**Search Strategies**

**PubMed Search Strategy:**

((Artificial Intelligence OR Machine Learning OR Natural Language Processing OR Deep Learning OR Supervised Learning OR Unsupervised Learning OR Neural Network OR Ensemble Machine Learning AND Healthcare OR Medicine OR Disease OR Diagnosis OR Prediction OR Screening OR Precision Medicine OR Clinical Decision Support OR Decision Support Systems, Clinical [Mesh] OR Evidence Based Care OR Diagnostic imag\* OR Evidence-Based Medicine OR Evidence Based Practice [Mesh])

**CINAHL Plus with full-text search strategy:**

( ("Artificial Intelligence"[Mesh] OR "Machine learning" OR "Artificial intelligence" OR NLP OR "Deep learning" OR "Supervised learning" OR "Unsupervised learning" OR "Neural network\*" OR "Ensemble machine learning") ) AND ( (healthcare OR Medicine OR Disease OR Diagnosis OR Prediction OR Screening OR "Precision medicine" OR "Clinical Decision support" OR "Decision Support Systems, Clinical"[Mesh] OR "Evidence based care" OR "Risk factor\*" OR "Evidence-Based Medicine"[Mesh] OR "Evidence-Based Practice"[Mesh]) )

**EBSCO Dentistry & Oral Science Source search strategy:**   
( ("Artificial Intelligence"[Mesh] OR "Machine learning" OR "Artificial intelligence" OR NLP OR "Deep learning" OR "Supervised learning" OR "Unsupervised learning" OR "Neural network\*" OR "Ensemble machine learning") ) AND ( (healthcare OR Medicine OR Disease OR Diagnosis OR Prediction OR Screening OR "Precision medicine" OR "Clinical Decision support" OR "Decision Support Systems, Clinical"[Mesh] OR "Evidence based care" OR "Risk factor\*" OR "Evidence-Based Medicine"[Mesh] OR "Evidence-Based Practice"[Mesh])

**Web of Science search strategy:**

((Artificial Intelligence OR Machine learning OR NLP OR Deep learning OR Supervised learning OR Unsupervised learning OR Neural networks OR Ensemble machine learning)) AND TOPIC:((healthcare OR Medicine OR Disease OR Diagnosis OR Prediction OR Screening OR Precision medicine OR Clinical Decision support OR Decision Support Systems OR Evidence based care OR Risk factors OR Evidence Based Medicine OR Evidence-Based Practice)) AND TOPIC: ((Child OR children OR teen OR adolescent OR baby OR toddler OR infant))

**Cochrane Library search strategy:**

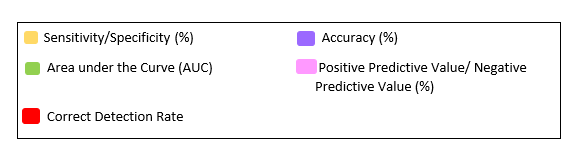
'(Artificial Intelligence OR Machine learning OR NLP OR Deep learning OR Supervised learning OR Unsupervised learning OR Neural networks OR Ensemble machine learning) in All Text AND (healthcare OR Medicine OR Disease OR Diagnosis OR Prediction OR Screening OR Precision medicine OR Clinical Decision support OR Decision Support Systems OR Evidence based care OR Risk factors OR Evidence Based Medicine OR Evidence-Based Practice) in All Text - (Word variations have been searched)'

Table of Included Studies

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **S.No** | **Author and year** | **Country** | **Subspecialty** | **Sample size** | **Purpose of the model** | **AI model utilized** | **Best average results** | | | |
| **Sensitivity/**  **Specificity** | **Accuracy** | **AUC** | **Other measures used** |
|  | Abbas H 2018 | USA | Psychiatry | 2643 | Diagnosis | Ensemble | 70%/67% | 72% | \_ | \_ |
|  | Abibullaev B 2012 | Korea | Psychiatry | 10 | Diagnosis | Ensemble | \_ | \_ | 0.97 | \_ |
|  | Adeli E 2019 | USA | Neurology | 24 | Prediction | Regression | \_ | \_ | \_ | Correlation  coefficient= 0.73 |
|  | Afzal 2013 | Netherlands | Pulmonology | 5032 | Diagnosis | Rule based system | 98%/95% | \_ | \_ | \_ |
|  | Aggarwal G2018 | India | Neurology | 48 | Diagnosis | Neural networks. Ensemble | \_ | 98% | \_ | \_ |
|  | Aghdam MA, 2018 | Iran | Radiology | 185 | Diagnosis | Deep learning | 84%/32.96% | \_ | \_ | \_ |
|  | Ahmadlou 2012 | USA | Neurology | 18 | Diagnosis | Neural networks | \_ | 95.5% | \_ | \_ |
|  | Ahmadlou M 2010 | Iran | Psychiatry | 17 | Diagnosis | Neural networks | \_ | 90% | \_ | \_ |
|  | Ahmed 2016 | Ireland | Neonatology | 54 | Diagnosis | Ensemble | \_ | 87% | \_ | \_ |
|  | Ahmed 2017 | Ireland | Neonatology | 17 | Diagnosis | Neural networks | \_ | 71.9% | \_ | \_ |
|  | Akdemir 2009 | Turkey | Cardiology | 2733 | Prediction | Neural networks | \_ | \_ | \_ | Correlation  coefficient= 0.99 |
|  | Aljabar P, 2010 | UK | Radiology | 140 | Diagnosis | Dimensionality reduction | \_ | \_ | \_ | Correlation  coefficient= 0.93 |
|  | Amarreh I 2014 | USA | Neurology | 49 | Diagnosis | Ensemble | 98.1/100% | \_ | \_ | \_ |
|  | Ambalavanan 2001 | USA | Neonatology | 810 | Prediction | Neural networks; Regression | \_ | \_ | 0.87 | \_ |
|  | Ambalavanan 2005 | USA | Neurology | 218 | Prediction | Neural networks | 90%/52% | \_ | \_ | \_ |
|  | Ambalavanan 2005 | USA | Neonatology | 8608 | Prediction | Neural networks; Regression | \_ | \_ | 0.854 | \_ |
|  | Amini 2016 | Iran | Neonatology | 4342 | Diagnosis | Neural networks; Regression; Ensemble | 100%/89% | \_ | \_ | \_ |
|  | Anand 2008 | USA | Pulmonology | 16817 | Diagnosis | Bayesian methods | \_ | \_ | 0.726 | \_ |
|  | Andersson A, 2007 | Sweden | Heme/Onco | 127 | Prediction | Instance based; | \_ | 97% | \_ | \_ |
|  | Ansari 2015 | Netherlands | Neurology | 35 | Diagnosis | Ensemble | \_ | \_ | \_ | Positive predictive value= 50% |
|  | Anzulewicz A 2016 | UK | Psychiatry | 82 | Diagnosis | Ensemble | \_ | \_ | 0.937 | \_ |
|  | Arabi 2006 | Ireland | Neonatology | 6 | Diagnosis | Neural networks | 91%/95% | \_ | \_ | \_ |
|  | Arle JE, 1997 | USA | Radiology | 33 | Diagnosis | Neural networks | \_ | 80% | \_ | \_ |
|  | Arlen 2016 | USA | Infectious Diseases | 255 | Diagnosis | Regression, Dimensionality reduction | \_ | \_ | 0.76 | \_ |
|  | Armstrong 2018 | Australia | Neurology | 1322 | Diagnosis | Decision tree | 24.5%/95.1% | 75% | \_ | \_ |
|  | Askari 2018 | Iran | Neurology | 200 | Diagnosis | Neural networks | 85.92/89.72 | \_ | \_ | \_ |
|  | Ataer-Cansizoglu E 2015 | USA | Others | 77 | Diagnosis | Ensemble | \_ | 95% | \_ | \_ |
|  | Aucouturier 2011 | Japan | Neurology | 14 | Diagnosis | Ensemble | \_ | \_ | \_ | Precision= 95% |
|  | Aydın 2016 | Turkey | Neonatology | 80 | Diagnosis | Regression; Instance based | \_ | 85% | \_ | \_ |
|  | Ball 2016 | London | Neonatology | 131 | Diagnosis | Neural networks | \_ | 80% | 0.92 | \_ |
|  | Bartz-Kurycki 2018 | USA | Neonatology | 13589 | Diagnosis | Regression; Ensemble | \_ | 95.99% | \_ | \_ |
|  | Bussu G 2018 | Netherlands | Psychiatry | 303 | Diagnosis | Ensemble | \_ | \_ | 0.65 | \_ |
|  | Baumgartner 2004 | Germany | Neonatology | 2585 | Diagnosis | Decision tree; Regression; Neural networks; Ensemble | \_ | 99.8% | \_ | \_ |
|  | Ben-Sasson A 2016 | Israel | Psychiatry | 195 | Diagnosis | Decision tree | \_ | \_ | 0.84 | \_ |
|  | Ben-Sasson A 2018 | Israel | Psychiatry | 115 | Diagnosis | Decision tree | \_ | \_ | 0.74 | \_ |
|  | Bhattacharyya 2013 | India | Neonatology | 16 | Diagnosis | Ensemble | 78%/72% | - | - | \_ |
|  | Blazadonakis M 1996 | Greece | Others | 335 | Prediction | Decision tree | \_ | 85.67% | \_ | \_ |
|  | Bokov 2016 | USA | Pulmonology | 186 | Diagnosis | Ensemble | 71.4%/88.9% | \_ | \_ | \_ |
|  | Bolón-Canedo V 2015 | Spain | Others | 34 | Diagnosis | Decision tree; Instance based; Bayesian methods; Ensemble | \_ | \_ | \_ | Classification error= 11.76 |
|  | Bone D 2016 | USA | Psychiatry | 567 | Diagnosis | Ensemble | 79.7% | \_ | \_ |  |
|  | Bonet- Carne E, 2015 | Spain | Radiology | 144 | Diagnosis | Neural networks, Regression, Decision tree | 86.2%/87.0% | \_ | \_ | \_ |
|  | Bornelöv S, 2013 | Sweden | Pulmonology | 5146 | Diagnosis | Rule based | \_ | 94.1% | \_ | \_ |
|  | Brahnam 2006 | USA | Neonatology | 26 | Diagnosis | Dimensionality reduction; Ensemble | \_ | \_ | 0.98 | \_ |
|  | Brown JM 2018 | USA | Others | 898 | Diagnosis | Deep learning | \_ | \_ | 0.80 | \_ |
|  | Calderoni S 2012 | Italy | Psychiatry | 38 | Diagnosis | Ensemble | \_ | 99% | \_ | \_ |
|  | Carpenter KLH 2016 | USA | Psychiatry | 1224 | Diagnosis | Decision tree | \_ | 100% | \_ | \_ |
|  | Ceschin R, 2018 | USA | Radiology | 130 | Diagnosis | Deep learning | \_ | \_ | 0.957 | \_ |
|  | Chan CH 2006 | Hong Kong | ICU | 547 | Prediction | Neural networks | 95.45%/95.59% | 95.54% | \_ | \_ |
|  | Chatzimichail 2013 | Greece | Pulmonology | 112 | Prediction | Ensemble | 89.02%/84.76% | 87.36% | \_ | \_ |
|  | Chen 2012 | US | Cardiology | 30 | Diagnosis | Dimensionality reduction; Neural networks; Ensemble | 89.02% 84.76% | 87.36% | ­\_ | \_ |
|  | Chen 2013 | Taiwan | Neonatology | 347,312 | Diagnosis | Ensemble | 100%/99.9% | 99.9% | \_ | \_ |
|  | Chen 2014 | China | Neonatology | 282 | Diagnosis | Ensemble; Neural networks; Decision trees; Dimensionality reduction; Regression | 92%/87.50% | \_ | \_ | \_ |
|  | Chen A 2017 | Netherlands | Neurology | 476 | Diagnosis | Ensemble | 70%/67% | 68% | \_ | \_ |
|  | Chong SL 2015 | Singapore | Emergency Medicine | 195 | Diagnosis | Neural networks | 94.9%/97.4% | \_ | 0.98 | \_ |
|  | Chu 2015 | Sweden | Radiology | 143 | Diagnosis | Ensemble | 94.2%/90.5% | 93% | 0.97 | \_ |
|  | Chu HC 2018 | Taiwan | Psychiatry | 15 | Diagnosis | Ensemble | \_ | 99.13% | \_ | \_ |
|  | Cic M 2013 | Croatia | Neurology | 20 | Diagnosis | Ensemble | \_ | 90% | \_ | \_ |
|  | Cohen IL 1993 | USA | Psychiatry | 138 | Diagnosis | Neural networks | \_ | 97% | \_ | \_ |
|  | Cohen IL 2016 | USA | Psychiatry | 660 | Diagnosis | Decision tree | \_ | 100% | \_ | \_ |
|  | Cooper 2018 | USA | Neonatology | 10051 | Prediction | Ensemble; Decision tree | \_ | \_ | 0.87 | \_ |
|  | Cooper J 2015 | US | Others | 51,008 | Prediction | Regression; Ensemble; Decision tree | 32.9%/ 98.8% | 93.3% | \_ | \_ |
|  | Correa M, 2018 | Lima, Peru | Radiology | 21 | Diagnosis | Neural networks | 90.9%/100% | \_ | \_ | \_ |
|  | Courtney 2008 | USA | Neonatology | 73040 | Prediction | Regression; Neural networks, Decision tree; Bayesian methods | \_ | \_ | 0.605 | \_ |
|  | Crippa A 2015 | Italy | Psychiatry | 30 | Diagnosis | Ensemble | 89.1%/ 82.2% | 84.9% | \_ | \_ |
|  | Crippa A 2017 | USA | Psychiatry | 44 | Diagnosis | Ensemble | 73%/87% | 81% | 0.80 | \_ |
|  | Da Laet T 2017 | Belgium | Neurology | 356 | Diagnosis | Regression; Bayesian methods | \_ | 93% | \_ | \_ |
|  | Daley M 2016 | USA | Neurology | 29 | Diagnosis | Ensemble | \_ | \_ | 0.91 | \_ |
|  | Das LT 2016 | USA | Emergency Medicine | 2691 | Prediction | Regression; Regularization; Decision tree; Ensemble | \_ | \_ | 0.87 | \_ |
|  | De Groote 2002 | Belgium | Pulmonology | 10 | Diagnosis | Neural networks | 75%/ 79.3% | \_ | \_ | \_ |
|  | de Wit S 2017 | Netherlands | Psychiatry | 126 | Diagnosis | Ensemble | 69%/94%% | 82% | 0.753 | \_ |
|  | Delavarian M 2011 | Iran | Psychiatry | 306 | Diagnosis | Ensemble, Dimensionality reduction, Instance based, Bayesian methods | 100%/100% | \_ | \_ | \_ |
|  | Delavarian M 2012 | Iran | Psychiatry | 294 | Diagnosis | Neural networks | \_ | 100% | \_ | \_ |
|  | Deleger L 2013 | USA | Emergency Medicine | 2100 | Diagnosis | Rule based system | 86.9% | \_ | \_ |  |
|  | Di Russo SM 2002 | USA | Emergency Medicine | 35,385 | Prediction | Neural networks | \_ | \_ | 0.966 | \_ |
|  | Du J 2016 | China | Psychiatry | 216 | Diagnosis | Ensemble | 93.22%/96.94% | 94.91% | 0.969 | \_ |
|  | Duchesnay E 2011 | France | Psychiatry | 58 | Diagnosis | Dimensionality reduction; Ensemble | 91%/ 77% | 88% | \_ | \_ |
|  | Duda M 2014 | USA | Psychiatry | 2616 | Diagnosis | Decision tree | 97.1%/83.5% | 95.8% | \_ | \_ |
|  | Duda M 2016 | USA | Psychiatry | 2925 | Diagnosis | Decision tree; Dimensionality reduction; Ensemble; Regularization | \_ | \_ | 0.965 | \_ |
|  | Duda M 2017 | USA | Psychiatry | 422 | Diagnosis | Regularization; Regression; Dimensionality reduction | \_ | \_ | 0.97 | \_ |
|  | Dugan TM 2015 | US | Others | 7519 | Prediction | Decision tree; Ensemble; Bayesian methods | 86%/85% | 86% | \_ | \_ |
|  | Elgendi 2014 | Canada | Cardiology | 27 | Diagnosis | Dimensionality reduction; | \_ | \_ | \_ | Lowest classification error= 22.22% |
|  | Elibol HM 2016 | USA | Psychiatry | 27,178 | Prediction | Dimensionality reduction | \_ | \_ | 0.80 | \_ |
|  | Emerson RW 2017 | USA | Psychiatry | 59 | Diagnosis | Ensemble | 81.8%/100% | 96.6% | \_ | \_ |
|  | Farion 2013 | Canada | Pulmonology | 240 | Prediction | Bayesian methods | \_ | 78.0% | \_ | \_ |
|  | Fergus 2013 | USA | Neonatology | 300 | Prediction | Decision tree; Dimensionality reduction; Instance based | 96%/90% | \_ | 0.940 | \_ |
|  | Fernandez 2016 | US | Cardiology | 2432 | Diagnosis | Instance based; Neural networks; Decision trees | 88%/82% | 84% | \_ | \_ |
|  | Fernandez 2018 | Czech Republic | Pulmonology | 384 | Diagnosis | Regression, Clustering | \_ | \_ | \_ | Adjusted odds ratio= 2.7 |
|  | Ferreira 2012 | Portugal | Neonatology | 227 | Diagnosis | Decision tree; Regression; Bayesian methods; Neural networks | \_ | \_ | 0.80 | \_ |
|  | Fetit AE, 2015 | UK | Radiology | 48 | Diagnosis | Bayesian methods; Neural networks; Regression; Instance based | 81.8%/100% | 96.6% | \_ | \_ |
|  | Fetit AE, 2015 | UK | Radiology | 121 | Diagnosis | Neural networks; Ensemble | \_ | 78.0% | \_ | \_ |
|  | Fetit AE, 2018 | UK | Radiology | 134 | Diagnosis | Neural networks; Ensemble | 96.6%/90.0% | 95% | \_ | \_ |
|  | Finney 2014 | Papa New Guinea | Infectious Diseases | 224 | Diagnosis | Decision tree; | \_ | 78% | \_ | \_ |
|  | Foland-Ross LC 2015 | USA | Psychiatry | 33 | Diagnosis | Ensemble | 69.3%/70.0% | 69.7% | \_ | \_ |
|  | Fontanella 2018 | UK | Pulmonology | 461 | Diagnosis | clustering | 84%/87% | \_ | 0.94 | \_ |
|  | Fraiwan 2011 | USA | Neonatology | 29 | Diagnosis | Neural networks | \_ | 84% | \_ | \_ |
|  | Galvez, 2017 | USA | Radiology | 3371 | Diagnosis | Natural Language Processing | 82.9%/97.% | \_ | 0.90 | \_ |
|  | Gang 2015 | USA | Pulmonology | 210 | Prediction | Deep learning ,Ensemble, Instance based, Bayesian | 44.7%/84.2% | 73.9 | 0.783 | \_ |
|  | Garcia Chimeo Y 2014 | Spain | Neurology | 56 | Diagnosis | Dimensionality reduction; clustering; Ensemble | 94%/100% | \_ | \_ | \_ |
|  | Garcia JO 2003 | Mexico | Others | 53 | Diagnosis | Neural networks | \_ | 97.43% | \_ | \_ |
|  | Georgoulas 2006 | Portugal | Neonatology | 80 | Diagnosis | Neural networks | \_ | \_ | 0.75 | \_ |
|  | Ghahrehbagi 2015 | Tehran | Cardiology | 50 | Diagnosis | Neural networks; Ensemble | 86.5%/88.4% | 87.4% | \_ | \_ |
|  | Gharehbagi 2017 | Sweden | Cardiology | 90 | Diagnosis | Ensemble | 85.6%/87% | 86.4% | \_ | \_ |
|  | Gholami 2010 | USA | Neonatology | 26 | Diagnosis | Ensemble | \_ | 91% | \_ | \_ |
|  | Giovanini-Chami L, 2012 | France | Pulmonology | 45 | Diagnosis | Ensemble | \_ | 91% | \_ | \_ |
|  | Girgull L 2012 | Germany | Emergency Medicine | 692 | Diagnosis | Neural networks, Ensemble | \_ | \_ | 1.00 | \_ |
|  | Gori I 2015 | Italy | Psychiatry | 41 | Diagnosis | Ensemble | \_ | 74% | \_ | \_ |
|  | Greene 2007 | Ireland | Neonatology | 7 | Diagnosis | Dimensionality reduction | 54.6%/77.3% | 68.3% | \_ | \_ |
|  | Greene 2008 | Ireland | Neonatology | 17 | Diagnosis | Dimensionality reduction | \_ | \_ | \_ | Correct detection rate= 90.7%, false detection rate= 9.43% |
|  | Greene DJ 2016 | USA | Neurology | 84 | Diagnosis | Ensemble | \_ | 76% | \_ | \_ |
|  | Grinspan ZM 2018 | USA | Neurology | 3516 | Prediction | Ensemble; Regression; Regularization | \_ | \_ | 0.841 | \_ |
|  | Grossi E 2016 | Italy | Psychiatry | 137 | Diagnosis | Neural networks | \_ | 800.19% | 0.795 | \_ |
|  | Grossi E 2017 | Italy | Psychiatry | 25 | Diagnosis | Neural networks; Bayesian methods; Instance based; Ensemble | \_ | 100% | \_ | \_ |
|  | Groves DJ, 1999 | UK | Heme/Onco | 1571 | Prediction | Neural networks | 75%/60% | \_ | \_ | \_ |
|  | Gui 2018 | Geneva | Neonatology | 84 | Prediction | Dimensionality reduction | \_ | \_ | 0.72 | \_ |
|  | Guo 2017 | China | Others | 101 | Diagnosis | Ensemble | \_ | 94.36% | \_ | \_ |
|  | Guo Y, 2014 | USA | Radiology | 10 | Diagnosis | Deep learning | \_ | \_ | \_ | Dice ratio=70.2 |
|  | Haas 2005 | USA | Neonatology | 1692 | Diagnosis | Rule based system | 71%/99.8% | \_ | \_ | \_ |
|  | Habibi 2016 | Tehran | Infectious Diseases | 148 | Diagnosis | Neural networks and Regression | \_ | 83% | \_ | \_ |
|  | Hajjar 2018 | France | Neonatology | 397 | Prediction | Neural networks | \_ | 84.3% | \_ | \_ |
|  | Hale AT, 2018 | USA | Radiology | 565 | Diagnosis | Neural networks | \_ | \_ | 0.977 | \_ |
|  | Hatzakis 2002 | Canada | Neonatology | 10 | Management | Rule based system | \_ | \_ |  | True positive = 60% |
|  | Held 2013 | Chile | Pulmonology | 30 | Diagnosis | Rule based | 89.7%/\_ | \_ | \_ | \_ |
|  | Held CM 2013 | Chile | Others | 30 | Diagnosis | Rule based | 89.7%/\_ | \_ | \_ | \_ |
|  | Heller MD 2013 | USA | Psychiatry | 52 | Diagnosis | Ensemble | \_ | \_ | \_ | F measure = 78% |
|  | Helm EJ, 2009 | UK | Radiology | 24 | Diagnosis | Rule based | 42%/100% | \_ | \_ | \_ |
|  | Heunis T 2018 | USA | Psychiatry | 62 | Diagnosis | Neural networks; Dimensionality reduction | \_ | 92.86% | \_ | \_ |
|  | Hicks SD 2018 | USA | Psychiatry | 456 | Diagnosis | Ensemble | 80%/88% | \_ | 0.88 | \_ |
|  | Hornero 2017 | USA | Pulmonology | 4191 | Diagnosis | Neural networks | 68.7%/94.1% | 90.2% | \_ | \_ |
|  | Hoshino 2012 | Japan | Others | 50 | Diagnosis | Regression | 100%/100% | \_ | 0.95 | \_ |
|  | Hsieh CW, 2007 | Taiwan | Radiology | 713 | Diagnosis | Neural networks | \_ | \_ | \_ | Correction rate = 87% |
|  | Hsieh CW, 2007 | Taiwan | Radiology | 909 | Diagnosis | Neural networks | \_ | \_ | \_ | Correction rate=  90 % |
|  | Hsieh CW, 2010 | Taiwan | Radiology | 550 | Diagnosis | Dimensionality reduction | \_ | \_ | \_ | Correct rate=  91.3 % |
|  | Hsieh CW, 2011 | Taiwan | Radiology | 534 | Diagnosis | Rule based, Regression | \_ | 96.2 | \_ | \_ |
|  | Hsu 2010 | Taiwan | Neonatology | 360 | Diagnosis | Ensemble | 95.9%/95.6% | 96.\*% | \_ | \_ |
|  | Hu S, 2017 | China | Radiology | 24 | Prediction | Regression | \_ | \_ | \_ | Dice ratio= 0.613 |
|  | Hu YH 2017 | Taiwan | Emergency Medicine | 125,940 | Prediction | Decision tree; Regression, Ensemble; Bayesian methods | 73.7%/ 59.9% | 66.8% | 0.723 | \_ |
|  | Iftikhar 2013 | Pakistan | Cardiology | 850 | Diagnosis | Neural networks | \_ | 92.13% | \_ | \_ |
|  | Ingalhalikar M 2011 | USA | Psychiatry | 75 | Diagnosis | Ensemble | 84%/73% | \_ | 0.81 | \_ |
|  | Jalali 2018 | USA | Neonatology | 71 | Diagnosis | Ensemble | 91%/- | \_ | \_ | \_ |
|  | Jamal W 2014 | UK | Psychiatry | 24 | Diagnosis | Ensemble | 80.7%/91.7% | 89.5% | \_ | \_ |
|  | Jamshidnezhad A 2016 | Iran | Emergency Medicine | not mentioned | Diagnosis | Neural networks; Ensemble | \_ | 71.4% | \_ | \_ |
|  | Ji 2014 | USA | Neonatology | 484 | Diagnosis | Dimensionality reduction | \_ | \_ | 0.843 | \_ |
|  | Jiao Y 2010 | China | Psychiatry | 38 | Diagnosis | Neural networks | \_ | 87% | 0.93 | \_ |
|  | Jin Y 2015 | USA | Psychiatry | 80 | Diagnosis | Neural networks | \_ | 76% | 0.80 | \_ |
|  | Jong 2016 | Netherlands | Infectious Diseases | 39 | Prediction | Ensemble; Dimensionality reduction | \_ | \_ | 0.971 | \_ |
|  | Kamaleswaran R 2018 | USA | ICU | 493 | Diagnosis | Deep learning; Ensemble; Regression | 76%/81% | \_ | \_ | \_ |
|  | Kang X, 2013 | USA | Radiology | Not mentioned | Diagnosis | Bayesian methods | \_ | \_ | \_ | Average error= 2.31 |
|  | Kanimozhiselvi CS 2016 | India | Psychiatry | 100 | Diagnosis | Instance based | 93.6%/100% | 95.2% | \_ | \_ |
|  | Karayiannsis 2006 | USA | Neonatology | 15 | Diagnosis | Neural networks | 83.8%/79.5% | \_ | \_ | \_ |
|  | Karayiannsis 2006 | USA | Neonatology | 54 | Diagnosis | Neural networks | 99.3%/93.7% | \_ | \_ | \_ |
|  | Karayiannsis NB, 2005 | USA | Neonatology | 43 | Diagnosis | Neural networks | 92.5%/92.5% | \_ | \_ | \_ |
|  | Kaur 2018 | USA | Pulmonology | 514 | Diagnosis | others | 86%/98% | \_ | \_ | \_ |
|  | Khalegi A 2015 | Iran | Psychiatry | 38 | Diagnosis | Neural networks | \_ | 91.83% | \_ | \_ |
|  | Kushki A 2015 | Canada | Psychiatry | 24 | Diagnosis | Ensemble, Rule based, Dimensionality reduction, Bayesian method, Decision tree | 99%/92% | 95% | \_ | \_ |
|  | Kim JR, 2017 | South Korea | Radiology | 200 | Diagnosis | Deep learning | \_ | \_ | \_ | Concordance rate= 69.5% |
|  | Kim JW 2015 | South Korea | Psychiatry | 78 | Diagnosis | Ensemble; Regression | \_ | 84.6% | 0.84 | \_ |
|  | Kong J, 2009 | USA | Heme/Onco | 36 | Diagnosis | Neural networks; Dimensionality reduction, Bayesian methods; Ensemble | \_ | 87.88% | \_ | \_ |
|  | Koolen 2017 | Finland | Neonatology | 67 | Diagnosis | Neural networks; Ensemble | 83%/87% | 85% | \_ | \_ |
|  | Vassilakis 2002 | Greece | Neurology | 122 | Diagnosis | Decision tree | \_ | 93.40% | \_ | \_ |
|  | Krishnan 2017 | UK | Neonatology | 272 | Prediction | Dimensionality reduction | \_ | \_ | \_ | Selection frequency= 0.817 |
|  | Kuhle 2018 | Canada | Neonatology | 30,705 | Diagnosis | Ensemble; Neural networks; | \_ | 75% | \_ | \_ |
|  | Laitenen 1998 | Finland | Cardiology | 125 | Management | Regression; Neural networks | \_ | \_ | \_ | Precision= 51% |
|  | Lamping 2018 | Germany | Infectious Diseases | 289 | Diagnosis | Ensemble | \_ | \_ | 0.78 | \_ |
|  | Larson 2018 | USA | Radiology | 15149 | Diagnosis | Deep learning | \_ | \_ | \_ | Root mean square error = 0.63 |
|  | Lauer 2005 | USA | Neurology | 8 | Diagnosis | Neural networks | \_ | 98.7% | \_ | \_ |
|  | Lee J 2006 | Canada | Neurology | 100 | Diagnosis | Neural networks | 79.4%/80.3% | 79.8% | \_ | \_ |
|  | Lenhard 2018 | Sweden | Psychiatry | 61 | Management | Ensemble; Regularization | \_ | 83% | \_ | \_ |
|  | Leroy 2018 | USA | Psychiatry | 4491 | Diagnosis | others | \_/99% | \_ | \_ | \_ |
|  | Lesnussa YA 2017 | Indonesia | Others | 172 | Diagnosis | Neural networks | \_ | 76.62% | \_ | \_ |
|  | Levy 2017 | USA | Psychiatry | 4532 | Diagnosis | Regression; Regularization; Ensemble | \_ | \_ | 0.93 | \_ |
|  | Li 2011 | Canada | Neonatology | 140 | Diagnosis | Neural networks | \_ | 95% | \_ | \_ |
|  | Liu X 2017 | China | Others | 866 | Diagnosis | Deep learning | 97.28%/96.83% | 97.07% | \_ | \_ |
|  | Ling SH 2016 | Australia | Endocrinology | 16 | Diagnosis | Neural networks; Regression | 78%/60% | \_ | \_ | \_ |
|  | Lingren T 2016 | USA | Others | 650 | Diagnosis | Bayesian methods; Ensemble | \_ | \_ | \_ | Positive predictive value= 89.5 |
|  | Liu 2016 | China | Psychiatry | 87 | Diagnosis | Neural networks | 93.1%/86.21% | 88.51% | 0.896 | \_ |
|  | Liu 2017 | China | Infectious Diseases | 2532 | Diagnosis | Ensemble | 82.4%/ 93.1% | 91.6% | 0.916 | \_ |
|  | Logvinenko 2015 | USA | Radiology | 3995 | Diagnosis | Regression; Neural networks | 32%/100% | \_ | 0.79 | \_ |
|  | Luca 2014 | Belgium | Neurology | 7 | Diagnosis | clustering | \_ | \_ | \_ | Positive predictive value= 89% |
|  | Lukic 2012 | Serbia | Neurology | 72 | Diagnosis | Neural networks; Regression | \_ | \_ | 1.00 | \_ |
|  | Luo 2017 | China | Cardiology | 33831 | Prediction | Ensemble; Regression | \_ | 99% | 0.93 | \_ |
|  | Maenner 2016 | USA | Psychiatry | 2,312 | Diagnosis | Ensemble | 84.0%/89.4% | \_ | 0.932 | \_ |
|  | Mago 2012 | India | Neurology | 56 | Diagnosis | Neural networks | \_ | 88.9% | \_ | \_ |
|  | Mai 2016 | USA | Infectious Diseases | 1685 | Diagnosis | Decision tree | 95.3%/19.6% | 72.2% | \_ | \_ |
|  | Mancini F 2011 | Brazil | Others | 84 | Diagnosis | Instance based; Decision tree; Ensemble | 95%/90% | 92% | 0.85 | \_ |
|  | Mani 2014 | USA | Neonatology | 299 | Diagnosis | Bayesian methods; Instance based; Decision tree; Regression; Ensemble | \_ | \_ | 0.65 | \_ |
|  | Mantini 2005 | Italy | Cardiology | 70 | Management | Dimensionality reduction | \_ | \_ | \_ | True negatives= 12.4%, false positive= 0.9% |
|  | Masala GH 2013 | Italy | Heme/Onco | 304 | Diagnosis | Neural networks; Instance based | 93%/91% | \_ | \_ | \_ |
|  | Matic 2016 | Netherlands | Neonatology | 53 | Diagnosis | Ensemble | \_ | \_ | \_ | True positives= 98% |
|  | Mendonca 2005 | USA | Radiology | 1277 | Diagnosis | Natural language processing | 71%/99% | \_ | \_ | \_ |
|  | Merey C 2012 | Canada | Neurology | 29 | Diagnosis | Neural networks; Ensemble | 89.6%/92.2% | 86.9% | \_ | \_ |
|  | Meyestre 2017 | USA | Infectious Diseases | 282 | Diagnosis | Ensemble | 71%/96% | 90% | \_ | \_ |
|  | Mikhno 2012 | USA | Neonatology | 179 | Prediction | Regression | \_ | \_ | \_ | Positive predictive value= 97.5% |
|  | Milosevic 2016 | Belgium | Neurology | 56 | Diagnosis | Ensemble | 90.91%/\_ | \_ | \_ | \_ |
|  | Milosevic 2017 | Belgium | Neurology | 51 | Diagnosis | Ensemble | - | \_ | 0.8 | \_ |
|  | Mohseni HR, 2006 | Iran | Neonatology | Not mentioned | Diagnosis | Neural networks | 72.4%/93.2% | \_ | \_ | \_ |
|  | Monasterio V, 2012 | USA | Neonatology | 27 | Diagnosis | Ensemble | 86%/91% | 90% | \_ | \_ |
|  | Mossotto 2017 | UK | Others | 287 | Diagnosis | Dimensionality reduction; Ensemble; | \_ | 83.3% | \_ | \_ |
| 1. \_ | Mourao-Miranda 2012 | UK | Psychiatry | 32 | Diagnosis | Bayesian methods | 75%/75% | 75% | 0.500 | \_ |
|  | Moustris 2012 | Greece | Pulmonology | 3602 | Prediction | Neural networks | \_ | \_ | \_ | Root mean square error= 0.837 |
|  | Mueller M, 2004 | USA | Neonatology | 183 | Prediction | Neural networks | \_ | 85% | 0.870 | \_ |
|  | Mueller M, 2006 | USA | Neonatology | 183 | Prediction | Neural networks | \_ | \_ | 0.87 | \_ |
|  | Munoz Organero 2018 | UK | Psychiatry | 22 | Diagnosis | Deep learning | 100%/90.91% | 93.75% | \_ | \_ |
|  | Murray PG 2018 | UK | Endocrinology | 228 | Diagnosis | Ensemble | \_ | \_ | 0.99 | \_ |
|  | Mutasa 2018 | USA | Radiology | 10289 | Diagnosis | Deep learning | \_ | \_ | \_ | Mean absolute error= 0.637 |
|  | Mwangi B, 2015 | USA | Psychiatry | 32 | Diagnosis | Ensemble | 68.75%/87.5% | 78.12% | 0.781 | \_ |
|  | Narzisi A, 2015 | Italy | Psychiatry | 56 | Management | Neural networks, Ensemble; Bayesian methods; Regression; | \_ | 90% | \_ | \_ |
|  | Nascimento LFC, 2002 | Brazil | Neonatology | Not mentioned | Prediction | Rule based | \_ | \_ | \_ | Correlation coefficient= 0.96 |
|  | Nascimento LFC, 2009 | Brazil | Neonatology | 1,351 | Diagnosis | Rule based system | 70%/98% | 90% | \_ | \_ |
|  | Navarro X, 2017 | France | Neonatology | 31 | Diagnosis | Regression; Dimensionality reduction; Instance based | \_ | 95% | 0.99 | \_ |
|  | Naydenova 2016 | Gambia | Infectious Diseases | 1581 | Diagnosis | Regression, Ensemble, | 98.2%/97.6% | \_ | 0.997 | \_ |
|  | Nguyen 2002 | USA | Infectious Diseases | 381 | Prediction | Neural networks, Regression | 75.0%/90.9% | \_ | 0.839 | \_ |
|  | Nguyen HT 2008 | Australia | Endocrinology | 16 | Diagnosis | Bayesian methods; Neural networks | 89.20%/\_ | \_ | \_ | \_ |
|  | Nguyen LB 2011 | Australia | Endocrinology | 5 | Diagnosis | Neural networks | 72%/55% | \_ | \_ | \_ |
|  | Nguyen LB 2013 | Australia | Endocrinology | 5 | Diagnosis | Neural networks | 75%/60% | \_ | \_ | \_ |
|  | Ni Y 2016 | USA | Emergency Medicine | 3345 | Prediction | Regression, Ensemble, Neural networks | \_ | \_ | 0.755 | \_ |
|  | Ni Y, 2015 | USA | Heme/Onco | 215 | Prediction | Natural Language Processing | \_/95% | \_ | \_ | \_ |
|  | Niel 2018 | France | Others | 14 | Diagnosis | Neural networks | \_ | \_ | \_ | Mean difference in dry weight= 0.497 kg |
|  | Ochab M, 2016 | Poland | Neonatology | 109 | Diagnosis | Regression | 79.08%/86.4% | 83.29% | \_ | \_ |
|  | Olliver S, 2003 | Canada | Infectious Diseases | 19 | Management | Neural networks | \_ | \_ | \_ | True positive rate = 60% |
|  | Orlandi S, 2016 | Italy | Neonatology | 38 | Diagnosis | Regression; Ensemble; Neural networks | \_/\_ | 87.34% | \_ | \_ |
|  | Orphanidou-Vlachou 2014 | UK | Radiology | 40 | Diagnosis | Neural networks; Dimensionality reduction | \_ | 93.3% | \_ | \_ |
|  | Ortiz SDC 2004 | Cuba | Others | 35 | Diagnosis | Neural networks | \_ | \_ | \_ | Correction rate= 85% |
|  | Ozdemir ME 2018 | Turkey | Others | 160 | Diagnosis | Neural networks; Instance based | \_ | 86.7% | \_ | \_ |
|  | Oztoprak H, 2017 | Cyprus | Psychiatry | 108 | Diagnosis | Ensemble | \_ | 100% | \_ | \_ |
|  | Paldino 2014 | USA | Neurology | 33 | Diagnosis | Ensemble | 100%/95.4% | \_ | \_ | \_ |
|  | Paldino 2017 | USA | Neurology | 45 | Prediction | Ensemble | \_ | \_ | \_ | Correlation coefficient= 0.95 |
|  | Palmu K, 2010 | Finland | Neonatology | 18 | Diagnosis | Dimensionality reduction | 96.6%/95.1% | \_ | \_ | \_ |
|  | Pan L, 2017 | China | Heme/Onco | 486 | Diagnosis | Ensemble; Regression; Decision tree | 75.6%/89.7% | 82.7% | 0.902 | \_ |
|  | Papadelis 2016 | USA | Neurology | 12 | Management | Neural networks | 96.96%/96.26% | \_ | \_ | \_ |
|  | Patel 2018 | USA | Pulmonology | 29362 | Prediction | Decision tree; Ensemble; Regularization | \_ | \_ | 0.85 | - |
|  | Peng X, 2013 | China | Psychiatry | 110 | Diagnosis | Ensemble | \_ | 90.18% | \_ | \_ |
|  | Pereira 2004 | Brazil | Infectious Diseases | 153 | Diagnosis | Dimensionality reduction | \_ | \_ | \_ | Overall agreement= 78.3% |
|  | Pestian JP, 2016 | USA | Psychiatry | 60 | Diagnosis | Ensemble | \_ | 96.67% | \_ | \_ |
|  | Phan P 2013 | Canada | Others | 1776 | Diagnosis | Instance based | \_ | 82% | \_ | \_ |
|  | Pifferi 2011 | Italy | Pulmonology | 130 | Diagnosis | Neural networks | 100%/79.6% | \_ | \_ | \_ |
|  | Plonski 2017 | Poland, France, Germany | Neurology | 236 | Diagnosis | Ensemble; Regression | \_ | \_ | 0.506 | \_ |
|  | Podda 2018 | Italy | Neurology | 29,557 | Prediction | Regression; Neural networks | \_ | \_ | \_ | Misclassification rate= 1.2% |
|  | Porcelli PJ, 2014 | USA | Neonatology | 92 | Prediction | Neural networks | \_ | \_ | \_ | Average absolute difference= 84.4g |
|  | Portakal O 2011 | Turkey | Heme/Onco | 54 | Diagnosis | Neural networks | 98%/76% | \_ | \_ | \_ |
|  | Precup D, 2012 | Canada | Neonatology | 53 | Prediction | Ensemble | \_ | 83.27% | \_ | \_ |
|  | Price T, 2014 | USA | Psychiatry | 60 | Diagnosis | Ensemble | \_ | 68% | \_ | \_ |
|  | Prosperi CF, 2014 | Turkey | Pulmonology | 822 | Diagnosis | Decision tree; Bayesian methods; Regression | \_ | \_ | 0.82 | \_ |
|  | Prosperi CF, 2014 | UK | Pulmonology | 822 | Diagnosis | Ensemble; Regression; Decision tree; Bayesian methods | \_ | \_ | 0.82 | \_ |
|  | Qiao J, 2015 | USA | Psychiatry | 18 | Diagnosis | Ensemble | \_ | 97.28% | \_ | \_ |
|  | Quader N, 2017 | Canada | Neonatology | 35 | Diagnosis | Ensemble | \_ | \_ | 0.985 | \_ |
|  | Qureshi MNI, 2016 | South Korea | Psychiatry | 212 | Diagnosis | Ensemble | \_ | 85.29% | \_ | \_ |
|  | Raboshchuk G, 2018 | Spain | Neonatology | Not mentioned | Prediction | Neural networks | \_ | \_ | \_ | Detection rate= 60% |
|  | Rajanayagam 2013 | Australia | Others | 54 | Diagnosis | Neural networks | 82.6%/96.0% | 91% | 0.96 | \_ |
|  | Rani P 2016 | India | Others | 64 | Diagnosis | Neural networks | \_ | 91% | \_ | \_ |
|  | Reed 1997 | US | Cardiology | 53 | Diagnosis | Ensemble | \_ | \_ | \_ | Correction rate= 88% |
|  | Reis MAM, 2004 | Brazil | Neonatology | 304 | Prediction | Rule based system | 76.5%/94.8% | \_ | 0.930 | \_ |
|  | Remm 2008 | Estonia | Infectious Diseases | 1905 | Prediction | Rule based system | \_ | \_ | \_ | Modified true skill statistic= 0.35 |
|  | Remm 2009 | Estonia | Infectious Diseases | 700 | Diagnosis | Ensemble; Decision tree | \_ | \_ | \_ | Modified true skill statistic= 0.338 |
|  | Retico A, 2016 | Italy | Psychiatry | 152 | Diagnosis | Ensemble | \_ | \_ | 0.82 | ­\_ |
|  | Rietveld 1999 | Netherlands | Pulmonology | 622 | Diagnosis | Neural networks | \_ | 43% | \_ | \_ |
|  | Rocha BH, 1994 | USA | Neonatology | 5,201 | Diagnosis | Rule based system | 84.5%/92.8% | \_ | \_ | \_ |
|  | Rodriguez Gutierrez 2014 | UK | Radiology | 40 | Diagnosis | Ensemble | \_ | 91.40% | \_ | \_ |
|  | Rosales-Perez A 2015 | Mexico | Others | 1603 | Diagnosis | Ensemble | 100%/ 98.42% | 99.42% | \_ | \_ |
|  | Ross 2018 | UK | Pulmonology | 1019 | Diagnosis | Ensemble, Neural networks, Regression, Bayesian | \_ | \_ | 0.829 | \_ |
|  | Rother 2015 | Germany | Pulmonology | 16 | Diagnosis | Neural networks, Rule based; Ensemble; Regression, Bayesian methods, Instance based | 98.8%/\_ | \_ | 1.00 | \_ |
|  | Saadah LM 2014 | UAE | Neonatology | 176 | Management | Neural networks | 82%/100% | \_ | \_ | \_ |
|  | Sajedi F 2013 | Iran | Neurology | 52 | Diagnosis | Neural networks | 97.2%/92.5% | 94.8% | \_ | \_ |
|  | Samanta B 2009 | USA | Neonatology | 103 | Diagnosis | Decision tree | 73%/58% | 65% | \_ | \_ |
|  | San PP 2016 | Australia | Endocrinology | 15 | Diagnosis | Neural networks | 79.10%/50.00% | \_ | \_ | \_ |
|  | Sanders 2006 | USA | Pulmonology | 2006 | Diagnosis | Bayesian methods | 85%/96.3% | \_ | 0.971 | \_ |
|  | Santori 2007 | Italy | Others | 148 | Diagnosis | Neural networks | 80.0%/5.9% | 76.92% | 0.70 | \_ |
|  | Sanz-Cortes M 2013 | Spain | Neonatology | 91 | Diagnosis | Ensemble | \_ | 95.56% | \_ | \_ |
|  | Saria S 2010 | USA | Neonatology | 138 | Prediction | Bayesian methods | \_ | \_ | 0.915 | \_ |
|  | Sato 2017 | Brazil | Psychiatry | 622 | Diagnosis | Ensemble | \_ | \_ | \_ | Mean frame displacement difference = 0.11mm |
|  | Saxe 2017 | USA | Psychiatry | 163 | Diagnosis | Ensemble; Regularization | \_ | \_ | 0.79 | \_ |
|  | Schadl K 2018 | USA | Neonatology | 66 | Diagnosis | Regression | 100%/100% | \_ | 1.0 | \_ |
|  | Schetinin V 2003 | UK | Neonatology | 42 | Diagnosis | Neural networks; Instance based | 68.9%/98.4% | \_ | \_ | \_ |
|  | Schilithz AOC 2014 | Brazil | Others | 1004 | Diagnosis | Instance based | \_ | \_ | \_ | GAP validity index= 1.8 |
|  | SchmiDecision tree-Rohlfing 2006 | Germany | Neurology | 19 | Diagnosis | Neural networks | \_ | 80% | \_ | \_ |
|  | Sears 2004 | USA | Psychiatry | 21563 | Diagnosis | Neural networks | \_ | \_ | 0.929 | \_ |
|  | Sepehri 2008 | Iran | Cardiology | 90 | Diagnosis | Neural networks | \_ | \_ | \_ | False positive= 5%, false negative= 6.67%, efficiency= 94% |
|  | Sepehri 2010 | Iran | Cardiology | 120 | Diagnosis | Neural networks | \_ | \_ | \_ | Efficiency= 93.60% |
|  | Sepehri 2016 | Tehran | Cardiology | 263 | Diagnosis | Ensemble | 87.29%/87.89% | 87.45% | \_ | \_ |
|  | Sherrif 2004 | UK | Pulmonology | 7318 | Diagnosis | Regression; Neural networks | \_ | \_ | \_ | Misclassification rate= 17.9% |
|  | Shimomura K 1994 | Japan | Neonatology | 267 | Diagnosis | Rule based | 76%/93% | \_ | \_ | \_ |
|  | Shono H 1992 | Japan | Neonatology | 80 | Diagnosis | Rule based | 71%/97% | \_ | \_ | \_ |
|  | Si Y 1997 | Canada | ICU | 74 | Diagnosis | Neural networks | \_ | 97% | \_ | \_ |
|  | Sikka K 2015 | USA | Others | 50 | Diagnosis | Regression | \_ | \_ | 0.94 | \_ |
|  | Silterra 2017 | Mozambique | Infectious Diseases | 105 | Diagnosis | clustering; Ensemble | \_ | 87.8% | \_ | \_ |
|  | Simayijiang Z 2013 | Sweden | Neonatology | 14 | Diagnosis | Ensemble | \_ | 71.40% | \_ | \_ |
|  | Smyczynska J 2015 | Poland | Endocrinology | 245 | Prediction | Neural networks; Regression | \_ | \_ | \_ | Coefficient of determination= 78.7% |
|  | Smyser 2016 | USA | Radiology | 100 | Diagnosis | Ensemble | \_ | 84.0% | \_ | \_ |
|  | Snowden S 1993 | UK | Neonatology | 184 | Management | Neural networks | \_ | \_ | \_ | Mean percentage error= 0.446, mean absolute error= 3.08 |
|  | Soleimani 2013 | Iran | Neurology | 1232 | Diagnosis | Neural networks; Regression | 39.1%/93.2% | \_ | 0.79 | \_ |
|  | Somkantha 2011 | Thailand | Radiology | 180 | Diagnosis | Neural networks | \_ | \_ | \_ | Mean absolute percentage error= 0.10 |
|  | Song Z 2007 | USA | Neonatology | 10 | Prediction | Ensemble | \_ | \_ | \_ | Dice matric= 0.8 |
|  | Stahl 2011 | Norway | Neurology | 82 | Diagnosis | Ensemble | 85.3%/95.5% | 93.7% | \_ | \_ |
|  | Strauss 2004 | Germany | Neurology | 48 | Diagnosis | Ensemble | 75%/80% | \_ | \_ | \_ |
|  | Sullivan 2014 | USA | Neurology | 3744 | Diagnosis | Ensemble; Bayesian methods | 66.7% | \_ | \_ | Precision= 76.8, f-measure= 71.4 |
|  | Takeuchi M, 2017 | Japan | Others | 767 | Diagnosis | Ensemble | 79.7%/87.3% | \_ | 0.916 | \_ |
|  | Tan 2017 | USA | Psychiatry | 215 | Diagnosis | Ensemble | \_ | 62.0% | \_ | \_ |
|  | Tanikawa C, 2010 | Japan | Radiology | 859 | Diagnosis | Natural language processing | \_ | \_ | \_ | Mean success rate= 82% |
|  | Tariq 2018 | USA | Psychiatry | 162 | Diagnosis | Ensemble | \_ | 100% | \_ | \_ |
|  | Taylor JA 2017 | USA | Neonatology | 530 | Diagnosis | Regression | 84.6%/100% | \_ | \_ | \_ |
|  | Temko A 2009 | Ireland | Neonatology | 17 | Diagnosis | Ensemble | \_ | \_ | 0.963 | \_ |
|  | Temko A 2012 | Ireland | Neonatology | 18 | Diagnosis | Ensemble | \_ | \_ | 0.968 | \_ |
|  | Temko A 2012 | Ireland | Neonatology | 17 | Diagnosis | Bayesian methods; Ensemble | \_ | \_ | 0.973 | \_ |
|  | Temko A 2015 | Ireland | Neonatology | 38 | Prediction | Ensemble | \_ | \_ | 0.950 | \_ |
|  | Temple MW 2015 | USA | Neonatology | 4693 | Prediction | Ensemble | \_ | \_ | 0.854 | \_ |
|  | Temple MW 2016 | USA | Neonatology | 4693 | Prediction | Decision tree; Ensemble | \_ | \_ | 0.837 | \_ |
|  | Thomas EM 2008 | Ireland | Neonatology | 17 | Diagnosis | Regression | 36.01%/91.23% | 82.72% | \_ | \_ |
|  | Toltzis P 2015 | USA | ICU | 150,000 | Prediction | Decision tree | \_ | \_ | 0.810 | \_ |
|  | Tong 2018 | China | Radiology | 847,750 | Diagnosis | Deep learning | \_ | \_ | \_ | Mean absolute error= 0.611 |
|  | Tong D L, 2014 | UK | Heme/Onco | 88 | Diagnosis | Neural networks | 98%/98% | \_ | \_ | \_ |
|  | Tong L, 2018 | China | Heme/Onco | 268 | Diagnosis | Dimensionality reduction; Regression; Ensemble | 99.49%/93.15% | \_ | 0.997 | \_ |
|  | Toti 2016 | USA | Pulmonology | 14,704 | Diagnosis | Rule based | \_ | \_ | \_ | Odds ratio= 1.54 |
|  | Townsend D 2008 | Canada | Neonatology | 20,488 | Prediction | Neural networks | 78.9%/92.2% | 88.8% | \_ | \_ |
|  | Traitruengsakul 2017 | USA | Neurology | 5 | Diagnosis | Ensemble | \_ | 98% | \_ | \_ |
|  | Tsien CL 2000 | Edinburgh | Neonatology | 123 | Diagnosis | Decision tree | 87.5%/100% | 99.8% | \_ | \_ |
|  | Tung W L, 2005 | Singapore | Heme/Onco | 327 | Diagnosis | Neural networks | \_ | \_ | \_ | Correction rate= 90% |
|  | Turi 2018 | USA | Pulmonology | 10687 | Diagnosis | Dimensionality reduction; Ensemble; Regularization | \_ | 79.6% | \_ | \_ |
|  | Tuti 2017 | Kenya | Infectious Diseases | 10,687 | Prediction | Dimensionality reduction; Ensemble | \_ | 79.6% | \_ | \_ |
|  | Twomey 2013 | Ireland | Cardiology | 24 | Diagnosis | Bayesian methods | 80%/\_ | \_ | \_ | \_ |
|  | Uddin | usa | Psychiatry | 34 | Diagnosis | Regression | \_ | 75% | \_ | \_ |
|  | Uddin 2011 | USA | Psychiatry | 48 | Diagnosis | Ensemble | \_ | 85.0% | \_ | \_ |
|  | Valimaki 1988 | Finland | Cardiology | 40 | Diagnosis | Decision tree | \_ | \_ | \_ | \_ |
|  | Van den Bulcke T 2011 | Belgium | Neonatology | 44,159 | Diagnosis | Dimensionality reduction, Regression | 10%/99.98% | \_ | \_ | \_ |
|  | Vaquerizo 2018 | USA | Pulmonology | 298 | Diagnosis | Neural networks | 68.1%/90.2% | \_ | \_ | \_ |
|  | Verive MJ 2000 | USA | ICU | 463 | Diagnosis | Neural networks | \_ | 88% | \_ | \_ |
|  | Wall 2012 | USA | Psychiatry | 1050 | Diagnosis | Decision tree | \_ | 99.80% | \_ | \_ |
|  | Wall 2012 | USA | Psychiatry | 2942 | Diagnosis | Decision tree | \_ | 100% | \_ | \_ |
|  | Walsh 2004 | USA | Emergency Medicine | 119 | Prediction | Neural networks | 78%/82% | 81% | \_ | \_ |
|  | Walsh 2004 | Ireland | Infectious Diseases | 119 | Prediction | Neural networks | 78%/82% | 81% | \_ | \_ |
|  | Wang 2017 | China | Psychiatry | 143 | Diagnosis | Regularization; | \_ | \_ | \_ | Mean absolute error= 3.3, root mean square error= 4.17 |
|  | Wang B 2018 | China | Others | 3770 | Diagnosis | Deep learning | 99.57%/99.20% | 99.50% | 1.00 | \_ |
|  | Wee CY 2017 | Singapore | Neonatology | 120 | Prediction | Ensemble | 50.95%/50.76% | 89.4% | \_ | \_ |
|  | Weeisenfeld NI 2009 | USA | Neonatology | 10 | Prediction | others | \_ | \_ | \_ | Mean predictive value= 0.93 |
|  | Wei J S, 2004 | USA | Heme/Onco | 49 | Diagnosis | Neural networks | 100%/94% | \_ | \_ | \_ |
|  | Werth J 2017 | Netherlands | Neonatology | 8 | Diagnosis | Ensemble | \_ | \_ | 0.87 | \_ |
|  | West | USA | Psychiatry | 82 | Diagnosis | Ensemble | 92%/63% | 81% | 0.81 | \_ |
|  | Wi 2017 | USA | Pulmonology | 500 | Diagnosis | natural language processing | 97%/95% | \_ | \_ | \_ |
|  | WI 2018 | USA | Pulmonology | 595 | Diagnosis | natural language processing | 92%/96% | \_ | \_ | \_ |
|  | Wolf M 1996 | Switzerland | Neonatology | 8 | Diagnosis | Ensemble | \_ | 99.40% | \_ | \_ |
|  | Wong 2017 | UK | Psychiatry | 267 | Management | Bayesian methods | \_ | \_ | 0.840 | \_ |
|  | Wu 2014 | USA | Pulmonology | 112 | Diagnosis | natural language processing | 90.94%/82.82% | \_ | \_ | \_ |
|  | Wu 2015 | USA | Psychiatry | 51 | Diagnosis | Ensemble | 76.0%/80.8 % | 78.4% | \_ | \_ |
|  | Xiao 2017 | China | Psychiatry | 85 | Diagnosis | Ensemble; Bayesian methods | \_ | 80.9% | 0.886 | \_ |
|  | Xu 2011 | USA | Pulmonology | 417 | Prediction | Ensemble | \_ | \_ | 0.66 | \_ |
|  | Yadav 2015 | USA | Radiology | 2,121 | Diagnosis | Decision tree | 89.7%/91.9% | \_ | \_ | \_ |
|  | Yasin 2017 | Malaysia | Pulmonology | 600 | Diagnosis | Deep learning | \_ | 92.82% | \_ | \_ |
|  | Yilmaz R 2017 | Turkey | Others | 44 | Diagnosis | Regression; Neural networks; | \_ | 90% | \_ | \_ |
|  | Yin 2004 | Taiwan | Neurology | 24 | Diagnosis | Neural networks, Dimensionality reduction | \_ | 91.7% | \_ | \_ |
|  | Young J 2012 | USA | Neonatology | 168 | Diagnosis | Neural networks | \_ | \_ | \_ | Percentage error= 5.06% |
|  | Youngstrom 2018 | Usa | Psychiatry | 1061 | Diagnosis | Regularization | \_ | \_ | 0.801 | \_ |
|  | Yu 2008 | China | Others | 103 | Diagnosis | Neural networks | \_ | \_ | \_ | Mean absolute percentage error= 4.66% |
|  | Zarchi MS 2018 | Iran | Others | 70 | Diagnosis | Neural networks | \_ | 83.10% | \_ | \_ |
|  | Zernikow B 1998 | Germany | Neonatology | 890 | Diagnosis | Neural networks | \_ | \_ | 0.954 | \_ |
|  | Zernikow B 1998 | Germany | Neonatology | 865 | Diagnosis | Neural networks | \_ | \_ | 0.935 | \_ |
|  | Zernikow B 1999 | Germany | Neonatology | 2144 | Prediction | Neural networks | \_ | \_ | \_ | Pearson linear coefficient= 0.92 |
|  | Zhai H 2014 | USA | ICU | 7298 | Management | Regression | 84.9%/85.9% | \_ | 0.912 | \_ |
|  | Zhang 2015 | USA | Radiology | 8 | Diagnosis | Deep learning | \_ | \_ | \_ | Dice ratio= 0.850 |
|  | Zhang 2017 | China | Infectious Diseases | 530 | Diagnosis | Ensemble | \_ | 89.2% | 0.948 | \_ |
|  | Zhang 2018 | USA | Psychiatry | 149 | Diagnosis | Ensemble | 84.81%/72.86% | \_ | \_ | \_ |
|  | Zhao Q 2015 | USA | Others | 48 | Diagnosis | Ensemble | \_ | 100% | 0.996 | \_ |
|  | Zimmer VA 2017 | Spain | Neonatology | 111 | Diagnosis | Instance based | 90%/97% | 93% | \_ | \_ |
|  | Ziv E 2013 | USA | Neurology | 24 | Diagnosis | Ensemble | \_ | \_ | \_ | Test error= 0.79 |
|  | Zou 2017 | Canada | Psychiatry | 730 | Diagnosis | Neural networks | \_ | 69.15% | \_ | \_ |
|  | Zylnoori 2012 | iran | Pulmonology | 278 | Diagnosis | Dimensionality reduction | 88%/100% | \_ | \_ | \_ |

Table 2: Performance of the various ML algorithms based on metrics

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Subspecialty** | **Disease/**  **Condition** | **Performance of Machine Learning Models** | | | | | | | | | | | |
| **Deep Learning** | **Ensemble Methods** | **Neural Network** | **Decision Trees** | **Regularization** | **Rule system** | **Regression** | **Dimension Reduction** | **Instance Based** | **Cluster-ing** | **Bayesian Network** | **Other** |
| **Neonatology** | Macrosomia |  | 100/89 | 64/63 |  |  |  | 60/64 |  |  |  |  |  |
| Seizures |  | 78-94/  72-88 | 72-93/  80-96 | 86/62 |  |  | 24-88/  68-92 | 55/77 |  |  | 0.96 |  |
| Metabolic disorder |  | 96-99/  96-99 | 92-97/99-100 | 92-99/99 | 100/99 |  | 88-95/98-100 |  |  |  |  |  |
| Prematurity |  | 99/86 | 80-85 | 93-97/  80-90 |  |  | 90-100/86-100 | 97/90 | 97/  57-70 |  | 0.59 |  |
| Neonatal jaundice |  |  | 0.81 | -/  33-41 | -/  50 |  | -/  54-56 | Selection frequency=0.663-0 | 85 |  | -/  56 |  |
| Respiratory Distress Syndrome |  |  |  |  |  |  | 97/- |  |  |  |  |  |
| Asphyxia |  | 88-98/- |  |  |  |  |  |  |  |  |  |  |
| Developmental Dysplasia of the Hip |  | 0.91 |  |  |  |  |  |  |  |  |  |  |
| Ventilator Weaning |  |  | Mean absolute error=0.8-10.9 |  |  |  |  |  |  |  |  |  |
| Neonatal pneumonia |  |  |  |  |  | 71/99 |  |  |  |  |  |  |
| Neonatal Sepsis |  | 0.61 |  | 0.65 |  |  | 0.61 |  | 0.54 |  | 0.64 |  |
| Neonatal surgical site infection |  | 0.68 |  |  |  |  | 0.67 |  |  |  |  |  |
| Epilepsy |  |  | 92-99/  92-98 |  |  |  |  |  |  |  |  |  |
| Hypoxic-Ischemic Encephalopathy |  | 0.71-0.95 | 100 |  |  |  |  |  |  |  |  |  |
| Sleep Stage Classification |  | 83/87 | 58-83/  87-99 |  |  | 52-63/  85-99 |  |  |  |  |  |  |
| Acute Pain |  | 80-94 |  |  |  |  |  |  |  |  |  |  |
| Apnea |  | 86/91 |  |  |  |  |  |  |  |  |  |  |
| Neonatal mortality |  | 0.89-0.93 | 72-79/  90-92 |  |  | 70-76/  95-98 | 0.791-0.87 |  |  |  | 0.69-0.91 |  |
| Broncho-pulmonary dysplasia |  |  |  |  |  |  | 84/86 |  |  |  |  |  |
| Necrotizing Enterocolitis |  |  |  |  |  |  |  | 0.84 |  |  |  |  |
| Nosocomial infections |  |  |  |  |  | 84/92 |  |  |  |  |  |  |
| RSV infection |  |  | 82/100 |  |  |  |  |  |  |  |  |  |
| Periventri-cular leuko-malacia |  | 91/- |  | 90/97 |  |  |  |  |  |  |  |  |
| Fscore=0.88 |  |
| Artefact detection in NICU monitoring |  |  |  | 58-88/  99-100 |  |  |  |  |  |  |  |  |
| NICU Length of Stay |  | 0.63-0.85 | Pearson coefficient= 0.87-0.92 | 0.56-0.74 |  |  |  |  |  |  |  |  |
| Brain hemorrhage |  |  | 0.93 |  |  |  |  |  |  |  |  |  |
| Brain disease |  |  |  |  |  |  |  |  | 80-90/  84-97 |  |  |  |
| **Neurology** | Cerebellar palsy |  | 85/96 | 97/93 |  |  |  | 0.89 |  |  |  | 76-93 |  |
| Epilepsy |  | 90-100/  95-100 | 75-96/  89-99 | 93 |  |  |  |  |  | 53-89/- |  |  |
| Neurological mortality |  |  | 90/  17-52 |  |  |  |  |  |  |  |  |  |
| Developmental disability |  | 70-79/  67-90 | 39/93 | 48/75 |  |  | 22-84/  80-93 | 84-95/  90-95 |  |  |  |  |
| EEG Sleep Classification |  | 90 |  |  |  |  |  |  |  |  |  |  |
| Meningitis |  |  | 95 |  |  |  |  |  |  |  |  |  |
| Brain Injury |  | 0.91 |  |  |  |  |  |  |  |  |  |  |
| Tourette Syndrome |  | 0.84 | 91 |  | 0.83 |  | 0.73 |  |  |  |  |  |
| Dysphagia |  | 90/92 | 79-90/  80-92 |  |  |  |  |  |  |  |  |  |
| Central auditory processing disorder |  | 65-80/  71-75 |  |  |  |  |  |  |  |  |  |  |
| **Psychiatry** | Autism Spectrum Disorder |  | 74-100/  63-94 | 93/82 | 98-100/  77-84 | 0.82-0.97 |  | 0.80-0.97 | 91-99/  77-92 | 93/100 | 94/100 | 99/92 | -/99 |
| Attention Deficit Hyperactivity Disorder | 60-100/  91-100.0 | 73-95/  87-100 | 86/93 | 0.93 | 0.82-0.97 |  | 0.73-0.97 | 95/100 | 95/100 |  | 95/100 |  |
| Psychosis |  | 69/94 |  |  |  |  |  |  |  |  |  |  |
| Substance Abuse |  | 97 | 0.83-0.92 |  |  |  |  |  |  |  |  |  |
| Suicide |  | 96 |  |  |  |  |  |  |  |  |  |  |
| Anxiety Disorder |  | 0.79 |  |  | 0.67-0.76 |  | 75-83 |  |  |  |  |  |
| Mood disorder |  | 69-77/  70-87 | 82-91 |  | 0.80-0.90 |  |  |  |  |  | 44-75/31-75 |  |
| **Radiology** | Brain Imaging | Dice ratio= 74.2-85 | 11-87/  75-99 |  |  |  |  |  |  |  |  |  |  |
| Tumor Imaging |  | 0.76-0.86 | 43-95/  75- 100 |  |  | 22-61/  48-100 | 71-100/  78-95 | 85-100 | 71-96/  86-95 |  | 57-96/  85-100 |  |
| Organ imaging |  |  |  |  |  |  |  |  |  |  | Average error= 2.67 |  |
| Respiratory morbidity |  |  |  |  |  |  |  |  |  |  |  | 91/86 |
| Prematurity |  | 90/94 |  |  |  |  |  |  |  |  |  |  |
| Pneumonia |  |  | 91/100 |  |  |  |  |  |  |  |  | 71/99 |
| Bone age | Concordance rate= 69 |  | 63-98 |  |  | 87 | Dice ratio= 0.48-0.78 | 92 |  |  |  |  |
| Deep Vein Thrombosis |  |  |  |  |  |  |  |  |  |  |  | 83/97 |
| 0.90 |
| Vesicouretric reflux | 18-64/  60-100 |  |  |  |  |  | 5-86/  25-99 |  |  |  |  |  |
| Trauma |  | 75/83 | 0.94-0.97 | 80-95/  91-92 |  |  |  |  |  |  |  |  |
| **Intensive Care** | Sepsis |  | 82/61 | 76/81 |  |  |  | 76/66 |  |  |  |  |  |
| ICU mortality |  |  | 0.39-0.95 |  |  |  |  |  |  |  |  |  |
| ICU monitoring |  |  | 45-97 |  |  |  |  |  |  |  |  |  |
| Hypomagnesaemia |  |  | 88 |  |  |  |  |  |  |  |  |  |
| Escalation of care |  |  |  |  |  |  | 85/86 |  |  |  |  |  |
| **Emergency Medicine** | Traumatic brain injury |  |  | 95/97 |  |  |  |  |  |  |  |  |  |
| Use of emergency department by asthmatics |  | 19/- |  | 24/- | 19/- |  | 23/- |  |  |  |  |  |
| Appendicitis |  | 59/71 |  |  |  | 86 |  |  |  |  |  |  |
| Trauma |  |  | 0.96-1.0 |  |  |  |  |  |  |  |  |  |
| Medical emergencies |  | 73/59 | 1.00 | 80/55 |  |  | 59/71 |  |  |  | 45/74 |  |
| **Infectious disease** | Hand foot mouth disease |  | 82/93 |  |  |  |  |  |  |  |  |  |  |
| Urinary Tract Infection |  |  | 0.76 |  |  |  |  |  |  |  |  |  |
| Bronchiolitis |  | 82/93 | 78/82 |  |  |  |  |  |  |  |  |  |
| Malaria |  |  |  | 58-78 |  |  |  |  |  |  |  |  |
| Ventriculo-peritoneal shunt infection |  |  | 83 |  |  |  | 55 |  |  |  |  |  |
| Respiratory Syncytial virus |  | 0.97 |  |  | 72-76 |  |  | 74 |  |  |  |  |
| Severe Immunodeficiency Response Syndrome |  | 0.70-0.87 |  |  |  |  |  |  |  |  |  |  |
| Pneumonia |  | 71-98/96-97 | 93-100/7-45 |  |  |  | 89-98/  82-98 | 72-78 |  | 87 |  |  |
| Enterobias |  | 0.32 |  | 0.33 |  | 0.75 |  |  |  |  |  |  |
| Meningitis |  | 89/85 | 73/93 |  |  |  | 75/91 |  |  |  |  |  |
| **Cardiology** | Murmurs |  | 89/90 | 86/82 |  |  |  |  | 80/90 |  |  |  |  |
| Aortic Diameter |  |  | Root mean square error=0.0096 |  |  |  |  |  |  |  |  |  |
| Pulmonary Hypertension |  |  |  |  |  |  |  | Lowest classification error= 22.2 |  |  |  |  |
| Valvular abnormality |  | 86-87/  87-88 | 83-87/  81-88 |  |  |  |  |  |  |  |  |  |
| Cardiac Monitoring |  |  | Efficiency= 93 |  |  |  |  |  |  |  |  |  |
| Kawasaki’s disease |  | 32.9-39.0/98.5-98.8 |  |  |  |  |  |  |  |  |  |  |
| Congenital Heart disease |  | 75-76/  81-90 | 92-99 | 80 |  |  |  | 88-93 | 81-95 |  |  |  |
| **Pulmonology** | asthma | 68.1/73.3 | 70.2-96.0/34.0-95.9 | 0.82 |  |  | 89.0-98.0/67.0-95.0 | 79.0-100.0/13.0-57.0 | 88.0/100.0 | 38.3/88.7 | 84.0/87.0 | 59.8-96.0/29.0-96.3 | 86.0-97.0/82.8-98.0 |
| Asphyxia | 92 |  |  |  |  |  |  |  |  |  |  |  |
| OSA | 6.0-68.7/75.0-94.1 |  | 61-75/90 |  |  |  |  |  |  |  |  |  |
| **Hematology/Oncology** | Leukemia |  | 58-76/85-89 | 51-75/  60-66 | 81/77 | 76/89 |  | 81/77 |  | 91-100/  92-100 |  |  |  |
| Neuroblastoma |  | 79-98/  82-99 | 84-100/  90-97 |  |  |  |  | 98 |  |  | 98-99 |  |
| Sarcoma |  |  | 70-93/- |  |  |  |  |  |  |  |  |  |
| thalassemia |  |  | 73-91/  80-89 |  |  |  | 98/98 | 81-99/  86-93 | 91/93 |  |  |  |
| Preclassification of Leukocytes |  |  | 98/76 |  |  |  |  |  |  |  |  |  |
| **Endocrinology** | Growth Hormone Deficiency |  |  | 0.99 |  |  |  | Root mean square= 0.64 |  |  |  |  |  |
| Hypoglycemia |  | 82-86/  76-85 | 64-92/  41-61 |  |  |  | 52-75/  50-52 |  |  |  | 89/- |  |
| **Others** | Obesity |  | 86-88/80-85 |  | 82-88/76-82 |  |  |  |  |  |  | 58/68-69 |  |
| Abnormal Gait |  |  | 82-94 |  |  |  |  |  |  |  |  |  |
| Stillbirth |  |  | 90 |  |  |  | 80-90 |  |  |  |  |  |
| Adolescent Idiopathic Scoliosis |  |  |  |  |  |  |  |  | 82 |  |  |  |
| Apnea |  |  |  |  |  | 89/- |  |  |  |  |  |  |
| Dysmorphic Syndromes |  |  | 70 |  |  |  |  |  | 50 |  |  |  |
| Deafness |  |  | 97 |  |  |  |  |  |  |  |  |  |
| Abnormal posture |  |  | 95/87-90 |  | 86-91/87-90 | 90.5/- |  |  | 90/95 |  |  |  |
| Decrease in creatinine |  |  | 80/76 |  |  |  |  |  |  |  |  |  |
| Inflammatory Bowel Disease |  | 83 |  |  |  |  |  |  |  |  |  |  |
| Acute liver failure |  |  | 83/96 |  |  |  |  |  |  |  |  |  |
| Fever |  |  | 76 |  |  |  |  |  |  |  |  |  |
| Dry Weight in Dialysis |  |  | Mean difference= 0.49 |  |  |  |  |  |  |  |  |  |
| Biliary atresia |  |  |  |  |  |  | 100/100 |  |  |  |  |  |
| Cataracts | 97/96 |  |  |  |  |  |  |  |  |  |  |  |
| Retinopathy of Prematurity | 99/99 | 79.7/87.3 | 91 |  |  |  |  |  |  |  |  |  |
| Down Syndrome |  | 77-100 |  |  |  |  |  |  |  |  |  |  |
| Acute Pain |  |  |  | 73-85 |  |  | 0.84-0.94 |  |  |  |  |  |
| Surgical morbidity |  | 32-39/98-99 |  |  | 39-41/98.5 |  | 37.5-41.5/98.4-98.5 |  |  |  |  |  |



**Reference List of studies**

1. Aarabi A, Wallois F, Grebe R. Automated neonatal seizure detection: a multistage classification system through feature selection based on relevance and redundancy analysis. *Clin Neurophysiol.* Feb 2006;117(2):328-340.
2. Abbas H, Garberson F, Glover E, Wall DP. Machine learning approach for early detection of autism by combining questionnaire and home video screening. *Journal of the American Medical Informatics Association.* Aug 2018;25(8):1000-1007.
3. Abibullaev B, An J. Decision Support Algorithm for Diagnosis of ADHD Using Electroencephalograms. *Journal of Medical Systems.* Aug 2012;36(4):2675-2688.
4. Adeli E, Meng Y, Li G, Lin WL, Shen DG. Multi-task Prediction of infant cognitive scores from longitudinal incomplete neuroimaging data. *Neuroimage.* Jan 2019;185:783-792.
5. Afzal Z, Engelkes M, Verhamme KMC, et al. Automatic generation of case-detection algorithms to identify children with asthma from large electronic health record databases. *Pharmacoepidemiology and Drug Safety.* Aug 2013;22(8):826-833.
6. Aggarwal G, Singh L. Evaluation of Supervised Learning Algorithms Based on Speech Features as Predictors to the Diagnosis of Mild to Moderate Intellectual Disability. *3d Research.* Dec 2018;9(4).
7. Aghdam MA, Sharifi A, Pedram MM. Combination of rs-fMRI and sMRI Data to Discriminate Autism Spectrum Disorders in Young Children Using Deep Belief Network. *Journal of Digital Imaging.* Dec 2018;31(6):895-903.
8. Ahmadlou M, Adeli H, Adeli A. Fractality and a Wavelet-Chaos-Neural Network Methodology for EEG-Based Diagnosis of Autistic Spectrum Disorder. *Journal of Clinical Neurophysiology.* Oct 2010;27(5):328-333.
9. Ahmadlou M, Adeli H, Adeli A. Fuzzy Synchronization Likelihood-wavelet methodology for Diagnosis of autism spectrum disorder. *Journal of Neuroscience Methods.* Nov 2012;211(2):203-209.
10. Ahmed R, Temko A, Marnane W, Lightbody G, Boylan G. Grading hypoxic-ischemic encephalopathy severity in neonatal EEG using GMM supervectors and the support vector machine. *Clin Neurophysiol.* Jan 2016;127(1):297-309.
11. Ahmed R, Temko A, Marnane WP, Boylan G, Lightbody G. Exploring temporal information in neonatal seizures using a dynamic time warping based SVM kernel. *Comput Biol Med.* Mar 1 2017;82:100-110.
12. Akdemir B, Oran B, Gunes S, Karaaslan S. Prediction of Aortic Diameter Values in Healthy Turkish Infants, Children, and Adolescents by Using Artificial Neural Network. *Journal of Medical Systems.* Oct 2009;33(5):379-388.
13. Aljabar P, Wolz R, Srinivasan L, et al. Combining morphological information in a manifold learning framework: application to neonatal MRI. *Med Image Comput Comput Assist Interv.* 2010;13(Pt 3):1-8.
14. Amarreh I, Meyerand ME, Stafstrom C, Hermann BP, Birn RM. Individual classification of children with epilepsy using support vector machine with multiple indices of diffusion tensor imaging. *Neuroimage Clin.* 2014;4:757-764.
15. Ambalavanan N, Carlo WA. Comparison of the Prediction of extremely low birth weight neonatal mortality by Regression analysis and by Neural networks. *Early Hum Dev.* Dec 2001;65(2):123-137.
16. Ambalavanan N, Carlo WA, Bobashev G, et al. Prediction of death for extremely low birth weight neonates. *Pediatrics.* Dec 2005;116(6):1367-1373.
17. Ambalavanan N, Nelson KG, Alexander G, Johnson SE, Biasini F, Carlo WA. Prediction of neurologic morbidity in extremely low birth weight infants. *J Perinatol.* Dec 2000;20(8 Pt 1):496-503.
18. Amini P, Maroufizadeh S, Samani RO, Hamidi O, Sepidarkish M. Factors Associated with Macrosomia among Singleton Live-births: A Comparison between Logistic Regression, Random Forest and Artificial Neural Network Methods. *Epidemiology Biostatistics and Public Health.* 2016;13(4).
19. Anand V, Downs SM. Probabilistic asthma case finding: a noisy or reformulation. *AMIA Annu Symp Proc.* Nov 6 2008:6-10.
20. Andersson A, Ritz C, Lindgren D, et al. Microarray-based classification of a consecutive series of 121 childhood acute leukemias: Prediction of leukemic and genetic subtype as well as of minimal residual disease status. *Leukemia.* Jun 2007;21(6):1198-1203.
21. Ansari AH, Matic V, De Vos M, Naulaers G, Cherian PJ, Van Huffel S. Improvement of an automated neonatal seizure detector using a post-processing technique. *Conf Proc IEEE Eng Med Biol Soc.* Aug 2015;2015:5859-5862.
22. Anzulewicz A, Sobota K, Delafield-Butt JT. Toward the Autism Motor Signature: Gesture patterns during smart tablet gameplay identify children with autism. *Scientific Reports.* Aug 2016;6.
23. Arle JE, Morriss C, Wang ZYJ, Zimmerman RA, Phillips PG, Sutton LN. Prediction of posterior fossa tumor type in children by means of magnetic resonance image properties, spectroscopy, and Neural networks. *Journal of Neurosurgery.* May 1997;86(5):755-761.
24. Arlen AM, Alexander SE, Wald M, Cooper CS. Computer model predicting breakthrough febrile urinary tract infection in children with primary vesicoureteral reflux. *J Pediatr Urol.* Oct 2016;12(5):288 e281-288 e285.
25. Armstrong R, Symons M, Scott JG, et al. Predicting Language Difficulties in Middle Childhood From Early Developmental Milestones: A Comparison of Traditional Regression and Machine Learning Techniques. *Journal of Speech Language and Hearing Research.* Aug 2018;61(8).
26. Askari E, Setarehdan SK, Sheikhani A, Mohammadi MR, Teshnehlab M. Designing a model to detect the brain connections abnormalities in children with autism using 3D-cellular Neural networks. *J Integr Neurosci.* 2018;17(3-4):391-411.
27. Ataer-Cansizoglu E, Bolon-Canedo V, Campbell JP, et al. Computer-Based Image Analysis for Plus Disease Diagnosis in Retinopathy of Prematurity: Performance of the "i-ROP'' System and Image Features Associated With Expert Diagnosis. *Translational Vision Science & Technology.* Nov 2015;4(6).
28. Aucouturier JJ, Nonaka Y, Katahira K, Okanoya K. Segmentation of expiratory and inspiratory sounds in baby cry audio recordings using hidden Markov models. *J Acoust Soc Am.* Nov 2011;130(5):2969-2977.
29. Aydın M, Hardalaç F, Ural B, Karap S. Neonatal Jaundice Detection System. *Journal of Medical Systems.* 2016;40(7):1-11.
30. Ball G, Aljabar P, Arichi T, et al. Machine-learning to characterise neonatal functional connectivity in the preterm brain. *Neuroimage.* Jan 1 2016;124(Pt A):267-275.
31. Bartz-Kurycki MA, Green C, Anderson KT, et al. Enhanced neonatal surgical site infection Prediction model utilizing statistically and clinically significant variables in combination with a machine learning algorithm. *American Journal of Surgery.* Oct 2018;216(4):764-777.
32. Baumgartner C, Bohm C, Baumgartner D, et al. Supervised machine learning techniques for the classification of metabolic disorders in newborns. *Bioinformatics.* Nov 22 2004;20(17):2985-2996.
33. Ben-Sasson A, Robins DL, Yom-Tov E. Risk Assessment for Parents Who Suspect Their Child Has Autism Spectrum Disorder: Machine Learning Approach. *Journal of Medical Internet Research.* Apr 2018;20(4).
34. Ben-Sasson A, Yom-Tov E. Online Concerns of Parents Suspecting Autism Spectrum Disorder in Their Child: Content Analysis of Signs and Automated Prediction of Risk. *J Med Internet Res.* Nov 22 2016;18(11):e300.
35. Bhattacharyya S, Biswas A, Mukherjee J, et al. Detection of artifacts from high energy bursts in neonatal EEG. *Comput Biol Med.* Nov 2013;43(11):1804-1814.
36. Blazadonakis M, Moustakis V, Charissis G. Deep assessment of machine learning techniques using patient treatment in acute abdominal pain in children. *Artificial Intelligence in Medicine.* Nov 1996;8(6):527-542.
37. Bokov P, Mahut B, Flaud P, Delclaux C. Wheezing recognition algorithm using recordings of respiratory sounds at the mouth in a pediatric population. *Computers in Biology and Medicine.* Mar 2016;70:40-50.
38. Bolon-Canedo V, Ataer-Cansizoglu E, Erdogmus D, et al. Dealing with inter-expert variability in retinopathy of prematurity: A machine learning approach. *Computer Methods and Programs in Biomedicine.* Oct 2015;122(1):1-15.
39. Bone D, Bishop SL, Black MP, Goodwin MS, Lord C, Narayanan SS. Use of machine learning to improve autism screening and diagnostic instruments: effectiveness, efficiency, and multi-instrument fusion. *Journal of Child Psychology and Psychiatry.* Aug 2016;57(8):927-937.
40. Bonet-Carne E, Palacio M, Cobo T, et al. Quantitative ultrasound texture analysis of fetal lungs to predict neonatal respiratory morbidity. *Ultrasound Obstet Gynecol.* Apr 2015;45(4):427-433.
41. Bornelov S, Saaf A, Melen E, et al. Rule-based models of the interplay between genetic and environmental factors in childhood allergy. *PLoS One.* 2013;8(11):e80080.
42. Brahnam S, Chuang CF, Sexton RS, Shih FY. Machine assessment of neonatal facial expressions of acute pain. *Decision Support Systems.* Aug 2007;43(4):1242-1254.
43. Brown JM, Campbell JP, Beers A, et al. Automated Diagnosis of Plus Disease in Retinopathy of Prematurity Using Deep Convolutional Neural Networks. *Jama Ophthalmology.* Jul 2018;136(7):803-810.
44. Bussu G, Jones EJH, Charman T, Johnson MH, Buitelaar JK, Team B. Prediction of Autism at 3 Years from Behavioural and Developmental Measures in High-Risk Infants: A Longitudinal Cross-Domain Classifier Analysis. *Journal of Autism and Developmental Disorders.* Jul 2018;48(7):2418-2433.
45. Calderoni S, Retico A, Biagi L, Tancredi R, Muratori F, Tosetti M. Female children with autism spectrum disorder: an insight from mass-univariate and pattern classification analyses. *Neuroimage.* Jan 16 2012;59(2):1013-1022.
46. Carpenter KL, Sprechmann P, Calderbank R, Sapiro G, Egger HL. Quantifying Risk for Anxiety Disorders in Preschool Children: A Machine Learning Approach. *PLoS One.* 2016;11(11):e0165524.
47. Ceschin R, Zahner A, Reynolds W, et al. A computational framework for the detection of subcortical brain dysmaturation in neonatal MRI using 3D Convolutional Neural Networks. *Neuroimage.* Sep 2018;178:183-197.
48. Chan CH, Chan EY, Ng DK, Chow PY, Kwok KL. Application of artificial Neural networks to establish a predictive mortality risk model in children admitted to a paediatric intensive care unit. *Singapore Med J.* Nov 2006;47(11):928-934.
49. Chatzimichail E, Paraskakis E, Sitzimi M, Rigas A. An intelligent system approach for asthma Prediction in symptomatic preschool children. *Comput Math Methods Med.* 2013;2013:240182.
50. Chen A, Wijnen F, Koster C, Schnack H. Individualized Early Prediction of Familial Risk of Dyslexia: A Study of Infant Vocabulary Development. *Frontiers in Psychology.* Feb 2017;8.
51. Chen W, Wang Y, Cao G, Chen G, Gu Q. A random forest model based classification scheme for neonatal amplitude-integrated EEG. *BioMedical Engineering OnLine.* 2014;13:S4-S4.
52. Chen W-H, Hsieh S-L, Hsu K-P, et al. Web-based newborn screening system for metabolic diseases: machine learning versus clinicians. *Journal of Medical Internet Research.* 2013;15(5):e98-e98.
53. Chen YR, Wang SY, Shen CH, Choy FK. Intelligent Identification of Childhood Musical Murmurs. *Journal of Healthcare Engineering.* Mar 2012;3(1):125-139.
54. Chong SL, Liu N, Barbier S, Ong ME. Predictive modeling in pediatric traumatic brain injury using machine learning. *BMC Med Res Methodol.* Mar 17 2015;15:22.
55. Chu C, Lagercrantz H, Forssberg H, Nagy Z. Investigating the use of support vector machine classification on structural brain images of preterm-born teenagers as a biological marker. *PLoS One.* 2015;10(4):e0123108.
56. Chu HC, Tsai WWJ, Liao MJ, Chen YM. Facial emotion recognition with transition detection for students with high-functioning autism in adaptive e-learning. *Soft Computing.* May 2018;22(9):2973-2999.
57. Cic M, Soda J, Bonkovic M. Automatic classification of infant sleep based on instantaneous frequencies in a single-channel EEG signal. *Comput Biol Med.* Dec 2013;43(12):2110-2117.
58. Cohen IL, Liu XD, Hudson M, et al. Using the PDD Behavior Inventory as a Level 2 Screener: A Classification and Regression Trees Analysis. *Journal of Autism and Developmental Disorders.* Sep 2016;46(9):3006-3022.
59. Cohen IL, Sudhalter V, Landon-Jimenez D, Keogh M. A Neural network approach to the classification of autism. *J Autism Dev Disord.* Sep 1993;23(3):443-466.
60. Cooper JN, Minneci PC, Deans KJ. Postoperative neonatal mortality Prediction using superlearning. *J Surg Res.* Jan 2018;221:311-319.
61. Cooper JN, Wei L, Fernandez SA, Minneci PC, Deans KJ. Pre-operative Prediction of surgical morbidity in children: comparison of five statistical models. *Comput Biol Med.* Feb 2015;57:54-65.
62. Correa M, Zimic M, Barrientos F, et al. Automatic classification of pediatric pneumonia based on lung ultrasound pattern recognition. *Plos One.* Dec 2018;13(12).
63. Courtney KL, Stewart S, Popescu M, Goodwin LK. Predictors of preterm birth in birth certificate data. *Stud Health Technol Inform.* 2008;136:555-560.
64. Crippa A, Salvatore C, Molteni E, et al. The Utility of a Computerized Algorithm Based on a Multi-Domain Profile of Measures for the Diagnosis of Attention Deficit/Hyperactivity Disorder. *Frontiers in Psychiatry.* Oct 2017;8.
65. Crippa A, Salvatore C, Perego P, et al. Use of Machine Learning to Identify Children with Autism and Their Motor Abnormalities. *J Autism Dev Disord.* Jul 2015;45(7):2146-2156.
66. Daley M, Dekaban G, Bartha R, et al. Metabolomics profiling of concussion in adolescent male hockey players: a novel diagnostic method. *Metabolomics.* Dec 2016;12(12).
67. Das LT, Abramson EL, Stone AE, Kondrich JE, Kern LM, Grinspan ZM. Predicting frequent emergency department visits among children with asthma using EHR data. *Pediatr Pulmonol.* Jul 2017;52(7):880-890.
68. De Groote A, Groswasser J, Bersini H, Mathys P, Kahn A. Detection of obstructive apnea events in sleeping infants from thoracoabdominal movements. *J Sleep Res.* Jun 2002;11(2):161-168.
69. De Laet T, Papageorgiou E, Nieuwenhuys A, Desloovere K. Does expert knowledge improve automatic probabilistic classification of gait joint motion patterns in children with cerebral palsy? *PLoS One.* 2017;12(6):e0178378.
70. de Wit S, Ziermans TB, Nieuwenhuis M, et al. Individual Prediction of long-term outcome in adolescents at ultra-high risk for psychosis: Applying machine learning techniques to brain imaging data. *Hum Brain Mapp.* Feb 2017;38(2):704-714.
71. Delavarian M, Towhidkhah F, Dibajnia P, Gharibzadeh S. Designing a Decision Support System for Distinguishing ADHD from Similar Children Behavioral Disorders. *Journal of Medical Systems.* Jun 2012;36(3):1335-1343.
72. Delavarian M, Towhidkhah F, Gharibzadeh S, Dibajnia P. Automatic classification of hyperactive children: comparing multiple artificial intelligence approaches. *Neurosci Lett.* Jul 12 2011;498(3):190-193.
73. Deleger L, Brodzinski H, Zhai HJ, et al. Developing and evaluating an automated appendicitis risk stratification algorithm for pediatric patients in the emergency department. *Journal of the American Medical Informatics Association.* Dec 2013;20(E2):E212-E220.
74. DiRusso SM, Chahine AA, Sullivan T, et al. Development of a model for Prediction of survival in pediatric trauma patients: Comparison of artificial Neural networks and logistic Regression. *Journal of Pediatric Surgery.* Jul 2002;37(7):1098-1103.
75. Du J, Wang L, Jie B, Zhang D. Network-based classification of ADHD patients using discriminative subnetwork selection and graph kernel PCA. *Comput Med Imaging Graph.* Sep 2016;52:82-88.
76. Duchesnay E, Cachia A, Boddaert N, et al. Feature selection and classification of imbalanced datasets: application to PET images of children with autistic spectrum disorders. *Neuroimage.* Aug 1 2011;57(3):1003-1014.
77. Duda M, Haber N, Daniels J, Wall DP. Crowdsourced validation of a machine-learning classification system for autism and ADHD. *Translational Psychiatry.* May 2017;7.
78. Duda M, Kosmicki JA, Wall DP. Testing the accuracy of an observation-based classifier for rapid detection of autism risk. *Translational Psychiatry.* Aug 2014;4.
79. Duda M, Ma R, Haber N, Wall DP. Use of machine learning for behavioral distinction of autism and ADHD. *Transl Psychiatry.* Feb 9 2016;6:e732.
80. Dugan TM, Mukhopadhyay S, Carroll A, Downs S. Machine Learning Techniques for Prediction of Early Childhood Obesity. *Applied Clinical Informatics.* 2015;6(3):506-520.
81. Elgendi M, Bobhate P, Jain S, et al. Spectral analysis of the heart sounds in children with and without pulmonary artery hypertension. *Int J Cardiol.* Apr 15 2014;173(1):92-99.
82. Elibol HM, Nguyen V, Linderman S, Johnson M, Hashmi A, Doshi-Velez F. Cross-Corpora Unsupervised Learning of Trajectories in Autism Spectrum Disorders. *Journal of Machine Learning Research.* 2016;17.
83. Emerson RW, Adams C, Nishino T, et al. Functional neuroimaging of high-risk 6-month-old infants predicts a Diagnosis of autism at 24 months of age. *Science Translational Medicine.* Jun 2017;9(393).
84. Farion KJ, Wilk S, Michalowski W, O'Sullivan D, Sayyad-Shirabad J. Comparing Predictions made by a Prediction model, clinical score, and physicians Pediatric asthma exacerbations in the emergency department. *Applied Clinical Informatics.* 2013;4(3):376-391.
85. Fergus P, Cheung P, Hussain A, Al-Jumeily D, Dobbins C, Iram S. Prediction of Preterm Deliveries from EHG Signals Using Machine Learning. *Plos One.* Oct 2013;8(10).
86. Fernandez D, Sram RJ, Dostal M, Pastorkova A, Gmuender H, Choi H. Modeling Unobserved Heterogeneity in Susceptibility to Ambient Benzo[a]pyrene Concentration among Children with Allergic Asthma Using an Unsupervised Learning Algorithm. *Int J Environ Res Public Health.* Jan 10 2018;15(1).
87. Fernandez IS, Sansevere AJ, Gainza-Lein M, Kapur K, Loddenkemper T. Machine Learning for Outcome Prediction in Electroencephalograph (EEG)-Monitored Children in the Intensive Care Unit. *Journal of Child Neurology.* Jul 2018;33(8):546-553.
88. Ferreira D, Oliveira A, Freitas A. Applying data mining techniques to improve Diagnosis in neonatal jaundice. *Bmc Medical Informatics and Decision Making.* Dec 2012;12.
89. Fetit AE, Novak J, Peet AC, Arvanitits TN. Three-dimensional textural features of conventional MRI improve diagnostic classification of childhood brain tumours. *NMR Biomed.* Sep 2015;28(9):1174-1184.
90. Fetit AE, Novak J, Rodriguez D, et al. 3D Texture Analysis of Heterogeneous MRI Data for Diagnostic Classification of Childhood Brain Tumours. *Stud Health Technol Inform.* 2015;213:19-22.
91. Fetit AE, Novak J, Rodriguez D, et al. Radiomics in paediatric neuro-oncology: A multicentre study on MRI texture analysis. *NMR Biomed.* Jan 2018;31(1).
92. Finney OC, Danziger SA, Molina DM, et al. Predicting Antidisease Immunity Using Proteome Arrays and Sera from Children Naturally Exposed to Malaria. *Molecular & Cellular Proteomics.* Oct 2014;13(10):2646-2660.
93. Foland-Ross LC, Sacchet MD, Prasad G, Gilbert B, Thompson PM, Gotlib IH. Cortical thickness predicts the first onset of major depression in adolescence. *Int J Dev Neurosci.* Nov 2015;46:125-131.
94. Fontanella S, Frainay C, Murray CS, Simpson A, Custovic A. Machine learning to identify pairwise interactions between specific IgE antibodies and their association with asthma: A cross-sectional analysis within a population-based birth cohort. *Plos Medicine.* Nov 2018;15(11).
95. Fraiwan L, Lweesy K, Khasawneh N, Fraiwan M, Wenz H, Dickhaus H. Time frequency analysis for automated sleep stage identification in fullterm and preterm neonates. *J Med Syst.* Aug 2011;35(4):693-702.
96. Galvez JA, Pappas JM, Ahumada L, et al. The use of natural language processing on pediatric diagnostic radiology reports in the electronic health record to identify Deep venous thrombosis in children. *J Thromb Thrombolysis.* Oct 2017;44(3):281-290.
97. Gang L, Stone BL, Fassl B, et al. Predicting asthma control deterioration in children. *BMC Medical Informatics & Decision Making.* 2015;15:1-8.
98. Garcia Chimeno Y, Garcia Zapirain B, Saralegui Prieto I, Fernandez-Ruanova B. Automatic classification of dyslexic children by applying machine learning to fMRI images. *Biomed Mater Eng.* 2014;24(6):2995-3002.
99. Garcia JO, Garcia CAR. Acoustic features analysis for recognition of normal and hypoacoustic infant cry based on Neural networks. In: Mira J, Alvarez JR, eds. *Artificial Neural Nets Problem Solving Methods, Pt Ii.* Vol 26872003:615-622.
100. Georgoulas G, Stylios CD, Groumpos PP. Predicting the risk of metabolic acidosis for newborns based on fetal heart rate signal classification using support vector machines. *IEEE Trans Biomed Eng.* May 2006;53(5):875-884.
101. Gharehbaghi A, Borga M, Sjoberg BJ, Ask P. A novel method for discrimination between innocent and pathological heart murmurs. *Medical Engineering & Physics.* Jul 2015;37(7):674-682.
102. Gharehbaghi A, Dutoit T, Sepehri AA, Kocharian A, Linden M. A Novel Method for Screening Children with Isolated Bicuspid Aortic Valve. *Cardiovascular Engineering and Technology.* Dec 2015;6(4):546-556.
103. Gharehbaghi A, LindÉN M, Babic A. A Decision Support System for Cardiac Disease Diagnosis Based on Machine Learning Methods..."Informatics for Health," Manchester, UK, April 2017. *Studies in Health Technology & Informatics.* 2017;235:43-47.
104. Gholami B, Haddad WM, Tannenbaum AR. Relevance vector machine learning for neonate pain intensity assessment using digital imaging. *IEEE Trans Biomed Eng.* Jun 2010;57(6):1457-1466.
105. Giovannini-Chami L, Marcet B, Moreilhon C, et al. Distinct epithelial gene expression phenotypes in childhood respiratory allergy. *The european respiratory journal.* 2012;39(5):1197‐1205.
106. Gori I, Giuliano A, Muratori F, et al. Gray Matter Alterations in Young Children with Autism Spectrum Disorders: Comparing Morphometry at the Voxel and Regional Level. *Journal of Neuroimaging.* Nov-Dec 2015;25(6):866-874.
107. Greene BR, de Chazal P, Boylan GB, Connolly S, Reilly RB. Electrocardiogram based neonatal seizure detection. *IEEE Trans Biomed Eng.* Apr 2007;54(4):673-682.
108. Greene DJ, Church JA, Dosenbach NU, et al. Multivariate pattern classification of pediatric Tourette syndrome using functional connectivity MRI. *Dev Sci.* Jul 2016;19(4):581-598.
109. Grigull L, Lechner WM. Supporting diagnostic Decisions using hybrid and complementary data mining applications: a pilot study in the pediatric emergency department. *Pediatric Research.* 2012;71(6):725-731.
110. Grinspan ZM, Patel AD, Hafeez B, Abramson EL, Kern LM. Predicting frequent emergency department use among children with epilepsy: A retrospective cohort study using electronic health data from 2 centers. *Epilepsia.* Jan 2018;59(1):155-169.
111. Grossi E, Olivieri C, Buscema M. Diagnosis of autism through EEG processed by advanced computational algorithms: A pilot study. *Computer Methods and Programs in Biomedicine.* Apr 2017;142:73-79.
112. Grossi E, Veggo F, Narzisi A, Compare A, Muratori F. Pregnancy risk factors in autism: a pilot study with artificial Neural networks. *Pediatric Research.* Feb 2016;79(2):339-347.
113. Groves DJ, Smye SW, Kinsey SE, et al. A comparison of Cox Regression and Neural networks for risk stratification in cases of acute lymphoblastic leukaemia in children. *Neural Computing & Applications.* 1999;8(3):257-264.
114. Gui L, Loukas S, Lazeyras F, Huppi PS, Meskaldji DE, Tolsa CB. Longitudinal study of neonatal brain tissue volumes in preterm infants and their ability to predict neurodevelopmental outcome. *Neuroimage.* Jan 2019;185:728-741.
115. Guo G, Guffey K, Chen W, Pergami P. Classification of Normal and Pathological Gait in Young Children Based on Foot Pressure Data. *Neuroinformatics.* Jan 2017;15(1):13-24.
116. Guo Y, Wu G, Commander LA, et al. Segmenting hippocampus from infant brains by sparse patch matching with Deep-learned features. *Med Image Comput Comput Assist Interv.* 2014;17(Pt 2):308-315.
117. Haas JP, Mendonca EA, Ross B, Friedman C, Larson E. Use of computerized surveillance to detect nosocomial pneumonia in neonatal intensive care unit patients. *Am J Infect Control.* Oct 2005;33(8):439-443.
118. Habibi Z, Ertiaei A, Nikdad MS, et al. Predicting ventriculoperitoneal shunt infection in children with hydrocephalus using artificial Neural network. *Childs Nerv Syst.* Nov 2016;32(11):2143-2151.
119. Hale AT, Stonko DP, Brown A, et al. Machine-learning analysis outperforms conventional statistical models and CT classification systems in predicting 6-month outcomes in pediatric patients sustaining traumatic brain injury. *Neurosurgical Focus.* Nov 2018;45(5).
120. Hatzakis GE, Davis GM. Fuzzy logic controller for weaning neonates from mechanical ventilation. *Proc AMIA Symp.* 2002:315-319.
121. Held CM, Causa J, Causa L, et al. Automated detection of rapid eye movements in children. *Conf Proc IEEE Eng Med Biol Soc.* 2012;2012:2267-2270.
122. Held CM, Causa L, Jaillet F, et al. Automated detection of apnea/hypopnea events in healthy children polysomnograms: preliminary results. *Conf Proc IEEE Eng Med Biol Soc.* 2013;2013:5373-5376.
123. Held CM, Heiss JE, Estevez PA, et al. Extracting fuzzy Rules from polysomnographic recordings for infant sleep classification. *IEEE Trans Biomed Eng.* Oct 2006;53(10):1954-1962.
124. Heller MD, Roots K, Srivastava S, Schumann J, Srivastava J, Hale TS. A Machine Learning-Based Analysis of Game Data for Attention Deficit Hyperactivity Disorder Assessment. *Games for Health Journal.* Oct 2013;2(5):291-298.
125. 14Helm EJ, Silva CT, Roberts HC, et al. Computer-aided detection for the identification of pulmonary nodules in pediatric oncology patients: initial experience. *Pediatr Radiol.* Jul 2009;39(7):685-693.
126. Heunis T, Aldrich C, Peters JM, et al. Recurrence quantification analysis of resting state EEG signals in autism spectrum disorder - a systematic methodological exploration of technical and demographic confounders in the search for biomarkers. *BMC Medicine.* 2018;16(1):N.PAG-N.PAG.
127. Hicks SD, Rajan AT, Wagner KE, Barns S, Carpenter RL, Middleton FA. Validation of a Salivary RNA Test for Childhood Autism Spectrum Disorder. *Frontiers in Genetics.* Nov 2018;9.
128. Hornero R, Kheirandish-Gozal L, Gutiérrez-Tobal GC, et al. Nocturnal Oximetry-based Evaluation of Habitually Snoring Children. *American Journal of Respiratory & Critical Care Medicine.* 2017;196(12):1591-1598.
129. Hoshino E, Hayashi K, Suzuki M, et al. An iPhone application using a novel stool color detection algorithm for biliary atresia screening. *Pediatr Surg Int.* Oct 2017;33(10):1115-1121.
130. Hsieh CW, Jong TL, Chou YH, Tiu CM. Computerized geometric features of carpal bone for bone age estimation. *Chin Med J (Engl).* May 5 2007;120(9):767-770.
131. Hsieh CW, Jong TL, Tiu CM. Bone age estimation based on phalanx information with fuzzy constrain of carpals. *Med Biol Eng Comput.* Mar 2007;45(3):283-295.
132. Hsieh CW, Liu TC, Jong TL, Tiu CM. A fuzzy-based growth model with principle component analysis selection for carpal bone-age assessment. *Med Biol Eng Comput.* Jun 2010;48(6):579-588.
133. Hsieh CW, Liu TC, Wang JK, Jong TL, Tiu CM. Simplified radius, ulna, and short bone-age assessment procedure using grouped-Tanner-Whitehouse method. *Pediatr Int.* Aug 2011;53(4):567-575.
134. Hsu K-P, Hsieh S-H, Hsieh S-L, et al. A Newborn Screening System Based on Service-Oriented Architecture Embedded Support Vector Machine. *Journal of Medical Systems.* 2010;34(5):899-907.
135. Hu S, Wei L, Gao Y, Guo Y, Wu G, Shen D. Learning-based deformable image registration for infant MR images in the first year of life. *Med Phys.* Jan 2017;44(1):158-170.
136. Hu YH, Tai CT, Chen SCC, Lee HW, Sung SF. Predicting return visits to the emergency department for pediatric patients: Applying supervised learning techniques to the Taiwan National Health Insurance Research Database. *Computer Methods and Programs in Biomedicine.* Jun 2017;144:105-112.
137. Iftikhar F, Shams A, Dilawari A. RCD: a toolkit for rheumatic valvular and congenital heart defect Diagnosis. *Neural Computing & Applications.* Nov 2013;23(6):1729-1735.
138. Ingalhalikar M, Parker D, Bloy L, Roberts TP, Verma R. Diffusion based abnormality markers of pathology: toward learned diagnostic Prediction of ASD. *Neuroimage.* Aug 1 2011;57(3):918-927.
139. Jalali A, Simpao AF, Galvez JA, Licht DJ, Nataraj C. Prediction of Periventricular Leukomalacia in Neonates after Cardiac Surgery Using Machine Learning Algorithms. *J Med Syst.* Aug 17 2018;42(10):177.
140. Jamal W, Das S, Oprescu IA, Maharatna K, Apicella F, Sicca F. Classification of autism spectrum disorder using supervised learning of brain connectivity measures extracted from synchrostates. *J Neural Eng.* Aug 2014;11(4):046019.
141. Jamshidnezhad A, Azizi A, Shirali S, Rekabeslamizadeh S, Haddadzadeh M, Sabaghan Y. Evaluation of Suspected Pediatric Appendicitis with Alvarado Method Using a Computerized Intelligent Model. *International Journal of Pediatrics-Mashhad.* Mar 2016;4(3):1465-1473.
142. Ji J, Ling XFB, Zhao YZ, et al. A Data-Driven Algorithm Integrating Clinical and Laboratory Features for the Diagnosis and Prognosis of Necrotizing Enterocolitis. *Plos One.* Feb 2014;9(2).
143. Jiao Y, Chen R, Ke XY, Chu KK, Lu ZH, Herskovits EH. Predictive models of autism spectrum disorder based on brain regional cortical thickness. *Neuroimage.* Apr 2010;50(2):589-599.
144. Jin Y, Wee CY, Shi F, et al. Identification of infants at high-risk for autism spectrum disorder using multiparameter multiscale white matter connectivity networks. *Hum Brain Mapp.* Dec 2015;36(12):4880-4896.
145. Jong VL, Ahout IM, van den Ham HJ, et al. Transcriptome assists prognosis of disease severity in respiratory syncytial virus infected infants. *Sci Rep.* Nov 11 2016;6:36603.
146. Kamaleswaran R, Akbilgic O, Hallman MA, West AN, Davis RL, Shah SH. Applying Artificial Intelligence to Identify Physiomarkers Predicting Severe Sepsis in the PICU. *Pediatric Critical Care Medicine.* Oct 2018;19(10):E495-E503.
147. Kang X, Safdar N, Myers E, et al. Automatic analysis of pediatric renal ultrasound using shape, anatomical and image acquisition priors. *Med Image Comput Comput Assist Interv.* 2013;16(Pt 3):259-266.
148. Kanimozhiselvi CS, Pratap A. POSSIBILISTIC LVQ NEURAL NETWORK - AN APPLICATION TO CHILDHOOD AUTISM GRADING. *Neural Network World.* 2016;26(3):253-269.
149. Karayiannis NB, Mukherjee A, Glover JR, et al. Detection of pseudo sinusoidal epileptic seizure segments in the neonatal EEG by cascading a Rule-based algorithm with a Neural network. *Ieee Transactions on Biomedical Engineering.* Apr 2006;53(4):633-641.
150. Karayiannis NB, Tao GZ, Xiong YH, et al. Computerized motion analysis of videotaped neonatal seizures of epileptic origin. *Epilepsia.* Jun 2005;46(6):901-917.
151. Karayiannis NB, Xiong Y, Tao G, et al. Automated detection of videotaped neonatal seizures of epileptic origin. *Epilepsia.* Jun 2006;47(6):966-980.
152. Kaur H, Sohn S, Wi CI, et al. Automated chart review utilizing natural language processing algorithm for asthma predictive index. *Bmc Pulmonary Medicine.* Feb 2018;18.
153. Khaleghi A, Sheikhani A, Mohammadi MR, et al. EEG classification of adolescents with type I and type II of bipolar disorder. *Australasian Physical & Engineering Sciences in Medicine.* Dec 2015;38(4):551-559.
154. Kim JR, Shim WH, Yoon HM, et al. Computerized Bone Age Estimation Using Deep Learning Based Program: Evaluation of the Accuracy and Efficiency. *AJR Am J Roentgenol.* Dec 2017;209(6):1374-1380.
155. Kim JW, Sharma V, Ryan ND. Predicting Methylphenidate Response in ADHD Using Machine Learning Approaches. *Int J Neuropsychopharmacol.* May 10 2015;18(11):pyv052.
156. Kong J, Sertel O, Shimada H, Boyer KL, Saltz JH, Gurcan MN. Computer-aided evaluation of neuroblastoma on whole-slide histology images: Classifying grade of neuroblastic differentiation. *Pattern Recognition.* Jun 2009;42(6):1080-1092.
157. Koolen N, Oberdorfer L, Rona Z, et al. Automated classification of neonatal sleep states using EEG. *Clin Neurophysiol.* Jun 2017;128(6):1100-1108.
158. Krishnan ML, Wang Z, Aljabar P, et al. Machine learning shows association between genetic variability in PPARG and cerebral connectivity in preterm infants. *Proceedings of the National Academy of Sciences of the United States of America.* Dec 2017;114(52):13744-13749.
159. Kuhle S, Maguire B, Zhang HQ, et al. Comparison of logistic Regression with machine learning methods for the Prediction of fetal growth abnormalities: a retrospective cohort study. *Bmc Pregnancy and Childbirth.* Aug 2018;18.
160. Kushki A, Khan A, Brian J, Anagnostou E. A Kalman filtering framework for physiological detection of anxiety-related arousal in children with autism spectrum disorder. *IEEE Trans Biomed Eng.* Mar 2015;62(3):990-1000.
161. Laitinen PO, Rasanen J. Measured versus predicted oxygen consumption in children with congenital heart disease. *Heart.* Dec 1998;80(6):601-605.
162. Lamping F, Jack T, Rubsamen N, et al. Development and validation of a diagnostic model for early differentiation of sepsis and non-infectious SIRS in critically ill children - a data-driven approach using machine-learning algorithms. *BMC Pediatr.* Mar 15 2018;18(1):112.
163. Larson DB, Chen MC, Lungren MP, Halabi SS, Stence NV, Langlotz CP. Performance of a Deep-Learning Neural Network Model in Assessing Skeletal Maturity on Pediatric Hand Radiographs. *Radiology.* Apr 2018;287(1):313-322.
164. Lauer RT, Smith BT, Betz RR. Application of a neuro-fuzzy network for gait event detection using electromyography in the child with cerebral palsy. *IEEE Trans Biomed Eng.* Sep 2005;52(9):1532-1540.
165. Lee J, Blain S, Casas M, Kenny D, Berall G, Chau T. A radial basis classifier for the automatic detection of aspiration in children with dysphagia. *Journal of Neuroengineering and Rehabilitation.* Jul 2006;3.
166. Lenhard F, Sauer S, Andersson E, et al. Prediction of outcome in internet-delivered cognitive behaviour therapy for paediatric obsessive-compulsive disorder: A machine learning approach. *International Journal of Methods in Psychiatric Research.* Mar 2018;27(1).
167. Leroy G, Gu Y, Pettygrove S, Galindo MK, Arora A, Kurzius-Spencer M. Automated Extraction of Diagnostic Criteria From Electronic Health Records for Autism Spectrum Disorders: Development, Evaluation, and Application. *Journal of Medical Internet Research.* Nov 2018;20(11).
168. Lesnussa YA, Patty HWM, Titawael CJ, Talakua MW. SYSTEM DIAGNOSIS SYMPTOMS OF FEVER ON CHILDREN USING ARTIFICIAL NEURAL NETWORK AND CERTAINTY FACTOR METHOD: A STUDY CASE OF FEVER PATIENT AT RSUD Dr. M. HAULUSSY HOSPITAL IN AMBON. *International Journal of Health Medicine and Current Research-Ijhmcr.* Dec 2017;2(4):723-729.
169. Levy S, Duda M, Haber N, Wall DP. Sparsifying machine learning models identify stable subsets of predictive features for behavioral detection of autism. *Molecular Autism.* Dec 2017;8.
170. Li L, Liqing H, Hongru L, et al. The use of fuzzy backpropagation Neural networks for the early Diagnosis of hypoxic ischemic encephalopathy in newborns. *Journal of biomedicine & biotechnology.* 2011.
171. Li X, Hu B, Shen J, Xu T, Retcliffe M. Mild Depression Detection of College Students: an EEG-Based Solution with Free Viewing Tasks. *J Med Syst.* Dec 2015;39(12):187.
172. Ling SH, San PP, Nguyen HT. Non-invasive hypoglycemia monitoring system using extreme learning machine for Type 1 diabetes. *ISA Trans.* Sep 2016;64:440-446.
173. Lingren T, Thaker V, Brady C, et al. Developing an Algorithm to Detect Early Childhood Obesity in Two Tertiary Pediatric Medical Centers. *Applied Clinical Informatics.* 2016;7(3):693-706.
174. Liu GJ, Xu Y, Wang XM, et al. Developing a Machine Learning System for Identification of Severe Hand, Foot, and Mouth Disease from Electronic Medical Record Data. *Scientific Reports.* Nov 2017;7.
175. Liu W, Li M, Yi L. Identifying children with autism spectrum disorder based on their face processing abnormality: A machine learning framework. *Autism Res.* Aug 2016;9(8):888-898.
176. Liu X, Jiang J, Zhang K, et al. Localization and Diagnosis framework for pediatric cataracts based on slit-lamp images using Deep features of a convolutional Neural network. *PLoS One.* 2017;12(3):e0168606.
177. Logvinenko T, Chow JS, Nelson CP. Predictive value of specific ultrasound findings when used as a screening test for abnormalities on VCUG. *Journal of Pediatric Urology.* Aug 2015;11(4).
178. Luca S, Karsmakers P, Cuppens K, et al. Detecting rare events using extreme value statistics applied to epileptic convulsions in children. *Artificial Intelligence in Medicine.* Feb 2014;60(2):89-96.
179. Lukic S, Cojbasic Z, Jovic N, et al. Artificial Neural networks based Prediction of cerebral palsy in infants with central coordination disturbance. *Early Human Development.* Jul 2012;88(7):547-553.
180. Luo YH, Li Z, Guo HS, et al. Predicting congenital heart defects: A comparison of three data mining methods. *Plos One.* May 2017;12(5).
181. Maenner MJ, Yeargin-Allsopp M, Van Naarden Braun K, Christensen DL, Schieve LA. Development of a Machine Learning Algorithm for the Surveillance of Autism Spectrum Disorder. *PLoS One.* 2016;11(12):e0168224.
182. Mago VK, Mehta R, Woolrych R, Papageorgiou EI. Supporting meningitis Diagnosis amongst infants and children through the use of fuzzy cognitive mapping. *BMC Med Inform Decis Mak.* Sep 4 2012;12:98.
183. Mai MV, Krauthammer M. Controlling testing volume for respiratory viruses using machine learning and text mining. *AMIA Annu Symp Proc.* 2016;2016:1910-1919.
184. Mancini F, Sousa FS, Hummel AD, et al. Classification of Postural Profiles among Mouth-breathing Children by Learning Vector Quantization. *Methods of Information in Medicine.* 2011;50(4):349-357.
185. Mani S, Ozdas A, Aliferis C, et al. Medical Decision support using machine learning for early detection of late-onset neonatal sepsis. *Journal of the American Medical Informatics Association.* Mar 2014;21(2):326-336.
186. Mantini D, Alleva G, Comani S. A method for the automatic reconstruction of fetal cardiac signals from magnetocardiographic recordings. *Physics in medicine and biology.* 2005;50(20):4763‐4781.
187. Masala GL, Golosio B, Cutzu R, Pola R. A two-layered classifier based on the radial basis function for the screening of thalassaemia. *Computers in Biology & Medicine.* 2013;43(11):1724-1731.
188. Matic V, Cherian PJ, Jansen K, et al. Improving Reliability of Monitoring Background EEG Dynamics in Asphyxiated Infants. *IEEE Trans Biomed Eng.* May 2016;63(5):973-983.
189. Mendonca EA, Haas J, Shagina L, Larson E, Friedman C. Extracting information on pneumonia in infants using natural language processing of radiology reports. *Journal of Biomedical Informatics.* Aug 2005;38(4):314-321.
190. Merey C, Kushki A, Sejdic E, Berall G, Chau T. Quantitative classification of pediatric swallowing through accelerometry. *J Neuroeng Rehabil.* Jun 9 2012;9:34.
191. Meystre S, Gouripeddi R, Tieder J, Simmons J, Srivastava R, Shah S. Enhancing Comparative Effectiveness Research With Automated Pediatric Pneumonia Detection in a Multi-Institutional Clinical Repository: A PHIS+ Pilot Study. *J Med Internet Res.* May 15 2017;19(5):e162.
192. Mikhno A, Ennett CM. Prediction of extubation failure for neonates with respiratory distress syndrome using the MIMIC-II clinical database. *Conf Proc IEEE Eng Med Biol Soc.* 2012;2012:5094-5097.
193. Milosevic M, Van de Vel A, Bonroy B, et al. Automated Detection of Tonic-Clonic Seizures Using 3-D Accelerometry and Surface Electromyography in Pediatric Patients. *IEEE J Biomed Health Inform.* Sep 2016;20(5):1333-1341.
194. Milosevic M, Van de Vel A, Cuppens K, et al. Feature selection methods for accelerometry-based seizure detection in children. *Med Biol Eng Comput.* Jan 2017;55(1):151-165.
195. Mohseni HR, Mirghasemi H, Shamsollahi MB, Zamani MR. Detection of rhythmic discharges in newborn EEG signals. *Conf Proc IEEE Eng Med Biol Soc.* 2006;Suppl:6577-6580.
196. Monasterio V, Burgess F, Clifford GD. Robust classification of neonatal apnoea-related desaturations. *Physiol Meas.* Sep 2012;33(9):1503-1516.
197. Mossotto E, Ashton JJ, Coelho T, Beattie RM, MacArthur BD, Ennis S. Classification of Paediatric Inflammatory Bowel Disease using Machine Learning. *Scientific Reports.* May 2017;7.
198. Mourao-Miranda J, Oliveira L, Ladouceur CD, et al. Pattern recognition and functional neuroimaging help to discriminate healthy adolescents at risk for mood disorders from low risk adolescents. *PLoS One.* 2012;7(2):e29482.
199. Moustris KP, Douros K, Nastos PT, et al. Seven-days-ahead forecasting of childhood asthma admissions using artificial Neural networks in Athens, Greece. *International Journal of Environmental Health Research.* 2012;22(2):93-104.
200. Mueller M, Wagner CL, Annibale DJ, Hulsey TC, Knapp RG, Almeida JS. Predicting extubation outcome in preterm newborns: a comparison of Neural networks with clinical expertise and statistical modeling. *Pediatr Res.* Jul 2004;56(1):11-18.
201. Mueller M, Wagner CL, Annibale DJ, Knapp RG, Hulsey TC, Almeida JS. Parameter selection for and implementation of a web-based Decision-support tool to predict extubation outcome in premature infants. *BMC Med Inform Decis Mak.* Mar 1 2006;6:11.
202. Munoz-Organero M, Powell L, Heller B, Harpin V, Parker J. Automatic Extraction and Detection of Characteristic Movement Patterns in Children with ADHD Based on a Convolutional Neural Network (CNN) and Acceleration Images. *Sensors.* Nov 2018;18(11).
203. Murray PG, Stevens A, De Leonibus C, Koledova E, Chatelain P, Clayton PE. Transcriptomics and machine learning predict Diagnosis and severity of growth hormone deficiency. *Jci Insight.* Apr 2018;3(7).
204. Mutasa S, Chang PD, Ruzal-Shapiro C, Ayyala R. MABAL: a Novel Deep-Learning Architecture for Machine-Assisted Bone Age Labeling. *Journal of Digital Imaging.* Aug 2018;31(4):513-519.
205. Mwangi B, Wu MJ, Bauer IE, et al. Predictive classification of pediatric bipolar disorder using atlas-based diffusion weighted imaging and support vector machines. *Psychiatry Res.* Nov 30 2015;234(2):265-271.
206. Narzisi A, Muratori F, Buscema M, Calderoni S, Grossi E. Outcome predictors in autism spectrum disorders preschoolers undergoing treatment as usual: insights from an observational study using artificial Neural networks. *Neuropsychiatric Disease and Treatment.* 2015;11:1587-1599.
207. Nascimento LF, Ortega NR. Fuzzy linguistic model for evaluating the risk of neonatal death. *Rev Saude Publica.* Dec 2002;36(6):686-692.
208. Nascimento LF, Rocha Rizol PM, Abiuzi LB. Establishing the risk of neonatal mortality using a fuzzy predictive model. *Cad Saude Publica.* Sep 2009;25(9):2043-2052.
209. Navarro X, Poree F, Kuchenbuch M, Chavez M, Beuchee A, Carrault G. Multi-feature classifiers for burst detection in single EEG channels from preterm infants. *J Neural Eng.* Aug 2017;14(4):046015.
210. Naydenova E, Tsanas A, Howie S, Casals-Pascual C, De Vos M. The power of data mining in Diagnosis of childhood pneumonia. *Journal of the Royal Society Interface.* Jul 2016;13(120).
211. Nguyen HT, Ghevondian N, Jones TW. Detection of nocturnal hypoglycemic episodes (natural occurrence) in children with Type 1 diabetes using an optimal Bayesian Neural network algorithm. *Conf Proc IEEE Eng Med Biol Soc.* 2008;2008:1311-1314.
212. Nguyen LB, Ling SS, Jones TW, Nguyen HT. Identification of hypoglycemic states for patients with T1DM using various parameters derived from EEG signals. *Conf Proc IEEE Eng Med Biol Soc.* 2011;2011:2760-2763.
213. Nguyen LB, Nguyen AV, Ling SH, Nguyen HT. Combining genetic algorithm and Levenberg-Marquardt algorithm in training Neural network for hypoglycemia detection using EEG signals. *Conf Proc IEEE Eng Med Biol Soc.* 2013;2013:5386-5389.
214. Nguyen T, Malley R, Inkelis SH, Kuppermann N. Comparison of Prediction models for adverse outcome in pediatric meningococcal disease using artificial Neural network and logistic Regression analyses. *Journal of Clinical Epidemiology.* Jul 2002;55(7):687-695.
215. Ni Y, Beck AF, Taylor R, et al. Will they participate? Predicting patients' response to clinical trial invitations in a pediatric emergency department. *J Am Med Inform Assoc.* Jul 2016;23(4):671-680.
216. Ni Y, Wright J, Perentesis J, et al. Increasing the efficiency of trial-patient matching: automated clinical trial eligibility pre-screening for pediatric oncology patients. *BMC Med Inform Decis Mak.* Apr 14 2015;15:28.
217. Niel O, Bastard P, Boussard C, Hogan J, Kwon T, Deschenes G. Artificial intelligence outperforms experienced nephrologists to assess dry weight in pediatric patients on chronic hemodialysis. *Pediatric Nephrology.* Oct 2018;33(10):1799-1803.
218. Ochab M, Wajs W. Expert system supporting an early Prediction of the bronchopulmonary dysplasia. *Computers in Biology and Medicine.* Feb 2016;69:236-244.
219. Olliver S, Davis GM, Hatzakis GE. Weaning infants with respiratory syncytial virus from mechanical ventilation through a fuzzy-logic controller. *AMIA Annu Symp Proc.* 2003:499-503.
220. Orlandi S, Reyes Garcia CA, Bandini A, Donzelli G, Manfredi C. Application of Pattern Recognition Techniques to the Classification of Full-Term and Preterm Infant Cry. *J Voice.* Nov 2016;30(6):656-663.
221. Orphanidou-Vlachou E, Vlachos N, Davies NP, Arvanitis TN, Grundy RG, Peet AC. Texture analysis of T1 - and T2 -weighted MR images and use of probabilistic Neural network to discriminate posterior fossa tumours in children. *NMR Biomed.* Jun 2014;27(6):632-639.
222. Ortiz SDC, Beceiro DIE, Ekkel T. A radial basis function network oriented for infant cry classification. In: Sanfeliu A, Trinidad JFM, Ochoa JAC, eds. *Progress in Pattern Recognition, Image Analysis and Applications.* Vol 32872004:374-380.
223. Ozdemir ME, Telatar Z, Erogul O, Tunca Y. Classifying dysmorphic syndromes by using artificial Neural network based hierarchical Decision tree. *Australas Phys Eng Sci Med.* Jun 2018;41(2):451-461.
224. Oztoprak H, Toycan M, Alp YK, Arikan O, Dogutepe E, Karakas S. Machine-based classification of ADHD and nonADHD participants using time/frequency features of event-related neuroelectric activity. *Clinical Neurophysiology.* Dec 2017;128(12):2400-2410.
225. Paldino MJ, Hedges K, Zhang W. Independent contribution of individual white matter pathways to language function in pediatric epilepsy patients. *Neuroimage Clin.* 2014;6:327-332.
226. Paldino MJ, Zhang W, Chu ZD, Golriz F. Metrics of brain network architecture capture the impact of disease in children with epilepsy. *Neuroimage-Clinical.* 2017;13:201-208.
227. Palmu K, Stevenson N, Wikstrom S, Hellstrom-Westas L, Vanhatalo S, Palva JM. Optimization of an NLEO-based algorithm for automated detection of spontaneous activity transients in early preterm EEG. *Physiol Meas.* Nov 2010;31(11):N85-93.
228. Pan LY, Liu GJ, Lin FQ, et al. Machine learning applications for Prediction of relapse in childhood acute lymphoblastic leukemia. *Scientific Reports.* Aug 2017;7.
229. Papadelis C, Ashkezari SF, Doshi C, et al. Real-time multi-channel monitoring of burst-suppression using Neural network technology during pediatric status epilepticus treatment. *Clin Neurophysiol.* Aug 2016;127(8):2820-2831.
230. Patel SJ, Chamberlain DB, Chamberlain JM, Cloutier R. A Machine Learning Approach to Predicting Need for Hospitalization for Pediatric Asthma Exacerbation at the Time of Emergency Department Triage. *Academic Emergency Medicine.* 2018;25(12):1463-1470.
231. Peng X, Lin P, Zhang T, Wang J. Extreme learning machine-based classification of ADHD using brain structural MRI data. *PLoS One.* 2013;8(11):e79476.
232. Pereira JC, Tonelli PA, Barros LC, Ortega NR. Clinical signs of pneumonia in children: association with and Prediction of Diagnosis by fuzzy sets theory. *Braz J Med Biol Res.* May 2004;37(5):701-709.
233. Pestian JP, Grupp-Phelan J, Cohen KB, et al. A Controlled Trial Using Natural Language Processing to Examine the Language of Suicidal Adolescents in the Emergency Department. *Suicide and Life-Threatening Behavior.* Apr 2016;46(2):154-159.
234. Phan P, Mezghani N, Wai EK, de Guise J, Labelle H. Artificial Neural networks assessing adolescent idiopathic scoliosis: comparison with Lenke classification. *Spine Journal.* Nov 2013;13(11):1527-1533.
235. Pifferi M, Bush A, Pioggia G, et al. Monitoring asthma control in children with allergies by soft computing of lung function and exhaled nitric oxide. *CHEST.* 2011;139(2):319-327.
236. Plonski P, Gradkowski W, Altarelli I, et al. Multi-parameter machine learning approach to the neuroanatomical basis of developmental dyslexia. *Human Brain Mapping.* Feb 2017;38(2):900-908.
237. Podda M, Bacciu D, Micheli A, Bellu R, Placidi G, Gagliardi L. A machine learning approach to estimating preterm infants survival: development of the Preterm Infants Survival Assessment (PISA) predictor. *Scientific Reports.* Sep 2018;8.
238. Porcelli PJ, Rosenbloom ST. Comparison of new modeling methods for postnatal weight in ELBW infants using prenatal and postnatal data. *J Pediatr Gastroenterol Nutr.* Jul 2014;59(1):e2-8.
239. Portakal O, Tavil B, Kuskonmaz B, Aytac S, Hascelik G. An Automated Image Analysis System Can be Beneficial in Preclassification of Leucocytes in Children With Hematological Disease. *Journal of Clinical Laboratory Analysis.* 2011;25(2):71-75.
240. Precup D, Robles-Rubio CA, Brown KA, et al. Prediction of extubation readiness in extreme preterm infants based on measures of cardiorespiratory variability. *Conf Proc IEEE Eng Med Biol Soc.* 2012;2012:5630-5633.
241. Price T, Wee CY, Gao W, Shen D. Multiple-network classification of childhood autism using functional connectivity dynamics. *Med Image Comput Comput Assist Interv.* 2014;17(Pt 3):177-184.
242. Prosperi MC, Belgrave D, Buchan I, Simpson A, Custovic A. Challenges in interpreting allergen microarrays in relation to clinical symptoms: a machine learning approach. *Pediatr Allergy Immunol.* Feb 2014;25(1):71-79.
243. Prosperi MCF, Marinho S, Simpson A, Custovic A, Buchan IE. Predicting phenotypes of asthma and eczema with machine learning. *Bmc Medical Genomics.* May 2014;7.
244. Qiao JP, Wang ZS, Geronazzo-Alman L, et al. Brain activity classifies adolescents with and without a familial history of substance use disorders. *Frontiers in Human Neuroscience.* Apr 2015;9.
245. Quader N, Hodgson AJ, Mulpuri K, Schaeffer E, Abugharbieh R. Automatic Evaluation of Scan Adequacy and Dysplasia Metrics in 2-D Ultrasound Images of the Neonatal Hip. *Ultrasound Med Biol.* Jun 2017;43(6):1252-1262.
246. Qureshi MNI, Min B, Jo HJ, Lee B. Multiclass Classification for the Differential Diagnosis on the ADHD Subtypes Using Recursive Feature Elimination and Hierarchical Extreme Learning Machine: Structural MRI Study. *Plos One.* Aug 2016;11(8).
247. Raboshchuk G, Nadeu C, Jancovic P, et al. A Knowledge-Based Approach to Automatic Detection of Equipment Alarm Sounds in a Neonatal Intensive Care Unit Environment. *Ieee Journal of Translational Engineering in Health and Medicine-Jtehm.* 2018;6.
248. Rajanayagam J, Frank E, Shepherd RW, Lewindon PJ. Artificial Neural network is highly predictive of outcome in paediatric acute liver failure. *Pediatric Transplantation.* Sep 2013;17(6):535-542.
249. Rani P, Rajkumar ER. Classification of retinopathy of prematurity using back propagation Neural network. *International Journal of Biomedical Engineering and Technology.* 2016;22(4):338-348.
250. Reed NE, Gini M, Johnson PE, Moller JH. Diagnosing congenital heart defects using the Fallot computational model. *Artif Intell Med.* May 1997;10(1):25-40.
251. Reis MA, Ortega NR, Silveira PS. Fuzzy expert system in the Prediction of neonatal resuscitation. *Braz J Med Biol Res.* May 2004;37(5):755-764.
252. Remm M, Remm K. Case-based estimation of the risk of enterobiasis. *Artificial Intelligence in Medicine.* Jul 2008;43(3):167-177.
253. Remm M, Remm K. Effectiveness of Repeated Examination to Diagnose Enterobiasis in Nursery School Groups. *Korean Journal of Parasitology.* Sep 2009;47(3):235-241.
254. Retico A, Giuliano A, Tancredi R, et al. The effect of gender on the neuroanatomy of children with autism spectrum disorders: a support vector machine case-control study. *Mol Autism.* 2016;7:5.
255. Rietveld S, Oud M, Dooijes EH. Classification of asthmatic breath sounds: preliminary results of the classifying capacity of human examiners versus artificial Neural networks. *Comput Biomed Res.* Oct 1999;32(5):440-448.
256. Rocha BH, Christenson JC, Pavia A, Evans RS, Gardner RM. Computerized detection of nosocomial infections in newborns. *Proc Annu Symp Comput Appl Med Care.* 1994:684-688.
257. Rodriguez Gutierrez D, Awwad A, Meijer L, et al. Metrics and textural features of MRI diffusion to improve classification of pediatric posterior fossa tumors. *AJNR Am J Neuroradiol.* May 2014;35(5):1009-1015.
258. Rosales-Perez A, Reyes-Garcia CA, Gonzalez JA, Reyes-Galaviz OF, Escalante HJ, Orlandi S. Classifying infant cry patterns by the Genetic Selection of a Fuzzy Model. *Biomedical Signal Processing and Control.* Mar 2015;17:38-46.
259. Ross MK, Yoon J, van der Schaar A, van der Schaar M. Discovering Pediatric Asthma Phenotypes on the Basis of Response to Controller Medication Using Machine Learning. *Annals of the American Thoracic Society.* Jan 2018;15(1):49-58.
260. Rother AK, Schwerk N, Brinkmann F, Klawonn F, Lechner W, Grigull L. Diagnostic Support for Selected Paediatric Pulmonary Diseases Using Answer-Pattern Recognition in Questionnaires Based on Combined Data Mining Applications-A Monocentric Observational ilot Study. *Plos One.* Aug 2015;10(8).
261. Saadah LM, Chedid FD, Sohail MR, Nazzal YM, Al Kaabi MR, Rahmani AY. Palivizumab Prophylaxis during Nosocomial Outbreaks of Respiratory Syncytial Virus in a Neonatal Intensive Care Unit: Predicting Effectiveness with an Artificial Neural Network Model. *Pharmacotherapy.* Mar 2014;34(3):251-259.
262. Sajedi F, Ahmadlou M, Vameghi R, Gharib M, Hemmati S. Linear and nonlinear analysis of brain dynamics in children with cerebral palsy. *Research in Developmental Disabilities.* May 2013;34(5):1388-1396.
263. San PP, Ling SH, Nguyen HT. Intelligent detection of hypoglycemic episodes in children with type 1 diabetes using adaptive Neural-fuzzy inference system. *Conf Proc IEEE Eng Med Biol Soc.* 2012;2012:6325-6328.
264. Sanders DL, Aronsky D. Prospective evaluation of a Bayesian Network for detecting asthma exacerbations in a Pediatric Emergency Department. *AMIA Annu Symp Proc.* 2006:1085.
265. Santori G, Fontana I, Valente U. Application of an artificial Neural network model to predict delayed decrease of serum creatinine in pediatric patients after kidney transplantation. *Transplant Proc.* Jul-Aug 2007;39(6):1813-1819.
266. Sanz-Cortes M, Ratta GA, Figueras F, et al. Automatic Quantitative MRI Texture Analysis in Smallfor- Gestational-Age Fetuses Discriminates Abnormal Neonatal Neurobehavior. *Plos One.* Jul 2013;8(7).
267. Saria S, Rajani AK, Gould J, Koller D, Penn AA. Integration of Early Physiological Responses Predicts Later Illness Severity in Preterm Infants. *Science Translational Medicine.* Sep 2010;2(48).
268. Sato JR, Biazoli CE, Salum GA, et al. Association between abnormal brain functional connectivity in children and psychopathology: A study based on graph theory and machine learning. *World Journal of Biological Psychiatry.* 2018;19(2):119-129.
269. Saxe GN, Ma SS, Ren JW, Aliferis C. Machine learning methods to predict child posttraumatic stress: a proof of concept study. *Bmc Psychiatry.* Jul 2017;17.
270. Schadl K, Vassar R, Cahill-Rowley K, Yeom KW, Stevenson DK, Rose J. Prediction of cognitive and motor development in preterm children using exhaustive feature selection and cross-validation of near-term white matter microstructure. *Neuroimage-Clinical.* 2018;17:667-679.
271. Schetinin V, Schult J. The combined technique for detection of artifacts in clinical electroencephalograms of sleeping newborns. *IEEE Trans Inf Technol Biomed.* Mar 2004;8(1):28-35.
272. Schetinin V, Schult J. A Neural-network technique to learn concepts from electroencephalograms. *Theory Biosci.* Aug 2005;124(1):41-53.
273. Schmidt-Rohlfing B, Bergamo F, Williams S, et al. Interpretation of surface EMGs in children with cerebral palsy: An initial study using a fuzzy expert system. *Journal of Orthopaedic Research.* Mar 2006;24(3):438-447.
274. Sears ES, Anthony JC. Artificial Neural networks for adolescent marijuana use and clinical features of marijuana dependence. *Subst Use Misuse.* Jan 2004;39(1):107-134.
275. Sepehri A, Kocharian A, Janani A, Gharehbaghi A. An Intelligent Phonocardiography for Automated Screening of Pediatric Heart Diseases. *Journal of Medical Systems.* 2016;40(1):1-10.
276. Sepehri AA, Gharehbaghi A, Dutoit T, Kocharian A, Kiani A. A novel method for pediatric heart sound segmentation without using the ECG. *Comput Methods Programs Biomed.* Jul 2010;99(1):43-48.
277. Sherriff A, Ott J, Team AS. Artificial Neural networks as statistical tools in epidemiological studies: analysis of risk factors for early infant wheeze. *Paediatric and Perinatal Epidemiology.* Nov 2004;18(6):456-463.
278. Shimomura K, Shono H, Kohara M, Uchiyama A, Ito Y, Sugimori H. Neonatal assessment using the Apgar fuzzy expert system. *Comput Biol Med.* May 1994;24(3):171-178.
279. Shono H, Oga M, Shimomura K, et al. Application of fuzzy logic to the Apgar scoring system. *Int J Biomed Comput.* Mar 1992;30(2):113-123.
280. Si Y, Gotman J, Pasupathy A, Flanagan D, Rosenblatt B, Gottesman R. An expert system for EEG monitoring in the pediatric intensive care unit. *Electroencephalogr Clin Neurophysiol.* Jun 1998;106(6):488-500.
281. Sikka K, Ahmed AA, Diaz D, et al. Automated Assessment of Children's Postoperative Pain Using Computer Vision. *Pediatrics.* Jul 2015;136(1):e124-131.
282. Silterra J, Gillette MA, Lanaspa M, et al. Transcriptional Categorization of the Etiology of Pneumonia Syndrome in Pediatric Patients in Malaria-Endemic Areas. *Journal of Infectious Diseases.* Jan 2017;215(2):312-320.
283. Simayijiang Z, Backman S, Ulen J, Wikstrom S, Astrom K. Exploratory study of EEG burst characteristics in preterm infants. *Conf Proc IEEE Eng Med Biol Soc.* 2013;2013:4295-4298.
284. Smyczynska J, Hilczer M, Smyczynska U, Stawerska R, Tadeusiewicz R, Lewinski A. Neural network models - a novel tool for predicting the efficacy of growth hormone (GH) therapy in
285. Smyser CD, Dosenbach NUF, Smyser TA, et al. Prediction of brain maturity in infants using machine-learning algorithms. *Neuroimage.* Aug 2016;136:1-9.
286. Snowden S, Brownlee KG, Smye SW, Dear PR. An advisory system for artificial ventilation of the newborn utilizing a Neural network. *Med Inform (Lond).* Oct-Dec 1993;18(4):367-376.
287. Soleimani F, Teymouri R, Biglarian A. Predicting developmental disorder in infants using an artificial Neural network. *Acta Med Iran.* Jul 13 2013;51(6):347-352.
288. Somkantha K, Theera-Umpon N, Auephanwiriyakul S. Bone age assessment in young children using automatic carpal bone feature extraction and support vector Regression. *J Digit Imaging.* Dec 2011;24(6):1044-1058.
289. Song Z, Awate SP, Licht DJ, Gee JC. Clinical neonatal brain MRI segmentation using adaptive nonparametric data models and intensity-based Markov priors. *Med Image Comput Comput Assist Interv.* 2007;10(Pt 1):883-890.
290. Stahl A, Schellewald C, Stavdahl O, Aamo OM, Adde L, Kirkerod H. An optical flow-based method to predict infantile cerebral palsy. *IEEE Trans Neural Syst Rehabil Eng.* Jul 2012;20(4):605-614.
291. Strauss DJ, Delb W, Plinkert PK. Objective detection of the central auditory processing disorder: a new machine learning approach. *IEEE transactions on bio-medical engineering.* 2004;51(7):1147‐1155.
292. Sullivan R, Yao R, Jarrar R, Buchhalter J, Gonzalez G. Text Classification towards Detecting MisDiagnosis of an Epilepsy Syndrome in a Pediatric Population. *AMIA Annu Symp Proc.* 2014;2014:1082-1087.
293. Takeuchi M, Inuzuka R, Hayashi T, et al. Novel Risk Assessment Tool for Immunoglobulin Resistance in Kawasaki Disease: Application Using a Random Forest Classifier. *Pediatr Infect Dis J.* Sep 2017;36(9):821-826.
294. Tan LR, Guo XY, Ren S, Epstein JN, Lu LJ. A Computational Model for the Automatic Diagnosis of Attention Deficit Hyperactivity Disorder Based on Functional Brain Volume. *Frontiers in Computational Neuroscience.* Sep 2017;11.
295. Tanikawa C, Yamamoto T, Yagi M, Takada K. Automatic recognition of anatomic features on cephalograms of preadolescent children. *Angle Orthod.* Sep 2010;80(5):812-820.
296. Tariq Q, Daniels J, Schwartz JN, Washington P, Kalantarian H, Wall DP. Mobile detection of autism through machine learning on home video: A development and prospective validation study. *Plos Medicine.* Nov 2018;15(11).
297. Taylor JA, Stout JW, de Greef L, et al. Use of a Smartphone App to Assess Neonatal Jaundice. *Pediatrics.* Sep 2017;140(3).
298. Temko A, Doyle O, Murray D, Lightbody G, Boylan G, Marnane W. Multimodal predictor of neurodevelopmental outcome in newborns with hypoxic-ischaemic encephalopathy. *Comput Biol Med.* Aug 2015;63:169-177.
299. Temko A, Lightbody G, Thomas EM, Boylan GB, Marnane W. Instantaneous measure of EEG channel importance for improved patient-adaptive neonatal seizure detection. *IEEE Trans Biomed Eng.* Mar 2012;59(3):717-727.
300. Temko A, Stevenson N, Marnane W, Boylan G, Lightbody G. Temporal evolution of seizure burden for automated neonatal EEG classification. *Conf Proc IEEE Eng Med Biol Soc.* 2012;2012:4915-4918.
301. Temko A, Thomas E, Boylan G, Marnane W, Lightbody G. An SVM-based system and its performance for detection of seizures in neonates. *Conf Proc IEEE Eng Med Biol Soc.* 2009;2009:2643-2646.
302. Temple MW, Lehmann CU, Fabbri D. Predicting Discharge Dates From the NICU Using Progress Note Data. *Pediatrics.* Aug 2015;136(2):E395-E405.
303. Temple MW, Lehmann CU, Fabbri D. Natural Language Processing for Cohort Discovery in a Discharge Prediction Model for the Neonatal ICU. *Appl Clin Inform.* 2016;7(1):101-115.
304. 319. Thomas EM, Greene BR, Lightbody G, Marnane WP, Boylan GB. Seizure detection in neonates: Improved classification through supervised adaptation. *Conf Proc IEEE Eng Med Biol Soc.* 2008;2008:903-906.
305. Toltzis P, Soto-Campos G, Shelton C, et al. Evidence-Based Pediatric Outcome Predictors to Guide the Allocation of Critical Care Resources in a Mass Casualty Event. *Pediatr Crit Care Med.* Sep 2015;16(7):e207-216.
306. Tong C, Liang BY, Li J, Zheng ZG. A Deep Automated Skeletal Bone Age Assessment Model with Heterogeneous Features Learning. *Journal of Medical Systems.* Dec 2018;42(12).
307. Tong DL, Boocock DJ, Dhondalay GK, Lemetre C, Ball GR. Artificial Neural network inference (ANNI): a study on gene-gene interaction for biomarkers in childhood sarcomas. *PLoS One.* 2014;9(7):e102483.
308. Tong LS, Kauer J, Chen X, Chu KQ, Dou H, Smith ZJ. Screening of nutritional and genetic anemias using elastic light scattering. *Lab on a Chip.* Nov 2018;18(21).
309. Toti G, Vilalta R, Lindner P, Lefer B, Macias C, Price D. Analysis of correlation between pediatric asthma exacerbation and exposure to pollutant mixtures with association Rule mining. *Artif Intell Med.* Nov 2016;74:44-52.
310. Townsend D, Frize M. Complimentary artificial Neural network approaches for Prediction of events in the neonatal intensive care unit. *Conf Proc IEEE Eng Med Biol Soc.* 2008;2008:4605-4608.
311. Traitruengsakul S, Seltzer LE, Paciorkowski AR, Ghoraani B. Developing a novel epileptic discharge localization algorithm for electroencephalogram infantile spasms during hypsarrhythmia. *Med Biol Eng Comput.* Sep 2017;55(9):1659-1668.
312. Tsien CL, Kohane IS, McIntosh N. Multiple signal integration by Decision tree induction to detect artifacts in the neonatal intensive care unit. *Artif Intell Med.* Jul 2000;19(3):189-202.
313. Tung WL, Quek C. GenSo-FDSS: a Neural-fuzzy Decision support system for pediatric ALL cancer subtype identification using gene expression data. *Artif Intell Med.* Jan 2005;33(1):61-88.
314. Turi KN, Shankar J, Anderson LJ, et al. Infant Viral Respiratory Infection Nasal Immune-Response Patterns and Their Association with Subsequent Childhood Recurrent Wheeze. *American Journal of Respiratory and Critical Care Medicine.* Oct 2018;198(8):1064-1073.
315. Tuti T, Agweyu A, Mwaniki P, Peek N, English M, Clinical Information N. An exploration of mortality risk factors in non-severe pneumonia in children using clinical data from Kenya. *Bmc Medicine.* Nov 2017;15.
316. Twomey N, Temko A, Hourihane JO, Marnane WP. Automated Detection of Perturbed Cardiac Physiology During Oral Food Allergen Challenge in Children. *Ieee Journal of Biomedical and Health Informatics.* May 2014;18(3):1051-1057.
317. Uddin LQ, Menon V, Young CB, et al. Multivariate searchlight classification of structural magnetic resonance imaging in children and adolescents with autism. *Biol Psychiatry.* Nov 1 2011;70(9):833-841.
318. Uddin LQ, Supekar K, Lynch CJ, et al. Brain State Differentiation and Behavioral Inflexibility in Autism. *Cereb Cortex.* Dec 2015;25(12):4740-4747.
319. Valimaki IA, Nieminen T, Antila KJ, Southall DP. Heart-rate variability and SIDS. Examination of heart-rate patterns using an expert system generator. *Ann N Y Acad Sci.* 1988;533:228-237.
320. Van den Bulcke T, Vanden Broucke P, Van Hoof V, et al. Data mining methods for classification of Medium-Chain Acyl-CoA dehydrogenase deficiency (MCADD) using non-derivatized tandem MS neonatal screening data. *J Biomed Inform.* Apr 2011;44(2):319-325.
321. Vaquerizo-Villar F, Alvarez D, Kheirandish-Gozal L, et al. Detrended fluctuation analysis of the oximetry signal to assist in paediatric sleep apnoea-hypopnoea syndrome Diagnosis. *Physiological Measurement.* Nov 2018;39(11).
322. Vassilakis KM, Vorgia L, Micheloyannis S. Decision support system for classification of epilepsies in childhood. *Journal of Child Neurology.* May 2002;17(5):357-363.
323. Verive MJ, Irazuzta J, Steinhart CM, Orlowski JP, Jaimovich DG. Evaluating the frequency rate of hypomagnesemia in critically ill pediatric patients by using multiple Regression analysis and a computer-based Neural network. *Crit Care Med.* Oct 2000;28(10):3534-3539.
324. Wall DP, Dally R, Luyster R, Jung JY, Deluca TF. Use of artificial intelligence to shorten the behavioral Diagnosis of autism. *PLoS One.* 2012;7(8):e43855.
325. Wall DP, Kosmicki J, DeLuca TF, Harstad E, Fusaro VA. Use of machine learning to shorten observation-based screening and Diagnosis of autism. *Translational Psychiatry.* Apr 2012;2.
326. Walsh CG, Ribeiro JD, Franklin JC. Predicting suicide attempts in adolescents with longitudinal clinical data and machine learning. *Journal of Child Psychology and Psychiatry.* Dec 2018;59(12):1261-1270.
327. Walsh P, Cunningham P, Rothenberg SJ, O'Doherty S, Hoey H, Healy R. An artificial Neural network Ensemble to predict disposition and length of stay in children presenting with bronchiolitis. *European Journal of Emergency Medicine.* Oct 2004;11(5):259-264.
328. Wan Y-T, Chiang C-S, Wuang Y-P, Chen SC-J. The effectiveness of the computerized visual perceptual training program on individuals with Down syndrome: An fMRI study. *Research in Developmental Disabilities.* 2017;66:1-15.
329. Wang BB, Xiao L, Liu Y, et al. Application of a Deep convolutional Neural network in the Diagnosis of neonatal ocular fundus hemorrhage. *Bioscience Reports.* Dec 2018;38.
330. Wang XH, Jiao Y, Li LH. PREDICTING CLINICAL SYMPTOMS OF ATTENTION DEFICIT HYPERACTIVITY DISORDER BASED ON TEMPORAL PATTERNS BETWEEN AND WITHIN INTRINSIC CONNECTIVITY NETWORKS. *Neuroscience.* Oct 2017;362:60-69.
331. Wee CY, Tuan TA, Broekman BFP, et al. Neonatal Neural Networks Predict Children Behavioral Profiles Later in Life. *Human Brain Mapping.* Mar 2017;38(3):1362-1373.
332. Weisenfeld NI, Warfield SK. Automatic segmentation of newborn brain MRI. *Neuroimage.* Aug 15 2009;47(2):564-572.
333. Werth J, Long X, Zwartkruis-Pelgrim E, et al. Unobtrusive assessment of neonatal sleep state based on heart rate variability retrieved from electrocardiography used for regular patient monitoring. *Early Hum Dev.* Oct 2017;113:104-113.
334. West PR, Amaral DG, Bais P, et al. Metabolomics as a Tool for Discovery of Biomarkers of Autism Spectrum Disorder in the Blood Plasma of Children. *Plos One.* Nov 2014;9(11).
335. Wi CI, Sohn S, Ali M, et al. Natural Language Processing for Asthma Ascertainment in Different Practice Settings. *Journal of Allergy and Clinical Immunology-in Practice.* Jan-Feb 2018;6(1):126-131.
336. Wi CI, Sohn S, Rolfes MC, et al. Application of a Natural Language Processing Algorithm to Asthma Ascertainment. An Automated Chart Review. *Am J Respir Crit Care Med.* Aug 15 2017;196(4):430-437.
337. Wolf M, Keel M, von Siebenthal K, et al. Improved monitoring of preterm infants by Fuzzy Logic. *Technol Health Care.* Aug 1996;4(2):193-201.
338. Wong HK, Tiffin PA, Chappell MJ, et al. Personalized Medication Response Prediction for Attention-Deficit Hyperactivity Disorder: Learning in the Model Space vs. Learning in the Data Space. *Frontiers in Physiology.* Apr 2017;8.
339. Wu MJ, Wu HJE, Mwangi B, et al. Prediction of pediatric unipolar depression using multiple neuromorphometric measurements: A pattern classification approach. *Journal of Psychiatric Research.* Mar 2015;62:84-91.
340. Wu ST, Juhn YJ, Sohn S, Liu H. Patient-level temporal aggregation for text-based asthma status ascertainment. *Journal of the American Medical Informatics Association.* 2014;21(5):876-884.
341. Xiao X, Fang H, Wu JS, et al. Diagnostic model generated by MRI-derived brain features in toddlers with autism spectrum disorder. *Autism Research.* Apr 2017;10(4):620-630.
342. Xu M, Tantisira KG, Wu A, et al. Genome Wide Association Study to predict severe asthma exacerbations in children using random forests classifiers. *BMC medical genetics.* 2011;12:90.
343. Yadav K, Sarioglu E, Choi HA, Cartwright WBt, Hinds PS, Chamberlain JM. Automated Outcome Classification of Computed Tomography Imaging Reports for Pediatric Traumatic Brain Injury. *Acad Emerg Med.* Feb 2016;23(2):171-178.
344. Yassin IM, Zabidi A, Ismail N, Zaman FHK, Shafie MF, Rizman ZI. INFANT ASPHYXIA DETECTION USING AUTOENCODERS TRAINED ON LOCALLY LINEAR EMBEDDED-REDUCED MEL FREQUENCY CEPSTRUM COEFFICIENT (MFCC) FEATURES. *Journal of Fundamental and Applied Sciences.* 2017;9:716-729.
345. Yilmaz R, Erkaymaz O, Kara E, Ergen K. Use of Autopsy to Determine Live or Stillbirth: New Approaches in Decision-support Systems. *Journal of Forensic Sciences.* Mar 2017;62(2):468-472.
346. Yin TK, Chiu NT. A computer-aided Diagnosis for distinguishing Tourette's syndrome from chronic tic disorder in children by a fuzzy system with a two-step minimization approach. *IEEE Trans Biomed Eng.* Jul 2004;51(7):1286-1295.
347. Young J, Macke CJ, Tsoukalas LH. Short-term acoustic forecasting via artificial Neural networks for neonatal intensive care units. *J Acoust Soc Am.* Nov 2012;132(5):3234-3239.
348. Youngstrom EA, Halverson TF, Youngstrom JK, Lindhiem O, Findling RL. Evidence-Based Assessment From Simple Clinical Judgments to Statistical Learning: Evaluating a Range of Options Using Pediatric Bipolar Disorder as a Diagnostic Challenge. *Clinical Psychological Science.* Mar 2018;6(2):243-265.
349. Yu J, Wang Y, Chen P. Fetal ultrasound image segmentation system and its use in fetal weight estimation. *Med Biol Eng Comput.* Dec 2008;46(12):1227-1237.
350. Zarchi MS, Bushehri S, Dehghanizadeh M. SCADI: A standard dataset for self-care problems classification of children with physical and motor disability. *International Journal of Medical Informatics.* Jun 2018;114:81-87.
351. Zernikow B, Holtmannspoetter K, Michel E, Pielemeier W, Hornschuh F, Westermann A. Artificial Neural network for risk assessment in preterm neonates. *Archives of disease in childhood fetal & neonatal edition.* 1998;79:F129‐134.
352. Zernikow B, Holtmannspoetter K, Michel E, Theilhaber M, Pielemeier W, Hennecke KH. Artificial Neural network for predicting intracranial haemorrhage in preterm neonates. *Acta paediatrica.* 1998;87(9):969‐975.
353. Zernikow B, Holtmannspotter K, Michel E, Hornschuh F, Groote K, Hennecke KH. Predicting length-of-stay in preterm neonates. *Eur J Pediatr.* Jan 1999;158(1):59-62.
354. Zhai HJ, Brady P, Li Q, et al. Developing and evaluating a machine learning based algorithm to predict the need of pediatric intensive care unit transfer for newly hospitalized children. *Resuscitation.* Aug 2014;85(8):1065-1071.
355. Zhang B, Wan X, Ouyang FS, et al. Machine Learning Algorithms for Risk Prediction of Severe Hand-Foot-Mouth Disease in Children. *Scientific Reports.* Jul 2017;7.
356. Zhang F, Savadjiev P, Cai W, et al. Whole brain white matter connectivity analysis using machine learning: An application to autism. *Neuroimage.* May 15 2018;172:826-837.
357. Zhang SY, Tjortjis C, Zeng XJ, Qiao H, Buchan I, Keane J. Comparing data mining methods with logistic Regression in childhood obesity Prediction. *Information Systems Frontiers.* Sep 2009;11(4):449-460.
358. Zhang W, Li R, Deng H, et al. Deep convolutional Neural networks for multi-modality isointense infant brain image segmentation. *Neuroimage.* Mar 2015;108:214-224.
359. Zhao Q, Rosenbaum K, Okada K, et al. Automated Down syndrome detection using facial photographs. *Conf Proc IEEE Eng Med Biol Soc.* 2013;2013:3670-3673.
360. Zimmer VA, Glocker B, Hahner N, et al. Learning and combining image neighborhoods using random forests for neonatal brain disease classification. *Med Image Anal.* Dec 2017;42:189-199.
361. Ziv E, Tymofiyeva O, Ferriero DM, Barkovich AJ, Hess CP, Xu D. A machine learning approach to automated structural network analysis: application to neonatal encephalopathy. *PLoS One.* 2013;8(11):e78824.
362. Zolnoori M, Fazel Zarandi MH, Moin M, Heidarnezhad H, Kazemnejad A. Computer-aided intelligent system for diagnosing pediatric asthma. *J Med Syst.* Apr 2012;36(2):809-822.
363. Zou L, Zheng JN, Mia CY, McKeown MJ, Wang ZJ. 3D CNN Based Automatic Diagnosis of Attention Deficit Hyperactivity Disorder Using Functional and Structural MRI. *Ieee Access.* 2017;5:23626-23636.