Advancements in Artificial Intelligence and Computer Vision for Biomedical Applications @SI-Lab

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Abstract

This paper summarizes recent research at the Signals and Images Lab (ISTI-CNR) leveraging artificial intelligence, machine learning, and computer vision to address complex biomedical challenges. We highlight advancements in trustworthy, explainable algorithmic foundations alongside their practical clinical applications across diagnostic imaging, physiological signal analysis and neuromotor rehabilitation.

Keywords

Raman spectroscopy, Physiological signals, Neuromotor rehabilitation, Dance movement therapy, Artificial Intelligence, Machine Learning, Generative AI, Explainable AI, Uncertainty Quantification, Trustworthy AI

1. Introduction

Artificial Intelligence (AI) and computer vision are driving a paradigm shift in biomedical research and clinical practice. Building on work of the Signals and Images Lab (ISTI-CNR), this paper details our recent methodological and applied contributions to this evolving field. We organize our ongoing research into three interconnected domains: foundational advancements in trustworthy and explainable algorithms (Section 2), novel frameworks for diagnostic medical imaging (Section 3), and the analysis of physiological signals for clinical practice and neuromotor rehabilitation (Section 4).

2. Foundational AI: Trustworthiness and Explainability

2.1. AI Trustworthiness and Generative AI

The opaque nature of Deep Learning (DL) limits its adoption in high-stakes clinical domains, such as DL-assisted biopsy [1]. To mitigate these risks, the FUTURE-AI framework provides comprehensive guidelines for developing trustworthy and deployable healthcare AI [2]. A critical strategy involves

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probabilistic and Bayesian DL to formalize epistemic and aleatoric uncertainties, preventing overconfident predictions and identifying out-of-distribution cases [3, 4]. We have systematized these Bayesian techniques and introduced synthetic benchmarks, such as the NADA shape generator, for the rigorous validation of probabilistic methodologies [5]. Furthermore, multimodal learning and explainability are being integrated for enhanced, interpretable lesion classification [6]. In generative AI, we leverage physics-informed neural networks to impose structural constraints; for example, generating high-fidelity cardiac MRI sequences using small sample sizes at a fraction of standard computational costs [7].

2.2. Explainable AI and Enhanced Reasoning

Traditional Explainable AI (XAI) algorithms rely on post-hoc visualizations that evaluate robustness but do not actively improve a model's intrinsic conceptual understanding. Drawing inspiration from physics-informed networks, we developed Batch-CAM, a training strategy for computer vision that forces models to reconstruct the spatial features driving their classifications [8]. By introducing a loss function that aligns activation maps with conceptual target prototypes during training, Batch-CAM natively integrates interpretability. Batch-averaging mitigates overfitting, while a contrastive loss penalizes the reconstructed space of misclassified images. Currently optimized for grayscale images, this prototype-alignment methodology aims to build systems that better mimic human reasoning, bridging the gap toward comprehensive world models.

2.3. Bio-Inspired Learning and Temporal Complexity

While standard artificial neural networks only superficially resemble biological brains, Spiking Neural Networks (SNNs) communicate via discrete pulses, offering superior energy efficiency and sensitivity to time-varying physiological signals. SNNs operate as non-linear dynamical systems and can be analyzed using the Temporal Complexity (TC) framework [9]. Recent studies correlate the structural topology of SNNs with TC metrics, demonstrating that distinct network configurations can produce equivalent, stable dynamical regimes [10, 11]. Furthermore, applying TC to Dense Associative Memory (DAM) models reveals critical behaviors associated with storage saturation, providing early indicators of "catastrophic forgetting" [12, 13]. Characterizing these phase transitions enables the design of robust memory architectures resilient to irreversible degradation.

3. AI in Medical Imaging and Diagnostic Biomarkers

3.1. Topological Machine Learning for Biomedical Signals

To capture complex structural patterns constrained by standard DL paradigms, we developed a Topological Machine Learning (TML) pipeline. By leveraging persistent homology, TML utilizes topological invariants for intrinsically multiscale data representation and classification [14]. We extensively applied this TML pipeline to Raman spectroscopy, achieving strong diagnostic classification performance across multiple clinical domains. Notable successes include the grading of chondrosarcoma [15], distinguishing Alzheimer's disease from other neurodegenerative pathologies [16, 17], and differentiating pancreatic cancer subtypes with 82% accuracy [18]. Furthermore, we leveraged the TML pipeline's intrinsic explainability to identify the most discriminative spectral bands associated with specific diseases [19]. Beyond spectroscopy, our current research within the EU project ProCAncer-I is adapting these topological descriptors to automatically assess the quality of multiparametric MRI sequences, aiming to predict diagnosticability in prostate cancer imaging.

3.2. AI in Oncology

Predicting therapeutic response in metastatic clear cell renal cell carcinoma (ccRCC) remains challenging [20, 21]. Radiomics addresses this by extracting sub-visual CT features to characterize tumor biology [22], evolving from histological subtyping [23] to treatment prediction. A recent multicenter study [24] utilized PyRadiomics [25] to identify non-invasive biomarkers for early efficacy assessment. While Random Forest analysis successfully linked textural heterogeneity to Objective Response Rates, moderate predictive performance (e.g., accuracy 0.59) underscores the necessity of multimodal strategies integrating radiological, clinical, and multi-omics data.

Beyond diagnostics, AI enhances cancer survivorship. The EU-funded MAYA project proactively manages long-term cardiovascular complications resulting from cancer treatments. The system utilizes an AI-powered smart mirror equipped with physiological sensors and conversational agents to provide continuous, personalized health monitoring and reduce cardiac risks.

3.3. AI in Point-of-Care Ultrasound

Point-of-Care Ultrasound (POCUS) provides portable but noisy imaging. To ensure clinical safety beyond black-box DL in lung ultrasound, we applied the Batch-CAM strategy (see Section 2.2) to align model representations with verifiable clinical artifacts, such as "comet-tails" [26]. Utilizing an embedded-friendly ConvNeXt-Tiny architecture, our model enforces pixel-wise L1 alignment between activation maps and target prototypes. Furthermore, batch-averaging these maps naturally reduces noise and sonographic variance, rendering explicit data augmentation redundant. Future work will integrate geometry-aware networks to advance robust, on-device diagnostics.

4. AI for Physiological Signals and Clinical Practice

4.1. AI and Probabilistic Modelling in Gastroenterology

In gastroenterology, DL and Bayesian architectures increasingly complement classical ML, which remains essential for analyzing conditions like Eosinophilic Esophagitis (EoE) [27]. Applying standard ML, we demonstrated that peripheral blood eosinophil counts successfully predict histological remission in EoE [28]. Concurrently, statistical analyses of patient questionnaires have quantified the impact of adaptive behaviors [29] and their correlation with hypervigilance [30], refining clinical pathways for both EoE and Lymphocytic esophagitis (LyE) [31]. To accelerate future AI applications, we developed *Time Series Scribe*, an open-source tool for annotating multidimensional ($\mathbb{R}^7$-channel) temporal pH signals acquired during esophageal manometry [32].

4.2. AI and Research in Autism Spectrum Disorder

Autism Spectrum Disorder (ASD) screening traditionally relies on parental questionnaires and structured clinical observations. To address the inherent limitations and subjectivity of these manual procedures, ML approaches are increasingly being deployed to assist practitioners. For instance, deep neural networks have been developed to extract specific facial features from a single image to support ASD classification [33]. Beyond initial screening, AI facilitates the continuous monitoring of behavioral interventions. A critical task is the detection of vocal stereotypy—atypical, repetitive sounds that require precise measurement for effective therapeutic management. Recent studies have demonstrated the efficacy of transformer models in not only classifying vocal stereotypy within audio recordings but also accurately estimating its duration [34]. Furthermore, the automated detection of movement stereotypy represents another promising behavioral marker currently under investigation, highlighting the broader potential of AI in quantitative behavioral analysis.

4.3. AI in Body Motion and Neuromotor Rehabilitation

Human-in-the-Loop Identity Preservation in Dance Movement Therapy

In Dance Movement Therapy (DMT), continuous participant identity preservation during automated multi-person tracking is critical for integrating motion trajectories with physiological data, such as ECGs [35, 36]. Because identity fragmentation and ID switches severely compromise dataset reliability [37], we developed a human-in-the-loop correction framework. This participant-centered environment enables end-users to explicitly repair automated tracking outputs through structured operations (e.g., swap, fusion, and transfer). By ensuring traceable and accurate kinematic tracking, this methodology secures the robust multimodal correlation of physical movement, biological data, and patient feedback required for quantitative therapeutic assessment.

AI for physiological fingerprinting in extreme conditions

A recent study of 39 ultra-marathon runners during an 866-km race utilized classical ML to analyze longitudinal oxy-inflammatory profiles [38]. Linear mixed models (LMM) identified early oxidative stress—specifically elevated baseline reactive oxygen species and early-stage lipid peroxidation—as the primary predictor of race withdrawal. Conversely, finishers demonstrated a distinct physiological trajectory characterized by a significant mid-race increase in Total Antioxidant Capacity (TAC). By integrating these biomarkers with psychological exertion scores, traditional ML algorithms effectively translate complex multidimensional data into predictive indicators of systemic stress and endurance.

Exergames and AI in Neuromotor Rehabilitation

To overcome traditional neurorehabilitation barriers and simultaneously stimulate motor and executive functions, we developed MRToL (Mixed Reality Tower of London), an immersive exergame based on the standard ToL clinical paradigm. Developed with responsive hand-tracking, the system automatically collects precise execution metrics (e.g., times, move counts, rule violations) that are subsequently processed via ML to extract higher-level kinematic and cognitive indices. Utilizing passthrough MR superimposes digital elements onto the real world. This facilitates the transfer of acquired skills to daily life and minimizes cybersickness, aligning with recent extensive reviews highlighting the critical role of body representation in XR-based motor neurorehabilitation [39]. Compatible with accessible headsets, MRToL offers a scalable, personalized solution for continuous, home-based therapeutic follow-up.

5. Conclusions

Our recent activities demonstrate AI's potential to advance healthcare, from complex diagnostics like Raman spectroscopy to physiological signal processing for neuromotor rehabilitation. Moving forward, ensuring clinical viability requires overcoming core algorithmic challenges in explainable AI and uncertainty quantification. Future research must prioritize trustworthy, transparent AI co-designed with healthcare professionals to achieve regulatory compliance, secure user acceptance, and guarantee widespread clinical adoption.

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Declaration on Generative AI

During the preparation of this work, the authors utilized generative AI technologies strictly to refine the initial draft and improve linguistic flow. All AI-assisted edits were subject to continuous human supervision and rigorous review.

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