Współczesna Gospodarka

Contemporary Economy
Electronic Scientific Journal
Współczesna Gospodarka (ug.edu.pl)

Vol.19 Issue 1 (2025) 35-47
*ISSN*2082-677X
DOI 10.26881/wg.2025.1.03

DRIVING DIGITAL BUSINESS TRANSFORMATION IN GREEN SMART CITIES WITH ARTIFICIAL INTELLIGENCE AND CLOUD COMPUTING

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Abstract

Purpose. The digital transformation of business in green smart cities is crucial due to the evolving needs of residents and businesses, as well as the increasing demands for enhancing efficiency, improving the quality of urban life, and protecting the environment. The aim of this publication is to characterize the directions of development in artificial intelligence (AI) and cloud computing that support digital transformation and sustainable urban development. It is worth noting that there is a gap in the literature, as clear ideas are lacking on how to effectively utilize deep learning based on artificial neural networks (ANN) in the cloud.
Methods. Basic research methods include critical analysis of the literature on the subject. In addition, modeling was used to simulate the use of deep learning and cloud computing in smart city management systems. Intensive computational experiments were carried out to analyze the quality of the solutions, which were determined by the proposed deep learning methods using ANN based on Long Short Term Memory (LSTM).
Results. The results of theoretical research and numerical experiments confirmed significantly contributing AI and cloud computing in the increasing the efficiency of the city and improving the quality of resident's life and protecting the natural environment.

Słowa kluczowe: deep learning, digital transformation, sustainable development.

Klasyfikacja JEL: G17, M15, O33.

Introduction

The digital transformation of business in a smart city is the process of implementing modern technologies and digital solutions to enhance processes and optimize resources, enabling greater efficiency and cost reduction. Introducing ICT into the city and business processes can benefit both entrepreneurs and residents. For business, digital transformation means streamlining and perfecting operations, as well as accelerating innovation and improving competitiveness. For residents, digitization means improving the quality of life and increasing the efficiency of city services. To achieve this, the city must rely on technologies that can analyze data and provide the information necessary to effectively perform its tasks. Artificial intelligence and cloud computing are priorities that redefine business activities due to the huge space of various data processing possibilities.

AI can be used to analyze data from a variety of sources, such as smart meters, sensors, and IoT devices, to find patterns and trends. In turn, cloud computing provides the computing power and storage required to process the vast amounts of data generated by various smart city systems. Moreover, cloud computing also enables data to be stored and accessed from anywhere, enabling city officials to access critical data and insights to make informed decisions.

The aim of the article is to characterize the directions of development of AI and cloud computing supporting the digital business transformation in a green smart city. Artificial intelligence technologies play a pivotal role in optimizing resource allocation, streamlining decision-making processes, enhancing urban efficiency, and ultimately improving residents' overall quality of life while maintaining respect for the natural environment. It is worth noting that there is a gap in the literature on the subject, as there are no clear ideas for the effective use of deep learning with the use of ANN in the cloud, for the digital business transformation in the key areas of smart city competitiveness.

As part of the basic research methods, a critical analysis of the literature on the subject was used. In addition, modeling was used to simulate the application of deep learning and cloud computing in smart city management systems. Intensive computational experiments were conducted to analyze the quality of the solutions, which were decided by the proposed deep learning methods using ANN based on LSTM.

It is advisable to ask the following questions. How to effectively support the harmonious development of a green smart city? How to apply AI and cloud computing in a smart city? The problem is also how to strengthen the potential of a city that is constantly in motion? How to perform surgery on the open heart of a living metropolis? I will try to answer these questions in this article.

This article contributes to the existing body of knowledge by proposing novel applications of deep learning and cloud computing for enhancing the operational efficiency and sustainability of green smart cities. It identifies a research gap in the effective use of cloud-based artificial neural networks to support urban digital transformation and provides conceptual models and case analyses to address this gap.

The rest of the article is organized as follows. Section I characterizes the levels of digital business transformation toward a smart city based on the implementation of digital technologies and new IT solutions. Section II describes deep learning models and cloud computing resources for the urban domain systems. Section III presents effective solutions based on the use of neural networks of the Long Short Term Memory class for cloud computing, with particular emphasis on prediction in financial systems. A special case of deep learning architecture based on artificial neural networks with short-term and long-term memory for stock market investments was considered. Finally, conclusions and recommended directions of development are presented.

1. Digital transformation levels of business in the smart city

Effective digital transformation of business is a key element in successfully implementing the concept of a green and smart city. It enables sustainable, eco-friendly, and holistic management of urban space, contributing to resource optimization and improved quality of life for residents (Letkiewicz, Szulc, 2022).

The process of digital business transformation in a smart city can be divided into several levels. The first level refers to the digitization and automation of business processes. At this level, the city introduces ICT to existing business processes, such as city administration, service for residents or health care to automate processes and increase their efficiency.

The second level concerns the integration of IT systems, such as transport, energy, water and sewage or lighting systems. Through system integration, it is possible to optimize resources and minimize costs.

The third level is associated with the proper analysis of data collected by various IT systems. This enables the city to make accurate decisions, such as optimizing traffic flow and water consumption or improving air quality.

The fourth level involves the appropriate use of the latest technological advancements, including artificial intelligence, for efficient processing and accurate forecasting of behaviors and trends. As a result, it becomes possible to take preventive actions based on precise predictions rather than relying on the intuition or experience of decision-makers.

The fifth level is the development of new ICT-based services. These include mobile applications that make life easier for residents, including automatic parking systems and e-commerce platforms.

A smart city leverages the power of artificial intelligence to transform urban life, introducing innovative service models characterized by greater efficiency and enhancing residents' quality of life, while redefining traditional approaches to managing urban spaces and resources (Yan, Jiang, Huang, 2023). To understand why deep learning with the use of artificial neural networks in the cloud and the latest computer technologies such a big impact on the digital business transformation of the green smart city has, it is worth briefly following their expansion (Kumar, 2022).

The evolution of AI and computational power, from early models like the McCulloch-Pitts neuron and Rosenblatt's perceptron to today's deep learning networks and supercomputers such as IBM's Blue Brain, has made it possible to implement advanced information infrastructures in cities. The increasing availability of high-performance computing enables real-time data processing and complex modeling, essential for smart city management.

The capabilities of artificial intelligence can propel cities into a future defined by sustainable growth, resilience, and cutting-edge innovation, fostering urban environments that harmonize progress with environmental stewardship and community well-being (Jiang, Zhang, Zhao et al. 2023). From intelligent transportation systems and energy management to public safety and healthcare, artificial intelligence permeates diverse aspects of urban life, delivering groundbreaking solutions and unprecedented efficiency in addressing the enduring challenges of urbanization (Paes, de Pessoa, Pagliusi et al., 2023; Karmaker, Islam, Kamruzzaman et al., 2023).

Efficient city management is enabled by an integrated system encompassing transport, energy, water and waste management, urban planning, air quality control, and public safety. The goal of such a system is to optimize resource use and improve residents' quality of life. It allows, among other things, for reducing traffic congestion through smart signaling, optimizing energy and water consumption, and improving waste collection.

Implementing the system requires the involvement of public administration, the private sector, residents, and research and development institutions, as well as investments in modern technological infrastructure — including computers, smartphones, routers, switches, and sensors. Digital transformation in a smart city is not limited solely to technological aspects. Implementing innovation also requires an appropriate organizational climate and a culture that supports change and collaboration (Grodzicki, 2023).

Key technologies include Big Data, the Internet of Things (IoT), and cloud computing (e.g., OpenStack), forming a multilayered smart city architecture (Figure 1). This setup enables the management of traffic, energy, and environmental monitoring through data flows between IoT devices, the cloud system, and decision-making units. Such integration enhances the city's attractiveness to both residents and investors (Balicki, Balicka, Dryja, 2021; Balicki et al., 2015).

Figure 1. The integration and digital transformation of urban management systems.

Source: Own study.

However, the challenges are enormous. The complex deep learning models of smart cities require a lot of computing power to train. For instance, Tokyo is the largest city in the world. Population is now estimated at 37 million, including metropolis with 13 million. Japanese designers of the fastest supercomputer Fugaku HPL use it extensively for deep learning. In the Linpack AI computational test, Fugaku achieves a computing power of 2 Eflop/s based on TensorFlow or PyTorch deep learning software. The possibilities of using supercomputers to carry out tasks in a smart city are therefore huge, as are the challenges (Balicki, 2014).

Investing in green and smart technologies is multifaceted. It can be directed to universities for student education or research. It may concern financial support for start-ups or advanced organizations. It can also refer to investing in the stock market in companies offering this class of products. The most advanced technology worth investing in is deep learning in each of the above-mentioned areas.

2. Deep learning models and cloud computing resources for city ecosystem

One of the key questions is how to rebuild a city that is constantly in motion? How to perform surgery on the open heart of a living metropolis? I will try to outline the answers to some questions. A smart city requires a well-thought-out concept.

The open cloud platform OpenStack enables flexible modification of the city infrastructure. It collaborated, among others with one of the fastest computers in Poland - Prometheus. Cloud computing platforms like OpenStack enable dynamic management of computational resources in smart cities. This allows for efficient allocation of workloads, real-time scaling, and optimization of urban services without the need for heavy physical infrastructure investments.

The advancement of deep learning applications in smart cities is remarkable, particularly in predicting risks and supporting preventive action. These algorithms not only analyze current data but also forecast future events with high accuracy. An increasing number of police departments in the U.S. use deep learning to anticipate crime locations—something traditional statistical methods have struggled to achieve effectively.

Such models classify emotions and behaviors by analyzing video, text, audio, facial expressions, and gestures. Pretrained networks like GoogLeNet, with 144 layers and millions of images, enable accurate object recognition across thousands of categories. Emerging technologies, including non-invasive brain–computer interfaces like Emotiv EPOC, further expand the potential for monitoring human responses. These solutions are continuously refined, enhancing the role of AI in public safety. (Balicki, Korłub, Paluszak, 2015).

Today, security threat maps are created with a level of precision that exceeds the capabilities of human teams. The HunchLab application performs this task almost flawlessly. Predictive policing tools such as HunchLab and PredPol use deep learning to identify areas with an elevated risk of crime. These systems enable more effective deployment of police resources, thereby enhancing public safety and residents' trust. The use of the deep learning application HunchLab resulted in approximately a 31% reduction in crime in Philadelphia, as well as an increase in trust toward the police. (Benbouzid, 2019). Both systems, PredPol and HunchLab, are supported by IoT to maintain interoperability with using a wireless technology including LPWAN communications important for smart cities projects. Data is stored on a cloud platform that is compatible with city council platforms.

In the smart city, the fight against crime goes hand in hand with the fight against pollution. Deep learning makes it possible to predict in which areas the air pollution will be highest, what the concentrations of individual pollutants will be, and whether there will be rare phenomena that are particularly dangerous, such as acid rain with a high concentration of sulfuric acid. Based on deep learning, both predictive and preventive models can be built.

In addition to clean air, energy is also necessary for harmonious functioning in the city. Therefore, investments in renewable sources of its acquisition, transmission and storage are crucial. Smart grids are characterized by more efficient energy routing, better monitoring, and improved data capture and measurement. Metering occurs at the city, building and home level.

Another important task is related to smart buildings with sensors technology used for monitoring and control, including heating, ventilation, lighting and air conditioning systems. In such an integrated system, it is very easy to charge for resource consumption. Thus, the resident does not pay a lump sum or for the availability of infrastructure, but only for the actual consumption of resources: energy, water, gas, and waste production. In this way, you can minimize the consumption of critical resources based on reliable data. Smart solutions are also needed in the field of water management, because by 2050 the demand for water is expected to increase by 1/3.

In the context of transport optimization in smart cities, a convolutional neural network (CNN) trained on a virtual machine running Fedora 30 (Intel Core i7, 2.7 GHz, 16 GB RAM) achieved 99% accuracy in detecting optimal vehicle routes in about one minute. The CNN Benchmark Dataset was used, featuring German traffic signs represented as 28×28 pixel matrices, with 570 training samples and 330 test samples (Houben et al., 2013).

For the classification of urban video scenes, an LSTM network was trained using the Cityscapes dataset, which contains 25,000 stereo videos depicting street scenes from 50 cities (Cordts, 2016). This process required significantly greater computational power — the previous machine configuration proved insufficient. The LSTM was implemented in the MATLAB R2021b environment and trained for 70 hours, with accuracy verified after every 377 iterations per epoch. Figure 2 shows the systematic increase in prediction accuracy during training: initially from 10% to 20%, reaching nearly 80% after approximately 1,200 iterations. The most significant improvements occurred between the first and second epochs, after which the results gradually stabilized, indicating model maturation. These findings confirm the potential of LSTM networks for pattern recognition in urban data and their application in smart city monitoring. The effective training of the LSTM network suggests its potential application in smart cities for forecasting traffic hazards, monitoring public safety, or optimizing urban traffic management.

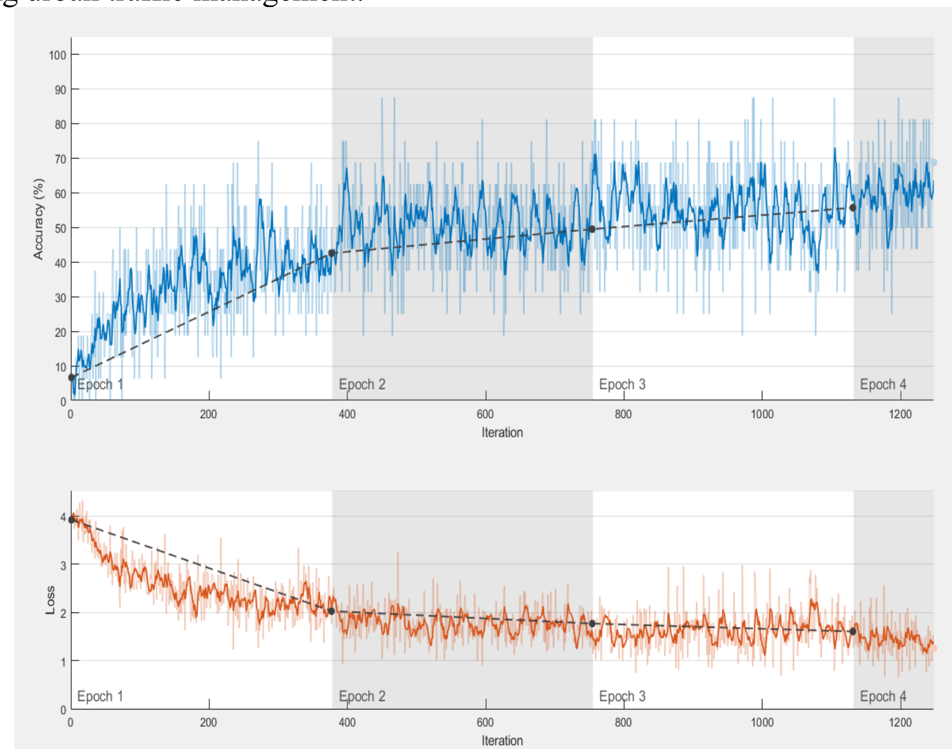

Figure 2. Training progress of the LSTM network on the Cityscapes Dataset

Source: Own study.

Deep learning is useful in virtually every aspect of our lives (Yüksel, Börklü, Sezer, Canyurt, 2023; Llauradó, Pujol, Tomás et al., 2023). Solutions that assist selected residents in their daily activities are tested. They recommend what to eat, when to sleep, with whom to talk to, and even where to live. This class of algorithms decide how much we pay for the ticket, whether we get a loan and what we will see in the news of our smartphone. A huge space of various data processing capabilities, enabling integrated management of a smart city, considering the improvement of the quality of resident's life (Aloqaily, Elayan, Guizani, 2023) and environmental protection, makes it worth developing solutions using deep learning models, those based on artificial neural networks in the computing cloud.

3. Long Short Term Memory neural networks in computing cloud

Efficient execution of data-intensive tasks in smart cities relies on parallel deep learning algorithms implemented on multi-threaded architectures, often hosted in cloud environments (Nichols, Singh, Lin at al., 2022; Clohessy, Acton, Morgan, 2014). These algorithms, essential for training neural networks, handle massive data streams generated by urban sensors. Edge computing plays a critical role in reducing transmission load by processing some data near the source, before reaching the cloud. Sensors act as interfaces between the physical world and digital systems, while actuators perform the reverse function (e.g., speed indicators or visual alerts).

To manage cloud workload, especially on legacy systems, virtual machine migration must be optimized—often via mathematical models and Pareto analysis (Balicki, Balicka, Dryja, 2021). Together, edge computing and resource-aware deep learning offer scalable and efficient solutions for smart city infrastructure management.

Deep learning implemented on supercomputers or in cloud computing is needed to perform many important tasks that affect both the development of cities and the entire economy. Important areas of application for deep learning in a smart city include finance (Balicka, 2020), such as assessing the creditworthiness of borrowers, identifying residents' spending patterns, and detecting financial fraud (Yobas, Crook, Ross, 2000; Mylonakis, Diacogiannis, 2010). Key financial tasks in a smart city where artificial neural networks can be applied include, among others, modeling investment risk within urban development programs. Thanks to their ability to analyze large financial data sets in real time, these systems can significantly improve the accuracy of risk assessment and support the credit decision-making process.

One of the possibilities of using deep learning implemented in cloud computing is the introduction of new financial systems, including currency systems. For example, grids are used to transact with the cyber currency Bitcoin, creating a rather unusual model for a social cyber currency. Forecasting trends in finance, including currency exchange rates as well as banking crises (Balicka, 2019; Oet, et.al., 2011), mortgage default risk (Zan et al., 2004) and corporate bankruptcy prediction (Brown 2011), are another important issue solved by parallel deep learning algorithms in the cloud.

In addition, an interesting solution is also the use of deep neural networks in the cloud to improve the accounting information system that supports decision-making processes in the enterprise (Balicka, 2023). To increase the effectiveness and security of accounts charts, modern IT systems are also necessary, which enable their dispersion in areas where the most important operations are carried out (Gierusz, Koleśnik, 2021). No less important is the use of deep learning models for precise cost estimation and settlement, which significantly improves decision-making processes, including in healthcare entities (Martyniuk, 2021).

In the context of the green smart city concept, the use of artificial intelligence to forecast stock market values gains particular importance. One of the key challenges faced by cities is securing financial resources for sustainable development. In this regard, stock market investments supported by advanced predictive models, such as LSTM neural networks, can serve as a modern tool for urban budget management. When properly implemented, they can generate financial surpluses that can then be reinvested in the development of green technologies and smart city infrastructure - such as intelligent energy grids, transportation systems, or solutions related to water and sewage management and waste management. These are crucial areas for the functioning of a "green smart city."

This mechanism aligns with the idea of sustainable development, using modern technologies not only for efficient operational management of the city but also as a means of acquiring funds for its further growth. The challenge of securing development funds affects all cities, which is why it is so important to seek innovative and effective investment approaches. In the context of optimizing investment strategies for the sustainable development of cities, quantum predictive models trained on neural networks play a key role in increasing forecast accuracy (Balicka, Balicki, 2024).

Investments in financial instruments, such as stocks, bonds, or investment funds, can bring tangible benefits to the city budget. However, they also carry the risk of losses, which is why investment decisions should be based on a thorough analysis of potential profits and risks. The application of deep learning models, such as LSTM, enables the creation of more accurate forecasts and the making of informed investment decisions. This approach can increase the chances of achieving budget surpluses, which can then be allocated to achieving environmental and technological goals consistent with the vision of an intelligent, green city of the future. Although implementing such solutions requires advanced technological infrastructure and careful risk analysis, it represents a forward-looking and innovative approach to financing urban development.

An effective approach to stock market investments are artificial neural networks with long-term memory (Gately, 1999). ANNs are learned based on historical data of time series that is available through technical analysis. Multilayer networks make it possible to predict the value of the studied features (Nazari, Alidadi, 2013). Prediction can apply to both numerical and symbolic values. In the case of the anticipation of numerical values, we speak of regression (Awad, Khanna, 2015), and in the case of symbolic values - classification. In the context of stock market prediction, we are dealing with a specific problem of predicting time series (Baesens, at. al., 2003). A training algorithm allows to adjust the synaptic weights (Davis, Karim, 2008). Analysing so many training sets requires a lot of computing power, which only supercomputers can provide. For this reason, some authors suggest a significant reduction in the intensity of downloading data from the stock exchange.

Long Short-Term Memory (LSTM) networks are designed to retain relevant information over time through a built-in memory mechanism that selectively stores or discards data (Kumar & Haider, 2021; Alsam et al., 2021). This capability is crucial in financial forecasting, where stock exchange data offer limited features - typically opening price, daily high and low, closing price, and trading volume - and are heavily influenced by random factors. These inputs must be preprocessed into time series and enriched with financial indicators before training a predictive model.

In this experiment, three models - LSTM, CNN, and Support Vector Regression (SVR) - were used to forecast the WIG20 index. As shown in Figure 3, the LSTM prediction (red line) closely follows the actual index values (green line), demonstrating its superior accuracy. The figure presents the simulated profit achieved by the LSTM and CNN models as a result of applying their forecasts to investment decisions.

The use of LSTM (Long Short-Term Memory) models represents a potential tool for supporting municipal budget management. Forecasting stock index values with LSTM can enhance the optimization of public funds and support the financing of sustainable projects within the smart city framework. By applying deep learning, cities can make more informed investment decisions, increasing the likelihood of generating budget surpluses.

Importantly, these financial gains can be reinvested in the development of green technologies and infrastructure- -such as intelligent energy networks, smart transportation systems, or water and waste management - key components of a green smart city. Although ambitious, this mechanism aligns with the principles of sustainable development by leveraging advanced technologies not only for operational governance but also as instruments for securing funding to achieve long-term urban goals.

Tasks related to financial activities in the smart city for which the support based on artificial neural networks was successfully applied include the analysis of the creditworthiness of bank customers (Yobas, Crook, Ross, 2000), risk analysis related to granting a mortgage loan (Zan, at.al., 2004), building bid strategies, forecasting index values (German Credit dataset, 2015) and directions of trends on the stock exchange, determination of risk classes of stock exchange financial instruments, detection of regularities in changes in the prices of financial instruments and forecasting of bankruptcies (Brown, 2011).

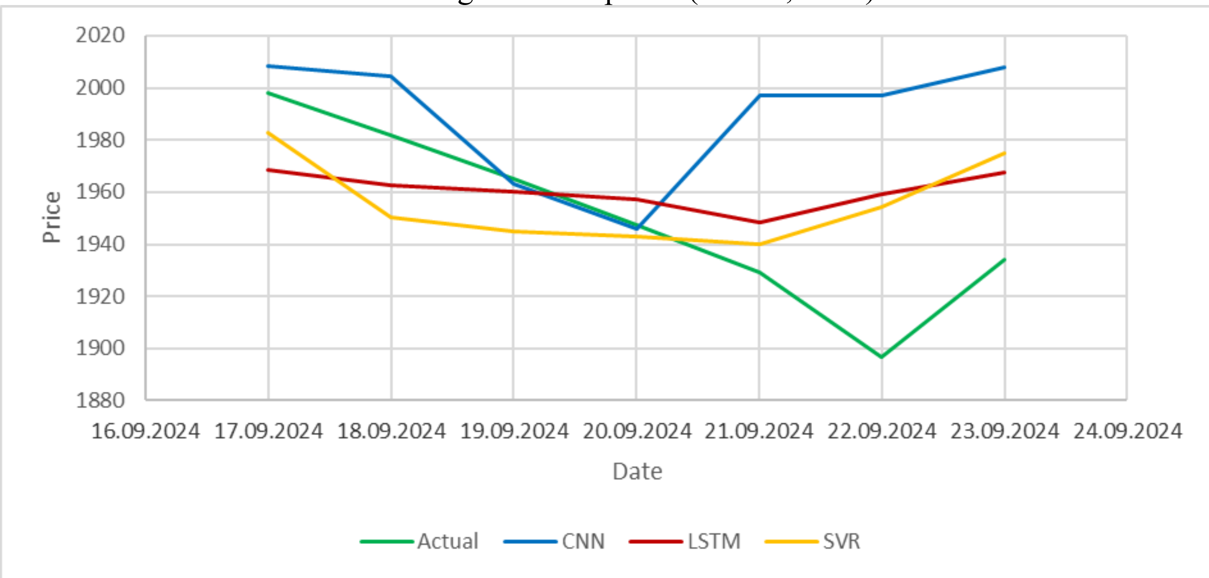

Figure 3. Simulation of achieving cumulative profit from the date of the transaction

Source: Own study.

Beyond finance, medicine and education are equally vital to the sustainable development of smart cities (Balicki, Korłub, Tyszka, 2016). A prominent example of deep learning and parallel computing in these fields is IBM Watson - a cognitive computing system used for medical diagnosis, achieving up to 90% accuracy in detecting lung cancer. Watson has also passed second-year medical exams and is expected to play a broader role in education and speech-enabled diagnostic support (Shouwei, Mingliang, Jianmin, 2013).

Artificial intelligence is also applied in climate risk modeling. For instance, ARIA Technologies uses supercomputers to simulate extreme rainfall events for insurance risk assessment. Similarly, projects like Blue Brain demonstrate the expanding role of AI in data analysis for finance and banking (Balicki at. al., 2015; Hanschel, Monnin, 2005).

Artificial neural networks are increasingly used in smart cities due to their ability to detect complex patterns in large datasets, especially where traditional models fail due to random variability. Their lack of prior assumptions allows them to identify short-term disturbances and emerging trends with high precision.

The models presented in this article represent only a fraction of AI's potential. For example, harmonic algorithms can support urban planning, optimize transport routes, reduce congestion and emissions, shorten travel times, and enhance energy efficiency by improving energy production and distribution systems.

Summary and recommendations

The study confirms the significant role of artificial intelligence and cloud computing in the digital transformation of green smart cities. AI supports urban data analysis, enabling process optimization, trend forecasting, and better alignment of services with citizen needs. Cloud computing offers scalable data processing without the need for costly infrastructure investments.

Combining deep learning with edge computing enables efficient handling of IoT-generated Big Data streams, reducing the burden on urban networks. The article discusses the use of LSTM, CNN, and SVR models in areas such as stock forecasting, medical diagnostics, energy management, and public safety. While conceptual in nature, the study highlights the practical potential of these models, especially through solutions like AI migration to edge servers and virtual machine teleportation.

The key contribution lies in demonstrating how selected AI models, supported by cloud and edge technologies, can enhance core smart city functions. Examples presented- -from predictive safety systems to environmental management- -illustrate how AI can improve operational efficiency and quality of life. These findings form a foundation for further empirical research.

Future studies should focus on validating the proposed solutions in real-world conditions and exploring CNN applications in cybersecurity and financial fraud detection.

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NAPĘDZANIE CYFROWEJ TRANSFORMACJI BIZNESU W ZIELONYCH INTELIGENTNYCH MIASTACH ZA POMOCĄ SZTUCZNEJ INTELIGENCJI I PRZETWARZANIA W CHMURZE

Abstrakt

Cel. Cyfrowa transformacja biznesu w zielonych inteligentnych miastach jest klczowa ze względu na zmieniające się potrzeby mieszkańców i przedsiębiorstw oraz rosnące wymagania dotyczące zwiększania efektywności, poprawy jakości życia w miastach i ochrony środowiska. Celem niniejszej publikacji jest scharakteryzowanie kierunków rozwoju sztucznej inteligencji (AI) oraz chmury obliczeniowej wspierających transformację cyfrową i zrównoważony rozwój miast. Waro zauważyć, że w literaturze przedmiotu istnieje luka, gdyż brakuje jasnych pomysłów na efektywne wykorzystanie głębokiego uczenia opartego na sztucznych sieciach neuronowych (ANN) w chmurze.

Metody. Podstawowe metody badawcze obejmują krytyczną analizę literatury przedmiotu. Dodatkowo zastosowano modelowanie w celu symulacji wykorzystania głębokiego uczenia i chmury obliczeniowej w systemach zarządzania inteligentnymi miastami. Przeprowadzono intensywne eksperymenty obliczeniowe w celu analizy jakości rozwiązań, które zostały ocenione na podstawie zaproponowanych metod głębokiego uczenia z wykorzystaniem ANN opartych na długiej pamięci krótkoterminowej (LSTM).

Wyniki. Wyniki badań teoretycznych i eksperymentów numerycznych potwierdziły znaczący wkład AI i chmury obliczeniowej w zwiększenie efektywności miasta, poprawę jakości życia mieszkańców oraz ochronę środowiska naturalnego.

Słowa kluczowe: głębokie uczenie, transformacja cyfrowa, zrównoważony rowój.

Klasyfikacja JEL: G17, M15, O33.

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