Review Article

Artificial Intelligence in Pediatric Healthcare - Part I: Foundations and Basic Concepts

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ABSTRACT

Artificial intelligence (AI) is rapidly transforming healthcare by enabling machines to analyze complex datasets, recognize patterns, and support clinical decision-making. Advances in machine learning (ML), deep learning (DL), and computational technologies, along with the widespread digitization of health records, have accelerated the integration of AI into medical research and clinical practice. In pediatric healthcare, AI has emerging applications in developmental screening, growth and nutrition monitoring, early disease detection, medical imaging interpretation, and prediction of clinical deterioration, particularly in neonatal and pediatric intensive care settings. However, the safe and effective use of AI in pediatric practice requires a clear understanding of its fundamental concepts, methodologies, data sources, and evaluation processes. This narrative review summarizes the foundational concepts of AI relevant to medicine and pediatrics, including the historical evolution of AI in healthcare, core methodologies, types of machine learning models, major clinical data sources, and the development pipeline of medical AI systems. This article is the first in a four-part series on AI in pediatrics; subsequent articles will discuss AI applications in ambulatory pediatrics, hospital and critical care settings, and the ethical and regulatory considerations related to the use of AI in child health.

Key words: Artificial Intelligence, Machine Learning, Pediatrics, Deep Learning, Child Health

Artificial intelligence (AI) has emerged as an important area of innovation in modern healthcare. Advances in data science and computational technologies have enabled the analysis of large volumes of health information and the extraction of clinically meaningful insights [1]. The widespread adoption of digital healthcare systems has generated extensive datasets from electronic health records, diagnostic imaging, laboratory systems, and physiological monitoring devices. AI methods can process and interpret these complex datasets, creating new opportunities to support medical research and clinical practice [1]. The expansion of digital health data has been accompanied by major improvements in computational capacity. Modern computing infrastructure allows large datasets to be analyzed rapidly using advanced analytical techniques [2].

These developments enable models to identify subtle patterns in clinical data that may not be detected using traditional statistical methods. As a result, AI is increasingly explored to improve diagnostic processes, predict disease outcomes, and optimize healthcare delivery [2]. In pediatric medicine, AI adoption presents both opportunities and challenges. Children represent a biologically diverse population with rapid developmental changes that influence disease presentation, physiological parameters, and treatment responses. These factors must be considered when developing data-driven models for pediatric care [3].

Additionally, pediatric datasets are often smaller and less standardized than adult datasets, which may limit the development and validation of robust AI systems. Therefore, paediatricians must actively participate in evaluating and implementing emerging AI technologies to ensure their suitability for pediatric populations [3]. As AI becomes more prominent in healthcare research and practice, clinicians are increasingly expected to understand its fundamental principles. Basic AI literacy is essential for interpreting research findings, critically evaluating new technologies, and participating in discussions about their safe and ethical use. This understanding is particularly important in pediatrics, where clinical decision-making must account for developmental variability, long-term outcomes, and ethical considerations in child healthcare [4].

Access this article online

Received – 26th March 2026
Initial Review – 27th March 2026
Accepted – 1st April 2026

Quick Response Code

DOI: 10.32677/ijch.v13i4.8200

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This article is the first in a four-part series examining AI in pediatric medicine. It focuses on the foundational principles of AI in healthcare, including its historical development, core methodologies, data sources used in medical AI systems, and the processes involved in developing these technologies.

2. Historical Evolution of AI in Medicine

The development of AI in medicine has progressed through several important stages, evolving from early rule-based systems to modern data-driven ML and DL technologies. Initial interest in applying computational methods to medical decision-making emerged during the 1950s and 1960s, when researchers explored the possibility of using computers to simulate aspects of human reasoning and support clinical diagnosis [5].

During the 1970s and 1980s, the first major AI applications in healthcare emerged as expert systems. Programs such as MYCIN [6] and INTERNIST-1 [7] used predefined rules and manually encoded medical knowledge to assist physicians in diagnosing diseases and recommending treatments. These systems demonstrated the potential of computer-assisted clinical decision support, but their reliance on static knowledge bases limited their adaptability and scalability as medical knowledge expanded.

The 1990s and early 2000s marked a shift toward ML approaches, where algorithms could learn patterns directly from clinical datasets rather than relying solely on manually programmed rules [8]. Advances in statistical learning methods have enabled more flexible predictive models, while developments in natural language processing (NLP) have enabled computers to extract information from unstructured medical texts, such as electronic health records (EHRs) and research literature [9].

A major breakthrough occurred in the 2010s with the emergence of DL, particularly neural network architectures capable of analyzing large-scale biomedical datasets [10]. DL models, such as convolutional neural networks (CNNs), have significantly improved performance in medical imaging analysis, enabling automated detection of conditions such as lung cancer and diabetic retinopathy with accuracy comparable to or exceeding that of human specialists (**Figure 1**) [10].

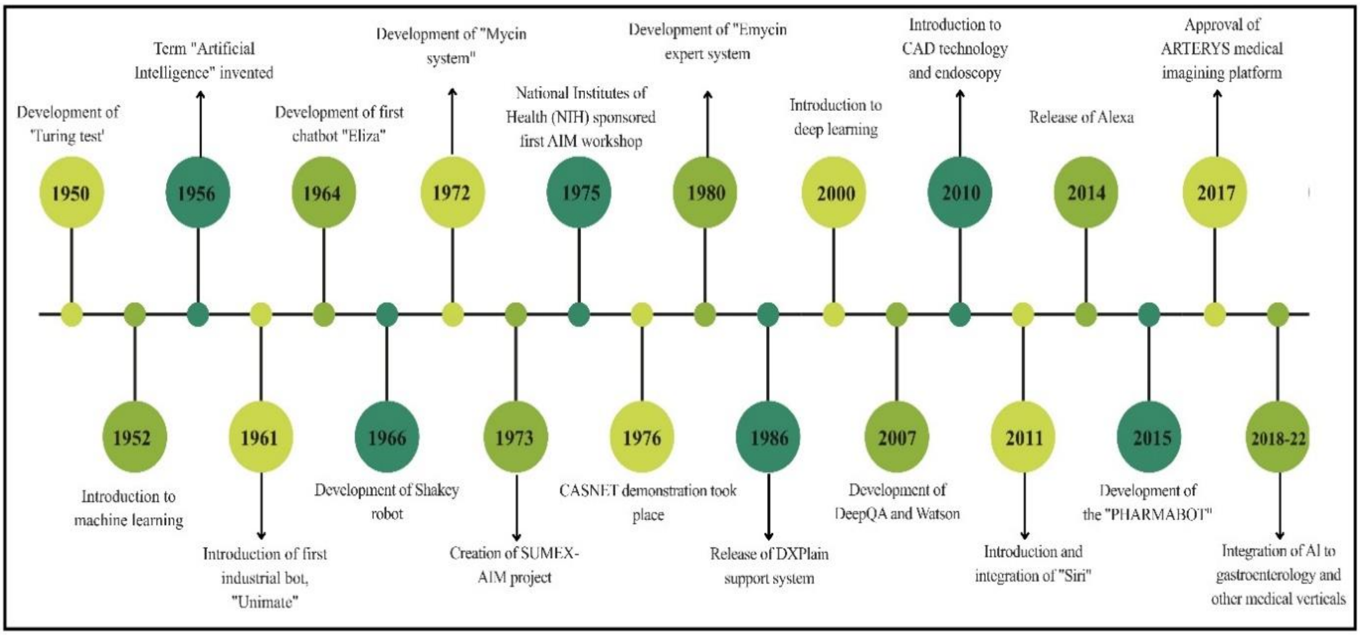

Figure 1: Evolution of artificial intelligence in healthcare.

In the current era, AI has expanded into numerous healthcare applications, including precision medicine, predictive analytics, robotic-assisted surgery, and clinical decision support systems. Modern AI systems integrate data from EHRs, genomic sequencing, imaging modalities, and wearable devices to support personalized treatment strategies and improve healthcare delivery.

3. Core Concepts of AI in Healthcare

AI in healthcare includes computational approaches that analyze medical data, recognize patterns, and support clinical decision-making. These methods enable the processing of complex datasets generated in modern healthcare systems, including clinical records, medical images, physiological signals, and genomic information (See Figure 2 & Table 1).

Table 1: Key AI Terminologies

Artificial Intelligence (AI): A field of computer science focused on developing systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, pattern recognition, and decision-making.

Machine Learning (ML): A subset of AI in which algorithms learn patterns from data and use these patterns to make predictions or classifications without explicit programming.

Deep Learning (DL): An advanced form of ML that uses multilayered artificial neural networks to analyze complex and high-dimensional data such as medical images, signals, and genomic information.

Natural Language Processing (NLP): A branch of AI that enables computers to understand, interpret, and analyze human language, commonly used for extracting information from clinical notes and electronic health records.

Computer Vision: An AI technique that allows computers to interpret and analyze visual information, such as medical images, including radiographs, CT scans, and MRI studies.

Generative AI: It refers to models that create new data resembling existing datasets by learning the underlying data distribution.

Algorithm: A set of computational rules or instructions used by a computer system to analyze data and generate predictions or decisions.

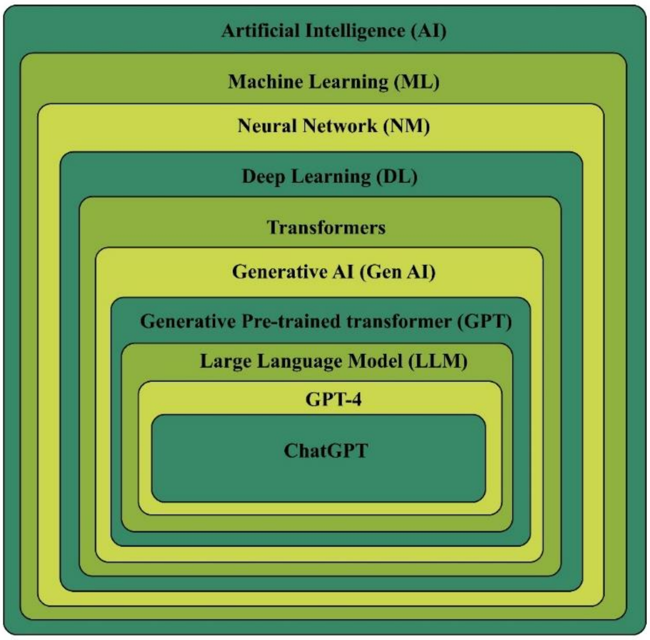

Figure 2: Key artificial intelligence terminologies used in healthcare.

3.1 Artificial Intelligence

AI refers to computer systems capable of performing tasks that normally require human intelligence, including learning, reasoning, pattern recognition, and decision-making. In healthcare, AI systems analyze large volumes of medical data to support diagnosis, risk prediction, treatment planning, and healthcare management. Unlike traditional rule-based software, AI systems can learn from new data and improve their performance over time [1]. By analyzing complex datasets, AI systems help clinicians identify clinically meaningful patterns that may not be easily detected through conventional analysis, potentially improving both clinical outcomes and operational efficiency.

3.2 Machine Learning

ML is a major branch of AI that develops algorithms capable of learning patterns from data without being explicitly programmed for every situation. Instead of relying solely on predefined rules, ML models are trained on datasets that enable them to identify relationships among variables and make predictions or classifications. In healthcare, ML is widely used in predictive analytics. Algorithms analyze historical clinical data to estimate the likelihood of events such as disease onset, treatment response, or clinical deterioration. These models can identify patients at risk of complications, detect abnormalities on diagnostic tests, and support treatment decisions, thereby enabling data-driven clinical decision support and personalized medicine [11].

3.3 Deep Learning

DL is a specialized subset of ML that uses multi-layered artificial neural networks to analyze complex data. Inspired by biological neural systems, these models learn hierarchical representations of data through iterative training. DL is particularly effective for high-dimensional data such as medical images, genomic sequences, and physiological signals [12]. A major advantage of DL is its ability to automatically extract relevant features from raw data without extensive manual feature engineering. For example, CNNs can analyze medical images to detect disease patterns, while recurrent neural networks (RNNs) can process sequential data such as time-series physiological signals. These capabilities have significantly advanced fields such as radiology, pathology, and biomedical signal analysis.

3.4 Natural Language Processing

Natural language processing (NLP) focuses on enabling computers to understand and analyze human language. In healthcare, NLP is valuable for analyzing unstructured clinical text, which represents a large portion of medical data. Clinical notes, discharge summaries, pathology reports, and other narrative records often contain critical clinical information that is not stored in structured databases [13]. NLP algorithms can extract key information such as diagnoses, symptoms, medications, and treatment outcomes from these documents. This transformation of textual information into structured data enables further analysis using ML methods, thereby improving data accessibility, supporting clinical research, and enhancing decision-making in healthcare systems [13].

3.5 Computer Vision

Computer vision enables machines to interpret and analyze visual information. In healthcare, it is primarily applied to medical imaging data such as radiographs, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and digital pathology images. These systems detect patterns and abnormalities to assist clinicians in image interpretation [14, 15]. AI-based computer vision models can rapidly analyze large volumes of imaging data, helping clinicians detect diseases, prioritize urgent findings, and reduce diagnostic workload [14]. Although these systems are intended to support rather than replace clinicians, they represent an important component of the expanding role of AI in healthcare.

4. Types of Machine Learning Models Used in Medicine

ML approaches in healthcare can be categorized based on how algorithms learn from data. These methods differ in their learning processes, types of input data, and clinical applications.

4.1 Supervised Learning

Supervised learning is one of the most widely used ML methods in healthcare. Here, algorithms are trained using labelled datasets where the correct output for each input is known. The model learns relationships between variables (such as patient characteristics, laboratory values, or imaging features) and clinical outcomes, enabling predictions on new data [16, 17].

Common supervised learning tasks include classification and regression. Classification models categorize data into predefined groups, such as distinguishing disease from non-disease states or classifying imaging findings. Regression models predict continuous outcomes, such as disease risk, length of hospital stay, or probability of complications. These methods are widely used in diagnostic imaging analysis and in predictive clinical models that identify patients at risk of disease progression or adverse outcomes [16, 17].

4.2 Unsupervised Learning

Unsupervised learning analyzes data without predefined labels and identifies hidden patterns or structures within datasets. These algorithms group observations into clusters based on shared characteristics [18, 19]. It is commonly used for pattern discovery and disease phenotyping. It can identify previously unrecognized patient subgroups with similar clinical features, genetic profiles, or disease trajectories. Such clustering methods have been applied to complex conditions such as asthma and sepsis, helping researchers better understand disease heterogeneity and guide personalized treatment strategies [18, 19].

4.3 Reinforcement Learning

Reinforcement learning involves algorithms that learn optimal decision strategies through interaction with an environment. The model receives feedback in the form of rewards or penalties based on its actions and adjusts its strategy to maximize cumulative rewards [20]. In healthcare, it is explored for dynamic treatment optimization, where models analyze longitudinal patient data to determine treatment strategies that improve outcomes. Potential applications include optimizing medication dosing, guiding intensive care interventions, and supporting personalized treatment planning [20].

4.4 Generative AI

Generative AI refers to models that create new data resembling existing datasets by learning the underlying data distribution, e.g., generative adversarial networks (GANs) and large language models (LLMs) [21]. Generative AI can produce synthetic datasets that preserve the statistical characteristics of real patient data while protecting patient privacy, enabling ML research and collaboration. Another emerging use is clinical documentation support, where LLMs assist with summarizing medical records, drafting clinical notes, and extracting key clinical information. These tools may reduce administrative workload and improve workflow efficiency, although careful evaluation is required to ensure accuracy and reliability [22] (Table 2).

Table 2: Hierarchy of AI Technologies Used in Medicine

Technology	Description	Data Type Suitability	Medical Application
Artificial Intelligence	Computer systems performing tasks requiring human intelligence	All medical data	Diagnostic support, risk prediction
Machine Learning	Algorithms learning patterns from data without explicit programming	Structured or tabular data	Predictive analytics for complications
Deep Learning (Neural Networks)	Multi-layer neural networks learning hierarchical representations	High-dimensional data such as images, signals, genomics	Medical image abnormality detection
Natural Language Processing	Computer understanding and interpretation of human language	Unstructured clinical text	Extracting diagnoses from clinical notes
Computer Vision	Machine interpretation of visual information	Medical imaging such as X-ray, CT, MRI	Detection of abnormalities in imaging
Reinforcement	Algorithms	Clinical	Treatment

Learning	learning optimal decisions through feedback	decision processes	optimization
Predictive Analytics	Statistical and machine learning models predicting future outcomes	Clinical datasets	Early warning systems
Generative AI	Models generating text, images, or synthetic datasets	Clinical documentation and synthetic data	Automated clinical documentation

5. Data Sources for AI in Pediatrics

AI systems depend on the availability of large, high-quality datasets. In modern healthcare, digital data are generated through routine clinical care, research activities, and patient monitoring. These datasets form the foundation for training and validating ML models.

5.1 Electronic Health Records

EHRs are a major source of clinical data for AI research. They include demographic information, diagnoses, laboratory results, medication histories, vital signs, clinical notes, and procedural data collected during routine care [23]. Because EHRs often contain long-term records, they provide valuable longitudinal data for studying disease progression and treatment outcomes.

In pediatric medicine, EHR data support predictive models that identify children at risk for specific conditions or complications. ML algorithms may analyze historical clinical data to predict disease progression, hospital readmission, or treatment response [24]. However, EHR datasets often contain challenges such as missing data, inconsistent documentation, and variations in clinical practice across institutions, which must be addressed during data preparation.

5.2 Medical Imaging

Medical imaging represents another major data source for AI applications. Modalities such as radiography, CT, MRI, ultrasound, and digital pathology generate large volumes of visual data suitable for ML analysis. Advances in image digitization and storage have enabled the development of large imaging repositories for training AI models [25].

In pediatric practice, imaging is essential for evaluating respiratory diseases, congenital abnormalities, neurological disorders, and oncologic conditions. DL models can analyze imaging datasets to detect abnormalities, quantify disease severity, and support diagnostic interpretation, potentially improving diagnostic efficiency and reducing variability [26].

5.3 Physiological Monitoring Data

Continuous physiological monitoring systems generate large volumes of time-series data that can be analyzed using AI. In NICUs and PICUs, monitoring devices record parameters such as heart rate, respiratory rate, oxygen saturation, blood pressure, and ECG signals, providing detailed information on physiological status over time [27, 28].

ML models can analyze these data streams to detect subtle physiological changes that may precede clinical deterioration. Predictive algorithms may identify patterns associated with early signs of sepsis, respiratory failure, or neurological complications, enabling earlier intervention and improved outcomes in critical care settings.

5.4 Genomic and Molecular Data

Advances in genomic sequencing technologies have generated large datasets that provide insights into the genetic and molecular mechanisms underlying many pediatric diseases. These datasets include DNA sequences, gene expression profiles, and other molecular markers influencing disease susceptibility and treatment response [29, 30].

AI methods are increasingly applied to analyze genomic data and identify clinically relevant genetic patterns. Genomic analysis is particularly important for studying rare genetic disorders, pediatric cancers, and inherited metabolic diseases. ML approaches can help identify disease-associated variants, predict disease risk, and support precision medicine strategies [29, 30].

5.5 Mobile Health and Wearable Technologies

The expansion of mobile health technologies has introduced new sources of patient-generated health data. Wearable devices, smartphone applications, and remote monitoring systems can continuously collect information on physical activity, sleep patterns, heart rate, and other physiological parameters, allowing health monitoring outside traditional clinical settings [31, 32].

In pediatric populations, mobile health tools support long-term monitoring of chronic conditions such as asthma, diabetes, and obesity [33]. Data from wearable devices can be integrated with clinical datasets to provide a more comprehensive understanding of patient health. When analyzed using AI methods, these data may facilitate improved disease monitoring, early detection of health risks, and personalized healthcare interventions (Table 3).

Table 3: Major Data Sources for AI Applications in Pediatrics

Data Source	Content Examples	Volume Characteristics	Pediatric Challenges
Electronic Health Records	Demographics, diagnoses, laboratory results, vital signs, clinical notes	High volume, longitudinal data	Missing data, inconsistent documentation
Medical Imaging	X ray, CT, MRI, ultrasound, pathology slides	High dimensional image data	Rare conditions limit training datasets
Physiological Monitoring	Heart rate, oxygen saturation, respiratory rate, EEG	Continuous time series data	Age dependent physiological variations
Genomic Data	DNA sequences, gene expression, molecular markers	High dimensional molecular data	Rare genetic disorders
Mobile Health and Wearables	Activity levels, sleep patterns, heart rate	Real time patient generated data	Compliance variability in children

6. Development Pipeline of Medical AI Systems

The development of AI systems in healthcare follows a structured, iterative process to ensure that models are reliable, clinically meaningful, and safe for implementation. Unlike traditional software, AI systems rely heavily on high-quality data, appropriate training strategies, and rigorous validation.

6.1 Data Collection and Annotation

The first step in developing medical AI systems is collecting relevant datasets from sources such as EHRs, imaging repositories, physiological monitoring systems, and other clinical databases [34]. Ensuring that the dataset represents the target patient population is essential for developing models that perform reliably across different clinical environments.

Following data collection, preprocessing and annotation are performed. Annotation involves labelling data so algorithms can learn meaningful patterns, e.g., radiologists may label imaging findings, while clinicians assign diagnoses or outcomes to patient records. Accurate labelling is critical because incorrect annotations can significantly reduce model performance. Expert clinicians often play an essential role in validating and annotating training datasets [35].

6.2 Model Training

After data preparation, ML algorithms are trained to identify relationships between input variables and clinical outcomes. During training, the algorithm iteratively adjusts its internal parameters to minimize prediction errors [36].

The type of algorithm used depends on the nature of the data and the clinical task; for example, DL models are commonly applied to imaging data, while other algorithms may analyze structured clinical datasets. The goal is to develop models capable of making accurate predictions on previously unseen data [37].

6.3 Internal Validation

Internal validation evaluates model performance using the dataset from which it was developed. This stage helps detect issues such as overfitting, where a model performs well on training data but poorly on new data. Techniques such as cross-validation or holdout testing are commonly used, where part of the dataset is reserved for testing. These methods provide an initial estimate of predictive performance [37].

6.4 External Validation

External validation tests the model using independent datasets from different institutions, patient populations, or clinical settings. This step determines whether the model can generalize beyond the original training dataset. It is particularly important in healthcare because variations in clinical practice, demographics, and data collection methods can influence model performance. Demonstrating consistent performance across diverse datasets is essential before clinical implementation.

6.5 Model Evaluation Metrics

The performance of medical AI models is assessed using statistical metrics that measure predictive accuracy and reliability. Commonly used metrics include sensitivity, specificity, and the area under the receiver operating characteristic curve (AUROC). Sensitivity measures a model's ability to correctly identify patients with a condition, which is particularly important in screening scenarios. Specificity measures the ability to correctly identify individuals without the condition, thereby reducing false positives. The AUROC summarizes overall diagnostic performance, with higher values indicating better discrimination. Together, these metrics provide a quantitative framework for evaluating whether AI models meet the standards required for clinical research and implementation.

6.6 FDA-Approval of AI tools

As of 2025, the FDA has authorized 500+ AI/ML-enabled medical devices, with the majority in radiology and cardiovascular imaging. Most AI tools are authorized via 510(k) clearance, demonstrating substantial equivalence to predicate devices. FDA approvals involving triage tools, image enhancement, predictive analytics, and autonomous diagnostics are increasing; however, fully autonomous AI systems (e.g., IDx-DR) remain relatively rare (Table 4).

Table 4: Selected FDA-Approved / Cleared AI Medical Devices (2000–2025)

Year	Device	Company	Specialty	Primary Indication / Use	Regulatory Pathway
2017	Arterys Cardio DL [38]	Arterys, Inc.	Radiology / Cardiology	Cardiac MRI image analysis	510(k)
2018	IDx-DR [39]	Digital Diagnostics	Ophthalmology	Autonomous detection of diabetic retinopathy from retinal images	De Novo
2018	ContaCT [40]	Viz.ai, Inc.	Radiology	Automated LVO stroke detection on CT angiography	De Novo
2018	OsteoDetect [41]	Imagen Technologies, Inc.	Radiology	Wrist fracture detection on X-ray	De Novo
2019	HeartFlow FFRct Analysis [42]	HeartFlow, Inc.	Cardiovascular	AI-based fractional flow reserve estimation from coronary CT	510(k)
2019	SubtleMR [43]	Subtle Medical, Inc.	Radiology	AI-enhanced MRI image reconstruction	510(k)
2020	Caption Guidance [44]	Caption Health	Radiology	AI guidance for acquiring diagnostic-quality echocardiograms	510(k)
2020	EchoGo Pro [45]	Ultromics Ltd	Radiology	AI analysis of echocardiograms for heart failure assessment	510(k)
2021	Paige Prostate [46]	Paige.AI	Pathology	AI detection of prostate cancer in whole-slide images	De Novo
2021	Viz ICH [47]	Viz.ai, Inc.	Radiology	Intracranial hemorrhage detection on CT	510(k)
2024	NeuroQuant [48]	CorTechs Labs, Inc.	Radiology	Automated brain MRI volumetric analysis	510(k)
2024	Tempus ECG-AF [49]	Tempus AI, Inc.	Cardiovascular	AI detection of atrial fibrillation risk from ECG	510(k)
2024	EchoGo Amyloidosis (1.0) [50]	Ultromics Limited	Cardiovascular	AI detection of cardiac amyloidosis via echocardiography	510(k)
2025	BriefCase-Triage [51]	Aidoc	Radiology	AI triage and detection of critical findings (e.g., PE, ICH)	510(k)
2025	Cleerly LABS (v2.0) [52]	Cleerly, Inc.	Radiology	Coronary artery disease quantification from CT	510(k)
2025	Genius AI Detection 2.0 [53]	Hologic, Inc.	Radiology	AI-assisted breast cancer detection in mammography	510(k)

CONCLUSION

Artificial intelligence is increasingly shaping the future of healthcare by enabling advanced analysis of large and complex biomedical datasets. In pediatric medicine, AI offers promising opportunities to improve clinical decision-making, enhance disease prediction, and support more personalized patient care. A clear understanding of AI concepts is therefore essential for pediatricians who will increasingly encounter AI-driven tools in clinical practice and research. By providing this conceptual foundation, this article aims to support the development of AI literacy among pediatric healthcare professionals, while subsequent papers in this series will explore AI applications in ambulatory pediatrics, pediatric inpatient and critical care settings, and the ethical and regulatory considerations surrounding its use in child health.

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Funding: None; Conflicts of Interest: None Stated.

How to cite this article: Agrawal A, Agrawal R. Artificial Intelligence in Pediatric Healthcare - Part I: Foundations and Basic Concepts. Indian J Child Health. 2026; 13(4):39-47.