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Building loss assessment using deep learning algorithm from typhoon Rusa

Ji-Myong Kim [a], Junseo Bae [b], Manik Das Adhikari [c], Sang-Guk Yum [c,*]

[a] Department of Architectural Engineering, Mokpo National University, Mokpo, 58554, South Korea
[b] Division of Smart Cities, Korea University, Sejong, 30019, South Korea
[c] Department of Civil Engineering, Gangneung-Wonju National University, Gangneung, 25457, South Korea

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ABSTRACT

Climate crises such as extreme weather events, natural disasters and climate change caused by climate transformations are causing much damage worldwide enough to be called a climate catastrophe. The private sector and the government across industries are making every effort to prevent and limit the increasing damage, but the results have yet to meet market demand. Therefore, this study proposes a method that uses a deep learning algorithm to predict the damage caused by typhoons. Model development is based on a Deep Neural Network (DNN) algorithm, and learning data is obtained by fine-tuning the network structure and hyper-parameters; the amount of damage caused by Typhoon Rusa was known as training data. The constructed DNN model underwent evaluation and validation by computation of mean absolute error (MAE) and root mean square error (RMSE). Furthermore, a comparative analysis was conducted to confirm the applicability of the proposed framework against a traditional multi-regression model to ensure the model's accuracy and resilience. Finally, this study offers a novel approach to predicting typhoon damage using advanced deep-learning techniques. Subsequently, government disaster management officials, facility managers, and insurance companies can utilize this method to accurately predict the extent of damage caused by typhoons. Preventive actions such as improved risk assessment, expanded insurance companies, and enhanced disaster responses plans can be implemented using these outcomes. Ultimately, the proposed model will help to reduce typhoon damage and strengthen general resilience to climate crises.

1. Introduction

1.1. *Climate change and natural disaster*

Climate crises caused by extreme weather events (e.g., heat waves, cold waves, droughts, heavy rains, floods, and tropical cyclones) and climate change-initiated disasters are responsible for a lot of damage to property and human life to such an extent that they are called climate catastrophes worldwide. Therefore, climate change is recognized as the greatest threat facing humanity. Hence, active

* Corresponding author.
E-mail addresses: jimy6180@gmail.com (J.-M. Kim), junseobae@korea.ac.kr (J. Bae), rsgis.manik@gmail.com (M.D. Adhikari), skyeom0401@gwnu.ac.kr (S.-G. Yum).

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efforts of all mankind are required to prevent and limit this enormous damage [1]. Extreme weather events caused by climate change are occurring with greater frequency and severity than in the past and, therefore, can cause more serious damage to buildings, facilities and people [2,3]. Moreover, the 5th Evaluation Report of the Intergovernmental Panel on Climate Change (2014) warns against destructive impacts such as changes in average sea level, acidification, heavy rainfall and global increase in average temperature, and that these phenomena may accelerate [4].

Escalating extreme weather events and increasing global population and wealth are causing avalanche losses worldwide. The damage caused by windstorms is becoming critical day by day. The weather disasters that occurred between 1980 and 2021 have revealed that tropical cyclones (or hurricanes) have caused the most damage, exceeding $1.1 trillion [5]. Additionally, tropical cyclones have been responsible for the highest number of deaths, claiming the lives of 6697 individuals during the same period. These statistics highlight the severe impact of tropical cyclones in terms of both economic losses and loss of life. As a representative example, Hurricane Harvey, Hurricane Irma and Hurricane Maria continually attacked coastal areas of the United States and countries such as Puerto Rico in about one month in 2017, resulting in a cumulative damage of approximately 293 billion dollars. All three of these hurricanes were Category 4, which caused heavy rains and wind damage [6]. Hurricane Harvey reportedly caused the most substantial damage, amounting to $125 billion. It was succeeded by Hurricane Maria, which caused $90 billion, and Hurricane Irma, which caused $77.6 billion in damage [6]. Also, in 2005, Hurricane Katrina devastated many states around the Gulf of Mexico, causing the greatest natural disaster in US history. Total damage from Hurricane Katrina is estimated at approximately $180 billion. Hurricane Katrina, a Category 5 hurricane, was convoyed by powerful heavy rains and strong winds and triggered storm waves to increase the damage [7]. Recently, in 2021, Hurricane Ida caused economic damages of $40 billion in the United States [5]. In Europe, an example is damage by extratropical cyclones. In particular, Cyclone Anatole, Cyclone Lothar and Cyclone Martin, which occurred successively in 1999, caused total damage of around EUR 13 billion, devastating Western European countries such as Switzerland, Germany and France [8]. In Asia, the damage caused by Typhoon Haiyan in 2013 is a characteristic example. Typhoon Haiyan hit countries such as China, Vietnam and the Philippines, causing about $300 billion in losses. Typhoon Haiyan was also noted as a typhoon that recorded a robust maximum wind speed when it invaded the land among tropical cyclones [9]. Kim et al. [10] presented the analysis results of typhoon changes and typhoon damage rates that have affected Korea over the past 50 years. This study found that the severity of typhoons increases with each decade, and the rate of typhoon damage increases significantly with increasing severity [10].

As mentioned earlier, a windstorm caused by extreme weather conditions generates deliberate damage worldwide, and this damage is expected to increase in the future. In response, many resources are invested at the private and government levels to prevent, reduce and repair major storm destruction. Hence, it is essential to accurately and scientifically forecast the damage that windstorms will inflict in order to allocate scarce resources as best as possible.

1.2. Literature reviews

As mentioned earlier, the damage caused by the windstorms is predicted to escalate. Thus, one alternative is to utilize a deep learning algorithm as a means of predicting increasing damage in an efficient and systematic manner. Deep learning algorithms are used for prediction and analysis in countless industries and academia, and their effectiveness is well known [11]. In particular, due to the nature of natural disasters, the presence of various sensitive factors and the complexity of the resulting damage, there are some disadvantages in the analysis, and the degree of consistency in the predictions also shows limits [9]. For example, in an existing catastrophe model used by insurance companies and vendors, the windstorm damage data is analyzed and quantified through a vulnerability function according to the building's characteristics. This vulnerability function describes the relationship between building characteristics and representative windstorm risk indicators (wind speed, rainfall, etc.) in a deterministic manner and expresses it as an average failure rate. Then, quantifying damage through the existing vulnerability function makes it difficult to react quickly to updated damage data and changing patterns of damage and natural disasters [12]. In addition, in a rapidly evolving big data environment, the demand for natural disaster damage analysis using deep learning algorithms will increase day by day to efficiently and quickly process and analyze datasets from natural disasters [13–17]. Therefore, predicting windstorm damage using deep learning algorithms could be a suitable alternative.

Many previous studies have been conducted using deep learning algorithms to quantify and forecast the damage inflicted by various natural disasters [18–25]. For example, a loss prediction model based on a deep learning algorithm for natural disasters has been developed to utilize natural disaster loss factors and disaster-caused construction damage data to predict disaster losses in construction works. As a result of the validation of this predictive model, the prediction error was lower than in the case of other models, which indicates the robustness and effectiveness of the deep learning algorithm model [18,25]. Building repair costs and efficient facility management plans in case of natural disasters were derived using a deep learning algorithm. This study constructed a model by learning and testing data on building maintenance, repair costs, and natural disaster factors using a deep learning algorithm. The developed model underwent a verification process and presented a higher predictive power than other models [19]. Khosravi et al. [20] presented a model for flood sensitivity assessment using the CNN (Convolutional Neural Network) algorithm. In this study, the model was constructed by analyzing CNN factors affecting different sensitivity to floods, such as slope, land use, curvature, vegetation, distance to rivers and road networks, geology and rainfall [20]. Al Najar et al. [21] recommended a method of using a deep learning algorithm to analyze changes in coastal areas caused by storms. This study demonstrates the accurate prediction of sea depth using a deep learning algorithm [21]. Moreover, an efficient and practical flood management system has been proposed by predicting the occurrence of floods through historical weather data and deep learning algorithms. This hybrid flood prediction model based on a deep learning algorithm illustrates the low prediction error in predicting the flood index and is expected to contribute to the modernization of the flood monitoring system and reduction of flood damage [22]. In addition, Shane Crawford et al. [23] conducted a study that estimated tornado wind speed and classified building damage using CNN model based on satellite images. Kaur et al. [25] also used satellite images and a CNN model to detect the damage caused by hurricanes. Additionally, a technique for predicting the risk of landslides caused by earthquakes based on satellite images and a CNN model was proposed by Yi and Zhang [24].

As seen earlier, various deep learning algorithms are actively used to predict and evaluate the damage caused by natural disasters, and the utility and practicality of deep learning algorithms complement existing models and techniques and contribute to progress. Furthermore, the deep learning algorithm contributes greatly to the strategy and decision-making of natural disaster risk management based on technological innovation and outstanding reliability. Therefore, this study proposes a framework for creating a deep learning algorithms-based model to predict the damages inflicted by typhoons.

1.3. Loss lessons from typhoon Rusa

Typhoon Rusa, which occurred in August 2002, is a natural disaster that caused the greatest damage in Korea. Although the central pressure and maximum wind speed were lower than those of the major typhoons (e.g., Typhoon Selma in 1987, Typhoon Maemi in 2003, etc.) which landed on the Korean Peninsula and caused a lot of damage, they recorded the maximum amount of rainfall (the greatest daily precipitation of 870.5 mm) and strong winds (43.7 m/s) during the typhoon, causing the greatest property damage in history. In particular, it is classified as being representative of a wet typhoon since it causes damage from a large amount of rainfall. Total property damage was 4.2 billion dollars, and it was a very catastrophic natural disaster that killed 246 people [26]. Typhoon Rusa occurred off the coast of Guam on August 23, passed through Kagoshima Prefecture, Japan, hit the south coast of Korea in the afternoon of August 31, crossed the Korean Peninsula to the east coast and faded into a tropical depression on the September 1 in the morning. The trajectory of Typhoon Rusa is shown in Fig. 1. Unlike the previous typhoons that landed in Korea, Typhoon Rusa maintained a central atmospheric pressure of 950 hPa until landing, maintained strong typhoon force and landed to increase damage. The reason Typhoon Rusa held such an exceptionally strong force is closely related to the change in typhoon patterns caused by climate change. At the time of Typhoon Rusa's invasion of Korea, the sea surface temperature on the south coast was 2∼3° higher than normal (26 °C), which was analyzed to indicate that the source of energy necessary for typhoon development was sufficiently supplied [27]. The Typhoon Committee removed the Rusa name in 2004 and replaced it with Nuri due to severe property damage and casualties from

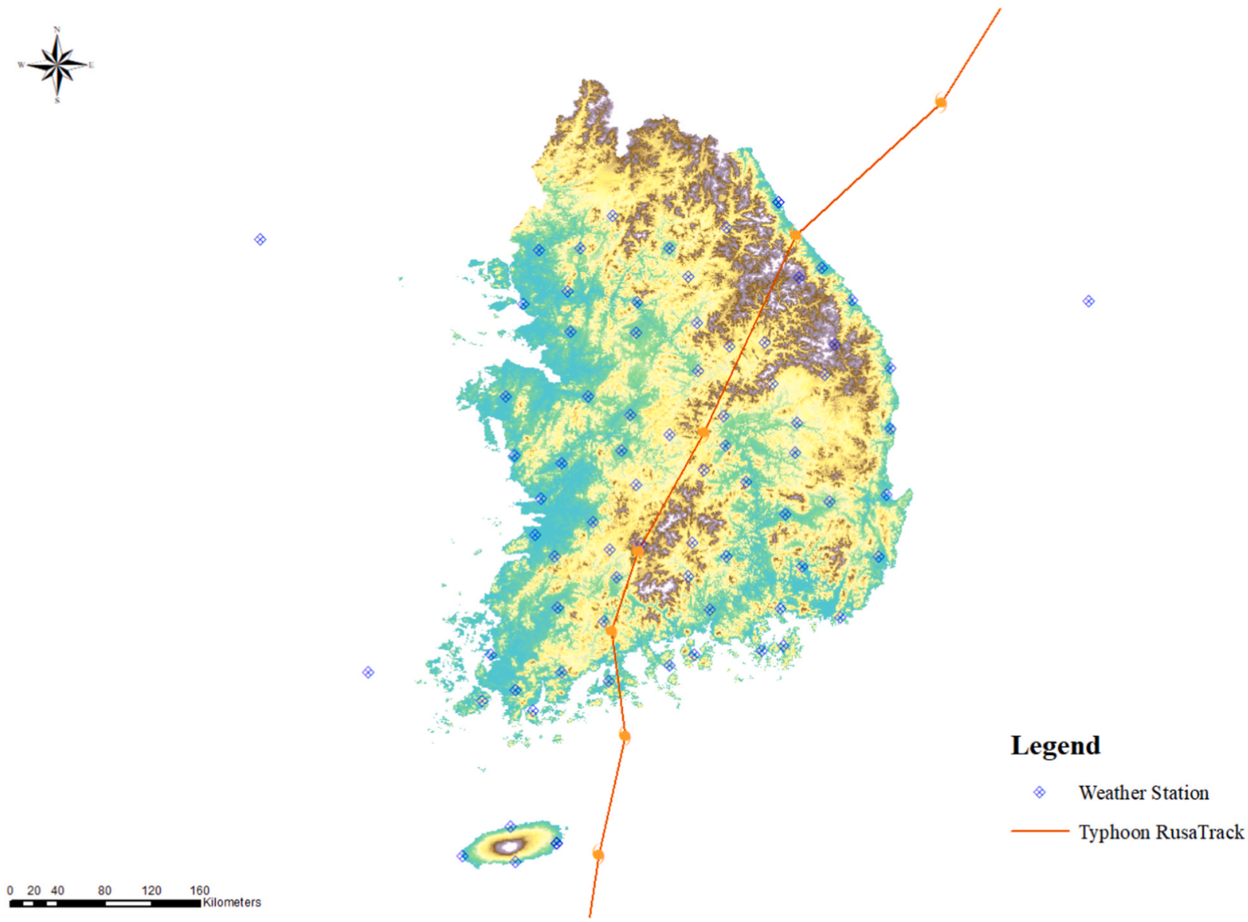

Fig. 1. Typhoon Rusa's Track.

the Rusa Typhoon [26].

Analyzing record-breaking natural disasters such as Typhoon Rusa and drawing conclusions is significant basic data for disaster management [28]. For example, insurers have suffered huge unexpected property losses after the most recent deadly natural disasters such as Hurricane Harvey, Hurricane Irma and Hurricane Maria, as well as Hurricane Sandy, Hurricane Ike and Hurricane Katrina. Surviving insurers had to develop survival strategies such as adapting premiums and insurance coverage [29]. Such extreme natural disasters are an imperative task that can threaten the lives of reinsurers and insurers. Thus, in order to prepare for extreme natural disasters, various important indicators and figures are obtained by analyzing extreme natural disasters. For instance, reinsurers and insurers designate catastrophe zones and set limit amounts for each catastrophe zone, trying to minimize losses that may result from a disaster. It is also used to determine the amount of the major catastrophe loss reserve and to allocate the portfolio by region. Moreover, extreme natural disaster analysis is mandatory to determine retention, excess loss reinsurance (XOL), liability limit (LOL) and probable maximum loss (PML) used in the insurance industry business and disaster management strategies. Retention, XOL and LOL are among the most important indicators in establishing a strategy for the determination of the extent of loss and the effective division and allocation of loss risk [30]. The PML is the worst-case maximum expected loss. Additionally, insurers and reinsurers require an advanced analysis of potential natural disaster risk in order to calculate reasonable premiums. The premium is composed of the net premium, profit, and business cost, of which the net premium consists of fire, lightning, explosion and aircraft risk (FLEXA) and natural disaster risk [31]. As discussed above, the damage analysis of extreme natural disasters is taken as the basic data to establish important management and business strategies for the efficient management of extreme natural disasters for reinsurers and insurance companies. Therefore, scientific and thorough analysis of extreme natural disaster cases is essential for effectively preparing and managing extreme natural disasters such as Typhoon Rusa.

2. Research method and aims

The aim of this study is to propose a framework for constructing a typhoon damage prediction model utilizing a deep learning algorithm based on typhoon Rusa's damaged data. The detailed workflow of this study is outlined below. Initially, data on the damage caused by Typhoon Rusa were collected from insurance companies. Subsequently, a damage prediction model was constructed using a

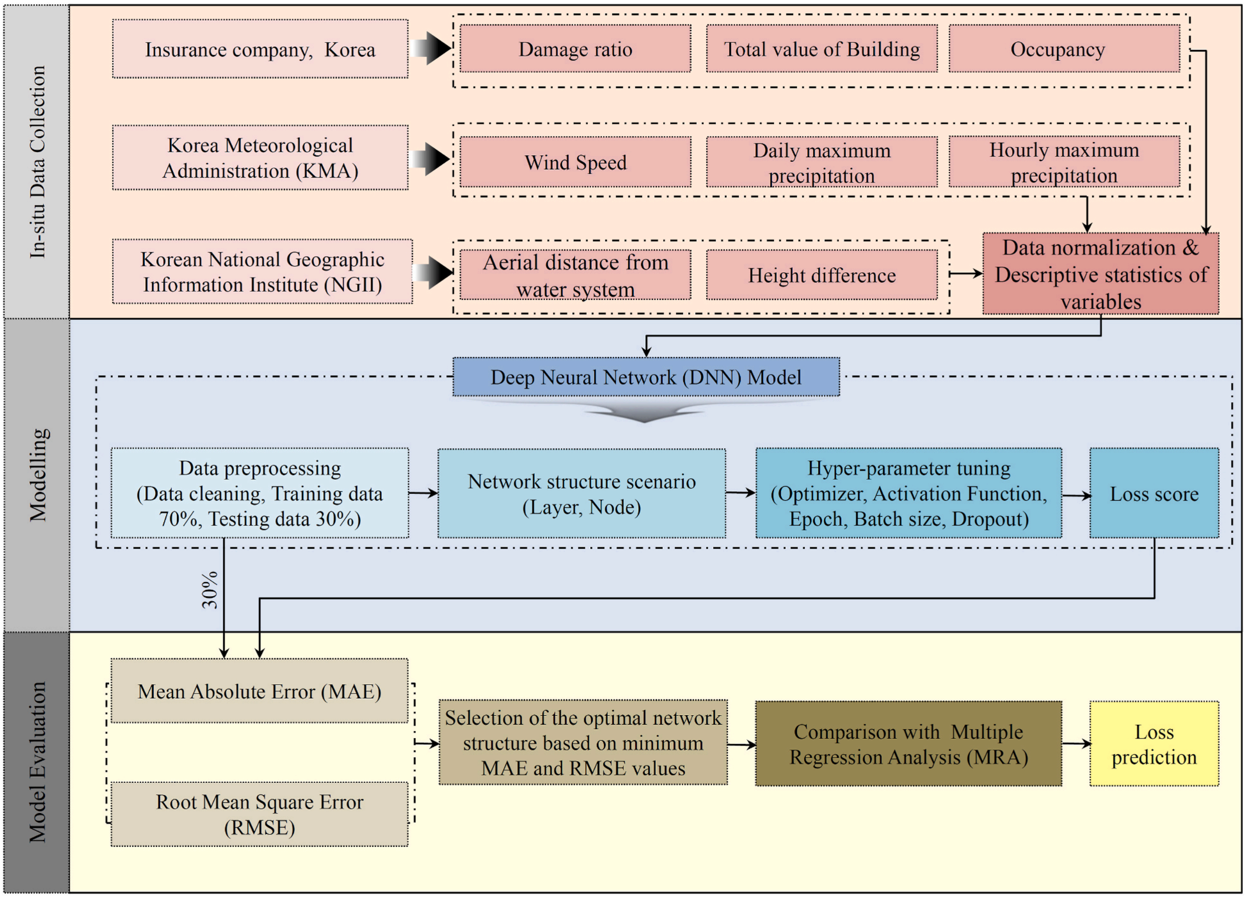

Fig. 2. The detailed workflow for the building loss assessment model.

deep learning algorithm from the collected dependent and independent variables. Lastly, to validate the DNN model, the prediction results are compared and verified with another model. In the present study, a multiple regression model was built, commonly adopted for prediction, using the same data that was utilized in the deep learning algorithm. Thereafter, the MAE (Mean Absolute Error) and RMSE (Square Mean Square Error) of the multiple regression analysis model and the deep learning algorithm model were calculated and compared and analyzed. The DNN model was created using Python 3.7, while the multiple regression analysis model was generated using SPSS (Statistical Package for Social Sciences) V23 software. The comprehensive framework and analysis procedure of the loss assessment model is presented in Fig. 2.

3. Data collection: Input and output variable

This study suggests a framework for creating a deep learning-driven model to accurately predict typhoon damage, which is the aim of this study, through the damage case of Typhoon Rusa, the extreme case of a natural disaster in Korea. In the case of Typhoon Rusa's damage data, a large insurance company in Korea collected data on claims payouts caused by the Typhoon. Damage data is provided from scratch, excluding all insurance terms and conditions and no personal data is included. Typhoon Rusa, along with Typhoon Maemi, is a representative case of extreme natural disasters, and during the invasion of Korea, it was sustained by devastating record rainfall and strong winds, causing a lot of damage to property and casualties. Property damage, in particular, has caused the greatest amount of damage from the disaster and is recorded as a representative disaster [26]. Typhoon Rusa landed on the south coast of the Republic of Korea on the afternoon of August 31, 2002, penetrated the center of the Korean Peninsula for about 18 h and escaped to the east coast on the morning of September 1. It stayed in the Korean Peninsula for a long time, and the damage was amplified by strong winds and rains strong enough to show massive rainfall of 870.5 mm on August 31 with an hourly rate of 100.5 mm, especially in Gangneung [27]. Fig. 3 shows the distribution of damage from Typhoon Rusa. Typhoon Rusa swept the Korean Peninsula for a long time with powerful heavy rains and strong winds, causing a lot of damage throughout the Korean Peninsula, so the navigable and dangerous semicircles of the typhoon remained indifferent.

The study's dependent (output) variable was the recording of a claim payment from a large insurance company in Korea due to

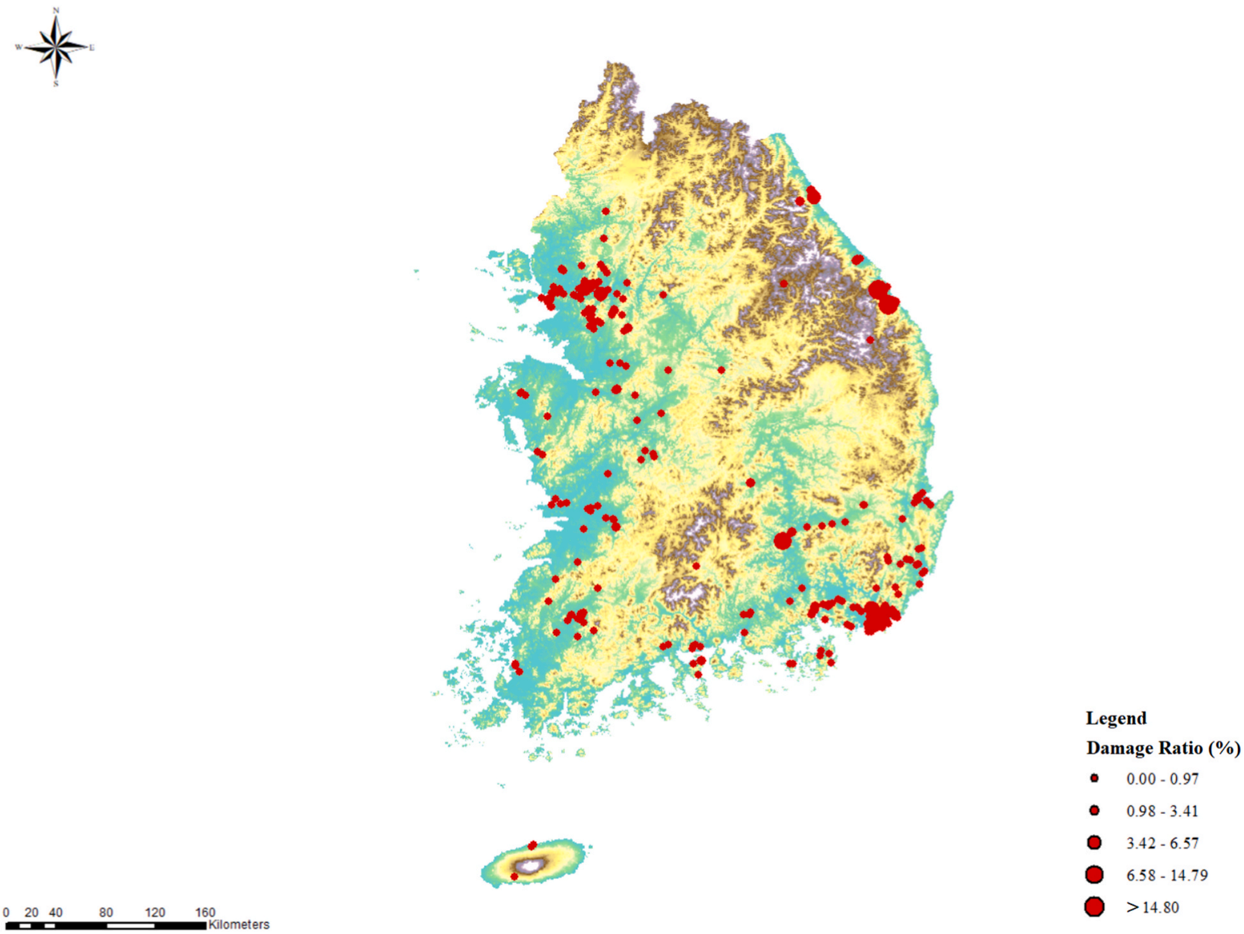

Fig. 3. Damage distribution of Typhoon Rusa.

Typhoon Rusa, and the collected damage data included the amount of the damage claim, total value of the buildings destroyed, occupancy, date of the damage, location of the damage and details of the damage. The amount of damage was applied as the damage factor divided by the total value of the damaged buildings. Table 1 presents a detailed description of the considered input variables.

The dependent and independent variables were gathered from the primary risk indicators utilized in typhoon research. For example, typhoon damage and total building value have a statistically negative correlation, and this relationship is widely used for typhoon risk quantification and vulnerability studies [9,28]. Occupancy is also one indicator often used to quantify and predict damage from typhoons, as the susceptibility of buildings to typhoons varies with occupancy [9,32]. The occupancy was introduced as a nominal variable, divided into 1) industrial building, 2) commercial building, 3) construction, 4) residential building, and 5) apartment. Wind speed is the primary indicator used to predict and measure typhoon damage, as it is the trigger that causes direct damage, such as missile collision, scattering and collapse caused by strong winds, and indirect damage, such as storm surge [33,34]. This study used a 10-min average maximum wind speed (m/s) during typhoon Rusa from the Korea Meteorological Administration (KMA), and wind speed information was collected from the location of each damaged building. As the distance between the water system and the damaged building has a statistically negative relationship, it is repeatedly used in calculation studies and assessments of susceptibility to typhoons [12,35]. Also, the height difference between the water system and the building is widely used in related studies as a vital indicator of vulnerability to floods and floods caused by typhoons [35,36]. The distance between the water system and the damaged building, as well as the difference in elevation between the water system and the building, were calculated using ArcGIS based on the damaged building's location. For these purposes, the high-resolution landcover and topography data (LiDAR DEM) collected from the Korean National Geographic Information Institute (NGII) was utilized [37]. Rainfall is a factor that causes damage such as flood, flooding and rain intrusion into buildings during typhoon attacks and is mainly used in research into the vulnerability and damage of natural disasters [34,38]. For this study, maximum daily and maximum hourly precipitation data were collected through the Korea Meteorological Administration (KMA). This study considered 1379 cases of damages caused by Typhoon Rusa. The independent variables, which include the total value of the building, occupancy, wind speed, aerial distance from the water system, height difference, daily maximum precipitation, and hourly maximum precipitation, are each associated with their corresponding statistics, as presented in Table 2. The total value of the building and the damage ratio were drawn to a normal distribution by transforming the log. The descriptive statistics of the output variable (i.e., damage ratio) ranged from −12.02 to 4.19, with a mean of −4.10 and a standard deviation of 2.25 (Table 2). Descriptive statistics offer valuable insights into data distribution by providing an in-depth overview of input and output variable ranges, central tendencies, and variability.

4. Development of a deep learning algorithm model

A deep learning algorithm is one of the machine learning techniques that includes an activation function, hidden layer, input layer, an output layer, weight and neuron. Extensive combinations are possible depending on the combination of components, and countless combinations of variables are possible to be applied to various data. Due to these advantages, deep learning algorithms are used in many different fields, such as prediction, regression, recognition and type classification, to prove their effectiveness [39,40]. The deep learning algorithms are categorized into Generative Adversarial Networks (GAN), Deep Neural Networks (DNN), Auto Encoder (AE), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), etc., according to the processing method and arrangement. For instance, DNN is extensively adopted for modeling multifaceted nonlinear interactions because infinite combinations of artificial neural networks are possible depending on the composition of the network structure and the combination of hyperparameters. In particular, it confirms the excellent performance of predicting and analyzing nonlinear data (e.g., natural disasters, construction works, etc.) of extraordinary complexity and high uncertainty [13,18,41]. Therefore, this study proposes an outline for the development of a DNN-based predictive model for analyzing and predicting data generated by Typhoon Rusa. The typhoon damage prediction model, derived from the DNN algorithm in this study, will improve the existing model and contribute to the mitigation of typhoon damage through advanced prediction techniques. Besides, the DNN algorithm-based typhoon damage prediction model will ultimately help prevent typhoon damage and reduce risk.

In the case of data pre-processing, the input data were normalized using the z-score normalization method. Furthermore, 70 % of

Table 1
Comprehensive description of input and output variables.

Variables	Explanation	Unit
Damage ratio	The damage ratio is the amount of damage divided by the total value of the damaged building (%)	Numeral
Total value of building	Total value of damaged buildings (KRW)	Numeral
Occupancy	Occupancy of the damaged building: 1) Industrial building, 2) commercial building, 3) construction, 4) residential building, and 5) apartment.	Nominal (1–5)
Wind speed	The 10-min average maximum wind speed (m/s) during Typhoon Rusa	Numeral
Aerial distance from water system	The aerial distance between the water system and the damaged building (m)	Numeral
Height difference	The height difference between the water system and the damaged building (m)	Numeral
Daily maximum precipitation	Maximum daily rainfall during Typhoon Rusa (mm)	Numeral
Hourly maximum precipitation	Maximum hourly rainfall during Typhoon Rusa (mm)	Numeral

Table 2
Summary of descriptive statistics for input and output variables.

Variables	N	Min.	Max.	Mean	Std. Deviation
Output Variable					
Damage ratio	1379	−12.02	4.19	−4.10	2.25
Input Variables					
Total value of building	1379	16.96	32.22	24.02	2.11
Occupancy	1379	1	5	3.71	1.61
Wind speed	1379	21	38	30.19	3.35
Aerial distance from water system	1379	0	11074	2492.85	2078.73
Height difference	1379	−49.00	32767.00	113.35	1682.01
Daily maximum precipitation	1379	31	870	108.37	87.47
Hourly maximum precipitation	1379	5	100	18.75	12.55

the input data is divided into training data, and 30 % of the data is allocated for testing. 30 % of the training data was assigned as validation data. The DNN algorithm model uses the backpropagation algorithm to find the optimal combination by updating the node weights between the input and output variables. As a result, the trial and error method becomes essential to identify the ideal hyper-parameter and network structure [42]. For instance, setting the batch size, dropout, epoch, optimizer and activation function in the hyper-parameter to make the DNN algorithm model an optimal set-up. The batch size defines the data learning unit of the DNN algorithm model and configures it for effective learning. The dropout rate is a regularization penalty to address the overfitting problem that may arise in the DNN algorithm model, and Epoch determines the number of learning times for the DNN algorithm model data. The optimizer adjusts the learning rate of the DNN algorithm model data to ensure safe learning. Finding the least cost function is determine by the activation function. Finally, various combinations of scenarios are derived in the network structure by arranging the number of nodes and the number of layers in order to find the optimal combination [42,43].

In this study, the ideal combination resulted from the network structure and hyperparameters used in previous studies on predicting damage from natural disasters and quantifying risk studies [13,18,41,44]. The learning number or epoch number was set to 1000, and the batch unit or learning unit setting was set to 5. Rectified Linear Unit (ReLu) was designated as the activation function, which has a result value of 0 and a differential reference. ReLu was introduced to address the limitation of the sigmoid function [45]. The optimizer used Adaptive Moment Estimation (Adam). Adam's method is easy to calculate and has a wide range of applications, and refers to the theory of moments based on the probabilistic objective function [46]. The network structure consists of three layers, and the dropout is specified as 0 and 0.2. The DNN backpropagation algorithm (Fig. 4a) and the construction of the DNN model (Fig. 4b) consist of input variables, a hidden layer, and the output (damage ratio).

To find the optimal combination of DNN models, the MAE (Mean Absolute Error) and RMSE (Root Mean Square Error) values were calculated for each scenario. The indicators commonly used to evaluate artificial neural network models are MAE and RMSE, which indicate the precision of the model through the deviation between the actual value and the predicted value [47]. For instance, MAE is the absolute value calculated by summing and averaging the residuals of the actual value and the result value. The prediction error increases as the MAE value rises. RMSE expresses the residual between actual value and predicted value on a uniform scale. The greater the RMSE value, the greater the prediction error. The learning outcomes of the model based on various network structurs scenarios and dropout rates are shown in Table 3. The network structure's final scenario was chosen among the scenarios with the lowest MAE and RMSE values of the learning outcomes. The learning outcome exhibited a smaller loss function with a dropout rate of 0 compared to a

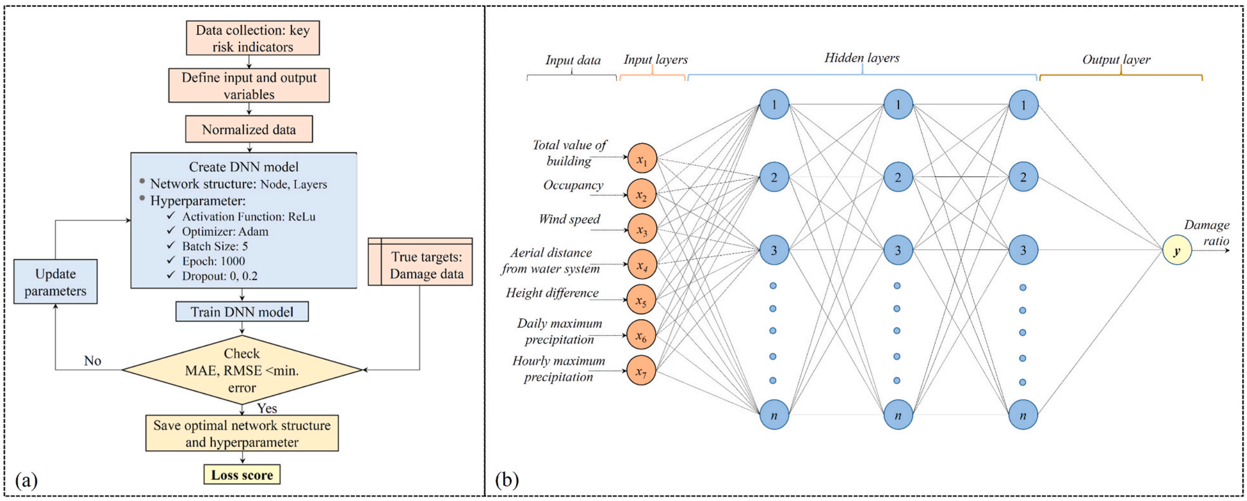

Fig. 4. (a) Model framework and DNN backpropagation algorithm, and (b) The layout of the DNN model.

dropout rate of 0.2. Moreover, MAE and RMSE decrease as the number of hidden layer nodes increases. In the network structure with 400-400-400 nodes in the hidden layers, both MAE and RMSE exhibit the lowest loss functions. Therefore, the optimization model network structure scenario and the number of hidden layer nodes are set to 400-400-400, and the dropout is set to 0. Table 4 confirms the optimal network structure and hyperparameters.

5. Model validation

In order to check if the final DNN model is overfitted, a simulation was performed utilizing validation data and test data. Table 5 illustrates the MAE and RMSE of the simulation results. The simulation of individual data resulted in MAE and RMSE values of 0.451 and 0.392 for the validation data, and 0.600 and 0.512 for the test data, respectively. The minimal difference between the MAE and RMSE values of the verification data and those of the test data suggests that the overfitting issue in the DNN model can be ignored.

In addition, to validate the final DNN model, a multiple regression analysis (MRA) model was developed using the same variables as applied in the DNN model. MRA is a widely used statistical method for prediction and quantification in both academic and industrial fields [3,18,48]. Subsequently, the MRA model was developed using the SPSS V23 software, and the model's MAE and RMSE values were calculated separately.

Table 5 illustrates the comparative results between the proposed DNN model and the conventional MRA model. The DNN model exhibits a lower prediction error rate than the MRA model, amounting to 46.5 % in the MAE and 53.8 % in the RMSE. As a result, the DNN algorithm model demonstrates enhanced dependability and resilience when it comes to forecasting building losses caused by typhoons. Wei and Yang [49] also observed the backpropagation algorithm outperformed the MRA model.

6. Discussion

This study suggests a framework for constructing a damage prediction model utilizing the DNN algorithm to forecast the damage induced by Typhoon Rusa. Data regarding the damage incurred from Typhoon Rusa was gathered from the insurance company, and input and output variables were formulated. To find the optimal combination of network scenarios and hyperparameters, the optimal model of the DNN algorithm was obtained by learning the training data for each scenario and finding the minimum cost function. Furthermore, validation data and test data were simulated to confirm the overfitting problem that may arise in the DNN algorithm model. Comparative analysis revealed that the proposed DNN model outperformed the conventional MRA model in terms of prediction error rate, with former showing a lower MAE 46.5 % and RMSE 53.8 %. Therefore, the DNN algorithm model used in this research demonstrates high robustness and consistency in predicting damage from typhoons. Moreover, it was again shown that the non-parametric model of the DNN algorithm presented an advanced fit for the analysis of nonlinear data with high uncertainty or complexity, such as typhoon damage, than the parametric MRA model [48,50].

Natural disaster managers or risk managers in the government or private sector will be able to predict typhoon damage with greater reliability than the existing model using the DNN algorithm model offered in this study. Moreover, it will have the potential to develop a highly reliable typhoon damage prediction model in the framework outlined in this study. Due to the sophistication and reliability of typhoon damage prediction, disaster or risk managers will be able to establish a stronger investment and budget strategy to prevent and reduce possible typhoon damage. For example, by preparing an emergency reserve or establishing a financial plan according to the size of individual assets and individual risk preferences. In addition, insurers and reinsurers can improve the adequacy of current insurance rates through the framework or model of this study and apply it to manage cumulative typhoon risk. Moreover, according to the predicted catastrophic risk, wind and flood insurance subscribers can establish and validate a disaster risk transfer strategy by determining the adequacy of insurance premiums and coverage of current insurance. Therefore, by predicting damage from extreme weather disasters such as Typhoon Rusa through the DNN algorithm model and framework of this study, the assessment criteria will

Table 3
Model learning result.

Network Structure Scenario	Dropout (0)		Dropout (0.2)	
	MAE	RMSE	MAE	RMSE
5-5-5	0.917	1.100	0.782	1.141
10-10-10	0.705	0.846	0.662	0.902
25-25-25	0.565	0.678	0.568	0.729
50-50-50	0.381	0.457	0.370	0.564
75-75-75	0.355	0.426	0.347	0.545
100-100-100	0.354	0.425	0.371	0.540
200-200-200	0.382	0.458	0.367	0.569
300-300-300	0.340	0.408	0.319	0.537
400-400-400	0.339	0.407	0.353	0.535
500-500-500	0.357	0.429	0.324	0.547
600-600-600	0.342	0.410	0.329	0.540
700-700-700	0.357	0.429	0.352	0.542
800-800-800	0.489	0.587	0.421	0.676
900-900-900	0.350	0.420	0.337	0.543
1000-1000-1000	0.358	0.430	0.334	0.544

Table 4
Comprehensive summary of optimal network structure and hyperparameter configuration.

Module	Configuration	Elements
Network structure	Node	3
	Layer	400-400-400
Network Hyperparameter	Activation Function Type	ReLu
	Optimizer	Adam
	Batch Size	5
	Number of Epoch	1000
	Dropout rate	0

Table 5
Result of model comparison.

Models	Validation data		Test data	
	MAE	RMSE	MAE	RMSE
Multiple Regression Analysis (MRA)	–	–	1.123	1.107
Deep Neural Network (DNN)	0.451	0.392	0.600	0.512
DNN/MRA (%)	–	–	−46.5 %	−53.8 %

provide the necessary for preventing, reducing, and transferring typhoon risk. This will ultimately provide security to reduce losses due to natural disasters.

Furthermore, the occurrence and severity of extreme natural disasters, such as heavy snow, drought, storm, flood, hail, and tornadoes, are expected to increase due to climate change because of global warming. The proposed model and framework can be used as reference material for natural catastrophe analysis and prognostic research in various fields. Additionally, the natural disaster risk indicators adopted in previous similar research in this study (i.e., the total value of the building, occupancy, wind speed, aerial distance from the water system, height difference, maximum daily and hourly precipitation) were utilized to developing a model and obtaining meaningful results, further enhancing the results of previous research. Moreover, it is believed to be applicable to other related studies using the natural disaster risk indicators applied in this study. In addition, devices using technologies such as the Internet of Things, unmanned transportation, robots, Information and Communications and sensors have been actively announced recently in various facilities, buildings and infrastructure. As the need for data analysis and utilization is estimated to increase rapidly for devices using these technologies, it will be possible to apply the proposed framework of this study to similar research. Therefore, using the results and framework of this study, it will be possible not only to use it in the sophisticated prediction of catastrophic events such as Typhoon Rusa but also to apply it as basic reference material for related studies in various areas of science and industry.

However, in order to reduce the prediction error of the DNN model developed in this study, it is necessary to discover further variables for the model development by excavating additional variables, such as terrain vulnerability, which may affect typhoon damage. Besides, since typhoon damage is limited to property damage in this study, it is necessary to update the model to include various future damages, such as human-made damage. Under the contract, this study utilized only collected damages caused by Typhoon Rusa by a large insurance company in Korea. Therefore, additional studies are required to secure additional damage data from multiple countries and other insurers and reinsurers and to compare and validate by further gathering other data on serious damage caused by typhoons. Additionally, the DNN algorithm model presented in this research has a lower prediction error than the conventional model; nevertheless, because of the peculiarities of the DNN algorithm, the weights and correlations between nodes exist as a black box. This can finally undermine the reliability and objectivity of the model as its user does not identify the process and justification for drawing the results. Therefore, it is necessary to better understand the model and data by the user and increase the reliability of the model through additional research using eXplainable AI (XAI), which can better explain decision-making, causation and prediction to users [51]. In addition to XAI, other advanced optimization algorithms, such as customized heuristics, meta-heuristics, hybrid algorithms, adaptive algorithms, and island algorithms, have also emerged as powerful tools for solving challenging decision problems across various domains [52–55]. These algorithms aim to find near-optimal solutions for complex optimization problems that are difficult to solve using traditional techniques. Their ability to handle complexity, improve convergence and solution quality, and adapt to problem conditions makes them valuable in various domains. However, the application of advanced optimization algorithms in the field of natural disasters is an area that requires further exploration. Natural disasters involve complex decision problems with multiple objectives, constraints, uncertainties, and trade-offs. Advanced optimization algorithms have the potential to address these complexities by considering multiple factors simultaneously and finding optimal or near-optimal solutions. Thus, as part of future research, we will attempt additional research based on advanced optimization algorithms along with the deep learning approach to perform robust and effective solutions that can contribute to more efficient and resilient disaster management practices.

7. Conclusions

The world is suffering from severe disasters due to climate change caused by global warming, and the damage caused by these disasters will increase. Moreover, as there is a need for accurate damage prediction to systematically and impartially manage natural disaster risk, especially those reflecting well-characteristics surges, a consistent and robust model for calculating the damage from natural disasters is mandatory. In addition, there is a growing need for an accurate damage prediction model for stable and independent financial management in the event of natural disasters.

Therefore, this study suggested a framework to creating a predictive model based on typhoon Rusa damage data and the DNN algorithm. In this study, the importance of the DNN algorithm model has been proven by comparison with other models, so it can be assumed that it will be used in future disaster damage prediction and model development. Therefore, using the outcomes and framework of this study, it will be possible to quantify the damage caused by a major disaster and help establish financial management guidelines and strategies through quantifying risk. Besides, it can be applied as basic data for other major disasters or other industries and research fields, and so it will ultimately contribute to the reduction of damage caused by natural disasters and the development of related technologies. For example, insurers and reinsurers can use the framework and findings of this study as a basis for determining key indicators and figures such as Excess of Loss Reinsurance, reserve, Liability Limit, Probable Maximum Loss, and insurance premiums. Additionally, it can be applied to manage the cumulative risk of natural disasters according to each company's portfolio, size of assets and risk orientation. Besides, the public sector will be able to use the framework of this study or the disaster risk indicators to develop a disaster prediction system or an assessment tool.

Data availability statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Ji-Myong Kim: Writing - review & editing, Writing - original draft, Supervision, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Junseo Bae:** Writing - review & editing, Methodology, Data curation. **Manik Das Adhikari:** Writing - review & editing, Validation, Software. **Sang-Guk Yum:** Writing - review & editing, Validation, Software, Resources, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] C. Lagarde, Climate change and central banking, Green Banking and Green Central Banking 24 (2021) 151, https://doi.org/10.1515/9783110752892-015.
[2] J.M. Kim, T. Kim, K. Son, S.G. Yum, S. Ahn, Measuring vulnerability of typhoon in residential facilities: focusing on typhoon Maemi in South Korea, Sustainability 11 (10) (2019) 2768, https://doi.org/10.3390/su11102768.
[3] J.M. Kim, K. Son, S.G. Yum, S. Ahn, Typhoon vulnerability analysis in South Korea utilizing damage record of typhoon Maemi, Adv. Civ. Eng. (2020) 1–10, https://doi.org/10.1155/2020/8885916.
[4] IPCC, Summary for Policymakers, Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects, Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, IPCC, Cambridge, UK, 2014, p. 1820.
[5] NOAA, Hurricane Costs, Office for Coastal Management, National Oceanic and Atmospheric Administration, 2022. https://coast.noaa.gov/states/fast-facts/hurricane-costs.html.
[6] United States National Hurricane Center (USNHC), Costliest US Tropical Cyclones Tables Update, National Oceanic and Atmospheric Administration, 2018. https://www.nhc.noaa.gov/news/UpdatedCostliest.pdf. (Accessed 30 June 2022).
[7] E.S. Blake, C. Landsea, E.J. Gibney, The Deadliest, Costliest, and Most Intense United States Tropical Cyclones from 1851 to 2010 (And Other Frequently Requested Hurricane Facts), 6, NOAA technical memorandum NWS NHC, 2011. https://repository.library.noaa.gov/view/noaa/6929.
[8] U. Ulbrich, A.H. Fink, M. Klawa, J.G. Pinto, Three extreme storms over europe in december 1999, Weather 56 (3) (2001) 70–80, https://doi.org/10.1002/j.1477-8696.2001.tb06540.x.
[9] J.M. Kim, T. Kim, K. Son, Revealing building vulnerability to windstorms through an insurance claim payout prediction model: a case study in South Korea, Geomatics, Nat. Hazards Risk 8 (2) (2017) 1333–1341, https://doi.org/10.1080/19475705.2017.1337651.
[10] J.M. Kim, S. Son, S. Lee, K. Son, Cost of climate change: risk of building loss from typhoon in South Korea, Sustainability 12 (17) (2020) 7107, https://doi.org/10.3390/su12177107.
[11] B.J. Gledson, D. Greenwood, The adoption of 4D BIM in the UK construction industry: an innovation diffusion approach, Eng. Construct. Architect. Manag. 24 (6) (2017) 950–967, https://doi.org/10.1108/ECAM-03-2016-0066.

[12] J.M. Kim, P.K. Woods, Y.J. Park, K. Son, Estimating the Texas windstorm insurance association claim payout of commercial buildings from hurricane Ike, Nat. Hazards 84 (1) (2016) 405–424, https://doi.org/10.1007/s11069-016-2425-7.
[13] J.M. Kim, S.G. Yum, H. Park, J. Bae, A deep learning algorithm-driven approach to predicting repair costs associated with natural disaster indicators: the case of accommodation facilities, J. Build. Eng. 42 (2021), 103098, https://doi.org/10.1016/j.jobe.2021.103098.
[14] S. Guha, R.K. Jana, M.K. Sanyal, Artificial neural network approaches for disaster management: a literature review (2010–2021), Int. J. Disaster Risk Reduc. 81 (2022), 103276, https://doi.org/10.1016/j.ijdrr.2022.103276.
[15] P. Berezina, D. Liu, Hurricane damage assessment using coupled convolutional neural networks: a case study of hurricane Michael, Geomatics, Nat. Hazards Risk 13 (1) (2022) 414–431, https://doi.org/10.1080/19475705.2022.2030414.
[16] T. Kim, J. Song, O.S. Kwon, Pre-and post-earthquake regional loss assessment using deep learning, Earthq. Eng. Struct. Dynam. 49 (7) (2020) 657–678, https://doi.org/10.1002/eqe.3258.
[17] E. Irwansyah, H. Young, A.A. Gunawan, Multi disaster building damage assessment with deep learning using satellite imagery data, Int. J. Intell. Syst. Appl. Eng. 11 (1) (2023) 122–131. https://www.ijisae.org/index.php/IJISAE/article/view/2450.
[18] J.M. Kim, J. Bae, S. Son, K. Son, S.G. Yum, Development of model to predict natural disaster-induced financial losses for construction projects using deep learning techniques, Sustainability 13 (9) (2021) 5304, https://doi.org/10.3390/su13095304.
[19] J.M. Kim, S.G. Yum, S. Son, K. Son, J. Bae, Modeling deep neural networks to learn maintenance and repair costs of educational facilities, Buildings 11 (4) (2021) 165, https://doi.org/10.3390/buildings11040165.
[20] K. Khosravi, M. Panahi, A. Golkarian, S.D. Keesstra, P.M. Saco, D.T. Bui, S. Lee, Convolutional neural network approach for spatial prediction of flood hazard at national scale of Iran, J. Hydrol. 591 (2020), 125552, https://doi.org/10.1016/j.jhydrol.2020.125552.
[21] M. Al Najar, G. Thoumyre, E.W. Bergsma, R. Almar, R. Benshila, D.G. Wilson, Satellite derived bathymetry using deep learning, Mach. Learn. 112 (2021) 1–24, https://doi.org/10.1007/s10994-021-05977-w.
[22] M. Moishin, R.C. Deo, R. Prasad, N. Raj, S. Abdulla, Designing deep-based learning flood forecast model with ConvLSTM hybrid algorithm, IEEE Access 9 (2021) 50982–50993, https://doi.org/10.1109/ACCESS.2021.3065939.
[23] P. Shane Crawford, A.M. Hainen, A.J. Graettinger, J.W. van de Lindt, L. Powell, Discrete-outcome analysis of tornado damage following the 2011 Tuscaloosa, Alabama, tornado, Nat. Hazards Rev. 21 (4) (2020), 04020040, https://doi.org/10.1061/(ASCE)NH.1527-6996.000039.
[24] Y. Yi, W. Zhang, A new deep-learning-based approach for earthquake-triggered landslide detection from single-temporal RapidEye satellite imagery, IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 13 (2020) 6166–6176, https://doi.org/10.1109/JSTARS.2020.3028855.
[25] S. Kaur, S. Gupta, S. Singh, D. Koundal, A. Zaguia, Convolutional neural network based hurricane damage detection using satellite images, Soft Comput. 26 (16) (2022) 7831–7845, https://doi.org/10.1007/s00500-022-06805-6.
[26] Ministry of Public Administration and Security, Disaster Annual Report (Natural Disaster), 2020. https://www.mois.go.kr/frt/bbs/type001/commonSelectBoardArticle.do;jsessionid=JUA7i1tRMjdNEOvPcYBqvMi.node50?bbsId=BBSMSTR_000000000014&nttId=89542.
[27] Korea Meteorological Administration National Typhoon Center, Typhoon white book. https://www.kma.go.kr/download_01/typhoon/typwhitebook_2011.pdf, 2011.
[28] J.M. Kim, P.K. Woods, Y.J. Park, T. Kim, K. Son, Predicting hurricane wind damage by claim payout based on Hurricane Ike in Texas, Geomatics, Nat. Hazards Risk 7 (5) (2016) 1513–1525, https://doi.org/10.1080/19475705.2015.1084540.
[29] C.C. Watson, M.E. Johnson, S. Martin, Insurance rate filings and hurricane loss estimation models, J. Insur. Regul. 22 (3) (2004) 39–64.
[30] D. Cummins, C. Lewis, R. Phillips, Pricing Excess-Of-Loss Reinsurance Contracts against Cat as Trophic Loss, Financing of Catastrophe Risk, University of Chicago Press, 1999, pp. 93–148. https://www.nber.org/system/files/chapters/c7949/c7949.pdf.
[31] P. Grossi, H. Kunreuther, D. Windeler, An introduction to catastrophe models and insurance, in: P. Grossi, H. Kunreuther (Eds.), Catastrophe Modeling: A New Approach to Managing Risk, Catastrophe Modeling, 25, Springer, Boston, MA, USA, 2005, pp. 23–42, https://doi.org/10.1007/0-387-23129-3_2.
[32] S.G. Yum, J.M. Kim, H.H. Wei, Development of vulnerability curves of buildings to windstorms using insurance data: an empirical study in South Korea, J. Build. Eng. 34 (2021), 101932, https://doi.org/10.1016/j.jobe.2020.101932.
[33] Z. Huang, D.V. Rosowsky, P.R. Sparks, Hurricane simulation techniques for the evaluation of wind-speeds and expected insurance losses, J. Wind Eng. Ind. Aerod. 89 (7–8) (2001) 605–617, https://doi.org/10.1016/S0167-6105(01)00061-7.
[34] J.M. Kim, K. Son, Y. Yoo, D. Lee, D.Y. Kim, Identifying risk indicators of building damage due to typhoons: focusing on cases of South Korea, Sustainability 10 (11) (2018) 3947, https://doi.org/10.3390/su10113947.
[35] S.G. Yum, J.M. Kim, K. Son, Natural hazard influence model of maintenance and repair cost for sustainable accommodation facilities, Sustainability 12 (12) (2020) 4994, https://doi.org/10.3390/su12124994.
[36] J.M. Kim, T. Kim, K. Son, J. Bae, S. Son, A quantitative risk assessment development using risk indicators for predicting economic damages in construction sites of South Korea, J. Asian Architect. Build Eng. 18 (5) (2019) 472–478, https://doi.org/10.1080/13467581.2019.1681274.
[37] National Geographical Information Institute, Digital elevation model, NGII. The Ministry of Land, Infrastructure and Transport, Korea, National Geographical Information Institute), 2018. https://www.ngii.go.kr/eng/main.do.
[38] J.M. Kim, K. Son, Y.J. Kim, Assessing regional typhoon risk of disaster management by clustering typhoon paths, Environ. Dev. Sustain. 21 (5) (2019) 2083–2096, https://doi.org/10.1007/s10668-018-0086-2.
[39] R.W. Allison, C.K. Hon, B. Xia, Construction accidents in Australia: evaluating the true costs, Saf. Sci. 120 (2019) 886–896, https://doi.org/10.1016/j.ssci.2019.07.037.
[40] A.T. Cabello, M. Martínez-Rojas, J.A. Carrillo-Castrillo, J.C. Rubio-Romero, Occupational accident analysis according to professionals of different construction phases using association rules, Saf. Sci. 144 (2021), 105457, https://doi.org/10.1016/j.ssci.2021.105457/.
[41] J.M. Kim, S.G. Yum, H. Park, J. Bae, Strategic framework for natural disaster risk mitigation using deep learning and cost-benefit analysis, Nat. Hazards Earth Syst. Sci. 22 (6) (2022) 2131–2144, https://doi.org/10.5194/nhess-22-2131-2022.
[42] S. Ahmed, Causes and effects of accident at construction site: a study for the construction industry in Bangladesh, Int. J. Sustain. Constr. Eng. Technol. 10 (2) (2019) 18–40. https://penerbit.uthm.edu.my/ojs/index.php/IJSCET/article/view/4499.
[43] G. Lee, C. Lee, C. Koo, T.W. Kim, Identification of combinatorial factors affecting fatal accidents in small construction sites: association rule analysis, Korean J. Constr. Eng. Manag. 21 (4) (2020) 90–99, https://doi.org/10.6106/KJCEM.2020.21.4.090.
[44] J. Bae, S.G. Yum, J.M. Kim, Harnessing machine learning for classifying economic damage trends in transportation infrastructure projects, Sustainability 13 (11) (2021) 6376, https://doi.org/10.3390/su13116376.
[45] J. Gu, Z. Wang, J. Kuen, L. Ma, A. Shahroudy, B. Shuai, T. Liu, X. Wang, G. Wang, J. Cai, T. Chen, Recent advances in convolutional neural networks, Pattern Recogn. 77 (2018) 354–377, https://doi.org/10.1016/j.patcog.2017.10.013.
[46] A. Ajayi, L. Oyedele, H. Owolabi, O. Akinade, M. Bilal, J.M. Davila Delgado, L. Akanbi, Deep learning models for health and safety risk prediction in power infrastructure projects, Risk Anal. 40 (10) (2020) 2019–2039, https://doi.org/10.1111/risa.13425.
[47] J.M. Kim, K.K. Lim, S.G. Yum, S. Son, A deep learning model development to predict safety accidents for sustainable construction: a case study of fall accidents in South Korea, Sustainability 14 (3) (2022) 1583, https://doi.org/10.3390/su14031583.
[48] T. Nguyen, A. Kashani, T. Ngo, S. Bordas, Deep neural network with high-order neuron for the prediction of foamed concrete strength, Comput. Aided Civ. Infrastruct. Eng. 34 (4) (2019) 316–332, https://doi.org/10.1111/mice.12422.
[49] W. Wei, X. Yang, Comparison of diagnosis accuracy between a backpropagation artificial neural network model and linear regression in digestive disease patients: an empirical research, Comput. Math. Methods Med. (2021), 6662779, https://doi.org/10.1155/2021/6662779.
[50] J. Schmidhuber, Deep learning in neural networks: an overview, Neural Network. 61 (2015) 85–117, https://doi.org/10.1016/j.neunet.2014.09.003.
[51] F. Chollet, Deep Learning with R. Version 1, Manning Publications Co., NY, 2017.
[52] H. Zhao, C. Zhang, An online-learning-based evolutionary many-objective algorithm, Inf. Sci. 509 (2020) 1–21, https://doi.org/10.1016/j.ins.2019.08.069.

[53] M.A. Dulebenets, An Adaptive Polyploid Memetic Algorithm for scheduling trucks at a cross-docking terminal, Inf. Sci. 565 (2021) 390–421, https://doi.org/10.1016/j.ins.2021.02.039.
[54] J. Pasha, A.L. Nwodu, A.M. Fathollahi-Fard, G. Tian, Z. Li, H. Wang, M.A. Dulebenets, Exact and metaheuristic algorithms for the vehicle routing problem with a factory-in-a-box in multi-objective settings, Adv. Eng. Inf. 52 (2022), 101623, https://doi.org/10.1016/j.aei.2022.101623.
[55] M. Rabbani, N. Oladzad-Abbasabady, N. Akbarian-Saravi, Ambulance routing in disaster response considering variable patient condition: NSGA-II and MOPSO algorithms, J. Ind. Manag. Optim. 18 (2) (2022) 1035–1062, https://doi.org/10.3934/jimo.2021007.