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Analysis of integrated real-time decision support systems based on neural networks and low-structured data

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Abstract. The study aimed to analyse and substantiate effective methods for analysing inefficiently structured data using neural networks to provide operational decision support in complex environments. The focus was on the use of artificial neural networks to analyse inefficiently structured data, such as sensor streams, to ensure efficiency, accuracy and adaptability in a dynamic environment. The research is aimed at creating innovative models and technologies that will improve the efficiency of management in complex situations, such as emergency response, process automation in critical industries and decision-making based on predictive analytics. The study investigated conceptual approaches to the development of integrated real-time decision support systems based on the analysis of poorly structured data using neural networks. The study proposed methods of adaptive learning that allow neural networks to process data efficiently in the face of constant changes. The research methodology included modelling a real-time architecture using a microservice approach and streaming data processing platforms such as Apache Kafka and Apache Flink. The study highlighted the role of neural networks in processing streaming data, in particular, convolutional networks for processing visual information, recurrent networks for sequence analysis, and transformers for multichannel analysis. Architectural solutions were developed that allow the processing of large amounts of data with minimal delays, ensuring the accuracy and adaptability of systems. The study presented approaches to the implementation of adaptive training of neural networks that minimise the risks of losing model relevance in a dynamic environment. The use of modern technologies, such as artificial neural networks, adaptive learning and integration with the Internet of Things, was used to create effective systems for rapid response to emergencies. The proposed methods help increase the efficiency of management in difficult conditions and create new prospects for innovation in various industries

Keywords: artificial intelligence; knowledge base; dynamic environment; network models; knowledge extraction

Introduction

The modern development of digital technologies poses new challenges for science and engineering related to the processing of large amounts of data in real-time. One of the key tasks that arise in this context is the development of integrated decision support systems capable of analysing unstructured data. Such data includes information flows from sensor networks, social media, video surveillance, telemetry and other sources where the data structure is incomplete, variable or non-standard. This issue is particularly relevant in the context of rapid response to emergencies, including natural disasters, man-made accidents or cyber threats. Effective decision-making in such circumstances requires not only fast data processing but also interpretation of data based on complex patterns and context. This is challenging due to the multifactorial nature of the problems, unpredictable developments, and limited time for analysis. Artificial neural networks (ANNs) offer significant prospects for solving these problems. They can learn from large amounts of data, identify hidden patterns and adapt to new conditions. However, the implementation of such systems faces several challenges. It is necessary to ensure sufficient performance of algorithms when working with real-time data streams. The processing of poorly structured data requires the development of effective methods for its preliminary preparation, cleaning and classification. In addition, there is the issue of trust in the decisions made by the system, which is especially important in critical scenarios.

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Modern research in the development of decision support systems was actively promoted using artificial neural networks to analyse inefficiently structured data. Significant progress in this area was made by A. Sherstinsky (2020), who proposed a model for sensor stream processing. The proposed approach, based on recurrent neural networks (RNNs), effectively detected anomalies in industrial systems in real-time, which was important for preventing accidents. S. Huang *et al.* (2020) analysed multi-module data from sensor networks. The authors argued that the integration of data from different sources significantly improves the prediction of crises, such as natural disasters. In turn, S.I. Nilima *et al.* (2024) studied the optimisation of deep models for resource-constrained environments, in IoT devices. Their results demonstrated that it is possible to significantly reduce data processing time without losing the quality of analysis. F. Fan *et al.* (2021) addressed the interpretation of artificial neural network solutions. The authors developed a methodology that explained the system's decision-making process, which increased user confidence, especially in critical scenarios such as medicine or defence. L.X. Yang & C.Y. Xiu (2023) addressed the adaptability of models by developing a technique Meanwhile, O. Trofymenko *et al*. (2024) studied the effectiveness of using neural networks and AI technologies in the form of intelligent agents to protect against cyberattacks and assess vulnerabilities and risks in the defence cyberspace. In particular, the authors noted the capabilities of AI to analyse large amounts of data in real time, identify patterns and make recommendations on how to address identified vulnerabilities. L.X. Yang & C.Y. Xiu (2023) addressed the adaptability of models by developing a technique that allowed updating the parameters of neural networks without the need for complete retraining, which was critical for working in dynamic environments. C. Wang *et al.* (2019) applied reinforcement learning methods to control autonomous drones during emergencies. Their approach proved to be effective in solving problems in challenging environments. The work was focused on creating systems that can operate in conditions of limited computing resources. The authors presented a method for optimising models based on convolutional neural networks (CNNs), which significantly reduced processing time without losing accuracy.

Despite significant progress in the field of decision support systems, there are still areas that require further research. There are a limited number of solutions that work efficiently with large-scale, unstructured data in real time, especially in scenarios with high information update rates. Explanatory ANN methods for complex multimodal data are not fully explored, which raises questions about the credibility of such systems.

The study aimed to analyse modern technologies for creating integrated real-time decision support systems capable of efficiently processing inefficiently structured data of various types. To do this, it was necessary to analyse methods for effectively integrating poorly structured data of various formats (text, sensor streams, video) into a single analytical system; to define an architecture that could handle large amounts of data in real-time with minimal delays.

Materials and Methods

The study analysed a combination of advanced technologies and methods for analysing low-structured data in real-time, with a particular focus on improving decision-making for critical systems such as emergency response or infrastructure monitoring. The main sources of data in this study were sensor networks and Internet of Things (IoT) devices, which generate significant amounts of low-structured information, including sensor data streams, text messages, and multimedia metadata. The Apache Kafka (n.d.) and Apache Flink (n.d.) platforms were used to process these data streams. They were essential for collecting and processing large amounts of data in real-time. Kafka was used for data integration, and Flink for continuous streaming data processing, which ensured its constant broadcast and quick analysis. These platforms can be used for the seamless integration of data from different sources, which is critical for monitoring critical infrastructure or emergency response systems.

The analysis of the poorly structured data was carried out using artificial neural networks (ANNs), in particular convolutional neural networks (CNNs) and recurrent neural networks (RNNs). CNNs were used to analyse video data from surveillance cameras, allowing the system to detect key features such as motion, object recognition, and context changes. At the same time, RNNs and transformers were used to process time series of sensor data and textual information, allowing the system to detect temporal patterns and make predictions based on past data. Adaptive learning methods were used to adapt to dynamic environments where data is constantly changing. Approaches such as unsupervised learning and online learning were used to ensure that the models could be continuously updated and improved without the need for complete retraining. A review of the key aspects and technologies used to develop real-time decision support systems that analyse unstructured data was conducted.

Multi-channel models were studied to analyse different types of information simultaneously. Integration was conducted through the Kafka and Flink platforms, which ensured the efficient combination of different data streams, including video, sensor data, and text messages. Multi-channel models combined CNN+RNN architectures or used transformers to process all data simultaneously, revealing hidden correlations and patterns. To reduce delays in re-accessing data, a data caching technique was applied. This made it possible to speed up access to the results of data processing, which is critical for decision-making in stressful situations. Adaptive learning algorithms, including stochastic gradient optimisation methods, were explored to allow networks to respond quickly to changes in conditions. These algorithms provided the ability to continuously update model weights based on new data coming in real-time.

Results

In the modern world, where the amount of data is growing exponentially, the concept of unstructured data is becoming increasingly relevant. This data – is a "bridge" between structured relational database tables and chaotic arrays of unstructured information. They contain a potential that can only be realised with a deep understanding of their nature. Loosely structured data can be compared to a large library, where books are not arranged according to a standard classification system, but each has tags or a short description. Such data includes JSON files, log entries, sensor streams, or media file metadata. They contain information that has a certain structure, but it is often incomplete, flexible, or even unstable. Another important feature is the dynamism of loosely structured data. Data can change depending on software updates, the introduction of new features, or changes in user behaviour. Thus, the system must be able to adapt to these changes while maintaining efficiency.

At the same time, the benefits come with challenges. Traditional approaches to data analysis are often not suitable for working with unstructured data. The complexity of integrating heterogeneous sources, the large number of missing values, and the constant change in structure create additional difficulties. However, it is these challenges that drive innovation (Hariri *et al.*, 2019). Artificial neural networks, due to their flexibility, create new opportunities for working with such data. They allow not only finding patterns but also explaining decisions, which is critical in complex scenarios such as emergency response.

Unstructured data is a challenge but also an opportunity for modern systems. They allow for the development of integrated solutions that can not only analyse information but also do so in real-time, providing a new level of efficiency in the decision-making process (Raptis *et al.*, 2019). Therefore, their research is the key to developing innovative approaches that can cope with modern requirements for processing heterogeneous information. For instance, the data stream from sensors in smart city systems can include numerical temperature readings, noise levels, images from surveillance cameras, and text reports from operators. Traditional methods of analysis require a clear structuring of information, but integrating such heterogeneous sources is a challenging task. In this context, neural networks are highly effective due to their ability to adapt to processing data with a complex and heterogeneous structure.

A key factor in modelling nonlinear relationships between data is choosing the right mathematical or statistical approach that can accurately reflect these relationships. For instance, when analysing streams from surveillance cameras, convolutional neural networks (CNNs) can be used to identify key features of images: objects, movement, and context changes (Ullah *et al.*, 2019). Recurrent neural networks (RNNs) can be used to remember the previous context and make predictions based on it (Dhruv & Naskar, 2020). Neural networks also allow the integration of different types of data. Thanks to multi-channel models such as combined CNN+RNN architectures or transformers, neural networks can process all these streams simultaneously, revealing correlations and patterns that were previously hidden. However, their value lies not only in the ability to analyse. Neural networks change the perception of poorly structured data, turning it from a problem into a source of competitive advantage. For example, emergency response systems can process huge amounts of information in real time, offering clear recommendations (Hancock & Khoshgoftaar, 2020). Such systems not only reduce decision-making time but also minimise errors that can occur due to human error.

Real-time architectural solutions are the basis for creating efficient and fast systems that can process large amounts of data with minimal delays. One of the most popular approaches is microservice architecture, where the system is divided into small, independent services, each responsible for a specific task. This enables flexible scaling of the system, updates of individual components without affecting the rest of the system, and increases resilience and reliability (Abirami & Chitra, 2020). To integrate data from various sources, such as sensors or video cameras, event-based platforms are used to respond to changes in real-time, activating the necessary actions without unnecessary delays. Another important element is the use of high-performance real-time data processing platforms such as Apache Kafka or Apache Flink. They can efficiently process data streams, ensuring their continuous flow and fast processing. Such platforms allow not only fast processing of information but also guarantee its reliable storage and the possibility of recovery in case of a system failure. In addition, to ensure high performance, parallel computing and distributed systems are often used to process large amounts of data using multiple servers, reducing the load on individual components and ensuring system resilience. The last important aspect is the optimisation of data caching, which reduces delays in re-accessing frequently used information. The use of the cache significantly speeds up access to processing results and allows for quick decision-making in critical situations. All of this together creates an architecture that can operate efficiently in real-time, providing high data processing speed, fault tolerance, and reliability in difficult conditions (Mehmood & Anees, 2020).

Adaptive training of neural networks in dynamic environments is a critical aspect for systems that process streaming data and need to constantly respond to changes in the environment. In such environments, traditional training methods that use static data sets may not be effective. Dynamic environments are typically characterised by constantly changing parameters, which require neural networks to be able to adapt to new conditions without the need for a complete retraining process from scratch (Liu *et al.*, 2020). This is especially important for applications that process data in real-time, such as emergency response systems, security monitoring, or financial forecasts. Adaptive neural network training involves continuously adjusting the model based on new incoming data. This may include using updated parameters or new architectures to provide more accurate predictions and analysis. This is often done using approaches such as unsupervised learning, where the network detects new patterns in the data on its own, as well as methods that allow networks to "forget" outdated or irrelevant data by focusing on the most relevant information (Han *et al.*, 2021). This avoids the effect of overfitting and maintains the accuracy of the model in the face of changing input data.

One of the most effective ways of adaptive learning is to use algorithms that incorporate real-time changes in the learning rate. For instance, methods based on stochastic gradient descent can change parameters during the learning process, depending on how quickly the input data changes (Kabudi *et al.*, 2021). This allows the network to respond quickly to changes in the environment, guaranteeing accuracy even in the event of unpredictable events. In addition, to operate effectively in dynamic environments, it is important to strike a balance between the speed of adaptation and the stability of the model. Too fast adaptation can lead to excessive fluctuations in the results, while too slow adaptation can lead to the loss of information relevance. For a neural network to work effectively in a dynamic environment, it is also necessary to apply approaches to data selection. Sampling new data that is most relevant to the current situation allows the model to remain effective even under changing conditions. This may include active learning methods, where the network independently determines what data, it needs to obtain to improve its performance, or the use of multi-channel models that allow analysis of information from different sources simultaneously. Thus, adaptive training of neural networks allows not only to maintain a high level of accuracy in real-time but also to make predictions based on the most relevant and updated information coming from the environment.

Table 1 provides an overview of the key aspects and technologies used to develop real-time decision support systems that analyse unstructured data. It summarises the most important components of such systems, including the integration of neural networks, the use of streaming data platforms, and adaptive learning for dynamic environments. These approaches allow for the rapid processing of large volumes of data in real-time, which is critical for effective emergency response and decision support in complex environments.

Table 1. Key aspects and technologies for real-time decision support systems based on neural networks and analysis of weakly structured data

A key area of focus	Description	Technical aspects and methods	Application examples
Inefficiently structured data analysis	Processing data that does not have a clear structure (e.g., sensor streams, text messages).	Artificial neural networks, data stream processing, and classification using deep networks.	Environmental monitoring, security, video analysis
Real-time neural networks	Use of neural networks to process data in real-time, which allows for immediate response to changes.	Recurrent neural networks (RNNs), deep neural networks, and ongoing learning.	Emergency response and traffic management
Real-time data integration	Collecting and processing data from various sources to provide up-to-date information for decision-making.	Streaming data processing platforms (Apache Kafka, Apache Flink), integration via API	Monitoring the parameters of critical infrastructure facilities
Response to emergency events	Prompt identification and response to events requiring immediate intervention.	Neural networks and active learning methods, event prediction through anomaly detection algorithms	Security systems, monitoring for responding to natural disasters
Decision support systems	Designing interfaces and mechanisms for quick decision-making based on data analysis.	Interfaces for visualising results, algorithms for classification and forecasting.	Automated emergency management systems, risk analysis
Adaptive learning and model updates	Continuous improvement of models based on new data to maintain the relevance and accuracy of forecasts.	Methods of updating neural networks (online training), using new data for adaptation.	Monitoring systems with automatic model updates
System reliability and resilience	Ensure uninterrupted operation even in the face of disruptions or unforeseen changes in data.	Backup, load balancing, disaster recovery.	Critical infrastructures, financial systems

Source: compiled by the author based on F. Gurcan & M. Berigel (2018), A.N. Navaz *et al.* (2019), S. Ashraf *et al.* (2022)

The application of the described technologies increases the accuracy and speed of decision-making, which allows the creation of effective systems to support real-time management decisions, such as monitoring the condition of critical facilities, managing traffic flows or responding to emergencies. In addition, neural networks provide adaptability and self-optimisation in the face of changing input data, which is important in situations requiring immediate action. The use of technologies for streaming data processing and adaptive learning allows for high accuracy of decisions even in unstable and unpredictable scenarios, making such systems highly beneficial for critical infrastructures and situations where every second counts (Semenenko *et al.*, 2024).

Integrated real-time decision support systems that analyse unstructured data can significantly improve management efficiency in complex situations. The use of neural networks to process real-time data streams allows the system to adapt to changing conditions, which is key to responding quickly to emergencies. The integration of streaming data processing technologies allows systems to operate efficiently under high loads, processing large amounts of information without significant delays. This ensures not only prompt decision-making but also their accuracy, as systems can constantly adapt to new data. Adaptive learning technologies allow neural networks to dynamically change their strategies depending on changes in input data, which is critical in areas such as infrastructure monitoring, transport management, or emergency response.

As a result, the use of such systems allows for more efficient and accurate decision-making in real-time, which is extremely important in an environment where every second counts for safety and effective management. Therefore, such technologies have great potential for use in various areas where it is necessary to respond quickly to changes and ensure reliable management in difficult conditions. The implementation of integrated real-time decision support systems is based on a combination of modern technologies and data processing methods. The basis of such systems is the analysis of unstructured data generated in large volumes and requiring fast processing to ensure timely decisions. This applies to data received from sensor networks, streaming platforms, and IoT devices.

Table 2 presents the main technologies and methods for designing integrated real-time decision support systems. It also shows the main technologies and methods used to design such systems. Key components are included, such as big data platforms, artificial intelligence algorithms such as neural networks, and models that support adaptive learning in dynamic environments. Such solutions are critical for industries operating under conditions of high uncertainty, including crisis management, transport, medicine, and energy. The presented methods help improve the accuracy, reliability and speed of data analysis.

Table 2. Basic technologies and methods for designing integrated real-time decision support systems

Technology/Method	Description	Application examples	Advantages	Challenges
Platforms for streaming data processing	Used to process large volumes of data coming in real-time. Main platforms: Apache Kafka, Apache Flink, Spark Streaming.	Monitoring the state of critical infrastructure, managing traffic flows	High processing speed, scalability	Difficulty of integration with other systems, need for high computing resources.
Neural networks for forecasting	Neural networks (especially LSTM, and GRU) are used to predict and classify data in real time.	Forecasting events in security systems, forecasting demand in retail	Improved forecast accuracy, ability to work with big data	The need for large amounts of training data, the risk of overtraining
Adaptive learning in real-time	Neural network models are constantly updated based on new data. This allows systems to adapt to changes in the environment.	Responding to changes in the security environment, adapting to changes in user behaviour	Fast adaptation to new conditions, reduced manual configuration costs	The need for constant evaluation and correction of models, the possibility of noise data
Integration with IoT (Internet of Things)	A combination of sensors, IoT devices and neural networks to provide real-time data collection.	Patient health monitoring, industrial process automation	Improved data accuracy, efficient resource management	Compatibility issues between different devices, data security issues
Response to emergency events	Use of systems for prompt decision-making during emergencies based on data from various sources.	Responding to natural disasters and accidents at industrial facilities	Speed of response, minimisation of human errors	High requirements for data accuracy, limited resources for real-time data processing

Source: compiled by the author based on M. Mohammadi *et al*. (2018), Y. Yan & H. Yang (2024)

The methods and technologies presented in the table demonstrate how an integrated approach to processing unstructured data allows for the creation of effective decision support systems. The use of streaming processing platforms such as Apache Kafka or Apache Flink ensures the speed of processing large amounts of information, while neural networks, especially LSTM and CNN, can accurately identify key patterns in the data. Adaptive learning, in turn, ensures that systems can quickly adapt to changes in the environment or changes in data structure.

However, the implementation of such systems requires a solution to several challenges. These include limited computing resources for training complex models in real-time, ensuring data security and privacy in cloud infrastructures, and the difficulty of integrating existing solutions with new technologies. These challenges require further research aimed at creating optimised, secure and scalable architectures that meet the needs of modern systems. At the same time, advances in technology are enabling the capabilities of such systems to be expanded, for example, by integrating them with quantum computing for even faster analysis and decision-making. This opens new perspectives for application in complex areas such as urban infrastructure management, automated transport systems, and environmental monitoring. Thus, the presented methods and approaches form the basis for the further development of this innovative field.

The conceptual development of a system for real-time analysis of unstructured data is based on the integration of modern data processing technologies, artificial intelligence and adaptive machine learning models. The main components of such a system are a data collection module, a real-time processing unit, an analytical module using neural networks, and an interactive interface for visualising results and supporting decision-making. Data sources, which include sensor networks and IoT devices, are integrated through standard protocols such as MQTT or APIs. This ensures a constant flow of data into the system. The streams of information, which can include text messages, video from surveillance cameras, and signals from sensors, are processed by streaming platforms such as Apache Kafka, Flink, or Spark Streaming. At this stage, the data is normalised, gaps are filled in, and it is brought to a common format (Mohan & Thyagarajan, 2023).

The key element of the system is the analytical module, where neural networks are used for multi-channel data processing. For instance, recurrent neural networks (LSTM, GRU) are used to analyse text messages, while convolutional neural networks process video to detect anomalies or dangerous events. In complex scenarios that require the integration of different types of data, combined architectures are used to process text, visual and sensory streams simultaneously. The system has an adaptive learning capability that allows the modelling of new patterns in the data as it is acquired. This ensures dynamic adaptation to changes, such as software updates, changes in user behaviour, or the emergence of new functionalities. As a result, the system can operate in conditions where traditional methods are ineffective (Haidur *et al.*, 2023). The analysis results are transferred to an interactive interface that allows operators to visualise data, get explanations for decisions made, and intervene promptly if necessary. If anomalies or dangerous situations are detected, the system generates recommendations for the relevant services, speeding up the response process. The proposed concept is suitable for real-time scenarios, such as security monitoring in smart cities. The system integrates data from various sources, such as video surveillance and sensor sensors, analyses it to identify critical situations and facilitates timely decision-making. The implementation of this concept will ensure high performance, adaptability and functionality in today's dynamic environments.

Discussion

Analysis of unstructured data and integrating it into real-time decision support systems has become an important aspect of modern information processing. With the rapid growth of data volumes, especially from diverse and dynamic sources such as sensor streams, social media and multimedia files, the challenge is not only to collect and store this information but also to process it efficiently and quickly. Unstructured data is inherently flexible and often incomplete, which poses significant challenges for traditional data analytics methods. However, they also have enormous potential for the development of innovative real-time systems that can adapt to rapidly changing conditions.

One of the main advantages of unstructured data is its ability to integrate diverse sources of information. In systems such as smart city monitoring or emergency response systems, data can come in a variety of formats – from text alerts and sensor measurements to video from security cameras. Neural networks, convolutional and recurrent models, have proven to be extremely effective in processing such complex multi-format data streams. Convolutional neural networks (CNNs) are suitable for image processing, which allows the analysis of video streams from surveillance cameras. Recurrent Neural Networks (RNNs) or Transformers, on the other hand, are effective with sequences of data, such as sensor measurements or text logs, remembering previous information and predicting future states. The research by B.A. Hammou *et al.* (2019) focused on the use of convolutional and recurrent neural networks for real-time processing of video and text data. The authors emphasised the role of adaptive learning, in particular online learning, to adjust models while processing current data. This coincides with current findings on the need for an adaptive approach to processing dynamic data, but this study has focused on the impact of infrastructure platforms on data flow.

In addition, the ability of neural networks to model non-linear relationships and adapt to changes in data significantly increases their effectiveness. In environments where data is constantly changing – such as real-time monitoring systems – neural networks can dynamically adjust their models based on new input data, which allows for accurate and timely decision-making. A. Novak *et al*. (2021) investigated the impact of neural networks on decision-making accuracy in environments were data changes in real-time. Scientists emphasised that the adaptability of neural networks can quickly adjust models based on new data, which is critical for efficient processing in situations such as emergencies. However, the study addressed technologies for predicting events based on historical data, not real-time.

Adaptive learning algorithms are key, allowing systems to quickly update their models in real-time based on new data. Traditional machine learning methods that rely on static datasets have proven to be insufficient in such environments where parameters are constantly changing. Y. Wang & S. Zou (2021) analysed the use of reinforcement learning to adapt models to a changing environment. The study considered the use of methods such as reinforcement learning to optimise models in the face of unstable data. In contrast, the current study focuses more on the need for adaptive learning due to real-time changes, without the need to rebuild the entire model.

In terms of architectural solutions, implementing real-time decision support systems requires a reliable and scalable infrastructure. Microservice architecture, for instance, provides flexibility and reliability by allowing individual components to operate independently while integrating into a single system. Streaming data processing platforms, such as Apache Kafka and Apache Flink, are essential for enabling the fast processing of large amounts of data in real-time while minimising latency. In addition, distributed computing systems and parallel processing allow for efficient analysis of large amounts of data, ensuring high performance even under heavy loads. B.G. Deepthi *et al.* (2023) explored the use of the Apache Flink platform for fast real-time data processing and its integration with neural networks to ensure accuracy and speed of decision-making. They also highlighted the importance of scalability. This is consistent with the findings of this paper, which emphasised the importance of an efficient infrastructure for processing large amounts of real-time data.

One of the most popular approaches to developing real-time systems is microservice architecture. It allows load balancing and provides flexibility and scalability. G. Ortiz *et al.* (2021) investigated the use of microservice architecture to create high-performance systems capable of processing large amounts of data in real-time. Scientists highlighted the advantages of this approach, such as flexibility, scalability, and load balancing between services to reduce latency. They emphasised the use of microservice architecture to ensure real-time efficiency. This coincides with the current findings, which emphasised the ability of such an architecture to handle large amounts of data and provide system flexibility. Furthermore, G. Ortiz *et al.* (2019) investigated the use of microservice architecture to build efficient systems capable of processing large amounts of data in real-time. The authors emphasised the advantages of this architecture, such as scalability, flexibility, and the ability to reduce delays due to optimised load balancing between services. Scientists emphasised the ability to distribute the load between services to reduce latency, while current results have focused more on the use of microservice architecture to provide flexibility and handle large amounts of data. M. Raparthi *et al.* (2021) analysed the potential of quantum computing to accelerate data analysis and decision-making. While this is an area that holds great promise, the current study did not focus on quantum technologies, but rather on the use of existing streaming platforms and neural network technologies to provide data processing speed.

The integration of neural networks with streaming data processing platforms has revolutionised many industries, from health and safety to traffic management and emergency response. However, there are several challenges, including the need for powerful computing resources to train complex models in real time and ensure data security. D. Kavitha & S. Ravikumar (2020) highlighted the importance of integrating neural networks with streaming data platforms to achieve real change in areas such as healthcare. The authors also highlighted the challenges, including the need for substantial computing resources and security challenges, associated with using these technologies in real time. However, scientists also emphasised the importance of new technologies, such as quantum computing, for the further development and optimisation of decision-making processes. Thus, the research and development of systems that analyse unstructured data in real time have become an important step towards improving the efficiency of decision-making in critical environments. Neural networks and adaptive learning provide the flexibility needed to handle dynamic data streams, and robust data platforms ensure that systems operate efficiently even under high loads.

These technologies have transformed industries such as emergency management and infrastructure monitoring. G. Huang *et al.* (2006) investigated the integration of neural networks for real-time analysis of unstructured data in critical environments, including emergency management and infrastructure monitoring. The study analysed adaptive learning, which allows systems to respond quickly to data changes, as well as problems arising from high loads on data processing platforms. Although both the current findings and the author's research focused on the integration of neural networks and adaptive learning, there are important differences between them. The current findings put more emphasis on the importance of real-time data processing with many variables and complex conditions, where flexible streaming data processing platforms such as Apache Kafka or Flink are used.

The integration of new technologies, such as streaming data platforms or quantum computing, still faces interoperability and data security issues. O. Petit *et al.* (2018) highlighted the difficulties encountered when integrating new technologies into existing systems. Among the main problems, the author highlighted the need for compatibility between different platforms, ensuring data security, and the difficulty of adapting new solutions to the specific requirements of certain industries. The authors, similarly, to the current study, emphasised the difficulties in integrating new technologies such as quantum computing and streaming data processing, including interoperability and security issues. Integrating emerging technologies such as neural networks and microservice architecture is important to optimise real-time data processing. Increasing the flexibility and adaptability of such systems helps to improve the accuracy of decision-making, especially in critical environments such as emergencies or infrastructure monitoring. However, despite the many benefits, there are significant challenges, including the need for high computing power and data security.

Conclusions

The current study examined methods for analysing sparsely structured data for real-time decision-making. The study has shown that unstructured data, due to its dynamism, can be effectively integrated into real-time monitoring systems. The use of neural networks allows the processing of variable data streams that arise due to software updates, changes in user behaviour or the addition of new features, ensuring that systems adapt to these changes. It was confirmed that neural networks are an effective tool for identifying hidden patterns in data and explaining decisions, which is important in critical situations such as emergencies. In addition, significant progress has been made in addressing the challenges of integrating various sources of unstructured data, including text messages, video streams and sensor signals, which has led to increased speed and accuracy of decision-making.

The study also highlighted the importance of using microservices architectures and streaming data processing platforms such as Apache Kafka and Apache Flink to ensure stable and efficient operation of real-time systems. This allows not only to ensure high data processing speeds but also to maintain their reliability and fault tolerance. By integrating adaptive learning into neural networks, systems can independently update their models in the face of constant change, which is critical for industries where reaction time is crucial. However, for the successful implementation of such systems, it is necessary to solve the problems associated with limited computing resources and data security. As a result, the implementation of integrated real-time decision support systems based on the analysis of unstructured data opens new prospects for the development of various industries, including critical infrastructure management, emergency response, automated transport management systems, and environmental monitoring. Further research could focus on optimising data processing methods and developing adaptive algorithms that allow for a more efficient response to changes in dynamic environments.

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Аналіз інтегрованих систем підтримки прийняття рішень у реальному часі на основі нейронних мереж та слабоструктурованих даних

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Анотація. Метою цієї роботи було дослідження та обґрунтування ефективних методів аналізу слабоструктурованих даних з використанням нейронних мереж для забезпечення оперативної підтримки прийняття рішень у складних середовищах. Основну увагу приділено використанню штучних нейронних мереж для аналізу слабоструктурованих даних, таких як сенсорні потоки, для забезпечення оперативності, точності та адаптивності в умовах динамічного середовища. Дослідження спрямоване на створення інноваційних моделей і технологій, які дозволять підвищити ефективність управління у складних ситуаціях, таких як реагування на надзвичайні події, автоматизація процесів у критичних галузях і прийняття рішень на основі прогнозної аналітики. У роботі досліджено концептуальні підходи до розробки інтегрованих систем підтримки прийняття рішень у реальному часі, які базуються на аналізі слабоструктурованих даних за допомогою нейронних мереж. Запропоновано методи адаптивного навчання, що дають змогу нейронним мережам ефективно обробляти дані в умовах постійних змін. Методологія дослідження включала моделювання архітектури реального часу з використанням мікросервісного підходу та платформ для потокової обробки даних, таких як Apache Kafka і Apache Flink. Висвітлено роль нейронних мереж у роботі з потоковими даними, зокрема згорткових мереж для обробки візуальної інформації, рекурентних мереж для аналізу послідовностей і трансформерів для багатоканального аналізу. Розроблено архітектурні рішення, які дозволяють обробляти великі обсяги даних із мінімальними затримками, забезпечуючи точність і адаптивність систем. Представлено підходи до реалізації адаптивного навчання нейронних мереж, що мінімізують ризики втрати релевантності моделі в динамічному середовищі. Використання сучасних технологій, таких як штучні нейронні мережі, адаптивне навчання та інтеграція з інтернетом речей, дозволяє створювати ефективні системи для оперативного реагування на надзвичайні події. Запропоновані методи сприяють підвищенню ефективності управління у складних умовах і відкривають нові перспективи для інновацій у різних галузях

Ключові слова: штучний інтелект; база знань; динамічне середовище; мережеві моделі; видобування знань