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MULTI-AGENT SYSTEM FOR PLANNING THE EDUCATIONAL CONTINGENT USING NEURAL NETWORKS

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Abstract. This paper is dedicated to the development and validation of an intelligent architecture for educational cohort planning, based on the integration of multi-agent systems with artificial neural networks. The research is motivated by the need to efficiently manage educational data flows characterized by high volume, temporal dynamics, and uncertainty, in the context of demographic and socio-economic changes. To this end, a formal model is proposed that describes agents' decision-making dynamics, inter-agent coordination mechanisms, and the neural learning process used to predict key educational indicators. To validate the proposed solution, an experimental dataset covering the period 2020–2024 was used, reflecting the educational trajectory from high school graduation to the completion of undergraduate studies. The experimental results highlight stable convergence of the learning process, a reduction in prediction error, and the model's ability to approximate nonlinear relationships between demographic and socio-economic factors and educational indicators. The multi-agent architecture enables efficient distribution of computational tasks, scalability, and adaptability to changes in the educational environment. The proposed solution provides robust decision support for educational management and may serve as an essential formal basis for the development of advanced intelligent systems for institutional planning.

Keywords: *decision support, parallel processing, educational data streams, machine learning, online learning, educational forecasting, distributed architectures, optimization, educational management, temporal data, neural inference, adaptivity.*

1. Introduction

Educational cohort planning involves complex processes of prediction, optimization, and coordination, characterized by temporal dynamics, uncertainty, and interdependence among multiple decision-making entities. Classical centralized models [1], based on statistical analyses or rigid expert systems [2, 3], exhibit significant limitations in terms of scalability, adaptability, and the ability to integrate heterogeneous and distributed educational data.

In this context, Multi-Agent Systems (MAS) [4] provide an appropriate computational framework for the distributed modeling of the educational planning process, in which autonomous, reactive, and cognitive agents represent educational institutions, academic programs, student cohorts, and decision-making factors. Each agent is endowed with local mechanisms for perception, reasoning, and action, while the global behavior of the system emerges from interactions such as cooperation, negotiation, and inter-agent coordination [5].

The integration of artificial neural networks [6, 7] into the MAS architecture [8] enables agents to be equipped with advanced machine learning and nonlinear prediction capabilities [9]. Neural models can be used to estimate enrollment dynamics, retention, and graduation flows, as well as to identify latent patterns in historical educational, demographic, and socio-economic data. In the proposed architecture, neural networks are implemented either at the agent level (agent-level learning) or at the level of global coordination, supporting the continuous adaptation of planning strategies [10–17].

The present research is oriented toward the development of an intelligent Multi-Agent System based on neural networks for educational cohort planning, in which learning, prediction, and decision-making mechanisms are integrated within a modular and scalable architecture. The proposed approach contributes to improving forecasting accuracy, optimizing the allocation of educational resources, and supporting strategic decision-making in a dynamic and uncertain educational environment.

2. Mathematical Model of the Proposed Multi-Agent System

Multi-Agent System (*MAS*) is defined as a tuple (1):

$$MAS = \langle A, E, O, I, P \rangle \tag{1}$$

where:

$A = \{a_1, a_2, ..., a_N\}$ is the set of agents involved in the monitoring and management of the educational process;

E is the dynamic educational environment, which represents a complex and adaptive learning system in which the interaction between actors, content, and technologies generates flexible, personalized, and evolving educational processes;

O represents the set of strategic objectives, achieved through an adaptive planning mechanism under variable environmental conditions (including educational cohort planning);

I represents the ensemble of communication and coordination relations among agents: communication (messages, signals, data), cooperation (coordinated work to achieve a common objective), negotiation and decision coordination, competition or conflict resolution, synchronization of actions in time and space, etc.;

P represents the agents' decision policies and models their decision-making behavior.

Each agent … $a_i, \forall i = 1,...,N$ is characterized by the set (2):

$$a_i = \langle S_i, A_i, \pi_i, ANN_i \rangle \tag{2}$$

where:

$S_i, \forall i = 1,...,N$ is the domain of internal configurations that describe the agent's state space $S_i = \{s_{i1}, s_{i2}, ..., s_{im}\}$ (observable states, internal states, latent states, etc.)

$A_i, \forall i = 1,...,N$ is the domain of operational decisions available to the agent $A_i = \{a_{i1}, a_{i2}, ..., a_{im}\}$, where each a is an action with respect to: the degree of freedom, the capacity to influence the environment, and the right and level of modeling of the decision-making process;

$\pi_i : S_i \to A_i, \forall i = 1,...N$ is the decision policy expressed by a function that governs the agent's behavior by mapping states S_i into actions A, with the aim of optimizing an objective O;

$ANN_i, \forall i = 1,...,N$ is the adaptive component of the system, responsible for learning the relationships among data through a neural network.

The global state of the educational system at time *t* is defined by the expression (3):

$$S(t) = \bigcup_{i-1}^{N} \left(S_i(t) \right) \tag{3}$$

For an educational agent a_i the state is defined by the expression (4):

$$S_i(t) = \left[E_i(t), R_i(t), C_i(t), D_i(t) \right] \tag{4}$$

where:

$E_i(t)$ is the number of enrollments in the study programs;

$R_i(t)$ is the proportion of participants who continue their educational trajectory (promotion rate);

$C_i(t)$ is the functional potential of the institution to fulfill its educational mission;

$D_i(t)$ is the set of population and socio-economic variables that influence the evolution of the educational system, expressed through demographic factors (population size, age distribution, birth and death rates, migration, etc.) and socio-economic factors (income level, employment rate, education level, access to resources and services, social status, public policies, and economic context, etc.).

3. Agent Model for Prediction of Educational Processes Based on Neural Network

The neural inference mechanism is based on artificial neural networks capable of learning complex and nonlinear relationships from historical and current educational data. It processes indicators such as retention rates, institutional capacity, and demographic and socio-economic factors to construct relevant internal representations of the system. Based on these representations, the model generates estimates regarding the future evolution of the educational cohort and the demand for resources. The mechanism continuously adapts by updating its parameters according to new data, thereby increasing prediction accuracy. In this way, neural inference provides decision support for strategic planning and the optimization of educational processes.

Let $x_i(t) \in \mathbb{R}^n$ be the input vector of agent a_i, defined by expression (5):

$$x_i(t) = \left[E_i(t-1), R_i(t-1), C_i(t-1), D_i(t-1) \right] \tag{5}$$

The prediction of the educational cohort is performed by a neural network based on expression (6):

$$\widehat{E}_i(t+1) = f_{Q_i}\left(x_i(t) \right) \tag{6}$$

where:

f_{Q_i} is the neural approximation function that models the complex and nonlinear relationships between the system's input and output variables. By adjusting its internal weights, it enables precise estimation of the behavior and future evolution of the educational process;

Q_i represents the set of trainable weights that encode the knowledge learned from the available data $x_i(t)$. These weights are iteratively adjusted during the training process to minimize the prediction error. They determine the model's ability to generalize and produce accurate estimates for new situations.

The associated loss function is the mathematical criterion (7) used to evaluate the difference between the values predicted by the model and the actual observed values. It quantifies the prediction error and provides an optimization signal for the learning process. By minimizing the loss function, the model adjusts its trainable weights to improve estimation accuracy. The choice of loss function directly influences the stability, convergence, and overall performance of the neural model:

$$L_i\left(Q_i\right)=\frac{1}{T}\sum_{t=1}^{T}\left\|E_i(t+1)-\widehat{E}_i(t+1)\right\|^2 \tag{7}$$

The decision-making dynamics of agents, implemented based on the neural model, reflect how decisions are continuously adapted according to the predictions and inferences generated by the neural network. The neural model processes the current states of the environment $x_i(t)$ and provides estimates that guide the selection of agents' actions. As new data become available, the model parameters are updated, resulting in corresponding modifications to the decision policies. This interaction between learning and decision-making enables agents to respond effectively to changes and uncertainties. Consequently, the global behavior of the multi-agent system becomes adaptive and oriented toward optimizing the established objectives O.

Accordingly, an agent's policy is defined as the formal mechanism (8) that establishes the mapping between perceived environmental states and selected actions. It functions as a decision rule that transforms available information into concrete operational decisions. The policy integrates the predictions provided by the neural model with the agent's objectives and constraints. By continuously updating its parameters, the policy allows the agent's behavior to adapt to changes in the environment. In this way, the agent can act autonomously, rationally, and in a manner oriented toward optimizing system performance:

$$\pi_i(t)=\arg\max_{\mathrm{a}\in\mathrm{A_i}}\left(\mathrm{E}\left[U_i\left(S_i(t),a\right)\right]\right) \tag{8}$$

In model (8) the utility function U_i is the mathematical criterion that quantifies the degree to which an agent's objectives are satisfied following an action or decision. It allows the comparison of alternatives and guides the decision-making process toward maximizing the overall performance of the educational system, where:

$$U_i=\alpha_i+\beta_i+\gamma_i, \tag{9}$$

Expression (9) defines the utility function U_i of agent i as a weighted combination of multiple performance criteria. The term α_i reflects the importance of decision accuracy, β_i measures the efficiency of resource utilization, and γ_i penalizes violations of constraints. The coefficients α,β,γ control the trade-offs between quality, efficiency, and adherence to limitations in the agent's decision-making process, subject to the condition $\left(\alpha,\beta,\gamma\right)\in\mathbb{R}^+$.

4. Inter-Agent Interaction and Coordination

Inter-agent interaction and coordination represent the process through which agents in an educational system communicate and cooperate to achieve their individual and collective objectives. This includes the exchange of information, synchronization of actions, and adaptation of strategies based on the behaviors of other agents. Through coordination, agents can avoid conflicts, optimize resource utilization, and enhance the overall efficiency of the educational system. Continuous interaction generates emergent dynamics, in which collective behavior is not merely the sum of individual behaviors. Thus, inter-agent cooperation and communication are essential for the adaptive functioning and performance of a complex multi-agent educational system.

Interactions are modeled using a graph (10), where nodes represent agents and edges indicate the relationships or information exchanges between them. This representation allows visualization of the communication structure and coordination flows within the system. Furthermore, graphs facilitate the analysis of collective dynamics and the identification of critical points for optimizing cooperation among agents:

$$G=\left(A,I\right), \tag{10}$$

where edges represent information exchanges (11):

$$m_{ij}(t)=\phi\left(S_i(t),S_j(t)\right). \tag{11}$$

The state of an agent (12) is updated according to a mechanism that integrates information received from the external environment and the outcomes of previous actions. This includes modifying internal values, objectives, and the level of available resources. The updating process is based on mathematical functions or neural models that determine how new data influence future decisions. Through this update, the agent can respond adaptively to environmental changes and the behavior of other agents. Thus, the agent's state continuously reflects the current situation and conditions its decision-making policies:

$$S_i(t+1)=\varphi\left(S_i(t),A_i(t),\sum_{j\in N_i}\left(m_{ij}(t)\right)\right) \tag{12}$$

5. The Overall Optimization Goal

The global optimization objective represents the main goal pursued by the entire Multi-Agent System as a whole. It synthesizes collective performance by integrating the results and actions of individual agents. The objective may include criteria such as maximizing efficiency, reducing costs, improving service quality, or adhering to constraints. Within the decision-making process, each agent adjusts its behavior to contribute to the achievement of this common objective. Thus, global optimization ensures coherence, adaptability, and overall performance of the educational system.

Educational cohort planning is formulated as a distributed optimization problem, in which multiple agents make autonomous but interdependent decisions for efficient resource allocation and activity scheduling. Each agent optimizes a local sub-objective while simultaneously contributing to the achievement of the global objective of the educational system. This approach allows continuous adaptation to demographic and socio-economic changes as well as to institutional constraints:

$$\min_{\{\pi_i\}}\sum_{i=1}^{N}L_i\left(Q_i\right), \tag{13}$$

subject to:

$$\sum_{i=1}^{N}\widehat{E}_i(t)\leq\sum_{i=1}^{N}C_i(t) \tag{14}$$

and $\widehat{E}_i(t)\geq 0,\ \forall i$.

Convergence and adaptivity are essential properties of intelligent and multi-agent systems. Convergence describes the system's ability to reach, over time, a stable state or an optimal solution through iterative learning and decision-making processes. Adaptivity reflects the agents' ability to modify their behavior in response to changes in the environment and new information. Together, these two characteristics ensure the stability of the system's operation under dynamic and uncertain conditions. Consequently, the system can maintain optimal performance even in the presence of disturbances or contextual variations.

The learning process is iterative, involving repeated updates of the model parameters based on prediction errors obtained at each step. At each iteration, the system evaluates current performance and adjusts its internal mechanisms to reduce deviations from the established objectives. This continuous process enables progressive improvement in accuracy and allows the model to adapt to new data and changing conditions:

$$Q_i^{(k+1)}=Q_i^{(k)}-\eta\nabla_{Q_i}ANN_i, \tag{15}$$

where η is the learning rate, a parameter that controls the magnitude of weight updates and influences the speed and stability of the model's convergence process.

The system converges to a distributed equilibrium as a result of repeated interactions among agents and local optimization processes. Each agent adjusts its decisions based on its own information and exchanges with other agents, without requiring centralized control. This equilibrium reflects a stable state in which local objectives are aligned with the system's global objective. Convergence is supported by learning mechanisms and inter-agent coordination. Thus, the system maintains stability and performance even in dynamic and uncertain environments:

$$\lim_{t\to\infty}\left\|S(t+1)-S(t)\right\|\to 0. \tag{16}$$

6. Synthesis of the Multi-Layer Architecture of the Multi-Agent System

The synthesis of the multi-layer architecture of the multi-agent system describes the hierarchical organization of the system's functional components across distinct levels. Each layer fulfills a specific role, ranging from data perception and collection to decision-making and global coordination. The proposed architecture (see Figure 1) is organized hierarchically into functional layers, enabling clear separation of responsibilities, modularity, reusability, and scalability. The system integrates a distributed multi-agent framework with neural learning mechanisms at both local and global levels.

Functional description of the multi-agent architecture:

Data & Environment Layer represents the external educational environment and provides the raw data necessary for the planning process, including historical educational information, demographic and socio-economic data, institutional capacities, and educational policy factors;

Perception & Preprocessing Layer handles data acquisition, filtering, and preprocessing from the educational environment, ensuring normalization, anomaly detection, and transformation into input vectors suitable for intelligent agents and neural models;

Multi-Agent Layer represents the set of specialized autonomous agents (institutional, program-level, cohort-level, and policy agents) that model the decision-making entities within the educational system and interact through mechanisms of cooperation, negotiation, and information exchange;

Decision & Planning Layer integrates the results of neural predictions into distributed decision-making policies, allowing agents to generate optimal plans for resource allocation and educational cohort sizing under institutional constraints;

Coordination & Communication ensures inter-agent synchronization and coordination through message exchanges, consensus mechanisms, and conflict resolution, contributing to the coherence of system-level decisions;

Execution & Feedback Layer implements the generated decisions, monitors the outcomes, and provides adaptive feedback to agents and neural models, supporting continuous learning and strategy adjustment.

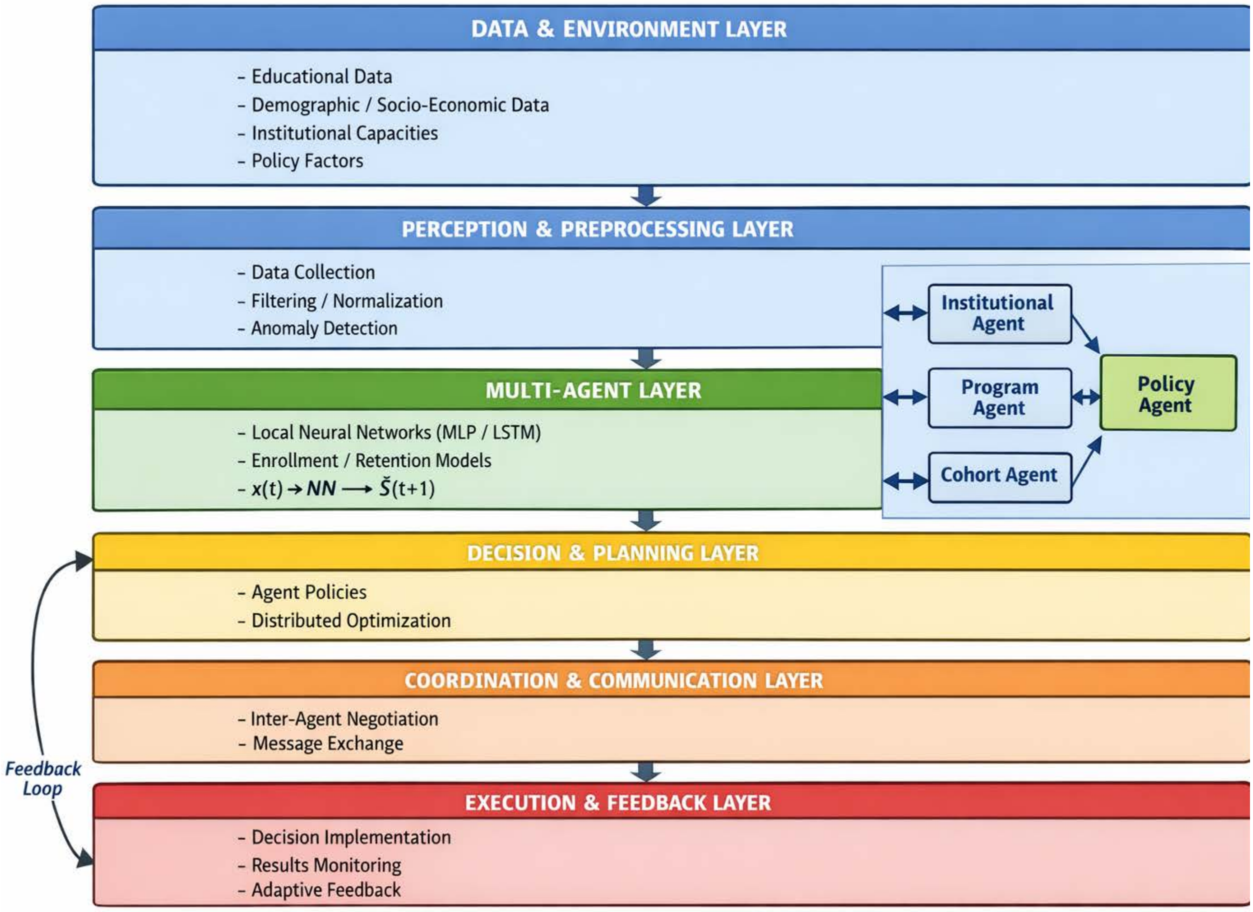

Figure 1. Layered architecture of the multi-agent system based on neural networks for educational contingent planning.

The multi-layer architecture is designed to apply the mathematical models defined earlier in this work, ensuring a direct correspondence between the theoretical formulation and practical implementation. Each layer incorporates components that reflect the variables, constraints, and optimization functions of the mathematical model. This alignment allows for experimental validation of theoretical hypotheses through simulations and controlled experiments. Consequently, the architecture facilitates the coherent integration of decision-making, learning, and coordination mechanisms within a unified formal framework.

7. Modeling the Dataset for ANN Training

Modeling the dataset for training the ANN represents the process of selecting, structuring, and preprocessing the data used to train the artificial neural network. This process includes preprocessing raw data to identify relevant variables (inputs and outputs), cleaning the data, handling missing values, and normalizing them to ensure stable learning. The dataset is organized as pairs of (input data, labels/target values) corresponding to the prediction objective. Additionally, the data are divided into training, validation, and test subsets to evaluate performance and prevent overfitting. Proper dataset modeling is essential for the accuracy, generalization, and efficient convergence of the neural network.

Thus, defining the educational dataset involves identifying and selecting relevant information for modeling and analyzing educational processes. This includes establishing input variables, performance indicators, and target values necessary for training intelligent models. The process requires structuring data from heterogeneous sources, such as academic records, demographic data, and institutional indicators. A rigorous dataset definition ensures the consistency, quality, and relevance of the results obtained.

Let the educational process be defined by the dataset (17):

$$D = \left\{ \left(\mathrm{x}^{(k)}, \mathrm{y}^{(k)} \right) \middle| k = 1,2,\ldots,K \right\}, \tag{17}$$

where:

$\mathrm{x}^{(k)} \in \mathbb{R}^n$ represents the input vector of the model, encompassing educational characteristics relevant for analysis and prediction. This may include indicators such as academic performance, retention rates, institutional capacity, and demographic factors. The input vector supplies the information required for the model to learn the relationships between input data and the predicted outcomes;

$\mathrm{y}^{(k)} \in \mathbb{R}^m$ represents the desired output vector of the model, corresponding to the predicted outcomes of the educational process. This may include indicators such as the forecasted educational cohort, retention rates, and graduation rates. The output vector enables the assessment of model performance and provides a basis for informed educational planning decisions;

n and m respectively, represent the dimensions of the input and output vectors;

K represents the set of subsets used for the ANN training process.

Figure 2 shows the structure of the raw data for modeling an educational process with admission based on the Baccalaureate diploma, a 4-year study program, and 8 semesters, as applied at the Technical University of Moldova.

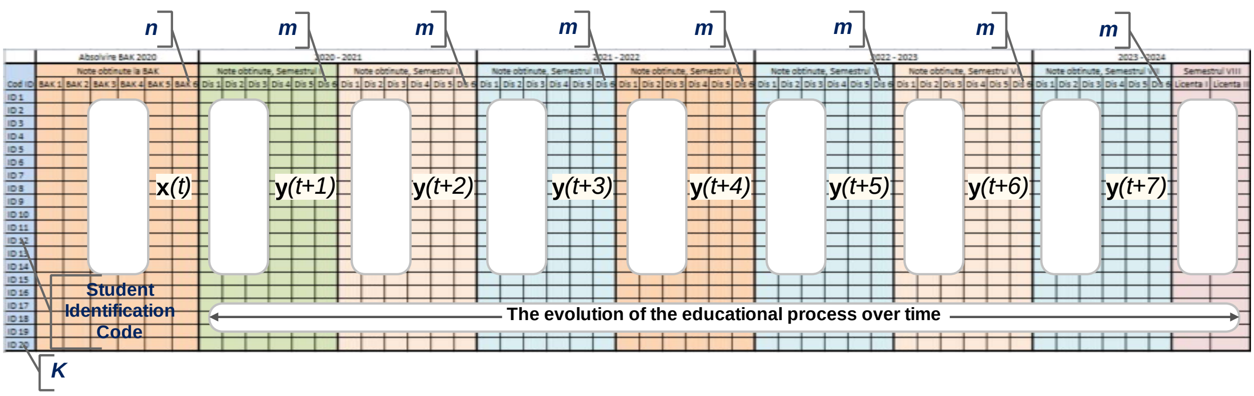

Figure 2. Raw data structure for modeling an educational process.

Specification of the raw data structure:

Student Identification Code - represents a unique identifier assigned to each student, used for academic records, management of educational data, and tracking the educational trajectory within the information system;

K - the number of data subsets, or the number of students involved in the modeling process;

n - the dimension of the input vector, or the number of grades obtained at BAK included in the modeling process;

m - the dimension of the output vector, or the number of grades (subjects) involved in the modeling process across the study semesters;

x*(t)* – the input vector of dimension *n*;

y*(t+1)*... **y***(t+8)* - the output vectors of dimension *m*.

For modeling the dataset used for ***ANN*** training, two variants of multi-agent computing architectures are analyzed:

a) ***Sequential***, as defined by the mathematical model (18):

$$\begin{aligned} &\mathrm{y}(t+1) = f_1\left(\mathrm{x}(t)\right); \\ &\mathrm{x}(t+1) = \mathrm{y}(t+1), \mathrm{y}(t+2) = f_2\left(\mathrm{x}(t+1)\right); \\ &\ldots \\ &\mathrm{x}(t+7) = \mathrm{y}(t+7), \mathrm{y}(t+8) = f_8\left(\mathrm{x}(t+7)\right). \end{aligned} \tag{18}$$

a) ***Complex***, as defined by the mathematical model (19):

$$\begin{aligned} &\mathrm{y}(t+1) = f_1\left(\mathrm{x}(t)\right); \\ &\mathrm{x}(t+1) = \bigcup\left(\mathrm{x}(t), \mathrm{y}(t+1)\right), \mathrm{y}(t+2) = f_2\left(\mathrm{x}(t+1)\right); \\ &\mathrm{x}(t+2) = \bigcup\left(\mathrm{x}(t+1), \mathrm{y}(t+2)\right), \mathrm{y}(t+3) = f_3\left(\mathrm{x}(t+2)\right); \\ &\ldots \\ &\mathrm{x}(t+7) = \bigcup\left(\mathrm{x}(t+6), \mathrm{y}(t+7)\right), \mathrm{y}(t+8) = f_8\left(\mathrm{x}(t+7)\right). \end{aligned} \tag{19}$$

8. Mathematical Model of Neural Network Learning Process

A multilayer neural network can be defined as a function composition that maps input data to output results through multiple hierarchical processing layers. Each layer performs a linear transformation followed by a nonlinear activation function. This structure allows the network to capture and represent complex, nonlinear relationships among the system's variables (20):

$$f_Q(\mathrm{x}) = f^{(L)}\left(f^{(L-1)}\left(\ldots\left(f^{(1)}(\mathrm{x})\right)\right)\right), \tag{20}$$

where the index L denotes the layer number in the ANN topology, and for each layer $l \subset L$ the function is defined as (21):

$$\begin{aligned} &\mathrm{z}^{(l)} = \mathrm{W}^{(l)}\mathrm{a}^{(l-1)} + \mathrm{b}^{(l)}, \\ &\mathrm{a}^{(l)} = \sigma^{(l)}\left(\mathrm{z}^{(l)}\right) \end{aligned}, \tag{21}$$

where:

$\mathrm{a}^{(0)} = \mathrm{x}$ the input vector containing the educational features;

$\mathrm{W}^{(l)} \in \mathbb{R}^{n_l \times m_l}$ the weight matrix, representing the numerical structure that defines the strength and influence of each connection between neurons. It is iteratively adjusted during training to enable the neural network to learn the complex relationships between input data and desired outputs;

$b^{(l)} \in \mathbb{R}^{n_l}$ the bias vector, which introduces a constant term to each neuron. It is adjusted during training to allow the network to modify the activation threshold and more accurately model the complex relationships between inputs and outputs;

$\sigma^{(l)}\left(z^{(l)}\right)$ the activation function, which applies a nonlinear transformation to the aggregated input signal of each neuron, allowing the neural network to capture complex relationships and introduce nonlinearity into the learning and prediction process.

The output of the neural network (22) represents the final result of the forward propagation process, obtained through the successive application of linear and nonlinear transformations to the input vector. It is expressed as an approximation of the unknown function that models the relationship between input data and the educational variables of interest. The prediction function is defined by the set of trained network parameters, including the weight matrices and bias vectors, which are optimized during the learning process. Through this function, the neural network estimates values such as enrollment numbers, retention rates, or graduation probabilities. The accuracy of the network's output depends both on the quality of the dataset used and on the architecture and regularization mechanisms of the neural model:

$$\widehat{y} = f_Q\left(x\right), \tag{22}$$

where: $Q = \left\{W^{(l)}, b^{(l)}\right\}_{l=1}^{L}$ defines the domain of the weight matrices and bias vectors for all layers of the ***ANN***.

For educational regression problems, the loss function is used to measure the difference between the model's predicted values and the observed real values. It quantifies the prediction error for indicators such as the estimated cohort, retention rate, or graduation rate. The loss function guides the training process by providing a clear optimization criterion. By minimizing it, the model adjusts its parameters to improve prediction accuracy. The choice of an appropriate loss function directly influences the stability and overall performance of the ANN model (23):

$$L(Q) = \frac{1}{N}\sum_{k=1}^{N}\left\| y^{(k)} - \widehat{y}^{(k)} \right\|^2, \tag{23}$$

where $\widehat{y}^{(k)} = f_Q\left(x^{(k)}\right)$.

The learning process occurs through parameter updates and is performed using gradient descent, an iterative optimization algorithm used to minimize the loss function. At each iteration, the model parameters are adjusted in the direction opposite to the gradient of the error, thereby reducing it. The step size of the updates is controlled by the learning rate, which affects the speed and stability of convergence. The process repeats until the loss function reaches an acceptable minimum or converges to a stable value. Thus, gradient descent enables the progressive improvement of the neural network's performance (24):

$$Q^{(t+1)} = Q^{(t)} - \eta \nabla_Q L. \tag{24}$$

For each layer we have (25):

$$\mathrm{W}^{(l)} \leftarrow \mathrm{W}^{(l)} - \eta \frac{\partial L}{\partial \mathrm{W}^{(l)}},$$
$$\mathrm{b}^{(l)} \leftarrow \mathrm{b}^{(l)} - \eta \frac{\partial L}{\partial \mathrm{b}^{(l)}}. \tag{25}$$

where η the learning rate, a key parameter that controls the size of the parameter update step during training. It influences both the convergence speed of the model and the stability of the optimization process. An appropriate learning rate ensures a balance between rapid learning and the accuracy of the solution obtained.

The error at the output layer represents the difference between the values predicted by the neural network and the actual values of the desired output. It is computed based on the loss function and reflects the level of discrepancy in the model's predictions. The output layer error serves as the starting point for the backpropagation process. By propagating this error backward through the network layers, the gradient required for updating the parameters is determined. Thus, the output layer error plays a central role in the adjustment and optimization of the entire neural network (26):

$$\delta^{(L)} = \left(\hat{\mathrm{y}} - \mathrm{y}\right) \odot \sigma'^{(L)}\left(\mathrm{z}^{(L)}\right). \tag{26}$$

For the hidden layers, we have (27):

$$\delta^{(l)} = \left(\mathrm{W}^{(l+1)T} \delta^{(l+1)}\right) \odot \sigma'^{(l)}\left(\mathrm{z}^{(l)}\right). \tag{27}$$

where $\odot$ denotes the Hadamard product, or element-wise multiplication.

Online and incremental learning for temporal data involves continuously updating the model as new observations become available. This type of learning allows rapid adaptation to changes in the data distribution and the dynamic evolution of the system. The model does not require full retraining; instead, it incrementally adjusts its parameters based on recent information. This approach is particularly suitable for educational systems, where data is generated sequentially and reflects temporal trends. Thus, online learning ensures updated predictions and real-time decision support (28):

$$Q(t+1) = Q(t) - \eta \nabla_Q L(t). \tag{28}$$

This allows the network to adapt to changes in the educational environment by continuously updating its parameters based on recent data. The network can efficiently respond to demographic changes, variations in educational demand, or modifications in institutional policies. By integrating new information, the model improves its predictive and generalization capabilities. Continuous adaptation contributes to maintaining output accuracy under dynamic conditions. Consequently, the neural network supports informed and flexible decision-making within the educational system.

Convergence of the learning process occurs when the loss function decreases monotonically and approaches a stable minimum over iterations. This requires an appropriate learning rate to balance convergence speed and algorithm stability. Additionally, the training data must be representative and sufficiently informative to enable model generalization. The network architecture and parameter initialization directly influence the ability to reach an equilibrium point. Under these conditions, the model parameters stabilize, and predictions become consistent and reliable (29):

$$\lim_{t \to \infty} \left\| Q^{(t+1)} - Q^{(t)} \right\| = 0, \tag{29}$$

while the loss function (23) is minimized either locally or globally.

9. Validation of research

For the purpose of validating the conducted research, an educational process for planning the student cohort was modeled, based on the dataset structure presented in Figure 2. For the modeling of the Artificial Neural Network (***ANN***), an experimental dataset was used, consisting of 20 subsets of historical data collected over the period 2020−2024. For ethical reasons and the protection of personal data, the dataset used for training is not presented in this work. The year 2020 corresponds to the completion of secondary education and admission to UTM, while 2024 represents the year of graduation from the bachelor's program at TUM. For modeling the dataset, a sequential computational architecture for the multi-agent system was selected, as defined by the mathematical model (18).

Following the training of the ANN model and its testing, the following were obtained: Graph of prediction accuracy by semesters (see Figure 3); Evolution of confusion matrices (see Figure 4); Omega Map: activation of the network's attention by semesters (see Figure 5); Histogram the final importance of the characteristics (see Figure 6).

The semester prediction accuracy graph (Figure 3) illustrates the evolution of the performance of a machine learning model over time. It shows how the accuracy of predictions changes from one semester to the next, depending on the available data and the training process. The rising values indicate an improvement in the model's ability to learn the relevant patterns. Decreases in accuracy may signal changes in data distribution or the need to adjust the model. The chart is a valuable tool for assessing the stability and reliability of medium- and long-term predictions.

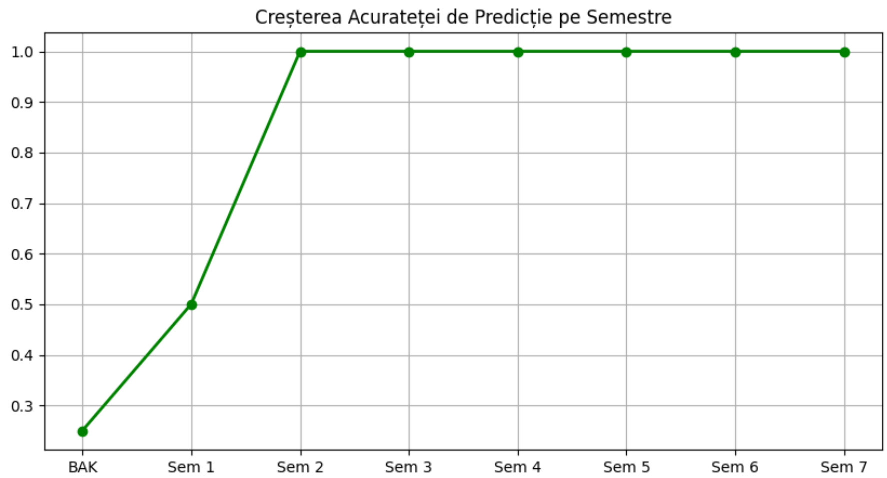

Figure 3. Prediction accuracy graph by semesters.

The evolution of confusion matrices (Figure 4) in artificial neural networks reflects how the model's classification performance improves throughout the training and validation process. The successive analysis of these matrices allows the observation of the reduction of False Positive and False Negative errors. As the network learns, the values on the main diagonal tend to increase, indicating a greater number of correct classifications. Comparing the confusion matrices between epochs or semesters highlights the stability and generalizability of the model. Changes in the structure of the matrix can signal imbalances between classes or problems of overlearning. Their evolution helps to identify classes that remain difficult to separate. Based on these observations, the hyperparameters or loss functions of the network can be adjusted. Confusion matrices thus provide a detailed insight into the internal behavior of the neural network. They complement overall metrics like accuracy or F1 score. Thus, the confusion matrix contributes significantly to the interpretation of behavior and the optimization of artificial neural networks.

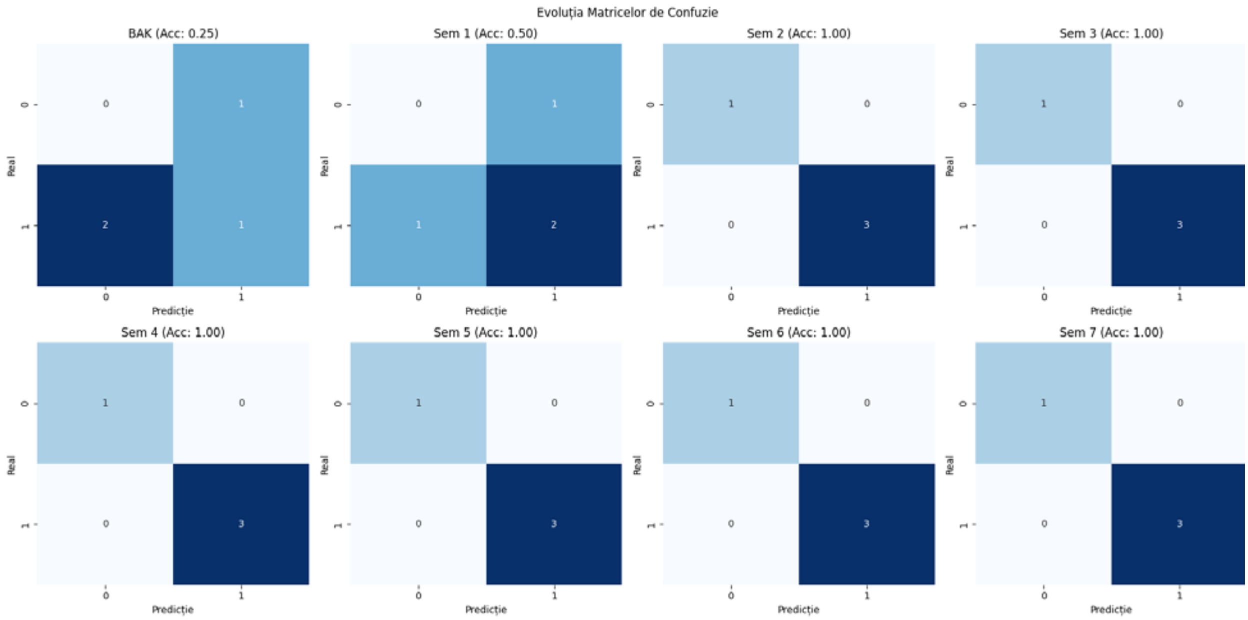

Figure 4. The evolution of confusion matrices.

The Omega semester attention map (Figure 5) is a method of visualizing how a neural network distributes attention over time-organized data by semesters.

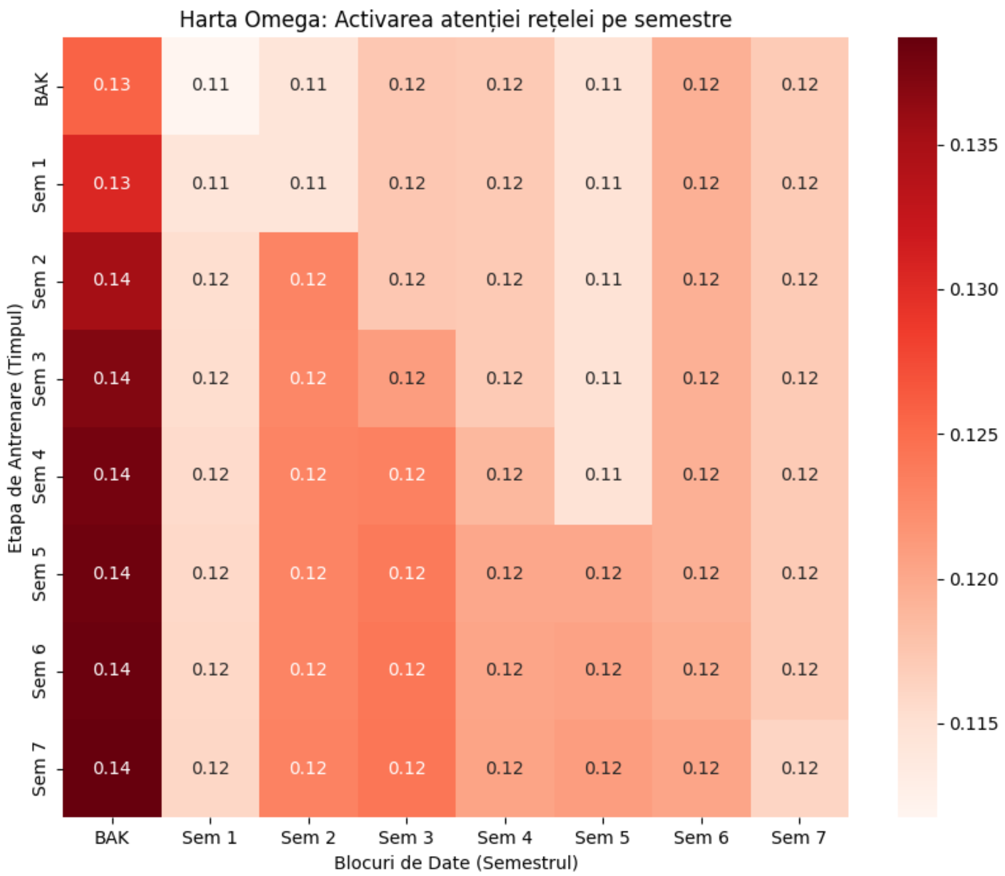

Figure 5. Omega Map: activating the network's attention by semesters.

This highlights the relative importance of each semester in the model's prediction or decision process. The values in the map reflect the level of activation of the attention mechanism, and are usually normalized within a standardized range. Semesters with high values indicate a significant contribution to the output of the neural network. On the other hand, low values signal little influence on the final result. The Omega map allows the identification of critical time periods for the evolution of the analyzed phenomenon. This helps to increase the interpretability of attention-based models. By analyzing the map, any imbalances or excessive dependencies of certain semesters can be detected. The information obtained can guide the optimization of the network architecture or the input data set. Thus, the Omega map becomes a valuable tool for the analysis, validation and improvement of temporal neural models specific to educational processes.

The final feature importance histogram (Figure 6) is a method of visualizing the contribution of each input variable to the decision of a machine learning model. It orders the features according to their level of influence on the model's results. The high values in the histogram indicate variables with a major impact on the final prediction. Low-importance features suggest limited or redundant contribution. Histogram analysis helps to understand the internal mechanisms of the model and increase interpretability. This can highlight hidden relationships between the model's input data and outputs. On the basis of the histogram, irrelevant features can be removed, simplifying the model. Reducing the number of variables can lead to decreased complexity and improved generalization. The final importance histogram is also useful for validating theoretical assumptions on data relevance. Thus, it is an important tool in the analysis and optimization of predictive models.

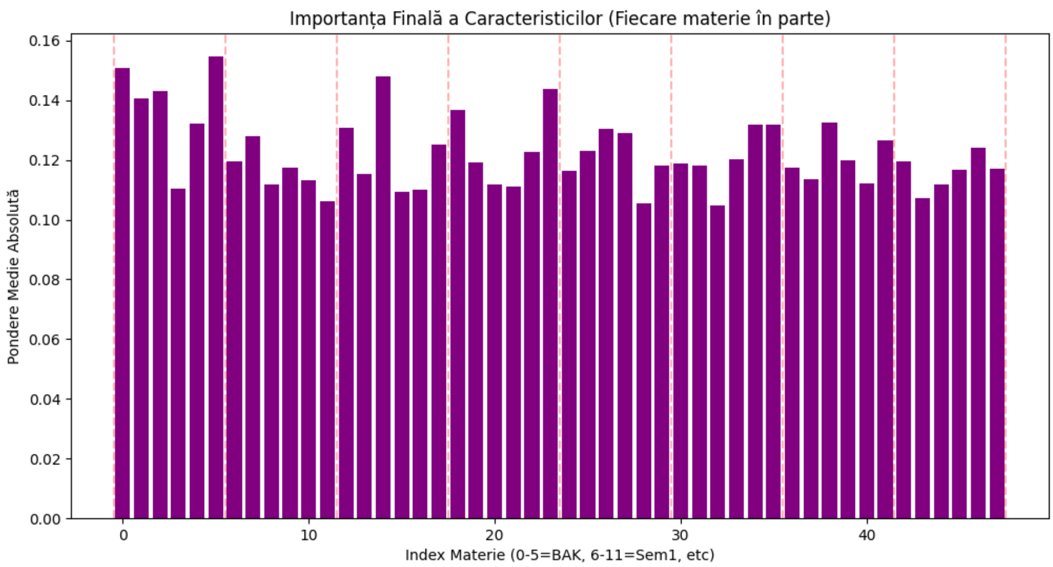

Figure 6. Histogram the ultimate importance of the characteristics.

10. Results and Discussion

Within this research, an intelligent decision-support model for planning the educational cohort was developed and validated, based on the integration of multi-agent systems with artificial neural networks. The proposed architecture enables efficient distribution of computational tasks and parallel processing of educational data streams. The neural network model was trained on an experimental dataset covering the period 2020–2024, yielding stable weight matrices. Analysis of the training process indicates proper convergence of the loss function and a progressive reduction in prediction error. The error propagation histogram confirms the stability and consistency of the learning process.

The results demonstrate the model's capability to approximate the nonlinear relationships between demographic, socio-economic factors, and educational indicators. The multi-agent system facilitates coordination of local agent decisions and their alignment with the global optimization objective. The use of online and incremental learning allows continuous adaptation of the model to changes in the educational environment. Predictions obtained for the student cohort, retention rate, and graduation rate are consistent and relevant for institutional planning.

Compared to traditional approaches, the proposed solution offers superior flexibility and scalability. The decision-making dynamics of the agents contribute to achieving a stable distributed equilibrium. The results highlight the importance of the quality of the dataset used for training. Expanding the dataset may lead to improved prediction accuracy. Overall, the research confirms the feasibility and effectiveness of the proposed architecture for decision support in educational management.

11. Conclusions

Following the conducted research, an intelligent architecture for planning the educational cohort was proposed and validated, based on the integration of multi-agent systems with artificial neural networks. The study demonstrated that the distributed approach enables efficient processing of educational data streams and coordination of decisions at the system level. The developed neural network model showed the ability to learn complex and nonlinear relationships among demographic, socio-economic factors, and educational indicators. Experimental results confirm stable convergence of the learning process and a significant reduction in prediction error.

The use of online and incremental learning allowed the continuous adaptation of the model to changes in the educational environment. The multi-agent system contributed to aligning local agent decisions with the global optimization objective. The obtained predictions provide relevant decision-support for institutional management and strategic planning. The research highlights the advantages of the proposed solution compared to traditional centralized methods, particularly in terms of scalability and flexibility. Although the results are promising, the model's performance depends on the quality and availability of the data used. Overall, the study confirms the feasibility and practical utility of distributed intelligent architectures for modern educational management.

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