Review

Not peer-reviewed version

Artificial Intelligence and Pediatrics: Synthetic Knowledge Synthesis

Jernej Završnik , Peter Kokol * , Bojan Žlahtič , Helena Blažun Vošner

Posted Date: 8 January 2024

doi: 10.20944/preprints202401.0564.v1

Keywords: pediatrics; artificial intelligence; synthetic knowledge synthesis; bibliometrics; machine learning

Review

Artificial Intelligence and Pediatrics: Synthetic Knowledge Synthesis

Jernej Završnik [1], Peter Kokol [1,2,3,*], Bojan Žlahtič [2] and Helena Blažun Vošner [1,4]

1 Community Healthcare Center dr. Adolf Drolc Maribor, Maribor, Slovenia
2 Laboratory for System Design, Faculty of Electrical Engineering and Computer Science, University of Maribor, Maribor, Slovenia
3 Faculty of Medicine, University of Maribor, Maribor, Slovenia
4 Faculty of Health and Social Sciences Slovenj Gradec, Slovenj Gradec, Slovenia
* Correspondence: peter.kokol@um.si

Abstract: Historically the use of artificial intelligence (AI) in paediatrics dates back to 1984 with the introduction of a computer-assisted medical decision-making system called SHELP. Since then, research on the use of AI in pediatrics has become much more popular, and the number of reviewed publications largely increased. Consequently, a need for a holistic research landscape enabling researchers and other interested parties to gain insights into, deepen their knowledge about or inform them about the use of AI in pediatrics arised. To fill this gap a novel methodology named synthetic knowledge synthesis was applied. Using SKS we identified most prolific countries, in-stitutions, source titles, funding agencies, research themes, research gaps and hot spots.

Keywords: pediatrics; artificial intelligence; synthetic knowledge synthesis; bibliometrics; machine learning

1. Introduction

Historically the use of artificial intelligence (AI) in paediatrics dates back to 1984 with the introduction of a computer-assisted medical decision-making system called SHELP, aimed to diagnose inborn metabolism problems [1]. Since then, research on the use of AI in pediatrics has become much more popular, and the number of reviewed publications largely increased in accordance with accelerated rates of scientific knowledge doubling, Web/Internet-based methods of scholarly communication, faster cycles of technological innovations in AI, and the Open Access and Open Science movements. Simultaneously, these phenomena have led to a surge in the availability of research literature in machine-readable formats providing opportunities to digitally synthesized research evidence. Consequently, Kokol et al. [2] developed a novel synthetics knowledge synthesis methodology (SKS), based on the triangulation of descriptive bibliometrics, bibliometric mapping, and content analysis. SKS integrates quantitative and qualitative knowledge synthesis as an augmentation of the traditional bibliometric analysis with machine learning-supported insights into the patterns, structure, and content of research publications. As such SKS overcomes some of the weaknesses of traditional knowledge synthesis approaches, requiring fewer resources, and is conducted semi-automatically. Additionally, it can be performed on big data size corpora of thousands or even ten thousand publications and not only on small manually selected samples of tens of publications. That makes knowledge synthesis reproducible, holistic, and less prone to bias.

The aim of this SKS study was to answer the following research questions:

- What is the volume and scope of the research on AI use in pediatrics?
- How is research spread geographically, focusing on developed and less-developed countries?
- What are the more prolific information titles/journals that inform the scientific community about research, and what are the sources through which the authors have the greatest opportunity to inform the community about the results of their research?
- Which founding bodies are more prolific in sponsoring the research?
- What are the most prolific research themes?
- What are the most used AI algorithms and approaches?

 doi:10.20944/preprints202401.0564.v1

- What are the most targeted pediatric diagnoses?
- What are the most used health applications in pediatrics?

In this manner, the study can help researchers and other interested parties gain new insights into, deepen their knowledge about or inform them about the use of AI in pediatrics.

2. Methods

The primary advantages of bibliometrics in general are that it supports the analysis of a vast number of publications and that it is domain-independent. Descriptive bibliometrics is used to analyze spatial and productivity characteristics of a corpus of publications [3–5]. The second component of SKS, bibliometric mapping, visualizes the relationships and associations between pairs of bibliometric units like words, phrases, authors, source titles or countries using text mining, co-unit analysis, and clustering algorithms. A bibliometric map is a network of nodes, where nodes represent bibliometric units, links represent relations between units, the proximity of nodes represents unit similarity, and the node size represents the unit popularity. Clusters represent units that are strongly associated. Bibliometrics maps can also be present in the overlay modes where overlays represent time stamps, citation density, and similar [6]. The third component is content analysis, a resourceful approach used in both quantitative and qualitative research for systematic and objective descriptions of phenomena described by various types of documents, in our case, research publications. Concept analysis can be used to create concepts, categories, and themes [7]. SKS is performed using the following steps:

- Harvest research publications on the topic of interest from the selected bibliographic database using an appropriate search string representing the research question(s) to be answered through knowledge synthesis.
- Perform descriptive bibliometric analysis using software built-in functionality.
- Use author keywords as meaningful units of information and execute bibliometric mapping using selected bibliometric software; in our case, VOSViewer [6]. Next using inductive content analysis, analyze the node size, links, and proximity between meaningful units in individual clusters to form categories and identify themes.
- Use author keywords as meaningful units of information and use VOSViewer to analyse their frequencies. Perform deductive content analysis with preconceived categories, namely Machine learning algorithm, AI approach, Pediatric diagnosis and Application in pediatrics.
- Use country names as meaningful units of information and execute time overlay bibliometric mapping using VOSViewer. Next, analyze the overlay colour, node size and links between countries to identify country cooperation and the average age of publications.

Scopus (Elsevier, Netherlands) was chosen as the source for the bibliographic database. To form a suitable corpus of publications the search was performed, using the following search query:

TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "intelligent system" OR "support vector machine" OR ("decision tree" AND (induction OR heuristic)) OR "random forest" OR "Markov decision process" OR "hidden Markov model" OR "fuzzy logic" OR "k-nearest neighbor" OR "naive Bayes" OR "Bayesian learning" OR "artificial neural network" OR "convolutional neural network" OR "recurrent neural network" OR "generative adversarial network" OR "deep belief network" OR "perceptron" OR "natural language processing" OR "natural language understanding" OR "general language model") and (pediatrics OR paediatrics))

We searched titles, keywords, and abstracts for the entire period indexed in Scopus without additional inclusion or exclusion criteria. The search was performed on 29th of November 2023.

3. Results and discussion

The search resulted in a corpus consisting of 4116 publications, including 2691 original articles, 652 conference papers, 388 review papers, 119 editorials, 110 short papers, notes 69 conference reviews, 9 books chapters, and 16 errata and 4 retractions.

3.1. Spatial characteristics of the body of research

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 8 January 2024 doi:10.20944/preprints202401.0564.v1

The first publications appeared in 198. Between 198 and 2004, research production was modest (with a maximum of 6 articles), following by a slightly positive linear trend till 2015 (Figure 1). The year 2016 saw exponential growth in research productivity that lasted until 2023, when it peaked at 996 articles. The exponential trend starting in 2016 might be the consequence of the release of the IBM Watson and its use in healthcare [8]. Around 2014 also the deep learning started to became popular in medicine [9].

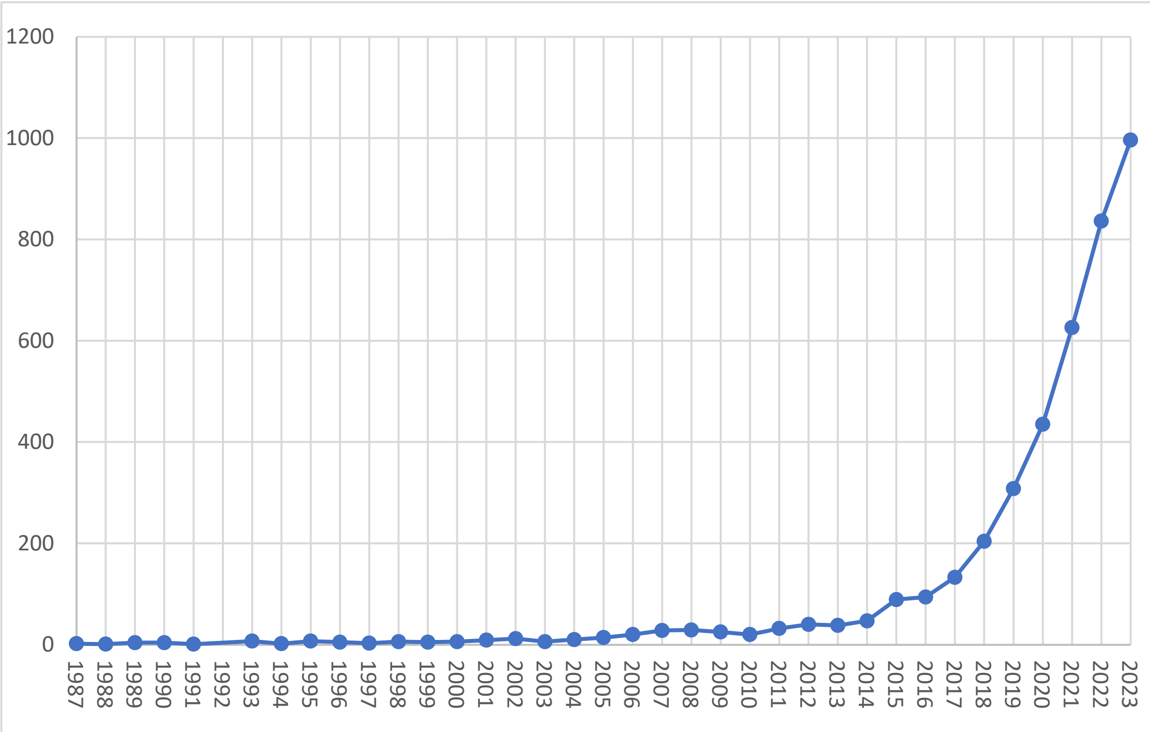

Figure 1. Dynamics of research literature on motivation in obesity and overweight.

Table 1 presents the 10 most productive countries out of a total of 121. The distribution of top productive countries highlights a regional concentration of research in more developed countries, as nine of them are members of the G20, and Spain is among the most economically developed countries with efficient health systems. The above list of countries is very similar to the Scimago list (Elsevier, Netherlands) of most productive countries in medicine. The only exception is Japan which is not in our list of top 10 productive countries but is in fifth in the Sc imago list. The reason might be that Japan is the healthiest country for the children according to World Health organisation [10]. Also the internatilaznization growed in this period, namely in the period 1987 to 1999 authors from 16 countries published research on AI in paediatrics. During the next decade this number grew to 34 countries and in the last period to 118 countries.

Table 1. Ten most productive countries.

Country	Number of publications
United States of America	1786
China	531
Canada	335
United Kingdom	330
Germany	211
India	185
Italy	179
Spain	146

 doi:10.20944/preprints202401.0564.v1

Australia	142
South Korea	132

Most prolific institutions among 976 were Harvard Medical School (n=151) The Children's Hospital of Philadelphia , USA (n=132), Boston Children Hospital (n=132), University of Toronto, Canada (n=121), Hospital for Sick Children, Toronto, Canada (n=112), Stanford University (N=109) and Cincinnati Childrens Hospital Medical Center (n=912).

The most prolific funding institutions among 402 were National Institutes of Health, USA (n=517), National Natural Science Foundation of China (n=202), U.S. Department of Health and Human Services (n=163), National Center for Advancing Translational Sciences, USA (n=108), National Heart, Lung, and Blood Institute, USA (n=95), National Cancer Institute, USA (n=79), Eunice Kennedy Shriver National Institute of Child Health and Human Development (n=77), national Science foundation (n=72), National Institute of Child Health and Human Development (n=66) and U.S. National Library of Medicine (n=59).. It is notable that 10 most productive funding institution came from only two countries, namely USA, and China. It is also interesting to note that 47.4% of papers are funded, which is significantly more than in many other research areas [11].

Articles have been published in 952 journals. Table 2 displays the 10 most prolific source titles Most of the journals are categorized in the first quarter (Q1) of journals lregarding the Socpus SJR impact factor. The impact factor values range from 0.21 to 1.67. The H-index, another important indicator of journal impact, ranges from 60 to 404. These statistics indicate that publications in the fields of AI in pediatrics are published in well-recognized and influential source titles, indicating the importance of the topic under consideration.

Table 2. Most prolific source titles.

Source title	Number of Publications	Impact Factors (SJR – Scopus 2021)	H-index	Quarter
Lecture Notes In Computer Science	155	0.32	209	Q3
Frontiers in Pediatrics	70	0.80	62	Q1
Scientific Reports	67	0.97	282	Q1
Pediatric Radiology	65	0.65	95	Q2
Progress In Biomedical Optics And Imaging Proceedings Of SPIE	50	0.21	60	N/A
Plos ONE	48	0.89	404	Q1
Pediatric Critical Care Medicine	40	1.42	100	Q1
Pediatric Research	34	1.04	165	Q1
IEEE Journal Of Biomedical And Health Informatics	30	1.67	146	Q1
Computer Methods And Programs In Biomedicine	29	1.12	124	Q1

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 8 January 2024 doi:10.20944/preprints202401.0564.v1

3.2. Content analysis

3.2.1.. Inductive content analysis

Thematic analysis was performed using SKS and VOSViewer software (Leiden University, Leiden, The Netherlands). The author keyword map is shown in Figure 2, and the synthesis of the results is presented in Table 3. Five themes and 10 categories were identified. The overview of the influential recent research is presented bellow.

Analysing complex signals using deep learning

In several interesting paediatrics application, deep learning was used to reduce noise in CT images, thus improving their quality and consequently enabled to reduce the radiation dose [12–14]. Additionally deep learning was used in fracture detection in children [15], tumour burden assessment [16] and interpreting chest radiography [17].

Deep learning with convolutional networks for complex decision making about bone age assessment and pneumonia treatment

As bone age is an important measure skeletal and biological maturity or growth disorders of children, deep learning has been used for bone age assessment using convolutional and regression neural networks based analysis of radiographs [18–21]. Proper and faster diagnosis of pneumonia at an early stage is imperative for optimal care of children. As, chest X-ray is considered the best imaging however very challenging modality for its diagnosis, an automated convolutional neural network-based transfer-learning approach has been used to detect pneumonia in pediatric chest radiographs [22]. A high accuracy in detecting pneumonia and classify its viral and bacterial types was achieved using Bayesian convolutional networks [23]. As an alternative method lung ultrasound can be used to diagnose community acquired pneumonia in children however must be performed by experienced physicians and is very time consuming, so convolutional networks have been used to optimize the task [24].

Deep learning in congenital heart diseases

Hiroki et al [25] demonstrate how to achieve improved diagnostic accuracy using deep learning model, comprising a convolutional neural network (CNN) and long short-term memory (LSTM),by analyzing electrocardiograms in pediatric populations. Automated segmentation of four dimensional MRI images using convolutional neural networks have been used in diagnosing congenital heart disease in children [26]. Automated machine learning echocardiographic diagnosis focusing on mitral regurgitation identification showed that it may enable enhanced screening, early diagnosis, and improved outcomes in pediatrics [27].

Critical clinical decision making and prediction with machine learning and natural language processing

Traditional machine learning and big data analysis in critical decision making were successfully use in an intelligent mobile application supporting decision making during COVID pandemics on whether children should go out for physical activities and whether schools should be reopened to preserve children psychological well being [28]. Random forest and gradient boosting machines were used in predicting the diagnosis, management and severity of appendicitis in children [29]. Machine learning has been also used to predict length of stay in pediatric UCI units [30]. Neural network using to extract information from textual data combined by a gradient boosting classifier was successfully used to predict and triage patient for admission in pediatric emergency departments [31]. Additionally a machine learning based system to improve efficiency of pediatric emergency departments focusing on minimizing time for decision making and predicting need for clinical testing was developed and used streamlining the triaging process for almost 23% [32].

Machine learning on electronic health records for predication and critical decision support in asthma and sepsis

Decision tree were used to associate demographic features with allergic outcomes in so called allergic march and possibility of transfer to asthma regarding race [33]. Decision trees were also used to explore the relationship between childhood asthma and the various risk factors reaching the 75.19% accuracy[34]. Neural networks were used to cough sound analysis to differentiate pneumonia

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 8 January 2024 doi:10.20944/preprints202401.0564.v1

from asthma [35]. Various traditional machine learning algorithms have been used to predict sepsis survival in infants with Meningococcal Septic Shock based on gene expression changes and clinical features [36].

Natural language processing of electronic health records; records

The emergence of electronic health records and AI based natural language processing , enabled the analysis of clinical data and offered a new perspectives for the diagnosis and management of pediatric patients. Various new possibilities appeared like diagnosis of rare diseases [37], predicting childhood and adolescent obesity [38], epilepsy treatment [39], infections predictions [40] or detecting child abuse [41].

Big data analysis for paediatric cancer patients

Pediatric cancer is fortunately a rare disease however due to low incidence, it presents a significant challenge in collecting enough data for analysis. Big data registry trials enable an advancement to study and treat pediatric cancers .[42] and in combination with precision medicine big data demonstrated clinical benefits [43]. More precisely big data analysis has been used in acute lymphoblastic leukemia classification [44] or oncology risk assessment [45].

MRI and EEG analysis in seizure detection in epilepsy and cerebral palsy

Segmentation, feature selection and classification of EEG and MRI signals

Support vector machines in combination with voxel-based morphometry showed to be capable to classify pediatric mesial temporal lobe epilepsy with hippocampal sclerosis with high accuracy [46]. In another study deep learning was used for classification of the type cerebral palsy in newborns by analyzing functional MRI [47].

Seizure detection in epilepsy and cerebral palsy

K-nearest neighbours showed to be the best machine learning algorithm to detect epileptic seizure activity in children when analysing EEG signals [48]. Feature selection in wavelet packet decomposed signal using random forest showed to improve the seizure detection accuracy in detecting seizures [49].

Using artificial intelligence for diagnosing

Artificial intelligence in diagnosing paediatric diseases has been used for various purpose like auscultation like identifying heart conditions base on analysis of auscultation murmur [50], COVID 19 diagnosis [51], rare diseases identification [52,53], clinical decision support [54] and similar.

Artificial intelligence based processing of radiography and radiology outputs for assessing bone age

Various studies showed artificial intelligence can be successful used in bone age assessment in paediatric populations [55–57] for example for hand wrist maturation [58] and adult height prediction [59]

Diagnosis of autism spectre disorder with artificial intelligence

Convolutional neural networks were used to implement automated facial expression recognition on mobile devices to provide an accessible diagnostic and therapeutic tool for those who struggle to recognize facial expressions like children with autism [60]. A method based on the radial basis function (RBF) neural network was used to support the design and evaluation of educational toys for children with autism [61].

Radiomics in paediatric cancer treatment

Radiomics has been successfully used in decision making concerning urological cancer in children. [62], neuro-oncology [63] and targeted cancer therapy [64]

Analysis of CT and MRI images for blastoma prognosis

Machine learning analyses of computed tomography images was used for non-invasive prediction of *MYCN* amplification status in pediatric neuroblastoma patients [65,66] , predicting risk of recurrence [67] and identification of high-risk neuroblastoma [68].

Table 3. Representative author keywords, Categories and themes in research concerning AI use in pediatrics (represent the number of keywords in a cluster and the numbers in parentheses the frequency codes).

Color	Representative author keywords (codes)	Categories	Themes
Green (n=21)	Deep learning (431); Convolutional neural network (152); Pneumonia (n=56); Transfer Learning (n=54); Bone age assessment (47); Covid 19 (43); Congenital heart diseases (n=29)	Deep learning with convolutional networks for complex decision making about bone age assessment and pneumonia; Segmentation of echocardiography images in congenital heart diseases	Analysing complex signals using deep learning
Red (n=26)	Machine learning (758); Pediatrics (464); Prediction (n=61); Natural language processing (n=60); Electronic health records (n=58); Clinical decision support (53); Asthma (39); Critica care (32), Data mining /26)Artificial neural networks (25); Sepsis (25); Cancer (24)	Machine learning on electronic health records for predication and critical decision support in asthma and sepsis; Natural language processing of electronic health records; Big data analysis for paediatric cancer patients	Critical clinical decision making and prediction with machine learning and natural language processing
Blue (n=14)	Classification (73); Support vector machines (63, Epilepsy (57); Segmentation (48); MRI (40); Random forest (39); Artificial neural networks (32); EEG (25)	Segmentation, feature selection and classification of EEG and MRI signals; Seizure detection in epilepsy and cerebral palsy;	MRI and EEG analysis in seizure detection in epilepsy and cerebral palsy
Yellow (n=11)	Artificial intelligence (420); Children (188); Radiology and radiography (50); Autism spectre disorder (34)Diagnosis /46); Bone age (30)	Artificial intelligence based processing of radiography and radiology outputs for assessing bone age, Diagnosis of autism spectre disorder with artificial intelligence	Using artificial intelligence for diagnosing

 doi:10.20944/preprints202401.0564.v1

Viollet (n=10)	Magnetic resonance imaging (48), Blastoma (46); Computer tomography (44); Radiomics (41);	Analysis of CT and MRI images for blastoma prognosis	Radiomics in peditric cancer treatment

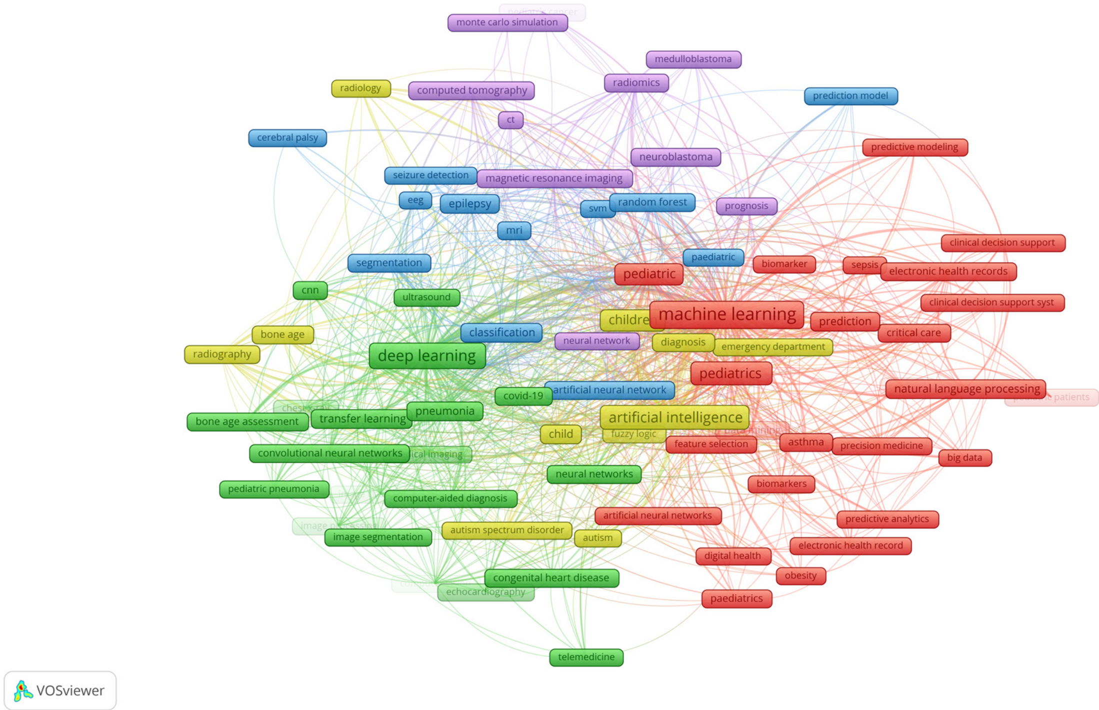

Figure 2. Authors keyword map, for keywords appearing in 15 or more publications.

3.2.2. Deductive content analysis

The results of the inductive content analysis including 15 most prolific representatives of preconcive categories Machine learning algorithms, AI approaches, Pediatric diagnoses and Applicationa in pediatrics are shown in Table 4. The most used machine learning algorithms are form the family of neural networks, followed by support vector machines and naïve Bayes. The most used AI approaches are Classfication, natural language processong and text mining. The AI is most used to help children with pneumonia, epilepsy, COVID and asthma. The most frequent apllications are signal and image processing, prediction and computer aided diagnosis, bone age assesment, decision making in critical care and clinical decision making in general.

Table 4. The results of the deductive content analaysis based on keywords emerging in five or more publications (the number in parantheseses present the number of publications in which a certain code emerge).

Machine learning algorithms	AI Approaches	Pediatric diagnoses	Applications in pediatrics
Deep learning (464)	Classification (95)	Pneumonia (71)	Bone age assesment (77)
Convolutional neural network (196)	Natural language processing (60)	Epilepsy (70)	Critical care (43)

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 8 January 2024 doi:10.20944/preprints202401.0564.v1

Transfer learning (54)	Data and text mining (31)	Covid 19 (43)	Prediction (146)
Support vector machine (51)	Feature selection and extraction (64)	Asthma (50)	Computer-aided diagnosis (86)
Artificial neural networks (111)	Monte carlo simulation (33)	Obstructive sleep apnea (12)	Signal and image processing (73)
Random forest (45)	Data augmentation (8)	Autism spectrum disorder (34)	Clinical decision support (112)
Fuzzy logic (16)	Big data (19)	Sepsis (35)	Radiomics (41)
Logistic regression (19)	Explainable artificial intelligence (10)	Cerebral palsy (17)	Computer vision (16)
Decision tree (18)	Digital health (16)	Kidney dieases (16)	Triaging (11
Ensemble learning (15)	Expert systems (6)	Cancer (47)	Anomaly detection (12)
Genetic algorithm (8)		Crohn's disease (12)	Epidemiology (14)
Bayesian methods (10)		Cystic fibrosis (10)	Length of stay (7)
		Mental health (12)	Metabolomics (10)
		Congenital heart disease (39)	Quality improvement (12)
		Blastoma (50)	Severity of illness (9)

3.3. Research co-operation

Country cooperation based on co-authorship is presented in Figure 3. As shown 54 countries have published 10 or more publications. The United States (n=52), United Kingdom (n=48), Spain (n=44), Australia (n=43), Germany (n=43), Canada (n=41), China (n=41), France (n=40), and Austri (n=39) were the countries with the most intensive international collaboration.

The most intensive bilateral cooperation existed between United States and Canada (132 publications), United States and China (93 publications), United States and United Kingdom (92 publications),United States and Korea (32 publications) and United States and Germany (56 publications). In Europe the more intenensive cooperation existed between Germany and United Kingdom (n=40), Germany and Italy (n=25), Italy and United Kingdom (n=26), and Netherland and Swiss (n=14). In other regions the notable cooperation existed between China and Hong Kong (n=18), Saudia Arabia and India with 12 publications and South Korea and China with 5 publications. The oldest average age of publications was found in Sweden, Ireland, Japan and Poland and the youngest in Singapore, Saudi Arabia, Pakistan and South Korea.

The most cited publications were from the United States, Germany, Finland, Belgium and, Mexico and Brazil and the less cited from Thailand, Croatia, Serbia, Israel, Japan, Russian Federation and Malysia (Fig. 4).

 doi:10.20944/preprints202401.0564.v1

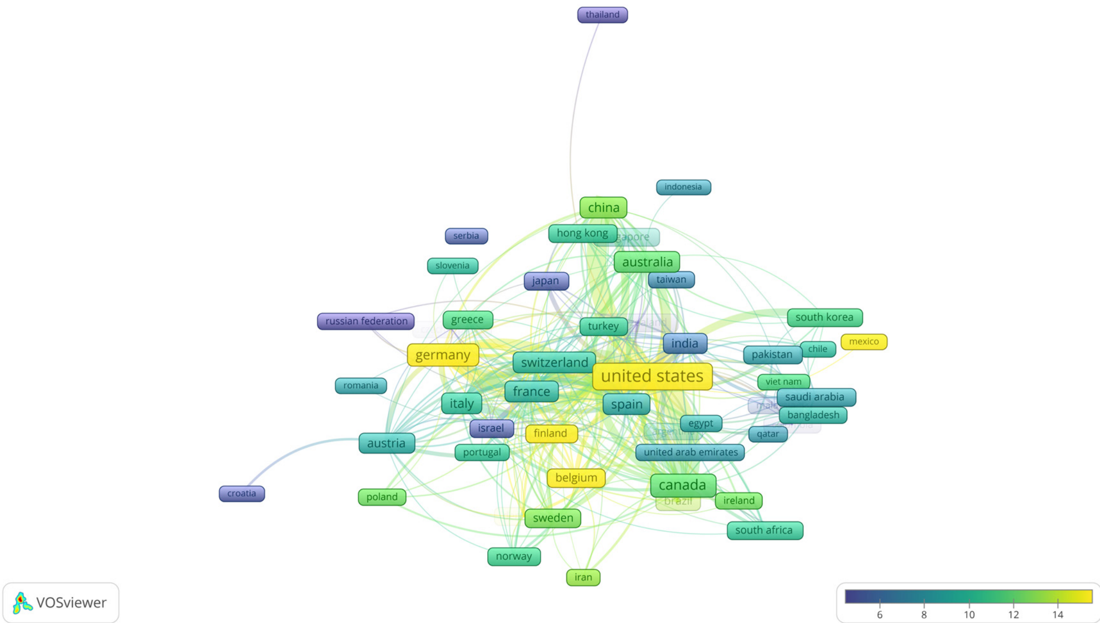

Figure 3. Country cooperation map based on co-authorships. The colors represent the average age of publications, and the square size represent the number of co-authorships with other countries. Countries with more 10 or more publications are shown.

4. Conclusions

The landscapes uncovered in this study are presenting a multi-dimensional facet and map of the weight loss and motivation problem, which can help community to solve theoretical and practical challenges. Obesity researchers and practitioners can use the study results to improve their understanding of the area and can catalyze their further knowledge development. On the other hand, it can inform novice researchers, interested readers, research mangers or patients without specific knowledge and help them to develop-op a perspective on the most important weight loss research dimensions. Finally, the landscape can serve as a guide to further research and a starting point to more formal knowledge synthesis endeavours like systematic reviews and meta-analyses.

Author Contributions: Authors contributed equally in the executing of the study and paper writting

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in the study are included in the manuscript. The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Sugiyama, K.; Hasegawa, Y. COMPUTER ASSISTED MEDICAL DIAGNOSIS SYSTEM FOR INBORN ERRORS OF METABOLISM.; 1984; Vol. 22, pp. 942–943.
2. Kokol, P.; Kokol, M.; Zagoranski, S. Machine Learning on Small Size Samples: A Synthetic Knowledge Synthesis. *Science Progress* **2022**, *105*, 00368504211029777, doi:10.1177/00368504211029777.

3. Pritchard, A. Statistical Bibliography or Bibliometrics? *Journal of Documentation* **1969**, *25*, 348–349.
4. Bellis, N.D. *Bibliometrics and Citation Analysis: From the Science Citation Index to Cybermetrics*; Scarecrow Press: Lanham, Md, 2009; ISBN 978-0-8108-6713-0.
5. Ball, R. *An Introduction to Bibliometrics*; Elsevier: Amsterdam, 2018; ISBN 978-0-08-102150-7.
6. van Eck, N.J.; Waltman, L. Software Survey: VOSviewer, a Computer Program for Bibliometric Mapping. *Scientometrics* **2010**, *84*, 523–538, doi:10.1007/s11192-009-0146-3.
7. Kyngäs, H. Qualitative Research and Content Analysis. In *The Application of Content Analysis in Nursing Science Research*; Kyngäs, H., Mikkonen, K., Kääriäinen, M., Eds.; Springer International Publishing: Cham, 2020; pp. 3–11 ISBN 978-3-030-30199-6.
8. Lee, H. Paging Dr. Watson: IBM's Watson Supercomputer Now Being Used in Healthcare. *Journal of AHIMA* **2014**, *85*, 44–47.
9. Liang, Z.; Zhang, G.; Huang, J.X.; Hu, Q.V. Deep Learning for Healthcare Decision Making with EMRs. In Proceedings of the 2014 IEEE International Conference on Bioinformatics and Biomedicine (BIBM); November 2014; pp. 556–559.
10. List of Healthiest Kids from These Countries in the World 2023 Available online: https://www.jagranjosh.com/general-knowledge/which-countries-have-the-healthiest-kids-1698217870-1 (accessed on 20 December 2023).
11. Kokol, P.; Železnik, D.; Završnik, J.; Blažun Vošner, H. Nursing Research Literature Production in Terms of the Scope of Country and Health Determinants: A Bibliometric Study. *Journal of Nursing Scholarship* **2019**, *51*, 590–598, doi:10.1111/jnu.12500.
12. Brady, S.L.; Trout, A.T.; Somasundaram, E.; Anton, C.G.; Li, Y.; Dillman, J.R. Improving Image Quality and Reducing Radiation Dose for Pediatric CT by Using Deep Learning Reconstruction. *Radiology* **2021**, *298*, 180–188, doi:10.1148/RADIOL.2020202317.
13. Wang, Y.-R.J.; Baratto, L.; Hawk, K.E.; Theruvath, A.J.; Pribnow, A.; Thakor, A.S.; Gatidis, S.; Lu, R.; Gummidipundi, S.E.; Garcia-Diaz, J.; et al. Artificial Intelligence Enables Whole-Body Positron Emission Tomography Scans with Minimal Radiation Exposure. *European Journal of Nuclear Medicine and Molecular Imaging* **2021**, *48*, 2771–2781, doi:10.1007/s00259-021-05197-3.
14. Koetzier, L.R.; Mastrodicasa, D.; Szczykutowicz, T.P.; van der Werf, N.R.; Wang, A.S.; Sandfort, V.; van der Molen, A.J.; Fleischmann, D.; Willemink, M.J. Deep Learning Image Reconstruction for CT: Technical Principles and Clinical Prospects. *Radiology* **2023**, *306*, doi:10.1148/radiol.221257.
15. Dupuis, M.; Delbos, L.; Veil, R.; Adamsbaum, C. External Validation of a Commercially Available Deep Learning Algorithm for Fracture Detection in Children. *Diagnostic and Interventional Imaging* **2022**, *103*, 151–159, doi:10.1016/j.diii.2021.10.007.
16. Peng, J.; Kim, D.D.; Patel, J.B.; Zeng, X.; Huang, J.; Chang, K.; Xun, X.; Zhang, C.; Sollee, J.; Wu, J.; et al. Deep Learning-Based Automatic Tumor Burden Assessment of Pediatric High-Grade Gliomas, Medulloblastomas, and Other Leptomeningeal Seeding Tumors. *Neuro-Oncology* **2022**, *24*, 289–299, doi:10.1093/neuonc/noab151.
17. Usman, M.; Zia, T.; Tariq, A. Analyzing Transfer Learning of Vision Transformers for Interpreting Chest Radiography. *Journal of Digital Imaging* **2022**, *35*, 1445–1462, doi:10.1007/s10278-022-00666-z.

18. Salim, I.; Hamza, A.B. Ridge Regression Neural Network for Pediatric Bone Age Assessment. *Multimedia Tools and Applications* **2021**, *80*, 30461–30478, doi:10.1007/s11042-021-10935-8.
19. Liu, C.; Xie, H.; Zhang, Y. Self-Supervised Attention Mechanism for Pediatric Bone Age Assessment with Efficient Weak Annotation. *IEEE Transactions on Medical Imaging* **2021**, *40*, 2685–2697, doi:10.1109/TMI.2020.3046672.
20. Ozdemir, C.; Gedik, M.A.; Kaya, Y. Age Estimation from Left-Hand Radiographs with Deep Learning Methods. *Traitement du Signal* **2021**, *38*, 1565–1574, doi:10.18280/ts.380601.
21. Deshmukh, S.; Khaparde, A. Faster Region-Convolutional Neural Network Oriented Feature Learning with Optimal Trained Recurrent Neural Network for Bone Age Assessment for Pediatrics. *Biomedical Signal Processing and Control* **2022**, *71*, doi:10.1016/j.bspc.2021.103016.
22. Salehi, M.; Mohammadi, R.; Ghaffari, H.; Sadighi, N.; Reiazi, R. Automated Detection of Pneumonia Cases Using Deep Transfer Learning with Paediatric Chest X-Ray Images. *British Journal of Radiology* **2021**, *94*, doi:10.1259/bjr.20201263.
23. Fernandes, V.; Junior, G.B.; de Paiva, A.C.; Silva, A.C.; Gattass, M. Bayesian Convolutional Neural Network Estimation for Pediatric Pneumonia Detection and Diagnosis. *Computer Methods and Programs in Biomedicine* **2021**, *208*, doi:10.1016/j.cmpb.2021.106259.
24. Fang, X.; Li, W.; Huang, J.; Li, W.; Feng, Q.; Han, Y.; Ding, X.; Zhang, J. Ultrasound Image Intelligent Diagnosis in Community-Acquired Pneumonia of Children Using Convolutional Neural Network-Based Transfer Learning. *Frontiers in Pediatrics* **2022**, *10*, doi:10.3389/fped.2022.1063587.
25. Mori, H.; Inai, K.; Sugiyama, H.; Muragaki, Y. Diagnosing Atrial Septal Defect from Electrocardiogram with Deep Learning. *Pediatric Cardiology* **2021**, *42*, 1379–1387, doi:10.1007/s00246-021-02622-0.
26. Fujiwara, T.; Berhane, H.; Scott, M.B.; Englund, E.K.; Schäfer, M.; Fonseca, B.; Berthusen, A.; Robinson, J.D.; Rigsby, C.K.; Browne, L.P.; et al. Segmentation of the Aorta and Pulmonary Arteries Based on 4D Flow MRI in the Pediatric Setting Using Fully Automated Multi-Site, Multi-Vendor, and Multi-Label Dense U-Net. *Journal of Magnetic Resonance Imaging* **2022**, *55*, 1666–1680, doi:10.1002/jmri.27995.
27. Edwards, L.A.; Feng, F.; Iqbal, M.; Fu, Y.; Sanyahumbi, A.; Hao, S.; McElhinney, D.B.; Ling, X.B.; Sable, C.; Luo, J. Machine Learning for Pediatric Echocardiographic Mitral Regurgitation Detection. *Journal of the American Society of Echocardiography* **2023**, *36*, 96-104.e4, doi:10.1016/j.echo.2022.09.017.
28. Ye, J. Pediatric Mental and Behavioral Health in the Period of Quarantine and Social Distancing with COVID-19. *JMIR Pediatrics and Parenting* **2020**, *3*, doi:10.2196/19867.
29. Marcinkevics, R.; Reis Wolfertstetter, P.; Wellmann, S.; Knorr, C.; Vogt, J.E. Using Machine Learning to Predict the Diagnosis, Management and Severity of Pediatric Appendicitis. *Frontiers in Pediatrics* **2021**, *9*, doi:10.3389/fped.2021.662183.
30. Castiñeira, D.; Schlosser, K.R.; Geva, A.; Rahmani, A.R.; Fiore, G.; Walsh, B.K.; Smallwood, C.D.; Arnold, J.H.; Santillana, M. Adding Continuous Vital Sign Information to Static Clinical Data Improves the Prediction of Length of Stay after Intubation: A Data-Driven Machine Learning Approach. *Respiratory Care* **2020**, *65*, 1367–1377, doi:10.4187/respcare.07561.

31. Roquette, B.P.; Nagano, H.; Marujo, E.C.; Maiorano, A.C. Prediction of Admission in Pediatric Emergency Department with Deep Neural Networks and Triage Textual Data. *Neural Networks* **2020**, *126*, 170–177, doi:10.1016/j.neunet.2020.03.012.
32. Singh, D.; Nagaraj, S.; Mashouri, P.; Drysdale, E.; Fischer, J.; Goldenberg, A.; Brudno, M. Assessment of Machine Learning-Based Medical Directives to Expedite Care in Pediatric Emergency Medicine. *JAMA Network Open* **2022**, *5*, doi:10.1001/jamanetworkopen.2022.2599.
33. Gabryszewski, S.J.; Chang, X.; Dudley, J.W.; Mentch, F.; March, M.; Holmes, J.H.; Moore, J.; Grundmeier, R.W.; Hakonarson, H.; Hill, D.A. Unsupervised Modeling and Genome-Wide Association Identify Novel Features of Allergic March Trajectories. *Journal of Allergy and Clinical Immunology* **2021**, *147*, 677-685.e10, doi:10.1016/j.jaci.2020.06.026.
34. Jeddi, Z.; Gryech, I.; Ghogho, M.; Hammoumi, M.E.L.; Mahraoui, C. Machine Learning for Predicting the Risk for Childhood Asthma Using Prenatal, Perinatal, Postnatal and Environmental Factors. *Healthcare (Switzerland)* **2021**, *9*, doi:10.3390/healthcare9111464.
35. Amrulloh, Y.; Abeyratne, U.; Swarnkar, V.; Triasih, R. Cough Sound Analysis for Pneumonia and Asthma Classification in Pediatric Population.; 2015; Vol. 2015-October, pp. 127–131.
36. Rashid, A.; Anwary, A.R.; Al-Obeidat, F.; Brierley, J.; Uddin, M.; Alkhzaimi, H.; Sarpal, A.; Toufiq, M.; Malik, Z.A.; Kadwa, R.; et al. Application of a Gene Modular Approach for Clinical Phenotype Genotype Association and Sepsis Prediction Using Machine Learning in Meningococcal Sepsis. *Informatics in Medicine Unlocked* **2023**, *41*, doi:10.1016/j.imu.2023.101293.
37. Garcelon, N.; Burgun, A.; Salomon, R.; Neuraz, A. Electronic Health Records for the Diagnosis of Rare Diseases. *Kidney International* **2020**, *97*, 676–686, doi:10.1016/j.kint.2019.11.037.
38. Colmenarejo, G. Machine Learning Models to Predict Childhood and Adolescent Obesity: A Review. *Nutrients* **2020**, *12*, 1–31, doi:10.3390/nu12082466.
39. Kanbar, L.J.; Wissel, B.; Ni, Y.; Pajor, N.; Glauser, T.; Pestian, J.; Dexheimer, J.W. Implementation of Machine Learning Pipelines for Clinical Practice: Development and Validation Study. *JMIR Medical Informatics* **2022**, *10*, doi:10.2196/37833.
40. Lanera, C.; Baldi, I.; Francavilla, A.; Barbieri, E.; Tramontan, L.; Scamarcia, A.; Cantarutti, L.; Giaquinto, C.; Gregori, D. A Deep Learning Approach to Estimate the Incidence of Infectious Disease Cases for Routinely Collected Ambulatory Records: The Example of Varicella-Zoster. *International Journal of Environmental Research and Public Health* **2022**, *19*, doi:10.3390/ijerph19105959.
41. Chafjiri, F.M.A.; Reece, L.; Voke, L.; Landschaft, A.; Clark, J.; Kimia, A.A.; Loddenkemper, T. Natural Language Processing for Identification of Refractory Status Epilepticus in Children. *Epilepsia* **2023**, *64*, 3227–3237, doi:10.1111/epi.17789.
42. Major, A.; Cox, S.M.; Volchenboum, S.L. Using Big Data in Pediatric Oncology: Current Applications and Future Directions. *Seminars in Oncology* **2020**, *47*, 56–64, doi:10.1053/j.seminoncol.2020.02.006.
43. Langenberg, K.P.S.; Looze, E.J.; Molenaar, J.J. The Landscape of Pediatric Precision Oncology: Program Design, Actionable Alterations, and Clinical Trial Development. *Cancers* **2021**, *13*, doi:10.3390/cancers13174324.
44. Jawahar, M.; H, S.; L, J.A.; Gandomi, A.H. ALNett: A Cluster Layer Deep Convolutional Neural Network for Acute Lymphoblastic Leukemia Classification. *Computers in Biology and Medicine* **2022**, *148*, doi:10.1016/j.compbiomed.2022.105894.

45. Pandey, A.; Malviya, R.; Dahiya, S. Risk Assessment in the Field of Oncology Using Big Data. In *Big Data in Oncology: Impact, Challenges, and Risk Assessment*; 2023; pp. 355–409 ISBN 978-87-7022-812-1.
46. Chen, S.; Zhang, J.; Ruan, X.; Deng, K.; Zhang, J.; Zou, D.; He, X.; Li, F.; Bin, G.; Zeng, H.; et al. Voxel-Based Morphometry Analysis and Machine Learning Based Classification in Pediatric Mesial Temporal Lobe Epilepsy with Hippocampal Sclerosis. *Brain Imaging and Behavior* **2020**, *14*, 1945–1954, doi:10.1007/s11682-019-00138-z.
47. Palraj, P.; Siddan, G. Deep Learning Algorithm for Classification of Cerebral Palsy from Functional Magnetic Resonance Imaging (fMRI) Classification of Cerebral Palsy from Functional Magnetic Resonance Imaging. *International Journal of Advanced Computer Science and Applications* **2021**, *12*, 718–724, doi:10.14569/IJACSA.2021.0120383.
48. Sethy, P.K.; Panigrahi, M.; Vijayakumar, K.; Behera, S.K. Machine Learning Based Classification of EEG Signal for Detection of Child Epileptic Seizure without Snipping. *International Journal of Speech Technology* **2023**, *26*, 559–570, doi:10.1007/s10772-021-09855-7.
49. Dong, F.; Yuan, Z.; Wu, D.; Jiang, L.; Liu, J.; Hu, W. Novel Seizure Detection Algorithm Based on Multi-Dimension Feature Selection. *Biomedical Signal Processing and Control* **2023**, *84*, doi:10.1016/j.bspc.2023.104747.
50. Oliveira, J.; Renna, F.; Costa, P.D.; Nogueira, M.; Oliveira, C.; Ferreira, C.; Jorge, A.; Mattos, S.; Hatem, T.; Tavares, T.; et al. The CirCor DigiScope Dataset: From Murmur Detection to Murmur Classification. *IEEE Journal of Biomedical and Health Informatics* **2022**, *26*, 2524–2535, doi:10.1109/JBHI.2021.3137048.
51. Struyf, T.; Deeks, J.J.; Dinnes, J.; Takwoingi, Y.; Davenport, C.; Leeflang, M.M.G.; Spijker, R.; Hooft, L.; Emperador, D.; Domen, J.; et al. Signs and Symptoms to Determine If a Patient Presenting in Primary Care or Hospital Outpatient Settings Has COVID-19. *Cochrane Database of Systematic Reviews* **2022**, *2022*, doi:10.1002/14651858.CD013665.pub3.
52. Ghosh, P.; Katkar, G.D.; Shimizu, C.; Kim, J.; Khandelwal, S.; Tremoulet, A.H.; Kanegaye, J.T.; Abe, N.; Austin-Page, L.; Bryl, A.; et al. An Artificial Intelligence-Guided Signature Reveals the Shared Host Immune Response in MIS-C and Kawasaki Disease. *Nature Communications* **2022**, *13*, doi:10.1038/s41467-022-30357-w.
53. Cohen, A.S.A.; Farrow, E.G.; Abdelmoity, A.T.; Alaimo, J.T.; Amudhavalli, S.M.; Anderson, J.T.; Bansal, L.; Bartik, L.; Baybayan, P.; Belden, B.; et al. Genomic Answers for Children: Dynamic Analyses of >1000 Pediatric Rare Disease Genomes. *Genetics in Medicine* **2022**, *24*, 1336–1348, doi:10.1016/j.gim.2022.02.007.
54. Padash, S.; Mohebbian, M.R.; Adams, S.J.; Henderson, R.D.E.; Babyn, P. Pediatric Chest Radiograph Interpretation: How Far Has Artificial Intelligence Come? A Systematic Literature Review. *Pediatric Radiology* **2022**, *52*, 1568–1580, doi:10.1007/s00247-022-05368-w.
55. Kim, P.H.; Yoon, H.M.; Kim, J.R.; Hwang, J.-Y.; Choi, J.-H.; Hwang, J.; Lee, J.; Sung, J.; Jung, K.-H.; Bae, B.; et al. Bone Age Assessment Using Artificial Intelligence in Korean Pediatric Population: A Comparison of Deep-Learning Models Trained With Healthy Chronological and Greulich-Pyle Ages as Labels. *Korean Journal of Radiology* **2023**, *24*, 1151–1163, doi:10.3348/kjr.2023.0092.

56. Prokop-Piotrkowska, M.; Marszałek-Dziuba, K.; Moszczyńska, E.; Szalecki, M.; Jurkiewicz, E. Traditional and New Methods of Bone Age Assessment-an Overview. *JCRPE Journal of Clinical Research in Pediatric Endocrinology* **2021**, *13*, 251–262, doi:10.4274/jcrpe.galenos.2020.2020.0091.
57. Thodberg, H.H.; Thodberg, B.; Ahlkvist, J.; Offiah, A.C. Autonomous Artificial Intelligence in Pediatric Radiology: The Use and Perception of BoneXpert for Bone Age Assessment. *Pediatric Radiology* **2022**, *52*, 1338–1346, doi:10.1007/s00247-022-05295-w.
58. Kim, D.-W.; Kim, J.; Kim, T.; Kim, T.; Kim, Y.-J.; Song, I.-S.; Ahn, B.; Choo, J.; Lee, D.-Y. Prediction of Hand-Wrist Maturation Stages Based on Cervical Vertebrae Images Using Artificial Intelligence. *Orthodontics and Craniofacial Research* **2021**, *24*, 68–75, doi:10.1111/ocr.12514.
59. Suh, J.; Heo, J.; Kim, S.J.; Park, S.; Jung, M.K.; Choi, H.S.; Choi, Y.; Oh, J.S.; Lee, H.I.; Lee, M.; et al. Bone Age Estimation and Prediction of Final Adult Height Using Deep Learning. *Yonsei Medical Journal* **2023**, *64*, 679–686, doi:10.3349/ymj.2023.0244.
60. Banerjee, A.; Mutlu, O.C.; Kline, A.; Surabhi, S.; Washington, P.; Wall, D.P. Training and Profiling a Pediatric Facial Expression Classifier for Children on Mobile Devices: Machine Learning Study. *JMIR Formative Research* **2023**, *7*, doi:10.2196/39917.
61. Qi, Y.; Han, J.-X. Rehabilitation Educational Design for Children with Autism Based on the Radial Basis Function Neural Network. *Journal of Healthcare Engineering* **2021**, *2021*, doi:10.1155/2021/2961546.
62. Shah, M.; Naik, N.; Somani, B.K.; Hameed, B.M.Z. Artificial Intelligence (Ai) in Urology-Current Use and Future Directions: An Itrue Study. *Turkish Journal of Urology* **2020**, *46*, S27–S39, doi:10.5152/tud.2020.20117.
63. Abdel Razek, A.A.K.; Alksas, A.; Shehata, M.; AbdelKhalek, A.; Abdel Baky, K.; El-Baz, A.; Helmy, E. Clinical Applications of Artificial Intelligence and Radiomics in Neuro-Oncology Imaging. *Insights into Imaging* **2021**, *12*, doi:10.1186/s13244-021-01102-6.
64. Migliozzi, S.; Oh, Y.T.; Hasanain, M.; Garofano, L.; D'Angelo, F.; Najac, R.D.; Picca, A.; Bielle, F.; Di Stefano, A.L.; Lerond, J.; et al. Integrative Multi-Omics Networks Identify PKCδ and DNA-PK as Master Kinases of Glioblastoma Subtypes and Guide Targeted Cancer Therapy. *Nature Cancer* **2023**, *4*, 181–202, doi:10.1038/s43018-022-00510-x.
65. Tan, E.; Merchant, K.; KN, B.P.; CS, A.; Zhao, J.J.; Saffari, S.E.; Tan, P.H.; Tang, P.H. CT-Based Morphologic and Radiomics Features for the Classification of MYCN Gene Amplification Status in Pediatric Neuroblastoma. *Childs Nerv Syst* **2022**, *38*, 1487–1495, doi:10.1007/s00381-022-05534-3.
66. Wu, H.; Wu, C.; Zheng, H.; Wang, L.; Guan, W.; Duan, S.; Wang, D. Radiogenomics of Neuroblastoma in Pediatric Patients: CT-Based Radiomics Signature in Predicting MYCN Amplification. *Eur Radiol* **2021**, *31*, 3080–3089, doi:10.1007/s00330-020-07246-1.
67. Feng, L.; Qian, L.; Yang, S.; Ren, Q.; Zhang, S.; Qin, H.; Wang, W.; Wang, C.; Zhang, H.; Yang, J. Clinical Parameters Combined with Radiomics Features of PET/CT Can Predict Recurrence in Patients with High-Risk Pediatric Neuroblastoma. *BMC Med Imaging* **2022**, *22*, 102, doi:10.1186/s12880-022-00828-z.
68. Wang, H.; Xie, M.; Chen, X.; Zhu, J.; Ding, H.; Zhang, L.; Pan, Z.; He, L. Development and Validation of a CT-Based Radiomics Signature for Identifying High-Risk Neuroblastomas

 doi:10.20944/preprints202401.0564.v1

under the Revised Children's Oncology Group Classification System. *Pediatric Blood & Cancer* **2023**, *70*, e30280, doi:10.1002/pbc.30280.