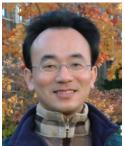




人工智慧在學什麼 (What is Artificial Intelligence Learning?)

臺北醫學大學 口腔醫學院 CFD 講座

Host: Prof. Li Sheng Chen College of Oral Medicine, Taipei Medical University Time: 12:10-13:00, Nov 23, 2020 (Monday) Place: 口腔醫學院1樓會議室1-1, TMU Address: N250 Wu-Hsing Street, Taipei, Taiwan



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Program Co-Chair, IEEE International Workshop on Empirical Methods for Recognizing Inference in TExt (IEEE EM-RITE 2012-) Publications Chair, The IEEE International Conference on Information Reuse and Integration (IEEE IRI)





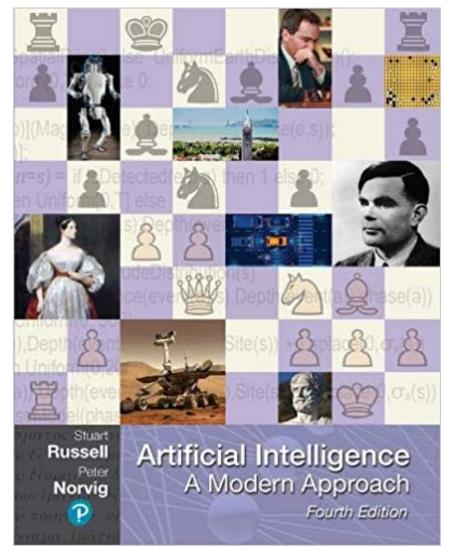


Outline

- Artificial Intelligence
- Machine Learning
- Deep Learning
- Al in Medicine

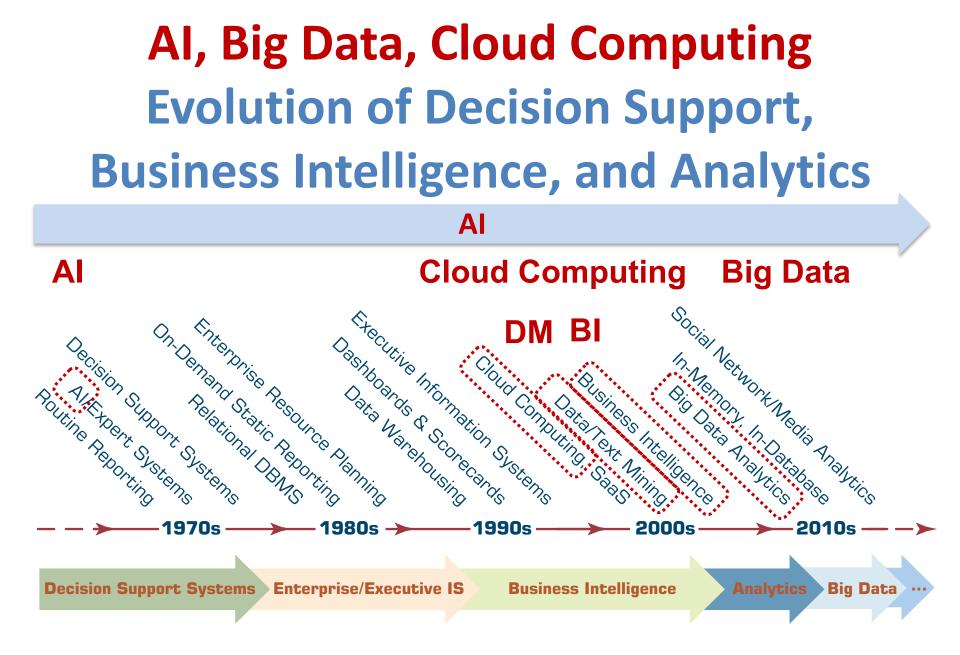
Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach,

4th Edition, Pearson



Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

https://www.amazon.com/Artificial-Intelligence-A-Modern-Approach/dp/0134610997/



Artificial Intelligence (A.I.) Timeline

A.I. TIMELINE



1961

UNIMATE

at GM replacing

assembly line

First industrial robot,

Unimate, goes to work

1966

A.I.

WINTER

Many false starts and dead-ends leave A.I. out

1998

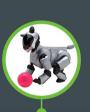
KISMET

Cynthia Breazeal at MIT introduces KISmet, an IBM defeats world chess emotionally intelligent robot insofar as it detects and responds to people's feelings

1950

TURING TEST Computer scientist Alan Turing proposes a intelligence' is coined test for machine

intelligence. If a machine can trick humans into thinking it is human, then it has intelligence



1999

Sony launches first consumer robot pet dog autonomous robotic AiBO (Al robot) with skills and personality that develop over time

by computer scientist, John McCarthy to

1955

A.I. BORN

Term 'artificial

describe "the science and engineering of making intelligent machines"

ODD

1964

Pioneering chatbot developed by Joseph Weizenbaum at MIT with humans

The 'first electronic person' from Stanford. Shakey is a general-

purpose mobile robot that reasons about its own actions

1997 **DEEP BLUE**

Deep Blue, a chess-

playing computer from champion Garry Kasparov

🔅 AlphaGo

2002

and clean homes

2011

Apple integrates Siri, vacuum cleaner from assistant with a voice iRobot learns to navigate interface, into the iPhone 4S

2011

WATSON

IBM's question answering computer Watson wins first place on popular \$1M prize television guiz show

2014

Eugene Goostman, a chatbot passes the Turing Test with a third of judges believing Eugene is human

2014

Amazon launches Alexa, Microsoft's chatbot Tay an intelligent virtual assistant with a voice interface that completes inflammatory and shopping tasks

2016

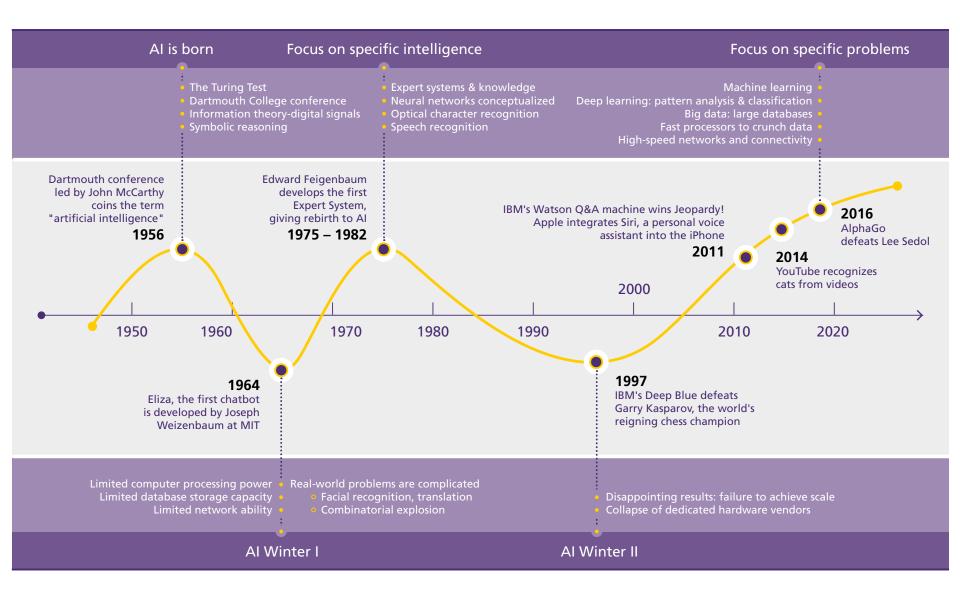
goes roque on social media making offensive racist

2017

ALPHAGO

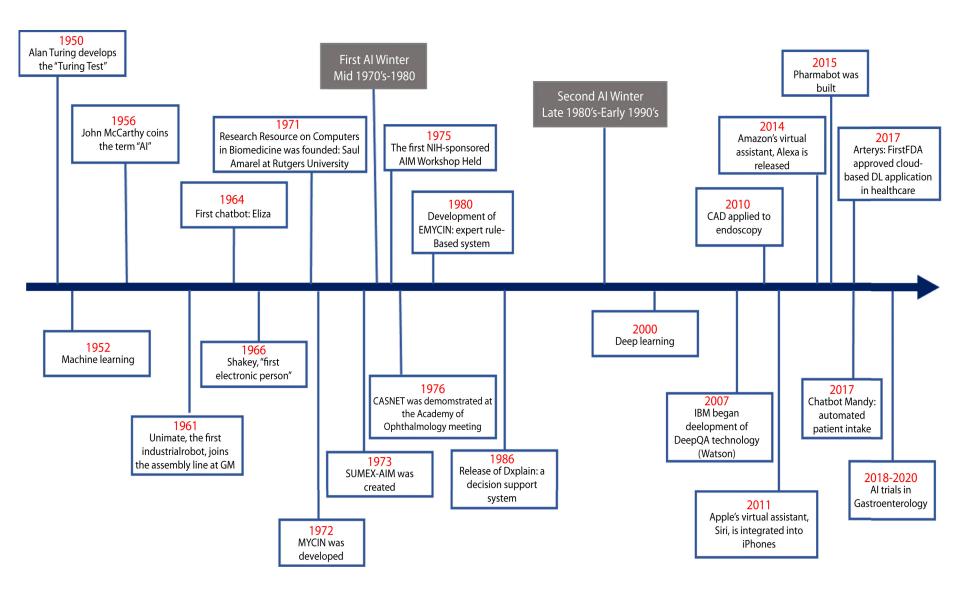
Google's A.I. AlphaGo beats world champion Ke Jie in the complex board game of Go, notable for its vast number (2¹⁷⁰) of possible positions

The Rise of Al



Source: DHL (2018), Artificial Intelligence in Logistics, http://www.globalhha.com/doclib/data/upload/doc_con/5e50c53c5bf67.pdf/

Artificial Intelligence in Medicine



Source: Vivek Kaul, Sarah Enslin, and Seth A. Gross (2020), "The history of artificial intelligence in medicine." Gastrointestinal endoscopy..



Definition of **Artificial Intelligence** (A.I.)

Artificial Intelligence

"... the SCIENCE and engineering of making intelligent machines" (John McCarthy, 1955)

11

Artificial Intelligence

"... technology that thinks and acts like humans"

Source: https://digitalintelligencetoday.com/artificial-intelligence-defined-useful-list-of-popular-definitions-from-business-and-science/

Artificial Intelligence

"... intelligence exhibited by machines or software"

Source: https://digitalintelligencetoday.com/artificial-intelligence-defined-useful-list-of-popular-definitions-from-business-and-science/

4 Approaches of Al



4 Approaches of Al

| 2. | 3. |
|-------------------|-----------------------|
| Thinking Humanly: | Thinking Rationally: |
| The Cognitive | The "Laws of Thought" |
| Modeling Approach | Approach |
| 1. | 4. |
| Acting Humanly: | Acting Rationally: |
| The Turing Test | The Rational Agent |
| Approach (1950) | Approach |

Al Acting Humanly: The Turing Test Approach (Alan Turing, 1950)

- Knowledge Representation
- Automated Reasoning
- Machine Learning (ML)

- Deep Learning (DL)

- Computer Vision (Image, Video)
- Natural Language Processing (NLP)
- Robotics

Artificial Intelligence: A Modern Approach

- 1. Artificial Intelligence
- 2. Problem Solving
- 3. Knowledge and Reasoning
- 4. Uncertain Knowledge and Reasoning
- 5. Learning
- 6. Communicating, Perceiving, and Acting
- 7. Philosophy and Ethics of AI

Artificial Intelligence: Intelligent Agents

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Artificial Intelligence: 2. Problem Solving

- Solving Problems by Searching
- Search in Complex Environments
- Adversarial Search and Games
- Constraint Satisfaction Problems

Artificial Intelligence: 3. Knowledge and Reasoning

- Logical Agents
- First-Order Logic
- Inference in First-Order Logic
- Knowledge Representation
- Automated Planning
- Quantifying Uncertainty

Artificial Intelligence: 4. Uncertain Knowledge and Reasoning

- Probabilistic Reasoning
- Probabilistic Reasoning over Time
- Probabilistic Programming
- Making Simple Decisions
- Making Complex Decisions

Artificial Intelligence: 5. Learning

- Multiagent Decision Making
- Learning from Examples
- Learning Probabilistic Models
- Deep Learning

Artificial Intelligence: 6. Communicating, Perceiving, and Acting

- Reinforcement Learning
- Natural Language Processing
- Deep Learning for Natural Language Processing
- Robotics

Artificial Intelligence: Philosophy and Ethics of AI The Future of AI

Al in Medicine

- Al algorithms now equal or exceed expert doctors at diagnosing many conditions, particularly when the diagnosis is based on images.
- Examples:
 - Alzheimer's disease (Ding et al., 2018)
 - Metastatic cancer (Liu et al., 2017; Esteva et al., 2017)
 - Ophthalmic disease (Gulshan et al., 2016)
 - Skin diseases (Liu et al., 2019c)

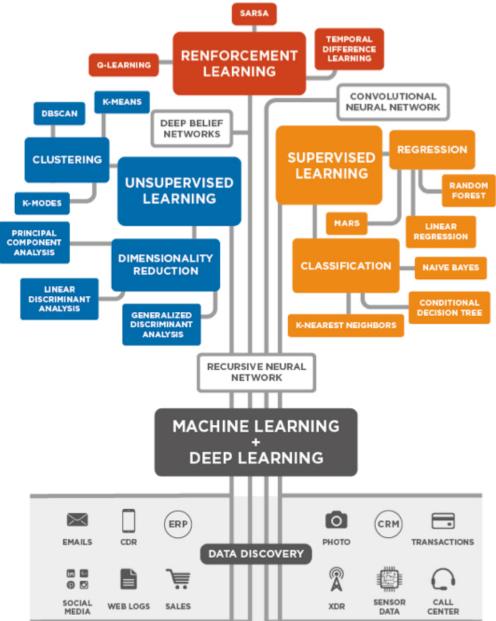
Al in Medicine

- A systematic review and meta-analysis (Liu et al., 2019a) found that the performance of AI programs, on average, was equivalent to health care professionals.
- One current emphasis in medical AI is in facilitating human–machine partnerships.
 - For example, the LYNA system achieves 99.6% overall accuracy in diagnosing metastatic breast cancer—better than an unaided human expert—but the combination does better still (Liu et al., 2018; Steiner et al., 2018)..

Al in Medicine

- The widespread adoption of these techniques is now limited not by diagnostic accuracy but by the need to demonstrate improvement in clinical outcomes and to ensure transparency, lack of bias, and data privacy (Topol, 2019).
- In 2017, only two medical AI applications were approved by the FDA, but that increased to 12 in 2018, and continues to rise.

3 Machine Learning Algorithms



Source: Enrico Galimberti, http://blogs.teradata.com/data-points/tree-machine-learning-algorithms/

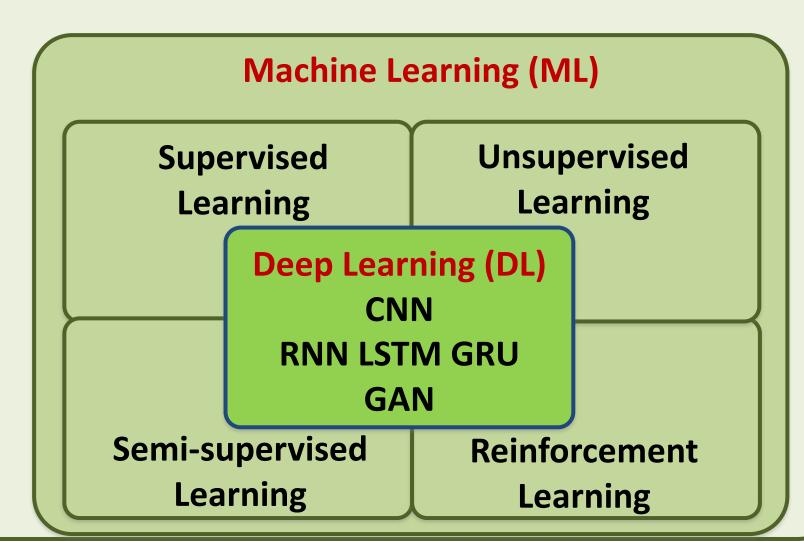
Artificial Intelligence Machine Learning & Deep Learning

ARTIFICIAL INTELLIGENCE Early artificial intelligence MACHINE stirs excitement. LEARNING Machine learning begins DEEP to flourish. LEARNING Deep learning breakthroughs drive AI boom. 00012 110 00101 1950's 1960's 1970's 1980's 1990's 2010's 2000's

Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

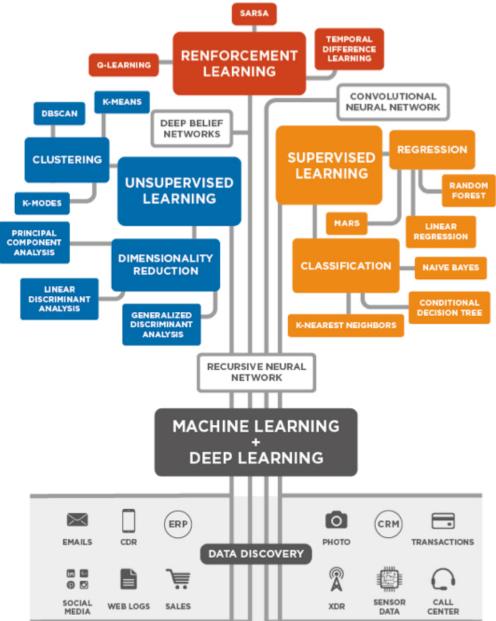
AI, ML, DL

Artificial Intelligence (AI)



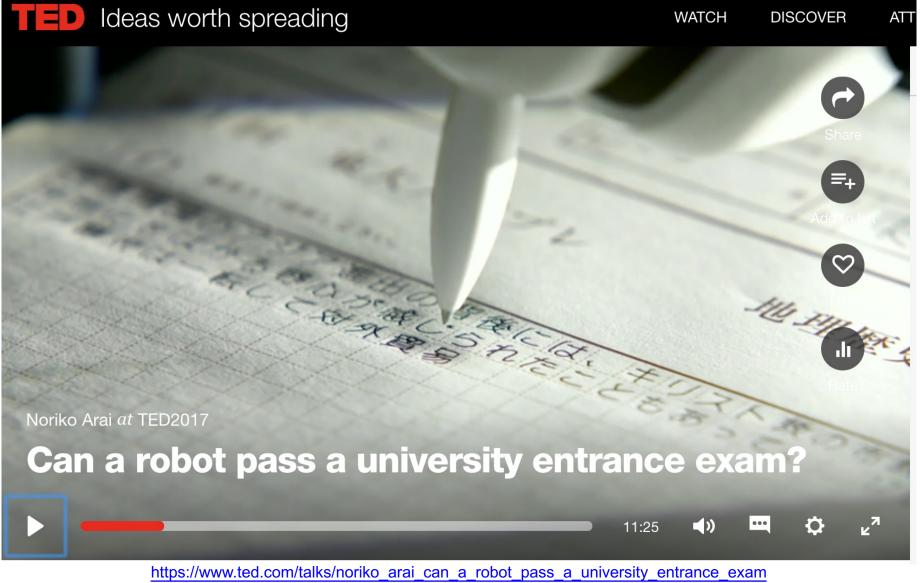
Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/deep_learning.html

3 Machine Learning Algorithms

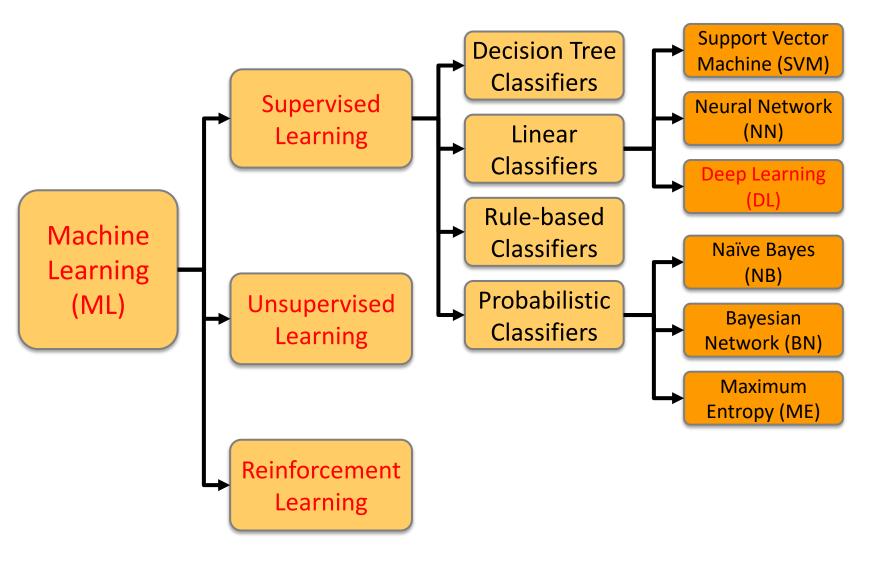


Source: Enrico Galimberti, http://blogs.teradata.com/data-points/tree-machine-learning-algorithms/

Can a robot pass a university entrance exam? Noriko Arai at TED2017

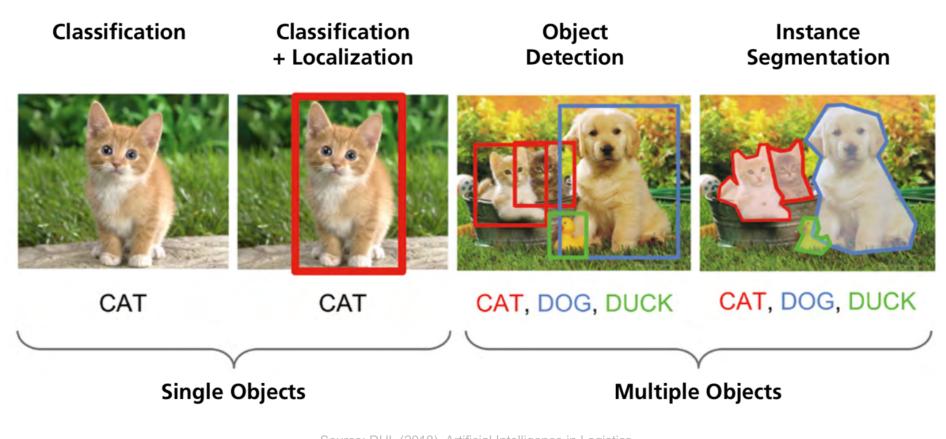


Machine Learning (ML) / Deep Learning (DL)



Source: Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.

Computer Vision: Image Classification, Object Detection, Object Instance Segmentation

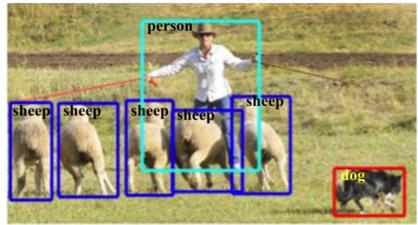


Source: DHL (2018), Artificial Intelligence in Logistics, http://www.globalhha.com/doclib/data/upload/doc con/5e50c53c5bf67.pdf/

Computer Vision: Object Detection



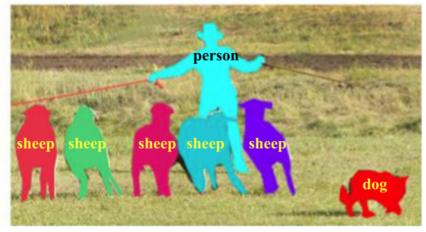
(a) Object Classification



(b) Generic Object Detection (Bounding Box)



(c) Semantic Segmentation



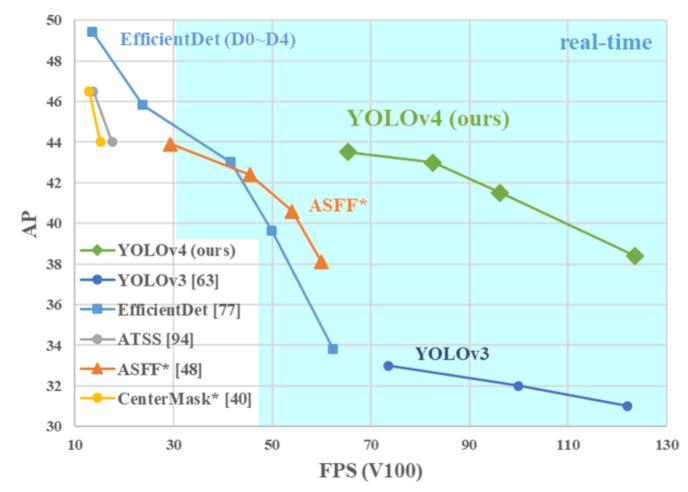
(d) Object Instance Segmetation

Source: Li Liu, Wanli Ouyang, Xiaogang Wang, Paul Fieguth, Jie Chen, Xinwang Liu, and Matti Pietikäinen. "Deep learning for generic object detection: A survey." International journal of computer vision 128, no. 2 (2020): 261-318.

YOLOv4:

Optimal Speed and Accuracy of Object Detection

MS COCO Object Detection



Source: Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao. "YOLOv4: Optimal Speed and Accuracy of Object Detection." arXiv preprint arXiv:2004.10934 (2020).

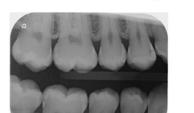
Labelling strategies for different dental image modalities **Bitewing radiographs**

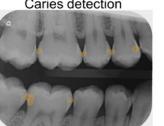


Labels/

a)

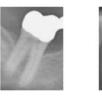
NILT Near Infrared-Light Transillumination





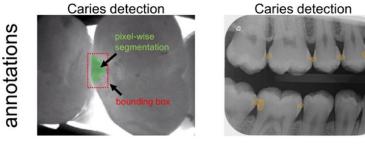


Teeth structures

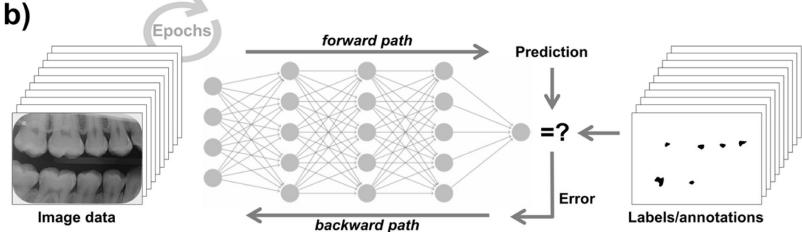


Periodontal bone loss 0 1 (yes) (no)

Tooth segments







Source: Falk Schwendicke, Tatiana Golla, Martin Dreher, and Joachim Krois. "Convolutional neural networks for dental image diagnostics: A scoping review." Journal of Dentistry 91 (2019): 103226.

Scope and Performance of Artificial Intelligence Technology in Orthodontic Diagnosis, **Treatment Planning, and Clinical Decision-making** – **A Systematic Review Journal of Dental Sciences (2020)**

Source:

| Serial no | Authors | Year of publication | Algorithm Architecture | Objective of the study | No. of images/ photographs for testing | Study factor | , | Comparison if any | accuracy/ average accuracy | Results (+) effective, (-)non effective (N) neutral | Outcomes | Authors suggestions/ conclusions |
|--------------|-------------------------------|------------------------|---------------------------|--|---|--------------|---|-----------------------------|---|---|---|---|
| 1 | Leonardi et al. ¹⁰ | 2009 | CNNs | CCNs-based AI system for automatic location of cephalometric landmarks | 41 | Landmarks | Lateral cephalometric radiographs | | Not clear | (+) Effective | An acceptable level of accuracy was obtained by the CCNs based system designed for automatic landmark detection | copies of the |
| 2 | Mario et al. ¹¹ | 2010 | PANNs | A paraconsistent artificial neural network (PANN) for analyzing the cephalometric variables for orthodontic diagnosis | 120 | Landmarks | • | 3 Experienced orthodontists | Not clear, | (+) Effective | The performance of the model was equivalent to that of the specialist's | Can be used as auxiliary support for orthodontic decision making |
| 3 | Arik et al. ¹² | 2017 | CNNs | Al based deep (CNNs) for automated quantitative cephalometry | 250 | Landmarks | Cephalometric radiographs | 2 Trained experts | Accuracy of 76% | | This system demonstrated higher performance when compared with the top benchmarks in the literature | None |
| 4 | Park et al. ¹³ | 2019 | CNNs | Comparing latest deep-CNN based systems for identifying cephalometric landmarks | 283 | Landmarks | Cephalometric radiographs | Multibox | 5% higher accuracy with (YOLOv3) than Single (SSD) | (+) Effective | You-Only-Look-Once model outperformed in accuracy and computational time than the Shot Multibox Detector | This model can be used in clinical practice for identifying the cephalometric landmarks |
| 5 | Kunz et al. ¹⁴ | 2020 | CNNs | An automated cephalometric X- ray analysis using a specialized (AI) algorithm | 50 | Landmarks | Cephalometric radiographs | 12 experienced examiners | Not clear | (+) Effective | Al algorithm was able to analyze unknown cephalometric X-rays similar to the quality level of the experienced human examiners | |

| Serial no | Authors | | Algorithm Architecture | | No. of images/ photographs for testing | Study factor | Modality | - | accuracy/ | Results (+) effective, (-)non effective (N) neutral | Outcomes | Authors suggestions/ conclusions |
|--------------|----------------------------|------|---------------------------|--|---|-----------------------|---|--------------------------------|---|---|---|--|
| 6 | Hwang et al. ¹⁵ | 2020 | CNNs | Deep -learning based automated system for detecting the patterns of 80 cephalometric landmarks | | Landmarks | Cephalometric radiographs | Human examiners | Detection error <0.9 mm | (+) Effective | cephalometric landmarks similar to | This system might be a viable option when repeated identification of multiple cephalometric landmarks |
| 7 | Xie et al. ¹⁶ | 2010 | ANNs | ANN based AI model for deciding if extractions are necessary prior to orthodontic treatment | | Tooth malocclusion | Lateral cephalometric radiographs | Not mentioned | Accuracy of 80% | | ANN was effective in determining whether extraction or non- extraction treatment was best for malocclusion patients | None |
| 8 | Jung et al. ¹⁷ | 2016 | ANNS | Artificial Intelligence expert system for orthodontic decision- making of required permanent tooth extraction | 156 | Tooth malocclusion | Lateral cephalometric radiographs | 1 Experienced orthodontists | Accuracy of 92% | | The success rates of the models were 92% for the system's recommendations for extraction vs non- extraction | neural network |
| 9 | Choi et al. ¹⁸ | 2019 | ANNS | ANN based model for deciding on surgery/non-surgery and determining extractions | 316 | Landmarks | Lateral cephalometric radiographs | 1 Experienced orthodontists | ICC value ranged from 0.97 to 0.99 | (+) Effective | This ANN based mode demonstrated higher success rate in deciding on surgery/ non-surgery and was also successful in deciding on the extractions. | l This ANN based model will be useful in diagnosing of orthognathic surgery cases. |
| 10 | Kök et al. ¹⁹ | 2019 | ANNs | Al algorithms for determining the stages of the growth and development by cervical vertebrae | 300 | Cervical vertebrae | Cephalometric radiographs | 1 orthodontists | Mean Accuracy of 77.02% | (+) f Effective | ANN could be the | None |

| Serial no | Authors | | Algorithm Architecture | ,, | No. of images/ photographs for testing | Study factor | , | | Evaluation accuracy/ average accuracy | Results (+) effective, (-)non effective (N) neutral | Outcomes | Authors suggestions/ conclusions |
|--------------|------------------------------|--------|------------------------------|--|---|-----------------------|---|--|--|---|---|--|
| 11 | Makaremi et al. ⁶ | 2019 | CNNs | CCNs-based AI system for determining of the degree of maturation of the cervical vertebra | 300 | Cervical vertebrae | Lateral cephalometric radiographs | Not mentioned | Mean Accuracy lesser than 90% | (+) Effective | This proposed model is validated by cross validation and is of use for orthodontists | This is a validated software and can be readily used by orthodontists |
| 12 | Lu et al. ²⁰ | 2009 | ANNs | ANN based model for predicting post-orthognathic surgery image | 30 | Face | Profile images | 1 orthodontists | | (+) Effective | The ANN based system demonstrated an improved accuracy and reliability in prediction | |
| 13 | Patcas et al. ²¹ | 2019 | CNNs | Al system for describing the impact of orthognathic treatments on facial attractiveness and age appearance | 2164 | Facial landmarks | Facial photographs | Not mentioned | Not Clear | (+) Effective | This CNN based Al system can be used for scoring facial attractiveness and apparent age in patients under orthognathic treatments. | None |
| 14 | Patcas et al. ²² | 2019 | CNNs | Al system for evaluating the facial attractiveness of patients who have undergone treatment for clefts and the facial attractiveness of controls and to compare these results with panel ratings performed by laypeople, orthodontists, and oral surgeons | 30 | Face | Frontal and profile images | 15 laypeople, 14 orthodontists, 10 oral surgeons | $\begin{array}{l} \text{Cleft cases} \\ \text{(all} \\ \text{Ps} \geq 0.19), \\ \text{For Control} \\ \text{group (all} \\ \text{Ps} \leq 0.02) \end{array}$ | Effective | Al system scores were comparable with the scores of the other groups for the cleft patients, but the scores were lower for the controls | There is a need for further refinement in this AI based system |
| 15 | Thanathornwong ²¹ | 3 2018 | Bayesian network (BNs) | Bayesian Network (BN) for predicting the need for orthodontic treatment | 1000 | Tooth malocclusion | Data sets | 2 Experienced orthodontists | AUC (0.91) | Effective | This BN based system; and demonstrated promising results with high degree of accuracy in the need for orthodontic treatment. | None |

| Serial no | Authors | | Algorithm Architecture | | No. of images/ photographs for testing | Study factor | | ŕ | | Results (+) effective, (-)non effective (N) neutral | | Authors suggestions/ conclusions |
|--------------|-------------------------|------|---------------------------|--|---|--------------|---|--------------------------------|---|---|---|--|
| 16 | Li et al. ²⁴ | 2019 | ANNs | ANN based model for orthodontic treatment planning | 302 | Landmarks | Extraoral and intraoral photos, lateral cephalometric radiographs | 2 Experienced orthodontists | Accuracy of 94.0% for prediction of extraction- non- extraction, (AUC) of 0.982 | Effective | The ANN based system demonstrated excellent accuracy levels in predicting for extraction- nonextraction, and also extraction and anchorage patterns | for guiding less- experienced |

ANNs = Artificial Neural Networks, CNNs = Convolutional Neural Networks, DCNNs = Deep Convolutional Neural Networks, BN = Bayesian Network, BN = Bayesian Network PANN = Paraconsistent Artificial Neural Network, ROC = Receiver Operating Characteristic curve, AUC = Area Under the Curve, ICC = Intraclass Correlation Coefficient.

Comparing latest deep-CNN based systems for identifying cephalometric landmarks (Park et al., 2019)

- CNNs
- Comparing latest deep-CNN based systems for identifying cephalometric landmarks
- 283
- Landmarks
- Cephalometric radiographs
- Single Shot Multibox Detector (SSD)
- 5% higher accuracy with (YOLOv3) than Single (SSD)
- (+)Effective
- You-Only-Look-Once model outperformed in accuracy and computational time than the Shot Multibox Detector
- This model can be used in clinical practice for identifying the cephalometric landmarks

Summary

- Artificial Intelligence
- Machine Learning
- Deep Learning
- Al in Medicine

References

- Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson
- Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson.
- Jared Dean (2014), Big Data, Data Mining, and Machine Learning: Value Creation for Business Leaders and Practitioners, Wiley.
- Mehmet Kaya, Jalal Kawash, Suheil Khoury, and Min-Yuh Day (2018), Social Network Based Big Data Analysis and Applications, Lecture Notes in Social Networks, Springer International Publishing.
- Varun Grover, Roger HL Chiang, Ting-Peng Liang, and Dongsong Zhang (2018), "Creating Strategic Business Value from Big Data Analytics: A Research Framework", Journal of Management Information Systems, 35, no. 2, pp. 388-423.
- Ting-Peng Liang and Yu-Hsi Liu (2018), "Research Landscape of Business Intelligence and Big Data analytics: A bibliometrics study", Expert Systems with Applications, 111, no. 30, pp. 2-10.
- Javier Mata, Ignacio de Miguel, Ramón J. Durán, Noemí Merayo, Sandeep Kumar Singh, Admela Jukan, and Mohit Chamania (2018), "Artificial intelligence (AI) methods in optical networks: A comprehensive survey", Optical Switching and Networking, 28, pp. 43-57
- Stephan Kudyba (2014), Big Data, Mining, and Analytics: Components of Strategic Decision Making, Auerbach Publications
- Falk Schwendicke, Tatiana Golla, Martin Dreher, and Joachim Krois. "Convolutional neural networks for dental image diagnostics: A scoping review." Journal of Dentistry 91 (2019): 103226.
- Vivek Kaul, Sarah Enslin, and Seth A. Gross (2020), "The history of artificial intelligence in medicine." Gastrointestinal endoscopy.
- Sanjeev B. Khanagar, Ali Al-Ehaideb, Satish Vishwanathaiah, Prabhadevi C. Maganur, Shankargouda Patil, Sachin Naik, Hosam A. Baeshen, and Sachin S. Sarode (2020). "Scope and performance of artificial intelligence technology in orthodontic diagnosis, treatment planning, and clinical decision-making-A systematic review." Journal of Dental Sciences.



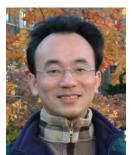




人工智慧在學什麼? (What is Artificial Intelligence Learning?)

臺北醫學大學 口腔醫學院 CFD 講座

Host: Prof. Li Sheng Chen College of Oral Medicine, Taipei Medical University Time: 12:10-13:00, Nov 23, 2020 (Monday) Place: 口腔醫學院1樓會議室1-1, TMU Address: N250 Wu-Hsing Street, Taipei, Taiwan



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