Evaluating the Effectiveness of Attention-Gated-CNN-BGRU Models for Historical Manuscript Recognition in Ukraine

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Abstract

This research focuses on evaluating the effectiveness of the Attention-Gated-CNN-BGRU model for Handwritten Text Recognition from historical documents, specifically from the archive of Khmelnytskyi Oblast, written in Ukrainian and Russian languages between 1861 and 1913. The methodology involved preprocessing, data augmentation, deep learning with attention mechanism, and expert assessment. The obtained results showed an average percentage of correctly recognized characters at 71.7%, demonstrating the high effectiveness of the model. A strong negative correlation between text complexity and recognition accuracy underscores the need for further improvement in Optical Character Recognition technologies. The main direction of future research will be adapting the model for recognizing texts written in the Ukrainian language using the Latin alphabet, which is crucial for preserving Ukraine's cultural heritage.

Keywords

Historical documents, Optical Character Recognition, Handwritten Text Recognition, deep learning

1. Introduction

The modern world of digital technologies opens new horizons for the preservation and study of historical documents, offering unique tools for exploring cultural heritage. One of the key directions in this field is the development and application of OCR systems, which automate the process of converting image-based text into machine-readable format. This, in turn, facilitates easier access to historical documents, their analysis, and interpretation. However, the characteristics of historical manuscripts, such as variability in writing styles, degree of preservation, and material erosion, pose challenges for researchers that require the development of specialized OCR algorithms and methods.

This scientific article is dedicated to analyzing the effectiveness of the Attention-Gated-CNN-BGRU model [1], specifically developed for text recognition from manuscripts. The research is based on a carefully curated dataset of documents from the state archive of Khmelnytskyi Oblast, covering the years from 1861 to 1919 and various funds reflecting the socio-historical aspects of the region during the specified period. The main focus of the research is on determining the accuracy of the OCR model in the context of variability in manuscript complexity, evaluating the impact of writing styles and document preservation on recognition quality, as well as analyzing potential directions for algorithm optimization.

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Given the importance of preserving historical heritage and the development of digital humanities, the results of this research aim not only to demonstrate the potential of modern OCR technologies in historical text analysis but also to provide valuable insights for further improvement of digital humanities tools.

The formulation of the problem. In the context of the development of digital technologies and the study of cultural heritage, there arises the problem of effectively recognizing text from historical manuscripts using OCR systems. This problem arises due to the diversity of writing styles, differences in the preservation state of documents and their materials, complicating the process of automated conversion of images into machine-readable form. Such technical challenges create the necessity for the development and enhancement of specialized OCR algorithms to effectively process historical manuscripts.

This article presents a method for evaluating the effectiveness of the Attention-Gated-CNN-BGRU model for text recognition from historical manuscripts, based on deep learning with attention mechanism. Chapter 2 discusses a review of related works; Chapter 3 describes the research methodology, including dataset description and document recognition approach; Chapter 4 is dedicated to the implementation of the algorithm and detailed analysis of the obtained results. Chapter 5 presents the research conclusions summarizing the main findings and emphasizing the prospects for further research in this field.

2. Related work

The development of artificial intelligence (AI) technologies is one of the key and significant trends of the present day. This is primarily explained by the ability of AI, or more accurately "computational" or "electronic" intelligence, to learn and self-learn, recognize and synthesize language and images. Worldwide practice already has results of AI activity in the field of historical research. For example, Swedish scientists were able to reconstruct a complex handwritten text from the 18th century, stored in the Swedish National Archives [2]. The object of this research was the decrees on freedom of the press from 1766, which were written in Latin script. Such breakthroughs in science prompt us to explore the capabilities of AI in interpreting handwritten texts from Ukrainian archives, which were written in Cyrillic.

In Ukraine, specialists from not only the Institute of Artificial Intelligence Problems of the Ministry of Education and Science of Ukraine and the National Academy of Sciences of Ukraine are working on the development and improvement of AI capabilities, but also scientific and pedagogical workers and researchers from departments and divisions of AI, computer science and applied mathematics, computer technologies and economic cybernetics, innovative technologies, intellectual information systems, mathematical modeling, AI systems, information security of many higher education institutions and research institutes of Ukraine. A leading role in this field is played by the team of the Research Institute of Intelligent Computer Systems of the Western Ukrainian National University (Ternopil) and the V.M. Glushkov Institute of Cybernetics of the National Academy of Sciences of Ukraine (Kyiv).

Modern research in the field of AI is actively developing, especially in the area of document interpretation, where information technologies are used for analysis, search, and interpretation of relevant texts. Significant important informational potential for our research[3] useful information on the creation of archival collections of websites within the framework of initiative documentation at the Central State Electronic Archives is described in the research [4]. In research [5] characterized the process of digitizing archival documents in foreign countries. The topical issue of the role of digital sources in the research [6]. In research [7] predicted the growing role of archive digitization in modern society.

Innovative approaches to preserving cultural heritage through the use of image recognition and augmented reality, as seen in the researchs [8-10], illuminate the development of the intersection of technology and history. These methodologies resonate with the fundamental principles of our research, which applies Attention-Gated-CNN-BGRU models for recognizing historical manuscripts in Ukraine, demonstrating the versatility and potential of deep learning in various fields. Similar to how [11, 12], utilized deep neural networks, and researchs [13, 14], applied multilevel data encoding, our study employs advanced machine learning algorithms to open new perspectives in the analysis and preservation of cultural heritage, affirming the critical role of technology in safeguarding and researching our collective past.

Research [15] explored offline handwritten text recognition (HTR) with reduced training datasets, proposing a model trained on crossed-out text to effectively recognize such words without compromising accuracy. In [16], methods for classifying handwritten words into a digital format were investigated, combining direct word classification using Convolutional Neural Networks (CNN) and character segmentation with Long Short-Term Memory (LSTM) networks. Additionally, the study in [17] addressed handwritten text conversion and storage in ASCII format, covering preprocessing, feature extraction, and classification using deep learning methods. The research in [18] enhanced HTR performance on lines with crossed-out words, while the approach in [19] proposed outperformed traditional OCR systems. The integration of HTR into OCR systems was discussed in [20], alongside outlining an HTR competition focusing on historical documents [21]. Effective practices in HTR, including basic architectures and datasets like IAM and RIMES, were described in [22], while the importance of image processing in handwritten text detection was emphasized in [23], showing potential in forgery protection and handwriting analysis. Lastly, the Attention-Gated-CNN-BGRU model [1] for Ukrainian HTR is freely available, trained on historical Ukrainian texts provided by researchers and libraries.

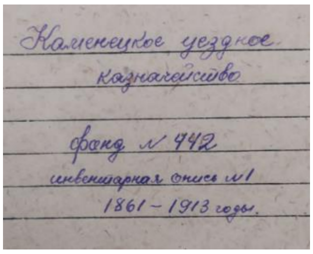
The Attention-Gated-CNN-BGRU model [1] for Ukrainian HTR is freely available, trained on historical Ukrainian texts and provided by researchers and libraries.The analysis of known solutions in the field of HTR, including the application of models like CRNN, and approaches to text classification and segmentation, underscores significant progress in this domain. However, this study focuses on analyzing the effectiveness of the Attention-Gated-CNN-BGRU model [1] for recognizing text from historical manuscripts, distinguishing itself through the use of attention mechanisms for detailed analysis of contextual relationships between characters. The approach in this research demonstrates improvements in recognizing complex historical texts, especially with crossed-out words and conditions of high text complexity, making it akin in concept to the works of Jose Carlos Aradillas et al. [15], but with an additional focus on adaptation to the specificity of Ukrainian handwritten text. This sets apart this study from others, providing a new approach to addressing the problem of text recognition in historical documents using deep learning and attention mechanisms, opening up prospects for further advancements in this field. The analysis of the text written in Ukrainian is given in the work [25-26].

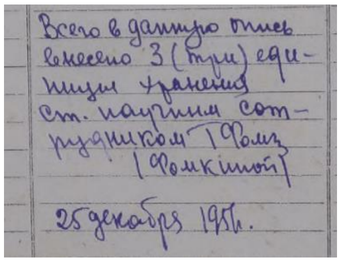
3. Methodology

3.1. Dataset Description

For this study, documents of varying readability levels were collected from the State Archives of Khmelnytskyi Oblast. Among the proposed documents, digitized descriptions of ancient records from the following funds were taken: Fund 442, Kamianets-Podilskyi County Treasury for 1861-1913; Fund 507, Office of the Chief of the South-Western Customs District for 1907-1913; Fund 596, Podilia Branch of Princess Tetiana Mykolaivna's Committee for Providing Temporary Assistance to Victims of Military Actions for 1914-1915; Fund 598, Investigative Court of the 2nd Division of Kamianets-Podilskyi County for 1875-1880; Fund 616, Kamianets-Podilskyi County Military Affairs for 1884-1919; as well as Fund 309, Isakovets Customs for 1931-1915, written in Ukrainian and Russian languages.

The dataset [24] for recognizing ancient handwritten text consists of 75 PNG-format images, examples of which are shown in Figure 1.





A) Easy to read **B) Difficult to read**

Figure 1: Examples of texts

3.2. Description of Document Recognition Approach

This research focuses on analyzing the effectiveness of the Attention-Gated-CNN-BGRU model for recognizing text from historical manuscripts. Modern challenges in OCR in historical documents include a variety of writing styles, document preservation levels, and character variability. This approach involves applying deep learning with attention to the context of characters and their interactions within words or text fragments, which enhances recognition accuracy compared to traditional methods. The implementation was done using the Python programming language. The approach consists of the following stages:

Stage 1. Data preprocessing:

1.1. Digital transformation: Each text sample I from historical manuscripts is converted into a digital format through scanning or photography, where I is represented as a matrix of pixels $I(x, y)$, where x and y are pixel coordinates.

1.2. Normalization: Applying normalization to each image I to standardize sizes and color intensities. The normalized image can be represented as

$$Inorm = f(I),$$

where f is the normalization function.

1.3. Data augmentation: Generating new samples Iaug from Inorm using transformations such as rotation, scaling, shifting, etc., to increase data diversity:

$$Iaug = g(Inorm),$$

where g is the augmentation function.

Stage 2. The Attention-Gated-CNN-BGRU model combines CNN for efficient visual feature extraction with gated recurrent units (GRU) and attention mechanism for modeling dependencies between characters. Step-by-step, this is presented as follows:

2.1. CNN: Using CNN to extract visual features $\phi(Iaug)$ from images, where ϕ is the feature extraction function implemented using CNN.

2.2. GRU and attention mechanism: Processing feature sequences $\phi(Iaug)$ using GRU and attention mechanism to model character dependencies and consider context:

$$\psi(\phi(Iaug)),$$

where ψ is the function implementing GRU and attention mechanism.

Stage 3. Model validation:

3.1. Word Error Rate (WER):

$$\text{WER}=\frac{S+D+I}{N}$$

where S is the number of substitutions, D is the number of deletions, I is the number of insertions, and N is the total number of words in the correct text.

3.2. Character Error Rate (CER):

$$CER = \frac{S + D + I}{M}$$

where M is the total number of characters in the correct text.

3.3. Levenshtein CER: Using the Levenshtein distance to calculate CER, where the Levenshtein distance between two strings is the minimum number of single-element edits (insertions, deletions, substitutions) required to transform one string into another.

Stage 4. Results analysis:

4.1. Performance evaluation: Analyzing the distribution of WER and CER errors to evaluate the model's effectiveness in recognizing text from historical manuscripts. Statistical methods are used to compare the model results with baseline indicators.
4.2. Impact of attention mechanism: Evaluating the contribution of the attention mechanism to the model's ability to identify complex characters and their contextual relationships through detailed analysis of corrected errors and improvements in recognition accuracy.
Further, this approach is described as an algorithm (Figure 2) for evaluating the effectiveness of the Attention-Gated-CNN-BGRU model for recognizing text from historical manuscripts, starting with data preparation, which includes data collection, digital transformation, and dataset augmentation from manuscripts. Next, model configuration involves integrating convolutional neural networks and gated recurrent units with attention mechanism for text analysis. Model validation is done using independent test datasets, and performance evaluation is based on word and character error rates. Results analysis includes comparison with baseline indicators, detailed recognition analysis, and identification of directions for further model improvement.

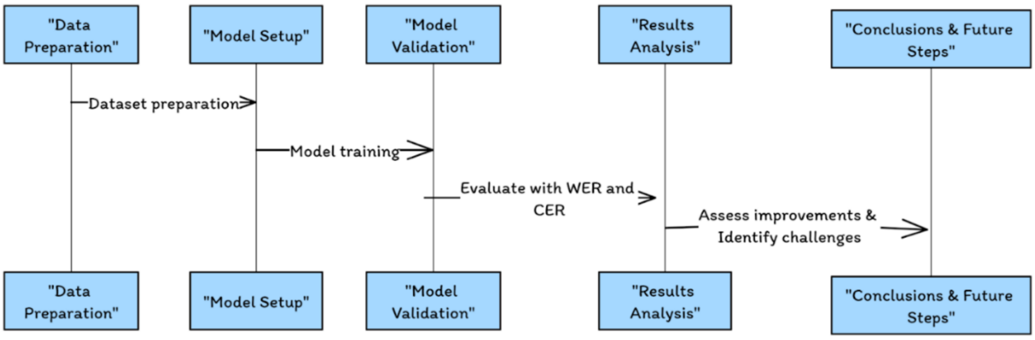


Figure 2. Structure of Document Recognition Approach

3.3 Approach to Expert Evaluation

Within the framework of this study, an expert evaluation methodology was used to assess the effectiveness of OCR models on historical manuscript materials. Five qualified experts analyzed the document samples, evaluating the difficulty of text recognition, the number of correctly recognized characters, the total number of recognized characters, and the total number of characters in each document. The approach proposed by the authors for this research for evaluation consists of the following stages:
Stage 1. Data preparation for analysis.
1.1. Collection of evaluations from experts ($EX1, EX2, EX3, EX4, EX5$) based on the following criteria:
1.1.1. Assessment of text recognition difficulty from 1 to 5, where 1 - very easy, 5 - very difficult.
1.1.2. Correctly recognized characters: the number of characters that were correctly recognized.
1.1.3. Recognized characters: the total number of recognized characters.
1.1.4. Total characters: the total number of characters in the original document.
1.2. Calculation of indicators:
1.2.1. Average assessment of text recognition difficulty ($SORT$):

$$SORT = \frac{\sum_{i=1}^{n} Assessment_i}{n}$$

where n is the number of experts, and Ratingi is the rating from expert i.
1.2.2. Average percentage of correctly recognized symbols ($SVPRS$):

$$SVPRS = \frac{\sum_{i=1}^{n} \left(\frac{Right\_recongised\_symbols_i}{All\_symbols} \times 100 \right)}{n}$$

1.2.3. Average number of recognized symbols (ANRS)

$$SKRS = \frac{\sum_{i=1}^{n} Recognised\_symbols_i}{n}$$

Stage 2. Analysis of the results:

2.1. Analysis of the overall effectiveness of the OCR model:

2.1.1. Calculating the average values for $SORT$, $SVPRS$, and $SKRS$ for all documents allows for the evaluation of the overall effectiveness of the OCR model.

2.1.2. Measuring the dispersion and standard deviation for each indicator helps understand the diversity of expert ratings and the variability of recognition results.

2.2. Impact of text complexity on recognition quality: Using correlation analysis between SORT and SVPRS helps determine how text complexity affects recognition quality. A positive correlation may indicate that as the complexity of the text increases, recognition efficiency decreases.

Stage 3. Interpretation of the obtained results:

3.1. The overall efficiency of the OCR model is determined through the analysis of the average values of $SORT$, $SVPRS$, and $SKRS$. High values of $SORT$ and $SKRS$ with low $AATRD$ indicate the model's ability to adapt to various conditions of handwritten text.

3.2. The results of analyzing the impact of text complexity on recognition quality provide insights into the limitations of the OCR model and directions for further improvement. Enhancing recognition accuracy under conditions of high text complexity may become a key aspect of model optimization.

The algorithm (Figure 3) for the experimental evaluation of OCR models on historical manuscripts begins with collecting expert ratings, where experts analyze text samples from manuscripts based on defined criteria such as text recognition complexity and the number of correctly recognized symbols. The second stage involves analyzing the overall efficiency of the models by calculating average values, dispersion, standard deviation of indicators, and conducting correlation analysis between text complexity and recognition quality. In the final stage, the obtained results are interpreted, allowing for the assessment of the overall efficiency of the models and determining optimization directions to improve recognition accuracy under conditions of high text complexity.

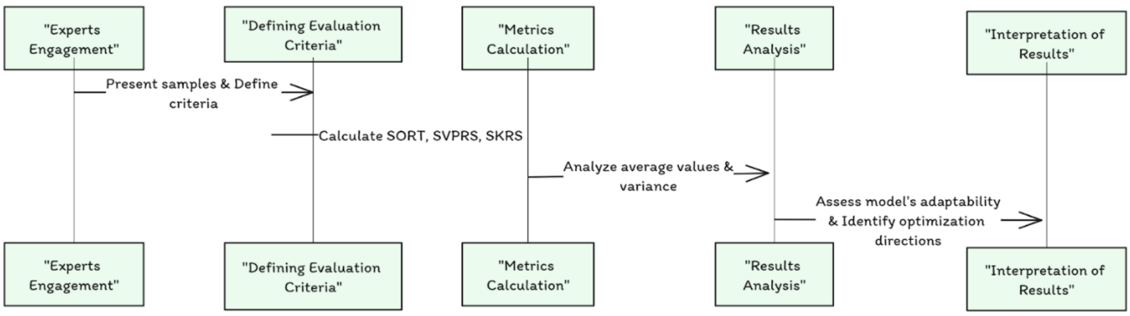


Figure 3. Structure of the OCR model effectiveness assessment approach

4. Result

In this section, a detailed analysis of the experiment results is presented, allowing for the evaluation of the effectiveness of applying OCR models to historical manuscripts, as described in section 3.1.

Table 1 below displays the results of recognizing the first five fragments of historical manuscripts using the OCR model. The data include links to the photos of the originals as well as the text recognized by the model. A comprehensive analysis of the entire dataset and detailed research results are available for review on GitHub [24], where an in-depth investigation of the OCR model's effectiveness on various fragments of historical documents is presented.

Upon completing the initial analysis of the text recognition results, a comprehensive expert evaluation was conducted, as detailed in section 3.3 of the documentation. The expertise involved a thorough examination of text complexity, recognition quality, and symbol identification accuracy, aimed at gaining a deeper understanding of the effectiveness of applying OCR models to historical documents. Prominent experts involved in the analysis included Senior Lecturer of the Department of Information and Socio-Cultural Activities at the Western Ukrainian National University, Volodymyr Yarych, Doctor of Historical Sciences Anatoliy Filinyuk from Ivan Ogienko Kamianets-Podilskyi National University, as well as candidates of Historical Sciences Serhiy Sydoruk and Serhiy Trubchaninov. Additionally, Valentina Filinyuk, a candidate of Philological Sciences and Associate Professor at Khmelnytsky Humanitarian-Pedagogical Academy, contributed to the expert assessment. Their professional approach and deep knowledge facilitated the identification of key aspects for further improvement of OCR technologies in the context of working with historical texts.

Table 1.
Results of recognizing the first 5 fragments

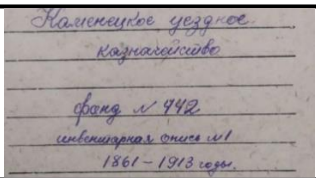
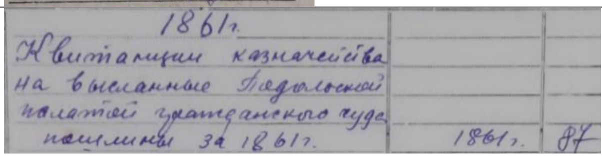
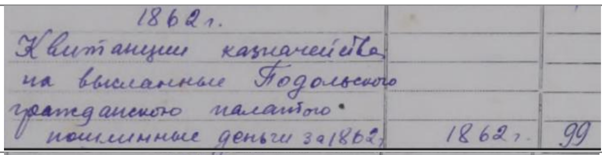
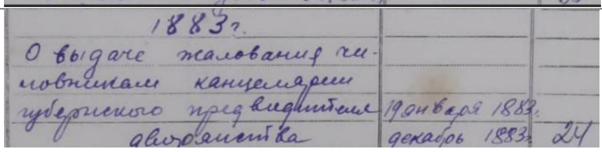
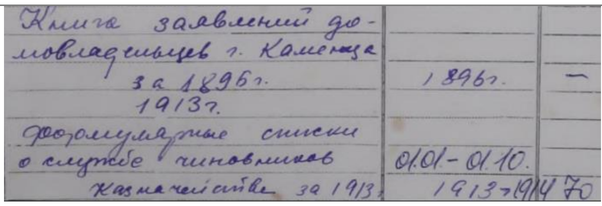
№ doc.	Link to the original photo:	Recognized text:
1		Каменецкое уездное. казначейство Фанд N 442 инвентарная опись л! 1861 – 1913 года.
2		Каннъ 1861г. Нвитанции казначенива на высланные Подолоской палатой гражданского чуда пошлины за 1861г. 1861г. 87
3		1862г. Хвитанции казначействе на высланные Подольского гражданскою палатого 99
4		1883г. О выдаче жалования чи- ловникам канцелярли ГанБаря 1883. губернского предвидинеля 24 декабрь 1883г дворянства
5		1896г. Ннига заявлений до- мовладеньцев г. Каменца 1896г. 3 а 1896г. 1913г фозомумярные списки о службе чиновников да-а 10 казначействе за 1913

Table 2 provides a statistical overview of the collected data, including the mean, variance, and standard deviation for the number of successfully recognized characters, the average complexity rating of texts, and the average accuracy percentage of recognition.

The analysis (Table 2) of the statistical indicators of text recognition results by the OCR model indicates overall effectiveness and challenges associated with processing historical documents. The arithmetic mean of the number of recognized characters is 107.33, with an average complexity rating of text recognition at 2.93, suggesting a moderate level of document complexity. The average percentage of correctly recognized characters is quite high at 71.7%, indicating a reasonably high accuracy of the OCR model. However, significant variance in the number of recognized characters (1908.14) and the average percentage of correctly recognized characters (576.72), as well as the standard deviation for these indicators (43.68 and 24.01, respectively), underscore the variability in recognition quality among different documents. The correlation value of -0.76 indicates a strong negative relationship between the average complexity rating of texts and the average percentage of correctly recognized characters, demonstrating that as the text complexity increases, the recognition efficiency decreases.

Table 2.
Summary of Expert Evaluation Results

	Characters recognised	SORT	SVPRS
Arithmetic Mean	107,33	2,93	71,7
Variance	1908,14	0,45	576,72
Standard Deviation	43,68	0,67	24,01
Correlation between SORT and SVPRS		-0,76	

The detailed analysis of the data [24] revealed variability in the accuracy of text recognition by the OCR model, which correlates with the complexity rating of the text, ranging from 1.0 to 4.6. Higher SVPRS values, reaching up to 100%, are observed in texts with lower complexity ratings, indicating the high efficiency of the model in recognizing less complex documents. However, a significant decrease in recognition accuracy to 1.74% and below is observed in texts with the highest complexity ratings (4.4 and above), highlighting the limitations of the current OCR model when working with highly complex historical materials. Documents numbered 69-75[24], written in Ukrainian using the Latin alphabet, demonstrated significantly lower recognition accuracy compared to others, as reflected in the average percentage of correctly recognized characters (SVPRS) ranging from 1.74% to 6.99%. Meanwhile, the complexity rating of these texts was the highest among all analyzed documents (4.4 and above), indicating significant challenges that the OCR model faces when working with texts written in the Latin alphabet but in the Ukrainian language. These results underscore the particular challenges associated with recognizing texts in languages using non-standard or less common alphabets and indicate a critical need for the development of specialized approaches and algorithms to enhance OCR accuracy in such conditions.

In conclusion, the analysis of the expert evaluation results and the statistical overview of the collected data regarding the efficiency of the OCR model confirm its significant potential utility in the study of historical texts. However, the high level of negative correlation between text complexity and recognition accuracy emphasizes the importance of further refinement and adaptation of OCR technologies to optimize working with complex historical materials. Special attention to texts written in non-standard alphabets, such as Ukrainian using the Latin alphabet, underscores the necessity for the development of specialized approaches to overcome these unique challenges, paving the way for improving accessibility and preservation of valuable historical heritage.

5. Conclusions

Within this study, an analysis of the effectiveness of the Attention-Gated-CNN-BGRU model for HTR from historical documents stored in the State Archives of Khmelnytskyi Oblast was conducted, primarily focusing on documents written in Ukrainian and Russian languages. The research concentrated on digitized descriptions of ancient deeds from 1861 to 1913. The utilized model demonstrated an SVPRS of 71.7%, indicating significant efficiency in the context of the complexity of the analyzed documents.

Comparing our results with similar solutions [1, 15] in this field, it can be noted that the incorporation of attention mechanism in the Attention-Gated-CNN-BGRU model provided significant advantages in recognition accuracy, especially for texts with high complexity and crossed-out words. This marked a significant advancement compared to traditional CRNN models, which often show decreased efficiency under similar conditions. The identified strong negative correlation (-0.76) between text complexity and recognition accuracy underscores the necessity for further development and optimization of models for handling highly complex historical manuscripts.

One of the main directions for future research is the development and adaptation of the model for effective recognition of texts written in Ukrainian using the Latin alphabet. This aspect is crucial for the preservation and study of Ukraine's cultural heritage, as a considerable number of historical documents of significant importance are written in this alphabet. The results of our study indicate the potential feasibility of effectively adapting existing technologies for recognizing such texts, but also emphasize the need for further developments in this area.

In conclusion, our research not only confirmed the high effectiveness of the Attention-Gated-CNN-BGRU model in recognizing handwritten text from historical documents but also identified promising directions for future work. Specifically, the development of models for recognizing texts written in Ukrainian using the Latin alphabet could be a key step in preserving and making important historical resources accessible, enriching our understanding of the past and promoting cultural exchange.

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