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An Innovative Approach of CNN-BiGRU based Post-Earthquake Damage Detection of Reinforced Concrete for Frame Buildings

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***Abstract* – The new and using an updated post-seismic damage assessment method, the residual deformations the damaged structure underwent during the earthquake are taken into consideration. Estimates of maximum deformations are made using both local and global residual deformations, as well as signs of damage that can be seen with the naked eye. The unique aspect of this technique is that it can account for both rotations and displacements at the same time. Uncertainties due to both stimulation and damage are directly considered. The resulting maximum displacements estimates can assist decide if the investigated structure is usable or repairable. Image preprocessing, feature extraction, and model training have received the bulk of attention as of late. Images are gathered in advance of an event and processed via preprocessing. For feature extraction, the proposed system used data on roof whole detection as well as on building height. CNN, BiGRU, and CNN-BiGRU models will be used to evaluate trainee progress. The suggested model outperforms several well-known alternatives, including CNN and BiGRU.**

***Keywords*— Bidirectional Gated Recurrent Unit (BiGRU), Convolutional Neural Network (CNN), Building Damage Detection.**

I. INTRODUCTION

Assessing the condition of existing structures after major earthquakes can be challenging at best. Most structural evaluations are accomplished based on licensed engineers' visual inspections. It might be difficult to determine precisely where in a building harm has occurred because these evaluations can be time-consuming and subjective. While there is a limit to what may be seen during an inspection of a structure's performance, both destructive and nondestructive methods have been proposed as alternatives. Over the past two decades, researchers have increasingly turned to vibration measurements as one of many nondestructive post-earthquake assessment methodologies to detect the location and extent of damage in buildings and bridges. It used a dataset of observed acceleration reactions for training, based on recordings of initial excitations. Damage to a five-story steel frame building was evaluated using a neural network architecture and a shaking table simulation of the Kobe earthquake. An RC mansion with seven levels! Vibration recordings from testing on the UCSD-NEES shaking table were used to evaluate the structure's resilience under a range of simulated damage scenarios. Several crucial real-world uses rely on researchers being able to precisely determine the fundamental (or "natural") massively sized (civil) engineering structures, frequency, and their constituent parts. These include tuning/design of meta-structures, resonant vibration absorbers, and dynamic energy harvesters, as well designing structural components that are susceptible to resonance with outside loading frequencies. So, there is potential for development of novel approaches to the On-site measurements of natural frequencies in engineering structures that have already been created. To do this, operational modal analysis (OMA), a methodology is commonly utilized to collect response acceleration time-histories from structures subjected to unobserved operational/ambient low amplitude broadband excitations. Higher than past two decades, researchers have focused extensively on wireless sensors/accelerometers to meet the expected purpose within the OMA framework. This is due to the fact that they provide low-cost and quick-to-deploy field instruments. Damage to a building can be predicted using historical data on structures with similar characteristics. The height or number of stories of a building can be used as a rough estimate for the fundamental vibration period, which is one of the most popular criteria used to quantify global stiffness. Similarly, estimates of the lateral load-resisting system can be derived from the structure's plastic deformation process. What happens to a building in terms of velocity, acceleration, or displacement depends on the building's structural qualities and the nature of the earthquake input. Intensity measures (IM) that are derived from earthquake ground acceleration are particularly detrimental to short-period constructions. To accurately predict the damage condition of the remaining buildings under varying intensity measures, it is necessary to establish an archetype (parametric model) of the buildings constructed based on their main structural characteristics, and this can be done by selecting the best and minimum set of buildings as the reference. Damage detection is an important issue in civil and mechanical engineering. Damage is defined as any change in material qualities, boundary conditions, or system connection that degrades the system's performance. The existence, kind, location, and extent of damage must often be determined in order to provide an accurate assessment. There has been a lack of adequate protection against earthquakes and other seismic events in many precast (industrial) buildings already in existence, as was made clear by recent earthquakes in Italy. Such events can cause structural damage to buildings and, in the worst-case scenario, human casualties. In the proposed approach of an earthquake, an integrated structural monitoring system might be of tremendous assistance to existing buildings, particularly those made of precast concrete.

II. Literature Survey

In order to better understand structural behavior and detect the presence/activation of potential damage mechanisms, structural health monitoring is becoming an increasingly important part of vulnerability assessments of historic (and cultural property) structures[1]. In the absence of empirically proved deterioration of the structural conditions, this knowledge helps to prevent the execution of intrusive repair procedures [2].After an earthquake, structural health monitoring (SHM) techniques and methodologies are used to assess the structural response of the monitored buildings to aftershocks, quantify the evolution of identified ongoing damage processes, evaluate the efficacy of provisional strengthening interventions, and act swiftly if an unsafe displacement pattern is recognized [3]. In this system, focus on how to analyze and interpret SHM data using data-driven approaches to detect the presence of continuing damage processes[4]. One method used to deal with this problem [5]is to correlate retrieved features. Numerous damage detecting technologies have been developed over the past three decades methods have been created and studied for usage in order to discover long-term aging and degradation in civil engineering structures and structural components by monitoring changes to modal-based damage sensitive indices. Operational modal analysis (OMA) or output-only modal analysis [6] can be used to determine the modal properties of operating structures, including their fundamental frequencies, mode shapes, and damping ratios situations. In the aftermath of disastrous earthquakes, the condition evaluation a multistory building containing OMA equipment is constructed has been shown to benefit from the aforementioned structural damage detection approaches in recent years. Decision-makers in earthquake-prone areas [7] will be better positioned to guarantee the structural safety and integrity of buildings following an earthquake if they take this into account. Considering the brief duration of earthquakes, this is a plausible assumption to make, provided that pre- and post-earthquake environmental elements known The modal features are unaffected by temperature or humidity, which are known to have an effect.[8] Consider the modal strain energy (MSE) damage index, which compares the Both in its uninjured (before the earthquake) and damaged (after the earthquake) states, the structure's modal characteristics, to determine the location of earthquake damage in a single-bay, full-scale, three-story steel frame building. Cutting through critical spots on the steel column sections' flanges to mimic the operation of a faux plastic hinge was used to simulate damage to the structure. to identify the long-term aging and degeneration of structural components and civil engineering structures, several damage detection techniques have been developed and explored in practice during the past three decades [9]. These methods keep an eye on damage-sensitive indices based on modal shifts. In contrast to the SDI and other legitimate damage indices [9], MC and MSE calculations do not require information about the building's Before and/or after a seismic event, it would not be possible to immediately obtain the mass distribution along its height. In health monitoring of beams and plates, modal strains have been proven to be sensitive and effective for damage localization [10]. Because of this, in this proposed system, frame buildings are evaluated as transversely vibrating structures throughout their height and as global lateral modes of vibration are found using traditional linear (operational) modal analysis. In addition, [11]used a miniature An illustration of a 38-story reinforced concrete (r/c) building that underwent seismic excitation from a shaking table to compare the ability To gauge earthquake-related damage, the MSE and five other modal-based damage sensitive indices are used. However, even with automation, this sort of assessment can only catch the most glaring issues, so serious hidden flaws still have a chance of being missed.[12] Structural health monitoring (SHM) systems, whose primary objective is damage diagnosis, can be used to evaluate a building's safety after an earthquake. Damage diagnosis, as used here, include determining whether or not damage has occurred, pinpointing its exact location, and estimating its severity. Inverse [13]and data-driven methods are the two most common ways. The system used outlier analysis to determine the degree to which a signal deviated from the norm, representing one of the earliest attempts at data-driven damage diagnosis. Different kernel-based damage detection methods were created, and their effectiveness was evaluated using experimental data. Clustering methods[14] and auto associative neural networks[15] were used for damage diagnosis and signal interpretation, respectively recordings. Currently, certified inspectors and structural engineers assess the impact of visible damage on critical structural components to ensure that a damaged building remains stable and maintains an adequate level of structural integrity. These professionals use guidelines provided by the Federal Emergency Management Agency (FEMA) and the Applied Technology Council (ATC).The earthquake that struck Port-au-Prince and the surrounding area on January 12, 2010 [16] destroyed more than 100,000 homes and damaged about 190,000.During qualitative structural inspections, damage is often classified into one of four categories. It grading the intensity of a structure as light, moderate, average, or heavy. Depending on the context, each of these phrases could judicial authority [17].This method focuses on spalling detection and property retrieval since it can indicate the remaining visible and non-visible damage to RC structural sections, and the authors have previously been successful in crack identification and property retrieval [18].Due to its long history of reliability, the precast reinforced concrete method is frequently employed in the building of institutional and manufacturing facilities. Inadequate hyperstaticity and other weaknesses make many already-built precast structures unfit for use in seismic regions [19]. That's why it's so important to use methods of structural health evaluation to analyze their seismic activity and keep an eye on their dynamic properties over time. Since vibration-based continuous monitoring systems can reveal whether or not the structures have sustained permanent damage following an earthquake or are accumulating damage over the course of the sequence [20], they can be of great benefit to precast RC buildings during earthquakes. Model updating strategies rely[21] on physics-based models of structures that are calibrated using actual structure measurements in order to detect, localize, and quantify the damage from the deviations in the updated system parameters.

III. Proposed System

Post-earthquake Damage Assessment of RC Buildings Guideline is based on the notion described ways to calculate damage ratings using the residual seismic capacity index R validity of these procedures through calibration with observed damage and the ratio of the starting capacity to the seismic capacity that is still available caused by the Hyogoken-Nambu (Kobe) earthquake are discussed in this proposed system, all in accordance Japanese Standard for Seismic Evaluation using RC Buildings.

A. Image Preprocessing

All Landsat8 photos originated at the USGS Earth Resources Observation and Science Center [25], where adjustments were made for geography, atmospheric conditions, radiometric accuracy, and geometric precision. Radiometric normalization, in addition to the aforementioned adjustments, is a critical part of this process. It is well-known that variations exist between sets of multitemporal remote sensing data due to many factors, including spectral, thematic, geographical, and radiometric resolution, temporal constraints, vegetation growth, atmospheric conditions, and soil moisture conditions [22]. It is required to rule out or reduce the influence of various other factors in order to accurately define the impacts of landslides.

To radiometrically normalize the Landsat-8 image collected prior to the occurrence, the image acquired after the quake was utilized as a reference. As there are some disturbances from land surface changes, the normalization coefficients were obtained by performing a robust linear regression between the bitemporal Landsat-8 images for each research region. The equation looks like this:

$$Obs_{post,h} = b_h \cdot Obs_{pre,h} + a_h \quad (1)$$

where Observed Post-Earthquake Band Surface Reflectance Obs_{post} and Observed Pre-Earthquake Band Surface Reflectance Obs_{pre} Landsat-8 photos, with the coefficients b_h and a_h arriving via robust linear regression. Cloudy and dark regions are left out of the linear regression.

B. Feature Extraction

The texture, geometric shape, color, and height of buildings are all distinguishing features in remote sensing photos. In order to interpret the damage class of a structure, one must first identify the most prominent image feature that can distinguish across damage classes. In this method, the proposed approach to employ a hybrid approach consisting of spectral and form features to categorize earthquake damage to buildings using height data from 3D point clouds and "roof-holes" spotted in UAV photographs.

1) Information Regarding Building Heights:

The UAV images are clearly advantageous for visual interpretation because of their great clear texture, spatial resolution, and many spatial characteristics. Due to the great resolution of the cameras, buildings in UAV photographs often display complex spectral information, resulting in the phenomenon of "the same object with different spectrum." Therefore, it is not enough to simply use spectral information from UAV photographs to categorize building damage.

Extracting 3D point clouds of each building from its boundaries is the first step in calculating their heights. A 3D model of each structure is reconstructed from the point clouds. After earthquakes, it was common practice to lower buildings to avoid further destruction [23]. The expansion or contraction of a city's skyline could be measured by calculating the mean and standard deviation of building heights. By examining the connection between these two variables, the system may predict the degree of damage to a building, such as complete collapse, partial collapse, or no collapse at all. Damage to buildings can be categorized in terms of their severity based on demographics such as mean and standard variation in building heights.

2) Roof-Hole Detection:

It is not possible to distinguish between slightly damaged and basically undamaged structures in the non-collapsed buildings based on building height alone. Damaged structures can be identified by the presence of small holes in the roof. The "roof-hole" phenomena can be discovered using a model constructed on the hierarchical Dirichlet process called the Chinese restaurant (CRF).

C. TRAINING THE MODEL:

1) CONVOLUTIONAL NEURAL NETWORK

By applying the convolution kernel to the input, the convolutional layer is able to derive the feature map. Multiple convolution kernels are equivalent to multiple feature extractors, whereas a single convolution kernel is equivalent to a single feature extractor. Multiple convolution kernels are used in feature extraction in general to improve the efficiency of using convolution kernels to extract features. The combination of w convolution kernels is denoted by $[O_1, O_2, O_3, \ldots, O_w]$ where O_w is the w-th convolution kernel size, which is the size of the convolution kernel window. The word "vector" refers to the width of the window used in the convolution kernel. W feature map vectors will be approximately calculated using w convolution kernels. Given that the sentence data is a $k \times l$ matrix, a convolution window of size h will result in a convolution kernel of size $n \times l$. In order to make it possible to extract regional traits from text, the proposed system will first slide n words according to Perform the convolution operation on the step length v using the convolution kernel input word windows $y_1^i, y_2^{i+1}, y_2^{i+2}, \dots y_{k-I+1}^k$

Assuming that the input sentence's word vectors total n vectors $y_1, y_2, \dots, y_k$, the convolutional layer's operation may be written as:

$$x_h = g(Z \cdot y_{h:h+i-1} + a) \tag{2}$$

where $g()$ is the nonlinear function, Z is the weight matrix, a is the bias vector, and i is the dimension of the convolution kernel; $y_{h:h+i-1}$ is the combination of vectors $y_h, y_{h+1}, \dots, y_{h+i-1}$; and is the tangent space. After extracting the kernel from a convolution, the system have an eigenvector y, which is

$$x = x_1, x_2, x_3, \dots, x_{k-i+1} \tag{3}$$

Each eigenvector is subjected to pooling processing by the pooling layer following the convolution operation, with the resultant multidimensional vector serving as a component of the pooled vector [24]. The pooling layer, which employs the most pooling, receives the output sequence from the convolutional layer algorithm. To generate a new vector y, the maximum pooling technique takes the largest element from the series $x = x_1, x_2, x_3, \dots, x_{k-i+1}$

$$x = \max(x_h) \tag{4}$$

2) BiGRU:

The Gated Recurrent Unit (GRU) which is a form of RNN. It is proposed to overcome problems with long-term memory and gradients in back propagation in a manner analogous to that of LSTM. Recurrent neural networks (RNNs) are capable of performing recursion in an evolutionary direction because of their connected neural network design and the sequential data they receive as input. Thanks to cyclic variables in the hidden layer, neurons can learn about both their own past and the pasts of other neurons at the same time.

The following formula can be used to determine the hidden layer unit A:

$$w_v = \omega(Z_w \cdot [i_{v-1}, y_v]) \tag{5}$$

$$s_v = \omega(Z_s \cdot [i_{v-1}, y_v]) \tag{6}$$

$$\tilde{\iota}_v = \tan i(Z \cdot [s_v * i_{v-1}, y_v]) \tag{7}$$

$$i_v = (1 - w_v) * i_{v-1} + w_v + \tilde{\iota}_v \tag{8}$$

where s_v and w_v represent the updating and reset gates, respectively; ω represents Sigmoid stands for the Sigmoid function; hyperbolic tangent function; and Z_s, Q_s, Z_w, Q_w and Q are matrices representing the training parameters. The current input y_v, the prior output i_{v-1} of the buried layer's neuron and the training parameter matrices Z and Q all contribute is in the possible activation stage present time. BiGRU networks are better suited because of their ability to comprehend the connection between the current load and the variables affecting the past and future loads. To getting the load data's deep characteristics. The formula is as follows:

$$x_2 = f(TB_2 + T'B'_2) \tag{9}$$

and B'_2 can be worked out as

$$B_2 = g(ZB_2 + Qy_2) \tag{10}$$

$$B'_2 = g(Z'B'_3 + Qy_2) \tag{11}$$

r_v, the value of the buried layer, is related to r_{v-1} in the forward computation. The value of the buried layer, denoted by r_v, is connected to r_{v-1} in the inverse calculation. The combined results of the forward and backward calculations will determine the final result. The bidirectional recurrent neural network uses the following calculating method:

$$p_v = f(Tr_v + T'r'_v)$$

$$r_v = g(Qy_v + Zr_{v-1}) \tag{12}$$

$$r'_v = g(Q'y_v + Z'r_{v-1}')$$

3) Multihead AM:

The human brain has a unique system for processing visual data, known as the visual attention mechanism. The human visual system undertakes a quick global sweep to locate the attentional object during scene perception. After that point, more of the brain's resources are dedicated there, helping to focus on the details of the task at hand while tuning out irrelevant information. Those with short attention spans might use this method to quickly zero in on the data that is most important to them. Over the course of human history, this protective mechanism evolved to ensure the survival of the species. The visual attention system in humans greatly improves the efficiency and accuracy with which visual information may be processed.

The central scaled dot-product attention is a subset of the standard attention. The following formula can be used to get the scaled dot-product focus given matrices$U \in S^{k*c}$, $N \in S^{k*c}$ and $T \in S^{k*c}$:

$$Attention(U, N, T) = \left(\frac{UN^V}{\sqrt{C}}\right)T \tag{13}$$

The hidden nodes of the neural network are denoted by c. Self-attention is the foundation of the multi-head attention process. Due to the nature of multi-head attention, $U = N = T$in the diagram represents the self-attention process. By using data from the current place with data from all previous positions, the proposed system can more accurately capture dependencies over the entire process. For example, each word in a sentence must go through the attention process computation.

In this method, multihead attention is utilized to perform a linear transformation on the three vectors U, N, T before they are incorporated into the calculations. Due to the use of "multihead attention," the computation scaled dot-product attention component must be repeated numerous times. Each calculation will provide a different linear projection of U, N, T; this is represented by the "heads" count. As an example, consider the h-th brain:

$$U' = U * Z_h^U$$

$$N' = N * Z_h^N \tag{14}$$

$$T' = T * Z_h^T$$

Since this layer is where the BI-GRU's output is fed,

$$U = N = T = x_v \tag{15}$$

The conclusion reached by this brain is

$$L_h = soft\,max\left(\frac{U'N'^V}{\sqrt{c}}\right)T' \tag{16}$$

IV. Result and Discussion

Accurate estimates of the residual behavior of damaged buildings facilitate the quantitative assessment of structural performance following natural disasters. An accurate estimate of the damage amount and distribution is necessary for predicting the residual behavior of earthquake-damaged structures.

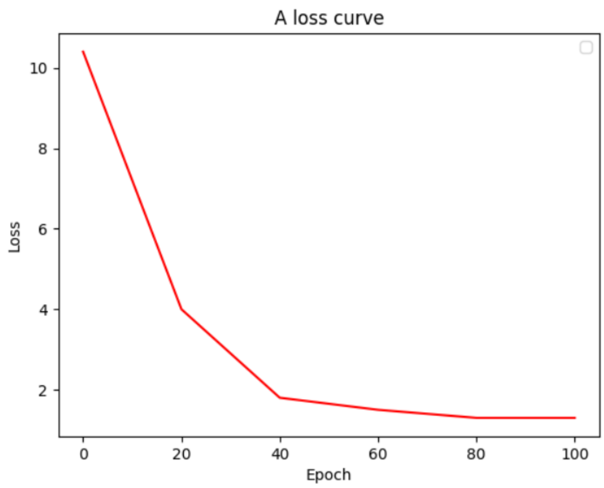

Fig. 1. Loss Value Curve of the Proposed Model

Meanwhile, after 100 epochs of training, the model converged, as can be seen in Figure 1. The model was trained using the SGD optimizer and a weight decay of 0.01, and validated using the cross-entropy loss function.

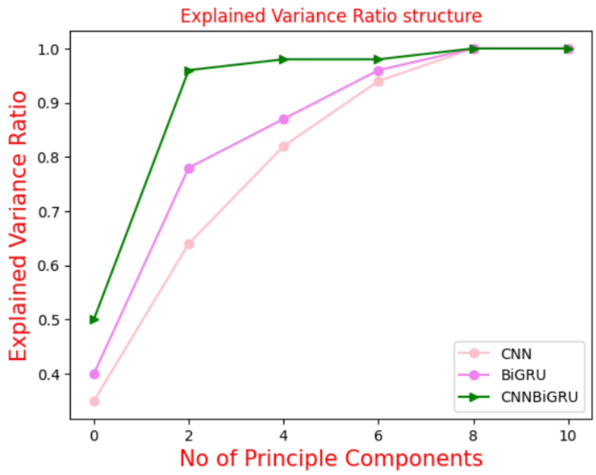

Fig. 2. Explained variance ratio of CNN-BiGRU

Figure 2 displays the explained variance ratios for these models after CNN-BiGRU is conducted after min-max normalization. For the CNN, BiGRU, and CNN-BiGRU, the bare minimum number of principal components necessary to achieve an 80% explained variance ratio is 3, 3, and 2, respectively.

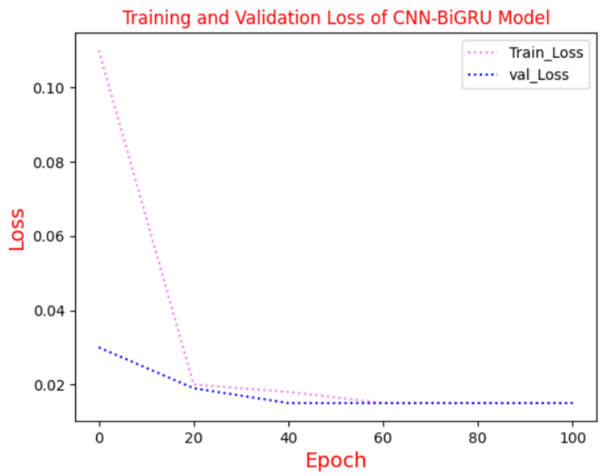

Fig. 3. Training and Validation Loss of CNN-BiGRU

While there are only a small number of datasets that include information about major earthquakes, CNN-BiGRU's strength in learning complex data makes it possible to discover patterns from these datasets. Figure 3 shows the fitting curves for our models; all of them are well Training and validation because the proposed system employ the dropout function.

V. Conclusion

Rebuilding a city after an earthquake requires careful planning to restore normalcy as quickly as feasible. After a major earthquake hits a town, it is critical that damage inspections be conducted as soon as possible to determine whether buildings may be safely occupied. Guidelines for Post-Earthquake Damage Evaluation and Rehabilitation uses their method for assessing the residual seismic capacity of earthquake-damaged reinforced concrete buildings. However, the data obtained from such assessments is bound to be approximate due to their rapid nature. After the initial inspections, a more in-depth and quantitative assessment of the damage must be performed. To decide what has to be done in a damaged building, engineers require a technical guideline. While modern algorithms such as CNN and BiGRU have their uses, they also have their drawbacks. To begin, the sequential nature of these algorithms' inputs makes model training a lengthy process. To solve these problems, a new CNN-BiGRU-based prediction approach has been created. In terms of accuracy (97.85 percent), the proposed model is superior to both the CNN and BiGRU alternatives.

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