

出國報告（出國類別：其他）

參加第 24 屆醫學影像計算與計算輔助 干預研討會 (MICCAI) (視訊會議)

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摘要

根據醫學影像發展的產業調查推估未來將有 15%~20%的醫學影像設備包含 AI 輔助，由於醫學影像電腦分析計算及輔助診斷的技術發展迅速，故本次公差參加第 24 屆醫學影像計算與計算輔助干預研討會 (MICCAI)，藉以蒐集相關資訊並掌握技術發展趨勢與臨床應用動態。

該研討會聚焦於醫學影像計算、人工智慧、輔助介入、醫療機器人、計算生物醫學等領域，會議內容包含不同技術類型（影像分割、電腦輔助診斷、影像重建、自我監督式學習、影像對位等）搭配不同的臨床應用（神經影像、肺部、組織病理學、眼科、乳房、心臟等）之國際上最先進的研究，該會議前後兩天亦包含多達 60 多場衛星會議，涉及面向非常完整，深度學習於各種技術面分類、各種醫學應用分類、涉及資料安全抗擾、運算加速、不確定性的量化、甚至到考量經濟可負擔的 AI 技術等等，與本所研發中的核醫影像分析軟體及放射影像高階醫材儀器系統之未來智慧化升級有密切關聯。

本次公差主要針對腦部神經影像的應用發展近況及相關臨床實務上面臨的議題進行資訊蒐集與了解。另外，在訓練數據不足的解決方案、開放平台、數據共享機制等重要議題，亦獲得國際上寶貴的經驗及討論觀點，對於本所計畫未來規劃與推動應有相當大的啟發及幫助。本次研討會中發表的內容都相當艱深且新穎，尚需詳加研究，會議發表之全文及資訊下載存查於實驗室電腦中，供相關研究同仁參考與延伸搜尋。

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一、目的

人工智慧在醫療領域的應用，使得醫療不但可以加入預測、預防的概念，更有助於縮短診斷時間、提升正確性，也促成醫療解決方案趨向個人化、智慧化。而國內政策大力支持下，相關資訊科技與醫療技術正結合朝該趨勢發展中。政策額度計畫「智慧化放射影像醫材研發」開發高效能核醫偵測探頭、腦功能智慧輔助軟體技術等，即是利用高靈敏偵測系統以及影像智慧分析技術來提升病灶偵測診斷之正確性。由於醫學影像電腦分析計算及輔助診斷的技術發展迅速，特別是圖形辨識、影像切割處理、影像偵測標註等更是應用範圍廣大。參加 2021 International Conference on Medical Image Computing & Computer Assisted Intervention 國際研討會，蒐集核醫或放射成像的影像輔助診斷相關技術或以此技術應用之臨床情境與相關技術資訊，可快速獲得該領域最新發展方向與技術應用趨勢。

二、過程

(一) 議程

因受 COVID-19 疫情影響，本次研討會改於網路線上舉行，除了 9/27 和 10/1 的衛星會議群的時間為 UTC 9:00-17:30 (台灣時間 17:00-隔天凌晨 1:30) 外，三天的主會議時間大約 UTC 8:00-19:30 (台灣時間 16:00-隔天凌晨 3:30) 長達 11 小時以上不間斷的會議議程。由於無須實際的路程與趕場，反而讓會議安排非常得緊湊及有效率。

		Tentative schedule 2021				
UTC	台灣時間	Sep-27	Sep-28	Sep-29	Sep-30	Oct-01
06:00	14:00					
06:30						
07:00				MSB Burnout Webinar	EC tutorial - Open Science Tools	
07:30			Yoga	Yoga	Yoga	
08:00	16:00		Poster session	Poster session	Poster session	
08:30			Industrial exhibition	CLINICCAI Oral session 1	Industrial exhibition	
09:00		Satellite Events	Poster session	Poster session	Poster session	
09:30			Industrial exhibition	CLINICCAI Poster session 1	Industrial exhibition	
10:00			Poster session	Poster session	Poster session	
10:30						
11:00			Oral session	CLINICCAI Oral session 2	Oral session	
11:30			Oral session	Oral session	Oral session	
12:00	20:00			CLINICCAI Poster session 2		
12:30			Opening Ceremony	Wim / RISE event	MICCAI Society meet. MICCAI Town hall	
13:00			Keynote Pierre Jannin	CLINICCAI Oral session 3	Industry forum	
13:30			Oral session	Oral session	Oral session	
14:00		Satellite Events	Oral session	CLINICCAI Poster session 3	Oral session	
14:30				Keynote Richard Satava	Keynote Fei-Fei Li	
15:00			Keynote Alyson McGregor			
15:30				CLINICCAI Awards & Closing		
16:00		Satellite Events	Poster session	Poster session	Poster session	
16:30			Industrial exhibition	Industrial exhibition	Industrial exhibition	
17:00			Poster session	Poster session	Poster session	
17:30	1:30					
18:00			Poster session	Poster session	Poster session	
18:30						
19:00				RSNA - MICCAI panel	Awards & Closing Ceremony	
19:30	3:30			RISE Networking event		
20:00	4:00		Startup village	WIM Networking event	Strasbourg event	
20:30			MSB Academia & Industry event			
21:00			Challenge assessment			
21:30			MSB Entrepreneurship webinar	MSB Games night		
22:00						
22:30						
23:00						

圖 1、MICCAI 會議完整議程表

(二)參加 2021 醫學影像計算與計算輔助干預研討會

2021 年 9/27~10/1 舉辦的第 24 屆 International Conference on Medical Image Computing & Computer Assisted Intervention (MICCAI) 是由醫學影像計算與計算輔助干預協會 (MICCAI)、法國史特拉斯堡大學 (University of Strasbourg, 一座具 483 年歷史的學校, 師生有 19 位諾貝爾獎獲得者)、法國 ICube 實驗室 (整合多個單位研究人員的實驗機構, 包含 17 個團隊約 650 人) 聯合舉辦的大型會議, 議程如圖 1。該研討會公認為是醫學影像計算、醫療機器人、人工智慧、輔助介入、計算生物醫學等領域之頂級國際會議。該會議前後兩天包含多達 60 多場衛星會議 (包含課程、工作坊、挑戰競賽分享會等)。根據官方統計數據, 531 篇投稿被接受 (接受率僅 33%), 60 篇口頭發表, 歷年統計數據如圖 2 所示, 與會人數約 2,602 人 (以研究人員為主, 少部分醫師及廠商)。研究發表的技術類型與應用屬性之占比如圖 3, 技術上以影像分割 (13%)、電腦輔助診斷 (11%)、影像重建 (9%) 為前三名, 應用屬性以神經影像 (6%) 最高, 肺、組織病理學、眼科、乳房、心臟等其他領域較平均皆 2%。另外, 所接受的論文之機構所在地區分布如圖 4, 其中亞洲 41%、北美 32%、歐洲 23%、澳洲 3%、中南美洲 1%, 以美國與中國為主要國家。此次公差主要針對核醫或放射成像的影像輔助診斷相關技術或以此技術應用之臨床情境資訊蒐集為主。

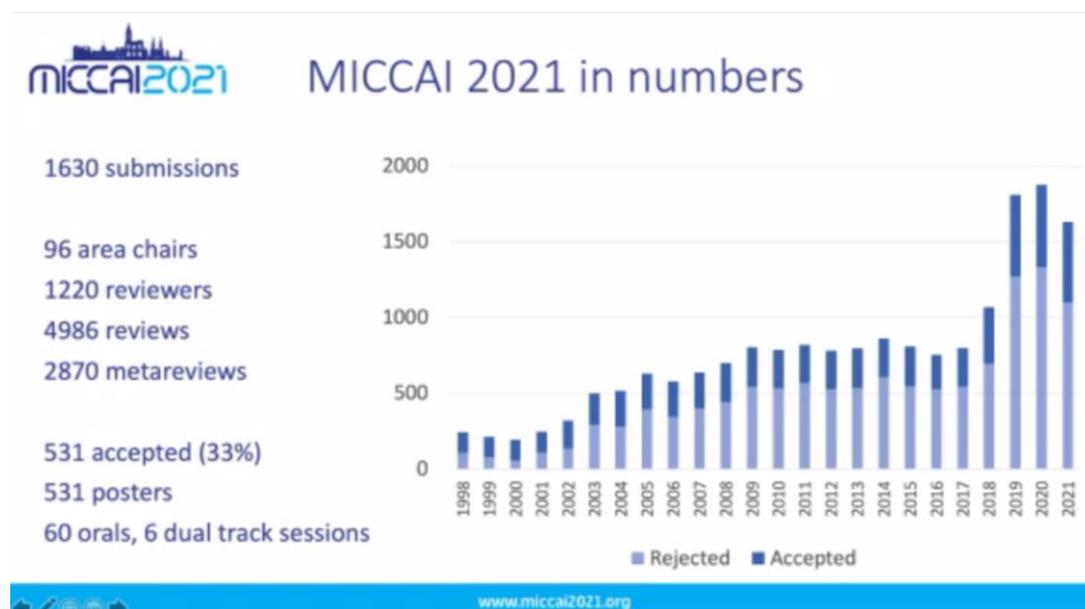


圖 2、MICCAI 會議歷年論文投稿與接受之數量統計

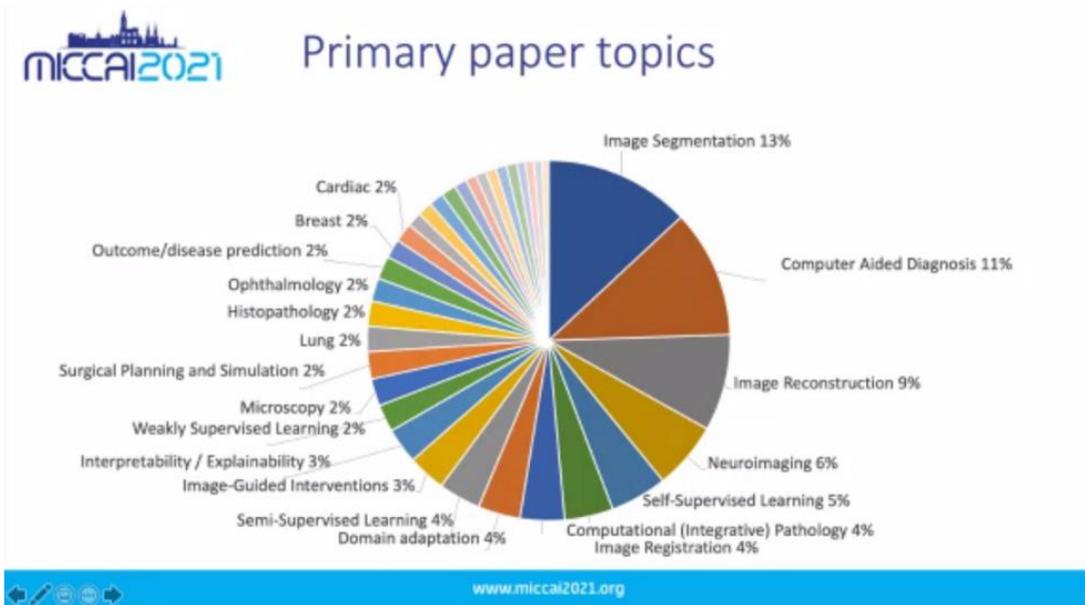


圖 3、MICCAI 2021 研究發表的技術類型與應用屬性之占比

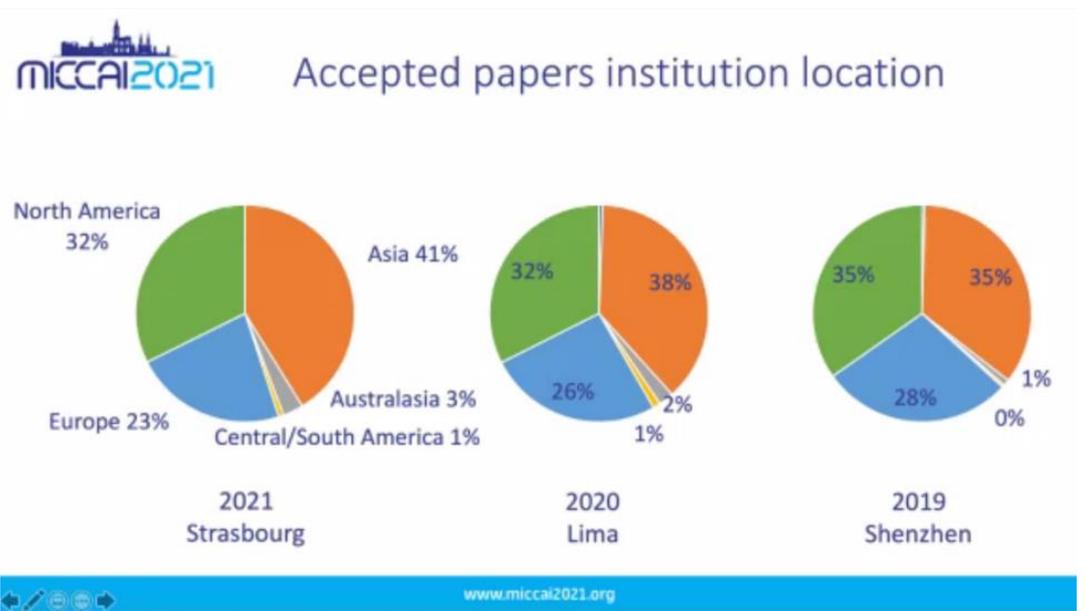


圖 4、MICCAI 2021 所接受的論文之機構所在地區分布

作者第一次參加 MICCAI，雖然是網路線上舉辦的研討會，但感受到主辦單位的用心，如圖 5 所示，每一個虛擬空間都盡量擬真，例如大廳、櫃台、海報報告的攤位、廠商的攤位，甚至是咖啡廳及夜景吧檯，努力營造出促進與會者間交流互動的場景與氣氛，減少網路上純粹報告者唱獨角戲的尷尬。參觀海報時的體驗相當新鮮，每個主題海報室列表於視窗右方，可以一次瀏覽所有海報室的參與人數（了解人氣）及是否有主講人進行報告中，切換不同主題海報室只要 1 秒鐘，相當方便。另外，也模擬以往現場觀看海報自由討論的情況，每個與會者具有一頭像符號代表，可以移動，也可以開視訊發表意見，或以貼圖表示心情或給予報告者掌聲。討論聲音的音量也依相距的遠近有差異，有走近人群參與討論的感覺，雖然大家遠至天涯但像在比鄰（如圖 6）。還有一些設計如圖 7 所示，參與會議像打遊戲似的，參與度越高積分越多，還有及時排行榜顯示，處處都能看到主辦方希望弭補未能實體與會交流之遺憾。該研討會是 AI 技術於醫學影像領域的頂級國際會議，除了發表的質量控管外，從其 69 組不同議題的衛星會議觀察，涉及面向非常完整，深度學習於各種技術面分類、各種醫學應用分類、涉及資料安全抗擾、運算加速、不確定性的量化、甚至到考量經濟可負擔的 AI 技術等等。作者有興趣了解的主題至少一半以上，參與時間有限只能取捨，選擇與執行計畫最相近的部分，其餘將透過會後錄影回放及相關資料攜回參考。

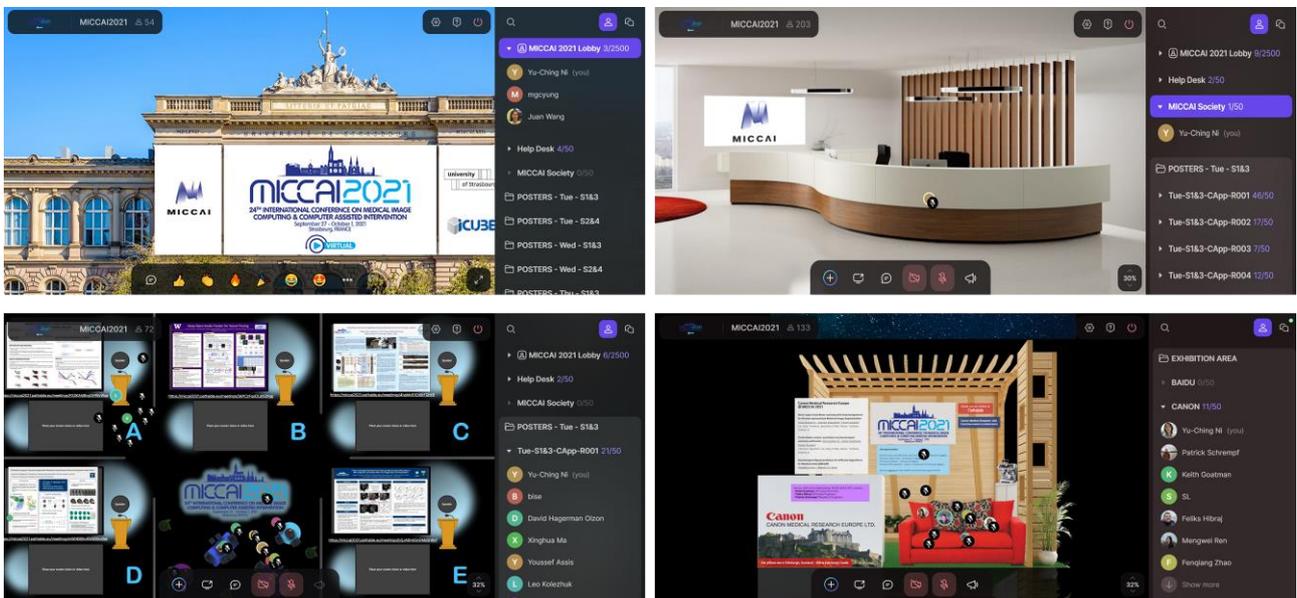


圖 5、MICCAI 2021 會議虛擬空間規劃多元

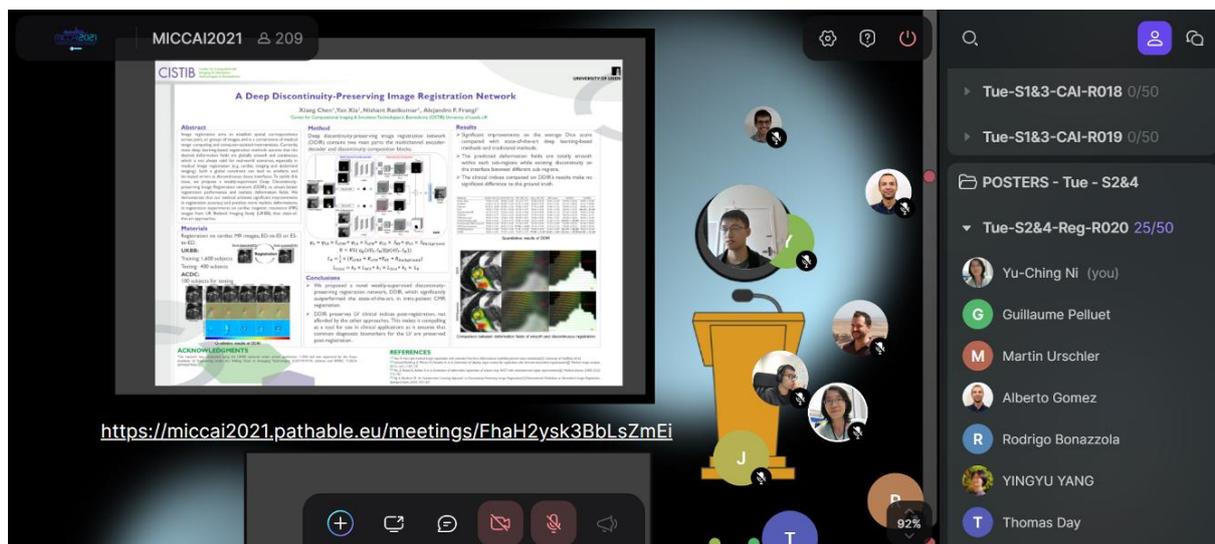


圖 6、MICCAI 2021 會議虛擬的海報室擬真感高且討論熱烈

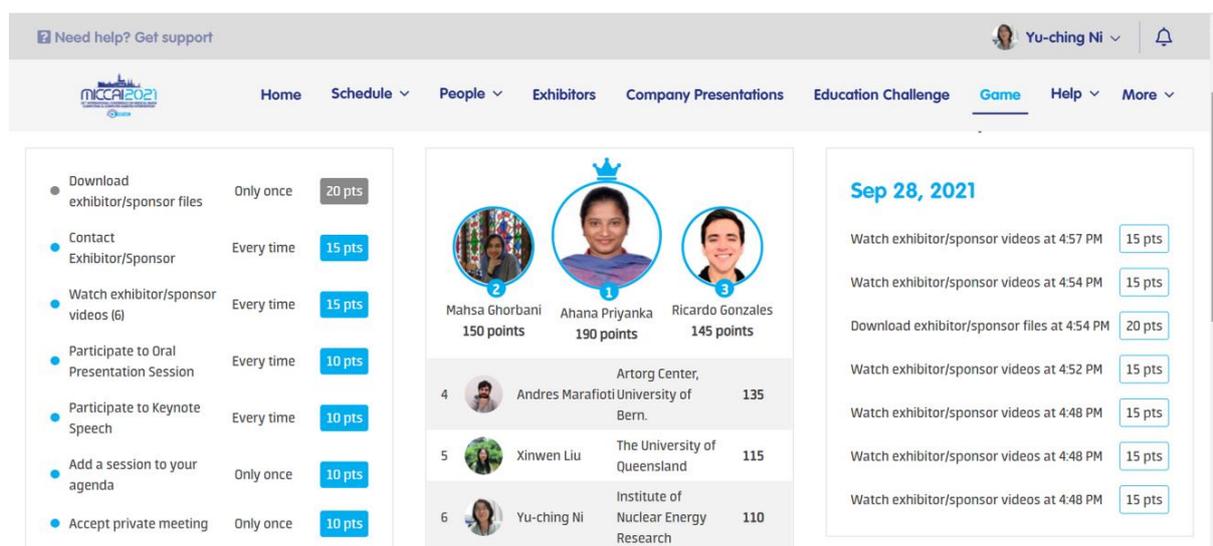


圖 7、MICCAI 2021 會議透過積分賽鼓勵與會者積極參與活動

大會演講安排也很特別，每一位講者都是重量級的學者，除了已在其研究領域中是協會主席等級的人物，更是在業界實務面具有豐富的經驗，但是所安排演講的主題沒有一個是介紹技術，反而是類似導師以更高視角來展現與說明我們平時沒有思考過的面向。大會演講時段包含 1. 第一場由法國雷恩大學 (University of Rennes) 醫學院的 INSERM (歐洲領先的生物醫學領域學術研究機構，約 15,000 人) 研究主任 Pierre Jannin 博士主講「實現數位科技在醫療保健中負責任的研究」。2. 由美國布朗大學 (Brown University) 急診醫學教

授，同時為知名婦女健康與性別健康倡導者 Alyson J. McGregor 博士主講「現代健康技術如何使醫學中的性別偏見長期存在」。3. 由美國華盛頓大學外科榮譽教授，也是開發第一個手術機器人（後來成為達文西手術機器人）的外科醫師 Richard M. Satava 博士主講「技術轉移：我們是否能將同樣的流程用於下一代使用定向能（directed energy）的無創手術中？」。4. 由史丹佛大學電腦科學紅杉教授（Sequoia Professor）以及聞名於世 ImageNet 創始人之一的李飛飛博士主講「用環境智能照亮醫療保健的黑暗空間」。聆聽演講之心得見心得(一)。

大會前後的衛星會議共有 69 組不同議題的會議或活動，由於時段多有重疊，作者選擇參與的項目為「Machine Learning in Medical Imaging (MLMI)」、「The 4th Workshop on Machine Learning in Clinical Neuroimaging (MLCN)」及「4th Workshop on Predictive Intelligence in Medicine (PRIME)」。詳細內容見心得(二)~(四)。

RSNA-MICCAI 2021 會議由北美放射學會 (Radiological Society of North America) 與醫學影像計算與計算輔助干預協會合辦的議程，使臨床醫師與科學家合作，促進成像定量與機器學習等技術於臨床上的成功。包含座談會、研討會及挑戰議題，每場次約 6~8 個講者報告其研究成果或主題觀點分享，作者選擇參與座談會來了解現今 AI 技術導入臨床實現之現況與挑戰，今年主題為「From Lab to Clinic: What's Needed to Bring AI into the Real World?」，詳細內容見心得(五)。

開放科學工具課程 (Tutorial on Open Science Tools) 共 4 場，介紹歐洲開放科學委員會相關的資源及工具，協助不論是研究成果、數據、計畫等更透明的共享途徑。透過瞭解國際間的資源與資訊搜尋方式，能夠更有效率的蒐集或共享數據與軟體，甚至是程式碼，聆聽課程之心得見心得(六)。

口頭與展示發表方面作者切換於「Label-efficient Learning + Image Registration」、「Computer Assisted Intervention + Clinical Applications」、「Advances in Machine Learning」、「Image Synthesis」、「Domain Adaptation」、「Computer Assisted Intervention + Microscopy + Neuroimaging」等幾個主題中，由於會議發表之海報與口頭報告錄影皆放置於虛擬平台中，發表之全文及資訊下載存查於實驗室電腦中，供相關研究同仁參考與延伸搜尋。詳細內容見心得(七)。

三、心得

(一) 由於整個會議的技術密度非常高，在每 10 分鐘內即介紹完一個複雜的技術研發，一場接著一場，高強度洗禮下頭腦轉得飛快。反觀大會演講的安排令人意外，像似一場場帶有深意的沉思，跳開技術的細節與框架，跟隨著大師的視角觀看我們汲汲營營想解決的技術問題之外的世界。

1. 由法國雷恩大學醫學院的 Pierre Jannin 主任主講「實現數位科技在醫療保健中負責任的研究」提到數位科技無所不在並且強烈影響我們的生活，雖然具有顯而易見的好處，然而我們已經意識到在社交、社會及環境面向與這項技術相關的挑戰。包含社交上的可接近性 (access)、隱私性等，在美國每人平均一個月網路費約 2,000 台幣，有 30% 的人對網路/電信費支付感到煩惱，而在所得較低的國家情況更顯嚴重，這些會造成排除性及使用性不公的問題；在社會上則是會受到主權與治理的影響、同溫層的屏蔽效應；在環境上主要是日益增加運算需求所造成的能源消耗、電腦產業的汙染等。如何在這些面向上與技術的發展取得平衡，雖然沒有直接的答案，然而講者希望在進行研究的每個人能夠意識到數位化的挑戰以及提高創新和負責任研究的透明度。
2. 美國布朗大學急診醫學的 Alyson J. McGregor 教授主講「現代健康技術如何使醫學中的性別偏見長期存在」揭示了當我們將女性排除在健康研究之外時，醫學中的性別偏見就開始了。近年累積了相當多資訊才發現男女健康上很多不同，如圖 8 所示不同年齡男女的體內賀爾蒙比例就有很大差異，當然也就造成身體及疾病上的本質差異。男性好發心血管、自殺、猝死、動脈瘤、衝動、心肌病、自閉症及反社會；女性則是自體免疫、沮喪、心律不整、髖部骨折、膽囊炎、腸躁、偏頭痛和失智症。在實證醫學中以乳癌檢測為例，在細胞研究時性別不明，動物實驗時 80% 雄性模型，人體試驗設計者 67% 為男性，而人口健康與保健系統研究中 51% 為女性，最後臨床端由 80% 女性來進行決策 (如圖 9)，講者也特別提到乳房檢測儀器是男性工程師發明的，然而商品是女性改良開發的，因為更能了解女性受測者的需求與心理。另外，醫學教科書及長久以來的研究無考量性別差異，造成醫療上很多的延誤診療，例如女性心臟病的典型特徵與男性 (一般認知) 不同，胸悶、脖子與背痛、冷汗、頭暈及疲勞等，常常被懷疑為其他疾病而造成遺憾。這些僅是冰山一角，性別在醫學中的探討及包容性才剛開始，透過研究者更多的察覺，將能免於過去的偏見模式永久化。

Hormones

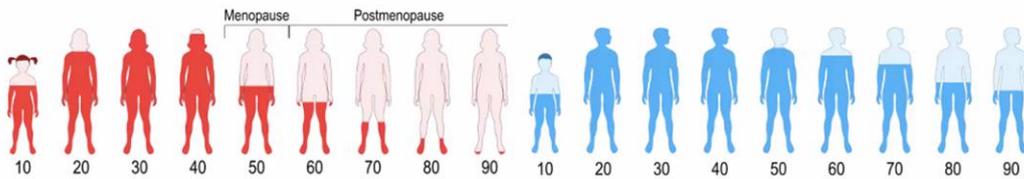


圖 8、男性與女性隨著年齡增加其賀爾蒙下降之情況差異[1]

Evidence-Based Medicine

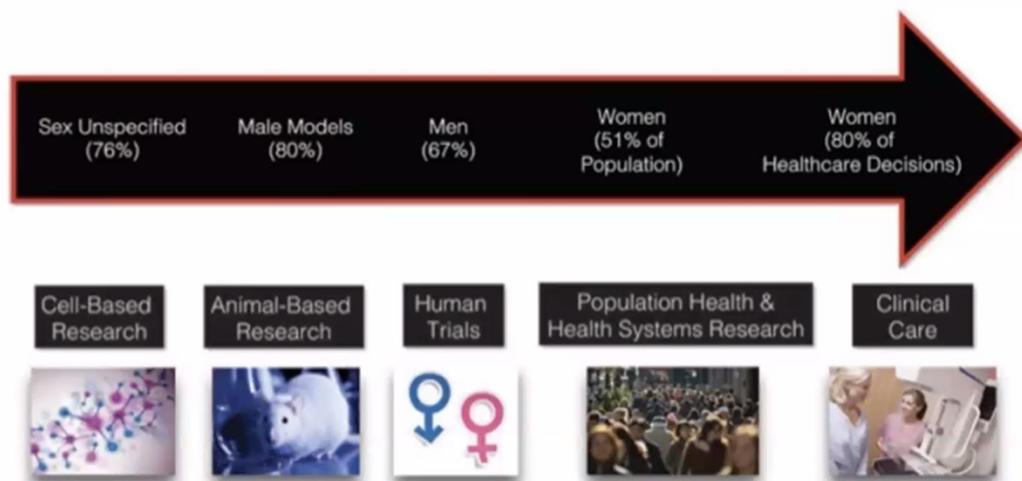


Image Source: M.Jenkins, LWBIWH, TTUHSC

圖 9、實證醫學流程中參與者的性別占比[1]

3. 第三場由 Richard M. Satava 教授主講「技術轉移:我們是否能將同樣的流程用於下一代使用定向能的無創手術中?」。Satava 教授是一位走在時代尖端的人物，除了多年在美國國防高級研究計畫局擔任生物醫學技術經理外，也擔任耶魯大學及 NASA 的醫學訊息遠程醫療及先進技術商業空間中心主任等，最為人所知的是發明第一個手術機器人的外科醫師，並於 1989 年建造了第一個用於外科手術的 VR 模擬器。他一直持續於 3D 成像、電漿醫學、定向能手術、遠距手術與機器人手術等領域研究。演講一開始就先教育與會者 (大部分是 AI 技術研發者，意味著很新、很前期的研究居多) 技轉的困難性與考量點，如圖 10 所示從左端的研究至右端的產品出售，中間經過技轉的途徑走向商業化，技術成熟度 (Technology readiness levels, TRL) 是整個新產品經歷整個生命周期不同階段的共同語言，能使資金補助與監管單位更有效投入資源，並且促進溝通與避免誤解。另外，也提到下一階段的手術將進入非侵入式的定向能方式，首先須認知到機器人 (robot) 不只是機器，而是一個資訊系統，手術將從目前組織和儀器 (有形的物理結構和物體) 進入到資訊和能量 (無形和非肉眼所見之功效) 的時代。圖 11 為使用超音波的一個例子，用影像導引來視覺化手術位置，以微米精度的機器人操控在細胞、分子甚至原子等級的非侵入式手術。其中閉環反饋迴路的一個循環診斷或治療能在 50 ms 以內，10 分鐘即能完成 12,000 個完整手術程序。講者最後也提醒，未來物聯網、人工智慧、量子計算及新的通訊技術與醫療保健應用結合帶來的改變與衝擊，除了期待亦要小心意想不到的後果。

Full Life Cycle Development

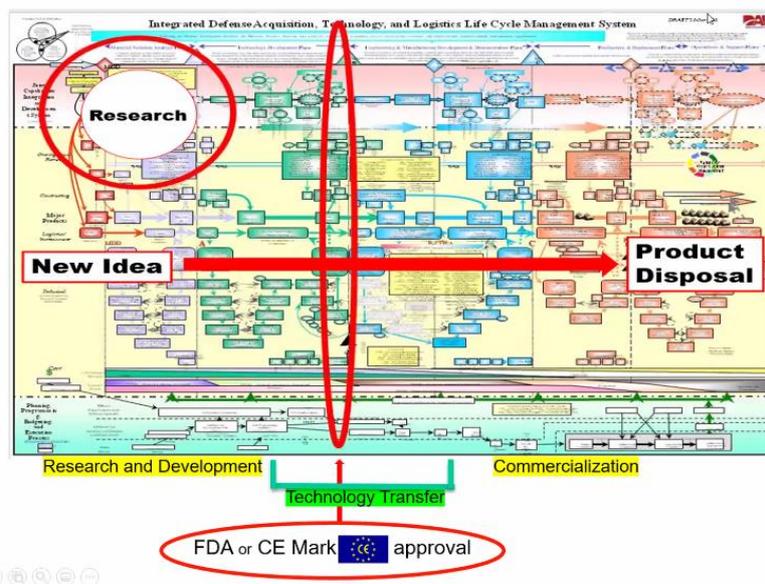


圖 10、產品開發的完整生命週期[2]

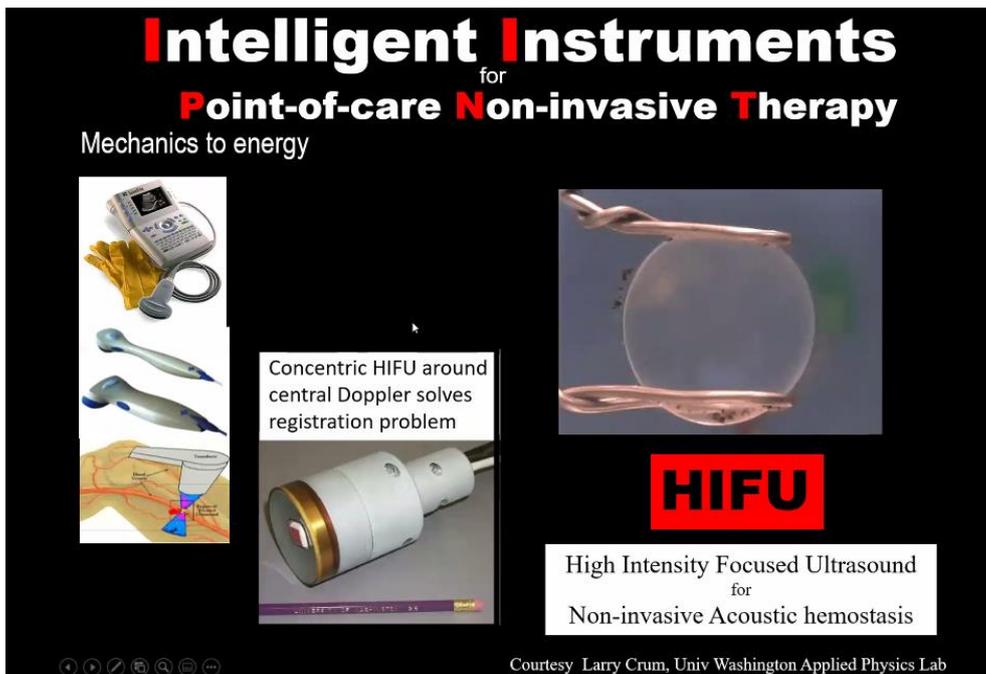
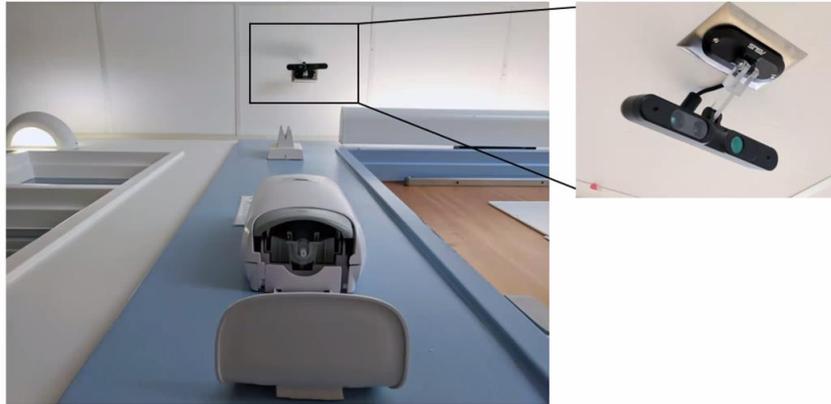


圖 11、智慧儀器於床邊非侵入式治療—以高強度聚焦超音波治療系統為例[2]

4. 由史丹佛大學電腦科學李飛飛教授主講「用環境智能照亮醫療保健的黑暗空間」。李教授曾擔任 Google 副總裁及 Google Cloud 的首席科學家，在人工智慧、機器學習、影像視覺及醫療保健領域有很深入的研究與貢獻。根據統計美國醫療疏失為致死原因的第三名，每年因醫療疏失死亡 (25 萬) 大於因車禍死亡 (3.7 萬) 的人數，講者所提的黑暗空間即是指醫療疏失致死，包含：手術室中程序錯誤/過度鎮定劑、檔案室潦草筆跡/錯誤編碼、藥局錯誤處方/劑量、老人照護中未偵測的跌落/不正常飲食、病房中空的靜脈注射/中心導管感染、嬰兒室中營養不足/異常睡眠等等。李教授團隊是希望透過智慧感測器和機器學習演算法來實現賦予醫療保健環境智能的目標，首先利用感測器來偵測及改變空間環境 (例如影像、氣味、壓力...等感測器)，再著辨認所有的活動，最後整合全臨床數據生態系統。李教授舉了相當多例子來介紹目前美國醫院所進行的一些計畫，其中一項“手部衛生”看似很簡單但值得深思。手部清潔對於進入加護病房來說很重要，然而因為疏忽美國每年有 9.9 萬人因院內感染而死亡。以往利用人工抽檢、RFID 偵測等方式，執行成效仍不佳，因為無法全時自動偵測人的行為，也干擾了原本的工作流程。現在採用深度攝影機安裝於酒精凝膠噴灑器上方如圖 12，透過影像自動判讀，如圖 13 紀錄及提醒人員手部消毒情況，甚至是在病房中手部接觸的部位都能追蹤顯示。這僅是一個小案例，在急診室或是老

人照護中心有更多的“行為活動”值得導入智慧化來協助安全的監護和品質的提升。另外，講者也特別針對隱私及法律的面向提出科學家在誠信及研究倫理上的提醒。

Depth sensors installed above alcohol-gel dispensers



Singh*, Haque*, Alahi, Yeung, Guo, Glassman, Beninati, Platchek, Fei-Fei, Milstein. *Journal of the American Medical Informatics Association* (2020)

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圖 12、深度攝影機安裝於酒精凝膠噴灑器上方[3]

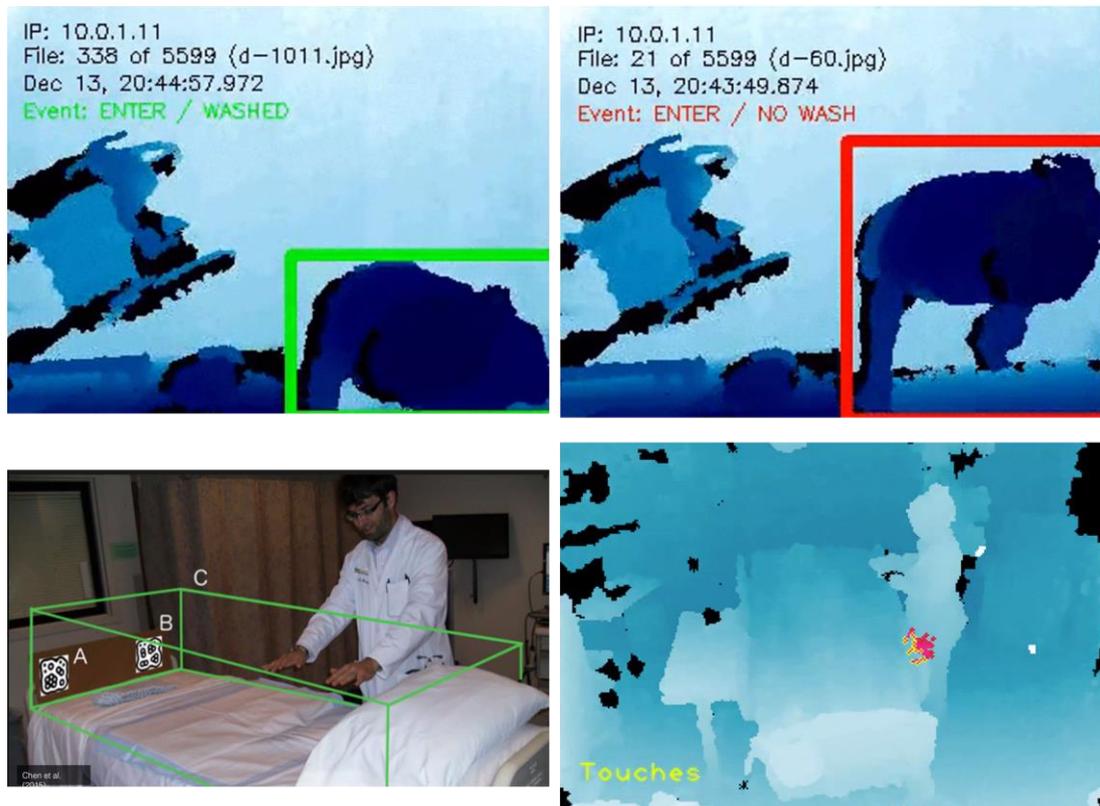


圖 13、影像自動判讀是否已完成手部清潔，並可追蹤手部觸碰點[3]

(二) 「Machine Learning in Medical Imaging (MLMI)」衛星會議之議程如附錄(二)所示，作者選擇第一場大會演講來進行詳細介紹，這是由德國癌症研究中心 (DKFZ) 資料科學與數位腫瘤學的董事總經理及海德堡大學 (Heidelberg University) 的 Klaus Maier-Hein 教授主講「Machine Learning in Medical Imaging—Current Challenges」。講者直接點出利用深度學習技術完成一個成功研究結果後，在實際臨床應用時所面臨的問題，包含：泛化 (Generalization)、異常 (Anomalies)、不確定性 (Uncertainty)、時間、現實 (Reality)。深度學習導入實際使用場域之流程 (Pipeline) 設計非常複雜，因為各種應用標的之成像性能差異很大，如圖 14 所示不同身體部位的造影方式 (如：X 光影像、CT 影像、螢光顯微鏡影像)、影像像素值、影像尺寸的非等向性、分類類別數目、訓練案例數目等皆不同，很不容易將成功的結果轉移至其他資料集。主要原因有耗費時間嘗試錯誤、經驗至上非專家很難上手、缺少標準化牽制研究的發展，雖然很多團隊試圖開發自動機器學習的架構來減輕這方面的困難，但尚在努力進展中。另外，在現實中所遇到資料分享、流程整合、廣泛驗證及可擴展性等皆是現階段大家最頭疼也最關注的問題，如圖 15 為一個解決方案的概念，考量隱私權，數據存放、分析以及整個流程都在左半邊醫院內部，右半邊為外部的 AI 方法/軟體儲存庫平台能持續訓練及擴展其應用性。

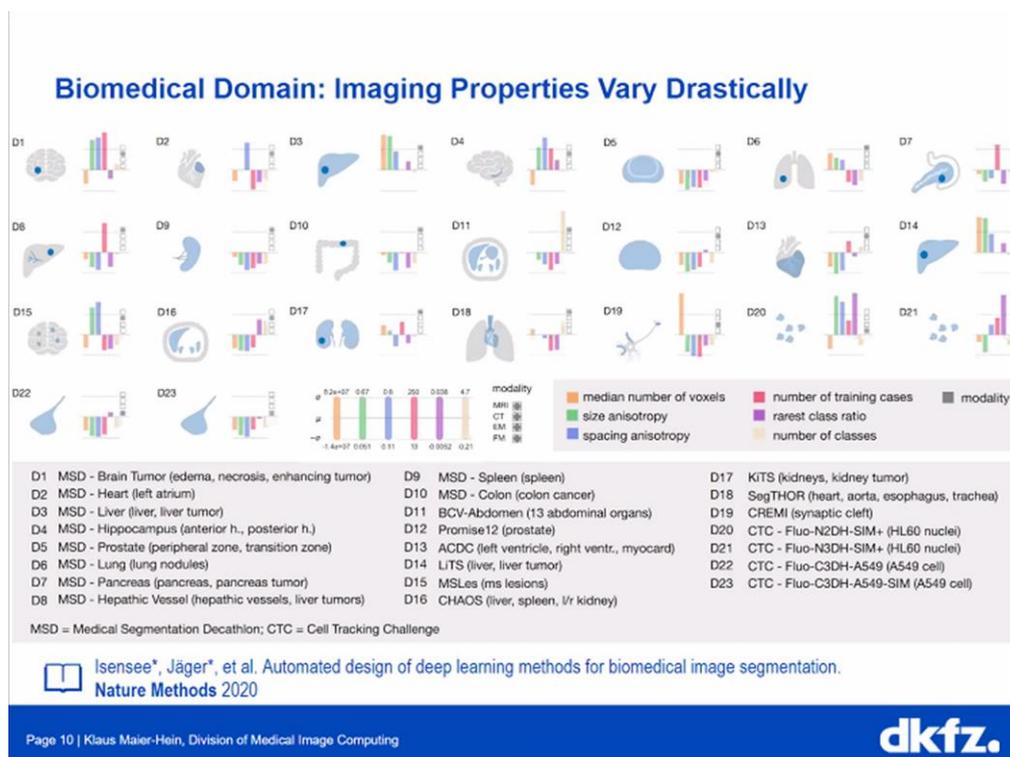


圖 14、各種醫學應用標的之成像性能差異很大[4]

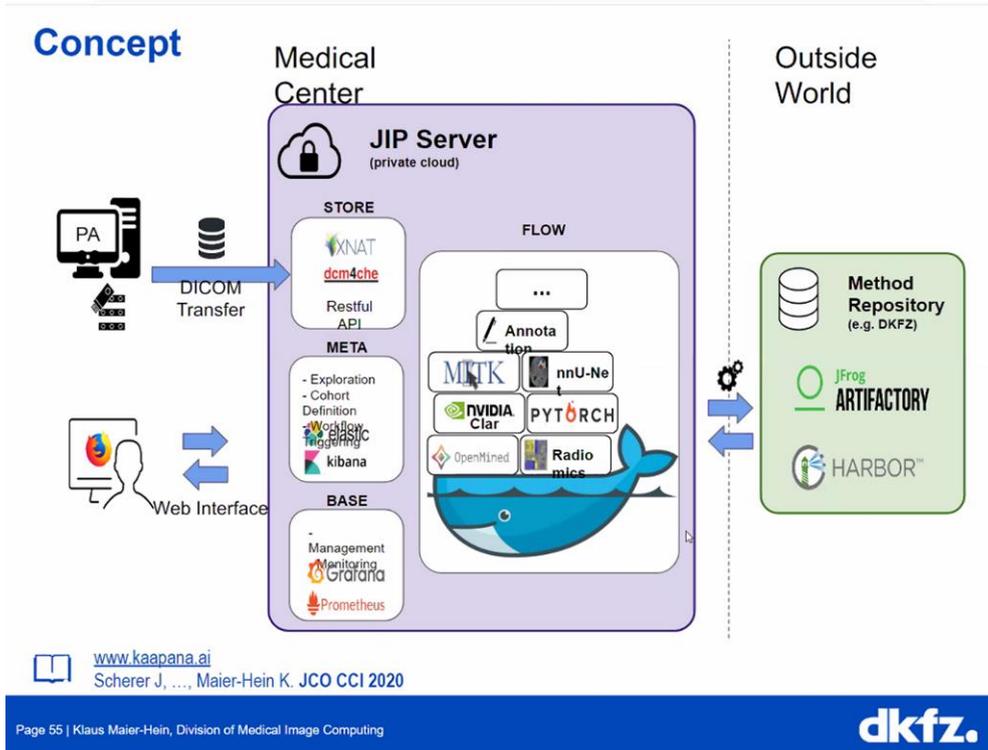


圖 15、解決資料分享、流程整合、廣泛驗證及可擴展性等問題之方案概念[4]

(三) 「The 4th Workshop on Machine Learning in Clinical Neuroimaging (MLCN)」衛星會議中大會演講由哈佛醫學院放射科/麻省理工學院 Adrian Dalca 助理教授主講「Unsupervised Learning of Image Correspondences in Neuroimaging」。透過非監督式學習 (不需人事先給定答案來讓 AI 學習) 開發影像對位技術並用於神經影像學，影像對位是神經影像學的基礎，讓不同的影像能對應至標準模板 (template) 來進行分析比對，也能作為手術前後的臨床比較基準或是校正造影中病人位置的偏移等。圖 16 顯示 AI 模型訓練欲將 m 轉換為 f ，透過模型學習到影像中每一個像素的偏移量，最後即能不使用人為標註的訊息獲得影像對位後的結果。圖 16 下方結果中由左至右， m 為腦部萎縮 (空洞較大) 的影像， f 為腦部尚未萎縮前的影像，而 $warped\ m$ 為經 AI 模型所預測之未萎縮前的影像，結果相似度很高，還利用 GPU 運算卡加速使 2.5 小時的運算時間降至 0.3 秒。另外一場大會演講由美國南加州大學神經影像和信息學研究所 Paul M. Thompson 副主任主講「AI and Deep Learning in Medical Imaging and Genomics: Lessons from ENIGMA's Global Studies of Brain Diseases」。Thompson 教授領導 ENIGMA (Enhancing Neuro Imaging Genetics Through Meta Analysis) 聯盟 (如圖 17)，這是一個由 45 個國家/地區的 2,000 位科學家組成的全球聯盟，他們對 33 種主要腦部疾病進行最大規模的研究，範圍從精神分裂症、抑鬱症、多動症、

雙相情感障礙和強迫症等等。ENIGMA 對超過 100,000 人的大腦掃描和全基因組數據的基因組篩選，以發掘影響大腦結構、疾病風險和大腦連通性的遺傳變異。遺傳變異性是否影響腦生長或退化的速率，圖 18 顯示研究不同年齡時不同腦區的變化結果。Thompson 教授回顧全球 ENIGMA 聯盟所有代表性的研究，印證團結力量大在數據時代的威力。搜尋更進一步資料發現雖然有 33 種主要腦部疾病的團體，但較缺乏失智症的部分，有相關的僅額葉型失智症及 Brain Age 兩個工作群組，仍值得追蹤相關資訊以了解是否有助於計畫執行。在多場口頭報告當中有一項研究很特別，由賓夕法尼亞大學 (University of Pennsylvania) 主導的研究團隊發表「Unfolding the medial temporal lobe cortex to characterize neurodegeneration due to Alzheimer's disease pathology using ex vivo imaging」，如圖 19 所示使用 18 組屍檢數據 (人死後腦組織樣本) 研究其中神經元纖維纏結和 MRI 影像內側顳葉形態測量特徵的關係，建立阿茲海默症早期病理變化中內側顳葉萎縮模式和病理結果的關係。非常稀少研究能取得號稱黃金標準的腦切片樣本數據來進行技術開發與驗證。

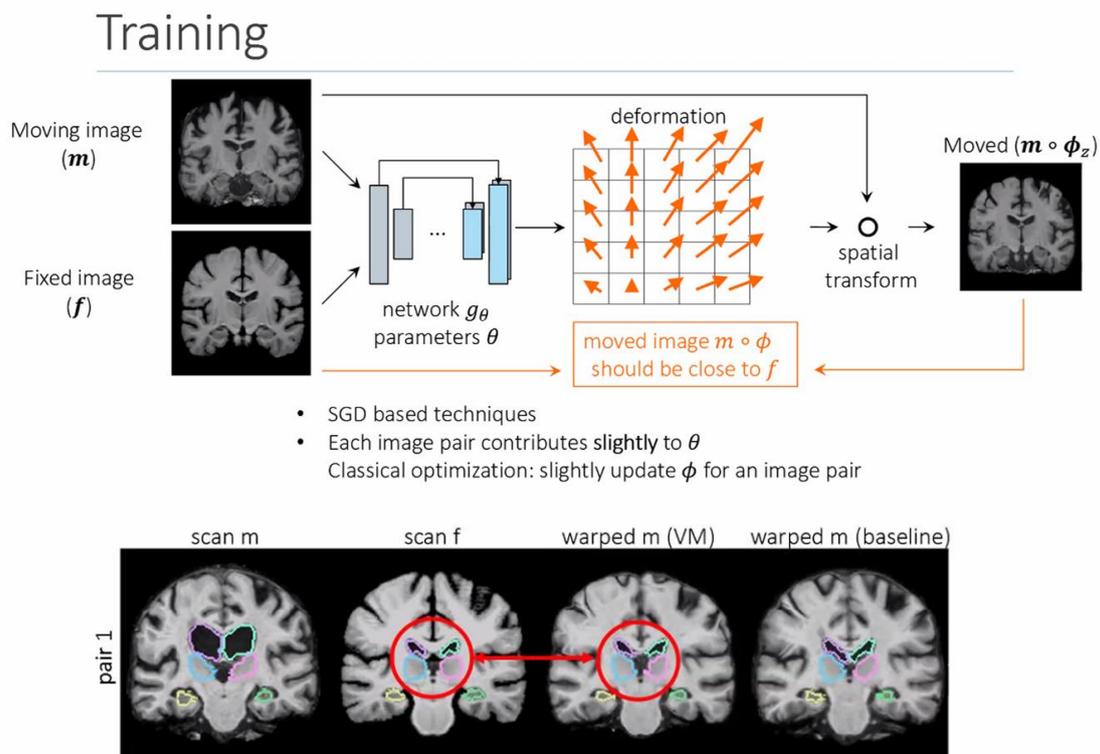


圖 16、以非監督式學習開發的影像對位技術概念及應用於神經影像學之效果[5]

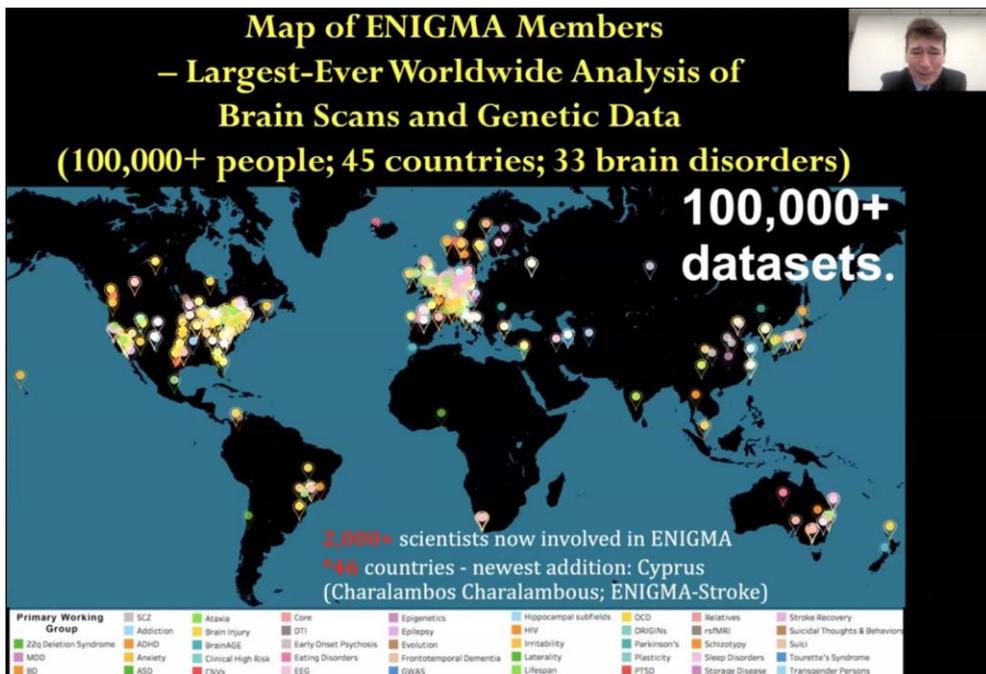


圖 17、ENIGMA 聯盟成員及工作群組分布全球[6]

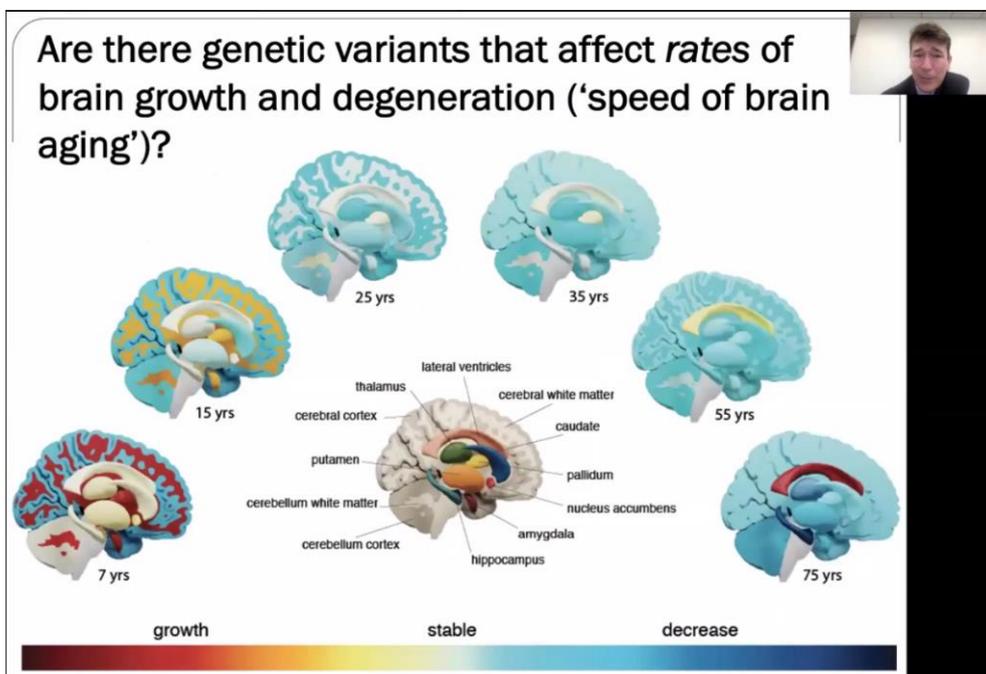


圖 18、遺傳變異性研究顯示不同年齡於不同腦區的生長或退化之速率變化[6]

Linking ex vivo MRI with serial histology

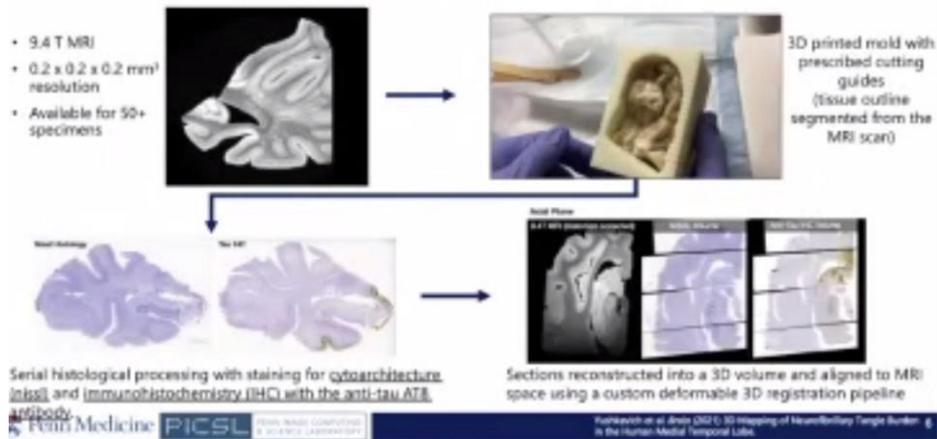


圖 19、研究腦組織樣本和 MRI 影像內側顳葉形態測量特徵的關係[7]

(四) 「4th Workshop on Predictive Intelligence in Medicine (PRIME)」衛星會議的會議主席為土耳其伊斯坦堡理工大學 (Istanbul Technical University) Islem Rezik 教授，說明為何要做智慧預測，原因包含 1.如果我們能利用有限的資源 (數據不足) 及低成本達到更早、更好的診斷，不是一件很棒的事嗎? 2.收集更少的數據且預測更多。 3.產生醫學數據橫跨所有維度，舉例來說，我們具有現在這個時間點的數據，透過映射及預報 (forecast) 產生對未來的預測 (predict)；也可以利用現在這個時間點的數據，透過映射及合成 (synthesize) 產生對過去的預測，我們只有現在這個時間點的訊息，卻能夠完整的獲得全時間維度的資訊。如圖 20 所示我們除了能在時間軸上預測，亦能於解析度軸上預測 (例如低解析度的影像預測出高解析度的影像)，甚至能於領域 (domain) 軸上預測 (例如 CT 影像預測出 MRI 影像)。更大的願景是醫療 AI 具有可負擔及公平性，例如在北美利用較充足的資源進行 AI 訓練，最後能在非洲等資源匱乏的區域進行測試及使用。該演討會的多場內容都相當精彩，在此作者選出兩場覺得很有啟發性的進行介紹。第一個是澳洲雪梨大學 (University of Sydney) 電機與信息工程學院高級講師 Luping Zhou 博士主講「Exploring Fine-grained Image-text Description for Diagnostic Captioning」。圖 21 右側即是一般所謂的看圖說故事，將照片經過 AI 辨識後能產生描述性的文字，例如有兩個小孩撐傘在岸邊的田野裡；左側則換成醫學影像經過 AI 辨識後能產生描述性的文字，也就是醫師報告自動產生器。澳洲在過去五年中放射科醫師平均工作量成長了 7 倍以上，而美國研究所中平均每位放射科醫師以一張影像 34 秒檢查的速度工作 8 小時以滿足工作量需求。因此，可靠的報告自動產生器將是臨床上非常有用的工具。這項研究十分挑戰，

除了需辨認出影像中的特徵，用詞需相當精確，疾病相關的用詞常被類似的影像特徵描述所淹沒。Zhou 博士團隊建立 self-boosting 架構來學習，並以 Pure Transformer based model、Image-text matching、Medical tag prediction、Term weighting 等技術來克服困難，其實作的成果相當好。另一個是英國倫敦帝國學院 (Imperial College London) 計算機系 Ben Glocker 教授主講「Deep Structural Causal Models for Counterfactual Inference」。他所談論的是一個很有意思的問題“因果關係”，很多研究都是探討相關性，然而了解因果關係才能找到解決問題的方向。利用類似圖論的表達方式能更直觀因果關係，也能很清楚各因素影響的方式，以圖 22 為例訓練/測試數據 (D) 可能會受到數據擷取的影響並且產生影像 (X)，而影像是從疾病發生造成身體結構改變所獲得的結果。影像 (X) AI 模型可以預測影像標註結果 (因果) 或是治療的預後 (因果)，也可以預測診斷結果 (反因果)。因果推論是關於數據生成過程假說在溝通及檢視時很有用的工具，如果將這些假設整合於 AI 模型學習中稱為 Causal Representation Learning。圖 23 是以 MRI 影像來研究年紀與腦體積的變化關係，年齡 (a)、生理性別 (s)、總腦體積 (b)、腦室體積 (v)、2D 影像 (x)，經模型能預測出任何年齡性別下之影像，而其總腦體積與腦室體積符合一般觀察的現象，Glocker 教授開發的 Deep SCMs 模型能滿足不同階層的因果關係，並且具可追溯性及合理的高維度反事實 (counterfactuals)。

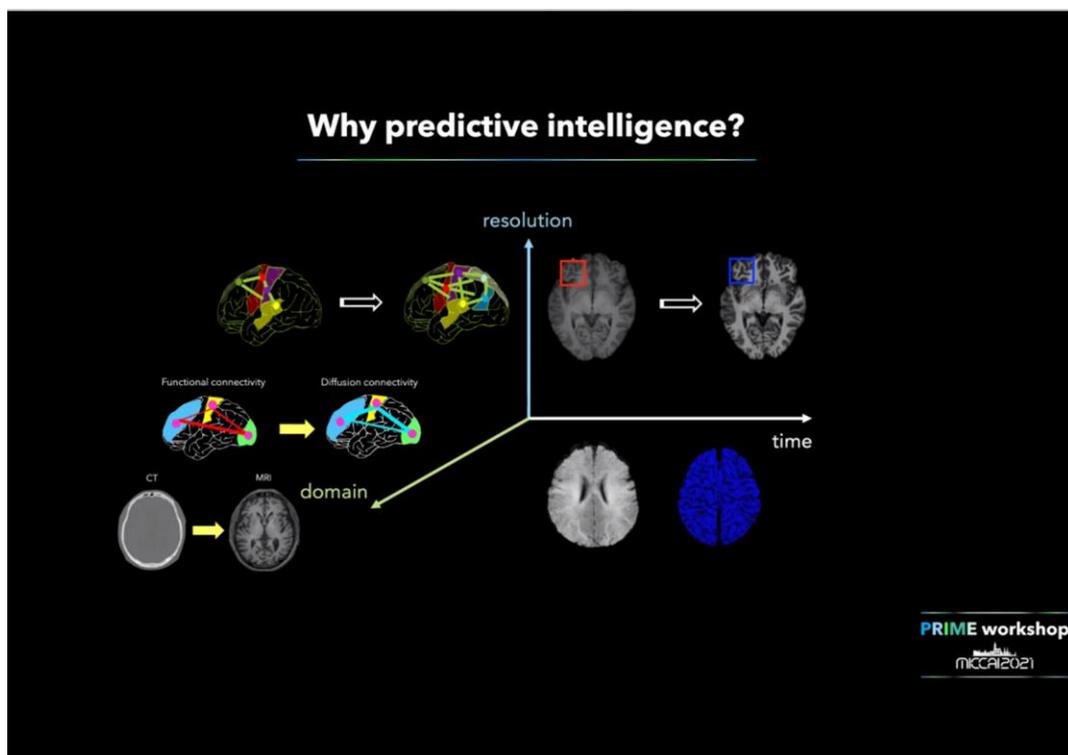


圖 20、時間軸、解析度軸和領域軸上的智慧預測[8]

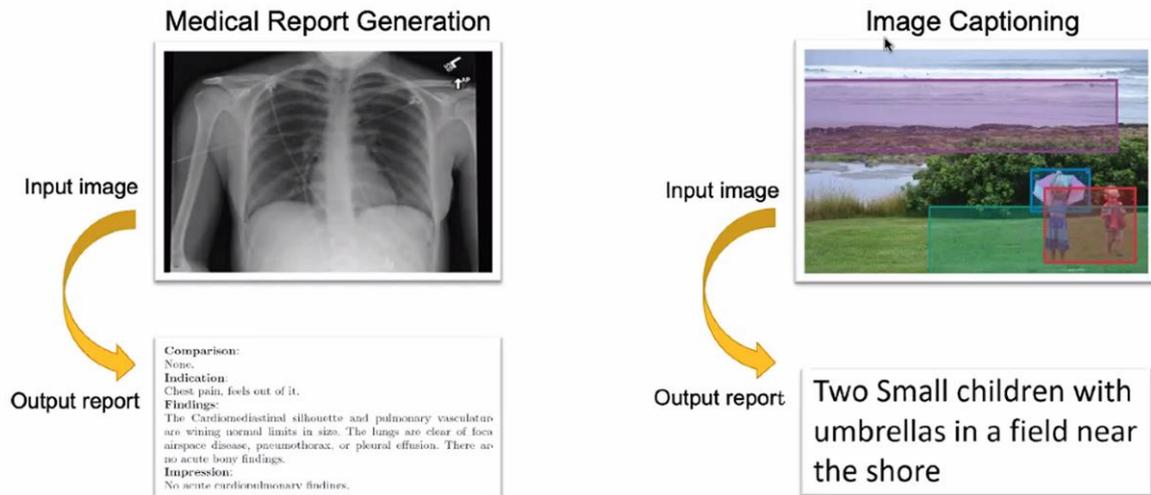


圖 21、照片自動字幕及醫學影像自動報告產生器[9]

Data Generating Process

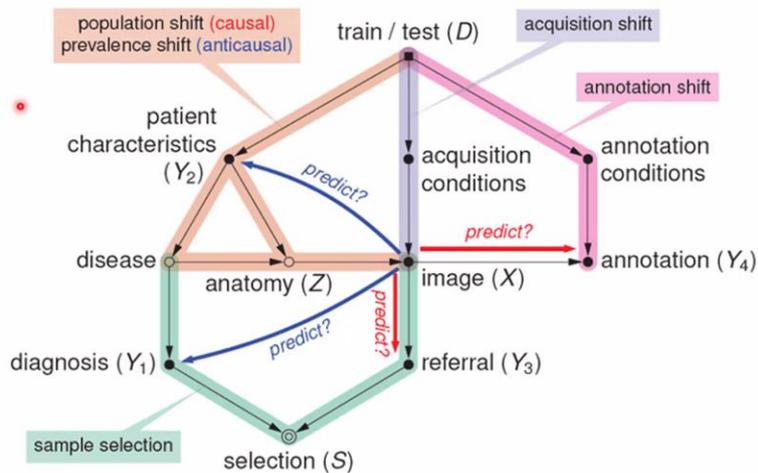


圖 22、數據生成流程之“因果關係”圖[10]

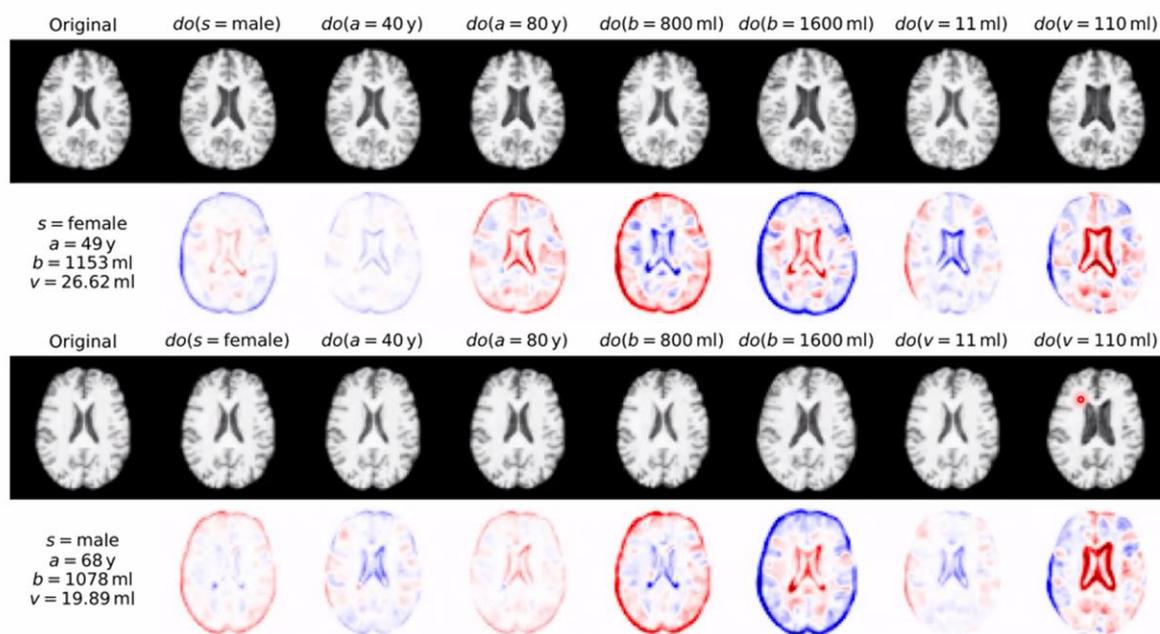


圖 23、預測任何年齡性別下之 MRI 腦部影像[10]

(五) RSNA-MICCAI 2021 會議是以臨床工作者視角出發的演講，座談會今年主題為「From Lab to Clinic: What's Needed to Bring AI into the Real World?」。其中美國 MD Anderson Cancer Center 放射科的 Carol C. Wu 醫師在「Clinical Implementation of AI Applications」報告提到以肺栓塞為例，AI 能協助偵測臨床遺漏的 25~50% 的案例、在醫護人力缺乏的時期協助分流，目的是提升準確率及效率，提高患者護理的安全性與品質，減輕放射醫師的負擔。然而在 AI 導入醫院的時期臨床部門及醫院需釐清，包含：評估資訊部門所花費的時間及精力是合理的、各種軟體使用之優先等級，以及對現行系統之影響與交互關係為何。如圖 24 卡通圖所示左圖顯示導入初期放射科醫師其實工作負擔更重，且有很多挑戰，包含：資料的轉換/連結問題、周轉時間、歧見的溝通、使用者的接受度等，然而在權衡成本（軟體、員工薪資）及效益（病患照護、效率、不堪疲累）的考量下，期望未來放射科醫師的生活能改善如圖 24 右圖。另外，史丹佛醫學和影像人工智慧中心聯合主任及史丹佛醫學中心放射科的 Matthew Lungren 教授報告「Clinical Imaging AI Translation: The Day 2 Problem」主要提醒 AI 技術進入臨床的障礙以及使用後應該思考的潛在問題。進入障礙除了如何“選擇”適合的 AI 服務外，還有“驗證” AI 服務是否能在實務上可行、何時失效、什麼方案最好，“整合”AI 服務與現行工作流程、如何串聯資訊系統/病例系統/通報系統、系統監控與更新、企業營運分析等。在 AI 服務於醫院使用後如

圖 25 所示，還有很多冰山下的問題仍待大家研究與解決，例如因為實際使用的數據也許會和 AI 訓練驗證數據集有母體差異，如何自動發現數據已有差異，AI 模型如何自動配合調整及成長等等，AI 服務於醫療使用相較於其他領域應用更複雜，仍有一段努力的空間來達成實用的終極目標。

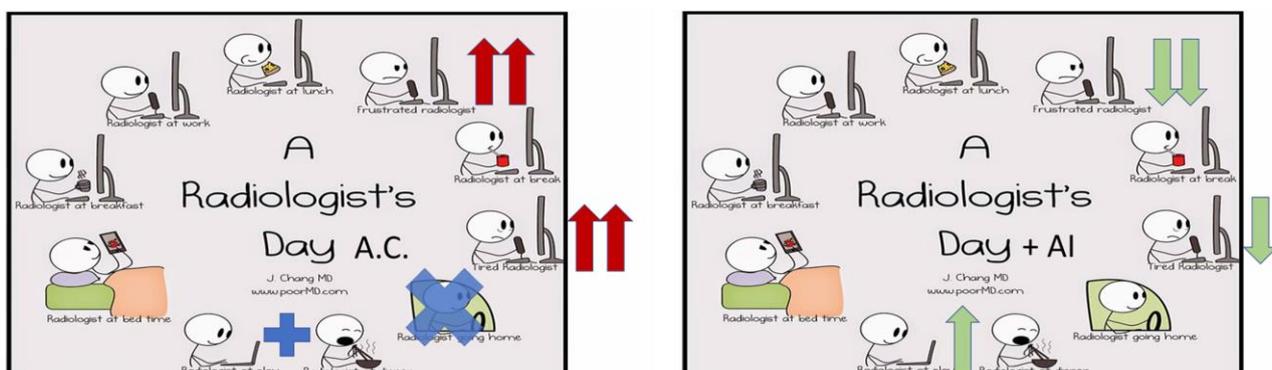
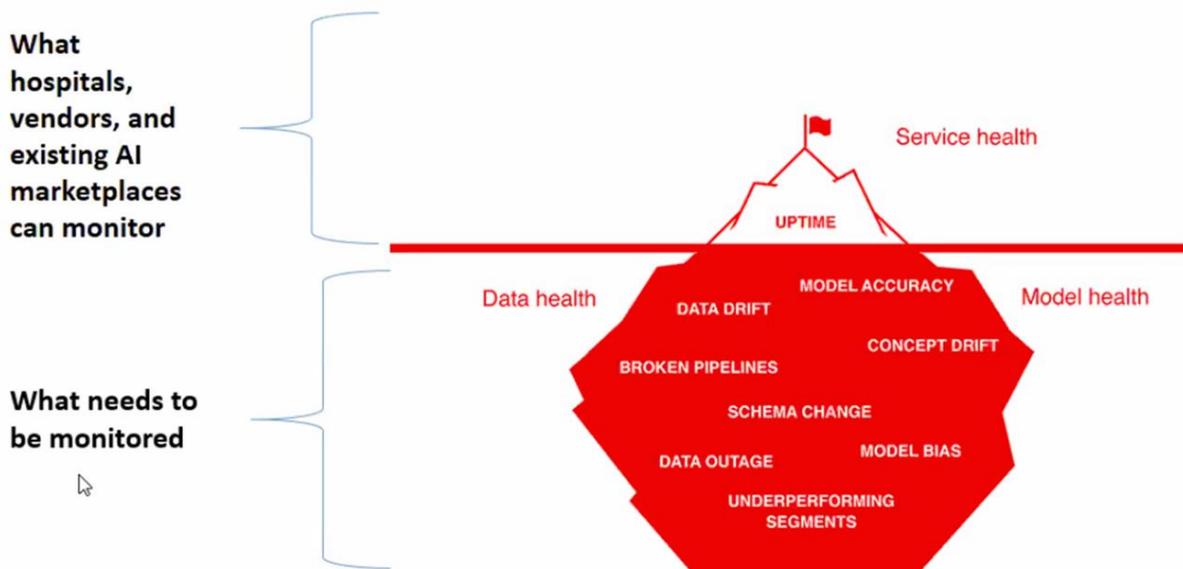


圖 24、以卡通圖顯示使用 AI 技術前後對放射科醫師的差異[11]



Credit: Evidently.ai

圖 25、AI 服務於醫院使用後尚待大家研究與解決之問題[12]

(六) 開放科學工具課程 (Tutorial on Open Science Tools) 介紹歐洲開放科學委員會相關的資源及工具，開放科學的核心原則 1.協作 2.開放獲取科學資訊 3.公平原則 4.文件的透明與正確，行動的領域包含科研的成果、研究用的基礎設施與服務、培訓和新技能。COVID-19 大流行期間全球百萬名科學家受惠於公開資料，而能快速應對以進行 COVID-19 相關研究。例如疫情相關發表後立即分享並連繫 WHO，一同使用具有相同收集程序或標準的數據，盡可能速度越快及範圍越廣。圖 26 是歐洲開放科學雲 (European Open Science Cloud, EOSC) 上 OpenAIRE 的服務，除了能搜尋研究計畫與成果發表外，也有共享數據、軟體與程式碼。另外，課程中還有介紹 amnesia 這個數據匿名化工具的使用，有助於在注重隱私及安全考量下，更便利的產生適合共同分享的數據。開放及共享的觀念及習慣需要時間培養，“As open as possible, as closed as necessary”也許彈性的看待開放科學是最好的方式。

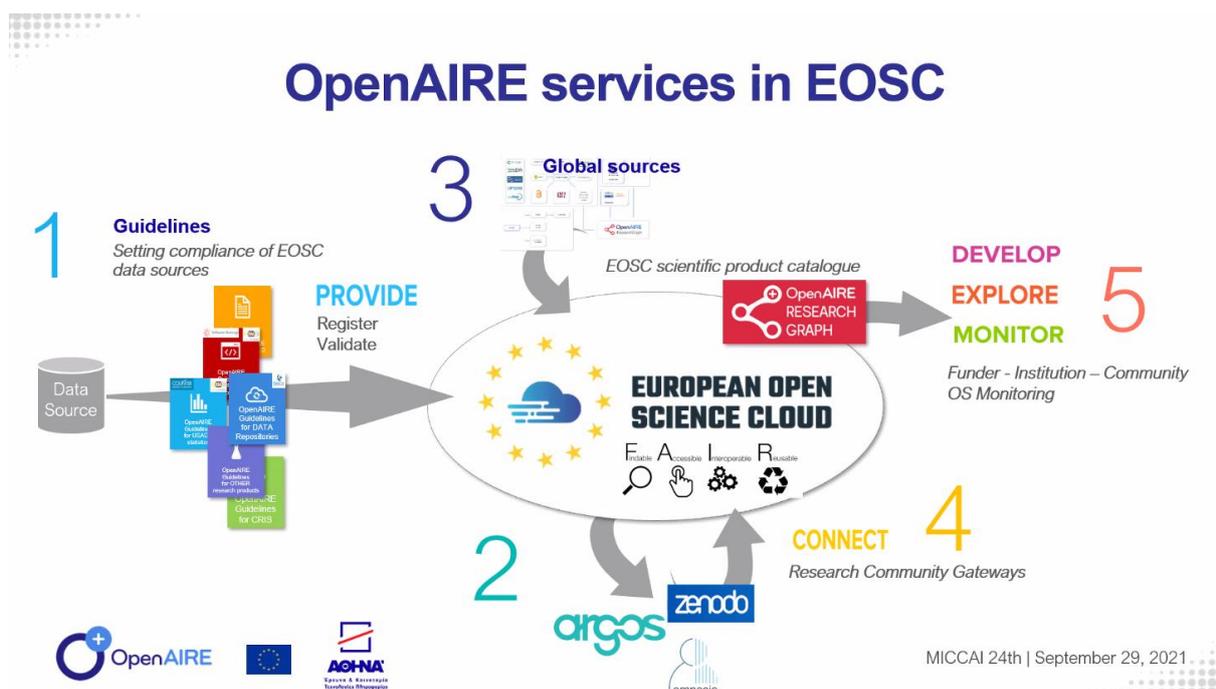


圖 26、歐洲開放科學雲上 OpenAIRE 的服務[13]

(七) 作者選擇一些應用與本所研究相關或是數據屬性相近的海報發表，研究重點詳述於下：

1. 第一篇海報(圖 27)為瑞士 Balgrist 大學醫院的研究「A new Approach to Orthopedic Surgery Planning using Deep Reinforcement Learning and Simulation」將 AI 導入到骨科手

術規劃過程中，採用強化學習 (Reinforcement Learning) 演算法克服不易獲得足夠的訓練資料及「正確」的標記答案的困難，透過骨頭幾何形狀的分析建立一個完整的手術過程模擬環境，並成功應用於實際病患資料。

2. 第二篇海報 (圖 28) 為四川大學的研究「Incorporating Isodose Lines and Gradient Information via Multi-task Learning for Dose Prediction in Radiotherapy」將 AI 導入至放射治療中來預測輻射劑量的分佈，使用監督式學習搭配三個自編碼 (Auto-Encoder) 的主幹網路 (Backbone Network)，分別對應等劑量線、梯度資訊和劑量分布，整合成一個端到端 (End-to-End) 的訓練架構，並巧妙設計損失函數的數學公式使其平衡，從旁導引劑量分布的主幹網路。
3. 第三篇海報 (圖 29) 為美國北卡羅來納大學教堂山分校的研究「Learning Spatiotemporal Probabilistic Atlas of Fetal Brain with Anatomically Constrained Registration Network」是透過現在的 MRI 腦影像，預測不同時間點的腦影像變化，採用類似生成對抗網路 (Generative Adversarial Network) 的方式建立 AI 模型，使用生成網路 (G) 預測未來某個時間點的腦影像，由判別網路 (D) 做影像對位，計算現在與下個時間點的形變向量。MRI 影像以多通道 (Multi-channel) 方式作輸入，使用不同組織分割後的影像齊頭並進訓練，最終以端到端的訓練架構跨接不同時間點的資料。
4. 第四篇海報 (圖 30) 為日本奈良科學與技術大學的研究「4D-Foot: A Fully Automated Pipeline of 4-Dimensional Analysis of the Foot Bones Using Bi-Plane X-ray Video and CT」是透過拍攝一組靜態的 3D CT 影像以及動態的 X 光影像，利用 AI 預測出動態的腳部骨骼動作。3D CT 採用一個自編碼的 U-Net，搭配貝氏統計原理使模型中間的 Latent Space 能適應統計分佈，得到影像分割圖並產生對應的標記點，動態的 X 光影像透過 AI 模型找到空間中的標記點，利用標記點將 2D-3D 對位，據此可進一步預測出腳部動作的骨骼結構。
5. 第五篇海報 (圖 31) 為香港大學與 VoxelCloud 公司合作的研究「SpineGEM: A Hybrid-Supervised Model Generation Strategy Enabling Accurate Spine Disease Classification with a Small Training Dataset」使用自我監督式學習 (Self-Supervised Learning) 作為主幹網路的預訓練模型 (Pre-trained Model)，來改善訓練數據量過少的痛點，應用在脊椎的 MRI 影像上。過程中利用 Random Transformation 作為資料擴增 (Data Augmentation) 的機制，大幅加強主幹網路的訓練效果，主幹網路是一個自編碼架構，完成訓練後，利用遷移學習 (Transfer Learning) 轉移編碼的權重，並搭配少量真實的數據作 Fine-tuning 達成任務。

6. 第六篇海報 (圖 32) 為新加坡 A*STAR 公司的研究「Few-Shot Domain Adaptation with Polymorphic Transformers」利用 Transformer 技術結合領域自適應 (Domain Adaptation) 改善 AI 模型落地時遇到不同儀器時效能不一的問題，應用於糖尿病視網膜病變影像。傳統作法會採用遷移學習技術，但資料如果是未標記或數量過少都難以訓練。一般 CNN (Convolutional Neural Networks) 模型可分為特徵提取的主幹網路架構，以及用於分類的 Top Layer，該研究嘗試在兩者中間加入一個 Polyformer 的轉換機制，由 Transformer 元件建構而成。傳統 Transformer 是學習影像小單元彼此之間的關聯性，這裡的 Polyformer 將不同的儀器與不同的模型都視為小單元，比照 Transformer 的作法讓 AI 自行學會儀器和模型之間的差異。
7. 第七篇海報 (圖 33) 為重慶郵電大學的研究「Medical Image Registration Based on Uncoupled Learning and Accumulative Enhancement」利用非成雙成對的 MRI 影像作 AI 模型的影像對位，將 Moving Image 對原本的 Fixed Image 做對位，兩邊同時經過自編碼模型進行訓練，中間使用 Uncoupled Spatial Encoder 巧妙的融合兩者，讓 Fixed Image 的 Encoder 能引導 Moving Image 的 Encoder 訓練，並以特徵抽離的方式搭配自我監督式學習方式讓 Moving Image 能在位置形變上與 Fixed Image 相同。
8. 第八篇海報 (圖 34) 為電子科技大學與商湯科技公司合作的研究「Contrastive Learning of Relative Position Regression for One-Shot Object Localization in 3D Medical Images」使用孿生神經網路 (Siamese Network) 搭建一個 One-Shot Learning 演算法，將 3D 影像投射在一個 Latent Space 上，再由 Latent Space 作位移變量 (Offset) 的預測。目標是進行 CT 影像的器官的標記點預測，自行學出器官的特徵點位，擺脫傳統歐幾里德空間的作法，標記點後續更可結合圖論做進一步的位移評估和空間定位，並能更好的做到器官分割。其中 Contrastive Learning 中的 Contrastive Predictive Coding 作法屬於自我監督式學習非常先進的技術。

A new Approach to Orthopedic Surgery Planning using Deep Reinforcement Learning and Simulation

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Introduction

Computer-assisted orthopedic interventions require surgery planning based on patient-specific three-dimensional anatomical models [1]. Beside the status-quo, which is manual planning, the state-of-the-art has addressed the automation of this process either through mathematical optimization [2,3] or supervised learning [4], the former requiring a handcrafted objective function and the latter sufficient training data. We propose a completely automatic surgery planning approach for femoral osteotomies based on Deep Reinforcement Learning (DRL), which is capable of generating clinical-grade surgical plans without needing patient data for training.

Methods

Our approach was applied to an orthopedic hip intervention called Femoral Head Resection Osteotomy (FHRO). Its goal is the reconstruction of a spherical geometry of the pathological femoral head achieved through two intra-articular osteotomies. An agent was trained based on Proximal Policy Optimization (PPO) to solve the task of placing the osteotomy cutting planes. Training was done on simulated (i.e., geometrical) data only, whereas inference was performed on real patient data.

Analytical Representation

For inference, the real patient data was represented analytically, where the pathological femoral head was simulated with an ellipsoid (EP) and the healthy femoral head as a sphere (G). Two elliptical areas (EN_{1,2}) were defined where blood vessels are located (Fig 1).

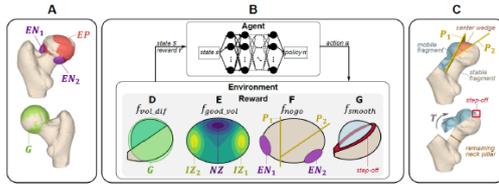


Fig 1: Overview of the DRL implementation. A) analytical representation derived from patient data, B) DRL method with the reward function terms (D,E,F,G), C) DRL output applied to the real patient mesh.

Environment

The reward function was designed such that it reflects the 5 clinical criteria used for state-of-the-art surgical planning: 1) spherical geometry of the reconstructed femoral head (Fig1-D), 2) resection of the necrotic central part of the femoral head (Fig1-E), 3) intact blood supply (Fig1-F), 4) minimal intra-articular step-off between the reattached fragments (Fig1-G) and 5) sufficiently large femoral neck pillar (Fig1-C).

Results and Discussion

In direct comparison to the Gold Standard (manual) planning solution (GS), our DRL planning solutions were classified as equally good or better in 80 percent (surgeon 1) and 100 percent (surgeon 2) of the cases.

case	1	2	3	4	5	6	7	8	9	10	11
S ₁	E	B	E	B	B	A	B	A	A	A	A
S ₂	E	B	B	E	B	B	B	E	A	A	A

Fig 2: Qualitative evaluation by a world-recognized FHRO expert (S₁) and a board-certified orthopedic hip surgeon (S₂) on 11 patients by grading solution into 'not acceptable' (NA), 'acceptable' (A), 'equally good as GS' (E) or 'better as GS' (B).

Conclusion

This work presents the development of a simulation environment tailored to orthopedic interventions based on an analytical representation of patient data that enabled the first successful application of DRL to orthopedic surgery planning.

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圖 27、第一篇海報「A new Approach to Orthopedic Surgery Planning using Deep Reinforcement Learning and Simulation」[14]

24th INTERNATIONAL CONFERENCE ON MEDICAL IMAGE COMPUTING & COMPUTER ASSISTED INTERVENTION
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Incorporating Isodose Lines and Gradient Information via Multi-task Learning for Dose Prediction in Radiotherapy

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Introduction

Motivation: Radiation therapy has been widely used in the treatment of cancer. However, making a high-quality radiotherapy plan is a quite time-consuming and subjective work. The motivation of this work is to automatically predict acceptable dose distribution in radiotherapy.

Challenges:

- Most previous methods dedicate to predicting the dose map through a single task, neglecting some influential details of the dose distribution, such as isodose lines and gradient information.
- Traditional MTL methods always integrate different tasks by sharing the shallow layers, neglecting the correlations of the output layers for different tasks.

Contributions:

- We propose a novel Multi-task model to predict acceptable dose distribution in radiotherapy.
- Isodose lines prediction task and gradient prediction task are designed to provide coarse-grained dose range and capture subtle texture information, respectively.
- We introduce two additional constraints to increase the dose prediction accuracy.

Conclusion

We propose a multi-task dose prediction network to automatically predict the dose distribution for the radiotherapy of rectal cancer patients. We explore an isodose lines prediction task and a gradient prediction task as two auxiliary tasks to help improving the performance of the main dose prediction task. We devise isodose consistency loss and gradient consistency loss for further performance improvement.

Acknowledgements

This work is supported by National Natural Science Foundation of China (NSFC 62071314) and Sichuan Science and Technology Program (2021YFG0326, 2020YFG0079).

Methodology

Consistency losses:

$$Loss_{IC} = \frac{1}{W \times H} \sum_{i=1}^N \begin{cases} \|Dec_{dose}(F) - d_{m+1}\|_2, & Dec_{dose}(F) > d_{m+1} \\ 0, & d_m \leq Dec_{dose}(F) \leq d_{m+1} \\ \|Dec_{dose}(F) - d_m\|_2, & Dec_{dose}(F) < d_m \end{cases}$$

$$Loss_{GC} = \frac{1}{W \times H} \sum_{i=1}^N \|S(Dec_{dose}(F)) - S(y)\|_2$$

Experimental Results

Methods	CT	IT	IT (%)
(1) DPT	0.834±0.019	2.48	0.064±0.020
(2) DPT+GPT	0.836±0.022	2.56	0.096±0.023
(3) DPT+GPT+Loss _{IC}	0.838±0.023	2.39	0.077±0.019
(4) DPT+GPT+DPT+Loss _{GC}	0.842±0.023	1.86	0.074±0.015
(5) DPT+GPT+DPT+Loss _{IC} +Loss _{GC}	0.849±0.025	1.84	0.074±0.011
(6) Proposed	0.854±0.018	0.47	0.081±0.024
Ground truth	0.858±0.035	-	0.081±0.017

圖 28、第二篇海報「Incorporating Isodose Lines and Gradient Information via Multi-task Learning for Dose Prediction in Radiotherapy」[15]



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Learning Spatiotemporal Probabilistic Atlas of Fetal Brain with Anatomically Constrained Registration Network

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INTRODUCTION

Construction of spatiotemporal probabilistic atlas of fetal brain

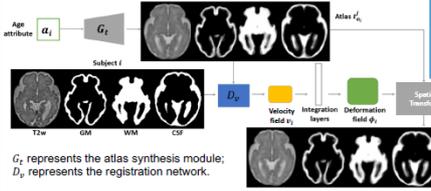
- Challenges**
 - Size, appearance and shape changing rapidly
 - Low tissue contrast
- Existing atlases**
 - Built at discrete time points
 - Ambiguous appearances
 - Time consuming for conventional methods

AIM

To develop an age-conditional multi-channel framework to construct temporally-continuous 4D probabilistic fetal brain atlas.

- Incorporating tissue segmentation maps
- Multi-channel architecture for atlas construction network
- Anatomical constraint for loss

METHODS



G_s represents the atlas synthesis module; D_r represents the registration network.

Fig. 1. The proposed age-conditional atlas construction framework.

$$L = \sum_i NCC_{local}(V_i^t, t_i^a \circ \phi_i) + \lambda_{AC} \sum_i \sum_j NCC_{local}(V_i^t, t_i^a \circ \phi_j) + \lambda_c \|u\|^2 + \frac{\lambda_d}{2} \sum_i \|u_i\|^2 + \frac{\lambda_s}{2} \sum_i \|V_i^t\|^2$$

RESULTS

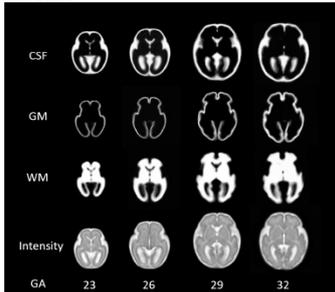


Fig. 2. Our 4D temporally-continuous fetal brain atlas at typical time points from 22 to 32 weeks of gestational age (GA), including intensity templates and tissue probability maps.

The network architecture is shown in Fig. 1. Let $V = [V_1^t, V_2^t, V_3^t, V_4^t, \dots, V_n^t, \dots, V_n^g, V_n^g, V_n^g, V_n^g]$ denote a fetal volumetric dataset containing n subjects ($i = 1, \dots, n$), with T2w image and three types of tissue labels ($j = 0, 1, 2, 3$, representing T2w image, GM, WM, CSF, respectively). a_i indicates the age attributes of subject i . We aim to jointly train two sub-networks that can align the multi-channel atlas to individual images.

- Anatomical Constraint (AC)

In order to enforce the tissue correspondence among the multi-channel inputs, we concatenate the intensity image and the tissue segmentation maps as input to the deformable registration network and incorporate a devised anatomical constraint (AC) into our loss function.

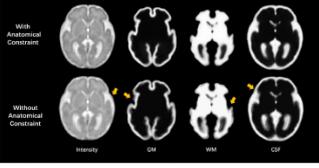


Fig. 3. Qualitative comparison of the 32-week atlases built with and without AC. Top row: the atlas constructed with AC. Bottom row: the atlas constructed without AC.

Metric	Tissue	Baseline	MC-By-GN	Ours w/o AC	Ours w/ AC	Ours
DSC (%)	CSF	N/A	85.1 ± 2.97	80.9 ± 2.54	84.9 ± 2.72	88.1 ± 2.60
	GM	N/A	72.0 ± 3.81	71.2 ± 4.73	87.6 ± 3.21	89.6 ± 2.82
	WM	N/A	91.2 ± 2.01	89.9 ± 2.24	94.1 ± 1.98	95.4 ± 1.12
ASD (mm)	CSF	N/A	0.454 ± 0.076	0.543 ± 0.089	0.431 ± 0.064	0.412 ± 0.048
	GM	N/A	0.390 ± 0.113	0.457 ± 0.124	0.293 ± 0.096	0.166 ± 0.056
	WM	N/A	0.519 ± 0.113	0.679 ± 0.146	0.456 ± 0.109	0.233 ± 0.095
95 th HD (mm)	CSF	N/A	1.58 ± 0.301	1.67 ± 0.342	1.47 ± 0.278	1.39 ± 0.215
	GM	N/A	1.31 ± 0.201	1.43 ± 0.282	1.07 ± 0.254	0.883 ± 0.219
	WM	N/A	1.74 ± 0.433	2.16 ± 0.467	1.43 ± 0.408	1.07 ± 0.414
CC (%)	N/A	96.1 ± 0.98	94.7 ± 1.0	93.7 ± 1.23	96.8 ± 0.557	97.8 ± 0.476

CONCLUSIONS

- An age-conditional atlas construction framework for fetal brain.
- An anatomical constraint for network loss.
- A 4D fetal atlas with tissue probability maps.

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1. Avants et al., "Symmetric diffeomorphic image registration with cross-correlation: evaluating automated labeling of elderly and neurodegenerative brain". Medical image analysis, 2008, 12(1): 26-41.
2. Dalca et al., "Learning conditional deformable templates with convolutional networks". In: Advances in neural information processing systems, 2019, pp. 806-818.

ACKNOWLEDGEMENTS

This work was partially supported by NIH grant MH117943.

圖 29、第三篇海報「Learning Spatiotemporal Probabilistic Atlas of Fetal Brain with Anatomically Constrained Registration Network」 [16]



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INTRODUCTION

- We aim to elucidate the mechanism of the foot by in-vivo measurement of the foot motion using bi-plane x-ray video and a stationary 3D CT.
- Clinical motivation includes the diagnosis of the foot disease due to collapse of the medial arch, evaluation of the supportive devices, and pre-and post-operative evaluation of the total talar replacement.
- Previous work includes the skin-marker-based motion capture [1], CT-X-ray registration with manual interaction [2], and automated registration of the pelvis [3,4], but none of them achieved fully automated accurate tracking of small bones like the foot.
- **GOAL: To implement a fully automated bi-plane 2D-3D registration pipeline appreciating robustness of CNNs and high accuracy of the optimization-based registration.**

METHODS

The input CT and biplane x-ray videos are processed by CNNs, Bayesian U-net [5] for bone segmentation and landmark extraction in CT, and DeepLabCut [6] for landmark extraction in x-ray videos. Then the intensity-based 2D-3D registration [7] is performed frame-by-frame using the proposed cost terms incorporating information of the landmark and intensity similarities. (code is available at <https://github.com/YoshitoOtake/4DFoot>)

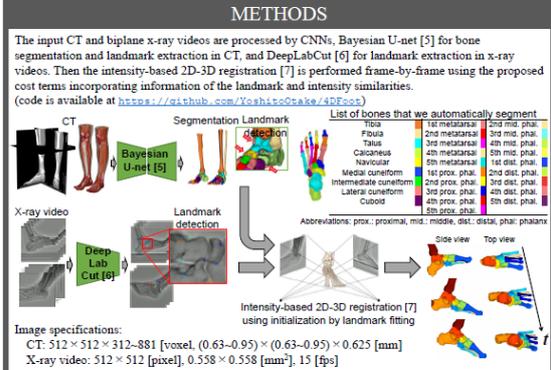
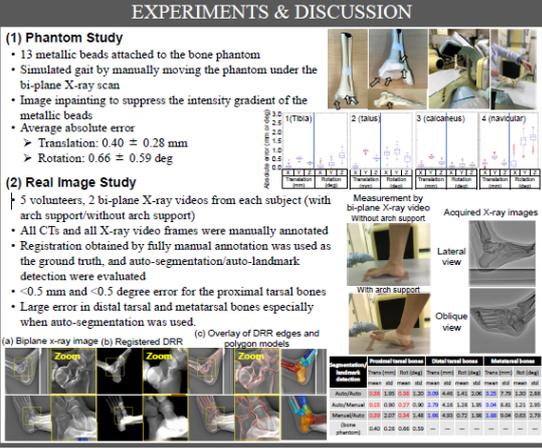


Image specifications:
CT: 512 × 512 × 312-881 [voxel], (0.63-0.95) × (0.63-0.95) × 0.625 [mm]
X-ray video: 512 × 512 [pixel], 0.538 × 0.558 [mm], 15 [fps]

EXPERIMENTS & DISCUSSION

- (1) Phantom Study
 - 13 metallic beads attached to the bone phantom
 - Simulated gait by manually moving the phantom under the bi-plane X-ray scans
 - Image inpainting to suppress the intensity gradient of the metallic beads
 - Average absolute error
 - > Translation: 0.40 ± 0.28 mm
 - > Rotation: 0.66 ± 0.59 deg
- (2) Real Image Study
 - 5 volunteers, 2 bi-plane X-ray videos from each subject (with arch support/without arch support)
 - All CTs and all X-ray video frames were manually annotated
 - Registration obtained by fully manual annotation was used as the ground truth, and auto-segmentation/auto-landmark detection were evaluated.
 - <0.5 mm and <0.5 degree error for the proximal tarsal bones
 - Large error in distal tarsal and metatarsal bones especially when auto-segmentation was used.



	Proximal tarsal	Distal tarsal	Metatarsal	Phalanx	Metatarsal	Phalanx
Translation error [mm]	0.08	0.12	0.15	0.10	0.12	0.10
Rotation error [deg]	0.10	0.15	0.20	0.12	0.15	0.12

CONCLUSION

Enabled by CNN-based initialization for a conventional optimization-based 2D-3D registration, we demonstrated a fully automated pipeline of 4D analysis of the foot bones (which we call "4D-Foot") and evaluated the accuracy using phantom and real images with fully manual annotation.

References:
[1] Benig, Anja Verena et al. (2020) "Pronation or foot movement: What is important." Journal of Science and Medicine in Sports, vol. 23, no. 4, 349-374.
[2] A. L. L. et al. (2020) "Compensatory Motion of the Subtalar Joint Following Total Ankle Arthroplasty." JBJS, vol. 102, no. 7, 600-608.
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[4] R. et al. (2019) "Towards Fully Automatic In-Vivo CT Registration." MICCAI, vol. 633-639.
[5] H. et al. (2018) "Automated Medical Segmentation from Coronal CT using Bayesian Inference for Personalized Musculoskeletal Modeling." IEEE TMI, vol. 37(4), 1030-1040.
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[7] Otake, Y. et al. (2022) "Intuitive image-based multiview 2D/3D registration for image-guided orthopedic surgery: incorporation of fluid-based deformable registration and optimization." IEEE TMI, vol. 41(4), 848-862.
Funding:
Japan Society for the Promotion of Science KAKENHI No. 19H01716, 20H04550, 21K06026

圖 30、第四篇海報「4D-Foot: A Fully Automated Pipeline of 4-Dimensional Analysis of the Foot Bones Using Bi-Plane X-ray Video and CT」 [17]

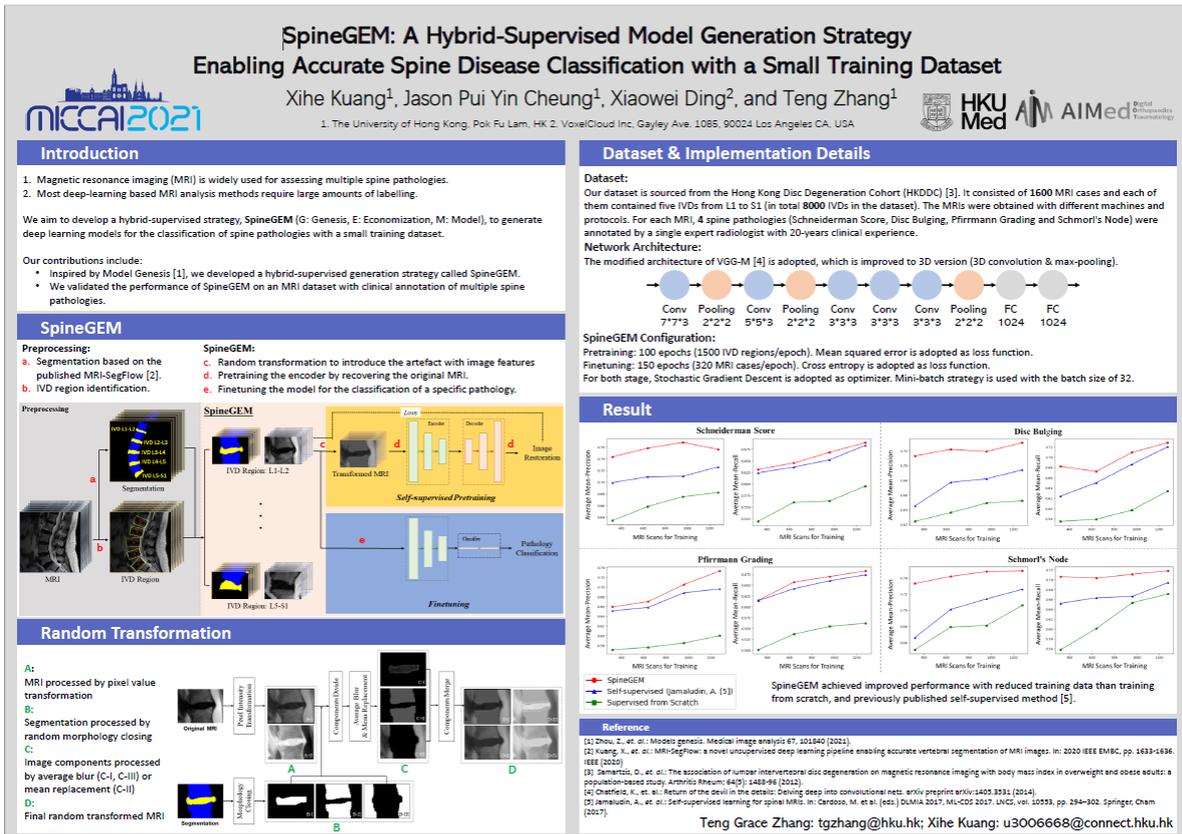


圖 31、第五篇海報「SpineGEM: A Hybrid-Supervised Model Generation Strategy Enabling Accurate Spine Disease Classification with a Small Training Dataset」 [18]

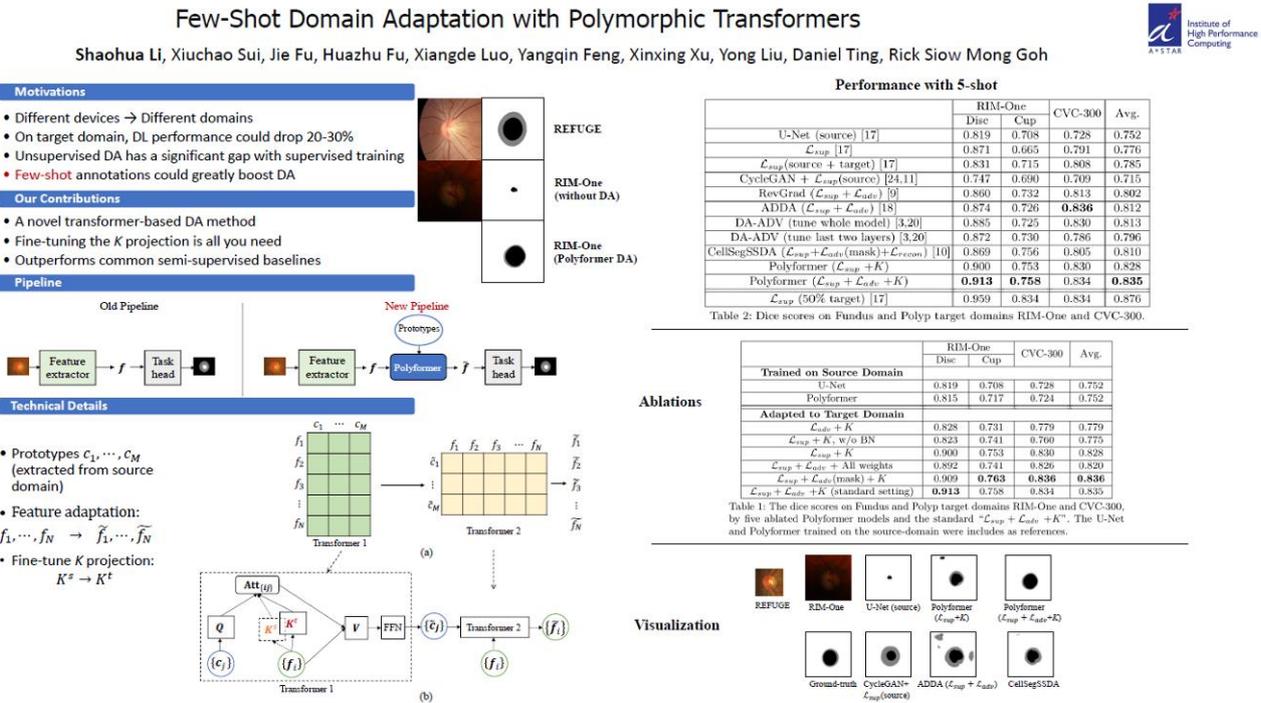


圖 32、第六篇海報「Few-Shot Domain Adaptation with Polymorphic Transformers」 [19]

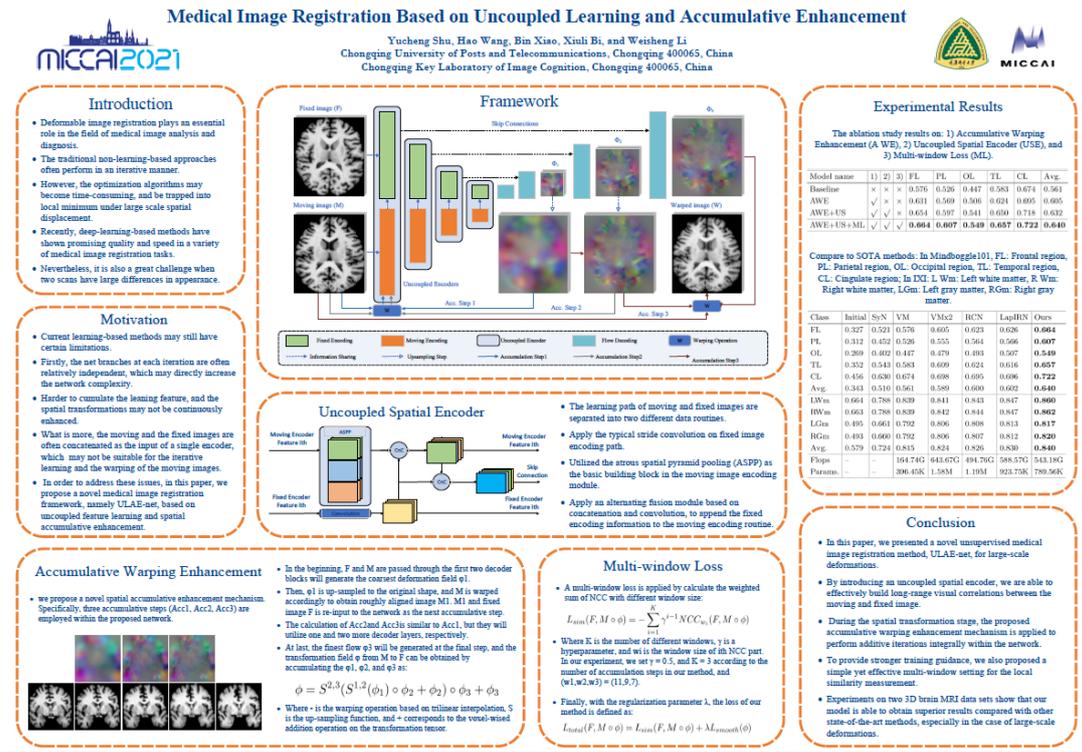


圖 33、第七篇海報「Medical Image Registration Based on Uncoupled Learning and Accumulative Enhancement」 [20]

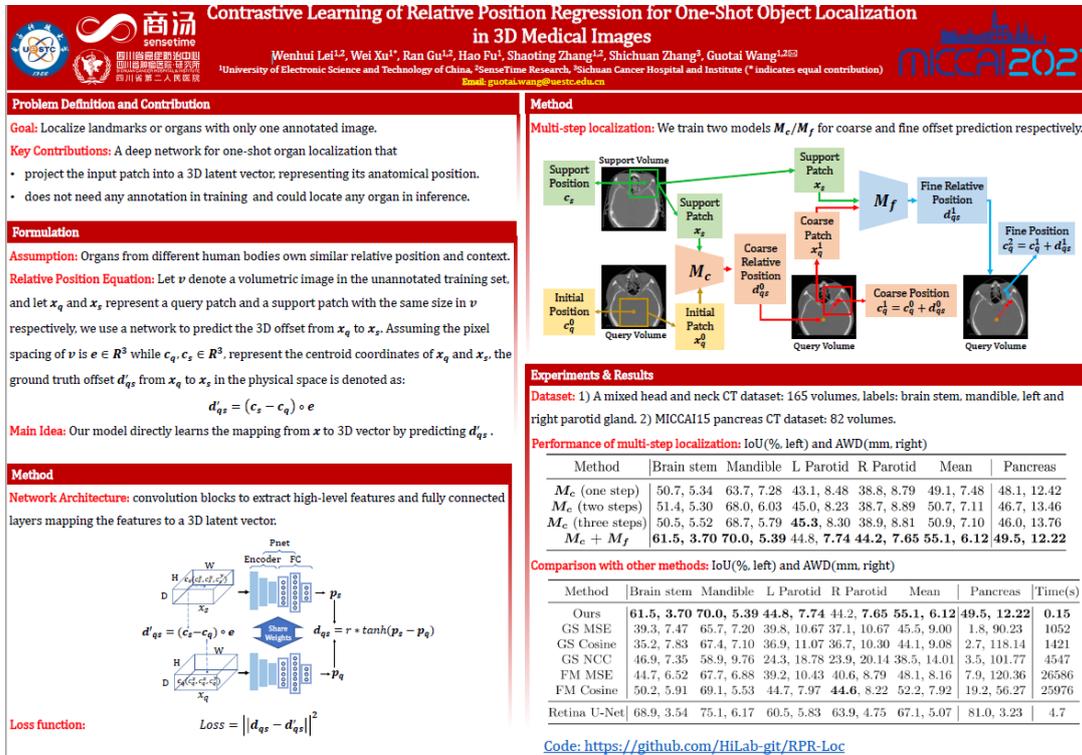


圖 34、第八篇海報「Contrastive Learning of Relative Position Regression for One-Shot Object Localization in 3D Medical Images」 [21]

四、建議事項

- (一) 根據後疫情時代之醫學影像國際市場趨勢與分析資料顯示，AI 與醫學影像整合已成為主要發展方向，尤其是面臨醫療人力不足或風險未知的情況，更是需仰賴電腦運算來輔助疾病程度篩檢與判斷，協助更有效率及精確地提供診療服務。然而，導入 AI 技術於醫療場域中面臨複雜的工作流程整合、法規及安全、AI 運行維護等因素影響成敗。建議本所研發計畫針對國內環境實況，與專長互補的團隊建立夥伴關係，實務地以放射影像技術解決目前醫界的痛點。
- (二) AI 技術發展的基礎是數據，尤其是 AI 落地應用時的效能以及適應程度更是取決於數據特性在母體中的代表性。公開資料庫與資料共享能夠提供數量夠大、涵蓋面向廣的數據，如何在兼顧隱私及相關規範下，促進資料的共享互惠機制，將有助於 AI 技術的發展與實用性。建議進行 AI 技術研發工作應同步關注國內外數據開放共享之發展趨勢。
- (三) 此次會議以視訊的方式參加，免去交通時差等困擾，所有與會者全時可傳送即時訊息聯繫，會議演講及發表皆留存影音檔提供重複瀏覽。有鑑於線上國際研討會的普及及便利性，針對 AI 技術日新月異的發展，會議中的資訊量極高，建議未來能 2 人以上參與，能更全面深入的吸收獲得第一手的訊息外，亦能增加本所研究人員與國外專家的接觸、激盪與交流。

五、附 錄

(一)衛星會議總議程(含 Workshop、Challenges、Tutorials)

Day/Time	Workshop Name	Acronym	Contact	Associated Challenge/Tutorial	Duration (F=Full day/H=Half day)
Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	ASMUS 2021: The 2 nd International Workshop on Advances in Simplifying Medical UltraSound	ASMUS	Yipeng Hu (University College London) yipeng.hu[at]ucl.ac.uk	-	F
Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	Uncertainty for Safe Utilization of Machine Learning in Medical Imaging	UNSURE	Carole Sudre (University College London) c.sudre[at]ucl.ac.uk	-	F
Oct 1 / 9:00-13:00 (UTC)	2 nd MICCAI Workshop on "Distributed And Collaborative Learning" (DCL)	DCL	Nicola Rieke (Nvidia) nrieke[at]nvidia.com	-	H
Sept 27 / CANCELLED	CVII-STENT (Computing and Visualisation for Intravascular Imaging and Computer Assisted Stenting)	CVII-STENT	Simone Balocco (University of Barcelona) balocco.simone[at]gmail.com	-	H
Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	Computational Biomechanics for Medicine XVI	CBM	Poul M. F. Nielsen (The University of Auckland) p.nielsen[at]auckland.ac.nz	-	F
Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	4 th Workshop on Predictive Intelligence in Medicine (PRIME)	PRIME	Islem Rezik (Istanbul Technical University) irezik[at]itu.edu.tr	-	F
Sept 27 / 9:00-13:00 (UTC)	OMIA8 - 8 th Ophthalmic Medical Image Analysis Workshop (OMIA8) and GAMMA Contest	OMIA8	Yanwu Xu (Baidu inc) xuyanwu[at]baidu.com	-	H
Oct 1 / 14:00-18:00 (UTC)	Deep Generative Models for Medical Image Computing and Computer Assisted Intervention (DGM4MICCAI)	DGM4MICCAI	Sandy Engelhardt sandy.engelhardt[at]med.uni-heidelberg.	AdaptOR	H
Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	Joint Workshop on Augmented Environments for Computer-Assisted Interventions (AE-CAI), Computer Assisted and Robotic Endoscopy (CARE), and OR 2.0 Context Aware Operating Theaters (OR2.0)	AE-CAI	Elvis Chen (Robarts Research Institute) chene[at]robarts.ca	-	F
Sept 27 / 14:00-18:00 (UTC)	iMIMIC - Interpretability of Machine Intelligence in Medical Image Computing	iMIMIC	Mauricio Reyes (University of Bern) mauricio.reyes[at]med.unibe.ch	-	H
Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	Brain-lesion workshop (BrainLes)	BrainLes	Alessandro Crimi a.crimi[at]sanoscience.org	RSNA-MICCAI Brain Tumor Segmentation (BraTS) (CH)	F
Oct 1 / 14:00-18:00 (UTC)	Machine Learning for Medical Image Reconstruction (MLMIR)	MLMIR	Tobias Wuerfl (Siemens Healthineers) tobias.wuerfl[at]fau.de	-	H

Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	3rd Workshop on Computational Pathology (COMPAY)	COMPAY	Francesco Ciompi (Radboud University Medical Center, Netherlands) francesco.ciompi[at]radboudumc.nl	-	F
Sept 27 / 14:00-18:00 (UTC)	Secure and Privacy-Preserving Machine Learning for Medical Imaging	PPML	Georgios Kaissis (Technische Universität München) g.kaissis[at]tum.de	Secure and Privacy-Preserving Machine Learning for Medical Imaging (TUT)	H
Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	3rd MICCAI workshop on "Domain Adaptation and Representation Transfer (DART): Learning Transferable, Interpretable, and Robust Representations"	DART	Konstantinos Kamnitsas (Imperial College London) konstantinos.kamnitsas12[at]imperial.ac.uk	-	F
Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	Computational Diffusion Magnetic Resonance Imaging (CDMRI) 2021	CDMRI	Tomasz Pieciak (Universidad de Valladolid, Valladolid, Spain) pieciak[at]pi.tel.uva.es	Diffusion-Simulated Connectivity Challenge (DISCO) (CH)	F
Oct 1 / 9:00-13:00 (UTC)	MICCAI Workshop on Perinatal Imaging, Placental and Preterm Image analysis (PIPPi 2021)	PIPPi	Roxane Licandro (MUW) roxane.licandro[at]meduniwien.ac.at	-	H
Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	6th International Workshop on Simulation and Synthesis in Medical Imaging (SASHIM)	SASHIM	David Svoboda (Masaryk University) svoboda[at]fi.muni.cz	-	F
Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	Machine Learning in Medical Imaging (MLMI 2021)	MLMI	Pingkun Yan (Rensselaer Polytechnic Institute) yanp2[at]rpi.edu	-	F
Sept 27 / 9:00-13:00 (UTC)	aFFordable healthcare and AI for Resource diverse global health (FAIR)	FAIR	Shadi Albarqouni (Helmholtz AI TU Munich) shadi.albarqouni[at]tum.de	-	H
Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	10th MICCAI Workshop on Clinical Image-based Procedures (CLIP 2021): Towards Holistic Patient Models for Personalised Healthcare	CLIP	Cristina Oyarzun Laura (Fraunhofer IGD) cristina.oyarzun.laura[at]igd.fraunhofer.de	-	F
Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	Statistical Atlases and Computational Modelling of the Heart	STACOM	Alistair Young (King's College London) alistair.young[at]kcl.ac.uk	Multi-Disease, Multi-View & Multi-Center Right Ventricular Segmentation in Cardiac MRI (M&MS-2) (CH)	F
Sept 27 / 14:00-18:00 (UTC)	Machine Learning in Clinical Neuroimaging (MLCN 2021)	MLCN	Seyed Mostafa Kia (Donders Institute) s.kia[at]donders.ru.nl	-	H
Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	The First MICCAI Workshop on Data Augmentation, Labeling, and Imperfections (DALI)	DALI	Nicholas Heller (University of Minnesota) helle246[at]umn.edu	-	F

Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	Lessons Learned from the development and application of medical Imaging-based AI technologies for combating COVID-19 (short name: LL-COVID19)	LL-COVID19	Michal Rosen-Zvi (IBM) rosen[at]il.ibm.com	-	F
Sept 27 / 14:00-18:00 (UTC)	Topological Data Analysis and its Applications for Medical Data	TDA	Mustafa Hajj (Santa Clara University) mustafahajj[at]gmail.com	-	H
Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	Multimodal Learning and Fusion Across Scales for Clinical Decision Support	ML-CDS	Xiang Li (Massachusetts General Hospital and Harvard Medical School) xli60[at]mgh.harvard.edu Tanveer Syeda-Mahmood stf[at]us.ibm.com	-	F

Day/Time	Challenge Name	Acronym	Contact	Associated Workshop	Duration (F=Full day/H=Half day)	DOI
Sept 27 / 14:00-18:00 (UTC)	2021 Kidney and Kidney Tumor Segmentation Challenge	KITS21	Nicholas Heller helle246[at]umn.edu	-	H	http://doi.org/10.5281/zenodo.3714971
Sept 27 / 9:00-13:00 (UTC)	Brain MRI reconstruction challenge with realistic noise	RealNoiseMRI	Melanie Ganz mganz[at]nru.dk	-	H	http://doi.org/10.5281/zenodo.4572639
Sep 27 / 9:00-13:00 (UTC)	Cross-Modality Domain Adaptation for Medical Image Segmentation	CROSSMoDa	Reuben Dorent reuben.dorent[at]kcl.ac.uk	-	H	http://doi.org/10.5281/zenodo.4573118
Oct 1 / 14:00-18:00 (UTC)	Deep Generative Model Challenge for Domain Adaptation in Surgery 2021	AdaptOR 2021	Sandy Engelhardt sandy.engelhardt[at]med.uni-heidelberg	DGM4MICCAI	H	http://doi.org/10.5281/zenodo.4572678
Sept 27 / 14:00-18:00 (UTC)	Diabetic Foot Ulcers Grand Challenge 2021	DFUC 2021	Moi Hoon Yap M.Yap[at]mmu.ac.uk	-	H	http://doi.org/10.5281/zenodo.3715019
Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	Diffusion-Simulated Connectivity Challenge	DISCO	Gabriel Girard gabriel.girard[at]epfl.ch	COMRI	F	http://doi.org/10.5281/zenodo.4572682
Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	Endoscopic Vision Challenge 2021	EndoVis	Stefanie Speidel stefanie.speidel[at]inict-dresden.de	-	F	http://doi.org/10.5281/zenodo.4572972
Oct 1 / 9:00-13:00 (UTC)	Fast and Low GPU Memory Abdominal Organ Segmentation in	FLARE21	Jun Ma junma[at]hjust.edu.cn	-	H	http://doi.org/10.5281/zenodo.4573114

Oct 1 / 14:00-18:00 (UTC)	Federated Tumor Segmentation	FETS	Spyridon Bakas sbakas[at]upenn.ed	DCL and/or BrainLes Workshop	H	http://doi.org/10.5281/zenodo.4573127
Oct 1 / 14:00-18:00 (UTC)	Fetal Brain Tissue Annotation and Segmentation Challenge	FETA	Kelly Payette kelly.payette[at]kispi.uzh.ch	PIPPi	H	http://doi.org/10.5281/zenodo.4573143
Sept 27 / 9:00-13:00 (UTC)	HEad and neCK TumOR segmentation and outcome prediction in PET/CT images	HECKTOR	Vincent Andrearczyk vincent.andrearczyk[at]hevs.ch	-	H	http://doi.org/10.5281/zenodo.4573154
Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	Learn2Reg - The Challenge (2021)	LEARN2REG	Mattias Heinrich heinrich[at]jimi.uni-luebeck.de	-	F	http://doi.org/10.5281/zenodo.4573967
Oct 1 / 9:00-13:00 (UTC)	Medical Out-of-Distribution Analysis Challenge 2021	MOOD	David Zimmerer dzimmerer[at]dkfz.de	-	H	http://doi.org/10.5281/zenodo.4573947
Oct 1 / 14:00-18:00 (UTC)	Mitosis DDomain Generalization Challenge 2021	MIDOG	Marc Aubreville marc.aubreville[at]thi.de	-	H	http://doi.org/10.5281/zenodo.4573977
Sept 27	Multi-Disease, Multi-View & Multi-Center Right Ventricular Segmentation in Cardiac MRI (M&Ms-2)	M&Ms-2	Carlos Martín-Isla carlos.martinisla[at]ub.edu	STACOM	H	http://doi.org/10.5281/zenodo.4573983
Oct 1 / 14:00-18:00 (UTC)	Quantification of Uncertainties in Biomedical Image Quantification 2021	QUBIQ 2021	qubiq.miccai[at]gmail.com	-	H	http://doi.org/10.5281/zenodo.4575203

Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	RSNA-ASNR-MICCAI Brain Tumor Segmentation (BraTS) Challenge 2021	BraTS2021	Spyridon Bakas brats2021[at]cbica.upenn.edu	BrainLes	F	http://doi.org/10.5281/zenodo.4575161
Sept 27 / 9:00-13:00 (UTC)	SARAS challenge for Multi-domain Endoscopic Surgeon Action Detection	SARAS-MESAD	Vivek Singh Bawa vsingh[at]brookes.ac.uk	-	H	http://doi.org/10.5281/zenodo.4575196
Oct 1 / 9:00-13:00 (UTC)	Towards the Automatization of Cranial Implant Design in Cranioplasty: 2nd MICCAI Challenge on Automatic Cranial Implant Design	AutoImplant 2021	Jianning Li jianning.li[at]icg.tugraz.at Jan Egger egger[at]tugraz.at	-	H	http://doi.org/10.5281/zenodo.4573985
Sept 27 / 14:00-18:00 (UTC)	VAscular Lesions DetectiOn	Where is VALDO	Carole Sudre carole.sudre[at]kcl.ac.uk	-	H	http://doi.org/10.5281/zenodo.3715641
Oct 1 / 9:00-13:00 (UTC)	Foot Ulcer Segmentation Challenge 2021	FU-Seg	Zeyun Yu yuz[at]uwm.edu	-	H	https://doi.org/10.5281/zenodo.4575313

Oct 1 / 9:00-13:00 (UTC)	PAIP2021: Perineural Invasion in Multiple Organ Cancer (Colon, Prostate, and Pancreatobiliary tract)	PAIP2021	Jinwook Choi jinchoi[at]snu.ac.kr	-	H	https://doi.org/10.5281/zenodo.4575423
Oct 1 / 14:00-18:00 (UTC)	Carotid Artery Vessel Wall Segmentation Challenge	VWS	Chun Yuan cyuan[at]uw.edu	-	H	https://doi.org/10.5281/zenodo.4575300

Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	RSNA-ASNR-MICCAI Brain Tumor Segmentation (BraTS) Challenge 2021	BraTS2021	Spyridon Bakas brats2021[at]cbica.upenn.edu	BrainLes	F	http://doi.org/10.5281/zenodo.4575161
Sept 27 / 9:00-13:00 (UTC)	SARAS challenge for Multi-domain Endoscopic Surgeon Action Detection	SARAS-MESAD	Vivek Singh Bawa vsingh[at]brookes.ac.uk	-	H	http://doi.org/10.5281/zenodo.4575196
Oct 1 / 9:00-13:00 (UTC)	Towards the Automatization of Cranial Implant Design in Cranioplasty: 2nd MICCAI Challenge on Automatic Cranial Implant Design	AutoImplant 2021	Jianning Li jianning.li[at]icg.tugraz.at Jan Egger egger[at]tugraz.at	-	H	http://doi.org/10.5281/zenodo.4573985
Sept 27 / 14:00-18:00 (UTC)	Vascular Lesions DetectiOn	Where is VALOO	Carole Sudre carole.sudre[at]kcl.ac.uk	-	H	http://doi.org/10.5281/zenodo.3715641
Oct 1 / 9:00-13:00 (UTC)	Foot Ulcer Segmentation Challenge 2021	FU-Seg	Zeyun Yu yuz[at]uw.edu	-	H	https://doi.org/10.5281/zenodo.4575313
Oct 1 / 9:00-13:00 (UTC)	PAIP2021: Perineural Invasion in Multiple Organ Cancer (Colon, Prostate, and Pancreatobiliary tract)	PAIP2021	Jinwook Choi jinchoi[at]snu.ac.kr	-	H	https://doi.org/10.5281/zenodo.4575423
Oct 1 / 14:00-18:00 (UTC)	Carotid Artery Vessel Wall Segmentation Challenge	VWS	Chun Yuan cyuan[at]uw.edu	-	H	https://doi.org/10.5281/zenodo.4575300

Day/Time	Tutorial Name	Contact	Associated Workshop	Duration (F=Full day/H=Half day)
Sept 27 / 9:00-13:00 (UTC)	MICCAI Hackaton: Bridging the gap to the clinics	Fabian Balsiger fabian.balsiger[at]insel.ch	-	H
Oct 1 / 9:00-13:00 (UTC)	SOFA: An open Source solution for physics simulation	Hugo Talbot hugo.talbot[at]sofa-framework.org	-	H
Sept 27 / 14:00-18:00 (UTC)	Tutorial on Deep 2D/3D modeling and learning in medical image computing	Cheng Peng cpeng26[at]jh.edu	-	H
Sept 27 / 9:00-13:00 + 14:00-18:00 (UTC)	Meta learning for medical image analysis	Hien V Ngyuen hvnguy35[at]central.uh.edu	-	F
Sept 27 / 14:00-18:00 (UTC)	Secure and Privacy-Preserving Machine Learning for Medical Imaging (PPML)	Georgios Kaissis (Technische Universität München) g.kaissis[at]tum.de	PPML	H

Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	Disease progression modeling with cross-sectional and longitudinal data	Igor Koval igor.koval[at]inria.fr	-	F
Sept 27 / 14:00-18:00 (UTC)	DREAM: Disentangled Representations for Efficient Algorithms for Medical Data	Sotirios Tsafaris s.tsafaris[at]jed.ac.uk	-	H
Oct 1 / 9:00-13:00 + 14:00-18:00 (UTC)	Weakly Supervised CNN Segmentation: Models and Optimization	Jose Dolz jose.dolz[at]jetsmtl.ca	-	F
Sept 27 / 14:00-18:00 (UTC)	NIH Cancer Imaging Data Repositories for Biomedical Data Science Research	Keyvan Farahani farahani[at]nih.gov	-	H
Oct 1 / 14:00-18:00 (UTC)	Multi-dimensional Anatomy for Computer Scientists (MD Anatomy) the thoracoabdominal cavity presented by clinicians	Juan M Verde juan.verde[at]ihu-strasbourg.eu	-	H
Oct 1 / 14:00-18:00 (UTC)	TOPGRAD - Tutorials on Publishing, Grant writing And career development	Markus Schirmer mail[at]markus-schirmer.com	-	H
Sept 27 / CANCELLED	PyRadiogenomics: A Python-based tutorial on Learning Radiogenomics Signature	Hassan Mohy-ud-Din (LUMS School of Science and Engineering) hassan.mohyuddin[at]lums.edu.pk	-	H
Sept 27 / 14:00-18:00 (UTC)	Best Practices for Research Funding Pursuit: What you have not known yet	Shandong Wu wus3[at]upmc.edu	-	H
Oct 1 / 9:00-13:00 (UTC)	Simple Toolchain for Upscaled and Distributed Training and Tuning of CNNs	Mike Marsh mmarsh[at]theobjects.com	-	H

(二)9/27 日參加的衛星會議詳細議程

Program of MLMI 2021

8:00 - 18:15 (UTC), Sep. 27, 2021, Strasbourg, France

(4:00 AM - 14:15 PM EDT on Monday, 27 September)

<i>Time (UTC)</i>		<i>Events</i>	<i>Session Chair</i>
8:00 - 8:05	5min	Introduction to the MLMI workshop	MLMI Chairs
8:05 - 8:50	45min	Keynote #1 (Klaus Maier-Hein, PhD)	Pingkun Yan
8:50 - 9:30	40min	Keynote #2 (Deyu Meng, PhD)	Chunfeng Lian
9:30 - 10:30	60min	Oral Session #1 (Computer-Aided Diagnosis) (5 papers)	Qian Wang Xiaohuan Cao
	Mingxin Jiang	Exploring Gyro-Sulcal Functional Connectivity Differences across Task Domains via Anatomy-Guided Spatio-Temporal Graph Convolutional Networks	MLMI2021-O-1
	Yu Li	Learning Infancy Brain Developmental Connectivity for the Cognitive Score Prediction	MLMI2021-O-2
	Zehong Cao	Diagnosis of Hippocampal Sclerosis from Clinical Routine Head MR Images using Structure-Constrained Super-Resolution Network	MLMI2021-O-3
	Sheng Wang	3DMeT: 3D Medical Image Transformer for Knee Cartilage Defect Assessment	MLMI2021-O-4
	Alexis M Perakis	Contrastive Learning of Single-Cell Phenotypic Representations for Treatment Classification	MLMI2021-O-5
10:30 - 10:45	15min	Break	
10:45 - 11:45	60min	Oral Session #2 (Segmentation) (5 papers)	Chunfeng Lian Xiaohuan Cao
	Ling Huang	Deep PET/CT fusion with Dempster-Shafer theory for lymphoma segmentation	MLMI2021-O-6
	Yunxiang Li	GT U-Net: A U-Net Like Group Transformer Network for Tooth Root Segmentation	MLMI2021-O-7
	Jianping Li	Morphology-guided Prostate MRI Segmentation with Multi-slice Association	MLMI2021-O-8
	Caiwen Jiang	Spine-rib Segmentation and Labeling via Hierarchical Matching and Rib-guided Registration	MLMI2021-O-9
	Xiao Zhang	CorLab-Net: Anatomical Dependency-Aware Point-Cloud Learning for Automatic Labeling of Coronary Arteries	MLMI2021-O-10
11:45 - 12:35	50min	Poster Session #1 (23 papers)	
	Tapabrata Rohan Chakraborty	Contrastive Representations for Continual Learning of Fine-grained Histology Images	MLMI2021-P-1
	Junrui Liu	Knee Cartilages Segmentation Based on Multi-scale Cascaded Neural Networks	MLMI2021-P-2
	Dongdong Gu	Multiresolution Registration Network (MRN) Hierarchy with Prior Knowledge Learning	MLMI2021-P-3

	Ivan Drokin	End-to-end lung nodule detection framework with model-based feature projection block.	MLMI2021-P-4
	Nimrod Sagie	Transfer learning with a layer dependent regularization for medical image segmentation	MLMI2021-P-5
	Shuangchi He	Statistical Dependency Guided Contrastive Learning for Multiple Labeling in Prenatal Ultrasound	MLMI2021-P-6
	Peng Liu	Semi-supervised Learning Regularized by Adversarial Perturbation and Diversity Maximization	MLMI2021-P-7
	Federica Proietto Salantri	Hierarchical 3D Feature Learning for Pancreas Segmentation	MLMI2021-P-8
	Heng Wang	Voxel-wise Cross-Volume Representation Learning for 3D Neuron Reconstruction	MLMI2021-P-9
	Yaocong Zou	Co-Segmentation of Multi-Modality Spinal Images Using Channel and Spatial Attention	MLMI2021-P-10
	Adam Harrison	Hetero-Modal Learning and Expansive Consistency Constraints for Semi-Supervised Detection from Multi-Sequence Data	MLMI2021-P-11
	Suhyeon Jeong	Biased Extrapolation in Latent Space for Imbalanced Deep Learning	MLMI2021-P-12
	Eren Bora Yilmaz	Automated deep learning-based detection of osteoporotic fractures in CT images	MLMI2021-P-13
	Reza Azad	Stacked Hourglass Network with a Multi-level Attention Mechanism: Where to Look for Intervertebral Disc Labeling	MLMI2021-P-14
	Fengbei Liu	Self-supervised Mean Teacher for Semi-supervised Chest X-ray Classification	MLMI2021-P-15
	Shiv Gehlot	Self-Supervision Based Dual-Transformation Learning for Stain Normalization, Classification and Segmentation	MLMI2021-P-16
	Wenzhao Wei	Deep Representation Learning for Image-Based Cell Profiling	MLMI2021-P-17
	Xiaoyang Han	Detecting Extremely Small Lesions with Point Annotations via Multi-task Learning	MLMI2021-P-18
	Runze Wang	Unsupervised Cross-modality Cardiac Image Segmentation via Disentangled Representation Learning and Consistency Regularization	MLMI2021-P-19
	Jiameng Liu	Multi-scale Segmentation Network for Rib Fracture Classification from CT Images	MLMI2021-P-20
	Kai Zhang	3D Temporomandibular Joint CBCT Image Segmentation via Multi-directional Resampling Ensemble Learning Network	MLMI2021-P-21
	Kai Lin	Extracting Sequential Features from Dynamic Connectivity Network with rs-fMRI Data for AD Classification	MLMI2021-P-22
	Peng Dong	Integration of Handcrafted and Embedded Features from Functional Connectivity Network with rs-fMRI for Brain Disease Classification	MLMI2021-P-23
12:35 - 12:55	20min	Breakfast/Lunch/Dinner Break	
12:55 - 13:45	50min	Keynote #3 (Ronald M. Summers, MD, PhD)	Pingkun Yan
13:45 - 14:45	60min	Oral Session #3 (Registration/Reconstruction) (5 papers)	Chunfeng Lian Xuanang Xu

	Dongdong Gu	Variational Encoding and Decoding for Hybrid Supervision of Registration Network	MLMI2021-O-11
	Jie Wei	Learning to Synthesize 7T MRI from 3T MRI with Few Data by Deformable Augmentation	MLMI2021-O-12
	Wenjun Shen	A Recurrent Two-stage Anatomy-guided Network for Registration of Liver DCE-MRI	MLMI2021-O-13
	Jupeng Li	Landmark-Guided Rigid Registration for Temporomandibular Joint MRI-CBCT Images with Large Field-of-View Difference	MLMI2021-O-15
14:45 - 15:00	15min	Break	
15:00 - 16:00	60min	Oral Session #4 (Computer-Aided Diagnosis) (5 papers)	Mingxia Liu Islem Rekik
	Hao Guan	Learning Transferable 3D-CNN for MRI-based Brain Disorder Classification from Scratch: An Empirical Study	MLMI2021-O-16
	Yingying Zhu	Learning Structure from Visual Semantic Features and Radiology Ontology for Lymph Node Classification on MRI	MLMI2021-O-17
	Diego Machado Reyes	Cardiovascular disease risk improves COVID-19 patient outcome prediction	MLMI2021-O-18
	Denis Parra	Clinically Correct Report Generation from Chest X-rays using Templates	MLMI2021-O-19
	Tejas Sudharshan Mathai	Detection of Lymph Nodes in T2 MRI using Neural Network Ensembles	MLMI2021-O-20
16:00 - 16:50	50min	Poster Session #2 (23 papers)	
	Zhuoyue Wu	Interpretable Histopathology Image Diagnosis via Whole Tissue Slide Level Supervision	MLMI2021-P-24
	Zhanghexuan Ji	Improving Joint Learning of Chest X-Ray and Radiology Report by Word Region Alignment	MLMI2021-P-25
	Zuhui Wang	Cell Counting by a Location-Aware Network	MLMI2021-P-26
	Islem Mhiri	StairwayGraphNet for Inter- and Intra-modality Multi-resolution Brain Graph Alignment and Synthesis	MLMI2021-P-27
	Xiao Qi	Multi-Feature Semi-Supervised Learning for COVID-19 Diagnosis from Chest X-ray Images	MLMI2021-P-28
	Yutong Yan	Deep active learning for dual-view mammogram analysis	MLMI2021-P-29
	Ignacio Sarasua	TransforMesh: A Transformer Network for Longitudinal Modeling of Anatomical Meshes	MLMI2021-P-30
	Tal Tlusty	Pre-biopsy multi-class classification of breast lesion pathology in mammograms	MLMI2021-P-31
	Anne-Marie Rickmann	STRUDEL: Self-Training with Uncertainty Dependent Label Refinement across Domains	MLMI2021-P-32
	Othmane Laousy	Deep Reinforcement Learning for L3 Slice Localization in Sarcopenia Assessment	MLMI2021-P-33
	Jaya Chandra Raju Brahmandam	MIST GAN: Modality Imputation using Style Transfer for MRI	MLMI2021-P-34

	Wenzheng Tao	A Gaussian Process Model for Unsupervised Analysis of High Dimensional Shape Data	MLMI2021-P-35
	Pooneh Roshanitabrizi	Standardized Analysis of Kidney Ultrasound Images for the Prediction of Pediatric Hydronephrosis Severity	MLMI2021-P-36
	Ugur Demir	Information Bottleneck Attribution for Visual Explanations of Diagnosis and Prognosis	MLMI2021-P-37
	Dayang Wang	TED-net: Convolution-free T2T Vision Transformer-based Encoder-decoder Dilation network for Low-dose CT Denoising	MLMI2021-P-38
	Ayaan Haque	Window-Level is a Strong Denoising Surrogate	MLMI2021-P-39
	Jun Luo	Knowledge-guided Multiview Deep Curriculum Learning for Elbow Fracture Classification	MLMI2021-P-40
	Ramy Ashraf Zeineldin	A Hybrid Deep Registration of MR Scans to Interventional Ultrasound for Neurosurgical Guidance	MLMI2021-P-41
	Qin Liu	SkullEngine: A Multi-Stage CNN Framework for Collaborative CBCT Image Segmentation and Landmark Detection	MLMI2021-P-42
	Qin Liu	Skull Segmentation from CBCT Images via Voxel-based Rendering	MLMI2021-P-43
	Sebastian Pölsterl	Alzheimer's Disease Diagnosis via Deep Factorization Machine Models	MLMI2021-P-44
	Pew-Thian Yap	Vox2Surf: Implicit Surface Reconstruction from Volumetric Data	MLMI2021-P-45
	Nahid Ul Islam	Seeking an Optimal Approach for Computer-Aided Pulmonary Embolism Detection	MLMI2021-P-46
16:50 - 17:00	10min	Break	
17:00 - 18:00	60min	Oral Session #5 (Segmentation/Classification) (5 papers)	Yuankai Huo Islem Rekik
	Jingya Liu	Rethinking Pulmonary Nodule Detection in Multi-view 3D CT Point Cloud Representation	MLMI2021-O-21
	Yue Sun	Multi-Scale Self-Supervised Learning for Multi-Site Pediatric Brain MR Image Segmentation with Motion/Gibbs Artifacts	MLMI2021-O-22
	Olivier Petit	U-Net Transformer: Self and Cross Attention for Medical Image Segmentation	MLMI2021-O-23
	Mengyang Zhao	VoxelEmbed: 3D Instance Segmentation and Tracking with Voxel Embedding based Deep Learning	MLMI2021-O-24
	Alina Dima	Segmentation of Peripancreatic Arteries in Multispectral Computed Tomography Imaging	MLMI2021-O-25
18:00 - 18:15	15min	Closing Remark & Best Paper Award Announcement	MLMI Chairs

The 4th Workshop on Machine Learning in Clinical Neuroimaging
(September 27, 14:00-19:30 UTC)

UTC time-zone	MLCN 2021 Virtual Workshop Program
14:00-14:05	Workshop Opening
Session 1: Machine Learning	
14:05-14:50	Keynote 1: Unsupervised Learning of Image Correspondences in Neuroimaging (Adrian Dalca)
14:50-15:05	Oral Presentation 1: Dynamic Sub-graph Learning for Patch-based Cortical Folding Classification (Zhiwei Deng)
15:05-15:20	Oral Presentation 2: PialNN: A Fast Deep Learning Framework for Cortical Pial Surface Reconstruction (Qiang Ma)
15:20-15:35	Oral Presentation 3: Towards Self-Explainable Classifiers and Regressors in Neuroimaging with Normalizing Flows (Matthias Wilms)
15:35-15:45	Coffee Break 1
Session 2: Clinical Neuroimaging	
15:45-16:30	Keynote 2: AI and Deep Learning in Medical Imaging and Genomics: Lessons from ENIGMA's Global Studies of Brain Diseases (Paul Thompson)
16:30-16:45	Oral Presentation 4: Distinguishing Healthy Ageing from Dementia: a Biomechanical Simulation of Brain Atrophy using Deep Networks (Mariana da Silva)
16:45-17:00	Oral Presentation 5: H3K27M Mutations Prediction for Brainstem Gliomas Based on Diffusion Radiomics Learning (Ne Yang)
17:00-17:15	Oral Presentation 6: Unfolding the medial temporal lobe cortex to characterize neurodegeneration due to Alzheimer's disease pathology using ex vivo imaging (Sadhana Ravikumar)
17:15-17:25	Coffee Break 2
Session 3: Discussion, Posters, and Conclusion	
17:25-18:10	Panel Discussion: Adrian Dalca, Christos Davatzikos, Emma Robinson, Paul Thompson
18:10-18:30	Poster Teasers 1-11
18:30-19:00	Poster Session
19:00-19:05	Best Paper Award and Closing Remarks
19:05-19:30	Virtual Drink

(三)10/1 日參加的衛星會議詳細議程

PRIME-MICCAI workshop

PRedictive **I**ntelligence in **ME**dicine will reshape our healthcare technologies

PRIME Program on October 1st, 2021

SESSION 1: 9:00-13:00 Asia/Europe (UTC)

09:00 - 09:15	Introduction and Welcome
09:15 - 9:45	<p style="text-align: center;">Oral Session 1</p> <p>P1 (09:15 - 9:20): Liver Tumor Localization and Characterization from Multi-Phase MR Volumes Using Key-Slice Parsing: A Physician-Inspired Approach <i>Bolin Lai (Ping An Technology (Shanghai) Co.,Ltd.); Yuhsuan Wu (Ping An Technology (Shanghai) Co.,Ltd.); Xiaoyu Bai (Northwestern Polytechnical University); Xiao-Yun Zhou (PAII INC); Peng Wang (Department of Hepatobiliary Medicine, Eastern Hepatobiliary Surgery Hospital, Naval Medical University, Shanghai); Le Lu (PAII Inc.); Lingyun Huang (PingAn Technology); Jing Xiao (Ping An Insurance (Group) Company of China); Heping Hu (Department of Hepatobiliary Medicine, Eastern Hepatobiliary Surgery Hospital, Naval Medical University, Shanghai); Yong Xia (Northwestern Polytechnical University, Research & Development Institute of Northwestern Polytechnical University in Shenzhen); Adam P Harrison (PAII Inc.)</i></p> <p>P2 (09:20 - 9:25): Multi-Task Deep Segmentation and Radiomics for Automatic Prognosis in Head and Neck Cancer <i>Vincent Andrearczyk (HES-SO Valais)*; Pierre Fontaine (HES-SO and Univ Rennes); Valentin Oreiller (HES-SO Valais); Joel Castelli (Rennes University); Mario Jreige (CHUV); John O Prior (CHUV); Adrien Depeursinge (HES-SO Valais-Wallis)</i></p> <p>P3 (9:25 - 9:30): Low-dose CT Denoising using Pseudo-CT Image Pairs <i>Dongkyu Won (DGIST); Eujin Jung (DGIST); Sion An (DGIST); Philip Chikontwe (DGIST (Daegu Gyeongbuk Institute of Science and Technology)); Sanghyun Park (DGIST)*</i></p> <p>P4 (9:30 - 9:35): Self-guided Multi-attention Network for Periventricular Leukomalacia Recognition <i>Zhuochen Wang (Shanghai Jiao Tong University)*; Tingting Huang (Department of Radiology, The First Affiliated Hospital of Henan University of Chinese Medicine); Bin Xiao (School of Biomedical Engineering, Med-X Research Institute Shanghai Jiao Tong University Shanghai China); Sheng Wang (Shanghai Jiao Tong University); Jiayu Huo (Shanghai Jiao Tong University); Zhong Xue (Shanghai United Imaging Intelligence Co., Ltd); Xiang S Zhou (United Imaging Intelligence); Fan Wu (Department of Radiology, The First Affiliated Hospital of Xi'an Jiaotong University); Heng Liu (Department of Radiology, Affiliated Hospital of Zunyi Medical University,); Haoxiang Jiang (Department of Radiology, The First Affiliated Hospital of Xi'an Jiaotong University); Qian Wang (Shanghai Jiao Tong University); Jian Yang (Hospital of Xi'an Jiaotong University)*</i></p> <p>P5 (9:35 - 9:40): FLAT-Net: Longitudinal Brain Graph Evolution Prediction from a Few Training Representative Templates <i>Guris Ozen (Istanbul Technical University); Ahmed Nebli (Higher Institute of Applied Science and Technologies (ISSAT), Universite de Sousse)*; Islem Rekik (Istanbul Technical University)</i></p> <p>P6 (9:40 - 9:45): Prediction of Pathological Complete Response to Neoadjuvant Chemotherapy using Multi-scale Patch Learning with Mammography <i>Ho Kyung Shin (Kyungpook National University); Wonhwa Kim (Kyungpook National University Chilgok Hospital); Hyejung Kim (Kyungpook National University Chilgok Hospital); Chanho Kim (Kyungpook National University); Jaell Kim (Kyungpook National University)*</i></p>
9:45 - 10:00	Group P1-P6 Q&A Session

10:00 - 11:00	 <p>Keynote Speech 1 and Q&A session [live]</p> <p>Speaker: Prof Luping Zhu, University of Sydney</p> <p>Title: Exploring Fine-grained Image-text Description for Diagnostic Captioning</p>
11:00 - 11:15	<p>Virtual Coffee Break</p>
11:15 - 11:50	<p>Oral Session 2</p> <p>P7 (11:15 – 11:20): False Positive Suppression in Cervical Cell Screening via Attention-Guided Semi-Supervised Learning <i>Xiaping Du (Shanghai Jiao Tong University)*; Jiayu Huo (Shanghai Jiao Tong University); Yuanfang Qiao (Shanghai Jiao Tong University); Qian Wang (Shanghai Jiao Tong University); Lichi Zhang (Shanghai Jiao Tong University)</i></p> <p>P8 (11:20– 11:25): A Few-shot Learning Graph Multi-Trajectory Evolution Network for Forecasting Multimodal Baby Connectivity Development from a Baseline Timepoint <i>Aïaa Bessadok (University of Sousse, Tunisia)*; Ahmed Nebli (Higher Institute of Applied Science and Technologies (ISSAT), Université de Sousse); Mohamed Ali Mahjoub (LATIS lab, National Engineering School of Sousse, ENISO, Sousse, Tunisia); Gang Li (University of North Carolina at Chapel Hill); Weili Lin (UNC Chapel Hill); Dinggang Shen (United Imaging Intelligence); Islem Rekik (Istanbul Technical University)</i></p> <p>P9 (11:25– 11:30): Mixing-AdaSIN: Constructing a De-biased Dataset using Adaptive Structural Instance Normalization and Texture Mixing <i>Myeongkyun Kang (DGIST); Philip Chikontwe (DGIST (Daegu Gyeongbuk Institute of Science and Technology)); Miguel Luna (DGIST); Kyung Soo Hong (Yeungnam University Medical Center); June Hong Ahn (Yeungnam University Medical Center); Sanghyun Park (DGIST)*</i></p> <p>P10 (11:35– 11:40): Anatomical Structure-aware Pulmonary Nodule Detection via Parallel Multi-Task RoI Head <i>Haoyi Tao (Shanghai Jiao Tong University)*; Yuanfang Qiao (Shanghai Jiao Tong University); Lichi Zhang (Shanghai Jiao Tong University); Yiqiang Zhan (United Imaging Intelligence, Shanghai, China); Zhong Xue (Shanghai United Imaging Intelligence Co., Ltd); Qian Wang (Shanghai Jiao Tong University)</i></p> <p>P11 (11:40– 11:45): Uncertainty-Based Dynamic Graph Neighborhoods For Medical Segmentation <i>Ufuk Demir (Istanbul Technical University)*; Atahan Özer (Istanbul Technical University); Yusuf Hüseyin Şahin (ITU); Gozde Unal (Istanbul Technical University)</i></p> <p>P12 (11:45– 11:50): A Multi-scale Capsule Network for Improving Diagnostic Generalizability in Breast Cancer Diagnosis using Ultrasonography <i>Chanho Kim (Kyungpook National University); Wonhwa Kim (Kyungpook National University Chilgok Hospital); Hyejung Kim (Kyungpook National University Chilgok Hospital); Jaell Kim (Kyungpook National University)*</i></p>
11:50 - 12:05	<p>Group O6-O10 Q&A Session</p>
12:05 - 13:05	 <p>Keynote Speech 3 and Q&A session</p> <p>Speaker: Prof Aasa Feragen, Danish University of Technology</p> <p>Title: Topology-aware image registration</p>

SESSION 2: 14:00-18:00 America/Europe (UTC)

14:00 - 14:30	<p style="text-align: center;">Oral Session 3</p> <p>P13 (14:00 - 14:05): Improving Tuberculosis Recognition on Bone-Suppressed Chest X-rays Guided by Task-Specific Features <i>Yunbi Liu (School of Biomedical Engineering, Southern Medical University); Gengeng Qin (Nanfang Hospital); Yun Liu (ETH Zurich); Mingxia Liu (University of North Carolina at Chapel Hill); Wei Yang (Southern Medical University)*</i></p> <p>P14 (14:05 - 14:10): Probabilistic Deep Learning with Adversarial Training and Volume Interval Estimation - Better Ways to Perform and Evaluate Predictive Models for White Matter Hyperintensities Evolution <i>Febrian Rachmadi (RIKEN)*; María del C. Valdés Hernández (University of Edinburgh); Rizal Maulana (Universitas Indonesia); Joanna Wardlaw (University of Edinburgh); Stephen Makin (University of Aberdeen); Henrik Skibbe (RIKEN)</i></p> <p>P15 (14:10 - 14:15): Foreseeing Survival through 'Fuzzy Intelligence': A cognitively-inspired incremental learning based de novo model for Breast Cancer Prognosis by multi-omics data fusion <i>Aviral Chharia (Thapar Institute of Engineering & Technology)*; Neeraj Kumar (Thapar University, India)</i></p> <p>P16 (14:15 - 14:20): Investigating and Quantifying the Reproducibility of Graph Neural Networks in Predictive Medicine <i>Mohammed Amine Gharsallaoui (Ecole Polytechnique de Tunisie)*; Furkan Tomaci (Istanbul Technical University); Islem Rekik (Istanbul Technical University)</i></p> <p>P17 (14:20 - 14:25): Improving Across Dataset Brain Age Predictions using Transfer Learning <i>Lara Dular (University of Ljubljana, Faculty of Electrical Engineering, Laboratory of Imaging Technologies)*; Ziga Spiclin (University of Ljubljana)</i></p> <p>P18 (14:25 - 14:30): Adversarial Bayesian Optimization for Quantifying Motion Artifact within MRI <i>Anastasia Butskova (Stanford University); Rain Juhl (Stanford University); Dženan Zukić (Kitware Inc); Aashish Chaudhary (Kitware Inc); Kilian Pohl (Stanford University); Qingyu Zhao (Stanford University)*</i></p>
14:30 - 14:45	<p style="text-align: center;">Group O11-O15 Q&A Session</p>
14:45 - 15:45	<p style="text-align: center;">Keynote Speech 2 and Q&A session</p> <div style="display: flex; align-items: center;">  <div> <p>Speaker: Prof Ben Glocker, Imperial College London</p> <p>Title: Deep Structural Causal Models for Counterfactual Inference</p> </div> </div>
15:45 - 16:00	<p style="text-align: center;">Virtual Coffee Break</p>
16:00 - 17:00	<p style="text-align: center;">Keynote Speech 4 and Q&A session [live]</p> <div style="display: flex; align-items: center;">  <div> <p>Speaker: Dr Gang Li, University of North Carolina</p> <p>Title: Learning-based Pediatric Neuroimage Analysis</p> </div> </div>

17:00 - 17:30	<p style="text-align: center;">Oral Session 4</p> <p>P19 (17:00– 17:05): Self Supervised Contrastive Learning on Multiple Breast Modalities Boosts Classification Performance <i>Shaked Perak (IBM Research)*; Mika Amit (IBM Research); Efrat Hexter (IBM Research)</i></p> <p>P20 (17:05– 17:10): Opportunistic Screening of Osteoporosis Using Plain Film Chest X-ray <i>Fakai Wang (University of Maryland, College Park)*; Kang Zheng (PAII Inc.); Yirui Wang (PAII Inc.); Xiao-Yun Zhou (PAII INC.); Le Lu (PAII Inc.); Jing Xiao (Ping An Insurance (Group) Company of China); Min Wu (University of Maryland); Kuo Chang-Fu (Chang Gung Memorial Hospital); Shun Miao (PAII)</i></p> <p>P21 (17:10– 17:15): Integrating Multimodal MRIs for Adult ADHD Identification with Heterogeneous Graph Attention Convolutional Network <i>Dongren Yao (University of North Carolina at Chapel Hill); Erkun Yang (UNC-Chapel Hill); Li Sun (Peking University Sixth Hospital/Institute of Mental Health); Jing Sui (Institute of Automation Chinese Academy of Sciences); Mingxia Liu (University of North Carolina at Chapel Hill)*</i></p> <p>P22 (17:15– 17:20): Template-Based Inter-modality Super-resolution of Brain Connectivity <i>Furkan Pala (Istanbul Technical University)*; Islem Mhiri (Université de Sousse); Islem Rezik (Istanbul Technical University)</i></p> <p>P23 (17:20– 17:25): The Pitfalls of Sample Selection: A Case Study on Lung Nodule Classification <i>Vasileios Baltatzis (King's College London)*; Kyriaki-Margarita Bintsi (Imperial College London); Loic Le Folgoc (Imperial College London); Octavio E Martinez Manzanera (King's College London); Sam Ellis (King's College London); Arjun Nair (University College London Hospital); Sujal Desai (The Royal Brompton & Harefield NHS Foundation Trust); Ben Glocker (Imperial College London); Julia A Schnabel (King's College London)</i></p> <p>P24 (17:25– 17:30): Towards Cancer Patients Classification Using Liquid Biopsy <i>Sebastian Cygert (Gdansk University of Technology)*; Andrzej Czyżewski (Gdansk University of Technology); Franciszek Górski (Gdansk University of Technology); Piotr Juszczyk (Gdansk University of Technology); Sebastian Lewalski (Gdansk University of Technology); Anna Superał (Medical University of Gdańsk); Krzysztof Pastuszek (Gdansk University of Technology)</i></p>
17:30 - 17:45	Group O16-O19 Q&A Session
17:45 - 18:00	Closing Remarks and Awards

參考文獻

1. slide from Alyson J. McGregor 「How Modern Health Technologies Often Perpetuate Gender Bias in Medicine」
2. slide from Richard M. Satava 「Tech transfer: Do we use the same processes for the next generation of non-invasive surgery with Directed Energy?」
3. slide from Fei-Fei Li 「Illuminating the Dark Space of Healthcare with Ambient Intelligence」
4. slide from Klaus Maier-Hein 「Machine Learning in Medical Imaging—Current Challenges」
5. slide from Adrian Dalca 「Unsupervised Learning of Image Correspondences in Neuroimaging」
6. slide from Paul M. Thompson 「AI and Deep Learning in Medical Imaging and Genomics: Lessons from ENIGMA’s Global Studies of Brain Diseases」
7. Sadhana Ravikumar, Laura Wisse, Sydney Lim et al., “Unfolding the Medial Temporal Lobe Cortex to Characterize Neurodegeneration Due to Alzheimer’s Disease Pathology Using Ex vivo Imaging”, Ahmed Abdulkadir et al. (Eds.): MLCN 2021, LNCS 13001, pp. 3–12, 2021.
8. slide from Islem Rekik 「Introduction of Predictive Intelligence in Medicine (PRIME)」
9. slide from Luping Zhou 「Exploring Fine-grained Image-text Description for Diagnostic Captioning」
10. slide from Ben Glocker 「Deep Structural Causal Models for Counterfactual Inference」
11. slide from Carol C, Wu 「Clinical Implementation of AI Applications」
12. slide from Matthew Lungren 「Clinical Imaging AI Translation: The Day 2 Problem」
13. slide from Elli Papadopoulou 「Introduction to Open Science and OpenAIRE」
14. Joëlle Ackermann, Matthias Wieland, Armando Hoch et al., “A new Approach to Orthopedic Surgery Planning using Deep Reinforcement Learning and Simulation”, M. de Bruijne et al. (Eds.): MICCAI 2021, LNCS 12904, pp. 540–549, 2021.
15. Shuai Tan, Pin Tang, Xingchen Peng et al., “Incorporating Isodose Lines and Gradient Information via Multi-task Learning for Dose Prediction in Radiotherapy”, M. de Bruijne et

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16. Yuchen Pei, Liangjun Chen, Fenqiang Zhao et al., “Learning Spatiotemporal Probabilistic Atlas of Fetal Brain with Anatomically Constrained Registration Network”, M. de Bruijne et al. (Eds.): MICCAI 2021, LNCS 12907, pp. 239–248, 2021.
 17. Shuntaro Mizoe, Yoshito Otake, Takuma Miyamoto et al., “4D-Foot: A Fully Automated Pipeline of 4-Dimensional Analysis of the Foot Bones Using Bi-Plane X-ray Video and CT”, M. de Bruijne et al. (Eds.): MICCAI 2021, LNCS 12904, pp. 182–192, 2021.
 18. Xihe Kuang, Jason Pui Yin Cheung, Xiaowei Ding, Teng Zhang et al., “SpineGEM: A Hybrid-Supervised Model Generation Strategy Enabling Accurate Spine Disease Classification with a Small Training Dataset”, M. de Bruijne et al. (Eds.): MICCAI 2021, LNCS 12902, pp. 145–154, 2021.
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 20. Yucheng Shu, HaoWang, Bin Xiao et al., “Medical Image Registration Based on Uncoupled Learning and Accumulative Enhancement”, M. de Bruijne et al. (Eds.): MICCAI 2021, LNCS 12904, pp. 3–13, 2021.
 21. Wenhui Lei, Wei Xu, Ran Gu et al., “Contrastive Learning of Relative Position Regression for One-Shot Object Localization in 3D Medical Images”, M. de Bruijne et al. (Eds.): MICCAI 2021, LNCS 12902, pp. 155–165, 2021.