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Application of the Convolution Neural Network in the Text Sentiment Analysis

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Abstract: *Sentiment analysis deals with the analysis of the opinions, attitudes and emotions of the people who wrote a certain text. The goal of text sentiment analysis is to detect positive, neutral or negative sentiments from the text. The ability to automatically recognize emotions from text has many practical applications, such as customer sentiment analysis, social media monitoring, and customer feedback analysis. In this paper, we considered the application of neural networks in text sentiment analysis, using the Python programming language and Keras as a deep learning Python library. In the experimental part of the work, we trained a convolution neural network to classify text into different classes depending on the recognized emotions. We obtained a model that we tested on a test data set and considered the classification accuracy of the obtained model.*

1. INTRODUCTION

The idea of constructing intelligent machines that would independently perform certain types of work instead of humans goes back to the distant past. Computer behavior is considered intelligent if it has the ability to draw conclusions based on certain facts. Operations such as detection and classification of objects from everyday life, as well as other similar operations that humans perform intuitively, are a problem for computers.

However, until now all forms of artificial intelligence have been limited to certain types of problems. In scientific research, there is a lot of discussion about artificial intelligence, i.e. the question arises whether intelligence can be reproduced by computers (Janicic & Nikolic, 2020). It can be said that artificial intelligence represents a scientific discipline that deals with the construction of computer systems whose behavior can be interpreted as intelligent (Dalbelo-Bašić et al., 2020). Also, it represents a scientific discipline on how to enable machines to perform tasks that, if performed by humans, would require intelligence (Dalbelo-Bašić et al., 2020).

Intelligence is a skill that characterizes human beings, although they do not always behave intelligently (Eletter & Yaseen, 2010). Artificial intelligence means any non-living system that shows the ability to deal with new situations. Since such an approach requires a high degree of computational processing, its implementation was not successful until the early 1980s. The development of neural networks, which are used in data analysis, is based on existing knowledge about the functioning of the human brain. Neural networks are widely used in social, economic, technical and natural sciences. Despite the fact that the development of neural networks is more recent, the extremely

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high success rate of their implementation is reflected in the area of prediction and classification (Novakovic, 2013).

A neural network model is developed by training on a larger number of samples. The most successful applications of neural networks come from researchers with experience in academia and industry. Neural networks have become a technology suitable for application in various fields. Neural networks receive input information and then transform it into an output. The goal of neural network research is the development of new network structures that would function analogously to the human brain or at least partially imitate its functions for solving practical problems.

Deep learning is a set of machine learning algorithms for training layered structures. Moreover, the layers in those models correspond to different levels of concepts, so that the same concepts at lower levels participate in the formation of different concepts at higher levels. Deep learning represents a new field of machine learning with the aim of bringing machine learning closer to its original goal, which is artificial intelligence.

In the paper, we discussed the application of neural networks in the analysis of text sentiment. Detection and recognition of emotions from text is a field of research that is closely related to the analysis of text sentiment (Velampalli et al., 2022; Murthy et al., 2020; Kumar et al., 2020; Wankhade et al., 2022; Yao, 2019). Text sentiment analysis aims to detect positive, neutral or negative feelings from the text, while emotion analysis aims to detect and recognize the types of feelings through the expression of the text, such as anger, disgust, fear, happiness, sadness and surprise. Text sentiment analysis has applications in various areas of business, such as: product analysis, brand tracking, market research, improving customer support, social media monitoring, and customer feedback analysis.

After the introduction, which describes the basic concepts of artificial intelligence, neural networks, with special reference to deep learning, the second part of the paper deals with the theoretical assumptions of deep learning and the convolutional neural networks. The third part of the paper describes the data set that will be used for neural network training. In the fourth part, we explained preprocessing of the data set. In the fifth, we explained the settings of the experimental research, the model obtained by training and the presentation of the accuracy of the text sentiment classification. The final part of the paper provides concluding considerations and guidelines for further research.

2. DEEP LEARNING AND CONVOLUTIONAL NEURAL NETWORKS

"Deep learning is a new field of machine learning research that was introduced to bring machine learning closer to one of its original goals: artificial intelligence (http://deeplearning.net/) ." Deep learning is a type of representational learning and as such is part of machine learning.

Machine learning is one of the fields of artificial intelligence. The factors that led to the transition from machine learning to artificial intelligence are: the exponential increase of available data, the existence of flexible models, the availability of computers with good performance at acceptable prices and the possibility of reducing the dimensionality of data with appropriate methods.

Deep architecture studies are motivated by the problem of slow training of neural networks. In the last ten years, significant progress has been made in this area. The success in training the structures of deep neural networks led to revolutionary changes in this area, as well as to the formation of a new scientific discipline - Data Science.

Convolutional neural networks (Convolutional Neural Network - CNN) can be classified as deep neural networks, which are associated with the concept of deep learning (Cen et al., 2020). These networks are a biologically inspired version of a multilayer perceptron, based on simulating the real recognition and inference processes used by humans. Therefore, the main element of which the network is made is the neuron.

Convolutional neural networks are designed to process data that comes in the form of multiple strings. The architecture of a typical CNN is structured as a series of blocks. The first blocks are composed of convolution and compression layers. Hidden layers are a combination of convolution, compression, a layer of converting data into a one-dimensional array and a fully connected layer. CNNs use multiple layers to filter the input data to achieve a high level of abstraction.

3. DATA SET FOR CONVOLUTIONAL NEURAL NETWORK TRAINING

Emotions play a key role in human communication. The ability to automatically recognize emotions from text has many practical applications, such as sentiment analysis, social media monitoring, and customer feedback analysis.

For this research, a data set by Cheela (n.d.) was used. The data set contains two columns, the first with 282822 texts and the second with a label for the corresponding emotion that expresses the given text: sad and happy. In the first column with text, there are 282782 unique values (Figure 1). The emotions shown in the second column in the observed data set have the following distribution: 53% happy and 47% sad. The data set has no missing values.

	text	emotion
0	carefully word blog posts amount criticism hea...	☹️
1	cannot remember little mermaid feeling carefre...	🙂
2	not feeling super well turns cold knocked next...	🙂
3	feel honored part group amazing talents	🙂
4	think helping also began feel pretty lonely lo...	☹️

Figure 1. View of a small part of the data set

Source: Own processing

4. DATA PREPROCESSING

To recognize the sentiment of the text, preprocessing the data is a particularly important step, so that the machine learning algorithms can process it better (Dwivedi et al., 2022). We used several different preprocessing methods, namely:

- lowercase,
- dropping the stop word,
- dropping punctuation,
- discarding unwanted characters,
- tokenization,
- normalization of emoticons and signs.

Convert to lowercase converts all case-based characters in a string to lowercase characters. In order to avoid different interpretation of tokens with the same meaning, all uppercase letters are changed to lowercase.

One of the main forms of preprocessing is filtering out useless data. In natural language processing, useless words (data) are called stop words. A stop word is a commonly used word (such as "the", "a", "an") that the search engine is programmed to ignore, both when indexing search entries and when retrieving them as search results. Stop words are a set of words that are often used in a language. The idea is that dropping stop words removes low-information words from the text so that the algorithm can focus on important words (Matović, 2021).

We can do the removal by storing a list of words that we think are stop words. In the paper, we removed stop words using NLTK (natural language tool) in Python which has a list of stop words of different languages. To check the list of stop words, we can type the following command in Python.

```
import nltk

from nltk.corpus import stopwords

print( stopwords.words (' english '))

{'ourselves', 'hers', 'between', 'yourself', 'but', 'again', 'there', 'about', 'once', 'during', 'out', 'very', ' having', 'with', 'they', 'own', 'an', 'be', 'some', 'for', 'do', 'its', 'yours', 'such', 'into', 'of', 'most', 'itself', 'other', 'off', 'is', 's', 'am', 'or', 'who', 'as', 'from', ' him', 'each', 'the', 'themselves', 'until', 'below', 'are', 'we', 'these', 'your', 'his', 'through', 'don', 'nor', 'me', 'were', 'her', 'more', 'himself', 'this', 'down', 'should', 'our', 'their', 'while', ' above', 'both', 'up', 'to', 'ours', 'had', 'she', 'all', 'no', 'when', 'at', 'any', 'before', 'them', 'same', 'and', 'been', 'have', 'in', 'will', 'on', 'does', 'yourselves', 'then', 'that', ' because', 'what', 'over', 'why', 'so', 'can', 'did', 'not', 'now', 'under', 'he', 'you', 'herself', 'has', 'just', 'where', 'too', 'only', 'myself', 'which', 'those', ' and ', 'after', 'few', 'whom', ' t', 'being', 'if', 'theirs', 'my', 'against', 'a', 'by', 'doing', 'it', 'how', 'further', 'was', 'here', 'than'}
```

You can also modify the list by adding words of your choice in the corresponding file that already contains stop words. We used all the above stop words in the paper, except that we only excluded the following words 'no', 'nor' and 'not' from the list because we considered that they affect the analysis of the semantics of the text.

We can do the punctuation removal by using NLTK (Natural Language Toolkit) in Python which has a list of punctuation characters to remove. We removed unwanted characters that do not affect the semantics of the text by removing all characters except az, AZ, and 0-9.

Word tokenization is the process of representing text as a list of tokens. In this paper, sentences are divided into word-level tokens, so the sentence "I am satisfied with the service" will be represented as the following list of tokens ["I", "am", "satisfied", "with", "the", "service"].

A good indicator of emotional polarity is emoticons. The emoticons in our work are: sad (‘ ☹ ’) and happy (‘ ☺ ’). In our work, we performed the following mapping:

```
df [‘emotion’] = df [‘emotion’ ].map ({

‘☹ ’ : 0,

‘ ☺’ : 1

})

df.head ()
```

and obtained the following data display (Figure 2):

	text	emotion
0	carefully word blog posts amount criticism hea...	0
1	cannot remember little mermaid feeling carefre...	1
2	not feeling super well turns cold knocked next...	1
3	feel honored part group amazing talents	1
4	think helping also began feel pretty lonely lo...	0

Figure 2. View of a small part of the data set after mapping

Source: Own processing

5. EXPERIMENTAL RESEARCH

For the purposes of experimental research, the open source software Jupyter Notebook and the Python programming language were used. The Python programming language is often used to write code for artificial intelligence purposes. We used TensorFlow as an open source library for developing and training machine learning models. Also, we used Keras as a deep learning Python library.

In this paper, we investigated the performance of convolutional neural networks in text sentiment analysis. In the paper, we used different filters to pass over our input and take all the attributes, to get the final output of the convolution layer. We then passed the output of this layer through a nonlinear activation function. ReLU is most often used, which we also use in our work.

One of the layers in convolutional networks is the pooling layer, which is used with the aim of progressively reducing the size of the data set and, thus the number of features, which leads to a reduction in computational complexity and faster network training. The two most commonly used methods are maximum pooling and average pooling. In the paper, maximum compression was used - the filter is passed over the matrix with the given step and the highest value (maximum compression) is selected and written into the output map (Dabović & Tartalja, 2017). It is further moved by a previously defined step, and the maximum value from that marked part is written to the next place in the output map (matrix) and so on until the end. Maximum compression is a form of non-linear pixel downscaling. The compression layer is used with the aim of progressively reducing the size of the data set, thus the number of features, which leads to a reduction in the complexity of the calculation (Dabović & Tartalja, 2017). In a neural network, the dence layer is a classically fully connected layer: every input node is connected to every output node.

A CNN model needs to know what shape the input should expect. The first layer in the sequential model should receive information about the form of the input. Only the first layer receives this information, as subsequent layers can perform automatic inference. To create the model, we use the following layers:

- *Conv1D* – convolutional layer.
- *MaxPooling1D* - compression by maximum.
- *Dense layer* - fully connected layer.
- *Dropout layer* - cancels the contribution of some neurons.

In this paper, we will model a CNN that has 3 convolution layers. After each convolution, we add a compression layer using max pooling. After the third convolutional layer, we will add a *Dropout layer* which is a mask that cancels the contribution of some neurons towards the next layer and leaves all others unchanged.

After the *Dropout layer*, we will add a fully connected layer to obtain a text sentiment feature map, based on which we perform the classification. The fully connected layer has "units = 1" because it has to predict based on the text whether someone has a positive or negative emotion.

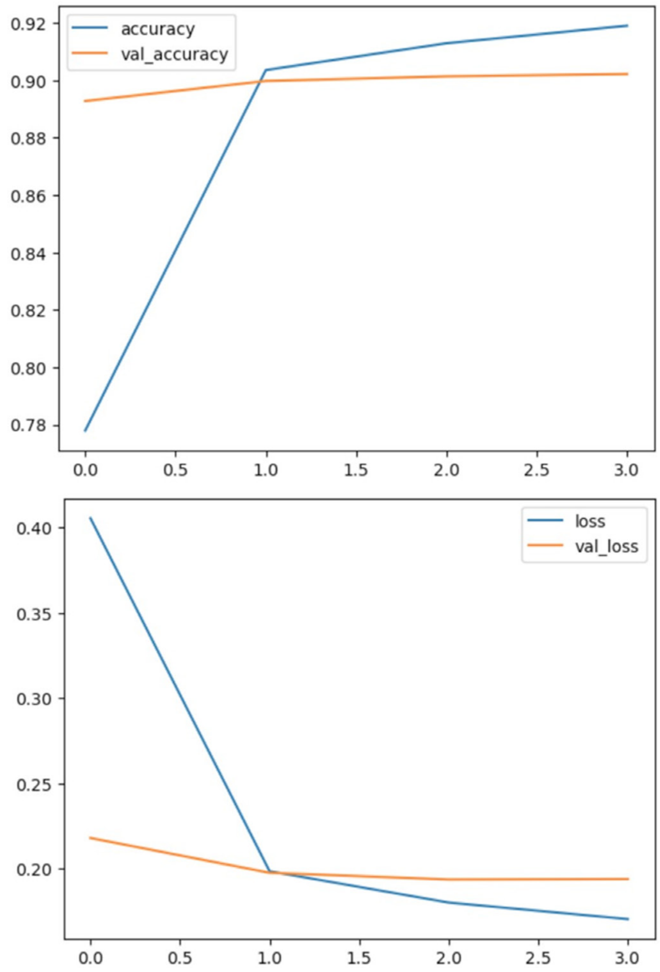

Figure 3. Accuracy and classification losses on the training and validation sets
Source: Own processing

In our work, we use the "adam" optimization function, which optimizes how quickly our model learns the correct image classification. The number of epochs is the number of complete passes through the training dataset, in our case it is 10. As a metric for our model, we use classification accuracy. The learning rate is used to control the rate at which the algorithm updates or learns the parameter estimate values. In other words, the learning rate regulates the weights of our neural network in relation to the loss gradient. In our case, it has a lower value (0.00005) due to the possibility of overtraining.

The loss function is a function that compares the target and predicted output values; measures how well the neural network models the training data. When training, we aim to minimize this loss between predicted and target results. In the paper, since we are considering a classification problem, binary cross entropy was used to select the category with the highest probability of belonging.

Figure 3 shows the values for classification accuracy and losses during training and validation. Epochs are shown on the horizontal axis, while accuracy and loss values are shown on the vertical axis. We can conclude that the classification accuracy increases until the fourth epoch and then decreases. The classification accuracy of the test data set for the best network parameters is 90.21%, while the losses amount to 0.1940.

6. CONCLUSION

Sentiment analysis of textual data is a scientific field that deals with the analysis of the thoughts, attitudes and emotions of the people who wrote the text. This paper discusses the problem of sentiment analysis of textual data using convolutional neural networks. First, the data is preprocessed with some of the standard preprocessing techniques in the word processing field. After that, using preprocessed data, we investigated the performance of convolutional neural networks in text sentiment analysis. In our further research on the sentiment analysis of textual data, we will use other machine learning models in order to obtain the highest classification accuracy and the least losses.

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