



Research Paper / Makale

Assessment and Application of Deep Learning Algorithms in Civil Engineering

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Abstract: In this study, the applicability of deep learning algorithms in the field of civil engineering has been investigated. Firstly, the information that is about deep learning algorithms has been given. Additionally, deep learning applications, which are made, in subjects such as classification, estimation, and interpretation in the field of civil engineering, have been examined. The applications are elaborated according to civil engineering's sub-branches that transportation, geotechnical and construction. The contributions of the realized applications' in view of success rates to civil engineering that were analyzed. As a result of the study, it is foreseen that in the studies where the number of data is high, high performance will be achieved in the use of deep algorithms.

Keywords : Civil Engineering; Classification; Deep Learning Algorithms; Deep Neural Network; Vision.

İnşaat Mühendisliğinde Derin Öğrenme Algoritmalarının Değerlendirilmesi ve Uygulanması

Özet: Bu çalışmada inşaat mühendisliği alanına derin öğrenme algoritmalarının uygulanabilirliği araştırılmıştır. Öncelikle derin öğrenme algoritmaları hakkında bilgiler verilmiştir. Ayrıca inşaat mühendisliği alanında sınıflandırma, tahmin ve yorumlama gibi konularda yapılan derin öğrenme uygulamaları incelenmiştir. Uygulamalar inşaat mühendisliğinin ulaştırma, hidrolik, mekanik, geoteknik ve yapı alt bilim dallarına göre detaylandırılmıştır. Gerçekleştirilen uygulamaların başarı oranları üzerinden inşaat mühendisliğine katkıları analiz edilmiştir. Çalışmanın sonucunda veri sayısının fazla olduğu çalışmalarda derin öğrenme algoritmalarının kullanımında yüksek başarımler elde edileceği ön görülmektedir.

Anahtar kelimeler: Derin Öğrenme Algoritmaları; Derin Sinir Ağı; İnşaat mühendisliği; Sınıflandırma; Görü.

1. Introduction

Civil engineering is a profession with a wide scope such as Building, Bridge, Road, Dam, Canal, Infrastructure Design and Construction [1-2]. In the same time, civil engineers can work interdisciplinary [3]. Civil engineering, environmental engineering, geotechnical engineering, structural engineering, transportation engineering, municipal or city engineering, construction, and water resources including a number of the sub has the expertise [2]. It has departments of structural, mechanical, hydraulic, geotechnical, transportation, earthquake engineering, and building management in civil engineering. Graduates of civil engineers can usually find jobs in project manager or similar positions. Therefore, civil engineers need to have satisfactory knowledge and

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general competence in understanding and ensuring safety [4]

The principles of Civil Engineering [1] which is one of the oldest branches of Engineering in the world, were well applied during the construction of the pyramids in ancient Egypt and the aqueducts in Rome [2]. Civil engineering has been work developed rapidly due to the need to rebuild buildings that had been demolished after the II. World War [3]. A civil engineer is a person who is the ability and knowledge to combine analytical and synthetic approaches to find and implement safe and economic solutions. In addition, the Civil Engineer acts professionally using construction activities consistent with a modern and viable urban environment, aiming at Sustainable Development and protection of the natural environment [5]. Finally, as a designer, Civil Engineers influence the ergonomics of construction with material properties and related methods [6].

Engineering applications are forced to move from traditional problem-solving and design capabilities to more innovative solutions [7]. The advances and developments in the information and technologies of today's rapidly developing world have been reflecting in engineering methods and techniques. Computer-aided methods play an increasing role in the professional life of Engineers [8]. Developments in computer technology and special technical software are closely related to civil engineering education and application areas. In recent years, studies on the application of artificial intelligence approaches have been prominent in civil engineering. In civil engineering, software applications are used in the design process and in different tasks. In addition, each software application has an optimized data structure [9]. Engineers, builders, planners, and contractors also use a variety of field-specific software to support their work [10].

Today, in the field of engineering, great importance is attached to systems that think and behave like humans. Machine learning is the motive for integrating human factors into engineering applications [11-12]. Machine learning is the concept that enables a model to learn and act according to an approach which is based on the functioning of neurons in the human brain. An artificial neuron model was created, inspired by the functioning of the neurons in the human brain [13]. This artificial neural network model was improved over the time and started to be used frequently in machine learning. Today, this artificial neural network design has been highly improved, and lead to the introduction of a new model called deep learning.

Deep learning provides high accuracy in crowded data sets [14]. Deep learning algorithms prefer in the applications of prediction [15], classification [16] and identification [17] as shown in the Figure 1. Deep Learning Algorithm has been used which has Deep Neural Network (DNN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) & Long short-term memory (LSTM) in these applications. It provides suitable estimation belongs to process and easiness in the plans that cost is expensive and feasibility is strange at the engineering services. Especially, into the civil engineering, the models developed with the actual data affect the process positively into the strange application processes. For example, in case of earthquake or natural disaster, damage determination can be made via the images received from the site [18]. Into the metropolises, estimation of traffic densities and determination of the car speed in related to this, decreases the accident risk in the roads [19]. In a similar way, car assistant systems provide the focusing to the road by the identification of the traffic warning signs at the roadside [20].

The following process of the study is as follows. Chapter 2 presents preliminary information about deep learning and algorithms used in civil engineering, and Chapter 3 provides an examination of applications in subdivisions of civil engineering such as transportation, hydraulics, mechanics, geotechnics and construction. In the conclusion part of the study, guidance is provided about how to integrate deep learning into future studies in civil engineering.

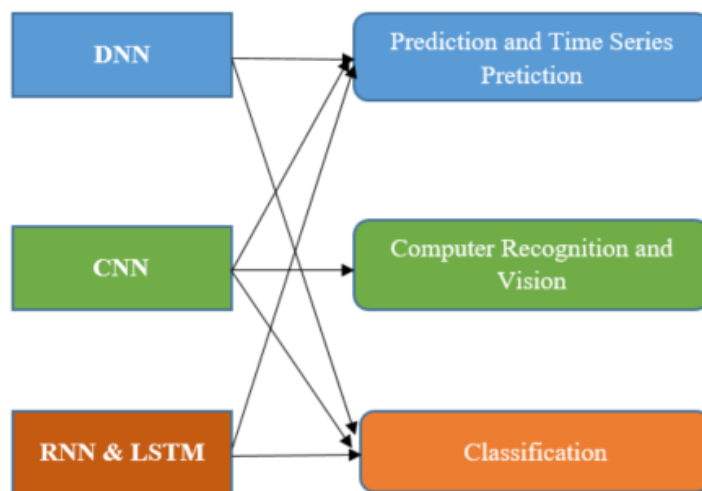


Figure 1. Model types using deep learning architectures

2. Preliminary Background On Deep Learning

Simply defined, deep neural networks (DNN) are machine learning techniques created by expanding traditional neural networks. DNN structures differ from machine learning techniques in that DNNs do not require feature extraction steps. As a result, DNN makes it possible to learn more complicated and non-linear features via increasing the number of layers and neurons [21]. In DNN structures, another feature is to apply a network trained with a particular dataset to different datasets via transfer learning. In other words, it means to use the abilities of a DNN that learns about cars in a network that tries to recognize a bus. The network architectures used in DNN are Convolution Neural Network (CNN), Recurrent Neural Network (RNN), Long Short Term Memory (LSTM), Restricted Boltzmann Machines (RBM), Deep Belief Network (DBN) and Deep/Stacked Auto encoder (DAE).

Developing a deep learning application requires lots of data and high-performance computers. The recent rise in the use of Graphical Processing Units (GPUs) and the fact that data in any area can now be processed in DNN have expanded the range of deep learning applications [22]. A review of the literature showed that DNN structures have been used in many applications such as object recognition [23], classification [16], prediction [15], image processing [24], voice recognition [22], sentence building [25], etc. In this part of the study, deep neural network architectures, highly preferred in civil engineering applications, are examined.

2.1. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNN) are a type of multilayer sensors. The CNN algorithm model was first inspired by the visual cortex of animals [26].

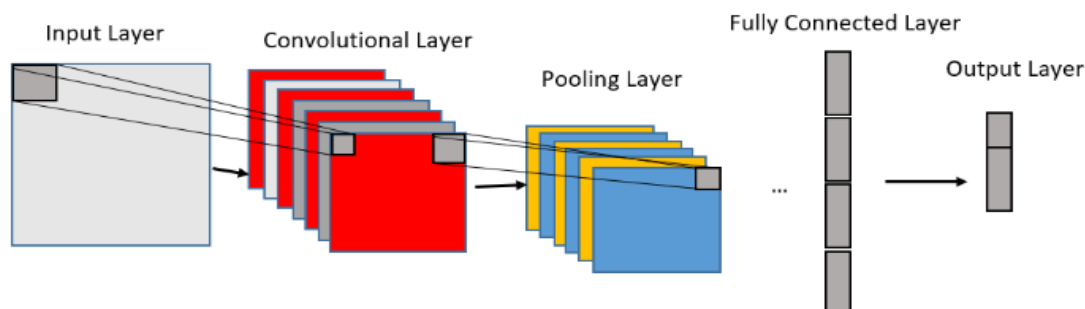


Figure 2. Structure of CNN

The CNN consists of one or more convolutional, activation, classifying, pooling and additional layers as shown in Figure 2. Each layer maintains its function, producing results on the classification layer. CNN, which is a multi-layer feed-forward artificial neural network, ensures that processes are carried out on image datasets. The first CNN network was used in the study entitled LeNet introduced by Le Cun et al. [27]. The algorithm is widely used algorithm in deep learning, especially in classification and detection / identification applications.

2.2. Recurrent Neural Network (RNN)

Recurrent Neural Networks (RNN), originally designed by Jeff Elman, are a class of artificial neural networks where connections between nodes form a directed loop [28]. The RNN not only receives input examples that are fed into the network, but also input examples already present in the time series. The task of this neural network is to use data fed consecutively. In conventional neural networks, inputs enter the network independently of each other [29]. However, in RNN, the output of each data in the sequence depends on the previous calculations. The unrolled architecture of a full RNN network is illustrated in Figure 3. Wherein x_t represent the data at time t , s_t represents the secret position at time t and o_t represents the output at time t .

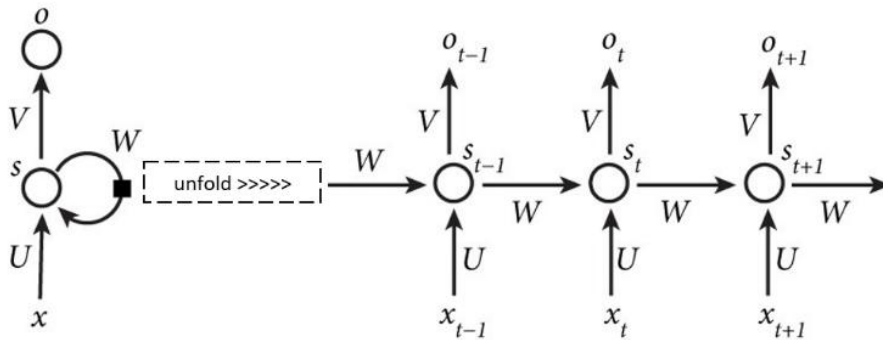


Figure 3. RNN's architecture for opening a network

2.3. Long Short Term Memory (LSTM)

It is a class of DNN first introduced as RNN and then modified by researchers taking into account RNN's shortcomings. LSTM networks that borrowed temporal sequences and their long-range dependencies from RNN consist of an input layer, one or more hidden layers, and an output layer [30]. Each hidden layer of LSTM has a unit called the memory cell. One LSTM cell structure shown in Figure 4 has an input gate (i), a forget gate (f) and an output gate (o).

$$\begin{aligned}
 i_t &= \sigma(W_{xi} x_t + W_{hi} h_{t-1} + W_{ci} c_{t-1} + b_i) \\
 f_t &= \sigma(W_{xf} x_t + W_{hf} h_{t-1} + W_{cf} c_{t-1} + b_f) \\
 c_t &= f_t c_{t-1} + i_t \tanh(W_{xc} x_t + W_{hc} h_{t-1} + b_c) \\
 o_t &= \sigma(W_{xo} x_t + W_{ho} h_{t-1} + W_{co} c_t + b_o) \\
 m_t &= o_t \odot h(c_t) \\
 h_t &= o_t \tanh(c_t), \\
 y_t &= W_{hy} h_t + b_y,
 \end{aligned} \tag{1}$$

These three gates determine the state of the cell at time t . In the LSTM structure, the input gate specifies what information is added to the cell state, the forget gate what information is removed from the cell state, and the output gate specifies what information from the cell state is used [18]. In LSTM, the input vector $x = (x_1, x_2, x_3, \dots, x_t)$ and output class $y = (y_1, y_2, y_3, \dots, y_t)$ unit activation functions are calculated and determined repetitively from $t=1$ to T according to the sequence shown in Equation 1.

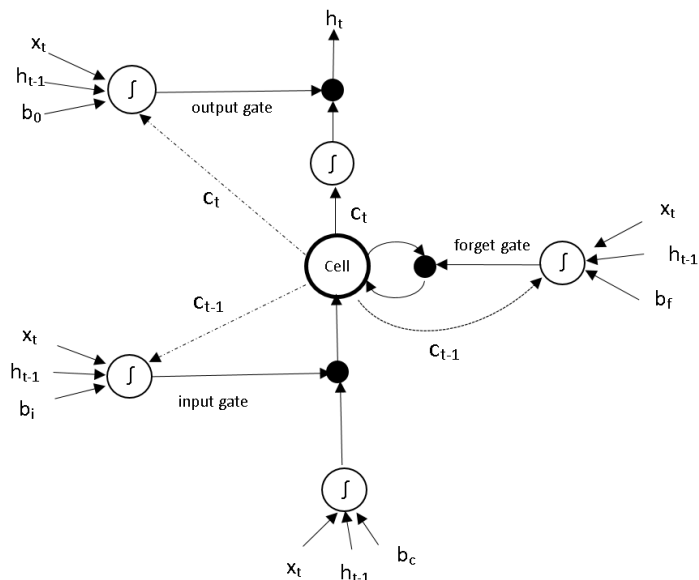


Figure 4. LSTM cell structure

2.4. Deep Belief Network (DBN)

DBN is a deep neural network consisting of a multilayered graphical model that aims to create the hierarchical representation of the dataset (Figure 5). DBN may be seen as the hidden layer of each network, a combination of simple, uncontrolled networks such as restricted RBM or automatic encoders which function as the visible layer of the next layer [31]. The layer in the DBN structure has an efficient, layer-by-layer procedure that determines how variables are connected to variables in the layer above [32]. In a study conducted in 2006 by Hinton et al., first, they created a DBN pile by using RBM and found that it could be trained [33].

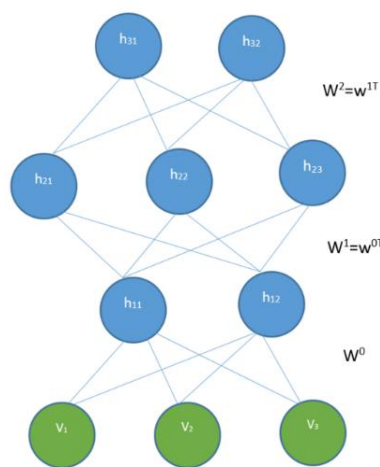


Figure 5. Architecture of DBN

3. Deep Learning Applications

3.1. Computer Recognition and Vision

Deep neural networks are being developed for computer vision and recognition used in the transportation infrastructure of civil engineering [34]. Studies aimed at recognizing traffic signs in particular play an important role in autonomous vehicles and driver assistance systems [35-38]. For example, when a driver travelling at high speed increases the speed from 40 km/h to 130 km/h, the angle of sight is reduced from 100° to 30°. In such cases, it is difficult for the driver to perceive roadside traffic signs. Automatic sign recognition of the in-vehicle assistants enables the driver to focus on the road. Neural networks and computer vision techniques are employed in applications developed for the solution of the problem. Ready-to-use datasets are generally used for accuracy and testing of the models in the literature, developed for the recognition of traffic signs (Table 1). On the other hand, some researchers convert traffic signs in their countries or regions into a dataset [39-40]. Data sets containing traffic signs have different visual characteristics as shown in Figure 6. Computer vision and recognition are modeled in deep learning using CNN architecture. Table 2 shows a summary of deep neural network models using traffic sign recognition in the literature in the last 5 years.



Figure 6. Samples of pictures used for traffic sign boards

One of the biggest challenges facing engineers today is the supervision, evaluation, maintenance and safe operation of the construction infrastructure. Such a study requires either manual approaches yielding slow and subjective results, or automated approaches based on complicated features. In the latter case, however, it is not known beforehand which features are important for the problem at hand. Basically, the problems are solved by means of deep neural networks.

Table 1. Datasets used in traffic sign recognition

Dataset	Categories
The German Traffic-Sign Detection Benchmark (GTSDDB)	3 super-categories
The German Traffic-Sign Recognition Benchmark (GTSRB)	43 categories
The Mapping and Assessing the State of Traffic Infrastructure (MASTIF)	31 categories
The Swedish traffic-sign dataset (STSD)	10 categories
The Laboratory for Intelligent and Safe Automobiles (LISA)	49 categories
The Tsinghua-Tencent	45 categories
The Belgium Traffic Signs (BTS)	62 categories
The DFG Traffic-Sign Dataset	200 categories

Cracks occur due to infrastructure errors or disasters at places where casting of concrete, steel, asphalt, etc. is used. In order to detect such damages, image processing techniques are applied on pictures of crack locations. This helps to detect and classify defects visible in the pictures. In this context, Cha et al. employed the CNN algorithm to develop a deep neural network model for the

detection of cracks in concrete and steel surfaces. For crack detection, 97% accuracy was attained in 332 images in total with this model [50]. In their study, Gao and Mosolam [51] proposed a model for the detection of cracks and damage resulting from a disaster. The ImageNet dataset was used in the model built on the CNN algorithm.

Table 2. Samples of deep learning models applied for traffic sign recognition

Paper	D	R	Dataset	Acc
Bangquan and Xiong (2019) [41]	+	+	GTSDB	98.6%
Tabernik and Skocaj (2019) [42]	+	+	DFG Traffic-Sign Dataset	96.5%
Wu et al. (2019) [43]	+	+	GTSDB	91.75%
Jose et al (2019) [44]	+	+	GTSRB	71,56%
			Indian Road Signs	84%
Wu et al. (2019) [45]	+	+	Taiwan Road Signs	83.5%
Eykholt et al. (2018) [46]	-	+	USA Traffic Signs	91%
Eykholt et al. (2018) [46]	-	+	GTSRB	95,7%
Sitawarin et al. (2018) [47]	+	+	GTSRB	98.5%
Zhang et al. (2018) [48]	-	+	GTSRB	99.84%
Zeng et al. (2017) [49]	-	+	GTSRB	99.54%

D: Detection R: Recognition Acc: Accuracy

The images in the dataset were classified by damage severity as no damage, slight damage and heavy damage. As a result of the study, 90% accuracy was achieved in the classification [51]. In the study called CrackNet, a CNN model was proposed for the detection of cracks in pavements. Additionally, the study was compared with traditional machine learning methods and it was suggested that the model developed produced better solutions [52]. In tunnels, damage assessment can be done during routine checks in addition to detection of crack damage attributable to technical aspect or a disaster. In their study, Makantasis et al. collected raw data from the tunnel with the help of a camera assembly they prepared. In the dataset obtained, damage assessment capabilities of traditional machine learning algorithms and CNN algorithm were tested. As a result of the study, it was reported that the CNN model produced the best result with 88% accuracy [53]. The accuracy rates of the studies and models on damage detection are shown in Table 3.

Table 3. Samples of CNN applied for damage recognition

Paper	Dataset	Accuracy
Mohtasham et al. (2019) [54]	Around 100,000 crack and 150,000 noncrack samples	96.26%
Gulgec et al. (2019) [26]	6,000 undamaged and 6,000 damaged samples	95.3%
Ye et al. (2019) [55]	FCN and CrackForest	95%
Fan et al (2018) [56]	SegNet (2,750 images)	98.61%
Abdeljaber et al (2018) [57]	128 samples	98.93 %
Cha et al (2018) [50]	600 samples	98.1%
Gao and Mosolam (2018) [51]	ImageNet	90 %
Modarres et al. (2018) [58]	Model of simply supported Euler–Bernoulli beam	99.6%
Cha et al (2017) [59]	332 samples	97%
Makantasis et al. (2015) [53]	Real-time data	88%

A review of computer vision and recognition applications shows that the models developed are based on CNN deep neural network architecture. In the field of civil engineering, CNN models

focus on traffic sign recognition and damage assessment/classification. In the studies conducted in this respect, ready-to-use datasets as well as datasets created within the scope of the study were used for training the deep neural network. In models offering high accuracy, datasets were partitioned into two sections 80% for training and 20% for testing. Tensorflow, ResNet or keras frameworks were preferred for the creation of model networks. In addition, in parameter selection of the model, learning rate and epoch were selected as 0.001 and 100, respectively, in general. As a result, infrastructure inspection, damage assessment and object identification applications via field images have produced successful results in civil engineering thanks to CNN deep neural network architecture.

3.2. Prediction

Predicting a situation through currently available data offers a great deal of ease for future works. In civil engineering, drawing conclusions based on data obtained from previous experiments or tests offers advantages in terms of time and cost. Particularly in the field of transportation, information facilitating the traffic situation of the region provides great convenience to drivers and authorities both. When the literature on prediction methods is examined, it is seen that models for estimating traffic density, speed and commuting times have been developed using deep learning methods.

DNNs have recently demonstrated their ability to estimate traffic flow. Although existing DNN models outperform traditional models, the spatial and temporal characteristics of traffic flow must be fully utilized to improve performance. In their study, Dabiri and Heaslip used twitter's spatial and temporal characteristics as data for predicting traffic flow density [60]. Mackenzie et al. [61] developed a hybrid LSTM model for traffic density prediction in South Australia based on actual data from the Sydney Coordinated Adaptive Traffic System. In general, traffic flow density prediction includes a time-series analysis. For this reason, the LSTM architecture is encountered more in the models developed.

Traffic speed prediction is the estimation of future speed based on past speed information taken from a road at certain intervals. Jia et al. proposed the Deep Belief Network model, a deep learning method for predicting traffic speed information. The DBN model was modeled with labeled data by using an uncontrolled method. The model was trained and tested for different prediction times based on traffic speed data collected from an arterial road in Beijing. Successful results were obtained from the study at 30-minute intervals [62]. Ma et al. developed a LSTM based model which determines the most appropriate time for traffic speed prediction. The training and testing of this model was conducted using actual data from traffic microwave detectors in Beijing [63]. Finally, Ma et al. proposed a CNN model using images of spatial and temporal traffic dynamics for traffic speed prediction. The proposed model was compared with different traditional machine learning algorithms and was found to have the highest accuracy [64].

Analysis of seismic hazard is a critical part of civil engineering projects. Seismic hazards such as earthquake, faulting, landslides and liquefaction are events that cause damage to structures. There are different methods for estimating ground motion such as physical modeling and on-site evaluation. The use of these methods is difficult and costly [21]. In the literature, deep learning methods are recommended for predicting seismic hazard. Wang et al. proposed a new spatial and temporal earthquake prediction system. In particular, a two-dimensional LSTM network, which can explore spatial-temporal correlations between earthquake formations and utilize correlations to make accurate earthquake predictions, was designed [65]. Derakhshani and Foruzan derived complex relationships from seismic data and generated a prediction model for basic ground motion parameters. The model was built on the NGA-West2 dataset provided by PEER (Pacific Earthquake Engineering Research Center) [21].

Although utmost importance is attached to traffic in the studies on transportation, the deep learning approaches to this matter are composed of LSTM and CNN + LSTM combinations (Table 4). The time-series prediction in these models should take into account both forward and backward dependencies of the data. The dataset used in the training of models consists of image or raw traffic data generally taken from special sensors. In measuring accuracy of the neural network used in the prediction process, errors between actual data and prediction data are measured. A review of the studies in the literature shows that five different error measurements whose formulations are presented are used. This evaluation criterion is respectively; Mean Absolute Error (MAE) (Equation 2), Mean Relative Error (MRE) (Equation 3), R2 (Equation 4), Mean Squared Error (MSE) (Equation 5) and Root Mean Square Error (RMSE) (Equation 6).

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - y'_i| \quad (2)$$

$$MRE = \frac{1}{n} \sum_{i=1}^n \frac{|y_i - y'_i|}{y_i} \quad (3)$$

$$R^2 = 1 - \frac{MSE(model)}{MSE(baseline)} \quad (4)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - y'_i)^2 \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - y'_i)^2} \quad (6)$$

Where, n denotes the number of prediction samples, y_i is the prediction value, and y^{\wedge} true is the true value.

3.3. Classification

Classification method is the grouping of the information or images in data sets for a specific purpose. Classification is highly recommended with deep learning methods. In civil engineering, classification is preferred for finding vehicle types in traffic by using deep learning algorithms, in natural disasters and accidents [78] for damage assessment of settlements or solving other infrastructure problems [83]. Classification from real-time images or visuals in the dataset is done by CNN architecture [84]. The classification does with the identification of the object from the visual in some applications. In this kind of situations, CNN and LSTM architectures are using together and hybrid models are establishing. Also, the classification can be made through the data set or real time data. It is seen that softmax activation function is generally used in the output classification layer of the studies.

Logistic regression [85] and Softmax Regression [86] were used in the classification of deep neural networks. Logistic regression produces result between 0 and 1 (Equation 7). Softmax Regression is an expansion of logistical regression and multiple classification is used (Equation 8).

$$y' = \frac{1}{1 + e^{-(w^T x + b)}} \quad (7)$$

$$P(y = j | z^{(i)}) = \phi_{soft\ max}(z^{(i)}) = \frac{e^{z_k^{(i)}}}{\sum_{j=0}^k e^{z_k^{(i)}}} \tag{8}$$

Images from the road, building, tunnel, Ocean are processed and interpreted by CNN deep learning algorithm. In classification studies with CNN, AlexNet, GoogleNet, ResNet, vgg19 architectures are widely used [87-91].

Table 4. Samples of deep learning applied for prediction

Paper	Dataset	Deep Model	Type	
Fu et al. (2016) [66]	PeMS (15.000 sensor data)	LSTM	Traffic Prediction	Flow
Wu and Tan (2016) [67]	110.000 past data.	CNN+LSTM	Traffic Prediction	Flow
Zhao et al. (2017) [68]	Beijing Traffic Management (25.11 million data)	LSTM	Traffic Prediction	Flow
Fandango and Kapoor (2018) [19]	Average vehicle speed for January 2017 to June 2017 from California Department of Transportation.	RNN+ LSTM	Traffic Prediction	Flow
Luo et al. (2019) [69]	Transportation Research Data Lab (TDRL)	LSTM	Traffic Prediction	Flow
Zheng et al. (2019) [70]	Real highway traffic dataset	Embedding + CNN+ LSTM	Traffic Prediction	Flow
Yang et al. (2019) [71]	Chongqing Transport Planning and Research Institute	LSTM	Traffic Prediction	Flow
Jia et al. (2016) [62]	The traffic data, including speed, flow and occupancy, are collected in 2-minute interval by the Beijing Traffic Management Bureau (BTMB)	DBN	Traffic Prediction	Speed
Li et al. (2017) [72]	METR-LA and PEMS-BAY dataset	Diffusion Convolutional Recurrent Neural Network (DCRNN)	Traffic Prediction	Speed
Wu et al. (2018) [73]	PeMS	CNN+RNN	Traffic Prediction	Speed
Zang et al. (2018) [74]	Elevated highways of year 2011	CNN+LSTM	Traffic prediction	speed
Wang et al. (2019) [75]	Collected from automatic vehicle identification (AVI)	Bi-LSTM	Traffic prediction	speed
Chu et al. (2018) [76]	New York taxi data with around 400 million records.	LSTM	Travel Prediction	Time
Sun et al. (2019) [77]	A bus speed dataset is calculated with the time span from May 06 to July 07, 2017.	LSTM	Travel Prediction	Time
Petersen et al. (2019) [78]	The dataset consists of 1,2Million travel time	Conv-LSTM	Travel Prediction	Time
Das et al. (2019) [79]	Dataset from the city of Porto and Beijing		Travel Prediction	Time
Huang et al. (2018) [80]	Real Data (2250 Seismic waves)	CNN	Seismic Detection	Event
Dicket et al. (2019) [81]	Total 608,362 data from 1 January 2010 to 1 January 2015	CNN	Seismic Detection	Event
Zhu et al. (2019) [82]	4986 events with 30,146 phases	CNN	Seismic Detection	Event

LTSM model has been recommended to determination and classification of the earthquakes made as a result of the earthquake in Mangalathu and Burton studies. Earthquake damages has degreed in 3 different colors and tested at 3423 damaged structure. As a result of model training 1552 green, 1674 yellow and 197 red sticker classification has been made. An accuracy of 86% has been

achieved in this classification [92]. Zhong et al have developed a CNN model that enables the classification of quality States in constructions. The Model performs output classification according to the word, which contains six different complaints. It has been compared with Bayesian and SVM algorithms to measure the success of the classification performed. As a result, the proposed CNN model has been shown to have the highest success [93]. A sampled list of classification studies in the field of deep learning is given in Table 5.

Table 5. Samples of deep learning applied for classification

Paper	Dataset	Deep Model	Acc
Mangalathu and Burton (2019) [92]	3423 Real Data	LSTM	86%
Wen et al. (2019) [94]	3000 Real Samples	CNN	95.97%
Ni et al. (2019) [95]	Civil Aviation Administration of China (CAAC)	DBN	-
Beckman et al. (2019) [96]	1091 Images	CNN	90.79%.
Kuyuk and Susumu (2018) [84]	305 Three Component Between 2000 and 2018 in Japan.	LSTM	98.2%.
Bentes et al. (2018) [97]	TerraSAR-X, multilook ground range detected images. A	CNN	94 %
Li et al. (2014) [98]	The imagery is composed of 144 spectral bands ranging from 380 to 1050 nm.	DBN	97%.
Buscombe and Ritchie (2018) [99]	31,500 high-resolution images from Google Earth imagery	DCNN	Between 88% and 97%

4. Conclusion

In this study, it has explained that how can deep learning algorithms apply in civil engineering and which techniques used for this. Firstly, the technical structure and working algorithms of deep learning architectures are explained. The use of deep learning in civil engineering applications is grouped as visual recognition, prediction, and classification. These groupings are detailed result-based as damage determination, traffic speed prediction, traffic signs knowing, maintenance and repair. When literature studies are examined, it is seen that the deep learning applications give more successful results on the high data sets. Real data sets are used in deep neural network models in recent years. These data sets have consisted of the data or visuals received from the regions, where the researchers are located. As the target areas of civil engineering consist of visual elements such as bilding, road, infrastructure, tunnel, and etc. CNN architecture is more preferred in the models. Especially, at a high cost and difficult applications of deep teaching algorithms are more advantageous. LSTM architecture is mostly used in prediction and classification based on a specific time series. As a result of these, it provides convenience using deep learning in civil engineering. It has been found that it is important to have a high dataset for the application of deep learning and to model the problem with the correct algorithm.

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