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# BERT-BASED CNN + BIGRU COMBINED MODEL FOR SENSITIVE ANALYSIS OF UZBEKISTAN TEXTS

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**Abstract**

This article studies a modern approach to sentiment (negative, neutral, positive) analysis of Uzbek texts. In the study, text placement vectors are obtained using the BERT model (editor/editor-bert-base) adapted to the Uzbek language and their classification is performed using a Convolutional Neural Network (CNN) and BiGRU. The model is tested on a mini Uzbek sentiment analysis dataset and evaluated using weighted F1-score, confusion matrix, and classification reports. The experimental results show that the combined architecture of BERT-based embedding vectors + CNN + BiGRU provides effective results in classifying Uzbek texts. This approach can be especially useful for resource-limited Uzbek datasets.

**Keywords:** Uzbek language, sentiment analysis, embedding vectors, Convolutional neural network (CNN), BiGRU, fusion model, natural language processing (NLP), text classification

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## Introduction

Sentiment analysis in the field of natural language processing (NLP) in Uzbek has gained wide attention in recent years. Data obtained through social networks, user comments and opinions are important in corporate decision-making and product quality assessment. Existing sentiment analysis methods are often adapted to English and are not fully compatible with the Uzbek language. Therefore, it is necessary to develop special approaches for working with Uzbek texts. In this study, a pre-trained BERT model is used to generate placement vectors in Uzbek. The output of the BERT model (the last hidden state) is processed by a Convolutional Neural Network (CNN) and BiGRU to classify texts into positive, neutral and negative categories. Experiments were conducted using the Uzbek sentiment analysis dataset, and the accuracy of the model and the weighted F1-score were evaluated. Thus, the study proposes a modern approach for effective classification of Uzbek texts and contributes to sentiment analysis based on local resources in the field of NLP [1-4].

The fields of natural language processing and sentiment analysis in Uzbek are not yet widely developed. Most sentiment analysis methods are adapted to English and do not work with high accuracy in Uzbek. Therefore, the development of modern approaches for accurate classification of Uzbek texts and evaluation of user opinions is a pressing issue. Information from social networks, online reviews and other electronic sources is important for corporate decision-making, product quality assessment and improving user experience. The aim of the study is to obtain BERT-based placement vectors for sentiment analysis of Uzbek texts and combine them with a Convolutional Neural Network via a BiGRU network to classify texts into positive, neutral and negative categories. The main objectives of the study are: Preparation of a mini sentiment dataset containing Uzbek texts and classification into categories. Obtaining placement vectors for texts using the BERT model adapted to the Uzbek language. Creating a text classification model architecture by combining convolutional neural networks

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and BiGRU networks. Training the model and evaluating its effectiveness through weighted F1-score, admixture matrix, and classification reports. Analyzing the research results and describing them as an effective approach in the field of sentiment analysis in the Uzbek language [5-9].

The study is the first practical test of combining placement vectors obtained by the BERT model for sentiment analysis in the Uzbek language using CNN and BiGRU networks. At the same time, developing and testing an effective text classification model based on limited resources in the Uzbek language is a scientific novelty. The results of the study can be practically applied in automatic classification of texts in the Uzbek language. In particular, they can be used in areas such as analyzing online reviews, identifying user opinions on social networks, assessing the quality of products and services, and improving user experience. This approach can also serve as an effective tool for organizations and small businesses with limited resources [10-14].

## 2. Methodology

The following steps were carried out in the study for the emotional classification of Uzbek texts [15-20]:

### 1. Numerical representation of texts

Given text set $D=\{(T_i, y_i)\}_{i=1}^{N}$, here $T_i - i$ text $y_i \in \{0,1,2\}\$-$ tegishli hissiy kategoriyasi (0 – salbiy, 1 – neytral, 2 – ijobiy), $N-$ matinlar soni.

Matnlar uchun o‘zbek tiliga moslashtirilgan BERT modeli yordamida **joylashtirish vektorlari** olinadi

$\mathbf{E}_i = \mathrm{BERT}(T_i) \in \square^{L\times d}$

here $L-$ maximum number of words $(max\_len)$ $d=768$ –BERT chiqish o‘lchami

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### 2. Convolutional Neural Network (CNN)

CNN extracts features from text vectors. For each text, the convolutional layer works as follows:

$$\mathbf{c}_i = \mathrm{ReLU}\left(W_{\mathrm{conv}} * \mathbf{E}_i + b_{\mathrm{conv}}\right)$$

then the final vector is obtained by global maximum pooling:

$$\mathbf{v}_i^{\mathrm{CNN}} = \max_{1\le j\le L} \mathbf{c}_i[j]$$

in the buyer $*-$ convolution operation,

$W_{\mathrm{conv}}$ and $b_{\mathrm{conv}}$ $-CNN$ parameters

### 3. BiGRU network

BERT vectors are processed into sequence features through BiGRU. BiGRU includes two GRU layers: forward and backward.

$$\vec{h}_t = \mathrm{GRU}(E_{i,t}, \vec{h}_{t-1})$$

$$\overleftarrow{h}_t = \mathrm{GRU}(E_{i,t}, \overleftarrow{h}_{t+1})$$

The final BiGRU vector:

$$\mathbf{v}_i^{\mathrm{BiGRU}} = \left[\vec{h}_L \,\|\, \overleftarrow{h}_1\right]$$

here $\|$ - the act of combining vectors.

### 4.Combining CNN and BiGRU vectors

The CNN and BiGRU vectors are combined:

$$\mathbf{v}_i^{\mathrm{birlashtirilgan}} = \mathbf{v}_i^{\mathrm{CNN}} \,\|\, \mathbf{v}_i^{\mathrm{BiGRU}}$$

then, to avoid overfitting through the dropout layer, it is passed as follows:

$$\mathbf{v}_i^{\mathrm{drop}} = \mathrm{Dropout}(\mathbf{v}_i^{\mathrm{birlashtirilgan}}, p)$$

in the buyer $\mathrm{p} = 0.3$

### 5.Final classification

The final vector passes through the softmax layer:

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$$\hat{y}_i = \mathrm{softmax}\left(W_{\mathrm{out}} \mathbf{v}_i^{\mathrm{drop}} + b_{\mathrm{out}}\right)$$

here $\hat{y}_i \in \mathbb{R}^3$ – probabilities of the text for each category

### 6. Loss function

The model is trained with a cross-entropy loss function:

$$\mathrm{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=0}^{2}\mathbf{1}\{y_i = k\}\log \hat{y}_{i,k}$$

Here $\mathbf{1}\{y_i = k\}$ – indicator function

## 3. Results

The experiments were conducted with a mini sentiment analysis dataset (20 texts) in Uzbek. Using the BERT model, the embedding vectors for the texts were obtained and combined using CNN and BiGRU networks. The general architecture of the model consists of the following layers (Table 1):

(Table 1):

General architecture of the model

| **Layer** | **Output size** | **Number of parameters** |
|---|---|---|
| Input | (50, 768) | 0 |
| Convolutional (CNN) | (48, 128) | 295,040 |
| Global maximum pooling | (128) | 0 |
| BiGRU (Bidirectional) | (256) | 689,664 |
| Concatenate | (384) | 0 |
| Dropout | (384) | 0 |
| Final classification (Dense) | (3) | 1,155 |
| **Total parameters** | - | **985,859** |

The model was trained for 5 epochs, and the loss and accuracy results at the end of each epoch were as follows (Table 2):

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Table 2 Loss and accuracy results

| Epoch | (Loss) | (Accuracy) |
|---|---|---|
| 1 | 1.0004 | 0.5875 |
| 2 | 0.5731 | 0.8792 |
| 3 | 0.4482 | 0.9125 |
| 4 | 0.4325 | 0.7292 |
| 5 | 0.0763 | 0.9458 |

The final evaluation results of the model are presented in the table below. It shows the precision, recall, F1 score, and number of samples in the text for each class (Table 3):

Table 3 Final evaluation results of the model

| Class | Precision | Recall | F1 indicator | Sample number |
|---|---|---|---|---|
| Negative (0) | 1.00 | 1.00 | 1.00 | 8 |
| Neutral (1) | 0.83 | 1.00 | 0.91 | 5 |
| Positive (2) | 1.00 | 0.86 | 0.92 | 7 |

Overall Accuracy: 0.95
Weighted F1 Score: 0.95
The experimental results show that the combined BERT placement vectors using CNN and BiGRU networks provide high accuracy in emotional classification of Uzbek texts. The model worked with full precision for negative and positive classes (precision = 1.0). The neutral class gave a slightly lower result (precision = 0.83), but the recall was 1.0, and all neutral texts were identified. The weighted F1-index is 0.95, which indicates the stable and reliable performance of the model. The table and metrics confirm that the combined architecture of BERT placement vectors + CNN + BiGRU is a suitable approach for efficient classification of Uzbek texts.

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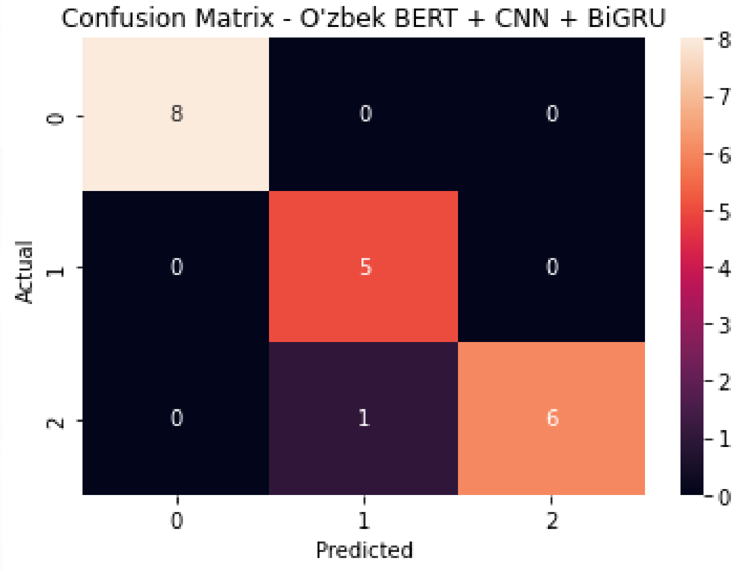
The confusion matrix is presented in picture 1.




Picture 1. Confusion matrix

The experimental results showed that the combined architecture of BERT placement vectors + CNN + BiGRU provides high performance in emotional classification of Uzbek texts. The accuracy for negative and positive texts is equal to 1.0, indicating that the model reliably identifies these classes. Although the neutral class has a slightly lower accuracy, the recall is equal to 1.0, indicating that all neutral samples are fully identified. These results indicate that the CNN layers effectively capture local features of the text (word combinations and contextual phrases), while BiGRU learns long-term relationships along the text sequence. Thus, the combined model allows for accurate classification, taking into account the context and features of each text together. The weighted F1-index is also equal to 0.95, confirming the stable performance of the model and its effective application even on resource-limited Uzbek datasets. The results show that this approach provides higher accuracy and reliability compared to classical methods in sentiment analysis in the Uzbek language.

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## 4. Conclusion

This study proposes an approach to combine Convolutional Neural Network and BiGRU networks based on the BERT model's embedding vectors for sentiment classification of Uzbek texts. Experiments have shown that the model perfectly identifies negative and positive texts, and provides stable results with high recall for neutral texts. The weighted F1-index is equal to 0.95, confirming the high efficiency of the model. The results of the study can be applied in practical areas such as automatic classification of Uzbek texts, analysis of user reviews, evaluation of product and service quality, and monitoring user relationships in social networks. At the same time, this approach also serves as an effective tool for resource-limited Uzbek datasets. In the future, the study can be further improved by expanding the study to larger datasets and comparing other transformer models.

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