The analysis of existing neural networks for natural language interfaces

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Abstract. This paper discusses the main types of neural networks and describes which are most suitable for solving problems within the framework of natural language user interfaces. The statistics of publications on the use of neural networks in various branches of science for the period from 2015 to 2020 are given, assumptions about the possible directions of integration of neural networks in the construction industry are made.

1. Introduction
Today, artificial neural networks, that is a set of algorithms is adopted, designed to recognize individual elements within the system and modelled on the principle of the human brain are gaining more and more development. This computational model can perform the tasks of decision making, visualization, forecasting, classification, and can find its application in various branches of science and technology.

A neural network, as a rule, is organized in three interconnected layers: input, hidden, which can include more than one layer, and output. The neural network communication scheme is shown in Fig. 1.

![Neural network communication scheme](image)

**Figure 1.** Neural network communication scheme
As you can see from the diagram, the input layer contains input neurons that send data to the hidden layer. Further information is sent to the exit. Each input neuron determines the weight of the criteria (synapse, that is a custom parameter that converts the network to a parameterized system), activation function (linear function, sigmoid function, piecewise-defined function, ReLU activation function), which calculates the output data taking into account the input and a specific output, providing the result.

Each neural network undergoes training - a process during which the optimization of the weight of each criterion takes place; accordingly, the errors and decision errors are minimized, and the neural network becomes more accurate. The main method used to solve this problem is the back-propagation method.

Currently, various types of neural networks and the problems of their development are given considerable attention, which is confirmed by scientific publications in various fields of science. The statistics on publications for the period 2015-2020 are presented in fig. 2. The articles and papers were selected by the keyword "neural network" in the following branches of knowledge: Physics and Astronomy; Engineering; Computer Science; Mathematics Materials Science; Energy Earth and Planetary Sciences.
According to the Fig.3 there are a lot of research works about different use of neural networks even in construction industry sphere [1-21]. A description of the most common neural networks according to the analysis of the main publications is presented below.

2. Main part

2.1. Rumelhart Multilayer Perceptron

A multilayer perceptron has three or more layers and uses a nonlinear activation function (logistic equation, hyperbolic function), which allows to classify data that is not linearly separable. Each node in the layer connects to all nodes in the next layer, making the network fully connected. An example of the use of multilayer processing of the perceptron in the framework of natural languages is machine translation and speech recognition.

Figure 4. The multilayer perceptron architecture

For multi-layer perceptron, the back-propagation algorithm is used. On the network, as shown in Fig. 6, there is a lot of input data - $a_1, ..., a_n$, a lot of outputs “conclusions” and a lot of nodes. Using end-to-end numbering without taking into account the topology of the columns, we number all the numbers from 1 to N. Where $\omega_{i,j}$ is the weight of the edge connecting the nodes $i$ and $j$. Provided that the correct answers within the network are accepted as $t_k, k \in \text{conclusions}$, the training example is known, then the error function calculated by the least squares method takes the form:

$$E(\{\omega_{i,j}\}) = \frac{1}{2} \sum_{k \in \text{conclusions}} (t_k - o_k)^2 \quad (1)$$
2.2. Convolutional Neural Network

The convolutional neural network contains one or more convolutional layers, combined or completely connected. Uses a variety of multilayer perceptrons discussed earlier. Convolutional layers use the convolution operation for input, passing the result to the next layer. This operation allows the network to be deeper with much smaller parameters.

![Convolutional Neural Network Architecture](image)

**Figure 5.** Convolutional neural network architecture

After each convolution, the resulting scalar result passes to the activation function, which is a certain nonlinear function. This function in fig. 3 is considered embedded in the convolution layer. Traditionally using hyperbolic tangent functions

\[ f(x) = \tanh(x), f(x) = |\tanh(x)| \] (2)

or smooth monotonous increasing nonlinear function (sigmoid)

\[ f(x) = \frac{1 + e^{-x}}{1 - e^{-x}} \] (3)

Convolutional neural networks show outstanding results in image processing and speech.

2.3. Recursive Neural Networks

A recursive neural network is a type of deep neural network formed by recursively applying the same set of criteria weights to a structure to make a structured prediction for input data of variable size. In the simplest architecture, the non-linearity and the weight matrix of the criteria, which are shared by the entire network, unites the nodes into the parent.

![Simple Recursive Network Architecture](image)

**Figure 6.** Simple recursive network architecture

In the simple architecture shown in fig. 6, network nodes converging to parents through a matrix of weights in a hidden layer are presented. This matrix is used repeatedly over the entire network and hyperbolic tangent (non-linear activation function)

\[ a_{1,2} = \tanh(w|b_1; b_2|) \]

Where \( w \) is the \( n \times 2n \) trained weight matrix.
2.4. **Recurrent Neural Networks**
A recurrent neural network is a variant of a recursive artificial neural network in which the connections between neurons form a directed cycle. This means that the output depends not only on the current input, but also on the state of the neuron of the previous step. This data allows users to solve natural language problems in the field of speech recognition and handwriting.

2.5. **Long term short-term memory**

![Figure 7. Block of long-term short-term memory with three nodes - entry, exit, forgetting](image)

Long-term short-term memory is a specific architecture of recurrent neural networks, which was developed to more accurately model time sequences and their dependencies. This architecture does not use the activation function in its repeating components, the stored values do not change, and the gradient does not tend to disappear during training. Typically, blocks have three or four “nodes” (for example, an inlet valve, an outlet valve, a shut-off valve) that control the flow of information in a logistic function. This type is used to create large acoustic models.

2.6. **Sequence models in sequence**
Typically, this model consists of two recurrent neural networks: an encoder that processes the input, and a decoder that produces the output. The encoder and decoder can use the same or different sets of parameters. Models are mainly used in machine translation systems, answering machines and chatbots.

2.7. **Shallow neural networks**
In addition to deep neural networks, small models are also popular and useful tools. For example, word2vec is a group of surfaces two-layer models that are used to embed words.

3. **Results**
The analysis of publications in the field under consideration allowed us to identify the main advantages and disadvantages of neural networks, as well as to determine their scope.

| Neural networks   | Advantages                                                                 | Disadvantages                        | Areas of use                                      |
|------------------|---------------------------------------------------------------------------|--------------------------------------|--------------------------------------------------|
| Rumelhart Multilayer Perceptron | training is carried out to stabilize the network weights, and not to minimize errors, which allows not to retrain the system | limitations in forecasting capabilities | machine translation, speech recognition, data analysis, business intelligence |
### Convolutional Neural Network
- Fewer parameters, which speeds up and simplifies the learning process
- Failure probability due to susceptibility to samples with minimal changes (fakes)
- Image and speech processing

### Recursive Neural Networks
- The possibility of learning a network without a teacher
- Probability of providing an approximate answer
- Natural language processing tasks

### Recurrent Neural Networks
- Timed event processing
- Fading gradient problem (fast loss of information over time)
- Natural language problems in speech recognition and handwriting

### Long term short-term memory
- Solve the problem of recurrent networks using an explicit memory cell and filters
- Huge resource consumption
- Tasks of creating large acoustic models

### Sequence models in sequence
- Repeats the advantages of recurrent neural networks, expanding the possibilities of application
- Complication of the model compared to recurrent networks
- Tasks of machine translation systems, answering machines and chat bots

### Shallow neural networks
- Optimized system with a clear goal
- Solving small specific problems
- Word embedding

## 4. Conclusions
Neural networks are more and more densely used in our life; moreover, they are the base of many solutions to complex problems from various industries. That fact is confirmed by many publications. Solving problems associated with decision support, decomposition, and decoding of images is currently being carried out using neural networks, but the first task that needs to be solved is to choose the right type of neural network for a specific request.

At the same time, the integration of neural networks in the construction industry is still developing, the most promising areas are design automation systems in construction and solving problems of organizing construction.

## Acknowledgments
This study was performed with the financial support of the RF Ministry of Education and Science, President Grant #NSh-3492.2018.8
References
[1] Das S, Swetapadma A and Panigrahi C 2019 A study on the application of artificial intelligence techniques for predicting the heating and cooling loads of buildings (Journal of Green Building vol 14 iss 3) 115-128
[2] Pezeshki Z and Mazinani S M 2019 Comparison of artificial neural networks, fuzzy logic and neuro fuzzy for predicting optimization of building thermal consumption: a survey (Artificial Intelligence Review vol 52, iss 1) 495-525
[3] Amin P, Cherkasova L, Aitken R and Kache V 2019 Automating energy demand modeling and forecasting using smart meter data (Proceedings - 2019 IEEE International Congress on Internet of Things, ICIOT 2019 - Part of the 2019 IEEE World Congress on Services) 8815658, 133-137
[4] Jayawardana, P, Thambiratnam D P, Perera N and Chan T 2019 Dual in-filled trenches for vibration mitigation and their predictions using artificial neural network (Soil Dynamics and Earthquake Engineering vol 122) 107-115
[5] Lei L, Zhou Y, Luo H and Love P E D 2019 A CNN-based 3D patch registration approach for integrating sequential models in support of progress monitoring (Advanced Engineering Informatics vol 41) 100923
[6] Tang Y, Xiao S and Zhan Y 2019 Predicting settlement along railway due to excavation using empirical method and neural networks (Soils and foundations vol 59) 1037-1051
[7] Renda A, Barsacchui M, Bechini A and Marcelloni F 2019 Comparing ensemble strategies for deep learning: An application to facial expression recognition (Expert Systems with Applications vol 136) 1-11
[8] Braun A and Bormann A 2019 Combining inverse photogrammetry and BIM for automated labeling of construction site images for machine learning (Automation in Construction vol 106) 102879
[9] Cheng M-Y and Cao M-T 2014 Accurately predicting building energy performance using evolutionary multivariate adaptive regression splines (Applied Soft Computing Journal vol 22) 178-188
[10] Orosa J A, Vergara D, Costa A M and Bouzon R 2019 A novel method based on neural networks for designing internal coverings in buildings: Energy saving and thermal comfort (Applied Sciences vol 9 iss 10) 2140
[11] Yaqubi M K and Salhotra S 2019 The automated cost estimation in construction (International Journal of Innovative Technology and Exploring Engineering vol 8, iss 7) 845-849
[12] Kim H, Ahn E, Shin M and Sim S-H 2019 Crack and Noncrack Classification from Concrete Surface Images Using Machine Learning (Structural Health Monitoring vol 18, iss 3) 725-738
[13] Shirhkanian A, Davarnia D and Azar B F 2019 Prediction of bond strength between concrete and rebar under corrosion using ANN (Computers and Concrete vol 23, iss 4) 273-279
[14] Abambres M, Rajana K, Tsavdaridis K D and Ribeiro T P 2019 Neural network-based formula for the buckling load prediction of I-section cellular steel beams (Computers vol 8, iss1) 2.26p
[15] Lehky D, Pan L, Novak D, Cao M Somodikova M and Slowik O 2019 A comparison of sensitivity analyses for selected prestressed concrete structures (Structural Concrete vol 20 iss 1) 38-51
[16] Hu M and Shealy T 2019 Application of functional near-infrared spectroscopy to measure engineering decision-making and design cognition: Literature review and synthesis of methods (Journal of Computing in Civil Engineering vol 33, iss 6 ) 04019034
[17] Cheng M-Y, Chang Y-H and Korir D 2019 Novel Approach to Estimating Schedule to Completion in Construction Projects Using Sequence and Nonsequence Learning (Journal of Construction Engineering and Management vol 145, iss 11) 04019072
[18] Chouhan S S, Kaul A and Singh U P 2019 Image Segmentation Using Computational Intelligence Techniques: Review (Archives of Computational Methods in Engineering vol 26 iss 3) 533-596
[19] Song X and Reif J 2019 Nucleic Acid Databases and Molecular-Scale Computing (*ACS Nano* vol 13, iss 6) 6256-6268

[20] Moreno-Garsia C F and Elyan E and Jayne C 2019 New trends on digitisation of complex engineering drawings (*Neural Computing and Applications* vol 31, iss 6) 1695-1712

[21] Cheng M-Y, Wibowo D K, Prayogo D and Roy A F V 2015 Predicting productivity loss caused by change orders using the evolutionary fuzzy support vector machine inference model (*Journal of Civil Engineering and Management* vol 21 (7)) 881-892