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[1,2]**Samigulina G.A.,**
Dr.Tech.Sc., professor, ORCID ID: 0000-0003-1798-9161,
e-mail: kz.galinasamigulina@gmail.com
[1,2]***Samigulina Z.I.,**
PhD, Associate Professor, ORCID ID: 0000-0002-5862-6415,
*e-mail: z.samigulina@kbtu.kz
[1,2]**Bekeshev D.D.,**
MSc degree, ORCID ID: 0009-0002-8168-6368,
e-mail: dauletb01@gmail.com
[3]**Kucherbaeva S.Z.,**
ORCID ID: 0009-0002-7864-1900,
e-mail: stestephaniya1960@mail.ru
[3]**Yarmukhamedova A.B.,**
ORCID ID: 0009-0001-5421-0666,
e-mail:only_alla@mail.ru

[1]Institute of Information and Computing Technologies,
«Intelligent Control and Forecasting Systems» Lab, Almaty, Kazakhstan
[2]Kazakh-British Technical University, School of Information Technology and Engineering,
Almaty, Kazakhstan
[3]Municipal State Institution «Comprehensive School No. 35»
of the Almaty City Education Department, Almaty, Kazakhstan

ARTIFICIAL INTELLIGENCE: A NEW BIO-INSPIRED APPROACH IN ENGINEERING EDUCATION

Abstract

A cognitive technology has been developed for the distance learning of technical disciplines, utilizing a bio-inspired approach based on a unified artificial immune system featuring neuroendocrine regulation of homeostasis during knowledge acquisition. To implement an intelligent distance learning system for the control of complex industrial automation objects – based on the proposed UAIS–NES technology – an integrated ontological model has been developed. This model consists of ontological sub-models for the immune, neural, and endocrine subsystems, serving as the foundation for a knowledge base designed to integrate cognitive technology into the educational process. Classes and subclasses have been defined, and their interactions analyzed, to facilitate a two-stage data processing workflow: specifically, the reduction of non-informative features and subsequent classification, both executed using bio-inspired algorithms. System quality assessment criteria have been established based on metrics categorized into mutually exclusive classes, distinguishing between favorable and unfavorable outcomes. Based on the results of data analysis utilizing this technology, a forecast is generated regarding the level of acquired professional engineering skills, the probability of successfully mastering the academic discipline, and the student's degree of readiness to tackle complex technical management challenges – all presented in the form of a digital student competency profile.

Keywords: engineering education, intelligent technology, artificial immune system, neuroendocrine interaction, homeostasis, ontological models, prediction of learning outcomes, digital student profile.

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Introduction

The modern world is changing rapidly due to the explosive development of artificial intelligence. Vast opportunities are emerging for the growth of the global economy [1] – a growth that, according to PwC Global Artificial Intelligence forecasts, is expected to amount to approximately $15 trillion in the near future. Consequently, a serious challenge has arisen: the large-scale training of qualified engineering personnel equipped with the skills to work with artificial intelligence. In this context, the need to rethink the outdated concept of higher technical education is highlighted, as it currently fails to meet the demands of production automation and data-driven decision-making. An analysis [2] of recent developments regarding the application of AI in engineering education has identified key research areas, including expert systems, machine learning, data analysis based on intelligent methods, and forecasting. The use of artificial intelligence in engineering education offers a range of advantages [3], such as: the capability for predictive analytics regarding academic performance during the knowledge acquisition process – along with its timely adjustment [4] – the development of a personalized approach to learning [5], the enhancement of students' interdisciplinary competencies, the application of digital twins [6] and augmented/virtual reality approaches [7], among many others. For instance, the emergence of generative AI in the educational process [8] enhances access to knowledge, fosters personalized learning, and ensures automation and interactivity. Nevertheless, a number of challenges arise concerning academic integrity, security, errors in assignments, and so forth. Another facet of the issue is the readiness of the teaching staff to meet the evolving demands of modern AI-driven production and to integrate innovative intelligent technologies into the educational process [9], in alignment with the "Industry 4.0" and "Industry 5.0" concepts. Thus, the development of innovative AI-based learning technologies represents a promising endeavor for fostering an effective and supportive educational environment for both students and educators. Furthermore, the ethical aspects of applying AI [10] in education remain highly relevant. It is also worth noting that the rapid advancement of AI necessitates – for the successful preparation of future technical specialists – the introduction of AI literacy training at the secondary school level [11]. Exploring technical AI concepts and innovative technologies – along with the ethical dimensions and career prospects – serves as an excellent motivator for students to pursue a high-quality higher education in engineering.

Approaches to distance learning and access to real industrial equipment utilizing AI are of particular interest [12]. The development of innovative intelligent technologies enables the modeling of engineering systems on complex, real-world industrial equipment, thereby allowing students to hone their practical skills in solving technical problems [13].

Progress in the field of bio-inspired AI approaches facilitates their application across various domains of science and technology, including intelligent educational technologies. Reference [14] examines the use of artificial neural networks (ANNs) in education. Based on a bibliometric analysis of articles from the Scopus database, currently in-demand directions for ANN application have been identified, such as: predictive analytics, adaptive learning, personalization, automated assessment and feedback, learning analytics, digitalization, academic integrity, and the management and administration of the educational process. For example, article [15] focuses on the generation of complex, high-quality questions using neural networks – a process crucial for assessing students' mastery of educational material. Deep learning and various ANN architectures are widely employed in this context. Paper [16] discusses the prospects of applying deep learning in engineering, particularly in mechanical and electrical engineering.

Recently, the approach of artificial immune systems – based on the human body's immunological response to the invasion of foreign agents – has also been undergoing active development. For instance, the research presented in [17] describes the development of a multimodal artificial immune system, based on negative selection mechanisms, for emotion classification; this system can be successfully applied in educational settings. Article [18] presents a mathematical model of an intelligent system for educational process management, employing a hybrid approach based on a self-organizing Kohonen network and an artificial immune system. Experimental results demonstrated the potential of this approach for implementation within the educational process.

In the Republic of Kazakhstan, digital educational ecosystems such as BilimClass, BilimLand, OnlineMektep, Kundelik.kz, and Microsoft Teams are widely employed to support and manage the educational process. These platforms facilitate the delivery of instructional content, maintenance of electronic gradebooks, monitoring of academic performance, and implementation of distance learning. However, their functionality is primarily focused on learning management, communication, and the provision of educational resources, rather than on the intelligent prediction and assessment of engineering competencies.

The proposed research focuses on the development of an intelligent technology based on the self-assembly of a Unified Artificial Immune System (UAIS) – featuring neuroendocrine regulation of homeostasis – for a remote learning system designed for technical students training on modern industrial equipment, exemplified by enterprises in the oil and gas sector.

The scientific novelty of the proposed research lies in the development of the UAIS-NES technology for learning data analysis and forecasting, inspired by the biological architecture of the human organism, specifically its neural, endocrine, and immune subsystems. The technology incorporates a self-assembly mechanism that automatically selects the optimal combination of modified algorithms for analyzing learner-related data. In addition, an integrated ontological model has been designed to enable intelligent knowledge representation and support adaptive learning processes.

This work continues a series of studies [19] aimed at developing an innovative distance learning technology for engineering personnel, utilizing a bio-inspired approach based on Artificial Immune Systems (AIS) to manage the educational process through the prediction of learning outcomes for students in technical disciplines. In [20], a unified artificial immune system was developed for the effective analysis of multidimensional student data. The proposed research focuses on implementing the concept of integrating the UAIS with neuroendocrine subsystems (NES) and the principle of homeostasis to enhance the operational efficiency of an intelligent distance learning system for students.

Materials and methods

These studies are interdisciplinary in nature, situated at the intersection of various fields of science and technology; they draw upon principles of theoretical immunology, molecular biology, automatic control theory, systems analysis, artificial intelligence, and information and cognitive technologies.

The data processing algorithms developed are grounded in mechanisms borrowed from the biological prototype of human physiological functioning. They utilize the principles of interaction among key subsystems: the immune, neural, and endocrine systems. These subsystems are interconnected and must maintain homeostasis [21]. Homeostasis is a specific state of physiological equilibrium in which the organism maintains resilience against internal and external disturbances. For instance, the neural subsystem (NS) [22] receives signals from the external environment via electrical impulses. Depending on these signals, it may trigger physiological responses to stress, pain, or other stimuli. Concurrently, the endocrine subsystem (ES) [23] releases the hormone cortisol, which influences the immune subsystem (IS) [24]. The immune subsystem (IS) regulates the intensity of the immune response.

Consequently, all three subsystems serve as crucial mechanisms for maintaining the organism's stable steady state – homeostasis. The presented subsystems are described in the form of artificial intelligence algorithms; however, they implement only specific mechanisms. For instance, in the case of the immune subsystem, algorithms based on clonal selection, negative selection, and immune networks have gained widespread adoption [24]. However, within a living organism, these mechanisms interact with one another; the first attempts to create a Unified Artificial Immune System (UAIS) were presented in [25]. Subsequently, in [26], the concept of a unified artificial immune system – comprising modified AIS algorithms – was developed. Study [27] examined neuro-endocrine-immune interactions for addressing optimization problems.

Thus, the development of novel modified algorithms – based on the biological model of the human organism and the principles of immunological homeostasis – for the processing of multidimensional data constitutes a pressing task, enabling the creation of more robust data processing mechanisms that are resilient to internal and external environmental perturbations.

Architecture of the UAIS-NES intelligent multidimensional data processing technology

Figure 1 illustrates the architecture of the UAIS-NES intelligent technology for multidimensional data processing. A biological prototype for the interaction of the subsystems (NS, IS, and ES) – designed to ensure homeostasis – is presented. To implement each of these subsystems for multidimensional data processing, corresponding modified algorithms have been developed [26].

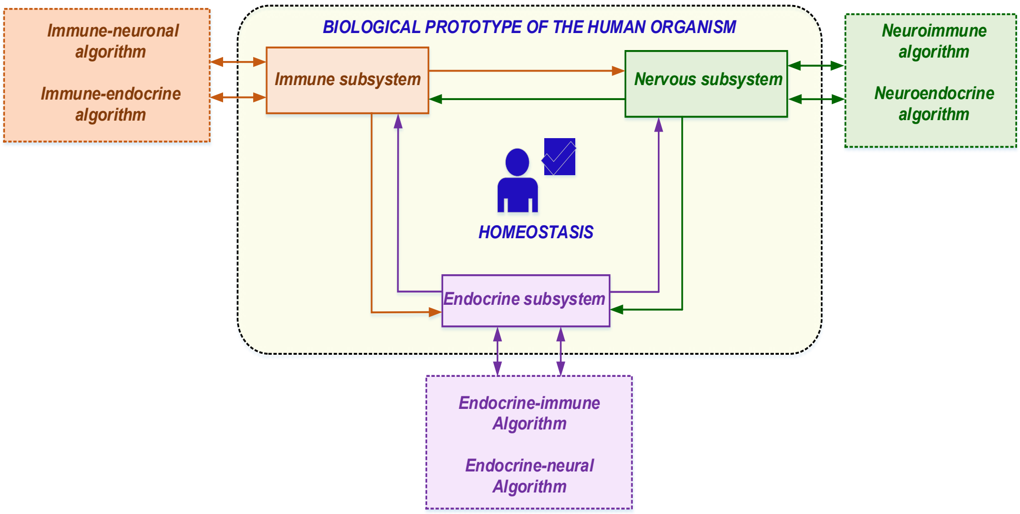

Figure 1 – Architecture of the UAIS-NES intelligent multidimensional data processing technology

- The immune subsystem consists of the following modified algorithms [26]: the immuno-neural (AISN) and the immuno-endocrine (AISE). The AISN algorithm operates as follows: data reduction is performed based on an artificial immune system. Subsequently, informative features are identified using the SHAP (SHapley Additive exPlanations) method [28]. Subsequently, the database – following the reduction phase – is fed into the neural component of the algorithm to address the classification task. The neural network architecture consists of a multilayer perceptron comprising three hidden layers containing 128, 64, and 32 neurons, respectively. The AISE algorithm is founded upon the following principle: data reduction is performed by the algorithm's immune component, while the classification task is resolved by the artificial endocrine algorithm. The artificial endocrine algorithm simulates the behavior of the endocrine subsystem based on hormonal regulation within the human body. The algorithm regulates agent behavior through the use of hormones. Hormones represent threshold values for data deviation, and their concentration varies in response to input signals [26].
- The neural subsystem consists of the following modified algorithms: neuro-immune and neuro-endocrine. The operating principle of these algorithms is analogous: the first component performs the task of data reduction, while the second component addresses the task of classification.
- The endocrine subsystem consists of modified endocrine-immune and endocrine-neural algorithms. The endocrine component is utilized for data dimensionality reduction, while the immune and neural components are responsible for classification.

Based on these subsystems, the UAIS self-assembly mechanism has been implemented. The core concept involves evaluating algorithm performance based on a series of metrics. A recommended threshold value is established for each algorithm; if the metrics fall within the «homeostasis» zone – that is, if they meet the specified thresholds – the modified algorithm in question is deemed to be performing effectively and may be utilized for decision-making. Thus, data analysis is conducted concurrently using all modified algorithms; however, only those algorithms whose metrics fall within the «homeostasis» zone are employed in the actual decision-making process.

Development of an ontological model for an intelligent distance learning system based on UAIS-NES technology

For the application of the UAIS-NES technology in the field of education, the most convenient form of knowledge representation is the ontological model. The Protégé software tool [29] was used as the development environment. The ontological model employs the reasoner HermiT for modeling and for determining the efficiency of algorithms. The model is a combination of three subsystems based on immune, endocrine and neural components for data reduction and solving the classification problem (Figure 1,2) [30]. The model implements four classes with the following functions:

- class 1. Parts_of_system determines which part of the system the object belongs to (contains two subclasses): First_part_data_reduction, Second_part_classifier (First_part_data_reduction, Second_part_classifier);
- class 2. First_part_data_reduction (this class comprises objects used as the first stage of data reduction). A subclass is defined as equivalent to a class of objects having at least one is_data_reducer_of relationship with an instance of the Subsystems class,
- class 3. Second_part_classifier (This subclass comprises objects that are used as the second stage of classification). This subclass is equivalent to the class of objects for which the is_classifier_of property is linked to at least one instance of the Subsystems class. (Second_part_classifier is_classifier_of some Subsystems);
- class 4. Quality_of_Systems has two subclasses – System_have_bad_result and System_have_good_result – which define system qualities based on the subclasses of the data property of the Metrics class ().

The System_have_bad_result subclass comprises individuals from the Systems class that exhibit poor metrics (System_have_bad_result ≡ Systems and (Accuracy some < 0.8)). Furthermore, this subclass does not intersect with the System_have_good_result subclass (System_have_bad_result ∩ System_have_good_result = ∅).

The System_have_good_result subclass comprises objects of the Systems class that possess favorable metrics. The Subsystems class encompasses all subsystems, comprising three subclasses: Endocrin_subsystem, Immune_subsystem, and Neural_subsystem.

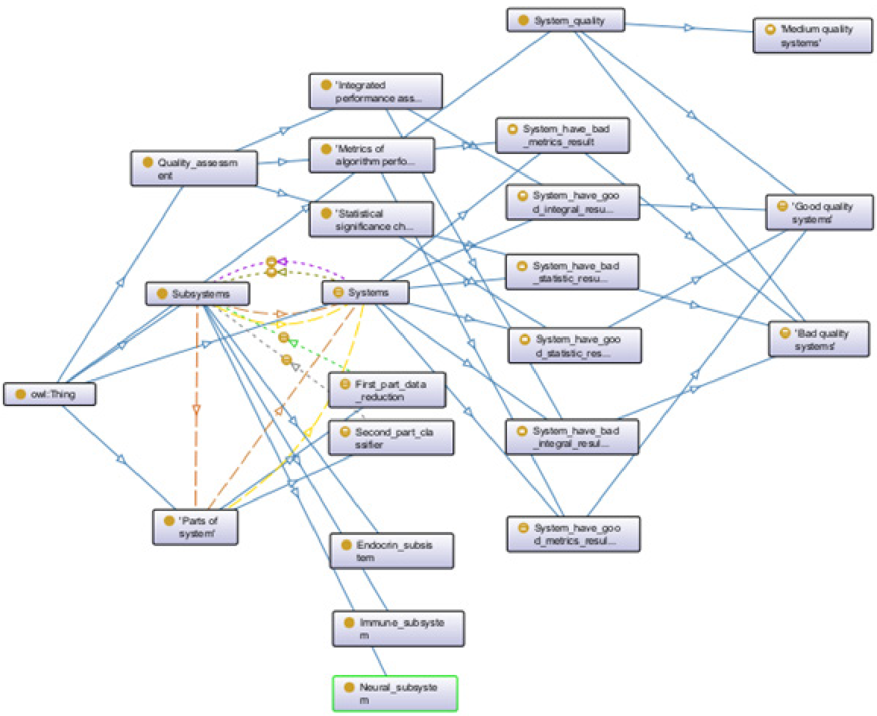

Figure 2 – Classes of the ontological model visualized using OntoGraf

Figure 3 presents individuals of the classes. The neural subsystem is implemented using a multilayer perceptron with three hidden layers and is designed to classify student academic performance data. The endocrine subsystem is based on a population of interacting agents whose behavior is regulated through hormone-like signals, enabling adaptive optimization throughout the learning process. The immune subsystem employs clonal selection and mutation mechanisms to generate and evolve antibodies that serve as classification prototypes.

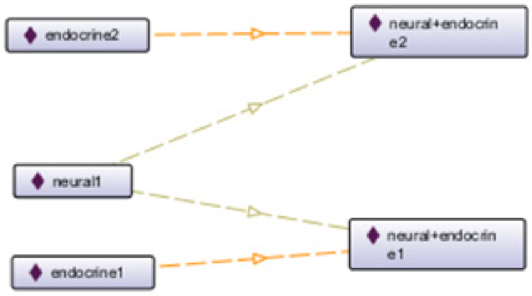

Figure 3 – Individuals of the ontological model classes

Within the UAIS-NES architecture, these subsystems operate in an integrated and coordinated manner. The definition of a homeostasis region makes it possible to evaluate subsystem performance according to predefined quality metrics and to automatically identify the most effective configuration for decision-making and learning outcome prediction.

For the formal representation of interactions among the UAIS-NES subsystems within the ontological model, each subsystem is defined as a separate subclass.

1. The Endocrin_subsistem subclass contains objects that represent the endocrine subsystem (which may relate to First_part_data_reduction or Second_part_classifier).

2. The Immune_subsystem subclass contains objects that represent the immune system (which may relate to First_part_data_reduction or).

3. The Neural_subsystem subclass represents a neural system (which may relate to First_part_data_reduction or).

The ontological model presents four properties of the object:

1. is_classifier_of – an object property that links a classification subsystem to a system;

2. is_data_reducer_of – an object property that links the data reduction subsystem to the system.

3. has_classifier_subsystem – this property is the inverse of is_classifier_of;

4. has_data_reducer_subsystem – this property is the inverse of is_data_reducer_of.

Based on the integrated ontological model UAIS-NES, a knowledge base has been developed for the implementation of intelligent technology into the educational process. Figure 4 presents the UAIS-NES technology in the form of an ontological model, comprising subclasses and individuals.

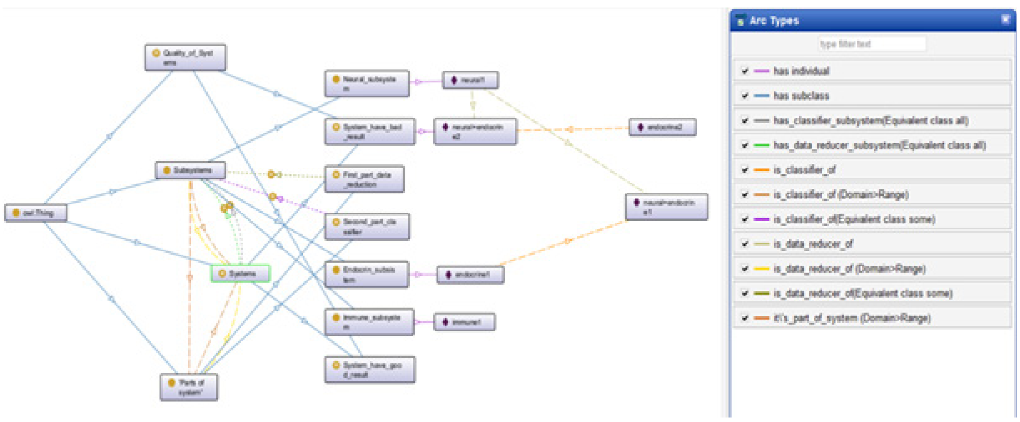

Figure 4 – UAIS-NES ontological model for implementation in the educational process

The developed ontological model enables data analysis based on UAIS-NES technology.

Intelligent distance learning system based on UAIS-NES technology

The operating principle of the intelligent distance learning system based on an ontological model is as follows (Figure 5). It is proposed to divide data processing into two levels:

1) First Level. Data analysis and career guidance based on the processing of student data during secondary education. To identify students' aptitudes, data analysis utilizing the BilimClass educational platform is recommended [31]. At the primary school level (Grades 1 through 4), data processing focuses on students' study of logic. In the middle school grades (5 through 9), the focus is on mathematics; in the upper school grades (9 through 11), it shifts to computer science and physics. Based on the results of data processing, a digital profile of the student is generated, which serves as a basis for assessing the student's aptitude for pursuing higher education in technical universities.

2) Second Level. Analysis of student data within the context of higher education institutions. The course structure and learning materials are hosted on the MS Teams platform [32]. During the learning process, a digital profile of the student's competencies is generated to assess their professional aptitude within the framework of engineering education. Based on the results of practical and laboratory assignments, a dataset is compiled containing grades, activity statistics, time spent on the platform, and other relevant metrics.

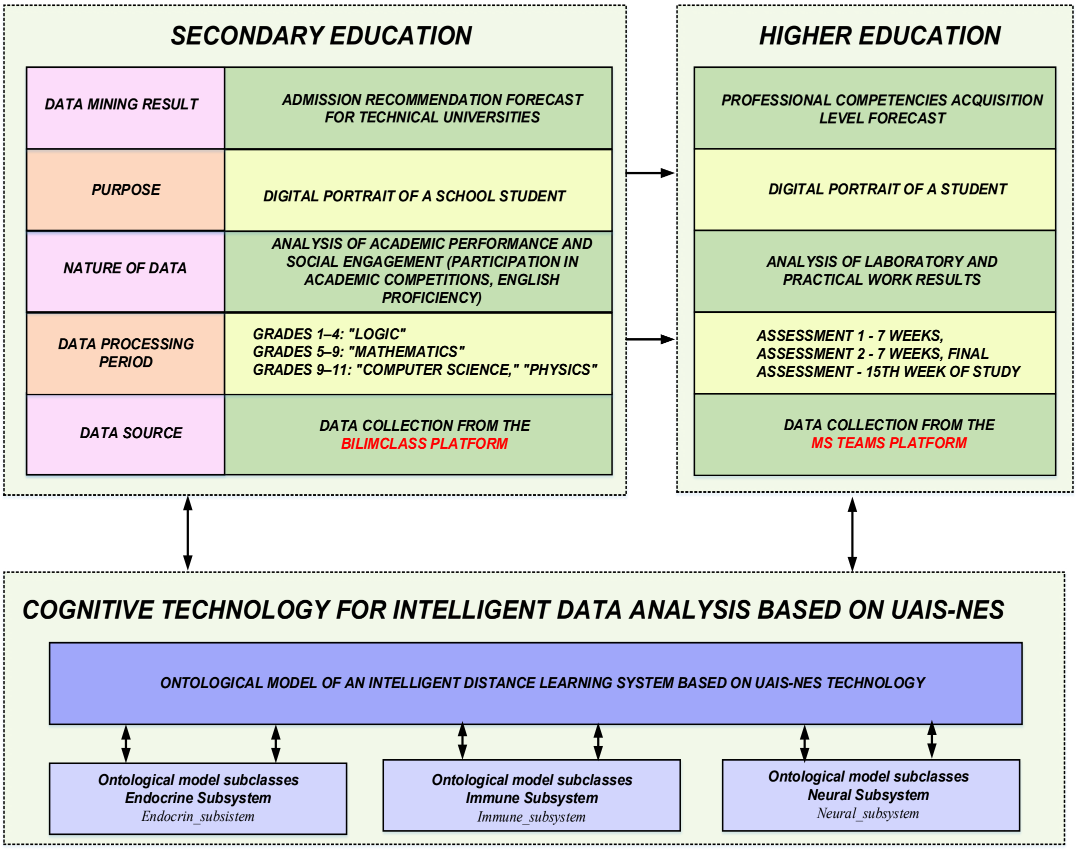

Figure 5 – Structural diagram of an intelligent distance learning system based on UAIS-NES technology

Following data analysis based on UAIS-NES intelligent technology, a forecast is generated regarding the level of acquired professional engineering competencies and the probability of successfully mastering a given discipline; simultaneously, the student's readiness to address complex technical management tasks is assessed, and the educational process undergoes real-time adjustment.

Results and discussion

Let us examine the structure of the developed ontological model. Figure 6 illustrates the data property hierarchy based on the OWL language [29]. The `topDataProperty` element serves as the root property of the model, from which all other properties inherit. These properties are divided into two major groups: Metrics and Parameters. The Metrics group contains information regarding the metrics used to evaluate the performance of the ontological model's algorithms (the neural, immune, and endocrine subsystems). The Parameters group contains the primary metaparameters for configuring the algorithms.

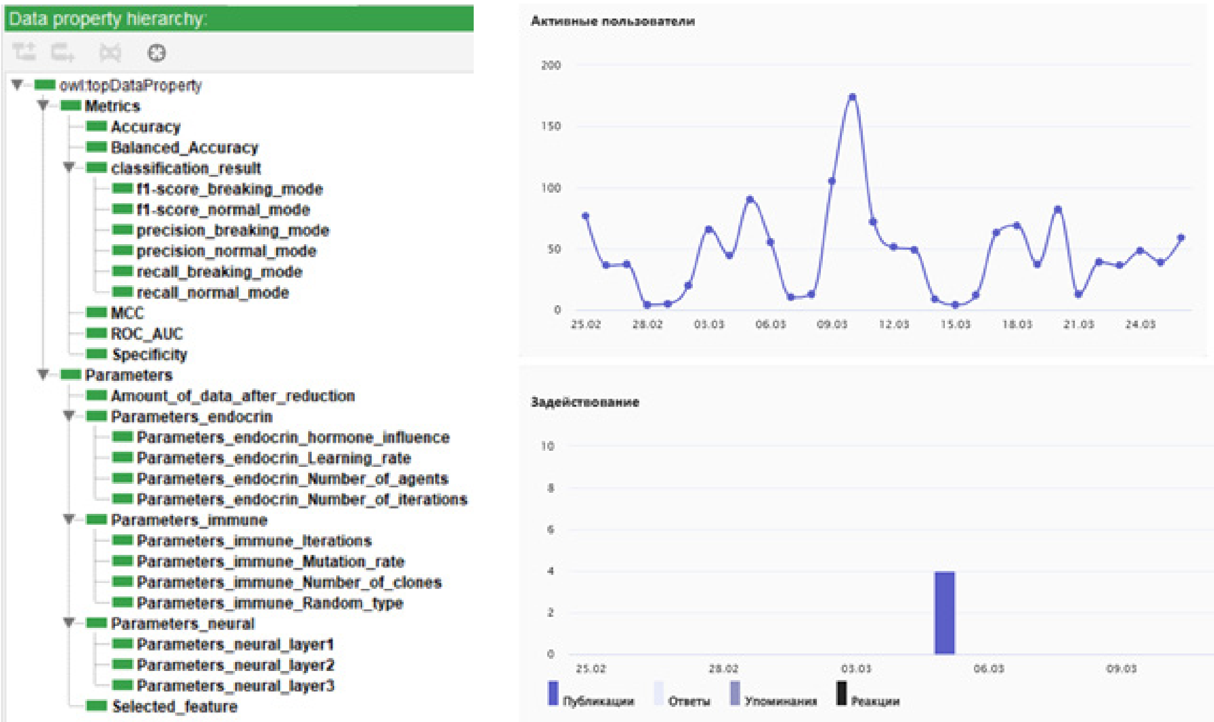

Figure 6 – Structure of the developed ontological model based on UAIS-NES technology

This model enables the comparison of the effectiveness of various combinations of bio-inspired modified algorithms on the same dataset, based on metric threshold values [30, 33, 34, 35]. Figure 7 displays a list of data instances from the ontological model.

A description of class instances is presented in Table 1. This parameter belongs simultaneously to multiple classes: endocrine_subsystem and second_part_classifier etc.

Table 1 – Parameters of the UAIS-NES subsystems

Subsystem	Parameter	Value	Description
Neural	layer1	64	Number of neurons in the first hidden layer
Neural	layer2	64	Number of neurons in the second hidden layer
Neural	layer3	64	Number of neurons in the third hidden layer
Endocrine	num_agents	100	Number of agents in the population
Endocrine	num_iterations	100	Number of training iterations
Endocrine	learning_rate	5	Hormonal adaptation coefficient
Endocrine	hormone_influence	0.1	Degree of influence of hormonal signals on agents
Immune	n_clones	100	Number of clones generated for each antibody
Immune	mutation_rate	1	Antibody mutation coefficient
Immune	iterations	50	Number of clonal selection iterations

Performance evaluation was conducted using the metrics presented in Figure 6, including Accuracy, Balanced Accuracy, ROC-AUC, F1-score, as well as Precision and Recall for each class. These metrics constitute the foundation of the algorithm performance assessment mechanism embedded within the ontological model and are used to evaluate the effectiveness of the proposed analytical approaches.

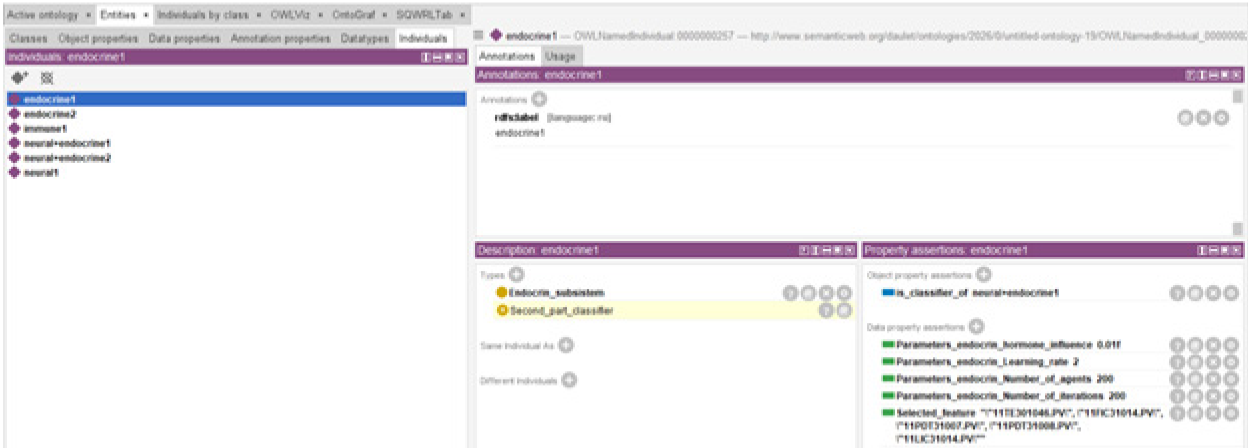

Figure 7 – List of data instances of the UAIS-NES ontological model

Thus, the ontological model comprises classes describing modified algorithms for the endocrine, immune, and neural subsystems – along with their properties in the form of parameters and metrics – as well as the values of data instances (individuals) representing specific model runs and their simulation results.

Conclusion

Representing an intelligent technology based on the UAIS-NES as an ontological model enables the structuring of data in a unified, formalized format. This approach renders the description of algorithms intelligible to both software developers and end users. The ontological model facilitates the integration of various models – specifically, modified algorithms for the endocrine, neural, and immune subsystems – by explicitly depicting their interactions and interdependencies. The Protégé software product enables logical inference, automatically identifies dependencies, and draws conclusions without human intervention. The set of experiments is represented as an intelligent knowledge base, wherein each algorithm is described as an object with its own parameters, metrics, and relationships.

The application of intelligent technology based on UAIS-NES in the field of education represents a promising avenue for training highly qualified technical specialists, ranging from secondary-level institutions to higher education establishments.

A certificate of entry into the state register of rights to copyright-protected objects has been obtained for the developed software [30].

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[1,2]Самигулина Г.А.,
т.ғ.д., профессор, ORCID ID: 0000-0003-1798-9161,
e-mail: kz.galinasamigulina@gmail.com
[1,2]*Самигулина З.И.,
PhD, доцент, ORCID ID: 0000-0002-5862-6415,
*e-mail: z.samigulina@kbtu.kz
[1,2]Бекешев Д.Д.,
магистр, ORCID ID: 0009-0002-8168-6368,
e-mail: dauletb01@gmail.com
[3]Кучербаева С.З.,
ORCID ID: 0009-0002-7864-1900,
e-mail: stestephaniya1960@mail.ru
[3]Ярмухамедова А.Б.,
ORCID ID: 0009-0001-5421-0666,
e-mail:only_alla@mail.ru

[1]Ақпараттық және есептеуіш технологиялар институты,
«Зияткерлік басқару және болжау жүйелері» зертханасы,
Алматы қ., Қазақстан
[2]Қазақстан-Британ техникалық университеті,
Ақпараттық технологиялар және инженерия мектебі,
Алматы қ., Қазақстан
[3]Алматы қаласы Білім басқармасының
«№35 жалпы білім беретін мектеп» коммуналдық мемлекеттік мекемесі,
Алматы қ., Қазақстан

ЖАСАНДЫ ИНТЕЛЛЕКТ: ИНЖЕНЕРЛІК БІЛІМ БЕРУДЕГІ ЖАҢА БИОИНСПИРАЦИЯЛЫҚ ТӘСІЛ

Аңдатпа

Білім алу процесінде гомеостазды нейроэндокриндік реттеу қағидатына негізделген біріздендірілген жасанды иммундық жүйені пайдалану арқылы техникалық мамандықтар бойынша қашықтан оқытудың когнитивтік технологиясы әзірленді. Ұсынылған БЖИЖ–НЭЖ (біріздендірілген жасанды иммундық жүйе – нейроэндокриндік жүйе) технологиясы негізінде өнеркәсіптік автоматтандырудың күрделі объектілерін басқаруға арналған интеллектуалды қашықтан білім беру жүйесін іске асыру үшін иммундық, нейрондық және эндокриндік ішкі жүйелердің онтологиялық модельдерінен тұратын интеграцияланған онтологиялық модель жасалды. Осы модель негізінде оқу процесіне когнитивтік технологияны енгізуге арналған білім базасы қалыптастырылды. Деректерді екі кезеңде өңдеу үшін сыныптар мен ішкі сыныптар әзірленіп, олардың өзара әрекеттесуі қарастырылды: атап айтқанда, ақпараттық емес белгілерді редукциялау және биоинспирациялық алгоритмдер негізінде жіктеу міндеттері шешілді. Жүйе сапасын бағалау критерийлері өзара бірін-бірі жоққа шығаратын сыныптарға (жақсы және нашар нәтижелер) бөлу арқылы метрикалар негізінде әзірленді. Технология негізінде деректерді талдау нәтижесінде алынған кәсіби инженерлік дағдылар деңгейі, пәнді сәтті меңгеру ықтималдығы және білім алушының күрделі техникалық басқару міндеттерін шешуге дайындығы деңгейі болжанады. Бұл көрсеткіштер студенттің құзыреттерінің цифрлық профилі түрінде ұсынылады.

Түйін сөздер: инженерлік білім беру, интеллектуалды технология, жасанды иммундық жүйе, нейроэндокриндік өзара әрекеттесу, гомеостаз, онтологиялық модельдер, оқу нәтижесін болжау, студенттің цифрлық профилі.

[1,2]Самигулина Г.А.,
д.т.н., профессор, ORCID ID: 0000-0003-1798-9161,
e-mail: kz.galinasamigulina@gmail.com
[1,2]*Самигулина З.И.,
PhD, доцент , ORCID ID: 0000-0002-5862-6415,
*e-mail: z.samigulina@kbtu.kz,
[1,2]Бекешев Д.Д.,
магистр техн. наук, ORCID ID: 0009-0002-8168-6368,
e-mail: dauletb01@gmail.com
[3]Кучербаева С.З.,
ORCID ID: 0009-0002-7864-1900,
e-mail: stestephaniya1960@mail.ru
[3]Ярмухамедова А.Б.,
ORCID ID: 0009-0001-5421-0666,
e-mail:only_alla@mail.ru

[1]Институт информационных и вычислительных технологий,
лаборатория «Интеллектуальные системы управления и прогнозирования»,
г. Алматы, Казахстан
[2]Казахстанско-Британский технический университет,
Школа информационных технологий и инженерии,
г. Алматы, Казахстан
[3]КГУ «Общеобразовательная школа №35» Управления образования г. Алматы,
г. Алматы, Казахстан

ИСКУССТВЕННЫЙ ИНТЕЛЛЕКТ: НОВЫЙ БИОИНСПЕРИРОВАННЫЙ ПОДХОД В ИНЖЕНЕРНОМ ОБРАЗОВАНИИ

Аннотация

Разработана когнитивная технология дистанционного обучения техническим специальностям с использованием биоинспирированного подхода на основе унифицированной искусственной иммунной системы с нейроэндокринным регулированием гомеостаза при получении знаний. Для реализации интеллектуальной системы дистанционного образования по управлению сложными объектами промышленной автоматизации на основе предложенной технологии УИИС – НЭС разработана интегрированная онтологическая модель, состоящая из онтологических моделей иммунной, нейронной и эндокринной подсистем на основе которой создана база знаний для внедрения когнитивной технологии в учебный процесс. Разработаны классы, подклассы и рассмотрены их взаимодействия для двухэтапной обработки данных в виде решения задачи редукции неинформативных признаков и классификации на основе биоинспирированных алгоритмов. Созданы критерии оценки качества системы на основе метрик с разделением на взаимоисключающие классы на основе хороших и плохих результатов. По результатам анализа данных на основе технологии осуществляется прогноз уровня полученных профессиональных инженерных навыков, вероятности успешного освоения дисциплины и определения степени готовности обучающегося к решению сложных технических задач управления в виде цифрового профиля компетенций студента.

Ключевые слова: инженерное образование, интеллектуальная технология, искусственная иммунная система, нейроэндокринное взаимодействие, гомеостаз, онтологические модели, прогнозирование результата обучения, цифровой портрет студента.