Modeling of highly loaded distributed system supporting the process of assessing the technical condition of objects

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Abstract

This study is aimed at computerizing the work of construction and technical expertise specialists. The need of developing a system to support the process of assessing the technical condition of buildings, constructures and infrastructure objects, as a component of the system of restoration of objects damaged and destroyed as a result of hostilities, conducted by the russian federation with the support of the republic of belarus on the territory of Ukraine from February 24, 2022, is shown. The main goals and functions of the system are indicated. The model of the system for assessing the technical condition of objects has been designed. The architecture of it is shown and the development of its ontology is described step by step. The key functions of the system are considered, in particular those that use artificial intelligence to increase the accuracy and speed of assessing the technical condition of objects. The key modules of the system are described in detail with the perspective of improving modern means of supporting building-technical expertise in the direction of transformation into an intelligent highly loaded distributed system. The areas of application of artificial intelligence in various modules of the system under development are outlined. The scientific novelty of the work is substantiated in the possibility of using artificial intelligence to extract fuzzy values and generate fuzzy rules for assessing the technical condition of examined objects. The practical significance of the architecture that is based on the microservice model, which ensures the flexibility and scalability of the solution, is reasoned. The perspective of using the semantic data analysis module as an independent part of other systems designed to perform other tasks in the construction industry is shown.

Keywords

Artificial intelligence, building-technical expertise, ontology development, intellectual search, semantic analysis

1. Introduction

As a result of the full-scale armed aggression of the russian federation with the support of the

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republic of belarus, which began on February 24, 2022, a lot of buildings, constructures and infrastructure objects (objects) have been damaged, partially or completely destroyed on the territory of Ukraine [1]. Currently, all front-line settlements continue to suffer from constant rocket, artillery and other shelling.

As of August 2024, the current front line is the longest in Europe since World War II at over 3,000 km, and the line of active combat is about 1,000 km. Considering this, it becomes clear that one of the priority tasks of the Ukrainian people after the successful end of the armed conflict is the quick and high-quality restoration of many destroyed and damaged objects.

A large number of citizens and organizations interested in speeding up the restoration of objects that have suffered destruction and damage dictates the need to create a publicly accessible, highly loaded distributed information and communication system that will be integrated into the process of rebuilding Ukraine. Solving this problem involves:

1. Inspection of the technical condition of objects, which is currently carried out by experts using unmanned aerial vehicles and satellite surveillance systems;
2. Entering all data into a single dedicated database;
3. Assessment of the technical condition of objects and formation of a report on their damage;
4. Entering generated reports into a dedicated database; 5. Planning of restoration works.

6. Performing restoration works.

2.Review of related studies

Fig. 1 shows the scheme of information support for the process of assessment and restoration of buildings, constructures and infrastructure objects, which is described in detail in [2].

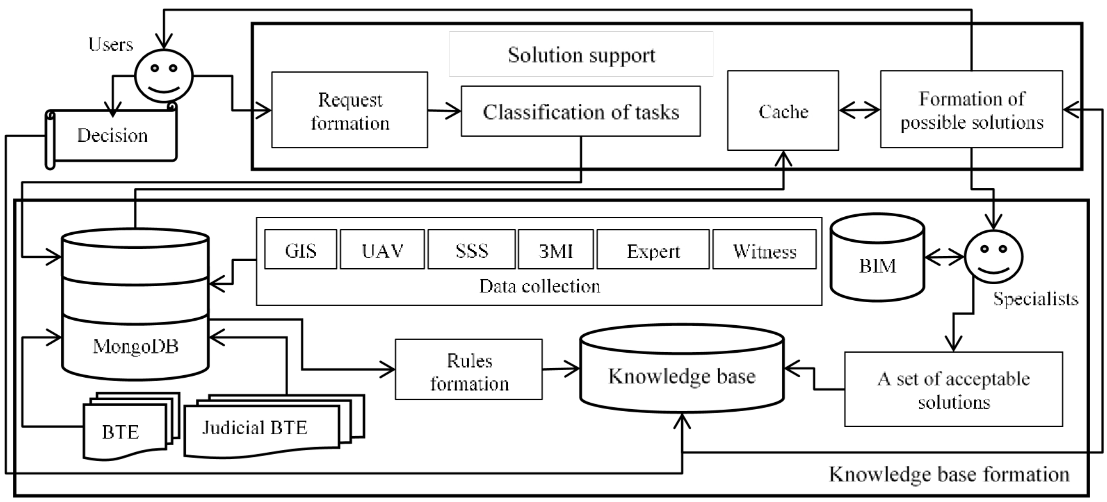

Figure 1: Scheme of information support for the process of assess and reconstruction of objects [2].

In Fig. 1 and below, the following abbreviations are used: BIM – building information modeling; BTE – building-technical expertise; DB – database; GIS – geographic information systems; UAV – unmanned aerial vehicles; SSS – satellite surveillance systems;

Fig. 1 shows that one of the tasks of information support system is the formation of the knowledge base of the system. Until now, this task was solved by experts, but in the conditions of large-scale destruction and the need to speed up the reconstruction of the country, these experts need reliable ontology-controlled expert systems that use artificial intelligence (AI) models and technologies.

The model of the system intended for informational support of the assessment process of damaged/destroyed immovable and movable properties of various purposes as a result of military operations is described in detail in [2].

Fig. 2 shows interaction Support System Real Estate Reconstruction Process (SSRERP) with citizens and organizations participating in this process [3].

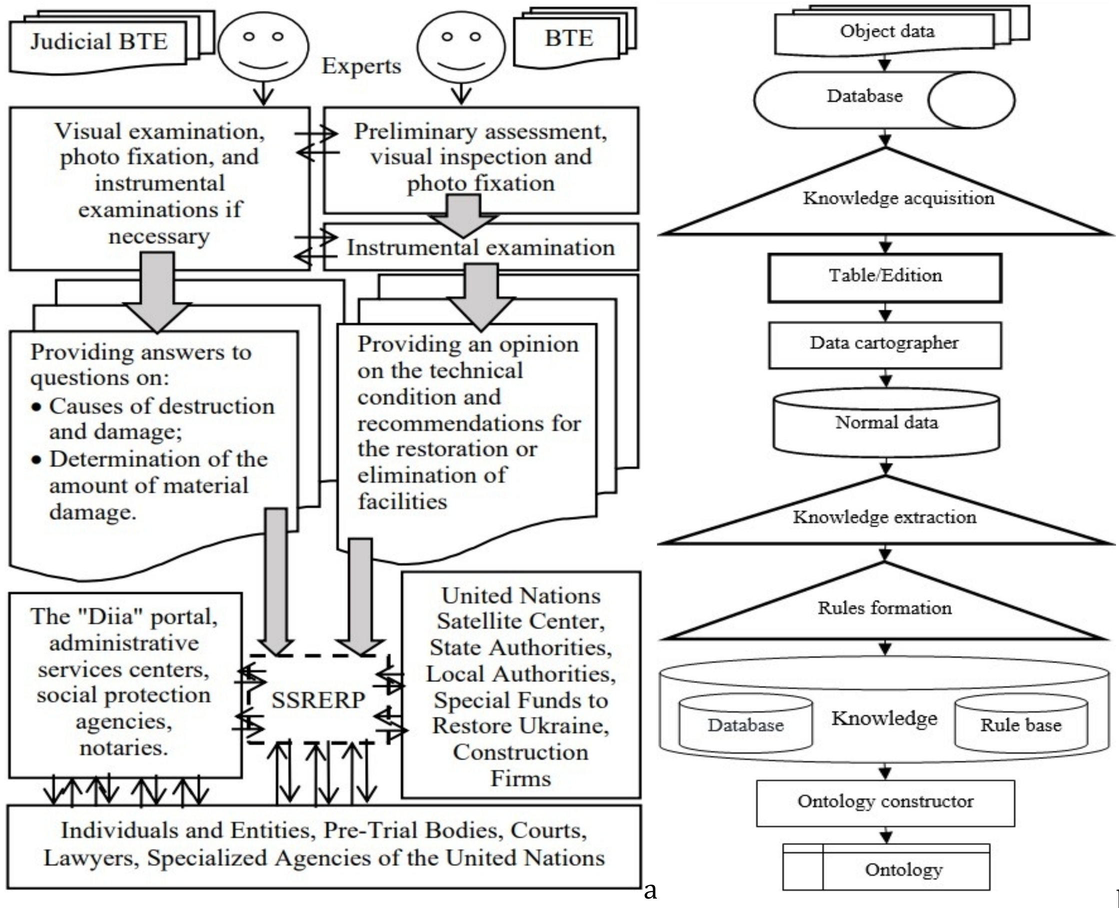

Figure 2: Scheme of SSRERP interaction with users (a) [3], structure of ontology creation system (b) [2, 4].

Fig. 2 shows that the SSRERP should be a distributed information and communication system, and the creation of the SSRERP ontology, the main purpose of which is to help experts determine the most effective and fastest solutions in the process of rebuilding the country [2, 4] requires:

- Collection of raw data related to specific objects. This data is stored in the database, which is the fundamental storage. The data is then analyzed and processed to extract meaningful information and gain knowledge. This process may involve manual expert curation, intelligent data analysis, or a combination of the two.
- Organizing the collected data into tables or other structured formats at the "Table/Edit" stage. This facilitates their visualization, editing and detection of regularities and inconsistencies.
- Data processing by a cartographer, which transforms structured data into a normalized format, ensuring compliance with certain standards and making them uniform for more complex processing.
- Extracting knowledge from normalized data at the stage of determining rules and relationships using machine learning methods, natural language processing or statistical analysis.
- Formulation of the rules that help structure this knowledge into a coherent system at the stage of rule formation.
- Further storage of the generated rules and enriched data in a specialized knowledge base along with a rule base tailored to support complex queries and analytics that the ontology builder uses to create an ontology that describes the categories and relationships in the data.

As a result, the structured ontology improves data interoperability, sharing, and reuse in applications such as semantic web services, AI, and information retrieval systems.

Currently, based on research [1 – 3], the following goals are identified, which should be implemented by the system being developed for the automation of the building-technical expertise process:

- To automate the derivation of rules for assessing the technical condition of damaged objects by finding and using effective solutions, including those that apply AI methods [5];
- To digitize the destruction and damage of objects in order to build a step-by-step reconstruction plan [6, 7];
- To provide proper government institutions, construction organizations and investors with information about the condition of damaged settlements or individual objects in order to formulate the concept of their rebuilding [8];
- To find and apply practical solutions and tools to accelerate the planning and execution of the reconstruction of damaged infrastructure objects, including those that use AI methods [9];
- To provide appropriate application tools for using the main functions of the system [10].

3. Model of the support system for the assessment of the technical condition of buildings, constructures and infrastructure objects

To understand the content of the problem and proposals for its solution Fig. 3 provides a diagram of the system for assessing the technical condition of objects.

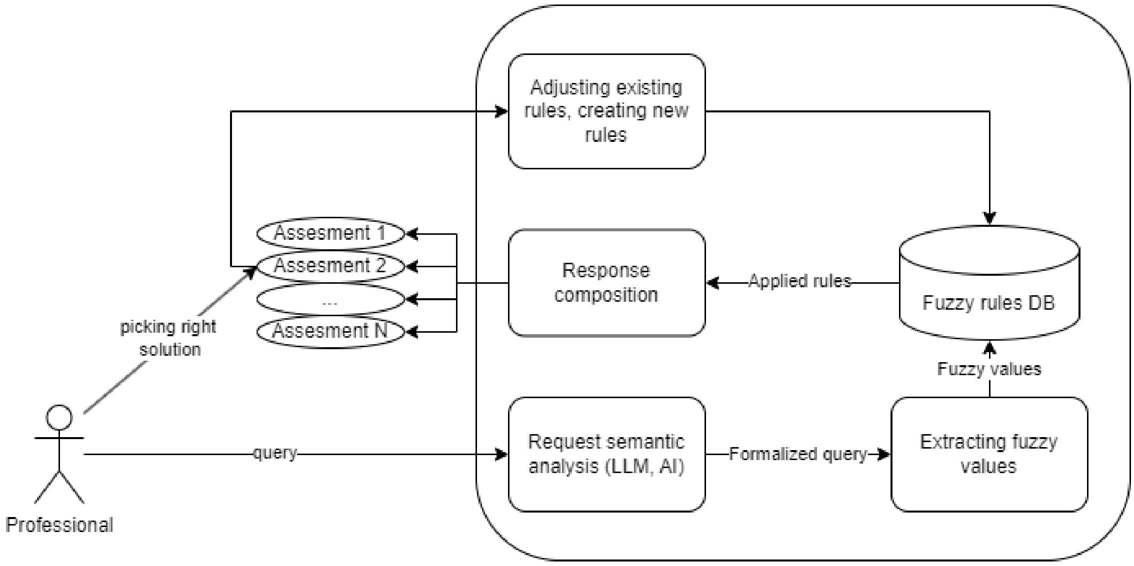

Figure 3: Scheme for assess the technical condition of objects.

To assess the technical condition of objects, the system should perform such functions as:

- Automatic damage classification.
- Forecasting the risks of further degradation processes.
- Integration with GIS for contextual analysis.
- Collection of historical and actual data about a specific object.
- Adaptive learning based on feedback.

The essence of the automatic damage classification function is that the system automatically identifies and classifies the types of damage based on the analysis of visual data such as photos, videos, UAV and SSS images [11]. This provides quick and accurate identification of objects and different degrees of their destruction and types of damage, which greatly simplifies further assessment and analysis.

The function of predicting the risks of further degradation processes analyzes the changes in the state of the object over time and predicts possible destruction, taking into account the current state, historical data and external influencing factors. As in [12], an IoTbased real-time monitoring system was developed to control product quality and safety risks in cold chains using a wireless network of sensors, cloud services, and fuzzy logic. This allows proactive decisions to be made to prevent further deterioration of the facility's technical condition.

The function of integration with GIS to analyze the impact of geographical and climatic factors on the condition of buildings allows to take into account the location of the object, natural conditions and other contextual factors [12]. This contributes to increasing the reliability of the models on the basis of which risks are assessed and decisions are made.

The data collection function provides the system with historical data about the object of examination, including previous repairs, used materials, technical inspections, natural and anthropogenic events that could affect its condition during construction and operation. The integration of this data with other modules allows more accurate assessment and forecasting of the technical condition of the facility.

The adaptive feedback-based learning feature enables the system to continuously improve its estimation models thanks to adaptive algorithms that learn from experts. This allows continuous adjustment of models and assessment methods.

Therefore, the system under development is able to create and modify rules for assessing the technical condition of objects, using feedback from the BTE specialist using the system.

3.1. System structure

Fig. 4 shows the structure of the system for assessing the technical condition of objects, which consists of the following parts:

1. Intelligent search and information gathering module;
2. Semantic analysis module;
3. Module for extracting relevant fuzzy values;
4. Module for generating new fuzzy rules and linguistic variables.

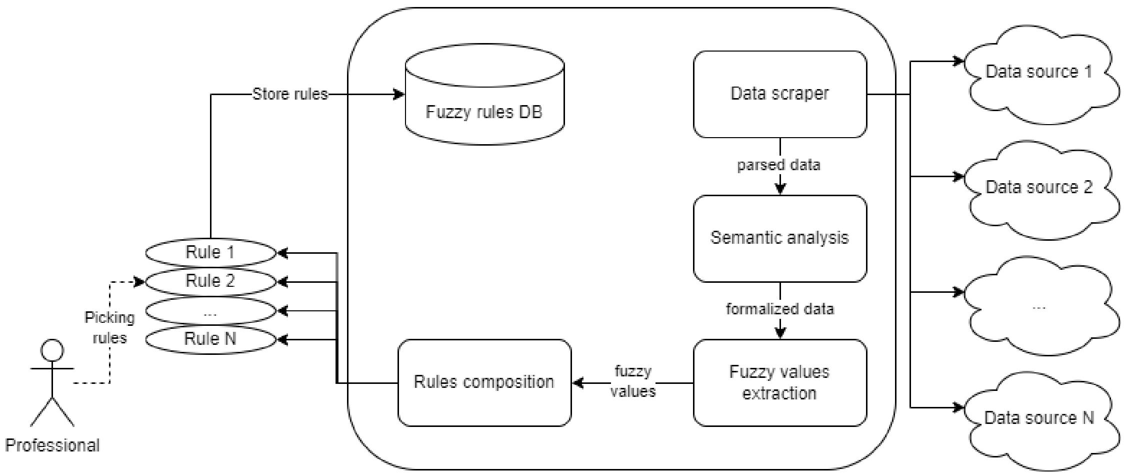

Figure 4: A model of the system for creating rules for assessing the technical condition of objects

Currently, the knowledge base of the system is being formed on the basis of technical documentation, performed assessments, comparison of these assessments with media file data regarding factors affecting the subject of examination.

3.2. Intelligent search and information gathering module

This module uses AI and parser generators to efficiently extract and group related documentation and multimedia content such as photos and videos. In the basis of the work of this module are:

- Web scraping based on artificial intelligence [13];
- Generators of parsers for collecting structured data [14];
- Collection of multimedia data;
- Intelligent data filtering and classification;
- Continuous monitoring and updating of data.

AI-driven web scraping techniques are used to automatically identify and collect relevant building data existing in known technical documentation databases. AI algorithms make it possible to highlight data relating to buildings of particular interest in this case. For example, photos and video materials from mass media that can be used for further analysis.

To work with various, often unstructured data from web sources, it is proposed to use parser generators. These tools automatically generate parsers that can interpret and structure heterogeneous information from different sources. Parser generators allow you to adapt to different data formats, such as HTML, JSON, XML and any documents based on them.

Capturing and processing multimedia content related to the corresponding buildings includes photos, videos, and documents.

Photos: Automatically download and classify building images from online listings, architectural websites or social media posts.

Video: Collecting and processing video content, such as virtual tours, drone recordings, and converting them into an analyzable form (such as still images).

Documents: Collection of different types of documents (drawings, survey or inspection reports, legal documents) by analyzing PDF, Word or other document formats found on the Internet.

AI-based classification algorithms classify collected data according to their type (images, videos, documents) and their relevance to specific buildings. The multimedia data collection module can distinguish high-quality relevant data from less useful content, ensuring that only the most relevant information is retained and analyzed.

Advanced filtering methods allow the system to determine priority data for processing, improving the quality of data collection available for further use in the system.

The module for continuous monitoring and updating of data should be designed in such a way that it is able to constantly: monitor new and updated existing information about buildings on the Internet; detect changes in the lists of already analyzed buildings; upload new, up-to-date media files: update documentation, ensuring the database remains relevant and complete.

In summary, it can be noted that the data collection module is a powerful tool for automating the process of collecting various data about objects of expertise from the Internet. Thanks to the integration of AI and parser generators, the module provides high accuracy, efficiency and adaptability.

3.3. Semantic analysis module

The semantic analysis module is a comprehensive system component designed to perform in-depth analysis of data collected about objects. This module uses large language models (LLM) and AI-based media analysis tools to extract meaningful information from both text documents and multimedia files [15, 16]. The module designed to transform raw data into useful information should provide a complete understanding of the attributes, condition and context of each individual building. For this, it must solve the following problems:

1. Analysis of textual data using LLM, as they are used to interpret the context and nuances of the text, identify key information. This means that the LLM can be used to specify a building, determine its historical significance, legal status and compliance with building regulations. The module can also automatically recognize and extract specific entities (such as building names, locations, owner information, damage and destruction facts) and relationships between them, facilitating the creation of structured knowledge bases. It is also worth noting that the use of LLM allows to generate concise summaries of voluminous documents that can be used to evaluate the accuracy and efficiency of the module during the system development stage.
2. Analyze media files using advanced AI techniques to extract meaningful data from multimedia files, including images and videos [17]. AI models analyze photos to identify and classify attributes such as architectural features, building materials and visible building damage. These models can also detect the presence of certain objects (solar panels, security devices etc.). The module processes the found video materials to extract relevant frames, which can be further processed by models working with photographs. It is also worth noting that a deeper analysis of video files that recorded the moment of inflicting damage to a certain building can be extremely useful for the further operation of the system. AI-powered tools automatically annotate and tag media files with relevant keywords, making it easy to organize, search, and retrieve important visual information that can be used by an expert to evaluate the performance of the entire system.
3. Integration of intermodal data from text and multimedia files, providing a holistic view of each object of examination [18, 19]. The module can correlate information obtained from text (a report mentioning, a crack in the wall) with visual evidence found in photographs or videos, ensuring consistency and increasing the reliability of the analysis. Certain semantic analysis data can be visualized in context by overlaying text annotations on photographs of buildings or by generating timelines of key events identified in both the text and the media file.
4. Generation of a knowledge graph that displays the relationships between different pieces of information related to buildings [20]. A great advantage of a knowledge graph is that system users can directly interact with this knowledge graph to perform dynamic queries, such as identifying buildings with similar attributes or exploring the impact of historical events on the current state of a building. This fact makes the whole system more flexible and easier to improve during the implementation process.

It is worth noting that the knowledge graph about the building created in the process allows the use of this module not only as an element of the system described in this article, but also as an independent part of other systems designed to perform the following tasks:

- Property management.
- Risk assessments [12].
- Compliance with legislation and building regulations, legal standards and safety standards by analyzing documents, certificates and visual inspections for compliance [1].
- Urban planning and development

3.4. Fuzzy values extraction module

The fuzzy value extraction module is a system component designed to interpret and quantify the information generated by the semantic analysis module.

Applying the principles of fuzzy logic, this module transforms qualitative descriptions and complex building data into fuzzy values that represent different aspects of the building's condition [21]. These fuzzy values make it possible to create new fuzzy rules for the system of assessing the technical condition of buildings by analyzing already existing expert assessments. The fuzzy value extraction module interacts directly with the semantic analysis module, using its structured output data, such as text summaries, media annotations, and knowledge graphs, as inputs for generating fuzzy values. The module collects key attributes and information defined by the semantic analysis module, including both qualitative descriptions and quantitative metrics.

The module uses fuzzy logic for the interpretation of input data, allowing to cope with uncertainties of a different nature inherent in the task of assessing the technical condition of buildings, constructures and infrastructure objects. For each relevant attribute of the subject of examination (such as structural integrity, safety compliance, aesthetic appeal), fuzzy sets are associated with corresponding membership functions. These functions map qualitative scores or numerical values to fuzzy values (eg, "low", "medium", "high"). It is also worth noting that the fuzzy value extraction module itself can use a set of predefined fuzzy rules, which in turn can combine other inputs (such as expert assessment results and visual evidences) to generate new fuzzy values.

The module builds an overall score based on multiple criteria, taking into account several attributes at the same time to obtain a composite fuzzy value for the building This allows you to get a holistic assessment that reflects the interaction between different factors. In this context, it is important that different attributes can be weighted according to their importance in the overall evaluation. For example, structural integrity may carry more weight than aesthetic appeal in determining the overall condition of a building.

The output of this module is a set of extracted fuzzy values obtained from the data, which is the result of the work of the semantic analysis module, as well as a set of additional complex fuzzy values and linguistic variables obtained by applying additional fuzzy rules.

3.5. Fuzzy rules creation module

The main purpose of this module is the creation of fuzzy rules that can be used in the system of assessing the technical condition of the object of examination. The key idea that makes it possible to automatically solve this problem is to compare already existing formalized expert assessments of the technical condition of the corresponding object with fuzzy values obtained as a result of the work of the fuzzy values selection module.

It is worth noting that in order to ensure the controllability of the learning process, this system must provide the possibility of interaction with the expert in such a way that he has the opportunity to review the generated fuzzy rules and all the necessary additional materials that were analyzed in the process of creating a specific rule.

4.Practical aspect of the system

Given that the number of objects undergoing destruction and damage continues to increase, more and more experts will be involved in the process of assessing their technical condition and subsequent reconstruction. Thus, the system will be highly loaded and the practical value of the work will be the creation of an application for these experts that will implement all its key functions.

The application will have a microservice architecture, which will allow it to be divided into small, independent services, each of which will perform a specific function. They will be developed, launched and expanded separately, which will significantly increase the flexibility and scalability of the system.

For the first time, such an architecture was mentioned in [2] and shown in Fig. 5.

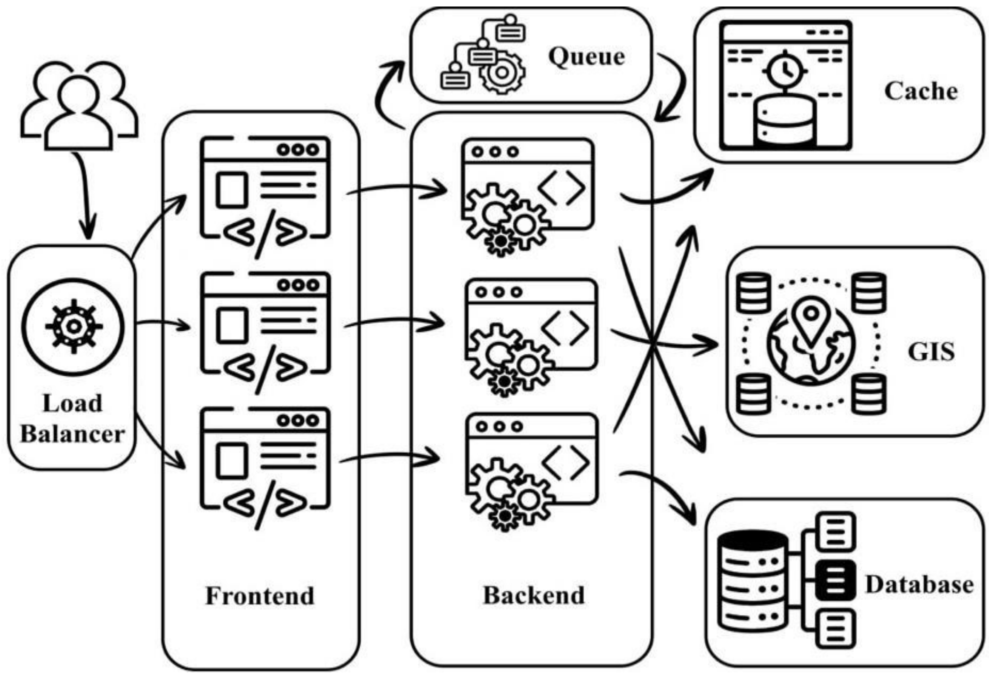

Figure 5: Architecture of the info-communication RERSS [2]

5. Discussion

In fact, the paper considers AI training with a teacher. At the same time, it is worth noting that this approach to learning the system has a significant drawback, such as the need to reproduce a sufficient number of assessment cycles and receive feedback from the teacher to achieve acceptable accuracy. This is a problem in the modern conditions that have developed in Ukraine, because BTE experts are excessively overloaded.

However, it is worth noting that learning with a teacher in the context of the task of assessing the technical condition of buildings, constructures of various purposes and objects of critical infrastructure is still the only alternative, because in the context of working with such objects, deep learning has a significant drawback – due to the multilayered and complex structure of neural network, it is difficult to predict how much weight the network has given to this or that factor influencing the state of the object. This fact is crucial, since the result of the technical condition assessment system is used to plan restoration works.

That is why a priori knowledge base is used to train the system being developed. However, due to the armed aggression on the territory of Ukraine, unfortunately, a large amount of data has appeared for training AI models, and deep learning will eventually allow to achieve a satisfactory accuracy of assessment by correcting existing fuzzy rules, creating new ones and generating additional linguistic variables.

Conclusion

1. The expediency of developing a system for supporting technical condition assessment processes as a component of the restoration system of buildings, constructures and infrastructure objects is shown and the advantageousness of its development as an intelligent, highly loaded distributed information and communication system to support the process of assessment and restoration of damaged buildings and infrastructure objects is substantiated, which is critically important in the post-war recovery of Ukraine.
2. The main modules of the system are described, which will allow obtaining a complete and reliable view of the state of objects, allow users to perform dynamic queries to identify similar objects, and increase the efficiency and accuracy of the technical assessment process.
3. It is shown that:

- the implementation of the system allows continuous monitoring and updating of data on objects of construction and technical expertise, which is critical for maintaining a high-quality knowledge base;
- the integration of artificial intelligence technologies will allow to significantly increase the accuracy and speed of assessing the technical condition of objects, which is a decisive factor for the rapid and successful recovery of Ukraine.

4. The further direction of research is the development of an application that will use large language models for semantic data analysis and will have a microservice architecture

that will allow it to be divided into small, independent services, each of which will perform a specific function.

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