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INTELLIGENT TECHNOLOGIES IN ELECTRONIC GEODETIC SYSTEMS OF PUBLIC SPATIAL MANAGEMENT: EVOLUTION FROM AUTOMATION TO DIGITAL-ETHICAL STANDARDS

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Abstract. *The article is devoted to the intellectualisation of electronic geodetic instruments (EGI) and the development of conceptual foundations for integrating artificial intelligence (AI) technologies into the geoinformation environment (GIS) to enhance the efficiency of spatial management systems. The research presents an architectural model of an intelligent spatial management system, which incorporates the interaction between electronic instruments, sensor modules, GIS platforms, and analytical AI services. A concept of EGI intellectualisation is proposed, based on three main vectors: autonomy of the measuring process (using machine learning (ML) for object recognition, self-diagnosis), adaptability to environmental conditions (through correction of environmental influences, noise reduction) and integrability within GIS. The paper describes the application of AI methods, including deep neural networks (YOLO, Mask R-CNN, U-Net, PointNet), for the automatic detection and classification of objects in images and point clouds, as well as for real-time assessment and correction of GNSS errors using neuro-Kalman filters. Practical implementation areas of the model include automated monitoring of engineering structure deformations and intelligent UAV data processing for the updating of topographic maps. According to the findings, the gradual integration of AI transforms EGI into intelligent sensors* *capable of independently assessing data quality and interacting with GIS, thereby providing a reliable foundation for "smart" cities and sustainable territorial development.*

Keywords: *intellectualisation, artificial intelligence (AI), electronic geodetic instruments (EGI), GIS environment, spatial management systems, object detection, GNSS correction.*

Problem Statement. Modern spatial management systems increasingly depend on the accuracy, speed and intelligent processing of geodetic data. The development of electronic geodetic instruments – such as total stations, GNSS receivers, drones, and laser scanners – has significantly improved the efficiency of measurement processes; however, most of these instruments still require human involvement at all stages of data acquisition, analysis, and interpretation. This limits their productivity and introduces risks of human errors. The growing volume of spatial information and the need for its operational analysis have led to the necessity of intellectualising geodetic systems, that is, incorporating artificial intelligence (AI) algorithms for the automated object recognition, data quality assessment, self-correction of measurements and real-time decision-making. Despite the active development of AI in related fields (robotics, remote sensing of the Earth, urban planning), the level of its integration into geodetic devices remains fragmentary and does not have a single methodological basis.

A critical issue lies in the absence of a conceptual model for implementing AI in the geoinformation environment, which combines data from different sources, ensures their semantic consistency and supports decision-making in spatial management systems. The development of conceptual foundations for the intellectualisation of electronic geodetic devices based on artificial intelligence will enhance the accuracy, autonomy, and adaptability of spatial management systems within the modern geoinformation environment.

Review of Recent Research and Publications. In recent years, the issue of integrating artificial intelligence into the field of geodesy and geographic information systems (GIS) has attracted considerable attention from researchers worldwide. The works of foreign scholars, in particular [1;2;3], consider approaches to automating the collection and processing of geodata using machine learning algorithms, neural networks, and computer vision. These studies demonstrate the potential for substantial improvement in positioning accuracy, optimisation of measurement routes, and automatic recognition of terrain objects. In Ukraine, the issue of intellectualising geodetic instruments is still at the conceptual stage. Scholarly works have considered the issues of digital transformation of geodetic processes [4;5], the development of automated territory monitoring systems [6;7], and the integration of GNSS data into the GIS environment [8]. However, most studies focus mainly on technical or software aspects, while the issue of developing intelligent models of interaction between instruments and GIS remains insufficiently studied. Some works are devoted to the use of artificial intelligence for the classification of satellite images, prediction of earth surface deformations [9], creation of 3D terrain models [10], analysis of spatial trends and geospatial analytics based on AI [11;12]. Nevertheless, their results are mostly of sectoral or experimental nature and do not form a unified methodological framework for applying AI in geodetic measurement systems.

The aim of the study is to formulate the conceptual foundations for the intellectualisation of electronic geodetic instruments, to propose an architecture for their integration into the GIS environment, and to provide practical recommendations for implementation.

Materials and Methods.

The research methodology is based on a combination of analytical, experimental, and computational approaches that together ensure a comprehensive assessment of the technological, algorithmic, and functional foundations of intelligent electronic geodetic instruments (EGI). As a primary source of empirical material, the study used datasets obtained from modern total stations, GNSS-receivers, electronic levels, LiDAR systems, and unmanned aerial vehicles equipped with optical and multispectral sensors. These datasets were applied to evaluate the accuracy, stability, and adaptability of measurement processes under varying environmental and operational conditions.

To investigate the potential of artificial intelligence for strengthening measurement reliability, the study employed several classes of machine learning models. Convolutional neural networks (CNN), U-Net and Mask R-CNN architectures were used for object detection and semantic segmentation of spatial imagery, while recurrent neural networks (LSTM) and hybrid models integrating Kalman filtering were applied to assess and compensate GNSS coordinate deviations caused by multipath effects, ionospheric disturbances, and obstacles in urban canyons. Additionally, ensemble learning methods—Random Forest and Gradient Boosting—were utilized to construct predictive models for error estimation based on meteorological and technogenic factors.

Experimental verification included comparative testing of traditional and AI-enhanced processing pipelines within a GIS-based environment. Spatial analyses, raster–vector integration, and topological consistency checks were performed using QGIS and ArcGIS Pro. Statistical evaluation of results relied on RMSE, MAE, and correlation metrics to validate improvements in positional accuracy. The methodological framework also incorporated system modelling of the proposed five-level architecture for integrating intelligent sensors into GIS workflows, ensuring that the findings reflect both theoretical robustness and practical applicability.

Results and Discussion. Artificial Intelligence (AI) is a broad and multifaceted field encompassing a wide range of approaches, technologies, and problem-solving methods. The acronym AI is currently associated, largely due to start-ups funded by major technology corporations (Microsoft, Google, Amazon, Meta, Apple, among others) and other organisations, with interactive large language models (LLMs) models such as ChatGPT, Gemini, Claude, and other, less widely known models. These commercial solutions are available by subscription or in limited versions to almost all users [2].

In general, artificial intelligence refers to the study and design of intelligent agents, where an intelligent agent is defined as a system that perceives its environment and performs actions that maximise its chances of success. Many real-world problems require an agent to operate under conditions of incomplete or uncertain information. Methods used for reasoning under uncertainty are probabilistic in nature, such as Bayesian networks, which serve a general tool for solving a wide variety of problems, including reasoning (using Bayesian inference algorithm), learning (through expectation-maximisation algorithm), planning (using decision networks) and perception (via dynamic Bayesian networks). The application of AI methods offers numerous advantages compared with traditional development and implementation strategies [13]: rapid access to accumulated knowledge (for example, knowledge-based systems), the ease of prototyping without the need for deep expert knowledge (for example, artificial neural networks) or systems capable of learning (for example, genetic algorithms).

Artificial intelligence methods and techniques are widely applied in geodesy and GIS. These include:

– automatic detection and classification of objects in images and point clouds;

– assessment and correction of GNSS measurement accuracy considering local signal conditions using AI;

– noise compensation and real-time data filtering (Kalman filters with built-in neural networks);

– semantic linking of measurement results to ontological models of spatial objects to facilitate integration into GIS.

Object detection is the process of identifying and localising objects of a specific class in a digital image. Modern approaches are based on deep convolutional neural networks (CNN), which are capable of automatically extracting features without prior manual tuning for automatic target identification (artificial or natural objects) and real-time interference filtering (Table 1). This is important for laser scanning and the operation of robotic total stations (e.g., Leica TS20) [14].

Table 1

Artificial intelligence methods for analysing geospatial data

Task category	Method (Architecture)	Characteristic	Application in GIS
Object detection	Faster R-CNN	Two-stage model combining Region Proposals with object classification and localisation. High accuracy, but slower than single-stage ones	Automatic recognition of buildings, roads, vehicles and green spaces in aerial and satellite images; detection of changes in development; analysis of territories in urban studies
	YOLO (You Only Look Once)	A single-stage object detector that performs classification and localisation in a single pass. Allows real-time object detection in images and videos	Rapid monitoring of traffic, detection of objects in the video stream from drones, operational detection of disasters
	Mask R-CNN	Mask R-CNN is an extension of Faster R-CNN for simultaneous detection and segmentation of object contours (instance segmentation)	Accurate selection of contours of individual objects (buildings, trees, vehicles); creation of high-precision cadastral maps
Classification and semantic segmentation	Fully Convolutional Networks (FCN)	A deep learning architecture that replaces fully connected layers with convolutional layers, allowing for classification maps (segmentation masks) for images of any size	Thematic mapping (forests, water sources, urban planning), analysis of satellite images, environmental monitoring, precision agriculture and land use assessment
	U-Net	A symmetric encoder-decoder architecture (U-shaped) that uses skip connections to pass high-resolution features from the encoder to the decoder. This provides high accuracy of object localisation	High-precision semantic and instance segmentation of objects (used in medicine and GIS for precise selection of areas)
	DeepLabv3+	An architecture that uses an advanced approach using Atrous Spatial Pyramid Pooling (ASPP) to capture context at different scales. High performance in semantic segmentation	Large-scale image processing, accurate semantic segmentation of complex scenes (for example, delimitation of urban areas and natural landscapes)
	SegNet	An encoder-decoder semantic segmentation architecture where the decoder uses pooling indices from the corresponding encoder layers for non-convolutional upsampling (unpooling). This reduces the need for memory	Semantic segmentation of road scenes, mobile robotic mapping, efficient processing of large volumes of geospatial data

Compiled by the authors based on [4, 12]

A point cloud is a set of three-dimensional coordinates representing the shape of the surface of objects obtained using LiDAR or photogrammetric scanning. Processing such data requires specialised algorithms, since the information is presented in the form of disconnected 3D points without colour or texture. Modern methods of automatic analysis include:

- PointNet and PointNet++ – the first neural networks that directly work with unstructured 3D points;

- PointCNN, KPConv and RandLA-Net – modified architectures optimised for large volumes of geospatial data;

- Voxel-based models that convert the point cloud into a voxel grid for processing by conventional CNNs.

These approaches enable automatic classification of objects (buildings, roads, trees, power lines, etc.); detection of changes in 3D terrain models; creation of digital surface and relief models with high detail [15].

Global Navigation Satellite Systems (GNSS) – including GPS, Galileo, GLONASS, BeiDou – are the main source of spatiotemporal data for geodesy, navigation, transport and environmental monitoring. The accuracy of GNSS measurements depends significantly on local conditions for signal reception: multipath propagation, antenna shading, atmospheric effects, radio interference and satellite geometry. Given the complexity of these factors, the use of artificial intelligence (AI) opens new opportunities for assessing, predicting and correcting errors in GNSS signals in real time. AI technologies are used for detecting anomalies in GNSS data in real time; modelling spatiotemporal patterns of errors; predicting the impact of local factors on signal quality; post-processing and operational correction of coordinates. Artificial intelligence methods for enhancing GNSS accuracy include classical machine learning algorithms such as Random Forest, Support Vector Regression (SVR), and Gradient Boosting; deep neural networks (DNN, LSTM, CNN); and hybrid GNSS–INS–AI models, the characteristics of which are presented in Table 2 [16].

Table 2

Artificial intelligence methods for estimating and correcting GNSS errors

AI model type	Input data	Functional purpose	Expected effect / accuracy	Application examples
Random Forest (RF)	Satellite signal parameters (SNR, number of satellites, elevation angle, DOP)	Forecasting coordinate errors based on statistical patterns	Reduction of positioning error by 20-30% compared to standard models	Signal quality analysis in urban environments
Support Vector Regression (SVR)	Time series of coordinates, signal level	Modelling the nonlinear dependence between signal level and coordinate displacement	Reduction of root mean square error (RMSE) to 1.5-2 m	Post-processing of GNSS tracks in transportation systems
Gradient Boosting / XGBoost	Meteorological and geometric parameters of observations	Correction of ionospheric and tropospheric influences	Improvement of coordinate stability by 25-40%	Agricultural GNSS observations
LSTM (Long Short-Term Memory)	Time series of signals, velocity, acceleration, Doppler measurements	Forecasting short-term coordinate displacements; adaptive noise filtering	Reduction of error in dynamic conditions to 1 m	Moving object monitoring, autonomous transportation
CNN (Convolutional Neural Network)	GNSS-accuracy spatial maps, digital terrain models	Identifying spatial patterns of errors, considering relief and buildings	Increase in positioning accuracy by 30-50%	Urbanised areas, urban canyons
DNN (Deep Neural Network)	Complex data GNSS + INS + meteorological parameters	Combined modelling of errors for different factors	Improvement in generalized accuracy by 40-60%	Geodetic measurements in difficult signal reception conditions
Ensemble Learning (hybrid models)	Various types of data from several receivers or sensors	Combining forecasts of different models to reduce random errors	Increase in stability and consistency of results	Real-time RTK/PPP systems

Compiled by the authors based on [1, 6, 14]

One of the key tasks in the processing of GNSS observations is the compensation of noise and random errors arising from signal instability, atmospheric effects, and dynamic conditions of receiver motion. For this purpose, the Kalman Filter is traditionally used – an optimal recursive algorithm that estimates the current state of the system (coordinates, velocity, acceleration) based on previous measurements and statistical characteristics of noise. Modern approaches combine Kalman filters with neural networks, forming Neural Kalman Filters. In such models, a neural network (usually LSTM or DNN) is trained to predict or adaptively estimate the parameters of process noise and measurements. Practical studies show that the integration of neural networks into the Kalman filter framework can reduce the mean positioning error by 30–50%, while ensuring smooth trajectories at a high measurement update rate (1–10 Hz) [17].

Semantic measurement binding involves matching the results of geodetic or GNSS observations with ontological models of spatial objects that describe the structure, properties and relationships of elements of the territory. This approach provides semantic interpretation of data when coordinates and geometry are combined with object attributes (type, function, state, affiliation, etc.). AI methods, in particular machine learning, natural language processing (NLP) and deep neural networks, make it possible to automatically determine the semantics of objects and assign ontological categories; to identify semantic relationships between objects, creating semantic graphs of space; to integrate heterogeneous data (from different sources such as GNSS measurements, LiDAR, cadastral databases, satellite images) in GIS and perform their semantic matching in a single information environment; to support intelligent analysis and queries [18].

The integration of artificial intelligence (AI) into geodetic technologies occurs gradually and covers all stages of the data life cycle – from field measurements to the construction of digital terrain models. In general, five main stages of such integration can be distinguished.

The data acquisition stage, during which AI is used to optimise the measurement process in real time – automatically selecting the best GNSS satellites, adaptively adjusting the measurement frequency and monitoring the quality of signals. In new generation devices (smart total stations, GNSS receivers), AI modules analyse the stability of observations and can automatically signal a decrease in accuracy or recommend re-measurement.

The preprocessing stage involves the use of machine learning algorithms to filter noise, compensate for multipass effects and remove erroneous measurements. At this stage, neuro-Kalman filters or recurrent neural networks (RNN, LSTM) are used to dynamically adapt filter parameters according to prevailing signal reception conditions.

The Processing and Interpretation stage, where AI performs automatic classification, object detection and images or point clouds segmentation, which significantly reduces the time of camera processing. This stage employs deep neural networks such as U-Net, Mask R-CNN, PointNet++, capable to recognise terrain objects (buildings, roads, vegetation, etc.) in three-dimensional data.

The Integration and Modelling stage entails the semantic linking of measurement results to ontological models of spatial objects, which ensures coordination with geographic information databases. At this stage, AI modules are responsible for reconciling coordinates, attributes and semantics, thereby automating the incorporation of new objects into GIS.

The Prediction Decision Support stage, as the final stage, uses AI to analyse trends in changes (deformations, settlements, ground movements) and predict their further development. Intelligent systems can offer optimal action scenarios in real time, for example, repeated measurements or correction of geodetic network parameters.

Accordingly, the concept of intellectualisation is based on three main vectors: autonomy of the measurement process, adaptability to environmental conditions, and integrability into the geographic information environment (GIS). The autonomy of the measurement process is achieved using built-in machine learning (ML) algorithms for object recognition and classification (laser scanning), automatic trajectory planning or positioning (independent selection of standing points, shooting sequence, correction of the UAV flight trajectory), self-diagnosis and calibration (analysis of internal device parameters, detection of sensor drift, temperature deformations or automatic correction of calibration constants). Adaptability, referring to the capability of EGIs to dynamically change measurement parameters depending on external conditions, is ensured through correction of atmospheric influences and adaptive noise reduction. Integrability enables intelligent EGIs to function as active nodes within a Spatial Management System (SMS), rather than merely as data collectors. This includes "smart" data acquisition (retrieving information from the central GIS database to optimise field work) and instantaneous data processing and analysis, facilitated by embedded AI modules performing Edge Computing – that is, primary processing and interpretation of data.

The architectural model of integrating intelligent electronic devices into the GIS environment provides for a generalised representation of the structure and interconnections among the components of an intelligent geodetic system within a geoinformation context. Its purpose is to determine the logical interaction between electronic geodetic devices, data collection and processing systems, artificial intelligence algorithms, and spatial process management subsystems. Five main levels are distinguished in the structure of the conceptual architecture: collection of primary geodata; data transmission and integration; intelligent processing; geoinformation analysis and visualisation; making management decisions (Figure 1).

Practical directions for implementing the proposed architectural integration model under real-world conditions demonstrate how the combination of geodetic technologies, artificial intelligence and geoinformation environment provides increased efficiency of spatial data collection, processing and analytics. One of the promising directions is automated monitoring of deformations of engineering structures, aimed at early detection of dangerous changes in the geometry of objects, such as bridges, dams or buildings. In this case, electronic total stations and GNSS receivers continuously record the coordinates of control points, transmitting information to the geographic information system, where artificial intelligence algorithms perform time series analysis and identify potentially dangerous trends. The results obtained enable rapid response to deformation processes, thereby helping to prevent emergency situations [6].

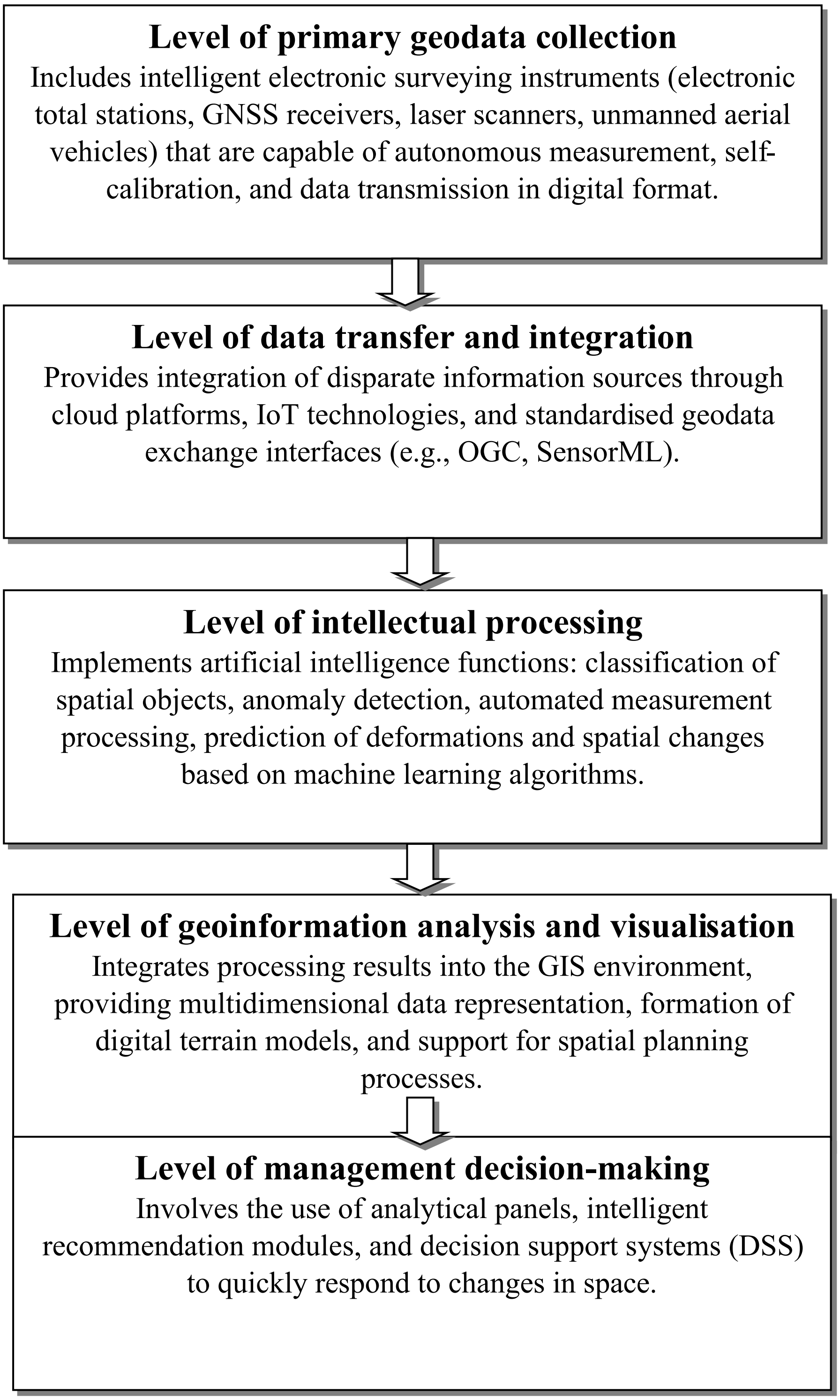

Figure 1. Architectural model for integrating intelligent electronic devices into a GIS environment

Compiled by the authors

A particular importance application concerns the monitoring of land-use changes caused by geodynamic processes and negative human activity. In this case, a network of geodetic sensors and GNSS stations provides constant monitoring of microdisplacements of the earth's surface, and machine learning algorithms predict risks based on the analysis of historical data, weather conditions, and geological characteristics [1;6].

Integration of data from geodetic instruments, satellite images and state cadastral databases with artificial intelligence algorithms provides automatic detection of changes in land use, contributing to increased transparency of land resource management and timely updating of cadastral information. Altogether, this demonstrates the versatility and practical significance of the intelligent architectural model, which provides flexible integration of geodetic instruments, data collection systems and analytical technologies of artificial intelligence in a single geoinformation space. Such integration enhances the accuracy, timeliness, and efficiency of spatial management processes [6;18].

Conclusions and Recommendations. The implementation of AI into electronic surveying instruments represents a new stage in the evolution of the geoinformation environment. The intellectualisation of electronic surveying instruments unlocks substantial potential for increasing the efficiency, accuracy, and automation of spatial management. Conceptual foundations covering autonomy, adaptability, and integrativity ensure the transformation of EGIs from conventional measuring instruments into intelligent sensors that actively participate in spatial management processes. The combination of local processing and cloud AI services facilitates the generation of adaptive solutions that account local data collection conditions. At the same time, ensuring data quality, interoperability, and security remains the main contemporary challenge. The recommended approach involves a phased, modular implementation, emphasising pilot testing, format standardisation, and the use of MLOps practices. This will lead to a significant increase in the efficiency, accuracy, and responsiveness of surveying operations, providing a robust foundation for the development of “smart” cities and sustainable territorial growth.

Future research should focus on optimising Edge AI for integrating in geodetic instruments, creating unified training datasets to increase the reliability of AI models in monitoring, risk management, and deformation forecasting.

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ІНТЕЛЕКТУАЛЬНІ ТЕХНОЛОГІЇ В ЕЛЕКТРОННИХ ГЕОДЕЗИЧНИХ СИСТЕМАХ ПУБЛІЧНОГО ПРОСТОРОВОГО УПРАВЛІННЯ: ЕВОЛЮЦІЯ ВІД АВТОМАТИЗАЦІЇ ДО ЦИФРОВО-ЕТИЧНИХ СТАНДАРТІВ

Анотація. *Стаття присвячена інтелектуалізації електронні геодезичні прилади (ЕГП) та розробленню концептуальних основ інтеграції технологій* *штучного інтелекту (ШІ) в геоінформаційне середовище (ГІС) з метою підвищення ефективності систем просторового управління. У досліджені представлено розроблену архітектурну модель інтелектуалізованої системи просторового управління, яка включає взаємодію електронних приладів, сенсорних модулів, ГІС-платформ та аналітичних ШІ-сервісів. Запропоновано концепцію інтелектуалізації ЕГП, яка ґрунтується на трьох основних векторах: автономність вимірювального процесу (за допомогою машинного навчання МН для розпізнавання об'єктів, самодіагностики), адаптивність до умов навколишнього середовища (через корекцію впливу навколишнього середовища, зменшення шуму) та інтегративність у ГІС. У роботі описано застосування ШІ-методів, включаючи глибинні нейронні мережі (YOLO, Mask R-CNN, U-Net, PointNet) для автоматичної детекції та класифікації об'єктів на зображеннях і хмарах точок, а також для оцінювання та корекції GNSS-похибок у реальному часі за допомогою нейро-Калманівських фільтрів. Практичні напрями впровадження моделі включають автоматизований моніторинг деформацій інженерних споруд та інтелектуальну обробку даних БПЛА для оновлення топографічних планів. Згідно з висновками, поетапна інтеграція ШІ перетворює ЕГП на інтелектуальні сенсори, здатні самостійно оцінювати якість даних та взаємодіяти з ГІС, що забезпечує надійну основу для «розумних» міст та стійкого територіального розвитку.*

Ключові слова: *інтелектуалізація, штучний інтелект (ШІ), електронні геодезичні прилади (ЕГП), ГІС-середовище, системи просторового управління, детекція об'єктів, GNSS-корекція.*