DIGITAL IMAGE PROCESSING FOR NEURODEVELOPMENTAL DISORDERS: A RESEARCH GAP ANALYSIS AND FUTURE DIRECTIONS

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Abstract

Neurodevelopmental disorders (NDDs), such as Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), and intellectual disabilities, affect millions of individuals worldwide, often manifesting in early childhood and persisting throughout life. Despite growing interest in early and accurate diagnosis, existing diagnostic approaches remain subjective, resource-intensive, and inconsistent across clinical settings. Digital Image Processing (DIP), powered by artificial intelligence (AI), has emerged as a promising tool for objectively analyzing neuroimaging and behavioral data to support early detection and monitoring. This paper presents a comprehensive analysis of current progress in AI-driven DIP for NDDs, identifies significant research gaps—including limitations in datasets, interpretability, and generalizability—and proposes future directions for scalable, ethical, and clinically integrable solutions.

Keywords

ADHD, Digital Image Processing, Early prediction, AI-Driven, ASD.

1. Introduction

M. J. Maenner et al. Neurodevelopmental disorders (NDDs) encompass a spectrum of conditions characterized by early-onset impairments in cognition, communication, motor skills, and behavior. These disorders—including Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), and inTellectual disability (ID)—often begin in childhood and persist throughout an individual's life, significantly affecting social integration, education, and quality of life [1].

L. D. Wiggins et.al. Traditional diagnostic approaches for NDDs are largely subjective, relying on behavioral observation, clinical interviews, and standardized questionnaires. While effective in some settings, these methods suffer from inconsistencies due to clinician bias, regional variability, and late-stage manifestation of symptoms. This often leads to delays in diagnosis and intervention—particularly in underserved communities or younger age groups, where subtle early signs are easily overlooked [2].

M. P. Milham et al. With the emergence of advanced neuroimaging modalities such as structural MRI, functional MRI (fMRI), and Diffusion Tensor Imaging (DTI), there is growing potential to detect early biomarkers of NDDs [3]. **I. Ashraf et al**. However, the complexity and volume of such data demand automated and intelligent analysis systems. Digital Image Processing (DIP), when integrated with artificial intelligence (AI)—especially deep learning—can extract high-level features from these images to support diagnosis, monitoring, and even prediction of developmental trajectories [4].

J. D. Greene et al. In recent years, DIP-based tools have shown promising results in identifying NDD-specific patterns such as abnormal brain connectivity, cortical thinning, delayed surface expansion, and atypical behavioral cues from video recordings [5]. Despite these advances, challenges remain in interpretability, dataset diversity, and model generalizability. This paper aims to bridge these gaps by reviewing the current state of AI-driven DIP for NDDs and outlining a research roadmap to develop scalable and ethical diagnostic systems.

2. Types of Neuro-Developmental Disorder

Neurodevelopmental disorders represent a group of chronic conditions arising from atypical development of the brain and nervous system. Key categories include:

2.1 Autism Spectrum Disorder (ASD): **M. J. Maenner et al.** ASD is characterized by persistent difficulties in social communication and restricted, repetitive patterns of behavior. It affects approximately 1 in 36 children globally [1]. **A. Adhikary et.al.** Structural and functional imaging studies have identified differences in cortical surface area, gray matter volume, and brain connectivity, particularly in regions such as the prefrontal cortex, amygdala, and cerebellum [6]. **Z. Duan et al.** DIP-based neuroimaging pipelines have been applied to detect these anomalies with increasing accuracy [7].

2.2 Attention Deficit Hyperactivity Disorder (ADHD): ADHD is defined by chronic patterns of inattention, impulsivity, and hyperactivity, affecting 5–7% of children worldwide. Neuroimaging studies have shown reduced volume in the prefrontal cortex, caudate nucleus, and cerebellum. Functional alterations in the default mode network (DMN) are also commonly reported. **Y. Liu et al.** DIP and AI-based models, particularly those using fMRI time series, have shown promise in detecting these abnormalities and aiding in subtype classification [8].

2.3 Intellectual Disability (ID): ID involves significant limitations in intellectual functioning and adaptive behavior. It often co-occurs with other NDDs and is associated with reduced brain volume, abnormal gyrification, and white matter deficits. Despite limited large-scale imaging datasets for ID, DIP tools can aid in analyzing structural irregularities using machine learning classifiers.

2.4 Other types: Other recognized neurodevelopmental conditions include:
Specific Learning Disabilities (e.g., dyslexia) – often involving reduced activity in the left temporoparietal region.
Developmental Coordination Disorder – associated with cerebellar and parietal lobe dysfunction.
Language Disorders – involving temporal and frontal lobe deficits.
S. Goswami et al. Each of these disorders has distinct neurobiological signatures that may be detected and quantified using advanced DIP methods [9].

3. Advances in AI-Driven DIP for NDDs

3.1. *Multimodal Neuroimaging Pipelines:* **A. Adhikary et.al.** Deep learning applied across structural MRI, fMRI, and DTI modalities has achieved diagnostic accuracies over 95% in large ASD cohorts (~1,100 subjects) [10].

3.2. *High-Fidelity ADHD Detection via fMRI:* **I. Ashraf et al.** Deep extreme learning machines applied to multi-center fMRI datasets have achieved classification accuracy exceeding 98%, surpassing classical SVM and ANN models [11].

3.3. *Graph Transformer for Brain Connectivity:* **Y. Leng et al.** A self-supervised graph transformer architecture using contrastive learning on resting-state fMRI data achieved AUROC of 0.826 and accuracy of 74% in ASD prediction [12].

3.4 *Explainable Pediatric ASD Assessment:* **A. Al-Nefaie et al.** An XAI framework aligned neural features with developmental biomarkers, offering visually interpretable outputs that boost clinical credibility [13].

4. Research Gaps in DIP for Neurodevelopmental Disorders

There are some of the research gaps found based on the reviews as follows: **Limited and Non-Standardized Pediatric Neuroimaging Data:** Public datasets like ABIDE and ADHD-200 offer limited demographic diversity and inconsistent acquisition protocols, reducing model generalizability across younger age groups and comorbidities. **Underutilization of Multimodal Fusion**: Most studies focus on single modalities (e.g. sMRI or EEG), while integrating multi-modal sources (structural, functional, behavioral, genetics) remains underexplored. **Lack of Explainability:** State-of-the-art transformer and graph-based DIP models remain largely "black-box." Clinical adoption requires tools that provide interpretable attention maps and rationale for decisions. **Early Detection in Younger Children:** Few DIP studies focus on infants and toddlers, when early intervention can be most effective. Lack of age-appropriate markers impedes timely diagnosis. **Integration into Healthcare Systems:** High-performing DIP models often fail to transition to clinical workflows, lacking integration with PACS, EHR, and clinician user interfaces. **Ethical, Privacy & Regulatory Considerations** [14]: **Dimitris Stripelis et.al.** Pediatric neuroimaging demands strict consent processes, data governance, and privacy-preserving architectures—areas where clinical translation remains nascent.

5. Conclusion and Future Enhancement

This work clearly addresses the types of Neuro-Developmental disorders, research gaps and recent advances of Neuro-conditions in AI. This research gaps persist in data diversity, clinical interpretability, multimodal integration, and system deployment, but by focusing on these research priorities, the field can move toward reliable, equitable, and objective diagnostic tools for ASD, ADHD, and related disorders—delivering early interventions and enhancing quality of life for neurodiverse populations.

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