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Editorial

Artificial intelligence and complex networks meet natural sciences

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Abstract This special issue delves into the transformative synergy between artificial intelligence (AI) and complex network science, showcasing cutting-edge research that spans theoretical foundations and practical applications across diverse domains of natural sciences. The collection, which included 9 reviews and 86 regular articles highlights how AI and network-based approaches are revolutionizing fields such as neuroscience, biomedicine, climate science, and nonlinear dynamics. Key themes include advances in machine learning methodologies, from federated learning to spiking neural networks, and their applications in medical diagnostics, biophysical modeling, and robotics. The issue also explores AI-driven insights into chaotic systems, synchronization phenomena, and neuromorphic computing, offering novel solutions to classical problems in nonlinear dynamics. In neuroscience, contributions demonstrate the power of graph-analytical methods combined with AI for understanding brain connectivity, diagnosing disorders, and developing brain–computer interfaces. Biomedical applications feature innovative AI tools for disease detection, personalized medicine, and medical imaging, while environmental research presents AI-enhanced climate modeling and sustainable resource management. The issue emphasizes the growing importance of interpretable AI, cross-disciplinary collaboration, and energy-efficient computing architectures. By bridging statistical physics, computer science, and life sciences, these works pave the way for future breakthroughs in understanding and harnessing complex systems.

1 Introduction

The intersection of artificial intelligence (AI) and complex network science has emerged as a transformative force in modern nonlinear sciences, enabling groundbreaking discoveries and innovative solutions to long-standing challenges [1, 2]. This special issue is dedicated to exploring the synergy between these fields, highlighting their

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profound impact on both theoretical advancements and practical applications across diverse domains-from physics and neuroscience to climate science and biomedicine.

The relevance of this interdisciplinary research has been underscored by the 2024 Nobel Prize in Physics, awarded to John J. Hopfield and Geoffrey E. Hinton for their pioneering contributions to neural networks. Hopfield's foundational work on associative memory models-Hopfield networks-bridged statistical physics and neural networks theory, providing deep insights into the dynamics of complex systems. Meanwhile, Hinton's revolutionary developments in deep learning, including backpropagation and Boltzmann machines, have redefined machine learning and its applications. Together, their research has laid the groundwork for modern AI, fostering cross-disciplinary collaborations between physics, computer science, and neurobiology [3].

This interdisciplinary approach has far-reaching implications:

- *In Machine Learning* Integrating statistical mechanics principles into neural networks enables advanced optimization strategies, such as simulated annealing. Topological insights enhance architectures like convolutional neural networks (CNNs) and graph neural networks (GNNs), improving their robustness and adaptability [4].
- *In Physics-Informed AI* Neural networks can model complex physical systems by incorporating energy-based constraints, topological priors, and principles from nonlinear dynamics. By embedding the structure of differential equations-particularly those governing chaotic and multistable systems-into AI architectures, researchers achieve more interpretable and physically consistent models [5]. In particular, recurrence neural networks and reservoir computing excel in learning nonlinear dynamical systems, from turbulent fluid flows to biological oscillators [6, 7]. Delay embedding and attractor reconstruction techniques, rooted in Takens' theorem, allow AI to infer latent dynamics from partial observations, aiding climate modeling and neuroscience. These approaches bridge theory of dynamical systems-such as bifurcation analysis and Lyapunov exponents-with modern deep learning, offering new tools to predict tipping points in climate, control robotic systems, and decipher neural activity patterns.
- *In Neuroscience* The brain, as a complex network, benefits from a combined statistical-topological perspective. Techniques from graph theory and persistent homology allow researchers to analyze functional connectivity networks, uncovering patterns linked to cognition and neurological disorders [8]. Machine learning technologies are revolutionising approaches to rapidly and accurately processing and understanding pattern brain activity, which holds promise for new ways of human–machine communication [9].
- *In Biomedicine* AI-driven network science is revolutionizing disease modeling, drug discovery, and personalized medicine [10]. By analyzing biological networks-such as protein-protein interactions and gene regulatory networks-researchers can identify novel biomarkers, predict drug responses, and uncover mechanisms of complex diseases like cancer and neurodegenerative disorders. Deep learning models, combined with topological data analysis, enhance medical imaging, enabling early and precise diagnostics [11]. The development of technologies for analyzing different types of neuroimaging at the intersection of complex network theory and machine learning with the use of graph neural networks and contrastive learning allows diagnosing mental illnesses with the highest accuracy [12, 13].
- *In Climate and Environmental Science* Complex network approaches help to decode climate variability, particularly in predicting extreme events like El Niño and monsoon onset, in particular, to identify teleconnections (long-range climate linkages) and overcome the 'spring predictability barrier,' extending forecast horizons by months [14–16]. Machine learning models trained on network-structured environmental data optimize resource management, track deforestation, and assess ecosystem resilience. Additionally, AI-powered network analysis aids in monitoring pollution spread and designing sustainable urban systems.

So, today, AI and complex network approaches are indispensable in deciphering complex patterns in large-scale non-stationary data, from functional brain networks to climate systems. Machine learning (ML), in particular explainable AI (XAI), plays a critical role in medical diagnostics, enabling early detection of neurological disorders through biomarker identification [17]. The works that contributed to our special issue correspond to these interdisciplinary directions, and we subdivide the contributions into five main fields:

1. *Frontiers of Machine Learning: Theory and Innovation* Exploring novel algorithms, architectures, and frameworks in AI/ML (e.g., federated learning, spiking neural networks, attention mechanisms, quantum ML, and AutoML).
2. *Chaos and Complexity: AI in Nonlinear Dynamics* Bridging machine learning with physics, chaos theory, and dynamical systems (e.g., chaotic systems, synchronization, robotics, memristors, and reservoir computing).
3. *Decoding the Brain: AI and Graph-Analytical Methods in Neuroscience* Advancing brain research with ML-from connectivity to disorders and consciousness (e.g., fMRI, EEG, schizophrenia, neuroplasticity, and brain-computer interfaces).
4. *Healing with Data: AI in Biomedicine* Transforming diagnostics, treatment, and healthcare with intelligent systems (e.g., cancer detection, mental health, medical imaging, and digital twins).

5. *Green Intelligence: AI for Climate and Environment* Harnessing ML to model ecosystems, predict climate trends, and protect resources (e.g., temperature forecasting, pollution mapping, and water management).

Below, we provide a detailed overview of the contributions within this special issue.

2 Frontiers of machine learning: theory and innovation

Here we mention the methodologically oriented contributions. Our classification is only for convenience and is not strict since many of the papers mentioned here are closely related to different applications.

Andrikov [18] reviews an open-source AutoML frameworks tailored for biophysical models, addressing the gap in existing tools by incorporating biomedical-specific fine-tuning and "out-of-the-box" functionalities. The study highlights applications in multimodal data integration, including cardiac signals, neuroimaging, genomics, and electronic health records, demonstrating how automated ML can enhance diagnostic accuracy and accelerate personalized medicine. While the framework shows promise in streamlining biophysical analyses, the author emphasizes the need for improved regulatory standards and validation methodologies.

Soloviev and Klinshov [19] investigate the intricate cost function landscape of a simple neural network in a regression task, revealing unexpected complexity despite the model's minimalistic design. The study identifies a vast multiplicity of local minima, most of which are highly suboptimal, with optimal solutions occupying only a narrow subset of the phase space. These global minima exhibit a distinctive geometry-combining steep and flat directions-which the authors link to the challenges faced by standard optimization algorithms. The findings underscore fundamental limitations in gradient-based training and prompt reconsideration of learning dynamics even in "simple" ML problems.

Appasami and Savarimuthu [20] implement a federated learning framework for secure MRI brain tumor classification, combining transfer learning from ImageNet with VGG-based CNNs. Their approach maintains 98.4% classification accuracy while preserving data privacy, demonstrating how distributed learning can achieve state-of-the-art performance in sensitive medical image analysis.

Anpilogov et al. [21] develop a novel method for assessing rowing proficiency by combining continuous wavelet transforms of gyroscopic data with interpretable machine learning (SIRUS algorithm). Their pilot study demonstrates that wavelet-spectral features from skilled and unskilled rowers under varying power loads can generate quantitative rules aligning with professional trainer evaluations, suggesting practical applications in sports training.

Makarov and Lipkovich [22] propose a transformer-based model for predicting future diseases from electronic health records, employing a two-stage training approach with BERT-inspired architectures. Their encoder-decoder models achieve complementary performance metrics (46.32% precision vs 46.17% recall across implementations), offering flexible solutions tailored to different diagnostic requirements in clinical prediction tasks.

Soloviev et al. [23] propose a novel dynamic convolution architecture for CNNs where kernels are generated based on input data. Their two-branch network, tested on MNIST, outperforms standard CNNs in both learning speed and accuracy. This approach shows promise for various applications including image analysis, time series forecasting, and physics-informed machine learning.

Kurbako et al. [24] demonstrate image recognition capabilities in compact spiking neural networks ($10 \div 50$ neurons) using spike-timing-dependent plasticity (STDP) learning, showing two distinct recognition modes: single-neuron specificity versus population coding patterns. Their noise-resistant system achieves unsupervised classification of simple binary images through emergent spike-timing dynamics.

Lobov et al. [25] investigate memory consolidation in spiking neural networks, showing STDP-driven synaptic rewiring enhances memory reliability by facilitating hub neuron formation. Their computational model resolves the plasticity-stability dilemma, revealing structural plasticity's critical role in balancing memory preservation and forgetting in biological networks.

Vadivel et al. [26] develop an event-triggered control scheme for synchronizing Markovian jump neural networks under cyber-attacks, formulating stability conditions via Lyapunov–Krasovskii functionals and LMI techniques. Their approach achieves resource-efficient state containment in complex-valued networks, with numerical simulations validating the method's effectiveness for bounded synchronization error control.

Some of the papers included in this Section focus on various innovative applications of machine learning technologies.

Atban et al. [27] propose a quantum-classical hybrid approach combining Variational Quantum Classifiers with meta-heuristic feature selection (PSO/ACO/ASO) for credit card fraud detection. Their PSO-optimized quantum model achieves 94.5% accuracy on imbalanced datasets using SMOTE-ENN balancing, demonstrating quantum machine learning's potential for financial security applications requiring high-dimensional data processing.

Chandrabanshi and Domnic [28] develop a visual speech recognition system using 3D-CNN with BiGRU-BiLSTM and multi-head attention to enhance face authentication security. Achieving 0.79% word error rate, their lip motion analysis provides robust liveness detection against sophisticated spoofing attacks in biometric systems.

Didmanidze et al. [29] optimize plant disease detection through a modified VGG16 architecture, outperforming ResNet-50 and EfficientNet in both accuracy and computational efficiency for tomato leaf analysis. Their lightweight deep learning solution addresses practical agricultural needs for deployable crop health monitoring tools.

Zhang et al. [30] design a two-stage PDSwin transformer for rice disease classification, combining Hard-GELU activation and PDsamp downsampling to boost Swin-T's speed by 15.4% while maintaining $94.8 \div 95.7\%$ accuracy across complex field backgrounds. The background-aware classification stage dynamically selects processing paths for different imaging conditions (close-up leaves vs field shots). The mobile-deployed solution processes images in under 0.8 s on mid-range smartphones, enabling practical use by farmers.

Ekinci et al. [31] combine Chimp Optimization Algorithm with BiLSTM networks to predict PEM fuel cell degradation, achieving 0.007 RMSE on industry datasets. Their ChOABiLSTM model demonstrates superior performance over conventional LSTM variants, offering precise voltage prediction for hydrogen energy system maintenance.

Laptev et al. [32] evaluate AI models for alcohol intoxication detection via speech analysis, finding gradient boosting (F1-score = 0.78) outperforms CNNs and logistic regression. Their comparative study of speech recognition systems under intoxication identifies Whisper as most robust, while cosine similarity emerges as the optimal metric aligning with human clarity assessments for safety applications.

Korchagin [33] develops a CNN-based emotion recognition system achieving $> 90\%$ accuracy, applied to evaluate bank advertising campaigns through neuromarketing paradigms. The study compares SVM/ANN/CNN performance for affective computing tasks, demonstrating practical utility in optimizing customer engagement strategies through real-world commercial case studies.

Telceken et al. [34] introduce an automated label conversion algorithm for YOLO-based medical image segmentation, streamlining ground-truth mask processing for polyp detection. Their contour extraction method preserves fine anatomical details through adaptive thresholding and morphological operations, showing improved performance across YOLOv5/v7/v8 architectures while reducing manual annotation effort in clinical imaging workflows. The algorithm's compatibility with DICOM format facilitates integration into existing medical imaging pipelines.

Ren et al. [35] propose EPC-GANet, a lightweight attention network for rice disease detection, combining partial convolution downsampling (PCDEM) and guided attention (EGAM) to achieve 97.1% accuracy with only 0.97 MB model size. The MaxDepth Pooling module enhances feature extraction from diseased leaf patterns while maintaining computational efficiency. Their mobile-compatible solution enables real-time field diagnosis without cloud dependency, particularly valuable in rural areas with limited connectivity.

Vishnuppriyan et al. [36] propose a novel dual-path deep learning architecture for citrus leaf disease detection, combining an Efficient Multiscale Cross Attention track with a Pyramid Vision Transformer (PVT) pathway. Their hybrid network achieves 96.7% accuracy by simultaneously capturing local multi-scale features through attention mechanisms and global contextual patterns via transformer architecture, outperforming conventional methods. This work represents the first integration of efficient channel attention with PVT for agricultural image analysis, offering a robust solution for automated plant disease monitoring.

Khvostenko et al. [37] develop a two-parameter text distortion model simulating ASR/OCR errors to study natural language redundancy and readability. Their synthetic distortion framework enables systematic evaluation of text processing robustness under noise conditions, providing insights for improving recognition systems' error tolerance and automatic readability assessment.

Atban et al. [38] develop a DL system for non-barcoded product recognition using their novel MAKBUL dataset (4500 RGB images across 30 categories). Their optimized DenseNet201 model achieves 96.56% accuracy through feature-level fusion, demonstrating transfer learning's effectiveness in retail automation. This research establishes foundations for reducing checkout times while suggesting future improvements through expanded datasets and varied environmental conditions.

Vodichev et al. [39] develop a real-time monocular distance estimation algorithm for autonomous forklifts, achieving $20 \div 25$ FPS processing with errors within 10% of actual distance ($0.05 \div 0.21$m range). Their geometric model, implemented on Jetson Orin NX, demonstrates practical viability for warehouse navigation through successful pallet detection tests.

3 Chaos and complexity: AI in nonlinear dynamics

These articles collectively advance nonlinear dynamics and ML applications, from chaos control to synchronization and coupling detection. They explore synchronization phenomena and bio-inspired neuromorphic computing, including chemical diodes and memristor-based systems, demonstrating cutting-edge synergies between dynamical systems theory and AI.

Valle et al. [40] propose a ML approach to control transient chaos in the Lorenz system. Using a transformer-based model, they predict safety functions to sustain chaotic trajectories without iterative fine-tuning. The method outperforms classical control techniques, maintaining chaos even under noise, and provides a comparative analysis of safety functions and their efficacy.

Calgan et al. [41] investigate the classification of fractional-order chaotic systems (FOS-H and FOS-K) using deep learning. By generating a large dataset of time series, they evaluate pretrained models like DarkNet-53 and GoogleNet, which achieve near-perfect accuracy even for unseen fractional orders. The study highlights GoogleNet's efficiency for real-time applications and contrasts deep learning with classical methods (e.g., SVM), showing superior adaptability to complex fractional dynamics.

Akgul et al. [42] employ deep learning to classify attractor projections of five Sprott chaotic systems (C, F, G, H, M). Using pretrained models (ResNet50, VGG19, etc.), they achieve 91.6–99.9% accuracy in identifying chaotic systems from generated time-series images. The high accuracy demonstrates the method's potential for real-world applications, such as analyzing complex industrial systems.

Roy et al. [43] solve a $(1+1)$-dimensional fractional Granular model using multilayer neural networks. By integrating fractional Lax pairs and custom activation functions, they derive breather, lump, and shock-wave solutions. Wave interactions (e.g., absorption/reabsorption) are visualized, highlighting the impact of fractional order on dynamics.

Sharifi et al. [44] propose a novel observer-based control strategy combining sliding mode methods with RBF neural networks for consensus tracking in non-linear synchronous generator systems. Their approach handles disturbances and unmodeled dynamics in multi-agent systems, using neural networks to identify follower agent dynamics while ensuring stability through Lyapunov theory. MATLAB simulations demonstrate the method's effectiveness in achieving asymptotic convergence of consensus errors.

Pavlov and Pavlova [45] investigate scaling properties of correlated/anti-correlated data using extended detrended fluctuation analysis (EDFA), revealing that negative scaling exponents emerge from stationary profiles of anti-correlated signals. Their findings enhance interpretation of EDFA applications in brain dynamics analysis, demonstrating how correlation types influence nonstationarity characterization in complex systems.

Hramkov et al. [46] compare phase extraction methods for biological time series, proposing a hybrid approach combining Hilbert transform and driven oscillator techniques. Testing on photoplethysmogram and RR-interval data shows their method reduces phase jump errors versus pure Hilbert methods while maintaining the accuracy of oscillator-based approaches, offering improved reliability for oscillatory signal analysis.

Vakhlaeva et al. [47] propose neural networks (fully connected, convolutional, recurrent) to detect unidirectional coupling in noisy, ultrashort time series of Van der Pol oscillators. While fully connected networks show noise resistance, convolutional networks excel at weak-coupling detection. The approach bypasses traditional model-based methods, offering promise for real-time applications like personalized medicine.

Korotkov et al. [48] investigate chaotic dynamics in coupled heteroclinic cycles with chemical synaptic connections, extending previous work on diffusive coupling. Their analytical and numerical study demonstrates how synaptic interactions between cycles—prevalent in neural systems—can generate and maintain chaotic behavior, while characterizing the bifurcation scenarios leading to chaos emergence and termination. The findings advance theoretical neuroscience by bridging heteroclinic network theory with biologically realistic coupling mechanisms observed in brain dynamics.

Moskalenko et al. [49] study intermittent generalized synchronization in unidirectionally coupled chaotic systems with attractors of differing topological complexity. They demonstrate that on-off intermittency occurs regardless of whether the driving system has a simpler or more complex attractor than the response system. The analysis is supported by numerical examples, including coupled Rössler–Lorenz systems and radiotechnical oscillators, with a discussion of the underlying mechanisms.

Ismailov et al. [50] develop a theoretical framework optimizing lift generation in flapping-wing systems through analytical modeling of wing-airflow interactions. Their study identifies an optimal angle of attack maximizing lift force, validated experimentally with commercial ornithopters, providing key parameters for intelligent flight control in bio-inspired aerial systems.

Maslennikov et al. [51] implement binary classification using ring-structured FitzHugh-Nagumo neuron reservoir computers, demonstrating how spatiotemporal dynamics transform nonlinear inputs into separable representations. Their biologically-inspired architecture bridges computational neuroscience and ML, with analysis of rate-based versus temporal encoding strategies informing neuromorphic computing designs.

Nazrin et al. [52] investigate Nd2O3-doped glasses using ANN modeling, demonstrating superior optical property prediction over linear regression ($R^2 = 0.99$) through hidden layer feature learning. Their machine learning approach captures nonlinear dopant concentration effects on refractive index and absorption spectra, validated through FTIR structural analysis showing TeO_3/TeO_4 unit transformations. The models successfully predict properties for new glass compositions, accelerating material development cycles.

Safonov et al. [53] design a chemical diode for neuromorphic computing using a Belousov–Zhabotinsky reaction-diffusion system. Photopolymerized gel layers enable unidirectional wave propagation, validated via a geometric-parameter-dependent mathematical model. The system mimics directional signal transmission in neural networks.

Das et al. [54] develop a novel Type II memristor for neuromorphic applications. As an autapse in an HR neuron model, it induces chaotic dynamics; as synaptic coupling, it enables phase synchronization in a bi-neuron network.

A memristor-based CNN kernel achieves 99% accuracy on MNIST, showcasing its potential for energy-efficient image recognition.

Petrov et al. [55] propose an analog-digital hybrid architecture for in-situ training of deep neural networks, featuring CMOS-integrated synaptic crossbars for matrix operations and digital weight storage. Their compiler-automated design methodology, supported by SPICE simulations, addresses power efficiency challenges in large-scale DNN implementations while maintaining backpropagation compatibility.

4 Decoding the brain: AI and graph-analytical methods in neuroscience

The articles on applications to neuroscience demonstrate the breadth of topics in neuroscience that can be approached in terms of applications of ML and graph-analytic approaches to classification, prediction, brain activity analysis, etc in both experimental research and computational neuroscience tasks. It should be noted that we have assigned the issues of diagnosis and therapy of brain diseases to this section and not to the Sect. 5.

There are four interesting reviews to note at the outset. In the first, Jonna and Natarajan [56] present a comprehensive review of ML/DL applications in EEG-based neurological disorder diagnosis, highlighting innovations like MIN2Net's deep metric learning and hybrid CNN-DWT architectures. The study emphasizes emerging trends in transfer learning, cloud integration, and transformer models for scalable real-time neurological monitoring systems.

In the second, Atanasova et al. [57] investigate functional connectivity alterations in opioid use disorder through resting-state fMRI analysis. Their mini-review synthesizes existing research on network disruptions (DMN, SN, ECN) while presenting original findings from 42 participants (19 opioid users). The study reveals significant connectivity impairments in cognitive control networks, particularly highlighting methodological challenges in the field. The authors emphasize the need for standardized protocols and longitudinal studies to advance personalized treatment approaches for addiction.

Khorev et al. [58] conduct a review of AI applications in mental healthcare, revealing shifting trends from robotics and human-computer interactions toward DL/virtual reality (VR) approaches, particularly for autism spectrum and cognitive impairment research. Their network-based review methodology maps the evolving landscape of computational psychiatry tools and therapeutic technologies.

Finally, Saranskaia et al. [59] review MEG-based brain state classification strategies, demonstrating how research objectives determine optimal data representation choices. They show sensor-level signals with classical ML (LDA/SVM) suit rapid diagnostics, while source-localized signals better serve anatomical mapping when combined with deep learning. The analysis systematically links methodological choices to specific applications like BCIs and functional connectivity studies.

A number of papers have focused on the diagnosis of brain diseases or the progress of therapies using ML/DL and graph-analytic approaches using various neuroimaging technologies.

Portnova et al. [60] investigate EEG responses to tactile stimuli in unconscious patients (coma, vegetative state) as a foundation for AI-driven classification of consciousness levels. The study identifies two distinct neural signatures: (i) a non-specific response (alpha/beta power increases, linked to sensorimotor activation and working memory), and (ii) a selective theta-rhythm decrease in central regions for pleasant touch (soft brush), exclusive to subacute coma patients. These differential patterns-especially beta-power as a marker of vegetative state and theta suppression as a subacute-phase indicator-highlight potential biomarkers for consciousness assessment. The findings pave the way for AI tools to refine diagnostics and prognostics in disorders of consciousness.

Mayorova et al. [61] also addresses socially relevant issues in the therapy of unconscious patients and investigate the neuromodulatory effects of cervical epidural spinal cord stimulation (SCS) in patients with chronic consciousness disorders, demonstrating through fMRI analysis that SCS enhances both intra- and interhemispheric functional connectivity in motor areas while preventing network disintegration observed in controls. This pilot study ($N = 9$ experimental vs $N = 9$ control) reveals SCS-induced reorganization of sensorimotor networks and nonspecific connectivity changes in consciousness-related systems, providing preliminary evidence for SCS's potential to modulate higher-order neural circuits, though the exact mechanisms require further elucidation. The work advances understanding of SCS neurophysiology while highlighting methodological challenges in interpreting connectivity changes in disordered consciousness.

Chronic consciousness disorders are also the focus of a paper by Khorev et al. [62] in which the authors examine the functional connectivity alterations in chronic consciousness disorders using resting-state fMRI, identifying significant disruptions in subcortical-cortical circuits (thalamus, caudate, raphe nuclei) through network-based statistics. Their synergistic approach combining permutation tests and geodesic metrics demonstrates impaired global efficiency and nodal strength, advancing objective diagnostic biomarkers for consciousness impairment.

Shanarova et al. [63] present a breakthrough in neuropsychiatric diagnostics, achieving exceptional classification accuracy (96.7% sensitivity, 97.7% specificity) for schizophrenia through an innovative combination of Blind Source Separation (BSS) for ERP decomposition and SVM machine learning, outperforming conventional ERP analysis methods and offering new insights into cortical dysfunction patterns.

Stoyanova et al. [64] alalyse the relationship between neural network structures and personality traits using combined unsupervised and supervised machine learning techniques. Analyzing resting-state fMRI data and Lowen bioenergetic test results, they identify specific correlations between network metrics (eigenvector centrality, clustering coefficient) and personality characteristics. Their hybrid approach achieves 90% precision in predicting these relationships, revealing three principal components that explain 99% of the data.

Paunova et al. [65] employ multivariate linear modeling of fMRI data during Stroop/n-back tasks to distinguish depressed patients (n=24) from controls ($n = 26$). Their analysis reveals distinct eigenvalue patterns in principal components that differentiate diagnostic groups, highlighting disrupted interactions between sensory, cognitive and emotional networks in Major Depressive Disorder at the systems level.

Trufanov et al. [66] identify metabolic abnormalities in cingulate gyrus subregions of post-COVID patients using MR-spectroscopy. They find decreased NAA, Cr, and glutathione levels correlate with cognitive symptoms, particularly in the posterior cingulate where elevated lipids and reduced glutamate suggest neuronal dysfunction. The findings support AI-assisted metabolic analysis for improved post-COVID syndrome diagnosis.

Another work aimed at studying the consequences of the pandemic of COVID-19 was the work of Turufanov et al. [67] in which the authors comsider post-COVID neurological sequelae through multimodal MRI and neuropsychological testing in 24 mild COVID-19 survivors. Their study reveals bilateral accessory nucleus atrophy (clinically significant on dominant side) accompanied by decreased default mode/visual network connectivity and increased fractional anisotropy in cognitive-associated white matter tracts, suggesting compensatory neural reorganization. The identified biomarkers—left accessory nucleus volume reduction, tract-specific FA increases, and Head test performance errors—enable comprehensive assessment of post-COVID cognitive impairments through combined neuroimaging and psychometric evaluation.

Grubov et al. [68] propose an error-aware CNN cascade for epileptic seizure detection that reduces false positives by an order of magnitude. Their two-stage approach combines wavelet-preprocessed EEG analysis with iterative error correction, showing clinical potential through testing on unrefined hospital recordings while maintaining high recall.

Tynterova et al. [69] investigate immunological markers for cerebral microangiopathy and Alzheimer's disease, analyzing cytokine profiles across 85 patients with cognitive decline. Their study reveals distinct cytokine patterns (elevated IL-6/IL-1β in microangiopathy vs reduced GM-CSF in Alzheimer's) and cognitive profiles, though machine learning models achieved limited discrimination (F1 ≤ 0.75). The findings highlight potential biomarkers while underscoring the need for larger multicenter studies to validate immunological signatures for differential diagnosis.

A number of articles were devoted to the issues of sensory substitution, sensorimotor integration and decoding of motor patterns of brain activity, which is relevant both for the tasks of creating brain–computer interfaces and for rehabilitating motor skills of patients.

Butorova and Sergeev [70] conduct a systematic analysis of the evolution of sonification methods for sensory substitution, identifying three traditional approaches (line-by-line conversion, holistic image auditoryization, 3D sonification) and two AI modernization directions (pre-/post-processing of data). The authors identify the key problem of cognitive overload of users and propose a classification scheme linking classical and modern methods.

Sagatdinov et al. [71] investigate recognition of arbitrary motion training from EEG, demonstrating $72 \div 77\%$ accuracy of binary classification using optimized ML models (SVM, random forest) with a combination of temporal and frequency features, where SHAP analysis revealed differential feature contribution to prediction.

Pitsik [72] detects age-related sensorimotor changes through a VR experiment combining recurrent quantitative analysis and parietal theta networks, revealing hypercompensation of working memory in the elderly during sequential sensorimotor tasks.

Muthureka et al. [73] address Cerebral Palsy handwriting recognition with a KMNR noise-filtering CNN, improving accuracy from 93.5 to 98.9% on a specialized 43,000-image dataset collected from 43 participants. Their preprocessing method uses k-means clustering to isolate digit strokes from tremor artifacts, enhancing F1-scores by $7 \div 13\%$ across benchmark models. The system's low latency (under 50 ms per image) meets real-time assistive technology requirements for motor-impaired users.

Several papers have focused on different aspects of research in cognitive neuroscience from issues of eye movement signal processing in cognitive visual tasks, to issues of assessing the brain's response to different types of tactile stimuli.

Antipov [74] investigates oculomotor patterns during prolonged exposure to ambiguous visual stimuli (Necker cube), revealing that fixation duration correlates with error rates while pupil dilation marks error-prone trials. Despite increasing fatigue, participants show improved performance over time, suggesting adaptive cognitive strategies in perceptual decision-making under ambiguity.

Badarin et al. [75] investigate the relationship between brain wave entropy and visual task performance in schoolchildren using recurrence time entropy analysis of EEG signals. Their study demonstrates that higher entropy in alpha and beta rhythms correlates with faster reaction times during visual search tasks, suggesting entropy as an effective indicator of visual information processing efficiency in children aged 8–11 years.

Kuc [76] identifies alpha-band frontal cortex scaling exponents (DFA-exponents) as neurophysiological markers of intelligence test performance in children 8–10 years old. The study demonstrates machine learning-validated correlations between long-range temporal EEG correlations and Raven's Matrices scores, suggesting resting-state brain dynamics as potential biomarkers for cognitive assessment.

Boronina et al. [77] investigate how repeated visual stimuli processing affects functional connectivity, showing decreased phase locking between occipito-parietal and central regions correlates with faster response times. Their EEG study distinguishes these adaptive connectivity changes from fatigue effects (measured via blink analysis), suggesting neural efficiency improvements rather than performance degradation mechanisms.

Khorev et al. [78] investigate neural correlates of affective touch using fMRI, revealing significant modulations in default mode network activity and specific changes in amygdala/orbitofrontal regions through ICA analysis. These findings elucidate neurobiological mechanisms underlying tactile-emotional processing, with implications for touch-based therapeutic interventions.

Three papers concerned studies of sleep and anaesthesia. So, Guyo et al. [79] examine age-related differences in EEG rhythm coordination during sleep-wake transitions, showing increased pairwise interactions between brain waves in older subjects during wakefulness. The study highlights how network-based analysis of cross-frequency coupling provides insights into aging-related changes in brain dynamics, with less pronounced effects observed during deep sleep stages.

In their complementary study [80], Guyo with coauthors discuss short-term sleep deprivation using the concept of cross-communication among different cortical rhythms. The work compares several approaches to assessing rhythms coordination from electrocorticogram signals to examine the extent to which short-term sleep deprivation can affect the cooperative dynamics of brain rhythms.

The study [81] explores the use of detrended cross-correlation analysis (DCCA) and its extended version (EDCCA) to analyze electrocorticogram (ECoG) signals in mice during transitions from wakefulness to anesthesia-induced sleep. The authors demonstrate that both methods are complementary, with DCCA and EDCCA revealing changes in cross-correlation characteristics across different scale ranges. The results highlight the potential of these approaches for monitoring anesthesia depth by detecting non-stationary dynamics and inhomogeneities in brain activity. The findings contribute to improving diagnostic tools for physiological studies involving complex neural networks. The work is supported by experimental data and statistical analysis, emphasizing the methods' reliability in identifying anesthesia-induced changes.

Several papers dealt with computational neuroscience issues and were related to modelling processes in neural networks both locally and globally using neural mass models.

Dogonasheva et al. [82] investigate cluster synchronization in modular PING networks, revealing how pyramidal cell adaptation currents (AHP/M-current) influence gamma rhythm organization. Their computational study demonstrates multistable cluster regimes controlled by inhibitory strength, providing insights into neural mechanisms underlying gamma band variability in cortical circuits.

Kovaleva et al. [83] develop a flexible working memory model incorporating both short-term plasticity and STDP in leaky integrate-and-fire neurons. Their simulations demonstrate STDP-driven formation of stimulus-specific neural clusters, with capacity dependencies matching previous short-term plasticity models. Increased STDP learning rates enhance memory capacity, validating the biological plausibility of dual-plasticity mechanisms.

Tsybina et al. [84] develop a spiking neural network model of low-threshold mechanoreceptors (LTMRs) to study their response characteristics to tactile stimuli. The model reveals distinct firing patterns: unmyelinated LTMRs show non-linear velocity dependence with peak firing at specific brush speeds, while myelinated types exhibit proportional velocity responses. All LTMR types demonstrate increased firing rates with greater applied force, suggesting their specialized roles in tactile encoding.

Badarin et al. [85] combine Wilson–Cowan modeling with reservoir computing to reconstruct missing BOLD signals while preserving functional connectivity patterns. Their whole-brain simulation demonstrates RC's effectiveness for neuroimaging data recovery, particularly for strongly connected regions, with reconstructed connectivity matrices closely matching original patterns despite amplitude variations.

5 Healing with data: AI in biomedicine

A large number of articles in the special issue were related to AI applications in various biomedical tasks. In this section, we have collected articles that are directly related to the issues of diagnostics and prognostics of various diseases.

We start our brief review with three important reviews. So, Mishkin et al. [86] systematically compare ML with traditional Cox regression for cardiovascular risk prediction, analyzing 58 studies. ML methods (particularly random forest and gradient boosting) show superior performance (mean AUC 0.82 vs 0.75), though 80% lack external validation, highlighting the need for standardized digital health data infrastructure to realize ML's potential in cardiology.

Garanin et al. [87] present a systematic review of digital twin applications in clinical medicine over the past decade. The study examines the technology's evolution, current implementations across medical specialties, and key ethical challenges in clinical adoption. The authors provide concrete examples of digital twin deployments while highlighting unresolved implementation barriers in healthcare settings.

Gençtürk et al. [88] systematically review AI approaches for CT-based midline shift detection, comparing symmetry-based, landmark-based, ML and DL methods. Their analysis identifies key challenges including pathological variations and data imbalance while highlighting DL's high accuracy (requiring large datasets) versus ML's reliability with well-processed data. This comprehensive evaluation provides critical insights for developing robust clinical decision-support systems in neuroimaging.

A number of papers were devoted to the application of nonlinear theory and topological analysis methods to the description of the course of diseases, i.e., to prognostic issues. So, Grubov [89] presents a concise review of extreme event analysis in biomedical data, covering: (i) physiological states generating extremes, (ii) signal types containing extreme events, and (iii) detection methods using extreme value theory. The work synthesizes current applications in medical diagnostics while advocating for expanded research into this emerging analytical paradigm for healthcare applications.

Shah et al. [90] introduce a topological data analysis approach for leukemia diagnosis, applying persistent homology to achieve 98.2% recall in classifying lymphoblasts from healthy cells. Their shape-based method offers robust automated analysis of blood smears, addressing critical challenges in ALL morphological identification.

However, the majority of articles are related to the application of different ML and DL technologies to the diagnosis of specific diseases.

Erdem et al. [91] develop an ensemble DL model for prostate cancer grading using whole slide images without manual region annotation. Their transfer learning approach, tested on real-world pathology data, shows high classification accuracy compared to patch-based methods, offering a practical solution for automated Gleason scoring while reducing pathologist workload.

Arslan and Yapici [92] evaluate ML approaches for obesity prediction, demonstrating that Extra Trees Classifier with SMOTE balancing achieves optimal performance (91.9% accuracy, 98.0% AUC). Their stratified k-fold validation on lifestyle/demographic data highlights effective strategies for handling class imbalance in public health applications.

Teke and Etem [93] present a novel lightweight machine learning framework combining GLCM and T-SNE for kidney tumor detection in CT images, achieving state-of-the-art accuracy (99.98% with Fine KNN) while optimizing computational efficiency. The hybrid approach effectively balances feature extraction and dimensionality reduction, making it suitable for real-time clinical applications. The study rigorously evaluates multiple classifiers and demonstrates robustness across two datasets. Future directions include expanding datasets and enhancing explainability. The work stands out for its methodological innovation and practical applicability in resource-constrained settings.

The same author team presents a machine learning approach to improve anemia diagnosis using complete blood count (CBC) data [94]. By combining ensemble methods (kNN, SVM, Random Forest) with feature selection techniques (ANOVA, Chi-square) and SMOTE for class balancing, the model achieved 99.67% accuracy. The study highlights the potential of AI-driven tools for early and precise anemia detection, aiding clinical decision-making.

Moumin et al. [95] compare ensemble and non-ensemble ML methods for heart disease detection, utilizing feature-selected data from IEEE DataPort. Their evaluation shows Random Forest achieves 92.4% accuracy, outperforming other models (KNN, XGB, GBM) and ensemble approaches (voting/stacking), demonstrating the efficacy of optimized feature selection combined with robust classification algorithms for cardiovascular risk prediction.

Paavankumar et al. [96] introduce a dual-track deep learning architecture combining Dense-UMAF networks with Data-efficient image Transformers (DeiT) for mammogram classification. The model attains 88.7% accuracy on CBIS-DDSM dataset by simultaneously capturing localized abnormalities (via UMAF) and global patterns (via DeiT) in breast lesions.

Çakır and Benli [97] evaluate machine learning approaches for stroke mortality prediction using routine blood test data from a Turkish tertiary hospital. Their comprehensive comparison of eight classifiers with five feature selection strategies identifies Random Forest as optimal (90.09% accuracy), with neutrophil/lymphocyte/basophil percentages emerging as key biomarkers. The study demonstrates that even a reduced three-parameter model maintains strong predictive power (83.96% accuracy), offering clinically viable tools for intensive care prognosis.

Telceken [98] develops Dual-Frequency Cepstral Coefficients (DFCC), a novel feature extraction method combining Mel and Gammatone filters with cube root/logarithmic transformations for heart sound classification. Achieving 93% accuracy across KNN, SVM and CNN classifiers, DFCC outperforms conventional methods by preserving time-frequency information through integrated DFT analysis.

Arslan et al. [99] propose a hybrid ANN-PSO model with Wavelet Packet Decomposition for obesity classification using flash electroretinogram signals. Their approach achieves superior performance (specific accuracies withheld) over traditional ANNs by extracting statistical features from cone responses and optimizing neural networks through particle swarm optimization.

Premanand and Narayanan [100] introduce ECG-ResViT, a novel hybrid CNN-Vision Transformer architecture achieving 99.13% accuracy in cardiac condition classification. By combining CNN's local pattern recognition with ViT's global dependency modeling, their solution outperforms existing methods (99.94% ROC-AUC) while maintaining computational efficiency for clinical deployment.

Jackson et al. [101] propose an attention-gated U-Net framework for colorectal polyp segmentation, with ConvNeXt encoder achieving top performance (Dice = 0.91, AUC = 0.99). Their systematic comparison of 7 encoder architectures across 3 public datasets demonstrates hybrid CNN-Transformers' superiority in combining local/global features for medical imaging.

Yapici and Arslan [102] develop an ML framework for thyroid cancer recurrence prediction, where Random Forest with SMOTE balancing achieves superior performance (specific metrics withheld). Their hybrid feature selection/balancing approach demonstrates clinical applicability while providing transferable methodology for imbalanced medical datasets.

Pehlivanoğlu et al. [103] present a hybrid tumor segmentation framework on their novel BTS-DS 2024 dataset (3956 MRIs across 14 tumor types), with YOLOv9e achieving 92.3% F1-score and 85.6% IoU through optimized anchor box configurations. The study establishes new benchmarks by integrating UNet's precision with YOLO's speed, demonstrating particular effectiveness in segmenting glioblastoma multiforme cases. The publicly available dataset includes rare tumor variants to support future research.

Bykova et al. [104] evaluate ML models (Decision Tree, Random Forest, CatBoost) for differentiating lung lesions using CT features from 363 patients. Their analysis achieves high diagnostic accuracy in distinguishing benign (hamartoma/tuberculoma) from malignant (NSCLC) lesions, with tissue change patterns emerging as key predictors. The study demonstrates ML's potential to reduce invasive procedures while noting need for larger validation cohorts.

Zakharov et al. [105] develop a CNN-based diagnostic system using surface-enhanced Raman spectroscopy of blood serum, achieving perfect sensitivity (1.0) and high specificity (0.9) for multiple sclerosis detection. The method additionally classifies disease severity via EDSS scores (77% accuracy), offering a cost-effective alternative to current MS diagnostic tools while requiring further clinical validation.

Bondala and Lella [106] propose DB-SCA-UNet, an enhanced U-Net architecture incorporating drop-block regularization and spatial-channel attention mechanisms for diabetic retinopathy detection. Their model addresses microvasculature segmentation challenges, demonstrating robust performance across three public datasets (DRIVE, STARE, CHASE_DB1) and one custom clinical dataset while mitigating overfitting through innovative channel dropout.

Muñoz-Mata et al. [107] develop a novel Parkinson's tremor classification system using wavelet scattering transform (WST) processed accelerometry data from finger sensors. Their method combines WST feature extraction with PCA dimensionality reduction and SVM classification, achieving exceptional performance (AUC=0.968, sensitivity = 99.2%, specificity = 94.4%) through sensor-fusion ensemble modeling. This accelerometer-based approach demonstrates significant potential for improving PD diagnosis and treatment monitoring in clinical settings.

6 Green intelligence: AI for climate and environment

Finally, the last section collected articles that collectively demonstrate how modern computational methods are transforming environmental monitoring and analysis. By combining data-driven approaches with domain-specific knowledge, researchers are developing powerful tools for modeling complex environmental systems, predicting environmental change, and optimizing resource management. Papers highlight key advances in processing temporal and spatial data, integrating physical models with machine learning, and creating practical solutions for real-world applications. A common thread is the emphasis on rigorous validation and interpretability, ensuring that these technologies can effectively support decision making. This research reflects the growing trend of interdisciplinary collaboration, where environmental sciences, computer science, and engineering come together to address pressing sustainability challenges through innovative analytics and intelligent systems.

da Silva et al. [108] apply Random Forest algorithms to predict monthly temperatures across Brazilian state capitals using a 60-year climate dataset. Their analysis reveals two key findings: (i) distinct breakpoints in the 1980s–90 s where both temperatures and greenhouse gas emissions began accelerating simultaneously in most locations, and (2) optimal prediction accuracy when combining historical temperature data with real-time GHG emissions. The Northeast region showed particularly precise forecasts, while emissions data alone best predicted temperature anomalies. This work demonstrates how machine learning can extract climate patterns from complex, non-linear systems while highlighting regional variability in prediction effectiveness.

Sergeev et al. [109] present an innovative application of Echo State Networks (ESN) for predicting PM2.5 dynamics in metropolitan areas, using Seoul's air quality data as a case study. Their reservoir computing approach demonstrates remarkable forecasting capabilities, with model accuracy improvements ranging from 9 to 67% across different evaluation metrics. The research reveals critical insights into temporal prediction limits, showing performance degradation when forecast windows exceed 6% of the training period. This work establishes ESN as particularly effective for environmental time-series forecasting in urban contexts, while providing practical guidance on optimal data sampling intervals (6-hour averages proved most effective) and dataset partitioning (800 training samples vs. $50 \div 100$ test samples).

In their complementary study [110], Sergeev with coauthors shifts focus to spatial distribution modeling, developing an enhanced Land Use Regression methodology incorporating both traditional and neural network approaches (MLP and CNN architectures) for mapping dust accumulation in snow cover. Their novel ring spatial variables technique, tested in Novy Urengoy, Russia, achieves $3 \div 26\%$ accuracy gains in neural network implementations compared to classical regression. The study not only compares six distinct modeling approaches through comprehensive metrics and Taylor diagrams, but also produces high-resolution (10 m) pollution maps that visually identify urban dust hotspots. This dual methodological contribution—combining advanced neural architectures with GIS-based spatial analysis—provides environmental scientists with powerful tools for both temporal forecasting and spatial mapping of particulate pollution.

These works demonstrate innovative applications of ML techniques to diverse environmental monitoring challenges, from temporal air quality prediction to spatial pollution mapping. The consistent use of rigorous validation methods (multiple accuracy indices, Taylor diagrams) across both studies highlights a commitment to robust, reproducible environmental modeling. The spatial modeling approach [110]presents a novel integration of ANN architectures with traditional land use regression, while the temporal forecasting work [110] advances reservoir computing optimization for urban air quality applications. Both studies emphasize practical implementation considerations, from optimal data preprocessing to results visualization for policymaking.

Bobakov et al. [111] conducted a systematic evaluation of five neural architectures for environmental time-series forecasting, comparing conventional deep learning models (LSTM, TCN, LSTNet) against graph neural networks (MTGNN, GCRN) processing greenhouse gas and meteorological data. Their results demonstrate GNN superiority across all metrics (MAE, RMSE, MAPE, NRMSE, R^2), particularly in capturing abrupt transitions, though with 30–40% greater computational demands. The study establishes valuable benchmarks for temporal-geospatial forecasting while providing practical model selection guidelines.

Pandian and Alphonse [112] developed a hybrid approach for water leak detection that combines an advection–diffusion physical model with ensemble machine learning methods. The authors proposed a three-tiered system integrating adaptive boosting, bagged SVMs and meta-learning, achieving significant improvements in leak localization accuracy (up to 92.3%) while reducing false alarms by 62%. The solution demonstrates particular robustness to climatic variations and sensor noise, validated through testing in real-world urban water distribution networks.

In their subsequent work [113], the same authors advanced their research by addressing covariate shift issues through an LSTM-Kalman filter hybrid model with attention mechanisms. This novel architecture showed remarkable adaptability to changing conditions, achieving up to 9% improvement in F1-scores for both leak detection and localization tasks. The incorporation of layer normalization and Wasserstein metrics significantly enhanced the model's stability across varying water demand scenarios—a critical feature for modern smart water management systems. Together, these studies make substantial contributions to intelligent infrastructure monitoring, offering complementary approaches ranging from ensemble methods to advanced deep learning architectures.

Both works demonstrate the researchers' progressive refinement of their methodology—from robust physical-model-assisted ensemble techniques to sophisticated temporal deep learning solutions—while maintaining focus on practical applicability in real-world water distribution systems. The consistent improvements in performance metrics across different test conditions validate their systematic approach to tackling the complex challenges of urban water infrastructure monitoring.

7 Discussion and outlook

This special issue highlights the transformative potential of integrating artificial intelligence and complex network science across diverse domains, ranging from neuroscience to climate modeling. The contributions demonstrate how ML can unravel nonlinear dynamics in brain networks, optimize environmental forecasting, and advance precision medicine-bridging theoretical insights with real-world applications. For example, the AutoML framework presented in [18] can be used to the multimodal biomedical data integration to enhance diagnostic accuracy and accelerate personalized medicine. The intersection of machine learning and nonlinear dynamics is further exemplified by novel solutions to classical problems such as oscillator coupling detection through deep neural networks [47], an approach with significant potential for future applications in personalized medicine. In neuroscience applications, graph-analytic methods combined with machine learning techniques show particular promise for advancing the diagnosis of various brain disorders. These include assessment of chronic consciousness disorders [61, 62], evaluation of post-COVID neurological complications [66, 67], and epilepsy detection [68]. Similarly, in environmental science, spatiotemporal machine learning approaches [108, 109, 112] have established new standards for urban pollution monitoring, temperature forecasting, and sustainable resource management, demonstrating the versatile applications of these methodologies.

Future research should prioritize the following directions:

- *Interpretability* Developing scalable explainable AI (XAI) frameworks to reconcile complex network dynamics with clinical and ecological decision-making [114, 115]
- *Cross-disciplinary standards* Establishing unified protocols for data sharing and model validation, building upon existing work in federated learning for medical imaging [20] and AutoML for multimodal data processing [18]
- *Neuromorphic computing* Advancing energy-efficient AI systems through memristor-based architectures [54] and analog-digital hybrid designs [55], inspired by biological neural networks [116]. Such technologies are closely related to biomorphic robotics [117, 118] and hold significant promise for developing locomotion and intelligent control systems for such robots [50].

By fostering stronger collaboration between physicists, clinicians, and data scientists, these advances will accelerate solutions to global challenges in healthcare, neurotechnology, and environmental sustainability.

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References

1. M. Zanin, D. Papo, P.A. Sousa et al., Combining complex networks and data mining: why and how. Phys. Rep. **635**, 1–44 (2016)
2. Y. Zou, R.V. Donner, N. Marwan et al., Complex network approaches to nonlinear time series analysis. Phys. Rep. **787**, 1–97 (2019)
3. C.H. Martin, G. Mani, The recent physics and chemistry Nobel Prizes, AI, and the convergence of knowledge fields. Patterns 5(12) (2024)
4. M.M. Bronstein, J. Bruna, Y. LeCun et al., Geometric deep learning: going beyond euclidean data. IEEE Signal Process. Mag. **34**(4), 18–42 (2017)
5. S. Cuomo, V.S. Di Cola, F. Giampaolo et al., Scientific machine learning through physics-informed neural networks: where we are and what s next. J. Sci. Comput. **92**(3), 88 (2022)
6. A.E. Hramov, N. Kulagin, A.N. Pisarchik et al., Strong and weak prediction of stochastic dynamics using reservoir computing. Chaos Interdiscip. J. Nonlinear Sci. **35**(3), 033140 (2025)
7. S. Pandey, J. Schumacher, Reservoir computing model of two-dimensional turbulent convection. Phys. Rev. Fluids **5**(11), 113506 (2020)
8. D.S. Bassett, O. Sporns, Network neuroscience. Nat. Neurosci. **20**(3), 353–364 (2017)
9. A.E. Hramov, V.A. Maksimenko, A.N. Pisarchik, Physical principles of brain-computer interfaces and their applications for rehabilitation, robotics and control of human brain states. Phys. Rep. **918**, 1–133 (2021)
10. O.E. Karpov, E.N. Pitsik, S.A. Kurkin et al., Analysis of publication activity and research trends in the field of AI medical applications: network approach. Int. J. Environ. Res. Public Health **20**(7), 5335 (2023)
11. M. Zitnik, F. Nguyen, B. Wang et al., Machine learning for integrating data in biology and medicine: Principles, practice, and opportunities. Inf. Fusion **50**, 71–91 (2019)
12. M.S. Kabir, S. Kurkin, G. Portnova et al., Contrastive machine learning reveals in eeg resting-state network salient features specific to autism spectrum disorder. Chaos, Solitons Fractals **185**, 115123 (2024)
13. E.N. Pitsik, V.A. Maximenko, S.A. Kurkin et al., The topology of fmri-based networks defines the performance of a graph neural network for the classification of patients with major depressive disorder. Chaos, Solitons Fractals **167**, 113041 (2023)
14. F. Cai, C. Liu, D. Gerten et al., Sketching the spatial disparities in heatwave trends by changing atmospheric teleconnections in the northern hemisphere. Nat. Commun. **15**(1), 8012 (2024)
15. T. Liu, D. Chen, L. Yang et al., Teleconnections among tipping elements in the Earth system. Nat. Clim. Change **13**(1), 67–74 (2023)
16. J. Runge, S. Bathiany, E. Bollt et al., Inferring causation from time series in Earth system sciences. Nat. Commun. **10**(1), 2553 (2019)
17. A. Bondala, K. Lella, Revolutionizing diabetic retinopathy detection using DB-SCA-UNet with drop block-based attention model in deep learning for precise analysis of color retinal images. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01334-9

18. A. Boronina, V. Maksimenko, A. Badarin et al., Decreased brain functional connectivity is associated with faster responses to repeated visual stimuli. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01290-4
19. I. Soloviev, V. Klinshov, Complex landscape of the cost function in a simple machine learning regression task. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01422-w
20. A. Butorova, A. Sergeev, From traditional algorithms to artificial intelligence: a review of sensory substitution sonification methods. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01596-x
21. E. Bykova, S. Suvorova, G. Pavel et al., Leveraging machine learning models for enhanced differentiation of hard-diagnosed lung lesions. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-024-01446-2
22. N. Makarov, M. Lipkovich, A transformer-based model for next disease prediction using electronic health records. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-024-01447-1
23. I. Soloviev, A. Kovalchuk, V. Klinshov, Dynamic convolution for image matching. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01373-2
24. A. Kurbako, D. Ezhov, V. Ponomarenko et al., Spike-timing dependent plasticity learning of small spiking neural network for image recognition. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01512-3
25. S. Lobov, A. Zharinov, D. Kurganov et al., Network memory consolidation under adaptive rewiring. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01595-y
26. R. Vadivel, S. Sabarathinam, G. Zhai et al., Event-triggered reachable set estimation for synchronization of Markovian jump complex-valued delayed neural networks under cyber-attacks. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01372-3
27. F. Atban, M. Küçükkara, C. Bayılmış, Enhancing variational quantum classifier performance with meta-heuristic feature selection for credit card fraud detection. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01703-y
28. P. Das, N. Pratyusha, S. Mandal et al., Synaptic coupling and synchronization for HR neural network developing a novel type ii non-linear memristor, potential to neuromorphic application. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01342-9
29. O. Didmanidze, M. Karelina, V. Filatov et al., Deep learning model for plant disease detection based on visual analysis of leaf infestation area. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-024-01450-6
30. J. Zhang, Y. Peng, H. Chen et al., A two-stage classification scheme for rice leaf diseases based on the PDSwin model for practical application scenarios. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01619-7
31. B. Ekinci, I. Dursun, Z. Garip et al., Prediction of PEM fuel cell performance degradation using bidirectional long short-term memory with chimp optimization algorithm. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01408-8
32. P. Laptev, V. Demareva, S. Litovkin et al., Machine learning-based detection of alcohol intoxication through speech analysis: a comparative study of AI models. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01508-z
33. S. Korchagin, Machine learning methods for emotion recognition in neuromarketing tasks. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01412-y
34. M. Telceken, M. Okuyar, D. Akgun et al., A new data label conversion algorithm for YOLO segmentation of medical images. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01338-5
35. Y. Ren, G. Li, J. Zhang et al., EPC-GANet: a lightweight attention guided network with expanded receptive field for rice leaf disease recognition. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01700-1
36. P. Vishnuppriyan, R. Karthik, B. Prabu et al., A dual path deep-learning network with multi-scale cross attention and pyramid vision transformer for citrus leaf disease detection. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01731-8
37. V. Khvostenko, N. Prikladovskaya, R. Meshcheryakov et al., Two-parameter model of synthetic distortions in the problem of assessing the readability of distorted texts. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01777-8
38. V. Grubov, S. Nazarikov, N. Utyashev et al., Error-aware cnn improves automatic epileptic seizure detection. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01292-2
39. N. Vodichev, D. Gavrilov, A. Leus et al., Real-time distance estimation algorithm for objects in warehouse based on monocular camera data for an autonomous unmanned forklift. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-024-01452-4
40. D. Valle, R. Capeans, A. Wagemakers et al., Controlling transient chaos in the lorenz system with machine learning. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01589-w
41. A. Hramkov, A. Karavaev, Y. Ishbulatov et al., Comparison of methods for extracting the instantaneous phase of a biological system from time series. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01588-x
42. A. Akgul, E. Deniz, B. Emin et al., Classification of sprott chaotic systems via projection of the attractors using deep learning methods. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01329-6
43. S. Roy, S. Raut, W. Albalawi et al., On the multilayer neural networks for analyzing the $(1+1)$-dimensional space-time fractional equation for granular model. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01705-w

44. A. Sharifi, A. Sharafian, Q. Ai, Observer-based control for consensus tracking of non-linear synchronous generators system using sliding mode method and a radial basis function neural network. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01281-5
45. A. Pavlov, O. Pavlova, Scaling features of correlated and anti-correlated data: numerical simulations and analysis of brain dynamics. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01332-x
46. S. Jonna, K. Natarajan, EEG signal processing in neurological conditions using machine learning and deep learning methods: a comprehensive review. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01606-y
47. A. Vakhlaeva, Y. Ishbulatov, E. Dubinkina et al., Application of neural networks to detection of unidirectional coupling between Van der Pol oscillators from ultrashort time series in the presence of noise. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01592-1
48. A. Korotkov, E. Grines, E. Syundyukova et al., Chaos in two heteroclinic cycles coupled with chemical synapses. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01723-8
49. O. Moskalenko, M. Kurovskaya, A. Koronovskii, Intermittent generalized synchronization in unidirectionally coupled systems with different topology of attractors. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01284-2
50. V. Khorev, G. Portnova, A. Kushnir et al., fMRI study of changes in large-scale brain networks during affective touch. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01330-z
51. O. Maslennikov, D. Shchapin, V. Nekorkin, Binary classification via spatiotemporal dynamics in reservoir computing rings of FitzHugh–Nagumo neurons. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01704-x
52. S. Nazrin, L. Burhanuddin, H. Zaman et al., Integrating machine learning and experimental data in modeling optical behaviors of neodymium oxide nanoparticle-doped glasses. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01572-5
53. D. Safonov, A. Lavrova, I. Proskurkin et al., A chemical diode for neuromorphic computing: design, simulation, and experimental validation of unidirectional signal transmission. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01506-1
54. V. Chandrabanshi, S. Domnic, A deep learning approach for strengthening person identification in face-based authentication systems using visual speech recognition. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01586-z
55. M.O. Petrov, E.A. Ryndin, N.V. Andreeva, Automated design of deep neural networks with in-situ training architecture based on analog functional blocks. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01369-y
56. A. Kuc, Frontal long-range temporal correlations as a predictor of child's IQ test performance using machine learning approach. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-024-01453-3
57. N. Atanasova, A. Todeva-Radneva, K. Stoyanova et al., Functional connectivity in resting-state fmri (rs-fmri) in opioid use disorder. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01591-2
58. V. Khorev, A. Kiselev, A. Badarin et al., Review on the use of ai-based methods and tools for treating mental conditions and mental rehabilitation. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01289-x
59. I. Saranskaia, B. Gutkin, D. Zakharov, Aim-based choice of strategy for meg-based brain state classification. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01587-y
60. G. Portnova, I. Skorokhodov, V. Podlepich, Eeg correlates of the tactile perception of patients in a vegetative state and coma: a step towards ai-based classification of unconscious states. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01409-7
61. L. Mayorova, M. Radutnaya, E. Bondar et al., Changes in functional connectivity of brain regions associated with movement and awareness under cervical epidural spinal cord stimulation in chronic disorders of consciousness: a pilot study. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01514-1
62. R.K. Malviya, R.R. Danda, K.K. Maguluri et al., Neuromorphic computing: advancing energy-efficient ai systems through brain-inspired architectures. Nanotechnol. Percept. **20**, 1548–1564 (2024)
63. N. Shanarova, M. Pronina, M. Lipkovich et al., Schizophrenia diagnosis using latent components of event-related potentials and machine learning approach. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01507-0
64. K. Stoyanova, D. Stoyanov, V. Khorev et al., Identifying neural network structures explained by personality traits: combining unsupervised and supervised machine learning techniques in translational validity assessment. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01411-z
65. R. Paunova, S. Kandilarova, D. Simeonova et al., Multivariate linear approach to fMRI data in stroop task performance in depression. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01594-z
66. A. Trufanov, I. Voznyuk, A. Kutkova et al., Biochemical changes in subregions of the cingulate gyrus in patients with post-covid syndrome. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-024-01444-4
67. A. Trufanov, I. Voznyuk, A. Kutkova et al., Structural and functional changes in the brain during post-COVID syndrome: neuropsychological and MRI study. Eur. Phys. J. Spec. Top. 1–16 (2025)
68. F. Atban, S.E. Guleryuz, Y.E. Kocaoglu et al., Deep learning based automated non-barcoded product identification system for in-person shopping. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01775-w
69. A. Tynterova, E. Barantsevich, M. Khoimov et al., Prospective immunological markers of cerebral microangiopathy and Alzheimer's disease. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01410-0

70. K. Muthureka, U. Srinivasulu Reddy, B. Janet, Noise filtering approach to improve handwritten digit recognition using customized CNN for cerebral palsy individuals. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01515-0
71. A. Sagatdinov, M. Lipkovich, V. Knyazeva et al., Temporal and frequency features play different role in recognizing preparation of voluntary movements from electroencephalogram. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01513-2
72. E. Pitsik, Recurrence quantification analysis and theta-band functional networks detect age-related changes in brain sensorimotor system: Vr-based approach. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01509-y
73. S. Paavankumar, R. Karthik, G. Idayachandiran et al., Classification of benign and malignant breast lesions in mammograms using dense-unified multiscale attention network and data-efficient image transformers. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01618-8
74. V. Antipov, Dynamics of oculomotor patterns during prolonged visual processing. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-025-01590-3
75. C. Pandian, P. Alphonse, Long short-term memory and Kalman filter with attention mechanism as approach for covariance shift problem in water leakage. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01285-1
76. C. Pandian, P. Alphonse, Reducing adversarial sensor data predictions in water leak management by applying the advection-diffusion and ensemble models. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01517-y
77. D. Andrikov, Open source ML framework algorithms for biophysical models. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01621-z
78. N. Ismailov, A. Guba, N. Kovalev et al., Optimization of lift force generation in flapping-wing systems: a theoretical approach for intelligent flight control. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01593-0
79. M. Pehlivanoğlu, I. İnce, B. Kindan et al., Towards advanced brain tumor segmentation: a novel hybrid architecture integrating UNet, FCN, and YOLO models on the newly introduced BTS-DS 2024 dataset. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01698-6
80. G. Guyo, O. Pavlova, A. Pavlov, Short-term sleep deprivation: considering brain rhythm coordination in the context of an integrated neural network. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01286-0
81. V. Adushkina, A. Pavlov, Characterization of cross-correlations in electrocorticograms of anesthetized mice. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01288-y
82. O. Dogonasheva, B. Gutkin, D. Zakharov, Cluster formation in modular pyramidal-interneuron gamma networks under spike-frequency adaptation. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01582-3
83. N. Kovaleva, V. Matrosov, S. Lobov et al., Flexible working memory model with two types of plasticity. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01585-0
84. S. Premanand, S. Narayanan, Ecg-resvit: a hybrid cnn-vit model for efficient ecg signal classification. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01781-y
85. A. Badarin, V. Klinshov, P. Smelov et al., Reservoir computing reconstructs blood-oxygen-level-dependent signals: whole-brain modeling study. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01702-z
86. I. Mishkin, A. Koncevaya, O. Drapkina, Prediction of cardiovascular events with using proportional risk models and machine learning algorithms: a systematic review. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-024-01451-5
87. A. Garanin, O. Aidumova, A. Kontsevaya, Clinical aspects of digital twins in medicine: a systematic review. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01518-x
88. T.H. Gençtürk, F.K. Gülağız, I. Kaya, Artificial intelligence and computed tomography imaging for midline shift detection. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01779-6
89. V. Grubov, Extreme events in biomedical data. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01415-9
90. W. Shah, A. Baloch, R. Jaimes-Reátegui et al., Acute lymphoblastic leukemia classification using persistent homology. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01301-4
91. A. Sergeev, A. Shichkin, A. Buevich et al., Reservoir computing for predicting pm 2.5 dynamics in a metropolis. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01287-z
92. A. Sergeev, A. Shichkin, A. Buevich et al., Using land use methodology to construct ring spatial variables for modeling and mapping spatial distribution of dust in snow cover. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01341-w
93. M. Teke, T. Etem, Cascading GLCM and T-SNE for detecting tumor on kidney CT images with lightweight machine learning design. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01842-2
94. M. Teke, T. Etem, M. Karhan, Enhancing anaemia diagnosis using ensemble machine learning and feature selection techniques on CBC data. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01838-y
95. Z. Moumin, I. Ecemis, M. Karhan, Heart disease detection using ensemble and non-ensemble machine learning methods. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01413-x

96. S. da Silva, E. Gabrick, A. de Moraes et al., Predicting temperatures in Brazilian states capitals via machine learning. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01710-z
97. U. Çakır, K.S. Benli, Performance evaluation of classification algorithms and feature selection methods for predicting stroke mortality based on blood test results. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01792-9
98. M. Telceken, A new feature extraction method for ai based classification of heart sounds: dual-frequency cepstral coefficients (dfccs). Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01613-z
99. R. Arslan, O. Erkaymaz, I. Yapici et al., Enhanced obesity classification with wavelet packet decomposition and ANN-PSO: a biomedical signal processing approach. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01603-1
100. S. Gordleeva, Y. Tsybina, I. Kastalskiy, Spiking neural network model of low-threshold mechanoreceptors system. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01371-4
101. H. Jackson, N. Iyer, A. Balasundaram et al., Hybrid deep learning approach using u-net with attention gates for colorectal cancer segmentation. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01780-z
102. I.S. Yapici, R.U. Arslan, Predictive analytics for thyroid cancer recurrence: a feature selection and data balancing approach. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01720-x
103. G. Guyo, V. Adushkina, A. Pavlov et al., Age-related distinctions in cooperative dynamics of brain rhythms during sleep-wake transitions. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01370-5
104. I. Anpilogov, N. Kruchynsky, E. Postnikov, Combining continuous wavelet transform and interpretable machine learning for evaluating rowing proficiency: a pilot study. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01701-0
105. A. Zakharov, I. Bratchenko, A. Neupokoeva et al., Deep learning of surface-enhanced Raman spectroscopy data for multiple sclerosis diagnostics. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-024-01449-z
106. Y.A. Tsybina, S.Y. Gordleeva, A. Zharinov et al., Toward biomorphic robotics: a review on swimming central pattern generators. Chaos, Solitons Fractals **165**, 112864 (2022)
107. B. Muñoz-Mata, G. Dorantes-Méndez, I. Rodrıguez-Leyva et al., Leveraging wavelet scattering transform on accelerometry data for classification of Parkinson s tremor. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01722-9
108. G. Appasami, N. Savarimuthu, Federated learning for secure medical MRI brain tumor image classification. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01516-z
109. G. Erdem, S. Omurca, E. Cakir et al., Prediction of pathological grade in prostate cancer: an ensemble deep learning-based whole slide image classification model. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01510-5
110. R. Arslan, I. Yapici, A novel hybrid approach to enhancing obesity prediction. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01620-0
111. V. Bobakov, S. Kuzmin, A. Butorova et al., Application of graph-structured data for forecasting the dynamics of time series of natural origin. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01368-z
112. H. Calgan, A. Gokyildirim, E. Ilten et al., Classification of fractional-order chaotic systems using deep learning methods. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-025-01604-0
113. A. Badarin, N. Brusinskii, V. Grubov et al., Recurrency time entropy of brain wave rhythms as an indicator of performance on visual search tasks in schoolchildren. Eur. Phys. J. Spec. Top. (2024). https://doi.org/10.1140/epjs/s11734-024-01348-3
114. K. Coussement, M.Z. Abedin, M. Kraus et al., Explainable ai for enhanced decision-making (2024)
115. D. Minh, H.X. Wang, Y.F. Li et al., Explainable artificial intelligence: a comprehensive review. Artif. Intell. Rev. **55**, 1–66 (2022)
116. V. Khorev, S. Kurkin, E. Pitsik et al., A synergistic approach for identifying disrupted functional brain subnetworks in patients with chronic disorders of consciousness due to anoxic brain damage. Eur. Phys. J. Spec. Top. (2025). https://doi.org/10.1140/epjs/s11734-024-01454-2
117. S.Y. Gordleeva, I. Kastalskiy, Y.A. Tsybina et al., Control of movement of underwater swimmers: animals, simulated animates and swimming robots. Phys. Life Rev. **47**, 211–244 (2023)
118. M.M. Alsaleh, F. Allery, J.W. Choi et al., Prediction of disease comorbidity using explainable artificial intelligence and machine learning techniques: a systematic review. Int. J. Med. Inform. **175**, 105088 (2023)