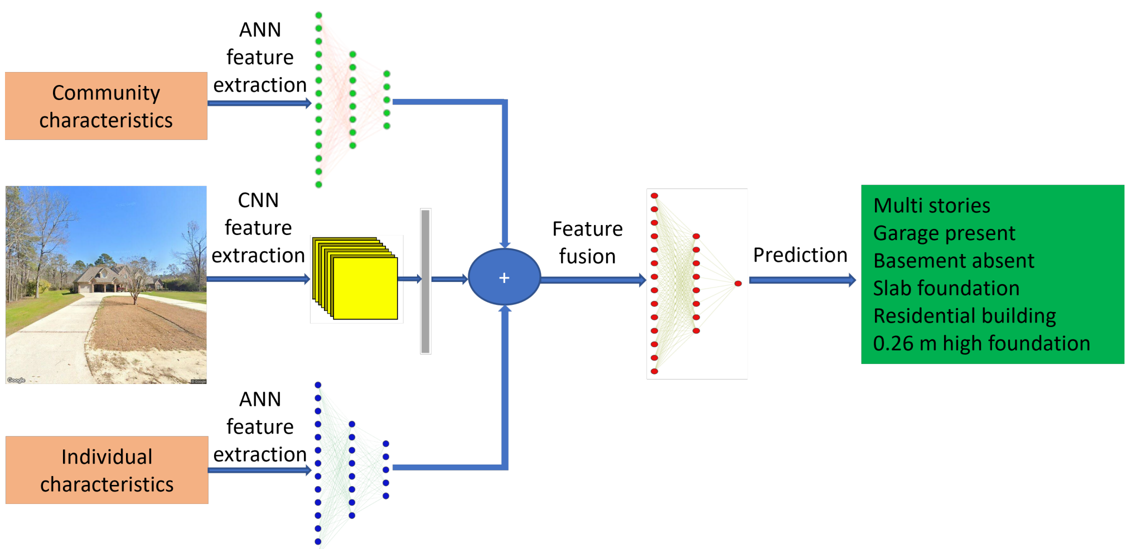

Figure 1. Overview of the proposed method.

RESULTS

Some sample predictions are illustrated in Fig. 2, and the overall performance metrics for the different setups are presented in Table I. The datasets for the first five attributes in the table are balanced. Hence accuracy is used as the evaluation metric. Likewise, foundation height estimation is evaluated using MAE since it is a regression problem. On 7,500 test images, the accuracy when predicting the type of foundation is 90.20%. Likewise, 91.77% of the 11,250 buildings are classified correctly on the building type prediction task and 90.21% of the 6,565 buildings are classified correctly on the number of stories task. Among the 676 buildings in the basement's presence prediction task, our method gives correct estimate in 95.56% of the cases, while an equally impres-

Fd.type acc. (%) N = 7,500	Bd.type acc. (%) N = 11,250	N.Stories acc. (%) N = 6,565	P.basement acc. (%) N = 676	P.garage acc. (%) N = 7,500	Fd.height MAE (m) N = 2,428
90.20	91.77	90.21	95.56	89.35	0.132

TABLE I. Performance of the data fusion model. MAE = Mean Absolute Error; acc. = accuracy. Likewise, the number of samples in the test set (support; N) are provided alongside the attributes.

sive accuracy of 89.35% is observed on 7,500 buildings when predicting the presence of garage. On arguably the most important attribute relevant for flood risk assessment, foundation height, we observe an MAE as low as 0.132 m on 2,428 buildings in the test set. These are useful performances in practical terms and will substantially improve the flood risk assessment of structures.

CONCLUSION

In this study, the effect of fusing images, census-type information about the neighborhood in which a structure is located, and information about the structure obtained from a real-estate database is studied in the context of building attribute estimation. Through experiments on six different building attributes necessary for flood risk estimation, we demonstrate that fusion of these heterogeneous data types is substantially effective. Beyond impressive performance, this method is directly being adopted to predict structural attributes for around 1.6 million buildings in the state of Louisiana, which is a testament to its practicality and scalability.

Single story	Multi stories	Multi stories	Single story
Garage present	Garage absent	Garage present	Garage absent
Basement absent	Basement absent	Basement absent	Basement absent
Slab foundation	Pier foundation	Slab foundation	Mobile foundation
Residential building	Residential building	Residential building	Mobile building
0.19 m high foundation	0.33 m high foundation	0.45 m high foundation	0.71 high foundation
(a)	(b)	(c)	(d)

Figure 2. Sample predictions of heterogeneous data fusion. All the classification attributes are predicted correctly. The actual foundation heights are (a) 0.1524 m, (b) 0.4572 m, (c) 0.4572 m, and (d) 0.762 m, which are reasonably close to the estimated heights.

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