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TRANSFORMING PHYSICS EDUCATION WITH NEURAL NETWORKS: MODERN APPROACHES AND TOOLS

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This article explores the current trend of using neural networks in teaching physics at the university level. The topic's relevance stems from the need to transform traditional teaching methods to meet the expectations of a new generation of students accustomed to interactive formats and digital technologies. The study aims to analyze modern neural network technologies employed in teaching various sections of physics, evaluate their effectiveness, and outline prospects for further development in this area. The research is based on a review of scientific publications on the subject and practical experiences of implementing neural network technologies in leading universities worldwide. The methodology involves systematic analysis, comparison, and generalization of existing neural network solutions. A detailed analysis of specific neural network technologies applied to different branches of physics is presented: long short-term memory (LSTM) and convolutional neural networks (CNN) for mechanics; generative adversarial network (GAN) and graph neural networks (GNN) for electromagnetism; deep reinforcement learning network (DRL) for thermodynamics; variational autoencoders network (VAE) and residual network (ResNet) for quantum physics; and deep convolutional networks and transformers for astrophysics.

The results demonstrate that implementing neural network technologies significantly enhances learning efficiency, facilitates the visualization of complex physical processes, automates computations, and enables personalized learning. It has been established that the application of various neural network architectures in the educational process fosters the development of critical thinking, a deeper understanding of physical concepts, and practical data-handling skills among students. Promising directions for further development include the creation of multimodal systems, the development of adaptive learning platforms, and the integration of virtual reality with neural network models.

Keywords: *neural networks, artificial intelligence, teaching physics, visualization, modeling, computational physics, deep learning, educational technologies.*

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INTRODUCTION

Modern university-level physics education faces several challenges, among which the difficulty of presenting complex theoretical concepts in an accessible format is particularly significant [1]. Traditional teaching methods often fail to meet the demands of the new generation, which is more familiar with interactive learning formats and digital tools.

Neural networks, as the foundation of modern artificial intelligence systems, offer unprecedented opportunities to transform the educational process in physics [2]. They enable the creation of dynamic models of physical phenomena, the visualization of abstract concepts, the automation of routine calculations, and the provision of personalized learning experiences [3].

The aim of this article is to analyze current neural network technologies utilized in teaching different sections of physics, assess their effectiveness, and outline the future potential of this area. This study is based on a comprehensive review of scientific literature and the practical experiences of integrating neural network technologies into the educational processes of leading universities.

NEURAL NETWORK TECHNOLOGIES IN TEACHING MECHANICS

Mechanics, as a fundamental branch of physics, forms the basis for further study of natural sciences. To improve the effectiveness of teaching mechanics, the architecture of neural networks such as long short-term memory, which allows modeling dynamic systems with high accuracy, has become widely used [4]. The process of modeling dynamic systems using a neural network is shown in Fig. 1.

```
[Initial Conditions]
    ├── Position (x₀)
    └── Velocity (v₀)
          ↓
+-------------------------+
|     LSTM Architecture    |
| (Processes time steps t) |
+-------------------------+
          ↓
[Predicted Position & Velocity over Time]
          ↓
[Overlay on Experimental Data Graph]
          ↓
[Error Analysis / Accuracy]
```

Fig. 1. Schematic visualization of the LSTM neural network modelling of body motion.

The PhysicsNet system, developed by researchers at the Massachusetts Institute of Technology, uses recurrent neural networks to predict the movement of bodies in a gravitational field, taking into account various factors of influence [5]. This system allows students to observe the change in motion trajectories when the initial conditions are modified in real time, which contributes to a deeper understanding of Newton's laws and conservation principles.

Another promising area is the use of convolutional neural networks to analyze videos of physical experiments. The MotionAnalyst system, developed at Stanford University, allows you to automatically detect and analyze the movement of objects in the video, build graphs of speed and acceleration versus time [6]. This greatly simplifies the process of processing experimental data and allows students to focus on interpreting the results rather than on mechanical calculations.

APPLICATION OF NEURAL NETWORKS IN TEACHING ELECTROMAGNETISM

Electromagnetism is characterized by concepts that are difficult to visualize, such as electromagnetic fields and waves. To overcome this problem, specialized neural network architectures based on generative adversarial networks have been developed.

As shown in Fig. 2, the FieldVisualizer is a system that uses GANs to generate three-dimensional visualizations of electromagnetic fields based on specified parameters [7].

```
[Input Parameters]
    ├── Field Source Type
    ├── Strength
    └── Orientation
          ↓
+---------------------+       +-----------------
|     Generator       | <───> |    Discriminator
+---------------------+       +-----------------
          ↓
[3D Vector Field Image (Colored Vectors)]
          ↓
[Interactive Viewport for Student]
```

Fig. 2. Schematic visualization of the FieldVisualizer neural network generating 3D images of electromagnetic fields.

This technology allows you to display invisible physical fields, demonstrate their interaction and dynamics in space and time. Students can interact with these visualizations by changing the parameters of field sources and observing the results of changes.

To analyze complex electrical circuits, the CircuitSolver neural network based on graph neural networks was developed [8]. This system is able to recognize circuit elements from students' handwritten notes, automatically convert them into digital circuits, and analyze their operation, including calculating currents, voltages, and powers. Thus, students receive instant feedback on the correctness of their solutions.

NEURAL NETWORKS IN TEACHING THERMODYNAMICS AND STATISTICAL PHYSICS

Thermodynamics and statistical physics operate with abstract concepts describing the behavior of large ensembles of particles. Deep reinforcement learning networks are particularly effective for modeling such systems.

The ThermoSim system, developed at the University of Tokyo, utilizes DRL architectures to simulate thermodynamic processes under varying conditions [9]. This system enables the visualization of molecular dynamics, the demonstration of phase transitions, and other complex phenomena at the microscopic level, thereby enhancing students' understanding of macroscopic thermodynamic laws (Fig. 3).

```
+----------------------------+
|    Thermodynamic System    |
|  (Particle Simulation Box) |
+----------------------------+
       ↑              ↓
  [Environment State]  ← Reward ←—+
       ↓                          |
+-----------------------+         /
|      DRL Agent        |         |
|  (Policy: actions like heat/cool)|
+-----------------------+         /
       ↓                          |
[Action: Increase/Decrease Energy] ┘
       ↓
[Observed Result: Phase Transition / ΔS]
```

Fig. 3. Schematic visualization of the system's interaction with the thermodynamic environment by the ThermoSim neural network.

For analyzing data from thermodynamic experiments, the EntropyPredictor neural network is used. Built on a hybrid architecture combining recurrent and convolutional layers, this system predicts entropy changes in complex systems based on input parameters [10]. It supports a clearer understanding of the second law of thermodynamics and its practical implications.

QUANTUM PHYSICS AND NEURAL NETWORK TECHNOLOGIES

Quantum physics is notoriously challenging due to its counterintuitive nature. To support learning in this field, the QuantumVisualizer neural network, as shown in Fig. 4, based on variational autoencoders, has been developed [11].

The QuantumVisualizer system enables the visualization of wave functions and quantum states, and illustrates concepts such as the Heisenberg uncertainty principle and quantum superposition in an interactive manner. This system also includes a module for simulating quantum experiments, such as the double-slit experiment and quantum entanglement, allowing students to experiment with parameters and observe real-time outcomes.

To solve the Schrödinger equation for complex quantum systems, the neural network, utilizing a deep residual network architecture, is employed [12]. This system can provide approximate solutions for quantum systems where analytical methods are inefficient or unavailable, significantly broadening the scope for educational exploration.

```
[Quantum Parameters (e.g., spin, potential)]
        ↓
+------------+      +-------------+
|  Encoder   | → → → |  Decoder    |
+------------+      +-------------+
        ↓
[Latent Space Representation]
        ↓
[Wavefunction Visualization (ψ(x,t))]
```

Fig. 4. Schematic representation of quantum state visualization by the QuantumVisualizer neural network.

NEURAL NETWORKS IN ASTROPHYSICS AND COSMOLOGY

Astrophysics and cosmology operate with huge amounts of data obtained from telescopes and other astronomical instruments. To analyze this data, the CosmicNet system based on deep convolutional neural networks was developed [13].

CosmicNet is capable of classifying galaxies, detecting exoplanets, and analyzing spectral data of stars (Fig. 5). The system also includes a module for visualizing cosmological simulations, allowing students to observe the evolution of the universe from the Big Bang to the present.

The GravityWaveNet neural network, built on the basis of transformers, is used to analyze gravitational waves recorded by the LIGO and Virgo detectors [14]. This system allows detecting and classifying gravitational wave signals from various astrophysical sources, which opens up new opportunities for studying extreme objects of the Universe.

```
[Input: Astronomical Image]
        ↓
+-----------------------------+
|   Convolutional Layers      |
| (Feature extraction, pooling)|
+-----------------------------+
        ↓
[Galaxy Classification (e.g., Spiral, Elliptical)]
        ↓
[Tag + Database Visualization]
```

Fig. 5. Schematic visualization of galaxy classification by the CosmicNet neural network.

CONCLUSIONS

The analysis of current neural network technologies in physics education demonstrates their substantial potential to transform teaching methodologies. The application of various neural network architectures to different sections of physics effectively addresses challenges related to data visualization, modeling, and analysis.

Integrating neural networks into the educational process fosters critical thinking, an intuitive understanding of physical principles and practical data handling skills. Furthermore, these technologies facilitate personalized learning by adapting to each student's individual pace and needs.

Promising areas for future neural network application development in physics education include creating multimodal systems integrating text, images and videos, developing adaptive learning platforms, and incorporating virtual and augmented reality into neural network-based learning environments.

Further research should focus on evaluating the effectiveness of different neural network architectures for specific educational tasks, developing integration strategies for traditional curricula and training educators to use these technologies effectively.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interests.

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ТРАНСФОРМАЦІЯ ФІЗИЧНОЇ ОСВІТИ ЗА ДОПОМОГОЮ НЕЙРОННИХ МЕРЕЖ: СУЧАСНІ ПІДХОДИ ТА ІНСТРУМЕНТИ

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У статті досліджуються сучасні тенденції використання нейронних мереж при викладанні фізики в закладах вищої освіти. Актуальність теми зумовлена нагальною необхідністю трансформації традиційних методів навчання для відповідності очікуванням нового покоління студентів, яке звикло до інтерактивних форматів та цифрових технологій. Метою дослідження є аналіз сучасних технологій нейронних мереж, які застосовуються у викладанні різних розділів фізики, оцінка їх ефективності та окреслення перспектив подальшого розвитку в цій сфері. Дослідження базується на ретельному огляді наукових публікацій з цієї тематики та на практичному досвіді впровадження нейронних мереж у провідних університетах світу. Методологія дослідження передбачає системний аналіз, порівняння та узагальнення наявних рішень на основі нейронних мереж. Представлено детальний аналіз конкретних технологій нейронних мереж, застосованих у різних галузях фізики: мережа з довготривалою короткочасною пам’яттю (LSTM) і згорткова нейронна мережа (CNN) - для механіки; генеративна змагальна мережа (GAN) і графова нейронна мережа (GNN) - для електромагнетизму; глибокі нейронні мережі з підкріпленням (DRL) - для термодинаміки; нейромережа, що базується на варіаційних автоенкодерах (VAE) і нейромережа, яка використовує архітектуру глибоких залишкових мереж (ResNet) - для квантової фізики; глибокі згорткові мережі та трансформери - для астрофізики.

Результати показують, що впровадження технологій нейронних мереж суттєво підвищує ефективність навчання, сприяє візуалізації складних фізичних процесів, автоматизує обчислення та забезпечує персоналізоване навчання. Встановлено, що застосування різних архітектур нейронних мереж у навчальному процесі сприяє розвитку критичного мислення, глибшому розумінню фізичних понять і формуванню практичних навичок роботи з експериментальними даними у студентів. Перспективними напрямами подальшого розвитку є створення мультимодальних систем, розробка адаптивних навчальних платформ та інтеграція віртуальної реальності з моделями нейронних мереж.

Ключові слова*: нейронні мережі, штучний інтелект, викладання фізики, візуалізація, моделювання, обчислювальна фізика, глибоке навчання, освітні технології.*