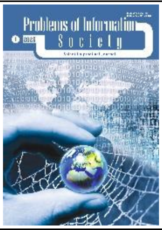

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Artificial intelligence solutions in centralized electronic document management systems

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ABSTRACT

The present era is gradually characterized by the transition from paper to electronic information carriers. Working with electronic documents necessitates specific methodologies that account for their distinctive features. In this regard, the article examines the significant role of Artificial Intelligence technologies in addressing challenges in electronic document management systems, such as analyzing unstructured data, ensuring accurate document categorization, and optimizing searches across extensive archives. Artificial Intelligence technologies such as Natural Language Processing, Machine Learning, and Optical Character Recognition play a crucial role in achieving these goals. The article analyzes the application of artificial intelligence at various stages of document management (digitization, text recognition, summarization, data extraction, classification, intelligent search, and business process optimization). As a result, Artificial Intelligence technologies simplify the process of document management, reduce the need for human intervention, increase accuracy, and enhance overall productivity.

1. Introduction

In the modern business world, document management is one of the primary tasks faced by every organization. Traditional methods of paper-based documentation are becoming increasingly less relevant and are being replaced by digital solutions. Electronic Document Management Systems are at the forefront of this transformation, transferring all stages of document creation, processing, distribution, and archiving into a digital environment.. This, in turn, provides organizations with a range of advantages, such as faster and more efficient document management, simplified search, enhanced collaboration, and strengthened security.

Cloud-based document management systems play a crucial role in centralizing and optimizing document workflows. In particular, cloud-based centralized systems, such as SESDA (Electronic Document Management System), represent a significant advancement in document management and workflow optimization for government institutions. In addition to providing substantial cost savings, these systems support e-government initiatives by offering secure backup and recovery solutions for data protection, enhanced security, dynamic business processes, integration solutions, advanced administration, detailed reporting and auditing capabilities, extensive execution operations, and control mechanisms. Cost efficiency, flexibility, and additional advantages make cloud-based systems an attractive option for government institutions aiming to modernize their document management processes. The flexibility, resilience, and broad capabilities of these systems make them an indispensable tool for contemporary public administration. Considering these advantages, cloud-based document management systems represent a critical step forward for government organizations.

Nevertheless, EDM systems often face difficulties in handling large volumes of unstructured data, accurately classifying documents, and optimizing search processes. These challenges increase the time required for document retrieval and processing, lead to human errors, and ultimately reduce the overall efficiency of the organization.

To address these challenges, Artificial Intelligence (AI) technologies provide a powerful solution. Methods such as Optical Character Recognition (OCR), Natural Language Processing (NLP), and Machine Learning (ML) fundamentally transform processes such as digitization of documents, content understanding, and automatic classification (Russell, Norvig, 2022; Abbasov, Rzayev, 2023). These technologies not only simplify the document management process but also reduce the need for human intervention, improve accuracy, optimize business processes, and enhance overall organizational productivity.

2. Related work

In (Deelman et al., 2019), the results of studying machine learning methods to discuss current challenges in the management of scientific workflows in distributed systems are presented. It is shown that there are certain potential problems associated with the use of machine learning, such as the collection of training data. The authors describe workflow- and task-level analysis, infrastructure-level analysis, cross-level analysis, on-line/off-line analysis, and the collection of training data. The authors argue that new workflow systems will be able to understand previous user queries, discover relevant information, and structure the computations necessary to deliver the desired results. Nevertheless, issues related to the use of machine learning methods in the scientific workflow domain remain unexplored. The reason for this lies in the difficulty of analyzing the processes used to obtain results. However, it can potentially provide a tool for comparing different scientific methods and their similarities and differences with other approaches. One option to overcome the corresponding challenges may be the use of machine learning methods. This approach was precisely applied in (Obukhov et al., 2019). The authors employed the concept of a decision-support subsystem based on the implementation of "User – Electronic Document Management System (EDMS) – Document" type interactions.

In the article, machine learning technologies were developed to automate the document processing workflow, using as an example the design documentation of an EDMS.

The obtained scientific results can be applied to solve the problems of automating information processing in various information systems. Furthermore, in (Obukhov et al., 2020), an adaptation algorithm was proposed by applying machine learning methods to address the problem of structural-parametric synthesis of an EDMS. The main scientific results achieved in this study include:

- formalized criteria for EDMS adaptation;
- an algorithm for the design and adaptation of the EDMS;
- the development of software for EDMS adaptation, including a trained neural network and an API (Application Programming Interface).

In (Levina et al., 2020), the results of a study on the use of automated data entry from scanned copies of contract department documents, in comparison with manual entry, are presented. Here, it is proposed to apply machine learning in the form of a neural network to improve the transfer of data from a scanned document copy into the management system. It is shown that machine learning enables the classification of information for analyzed documents, which ensures the selection of the correct template during the creation of an electronic document. The choice of appropriate tools for developing a software module for data extraction was justified, and its operating principle was described. However, questions concerning the use of numerous machine learning models for text classification are not addressed. This may be due to the complexity of applying classification methods to large-scale documents. An approach based on classification methods was applied in (Goodrum et al., 2020).

In (Goodrum et al., 2020), OCR was employed to create and evaluate multiple machine learning models for text classification, including both "bag of words" and deep learning approaches. The authors evaluated the system at three different classification levels, using both the entire document and individual document pages. They also compared various text processing techniques. However, the article presents only a comparison of classification methods but does not provide a semantic map for subsequent document classification. This may be due to the difficulties associated with presenting a semantic map for document classification.

In (Kostkina et al., 2018), the results of a study on a specific approach based on the use of a semantic map as a feature reduction method for document classification are described. The authors investigated the impact of this approach on the quality of document classification and described its application in carrying out document classification. However, questions concerning the use of agent technologies are not considered here. For this reason, there may be challenges related to the provision of agent technologies for documents, which makes the corresponding research infeasible. The study applied an approach based on the development of a new architecture using agents. (Kostkina et al., 2018) further presents the results of research on a new concept of knowledge classification integrated into a cognitive agent architecture, which accelerates its inference process. The authors described the new architecture, where the agent, instead of attempting to extract the entire rule base, is capable of selecting only the working rule class. Nevertheless, questions regarding the use of multi-agent technologies and topic modeling are not considered.

One possible option for overcoming the relevant challenges may be the development of a document management system model by utilizing machine learning, AI tools, and multi-agent technologies.

3. Material and methods

Many organizations, particularly government institutions and private companies that interact extensively with the public, receive a large number of applications, proposals, complaints, and other documents on a daily basis through various channels (mail, fax, email, etc.). The majority of these documents—especially those received from citizens—are unstructured (scanned paper documents, electronic messages, and other formats). Reading such documents page by page, preparing summaries, analyzing, classifying, and registering them leads to delays, human errors, and additional loss of time and resources. This, in turn, negatively affects the organization's operational principles and service delivery.

Although electronic document management systems offer many advantages, the organization and utilization of unstructured data remain challenging. Therefore, for organizations aiming to provide efficient and high-quality services, the application of artificial intelligence-based solutions is essential (Rzayev, 2012; Rzayev, 2016).

3.1. Problem definition

The modern level of development of information technologies, computer equipment, and the qualitative transformation of algorithms for the automation of information systems contribute to the improvement of SESDA through the introduction of AI technologies. It is necessary to develop a procedure for implementing AI tools that will allow to take work with electronic documents to a higher level: automate the procedure for entering and registering documents, generate documents based on templates built into the SESDA, and send internal documents of the organization along pre-defined routes – approval, signing/confirmation, and execution processes.

In particular, based on the processing of structured document metadata, it is necessary to ensure the implementation of analytical algorithms of AI technologies to ensure accelerated registration of a specific document in the SESDA without operator participation.

3.2. Problem solution

AI technologies, by enabling the automatic classification of documents, data extraction, and the automation of other processes, provide the following solutions for the management of unstructured documents (Fig. 1).

The first step in managing unstructured documents is their digitization and recognition. This process involves converting physical documents into digital format and then recognizing the content within these digital documents (Glushko and McGrath, 2015).

OCR technology converts printed or handwritten text within scanned documents and images into machine-readable text.

For image recognition, Convolutional Neural Networks (CNNs) are used to identify patterns in the pixels of an image and recognize characters. In the sequential recognition stage, Long Short-Term

Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), are employed to accurately recognize and convert text sequences. By considering the sequence and context of the text, LSTMs ensure precise recognition of each character. This method is designed to correctly identify each symbol or word and convert it into digital format.

By applying OCR technology, organizations can significantly reduce the time and effort required to digitize physical documents, enabling them to manage large volumes of documents efficiently and accurately. Tools such as Tesseract OCR, Google Cloud Vision OCR, and ABBYY FlexiCapture ensure accurate data extraction and preparation for subsequent automation and analysis.

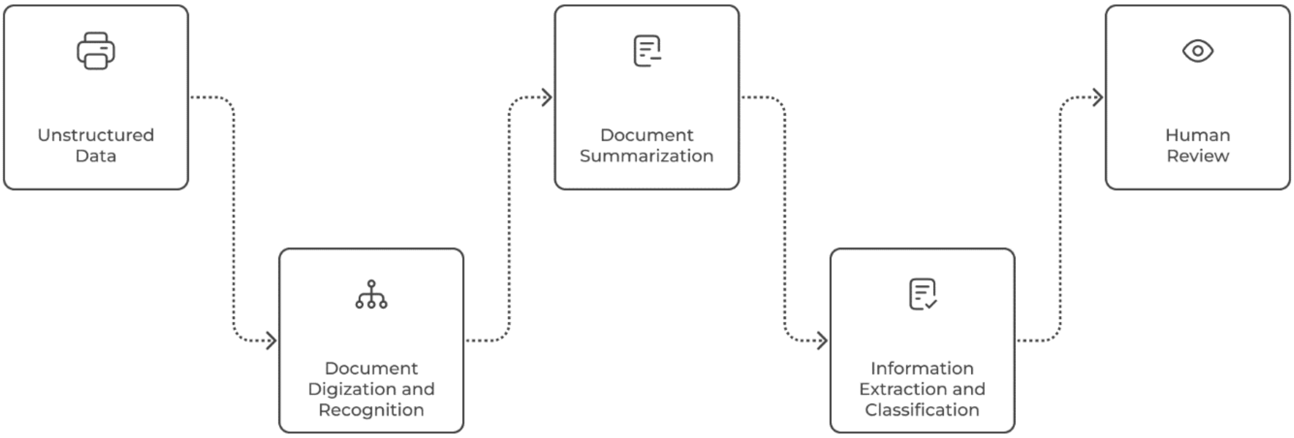

Fig. 1. Digitization and Recognition of Documents

3.3. Intelligent management of unstructured documents

Automatic generation of reports in the SESDA can be based on computer analysis based on the allocation of structured data of the of contextual documents. The following reasoning shows how AI technologies can significantly improve the functioning of business processes.

Document summarization. After the digitization and recognition of documents, one of the most important stages is the creation of a short summary of the document. Document summarization is the creation of a shorter version of the document that retains the essential information. This process is carried out using NLP techniques and Large Language Models (LLMs). There are two main approaches to document summarization:

- *Extractive Summarization*. This method identifies the most important sentences or expressions in a document based on their relevance and significance, and combines them to form a summary. Algorithms such as TextRank are used in this approach. These algorithms rank sentences based on importance and select the most relevant ones. Tools such as Sumy and Gensim implement this method.
- *Abstractive Summarization*. This approach involves AI tools understanding the meaning of the document and generating a new, concise summary in their own words. Advanced language models such as BERT and GPT-4, trained on large-scale text datasets, are utilized for this purpose.

The application of these technologies enables organizations to manage large volumes of documents more effectively, accelerate the search process, and provide quicker access to necessary information. It reduces the time required for document analysis and allows decision-makers to quickly grasp key points without reading the full content. Furthermore, short summaries enhance search capabilities, making it easier to locate specific information within large document collections.

Information extraction. Information extraction refers to the automatic retrieval of key information from unstructured documents. This process is mainly implemented through NLP technologies and ML models (Myers et al., 2012).

Named Entity Recognition (NER). NER methods identify and classify important entities such as personal names, organization names, locations, dates, and contact information within the text. This method is widely used for extracting key information from documents.

Relation Extraction. Part-of-Speech Tagging (POS Tagging) and Syntactic Parsing methods analyze the grammatical structure of sentences to determine relationships between words and expressions. POS Tagging assigns each word its part of speech (e.g., noun, verb, adjective), while Syntactic Parsing defines the structure of the sentence. These approaches are significant for extracting and linking information in documents.

Data classification. The classification process refers to categorizing documents or extracted data into predefined groups. This process is carried out using various ML algorithms and Deep Learning models.

Text Classification. Text classification methods are used to assign documents or text fragments to specific categories. Algorithms such as Naive Bayes, Support Vector Machines (SVM), Random Forests, and Neural Networks are applied for this purpose.

Document Clustering. Clustering methods group similar documents together. This approach is used for the automatic grouping of documents. For instance, clustering algorithms such as K-means can group documents with similar topics.

As a result of applying these technologies, organizations can efficiently manage unstructured data, make more cost-effective use of resources, and deliver higher-quality services to clients. Ultimately, automatic information extraction and classification contribute to faster and more accurate execution of workflows and enhance decision-making processes.

Example (Text of a citizen's request submitted to the organization): "I, Ali Valiyev, a citizen residing on Nizami Street, would like to report issues with the water supply. Over the past week, water outages have persisted, and this situation is causing us serious concern. I kindly request that you resolve this issue as soon as possible. Due to the water outages, our daily activities are significantly disrupted. For instance, children's school preparation and household tasks have become difficult. I ask you to take additional measures to resolve this problem."

Process sequence:

- *Digitization*: The request is converted into digital format using OCR technology.
- *Summarization*: "Ali Valiyev reports issues with the water supply on Nizami Street. Water outages continue and cause concern. Requests resolution. Daily activities are disrupted due to outages."
- *Information Extraction*: 1) Person's name: "Ali Valiyev"; Location: "Nizami Street"; Problem: "Water outages"; Effects: "Children's school preparation and household tasks become difficult."
- *POS Tagging and Syntactic Parsing*: The phrase "issues with the water supply" is identified as the subject of the complaint.
- *Data Classification*: 1) Category: "Complaint"; 2) Problem type: "Water supply."
- *Clustering of Requests*: all requests concerning the water supply are grouped and forwarded to the relevant department.
- *Result*: Automatic and accurate management of requests reduces workload, accelerates responses to citizen complaints, and enhances citizen satisfaction. Government agencies can utilize resources more efficiently and provide faster, higher-quality services.

3.4. Business Process Optimization

In the contemporary business environment, the effective and rapid management of documents is essential for every organization. Although EDM systems promise a faster, more transparent, and more secure working environment compared to traditional paper-based methods, previous-generation EDM systems face a number of challenges. These systems are typically static and manually configured, and they cannot adapt flexibly to changing conditions or the evolving requirements of the organization. Any modification or exceptional situation requires manual intervention, which leads to time loss and an increased risk of errors.

The transition to dynamic business processes eliminates many of the shortcomings of traditional static models. In particular, it provides significant progress in terms of flexibility and adaptability to change. Moreover, dynamic workflows ensure more efficient management of complex business processes thanks to automation and optimization capabilities. This, in turn, increases productivity and improves work quality. However, issues such as the lack of self-improvement and learning ability, as well as the unfair and inefficient distribution of workload, still remain.

By leveraging AI, ML, and NLP technologies, the following solutions are proposed to address the aforementioned shortcomings (Henderson and Pratten, 1995).

User history analysis: The AI system analyzes the user's history, which includes their past behaviors and work experience, to determine which users are more frequently selected, achieve more successful results, and are more effective for each correspondence category, document type, and subject. This, in turn, prevents repetitive tasks and misdirected assignments, minimizing time and resource loss.

Evaluation of workload and performance: Considering employees' current workload, the number, type, and deadlines of tasks, as well as their vacations and other planned activities, working hours, and productivity, the system distributes assignments in the most efficient way. Additionally, AI solutions evaluate each user's performance based on criteria such as timely completion of tasks, quality, and accuracy of work, identifying the highest-performing users. This creates a transparent work environment and helps employees better realize their potential.

Calculation of suitability level: Based on all the factors mentioned above, the system calculates the suitability level of each user for a given task and provides a list of the most suitable candidates. This helps decision-makers make the best choice and ensures fair distribution of tasks.

*Example***.** For the evaluation of workload and productivity, the system shows the user`s currently assigned tasks, their deadlines, the types of tasks, the user's availability during the selected execution period (Table 1), and whether additional assignments are expected. It also reflects the user's experience with certain correspondence categories, document types, and subjects, as well as the efficiency score assigned by the system based on the execution of previous tasks (Tables 2 and 3).

Table 1. Current task data of users

Username	Number of tasks	Task types	Execution period
User A	30	Execution (20) Registration (10)	7 days (5 tasks, priority: high); 14 days (15 tasks, priority: medium); 21+ days (10 tasks, priority: low)
User B	15	Execution (10) Registration (5)	3 days (8 tasks, priority: high); 7 days (7 tasks, priority: medium); 21+ days (10 tasks, priority: low)
User C	5	Registration (5)	30+ days (5 tasks, priority: low)

Table 2. Correspondence data processed by users

Username	Correspondence category	Correspondence type	Subjects
User A	Internal correspondence, organizational requests, citizen requests	Reports, applications, complaints, proposals	Human resources, finance, customer services
User B	Citizen requests	Applications, complaints, information requests	Social assistance, housing issues, infrastructure
User C	Internal correspondence, citizen requests	Reports, applications	Personnel issues, recruitment, labor relations

Table 3. User delegation data table

Username	Current status	Expected delegation
User A	At work	None
User B	At work	None
User C	At work	On leave between June 1–10

As a result, using the AI tools discussed above, the data presented in Tables 1, 2, and 3 were obtained empirically and processed to identify users along with their levels of suitability and efficiency, as shown in Table 4. According to Saaty (1980), the suitability and efficiency scores presented in Table 4 were obtained using a multi-criteria AI-based evaluation framework that integrates workload indicators, task urgency, user expertise, availability constraints, and historical performance metrics. Here, User A demonstrates the highest results in terms of both suitability and efficiency. Therefore, with respect to the execution of the current task, User A is the most appropriate alternative.

Table 4. Users' Delegation Data Table

Username	Suitability (%)	Efficiency (%)
User A	90%	85%
User B	70%	70%
User C	75%	92%

3.5. Intelligent search system

One of the main functionalities most demanded by users, and which significantly facilitates their daily work, is the ability to quickly search for and locate the required information or resource. This feature is especially important in systems with a large volume of information. While EDMS provides organizations with extensive capabilities for the effective and rapid management of documents, the limitations of traditional search methods hinder the full efficiency of these processes. Traditional search methods encompass two main approaches: field-based and keyword-based search. Although these methods offer certain advantages in locating documents, they also encounter a number of problems.

Field-based search. Field-based search methods allow searching based on pre-defined attributes and correspondence data. For example, searches can be conducted by document number, date, executor, type, execution period, or signing person. This method helps users quickly find information based on specific attributes. However, it complicates searching within unstructured data or the content of documents.

Example. If an organization searches for documents by the signing person or execution period, users can only search based on these attributes and cannot perform a search within the full content of the document.

Keyword-based search. Keyword-based search methods allow users to find information by entering specific words or phrases. This method also covers unstructured data, enabling searches across a broader range of information. However, keyword-based searches often fail to produce precise results, requiring users to review numerous results to find the necessary information. When keywords are not chosen correctly or synonyms are not considered, search results may lack accuracy. Keyword-based searches can struggle to respond accurately to complex queries consisting of multiple keywords. When several keywords are entered, the system searches for each keyword individually, which may result in a large number of unrelated results. Users must review numerous results to locate the required information.

Example. If a user searches for the words "citizen request water supply," the system searches for each keyword ("citizen," "request," "water supply") separately. This leads to multiple and repeated results reflecting each keyword, which can confuse the user and make it difficult to find the desired information.

AI technologies offer the following solutions to overcome the shortcomings of traditional search methods and enhance the accuracy and efficiency of search systems.

NLP technologies allow users to input search queries in natural language form, understanding these queries and delivering relevant results. NLP technologies analyze the context and meaning of the text to provide accurate search results.

Example. When a user enters the query "projects approved in the first quarter," NLP technologies understand the query and retrieve relevant documents approved in January, February, and March.

Semantic search technologies perform searches not only based on keywords but also on the meaning and context of the text. These technologies consider synonyms and related terms to provide more precise results.

Example. When a user searches for the term "complaint letter," the system also considers "objection" and "request" to find relevant documents.

ML technologies Machine Learning (ML) technologies learn from users' search behaviors to refine results and deliver outcomes tailored to individual needs. ML algorithms analyze past search behaviors to provide more relevant results in future searches. For instance, the system identifies which keywords or queries lead to specific results and leverages this knowledge to improve accuracy. Additionally, it examines user interactions with search results, such as which entries are clicked or viewed most frequently. Through these analyses, the system gains a better understanding of users' search intents and delivers more suitable results (Gift, 2018).

Example. If a user frequently views certain correspondence categories, types, and topics, the system analyzes these behaviors. Thus, when new documents in those categories arrive, the system sends notifications to the user. Likewise, if a user spends more time on certain types of documents, the system prioritizes these document types and displays them higher in the results.

Although traditional search methods have notable limitations, Artificial Intelligence (AI) technologies effectively address these challenges. Techniques such as Natural Language Processing (NLP), semantic search, and Machine Learning (ML) enhance the search process, delivering more accurate and efficient results. The implementation of these technologies enables organizations to manage information more effectively while allowing users to access the required information more quickly and with greater ease.

NLP, ML, and OCR may appear "intertwined" because they are essentially similar. Both NLP and OCR are products of ML. However, what differentiates them is their specific application.

A summary of the differences among NLP, OCR, and ML is presented in Table 5.

Table 5. Summary of Differences between NLP, OCR, and ML

OCR	NLP	ML
A text recognition technology	A natural language processing technology	An AI technology that simulates human learning in machines
Has significant applications	Has a considerable number of applications	Possesses numerous advanced applications
Relies on NLP and ML to fully perform its function	A product of ML	An independent technology that does not rely on other tools
Input type: scanned images or documents	Input type: textual data (speech, text, etc.)	Input type: structured, unstructured, or semi-structured data

OCR is applied to work with images and recognize text within them. NLP is used to work with text and check it for semantic and grammatical errors. On the other hand, ML has been applied within the EDMS framework to develop various models.

4. Discussion

This article examined the significant role of AI technologies in EDMS and demonstrated how they are used to address issues such as the analysis of unstructured data, the classification of documents into categories, and the optimization of search processes. AI technologies such as NLP, ML, and OCR are the primary tools for developing modern EDM systems (OCR\ML\NLP, 2025).

Thus, AI technologies make document management simpler, more accurate, and more efficient, reduce the need for human intervention, and increase overall organizational productivity. These technologies are applied in stages such as document digitization, text recognition, summarization, data extraction, classification, intelligent search, and business process optimization (Luger and Stubblefield, 2017).

As a result of the application of AI technologies, organizations manage unstructured data more effectively, ensure accurate classification of documents, and optimize search processes. This leads to more efficient use of resources, improved service quality, and enhanced overall work productivity. The wide adoption of AI technologies by government institutions and other organizations will enable the establishment of more effi-cient and modern management systems in the future.

Conclusion

The current level of development in information technology, computer equipment, and the qualitative transformation of information system automation algorithms are contributing to the improvement of centralized electronic document management systems.

The study proposes artificial intelligence-based solutions for centralized electronic document management systems, overcoming the shortcomings of traditional search engines.

The SESDA developed by SINAM Ltd Company applies a method of extracting significant information (metadata) from structured and unstructured document fields.

The collection and processing of unstructured data is implemented using AI technologies such as optical character recognition, machine learning, and natural language processing.

The results of the system introduction showed that AI-based solutions simplify the document management process, reduce the need for human intervention, increase accuracy, and enhance overall productivity.

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