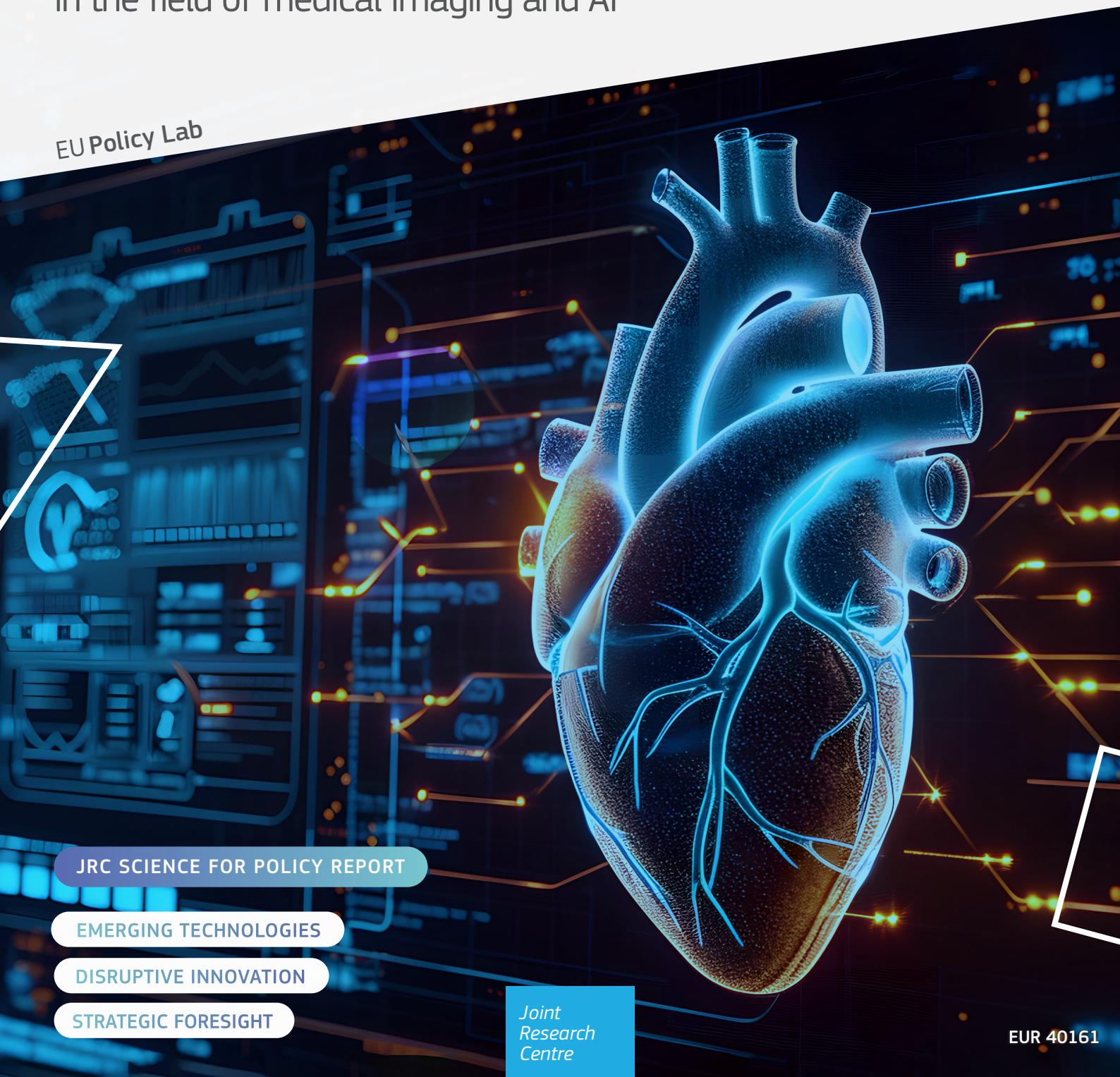
ISSN 1831-9424

European Commission

IMAGING THE FUTURE

Horizon scanning for emerging technologies and breakthrough innovations in the field of medical imaging and AI

EU Policy Lab



JRC SCIENCE FOR POLICY REPORT

EMERGING TECHNOLOGIES

DISRUPTIVE INNOVATION

STRATEGIC FORESIGHT

Joint Research Centre

EUR 40161

Contact information
EU Policy Lab
Unit S.1 - EU Policy Lab: Foresight, Design and Behavioural Insights
Joint Research Centre, European Commission, Brussels, Belgium
JRC-FORESIGHT@ec.europa.eu

EU Science Hub
https://joint-research-centre.ec.europa.eu

JRC140099

EUR 40161

Print	ISBN 978-92-68-23178-4	ISSN 1018-5593	doi:10.2760/0991947	KJ-01-24-214-EN-C
PDF	ISBN 978-92-68-23026-8	ISSN 1831-9424	doi:10.2760/1426669	KJ-01-24-214-EN-N

Luxembourg: Publications Office of the European Union, 2024

Declaration of AI-assisted technologies in the writing process:
During the preparation of this work the authors used Chat GPT and GPT@EC in order to summarise texts. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

How to cite this report: European Commission, Joint Research Centre, Mochan, A., Farinha, J., Bailey, G., Rodriguez, L., Zanca, F. and Polvora, A., *Imaging the Future - Horizon scanning for emerging technologies and breakthrough innovations in the field of medical imaging and AI*, Publications Office of the European Union, Luxembourg, 2024, https://data.europa.eu/doi/10.2760/1426669, JRC140099

IMAGING THE FUTURE

Horizon scanning for emerging technologies and breakthrough innovations in the field of medical imaging and AI

Authors:

Antonia MOCHAN (JRC)

João FARINHA (JRC)

Gwendolyn BAILEY (JRC)

Lourdes RODRIGUEZ (External Expert)

Federica ZANCA (EISMEA)

Alexandre PÓLVORA (EISMEA)

This report is part of the project FUTURINNOV, (FUTURe-oriented detection and assessment of emerging technologies and breakthrough INNOVation), a collaboration between the European Commission's (EC) Joint Research Centre (JRC) and the European Innovation Council (EIC), the EC's flagship program for deep tech, implemented by the European Innovation Council and SMEs Executive Agency (EISMEA).

This report contains the results of a thematic Horizon Scanning process, including a brief description of the methodology followed. It is the result of a participatory process involving external experts. Therefore, the views expressed herein do not necessarily reflect the views of the European Commission.

Contents

Abstract

This report documents the process and findings of a horizon scanning exercise, part of a series under the FUTURINNOV (FUTURe-oriented detection and assessment of emerging technologies and breakthrough INNOVation) project, a collaboration between the European Innovation Council (EIC) and the Joint Research Centre (JRC), aiming to bolster the EIC's strategic intelligence through foresight and anticipatory methodologies.

The workshop, held on 17 September 2024, had as its primary goal the evaluation and prioritisation of trends and signals on emerging technologies and breakthrough innovation, across all technology readiness levels (TRLs), within the EIC's Medical Imaging and AI portfolio.

Signals for the workshop were gathered from experts, literature review, and text/data mining of patents, publications, and EU-funded projects. These signals were then scrutinised for their significance to the field's future by a diverse group of sector experts which led to the identification of eight key topics: generative AI for healthcare; digital twins; multimodal data analysis; explainable AI in medical imaging; application of AI to specific diseases/conditions; XR - augmented and virtual realities; tensor-valued diffusion encoding, and AI-generated synthetic data for training AI. Furthermore, the workshop identified additional wild cards with high novelty and disruptive potential such as: blockchain, edge computing and differential privacy for secure, AI-driven medical imaging and collaborative healthcare optimisation and quantum medical imaging.

Participants also highlighted various factors that could influence the development, adoption, and promotion of these emerging technologies, which can be grouped under the following categories: Technological advancements and cross-sector applications; data infrastructure, AI models, and regulatory frameworks; workforce, education and societal factors; clinical efficiency and patient outcomes; trust, ethics, and AI adoption; financial pressures and industry investment in AI healthcare.

Acknowledgements

The authors acknowledge the contribution of:

— **Michela Bergamini, Marcelina Grabowska** and **Olivier Eulaerts** of DG Joint Research Centre, Text and Data Mining Unit.

— **Alexandra de Maleville,** of DG Joint Research Centre, Strategic Autonomy for Space and Security Unit, for her support during the workshop.

We are also grateful for the time and contributions of the workshop participants. In line with our commitment to them, their names and affiliations (where available) are listed, but no comments or statements are attributed directly.

— **Albane Grandjean**, Gleamer

— **Alberto Torresin**, Università degli Studi di Milano

— **Alberto Traverso**, Libera Università Vita-Salute San Raffaele

— **Carlo Maccia**, Centre d'Assurance de qualité des Applications Technologiques dans le domaine de la Santé (CAATS)

— **Christopher Cawthorne**, KU Leuven

— **Daniele Ravanelli**, Azienda Provinciale per i Servizi Sanitari della Provincia Autonoma di Trento (APSS)

— **Gabriele Guidi**, Azienda Ospedaliera - Universitaria di Modena

— **Gloria Miori**, Azienda Provinciale per i Servizi Sanitari (APSS)

— **Henning Müller**, University of Applied Sciences Western Switzerland

— **Jenny Ceccarini**, Mission Lucidity

— **Luca Berta**, Azienda Ospedaliera Universitaria - Città della Salute e della Scienza di Torino

— **Paul Deak**, GE Healthcare

— **Peter Mildenberger**, IHE International

— **Pieter Slagmolen**, Materialise

— **Sergey Morozov**, 3R - Réseau Radiologique Romand

— **Valentin Comte**, Joint Research Centre, European Commission

The authors are also grateful for the contributions received during the signal collection process from many other experts who were unable to participate in the workshop.

Executive summary

The Medical Imaging and AI horizon-scanning workshop on 17 September 2024 was the fifth in a series of horizon-scanning workshops carried out as part of the FUTURINNOV project.

FUTURINNOV, a joint project of the European Innovation Council (EIC) and the Joint Research Centre (JRC), is designed to support the EIC in building strategic intelligence capacity through foresight and other anticipatory approaches.

The objective of this workshop was to assess and prioritise trends and signals of novelty within all Technology Readiness Levels (TRLs) in the scope of the recently created EIC portfolio of Medical Imaging and AI.[1]

Medical Technologies and Medical Devices, as well as Health and Biotechnology, were already covered by the EIC portfolio set. The recent focus of the EIC on Medical Imaging and AI, that led to the creation of a specific portfolio on this domain, demonstrates a commitment to move European innovation forward in the medical devices domain by improving patient care and taking advantage of the significant developments of AI as an enabling technology.

The workshop was based on signals which were sourced from experts[2], a literature review and text/data mining of patents, publications, and projects. Section 2.1 provides a more detailed description of how the signals were sourced.

These signals were assessed for their importance to the future of this domain during a participatory workshop with a group of experts, all well-versed in the issues but coming from different sectors. This diversity of perspectives is a key success factor for harnessing the collective intelligence of the group. The methodology used is described in Section 1.4.

Through the process of clustering and filtering, eight topics related to emerging technologies and disruptive innovations were deemed to be of particular interest:

- Generative AI for healthcare
- Digital twins
- Multimodal data analysis
- Explainable AI
- Application of AI to specific diseases/ conditions
- XR - Augmented and Virtual Realities
- Tensor-valued diffusion encoding
- AI generated synthetic data for training AI (including for medical imaging)

Additionally, participants selected the following wild cards as individual signals that bear the most novelty and disruptiveness potential:

- Blockchain, edge computing and differential privacy for secure, AI driven medical imaging collaborative healthcare optimisation
- Quantum medical imaging

The signals that were highlighted in the workshop can be found in Section 2.

Participants were also asked to identify factors that could drive, enable or hinder the development, take-up and promotion of emerging technologies, with a particular focus on the selected topics. The identified factors fall into one or more of the following categories:

- Financial pressures and industry investment in AI healthcare
- technological advancements and cross-sector applications
- Data infrastructure, AI models, and regulatory frameworks
- Workforce, education, and societal factors
- Clinical efficiency and patient outcomes
- Trust, ethics, and AI adoption

[1] The EIC PM portfolio names used throughout this report are a simplification of the official denomination, agreed with the EIC Strategic Intelligence Team.

[2] A wider pool of experts, which included all those invited to the workshop, was approached to contribute signals.

1 Introduction

1.1 Project objectives

FUTURINNOV (FUTURe-oriented detection and assessment of emerging technologies and breakthrough INNOVation) is a collaboration between the European Commission's (EC) Joint Research Centre (JRC) and the European Innovation Council (EIC), the EC's flagship program for deep tech, implemented by the European Innovation Council and SMEs Executive Agency (EISMEA).

FUTURINNOV was designed to support the EIC in building strategic intelligence capacity through foresight and other anticipatory approaches. In this way, it supports activities focused on funding targets, programme design, policy feedback, and institutional governance.

1.2 Work Package objectives and methodology

The project is structured into 5 work packages (WP), one of which focuses on Horizon Scanning (HS) in fields that are relevant to the EIC.

HS is a qualitative method of undertaking foresight which is aimed at the early discovery of developments not yet on the radar of most experts, decision makers, or the general public, and whose potential is not widely recognised.

HS is not a predictive tool. It encourages the exploration of novelties that offer opportunities and challenges in the medium or long-term.[3] [4] [5]

This WP is formed of a series of workshops that follow a tailor-made approach to HS. This approach uses collective detection, clustering, and sense-making of signals, trends and contextual factors relating to emerging technologies and breakthrough innovations.

The understanding of what constitutes a signal or a trend may vary [6] [7]. As it is not yet consensual, for the purposes of this project they are understood as tangible manifestations of novelty in science, technology, innovation, markets, media, and other fields. What distinguishes a trend from a signal in this context is a different level of consolidation. Both can be drawn from scientific literature, reports and news articles on early technological developments, patents and other data sources.

Each workshop is usually dedicated to a specific EIC Programme Manager's (PM) portfolio, or a potential new domain deemed of interest by the EIC and is anchored in a participatory exercise preceded by stakeholder engagement, qualitative desk research and quantitative data analytics.

Outcomes will support the strategic intelligence activities of the EIC and may be used to inform future funding topics for EIC Challenges and other EC calls. They can also provide input for

[3] Amanatidou, E., Butter, M., Carabias, V., Könnölä, T., Leis, M., Saritas, O., ... & van Rij, V. (2012). On concepts and methods in Horizon Scanning: Lessons from initiating policy dialogues on emerging issues. Science and Public Policy, 39(2), 208-221.

[4] Farinha, J., Vesnic Alujevic, L. and Polvora, A., Scanning deep tech horizons: participatory collection and assessment of signals and trends, Publications Office of the European Union, Luxembourg, 2023, doi:10.2760/48442, JRC134369

[5] Dannemand Andersen, P., Bevolo, M., Ilevbare, I., Malliaraki, E., Popper, R. and Spaniol, M.J., Technology Foresight for Public Funding of Innovation: Methods and Best Practices, Vesnic Alujevic, L., Farinha, J. and Polvora, A. editor(s), Publications Office of the European Union, Luxembourg, 2023, doi:10.2760/759692, JRC134544.

[6] Rossel, P. (2012). Early detection, warnings, weak signals and seeds of change: A turbulent domain of futures studies. Futures, 44(3), 229-239. https://doi.org/ 10.1016/j.futures.2011.10.005.

[7] van Veen, B. L., & Ortt, J. R. (2021). Unifying weak signals definitions to improve construct understanding. *Futures*, *134*, 102837.

EIC and EC reports, as well as to support other EU policy making initiatives.

This was the fifth in a series of horizon-scanning workshops carried out as part of the FUTURINNOV project.[8]

1.3 Workshop objectives and scope

The objective of this workshop was to assess and prioritise trends and signals of novelty within all Technology Readiness Levels (TRLs) in the scope of the EIC portfolio of Medical Imaging and AI.

Medical Technologies and Medical Devices, as well as Health and Biotechnology, were already covered by the EIC portfolio set. The recent focus of the EIC on Medical Imaging and AI, that led to the creation of a specific portfolio on this domain, demonstrates a commitment to move European innovation forward in the medical devices domain by improving patient care and taking advantage of the significant developments of AI as an enabling technology.

1.4 Process

The workshop was held online on 17 September 2024. 16 experts attended, alongside the EIC Programme Manager Federica Zanca and the project team. The selection of experts included researchers, representatives from startups, established businesses, and policy makers. This diversity was key to bringing different perspectives to the conversation and their collective intelligence helped to build significant insights around the topics at hand.

The workshop was split into four broad sections.

1.4.1 Introduction

The main facilitator started the workshop with an explanation of the objectives as described in section 1.3. At this point it was made clear that no comments or statements would be attributed directly to individual participants.

Following a short presentation of the EIC, focused on the agency's objectives, budget and funding mechanisms, all participants were invited to introduce themselves, including the EIC Programme Manager Federica Zanca.

The methodology, namely the steps and objectives of the session, was also explained to participants, including how outputs might be used as an evidence base for future EIC funding topics or in EIC feedback to policy activities with other services of the European Commission.

1.4.2 Breakout groups

The participants were then assigned to two breakout groups. The groups had been allocated in advance to ensure a mix of profiles. Involving people who are subject matter experts but bring different perspectives to the discussion, can create more interesting outcomes.

In the breakout groups, participants were first asked to select the signals (see section 2.1) that they considered *most interesting for the future of medical imaging and AI* and then to assign them to broad Technology Readiness Levels.

[8] From this series, only two reports have been published to date. The report on Quantum Technologies: European Commission, Joint Research Centre, Mochan, A., Farinha, J., Bailey, G., Rodriguez, L., Nik, S. and Polvora, A., (Dis)Entangling the Future - Horizon scanning for emerging technologies and breakthrough innovations in the field of quantum technologies, Publications Office of the European Union, Luxembourg, 2024, https://data.europa.eu/doi/10.2760/6199218, JRC139022. And the report on Advanced Materials for Energy: Mochan, A., Farinha, J., Bailey, G., Rodriguez, L., Matteucci, F. And Polvora, A., Materialising the Future - Horizon scanning for emerging technologies and breakthrough innovations in the field of advance materials for energy, Publications Office of the European Union, Luxembourg, 2024, https://data.europa.eu/doi/10.2760/5639916, JRC139310.

They presented their selections to the group, explaining why they had chosen those specific topics. The participants in each group then asked questions about the individual selections and were invited to cluster together signals that were closely connected.

Next, participants were invited to add any relevant topics not yet raised in the discussion. These additional points were added and identified as such.

The following stage was to invite the participants to identify signals they felt answered the question: *What are the technologies and innovations that are more likely to breakthrough/grow/advance in the next 5 to 10 years?*

Once the signals were filtered in this way, there was a further discussion on interconnections aiming to reach a final 5-10 signals and/or clusters of signals which were agreed by the group.

The final step of the group exercise was to select individual signals that participants considered the most novel and potentially disruptive, that could act as a wild card[9] for this EIC portfolio. Participants had three votes to select signals from the pool captured before the workshop or proposed during the previous steps.

1.4.3 Plenary discussion and selection of topics

The groups returned to the plenary after the break-out groups for a collective presentation and discussion.

As the presentations took place, connections between the results of each group were mapped on the virtual board by the facilitators.

Following this step, a consolidated list that encompassed all topics identified by the two groups was highlighted and participants were given three votes to allocate to items on the list. This led to a ranking of the items discussed during the workshop. The results are set out in Section 2.3.

A second round of voting was then organised, to select the top wild cards. Participants were given one vote each. Those results, identifying the top wild cards, are also presented in Section 2.3.12.

1.4.4 Contextual factors

In the final exercise of the workshop, participants were asked to identify contextual factors that could drive, enable or hinder the development and uptake of the selected signals, and their underpinning emerging and disruptive technologies and innovations.

Some of these contextual factors were identified during the signal collection process and so were added in advance by the facilitators.

[9] The idea of the wild card is to guard against potentially impactful innovations being lost through the process of clustering.

2 Workshop outcomes

2.1 Signal collection

The signals presented at the workshop were collected from three main sources.

The first source of signals was a literature review. For this review, the JRC gathered third party reports[10] - both sector- and non-sector-specific - which were recent (since 2022) and represented a wide geographic coverage. The JRC then extracted from these reports those signals which were assessed as sufficiently novel and impactful.

The second source of signals was a pool of experts[11]; who submitted signals via an online collection form. For each signal, they were asked to provide:

- Title
- Summary
- Domain(s) of application
- Maturity level
- A source URL or bibliographic reference
- An indication of the underlying technology

Experts were also provided with a guidance document to explain the process of signal collection.

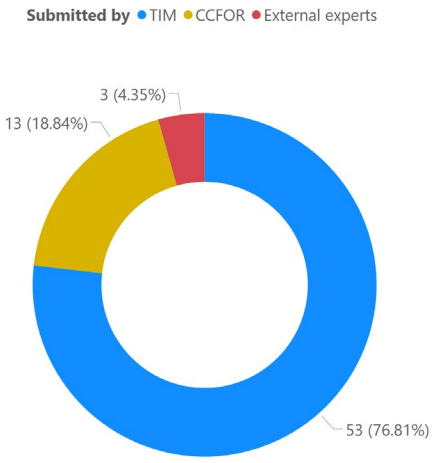
The third source of signals was the JRC's text and data mining service, TIM Analytics. This service scours scientific publications, patents and EC funded proposals and uses a customised indicator to determine the "activeness" of certain keywords/sets of documents.[12]

This indicator is defined as the ratio between the number of documents retrieved for the last three years, and the total number of documents in the dataset which range more than a decade. A sudden increase in the activity in a certain domain area could suggest a weak signal becoming a strong(er) signal, manifested by a growing number of documented scientific and innovative outputs.

From the three sources, the JRC collected 69 signals: 13 from the literature review, 3 from experts, and 53 from text and data mining.

Figure 1 below shows the diversity of sources for the signal collection. The literature review sources are marked as coming from CCFOR, or Competence Centre on Foresight. The signals coming from text and data mining are marked as submitted by TIM.

Figure 1. Signals collected for use in the Medical Imaging and AI workshop by different streams.



Source: Authors.

Figure 2 (on the next page) shows the diversity of signals collected in terms of maturity of the technology. 7 were considered as novel, 34 as

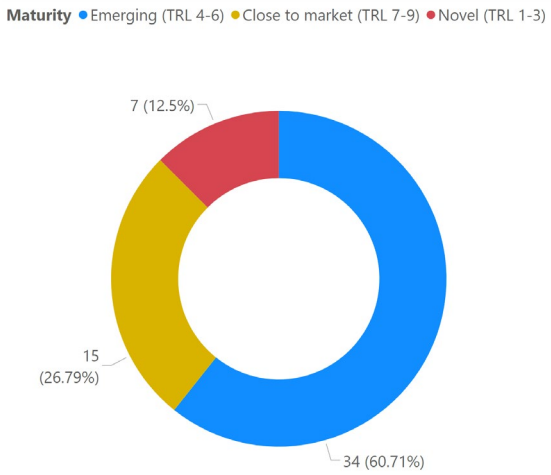
[10] Reports not authored or published by the European Commission.

[11] A wider pool of experts, which included all those invited to the workshop, was approached to contribute signals

[12] For these signals, descriptions were generated from the abstracts of the most cited scientific papers, with AI assistance. See annex 2 for more details.

emerging, and 15 as close to market, and 13 were unassigned.

Figure 2. Diversity of maturity of signals used in the Medical Imaging and AI workshop.



Source: Authors.

2.2 Group results

The following sections contain the results of the breakout groups' work, namely the clusters and signals that were considered of high relevance by participants. Some signals have a number, which refers to the original list sent to participants before the workshop (see Annex 2). Signals without a number were proposed by participants during the workshop.

2.2.1 Group A

Group A selected the following signals and micro-clusters[13] as most interesting to explore:

- **Digital twins**
  - Digital twin continuous monitoring technology (1052)
  - Digital twins for personalized medicine (1056)
  - Synthetic images for clinical trial or AI training
- **Generative AI to produce reports and explain itself**
  - Weakly/Self Supervised Segmentation (957)
  - Explainable segmentation (954)
  - Explainable AI in medical imaging (966)
  - Large language models make radiology reports more patient friendly (1099)
- **Application of AI to specific diseases/conditions**
  - Diagnosis of eye-related disease based on automated analysis of retinal images (933)
  - AI for disease prediction (1058)
- **AI generated synthetic data for algorithm training**
- **Multimodal data analysis (text, visual information etc)**
- **Paper-based wearable electronics (211)**
- **AI classified histopathology images (939)**
- **Lesion network mapping (962)**
- **Tensor-valued diffusion encoding (984)**

The group selected the following as **wild cards** (see Section 1.4.3):

- Multimodal data analysis (text, visual information etc)
- AI generated synthetic data for training AI, including for medical imaging (1063)
- Explainable AI in medical imaging (966)

During the discussion, the group highlighted three key levels of technology worth focusing on.

Firstly, everything related with acquiring the right data for further AI application, specifically in areas such as:

[13] The term "micro-clusters" refers to small aggregations of around three connected signals.

- Histopathology (study of tissues)
- Eye disorder diagnostics
- Brain lesion segmentation and differentiation

Secondly, data analysis automation with a focus on tools that could minimise human effort by automating processes such as:

- Segmentation and structuring of medical images
- Analysing this data for clinical purposes
- Incorporating generative AI to enrich data for clinical trials and research.

Finally, the group emphasised the development of digital twins to simulate clinical trials in silico (virtually). This would enhance the generalisability of AI solutions in medicine and reduce costs by allowing virtual experimentation before actual trials.

Other insights were touched upon, like paper-based wearable electronics for digital diagnostics and body signal collection, which could further facilitate data gathering.

2.2.2 Group B

Group B selected the following signals and micro-clusters as most interesting to explore:

- **Digital twins**
  - Home health care: telemedicine, chatbots
  - Digital twins for personalized medicine (1056)
  - Digital twin continuous monitoring technology (1052)
  - Personalised treatment in monitoring only
- **Generative AI for healthcare (1263)**
  - Multimodal image fusion (971)
  - Blockchain, Edge Computing and Differential Privacy for Secure, AI-Driven Medical Imaging and Collaborative Healthcare Optimization (1267)
  - Diagnosis, monitoring, and treatment of ocular diseases Multimodal medical imaging
  - Multimodal learning
- **Automation of personalised treatment**
- **XR - Augmented and Virtual Realities**
  - Virtual and augmented reality (XR) to look at tissue for segmentation - ultrasound to operate
- **Chip-based imaging technology - nano sensor**
  - Multi-parametric machine learning-based data platform for disease stratification derived from complementary organ-on-chip systems
- **Explainable AI in medical imaging (966)**
- **Speech AI**
  - A new biomarker for early detection for brain disorders
- **Intra-op AI (image-based navigation)**
  - Soft tissue organs
  - Enhances precision, efficiency, and patient outcomes

The group selected the following as **wild cards** (see Section 1.4.3)

- XR, augmented and virtual realities to look at tissue for segmentation - ultrasound to operate
- Explainable AI
- Quantum medical imaging (1102)
- Blockchain, Edge Computing and Differential Privacy for Secure, AI-Driven Medical Imaging and Collaborative Healthcare Optimization (1267)

The group emphasised the potential of automation and personalisation in healthcare, particularly in enabling early diagnostics and customised treatments through data-driven approaches tailored to individual patients.

Extended Reality (XR), including augmented and virtual reality (AR/VR), was seen as a transformative tool in healthcare, especially for imaging and treatment planning. These technologies

offer new ways to visualise and interact with medical data, enhancing precision and patient outcomes.

The group also discussed chip-based imaging technologies and nano sensors, which are paving the way for more accurate in vitro (laboratory) testing through humanised disease models. These advancements are applicable across various medical fields, offering improved testing and diagnosis.

Explainable AI (XAI) was another major focus, with the group stressing the importance of transparent and interpretable AI systems in healthcare. This is particularly relevant for speech AI and conditions like eye disorders, where clear explanations of AI-driven decisions are crucial for trust and clinical use.

Multimodal medical imaging was highlighted as a valuable approach, especially for ocular diseases. By combining different imaging techniques, healthcare providers can obtain a more comprehensive view of conditions, improving diagnostic accuracy and treatment precision.

Finally, digital twins were recognized for their potential to simulate disease models and personalize treatments, echoing Group A's discussions. This technology holds significant promise for the future of healthcare innovation.

2.3 Final results

After further clustering and a final voting step (see section 1.4.3) the following topics were selected as the most interesting for further exploration by the EIC.

2.3.1 Generative AI

Generative AI is augmenting medical imaging by improving processes like the generation of explainable reports and the accuracy of image segmentation. A key advancement in this second front is the integration of weakly and self-supervised segmentation, that utilizes deep learning techniques, such as neural networks, reducing reliance on pixel-level annotations and effectively addressing complex image deformations. The use of attention-guided multi-scale deformation fields and dense registration networks, in contrast with traditional methods, enhances segmentation performance for cases such as COVID-19 lesions and thyroid nodules.

In parallel, Explainable AI (XAI) frameworks, as explained in the next page, are contributing to more transparent and interpretable outputs. Gradient-Weighted Class Activation Mapping (Grad-CAM) visualisations and modality-specific feature importance (MSFI) metrics are being employed to improve the transparency of AI decision-making, while Generative Adversarial Networks (GANs) help reduce image artifacts, thereby improving diagnostic outcomes.

These innovations are expanding the potential role of Generative AI in increasing both the accuracy and trustworthiness of medical imaging systems.

2.3.2 Digital Twins

Digital Twins are promising to transform medical imaging and AI, especially in personalised medicine and clinical research. By creating virtual patient replicas, digital twins could integrate real-time health data from imaging, genomics, and biosensors, enabling tailored treatment and precise diagnosis. Latest advancements include using synthetic images for AI model training and virtual clinical trials, reducing the need for large datasets and accelerating drug development.

However, challenges from limited data remain due to privacy regulations, fragmented sources, interoperability issues, inconsistent data quality, high costs, evolving technologies, and ethical considerations. Hurdles also persist in the evolving nature of Digital Twins, which require sophisticated models to reflect patient responses.

Legal and ethical concerns about synthetic data use and ownership also persist. Despite these constraints, Digital Twins offer significant potential for continuous monitoring, integrating technologies like PPG (Photoplethysmogram)

and ECG (Electrocardiogram) for comprehensive cardiac care, while advancing telemedicine and precision healthcare.

2.3.3 Multimodal data analysis

Multimodal data analysis in medical imaging offers diagnosis and treatment enhancement by integrating diverse data sources like text, images, and biomarkers.

Breakthroughs in multimodal deep learning and graph neural networks are allowing comprehensive analysis of data from modalities such as echocardiography, histology, and biochemical biomarkers. This has improved therapy response prediction in areas like cardiac resynchronisation and cancer treatment.

Additionally, multimodal image fusion combines anatomical and physiological data to enhance segmentation and diagnosis, particularly for brain lesions and ocular diseases. Advanced techniques like generative adversarial networks (GANs) and transformers further reduce image artifacts and integrate long-range dependencies.

2.3.4 Explainable AI

Explainable AI (XAI) in medical imaging is key to advance transparency, by offering clear, interpretable insights into AI decision-making, addressing the “black box” nature of traditional models.

This concept includes techniques like feature attribution maps and modality-specific feature importance (MSFI) metrics to highlight key features influencing AI decision-making, helping clinicians understand and trust the outcomes.

It is worth noting two recent improvements in the field of medical imaging: topology-aware networks for analysing complex structures, such as deformed glands in histopathology, and uncertainty prediction models that enhance both accuracy and reliability. Other use of XAI is in image retrieval tasks, like detecting COVID-19 in chest X-rays.

2.3.5 XR - Augmented and virtual realities

Extended Reality (XR), encompassing Augmented Reality (AR) and Virtual Reality (VR), have potential applications in medical imaging by enhancing visualisation, training, and diagnostics.

These include using AR to overlay real-time imaging data onto a patient’s body during surgeries, which can contribute to the precision and outcomes of these procedures. In diagnostics, employing VR to create immersive 3D models of complex anatomical structures, might help clinicians better understand and diagnose conditions like tumours or vascular abnormalities.

The integration of AI-driven imaging with XR technologies may allow for more accurate simulations and personalised treatment planning.

2.3.6 Tensor-valued diffusion encoding

Tensor-valued diffusion encoding is an advanced technique in medical imaging, particularly in diffusion MRI (Magnetic Resonance Imaging), offering enhanced characterisation of tissue microstructures. This approach uses multidimensional diffusion encoding strategies to gather complex data, enabling the separation of various tissue environments with minimal assumptions.

By introducing the concept of the "shape of the b-tensor", this technology can differentiate diffusion anisotropy and orientational order, a capability beyond conventional methods. Key innovations include its application in preoperative prediction of meningioma characteristics, non-invasive breast tumour analysis, and white matter fibre mapping in the brain.

The integration of motion compensation and MRI fingerprinting allows for efficient and accurate imaging, making tensor-valued diffusion encoding a powerful tool for deep tissue analysis and improved diagnostic precision in clinical settings.

2.3.7 AI generated synthetic data for training AI (including for medical imaging)

AI-generated synthetic data may address the challenges of current limited and diverse datasets for training AI models, specifically in the health sector, as mentioned in subsection 2.3.2 - Digital Twins. Using technologies like Generative Adversarial Networks (GANs), synthetic data is created to mimic real medical images, enabling AI to be trained on large, varied datasets without the need for extensive, real-world data collection.

This improves model accuracy in detecting and diagnosing conditions such as tumours and cardiac issues, while also overcoming issues of data scarcity and privacy concerns.

The novelty lies in generating realistic and diverse data that reflects a wide range of patient conditions, speeding up AI training processes, and enabling more robust medical imaging analysis.

2.3.8 Application of AI to specific diseases/conditions

While not being a technology per se, but an application, participants highlighted the use of AI for specific disease prediction and diagnosis as a relevant topic to focus.

Recent advancements include AI-driven analysis of retinal images, where deep learning and transformers are used to detect conditions like diabetic retinopathy, macular degeneration, and glaucoma with high precision, automating processes such as image segmentation and classification.

In broader disease prediction, AI models have shown great promise in predicting outcomes for heart disease, stroke, and COVID-19, offering faster and more accurate diagnostics compared to traditional methods.

The integration of other emerging technologies like blockchain, can ensure additional data security, while with 5G enables real-time monitoring. The aspiration is not only to enhance diagnostic accuracy and early detection but also provide personalised and secure healthcare solutions.

2.3.9 Wild card final selection

As mentioned in Sections 1.2.2 and 1.2.3, each breakout group selected a short-list of signals as wild cards. During the plenary, participants considered those results and selected the following signals as the final wild cards:

Blockchain, edge computing and differential privacy for secure, AI-driven medical imaging and collaborative healthcare optimisation

The integration of blockchain, edge computing, and differential privacy bears the potential to improve AI-driven medical imaging as well as to contribute to healthcare optimisation by enhancing data security and collaboration between healthcare providers.

Edge computing enables local processing of medical images, ensuring sensitive patient data remains secure without needing transmission to central servers. Differential privacy and synthetic data generation further protect individual privacy, allowing AI models to train on diverse datasets without risking patient confidentiality.

Blockchain technology ensures tamper-proof data sharing among healthcare institutions, improving resource allocation and patient care.

This integrative approach combined further with telemedicine and remote devices, offers some potential in supporting secure diagnostics and proactive healthcare planning, especially for vulnerable populations and localised pandemics.

Quantum medical imaging

Quantum medical imaging is an emerging field that applies quantum principles to enhance diagnostic capabilities. One breakthrough development is positronium imaging in PET scans, which leverages the properties of positronium (a system of an electron and positron) to

improve cancer diagnostics. This technique enables the differentiation of healthy and cancerous tissues by measuring positronium's lifetime and production probability, offering enhanced sensitivity and specificity.

Quantum medical imaging, can explore quantum entanglement and open up new possibilities in understanding tissue environments. These advancements significantly enhance data processing, sensitivity, and diagnostic precision, positioning quantum imaging as a transformative tool in AI-driven medical imaging.

The full list of items that received votes, as well as the signals that were selected to support each topic, are listed in Annex 1.

More details on the full set of signals that were collected and considered for this process, including the original sources, can be found in Annex 2.

2.4 Drivers, enablers and barriers

Participants were also invited to identify drivers, enablers and barriers that could affect the development and take-up of technologies and innovations in medical imaging and AI, with a particular focus on those selected in the previous step.

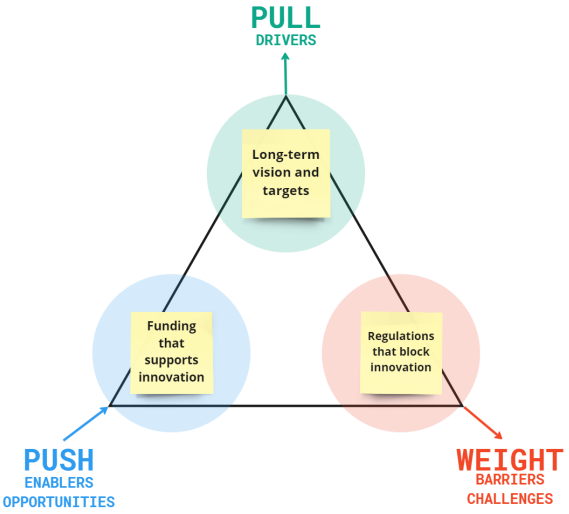
Some of these contextual factors can act in multiple ways. For example, standards can hinder through stifling innovation or can enable by creating an environment for interoperability.

Regulations can also play multiple roles, namely acting as barriers for development of novel solutions, but on the other hand, driving and aligning those innovations with ethical and legal frameworks.

In that sense, emphasis was on identifying the factor rather than finding the ideal categorisation. These insights provide a complementary view regarding the main issues affecting the healthcare sector and represent a potential input for further discussion.

The contributions were mapped through an adapted version of the "Futures Triangle" framework [14].

Figure 3. Visual representation of the adapted version of the "Futures Triangle" framework used in the workshop, including some examples given to the participants.



Source: Authors.

The main elements highlighted by the participants are listed below.

2.4.1 Drivers

Drivers are considered as guiding forces, elements that pull new developments.

---

[14] Inayatullah, S. (2023). *The Futures Triangle: Origins and Iterations*. World Futures Review, 15(2-4), 112-121. https://doi.org/10.1177/19467567231203162

Technological Advances

The rapid development of AI technologies, including large language models (LLMs), generative AI, and explainable AI (XAI), is driving innovation in healthcare. These technologies are enabling more effective tools for medical imaging, such as faster diagnosis, synthetic data generation, and personalised treatment suggestions, which are expected to transform patient care and clinical decision-making.

Financial Pressures and Industry Investment in AI Healthcare

Financial pressures from aging populations and strained healthcare systems are pushing healthcare providers to explore AI as a cost-effective solution. AI is improving efficiency, reducing costs, and offering strong returns on investment. Industrial investments, especially in pharmaceuticals, are accelerating AI-driven advancements in drug development and healthcare innovation. Policymakers can identify a direct link between investment in AI development and adoption and its impact in cost-saving and operational efficiency.

Regulatory Frameworks and AI Model Integration

The integration of AI models relies on trusted platforms, robust data-sharing infrastructures, and understanding data interactions. Regulatory frameworks, like EU directives, can secure ethical and safe AI deployment. Hybrid networks for large language models (LLMs) and generative AI (GenAI) are enhancing AI's ability to analyze complex medical data, improving clinical decisions.

Education, Collaboration, and AI Adoption

Education and collaboration are considered key drivers for AI adoption in healthcare. Ensuring healthcare professionals are trained on AI tools, including risks and benefits, will enhance clinical integration. Cross-disciplinary collaboration between clinicians and AI developers may foster alignment with clinical needs, building trust and helping accelerate the adoption of AI technologies for improved patient outcomes.

2.4.2 Enablers

Enablers provide opportunities for further development and give a push to the technologies.

Data Infrastructure and Standardization for AI

Robust data infrastructures and standardization are considered critical enablers for AI in healthcare. Elements such as standardization of data reuse, open access databases, and blockchain can facilitate secure data sharing. Application Data Infrastructure and European data standards ensure interoperability, while open access AI models like the ones from Meta and others may lower barriers for AI development and integration.

Technological Advancements and Cross-Sector Applications

AI's social applicability in healthcare and the growing use of pathfinder applications are crucial enablers for its expansion across various sectors. Existing AI technologies from other fields are being adapted, accelerating innovation. Virtual data sharing, supported by Internet of Things (IoT) interoperability, is allowing real-time data integration, enhancing AI's diagnostic and treatment capabilities. The adoption of Large Language Models (LLMs) in the general population and AI's role in reducing patient and worker exposure may further extend its reach in healthcare.

Workforce, Societal Drivers, and Adoption Pressure

Aging population and the shortage of doctors, as mentioned before in the drivers, are key elements at play in the development and adoption of AI in healthcare. Besides the economic factors, it also creates a societal push for AI adoption. Collaboration between healthcare and AI experts is considered crucial to align AI tools with clinical needs, while increased

awareness of AI's potential in STEM (Science Technology, Engineering and Mathematics) fields will drive further innovation. The expanded academic focus on AI and the rise of spinouts are fostering the development of new AI tools, while societal drivers such as workforce shortages can accelerate their adoption.

Ethical and Trust-Centred AI Implementation

The increasing demand for trustworthy AI and ethical AI is regarded as a key enabler in AI adoption. Epistemic AI can play a role in addressing transparency and trust issues. Establishing a clear framework for ethical AI use in healthcare is crucial to ensure the safe deployment of AI systems, particularly in sensitive applications like diagnostics and treatment. Trust-building will also rely on cross-disciplinary collaboration and the development of transparent AI tools that clinicians and patients alike can rely on.

2.4.3 Barriers

Barriers are factors that do (or could) hinder technological advances.

Data Accessibility and Standards

As mentioned in the enablers, one of the most significant barriers is the lack of open-access databases and the absence of clear, consistent data standards. Without access to large, diverse datasets, AI models cannot be effectively trained or validated, limiting their potential impact. Policymakers can play a pivotal role in promoting data-sharing initiatives and standardization across countries and healthcare systems.

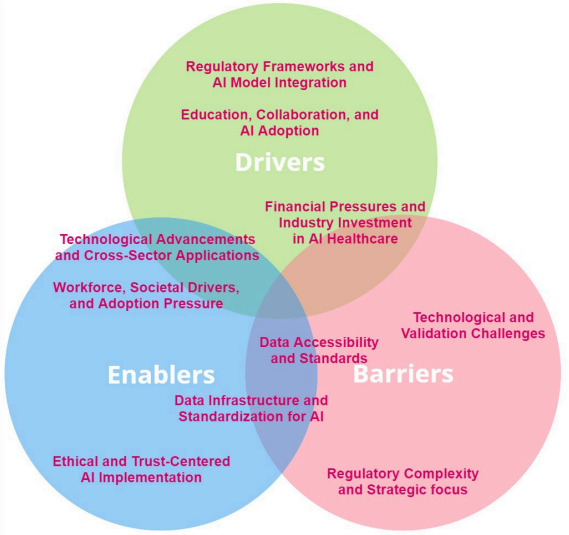
Technological and Validation Challenges

Unclear frameworks for risk assessment and the need for more clinical evidence may slow down the integration of AI technologies. Additionally, cybersecurity threats pose risks to the data used in AI models. Policymakers can support the development of robust validation methodologies and encourage investment in cybersecurity measures, ensuring that AI technologies are reliable and secure for clinical use.

Regulatory Complexity and Strategic focus

Regulation, as well as a driver, it is also considered a barrier, as fragmented and overly complex regulatory frameworks are slowing down AI adoption in healthcare, particularly in medical imaging. Inconsistent regulations across countries further complicate the process. Policymakers can address this issue by focusing on harmonizing regulatory standards. In addition, strategic focus on relevant healthcare problems is often lacking, leading to misaligned AI developments that do not meet clinical needs.

Figure 4. Analysis of identified contextual factors to highlight potential overlaps.



Source: Authors.

3 Conclusions

The results presented earlier, will support the strategic intelligence activities of the EIC and may be used to inform future funding topics for EIC Challenges and other EC calls.

Further to these, the following summary conclusions have been drawn by the authors from the various exercises throughout the workshop and experts' discussions.

They can provide an overview and complementary insights for policy-makers and the EIC in their mission to support the field of Medical Imaging and AI.

3.1 Emerging technologies

During the workshop, experts identified several emerging technologies with transformative potential in healthcare. Generative AI and digital twins were highlighted as particularly promising, enabling the generation of synthetic data to address data scarcity, supporting personalised treatment planning, and simulating complex clinical scenarios.

Digital twins, in particular, were noted for their ability to dynamically evolve in response to patient treatments, improving precision in modelling disease progression and treatment outcomes.

3.2 Data

Despite this potential, several challenges were raised, including limited access to well-annotated datasets and a lack of sufficient data digitalisation, particularly in areas like pathology.

The experts stressed the importance of creating open-access databases and establishing standardized data-sharing protocols to enable AI model training and ensure consistent integration across healthcare systems.

The European Health Data Space initiative was acknowledged as a potential solution to the data-sharing challenges, but building the necessary infrastructure and harmonising regulations across countries is expected to take several years.

Multimodal data analysis and explainable AI were also pointed out, recognising the value of integrating multiple data sources—such as medical imaging, genomic data, and electronic health records—to provide more comprehensive diagnostic and treatment options.

XR Augmented and Virtual Reality technologies were noted for their potential in medical training, surgery, and diagnostics, offering new ways to interact with and visualise medical data.

3.3 Collaboration and trust

A key enabler discussed was the importance of collaboration between healthcare professionals and AI experts. This collaboration, along with education programs aimed at increasing AI literacy among clinicians, was seen as essential to building trust in AI tools and aligning their development with real-world clinical needs.

However, there is still considerable mistrust of complex AI technologies, particularly when it comes to the explainability of AI-driven decisions in high-stakes areas like disease prediction and personalised treatment. Clinicians often express concerns about relying on AI systems that are not fully transparent or understandable.

3.4 Regulation and investment

Regulatory challenges were also a recurring theme. Experts pointed to fragmented regulatory frameworks across different regions, particularly around data privacy and the legal complexities of synthetic data, as significant barriers to adoption.

The participants underscored the importance of focused investment in AI infrastructure and education to ensure the successful and responsible integration of generative AI, digital twins, and other emerging technologies into healthcare systems.

As a final reflection, while the potential of these technologies is immense, their advancement is contingent on addressing key barriers such as data accessibility, regulatory alignment, and clinical validation.

List of abbreviations and definitions

Abbreviations	Definitions
AI	Artificial intelligence
AR	Augmented Reality
CCFOR	Competence Centre on Foresight
EC	European Commission
ECG	Electrocardiogram
EIC	European Innovation Council
EISMEA	European Innovation Council and SMEs Executive Agency
EU	European Union
GAN	Generative Adversarial Networks
Grad-CAM	Gradient-Weighted Class Activation Mapping
HS	Horizon scanning
JRC	Joint Research Centre (the scientific service of the European Commission)
LLMs	Large Language Models
MR	Magnetic Resonance
MRI	Magnetic Resonance Imaging
MSFI	Modality Specific Feature Importance
PM	Programme Manager
PPG	Photoplethysmogram
TIM	Tools for Innovation Monitoring
TRL	Technology Readiness Level
R&I	Research and Innovation
SMEs	Small and Midsize Enterprises
STEM	Science, Technology, Engineering and Mathematics
STEP	Strategic Technologies for Europe Platform
VR	Virtual Reality
WP	Work package
XAI	Explainable AI
XR	Extended Reality

List of figures

Annexes

Annex 1. Full list of topics (signals and clusters) that received votes in plenary

Topics in green were selected as the final list. Non-numbered topics (including both signals and clusters) were proposed by participants during the workshop. For more details on numbered signals see annex 2.

	Generative AI for Healthcare (1263)	10 votes
	Digital Twins	6 votes
	Multimodal data analysis (text, visual information, etc)	5 votes
	Explainable AI	4 votes
	XR, Augmented and Virtual Realities	2 votes
	Tensor-valued diffusion encoding (984)	2 votes
	AI generated synthetic data for training AI (including medical AI)	2 votes
	Application of AI to specific diseases/conditions	2 votes
	Chip based imaging technology - nanosensor	1 vote
	AI classified histopathology images (939)	1 vote
	Lesion network mapping (962)	1 vote
	Intra-op AI (image-based navigation)	1 vote

Annex 2. Full list of signals sent to participants before the workshop.

For more information on the signal collection, please see section 2.

NUMBER | TITLE
1267 | Blockchain, Edge Computing and Differential Privacy for Secure, AI-Driven Medical Imaging and Collaborative Healthcare Optimization
SUGGESTED MATURITY
Novel (TRL 1-3)
SUMMARY DESCRIPTION
"This signal emphasizes a transformative approach for European healthcare through the integration of edge computing, differential privacy, and blockchain technology, aimed at revolutionizing medical imaging, data management, and hospital operations. The proposed system leverages edge computing to process medical images locally on devices, ensuring that sensitive patient data remains secure and does not need to be transmitted to central servers. By utilizing differential privacy and synthetic data generation, the system enhances security, enabling AI models to train on diverse datasets without compromising individual privacy. Moreover, by incorporating remote devices and telemedicine systems that capture only specific signals from patients—without disclosing their full clinical or pathological data—the system can facilitate the design of diagnostic and therapeutic pathways and targeted screening. This approach is particularly effective in addressing localized pandemics or emerging pathologies within specific regions. The integration of chatbots, blockchain, and differential privacy systems also offers robust support for socially vulnerable patients, particularly those with chronic conditions and aging populations. In addition, these AI-driven support mechanisms can be applied to preventive healthcare for children, addressing the risks associated with the improper and continuous use of IT systems. By monitoring emerging pathologies in younger populations, the system enables proactive territorial health planning to manage or mitigate necessary treatments for these new generations. The use of blockchain in collaborative learning ensures secure, tamper-proof data sharing among healthcare institutions across Europe. This capability can optimize waiting lists and resource allocation through AI, resulting in improved patient outcomes and more efficient healthcare delivery. The decentralized nature of this approach not only enhances privacy and security but also reduces latency and increases the reliability of AI-driven diagnostics and management systems, paving the way for a more resilient and responsive European healthcare infrastructure"
SOURCE
A source was not provided during the submission stage, but as the signal was deemed relevant during the workshop, it was kept in this final report.

NUMBER | TITLE
1263 | Generative AI for healthcare
SUGGESTED MATURITY
Novel (TRL 1-3)
SUMMARY DESCRIPTION
Generative AI refers to machine/deep-learning models that can generate high-quality text, images, and other content based on the data they were trained on. The capability of generating synthetic data will have a strong impact in healthcare for the following applications: virtual clinical trials; medical image fast reconstruction, drug compound generation, adaptive therapy optimization, clinical decision support systems, digital twins.
SOURCE
https://implementationscience.biomedcentral.com/articles/10.1186/s13012-024-01357-9

NUMBER | TITLE
1130 | Potential of oculomics as biomarkers for disease
SUGGESTED MATURITY
Close to market (TRL 7-9)
SUMMARY DESCRIPTION
development and application of novel, noninvasive ocular (eye) imaging technologies, machine learning algorithms, and other tools to identify highly sensitive and specific biomarkers for diseases that affect the entire body. Oculomics can have a significant impact on early detection of diseases before the onset of symptoms, and can help clinicians with early disease intervention, risk assessment, tracking disease progression, and supportive therapeutics. Ocular imaging technologies provide a unique opportunity for measurements of diabetes, hypertension, stroke, and coronary, inflammatory, metabolic, and renal diseases. Because of is noninvasive nature, Oculomics has the potential to provide advanced health care to all communities, including rural and underserved communities throughout the world.
SOURCE
National Institutes of Health NIH website https://commonfund.nih.gov/venture/oculomics

NUMBER | TITLE
1104 | CoDLRBVS: Cognitive deep learning approach for retinal blood vessel segmentation
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
This paper presents CoDLRBVS, a pioneering cognitive-based deep learning model for medical image processing, namely retinal blood vessel segmentation. The model demonstrates a remarkable balance across performance metrics, achieving notable mean accuracy of 96.7%, precision of 96.9%, sensitivity of 99.3%, and specificity of 80.4% across all of the studied datasets, positioning it as a strong contender among existing state-of-the-art methods. The model's high specificity significantly mitigates false positives, which is vital for precise segmentation. Hence, the novelty of our approach lies in its balanced performance, avoiding the common trade-offs among sensitivity, specificity, and accuracy observed in other methods.
SOURCE
Nature A cognitive deep learning approach for medical image processing https://www.nature.com/articles/s41598-024-55061-1

NUMBER | TITLE
1103 | Medical Vision Generalist: a unified framework for medical imaging
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
The paper "Medical Vision Generalist: Unifying Medical Imaging Tasks in Context" introduces Medical Vision Generalist (MVG), a foundation model designed to tackle a diverse array of medical imaging tasks within a unified framework. The tasks include cross-modal synthesis, image segmentation, denoising, and inpainting, all encompassed within an image-to-image generation context. MVG employs a hybrid learning approach, combining masked image modeling (MIM) with autoregressive training, optimized for the multifaceted nature of medical imaging. The researchers designed MVG to standardize the inputs and outputs exclusively as images, thereby unifying the varied nature of medical imaging tasks. By treating tasks as image generation processes conditioned on prompt image-label pairs alongside input images, this innovative approach enables flexibility and adaptability across different imaging modalities and datasets.
SOURCE
Medical Vision Generalist: Unifying Medical Imaging Tasks in Context https://arxiv.org/pdf/2406.05565

NUMBER | TITLE
1102 | Quantum medical imaging
SUGGESTED MATURITY
Novel (TRL 1-3)
SUMMARY DESCRIPTION
Medical imaging is considered one of the most important areas within scientific imaging due to the rapid and ongoing development in computer-aided medical image visualisation, advances in analysis approaches, and computer-aided diagnosis. Here, the principles of quantum computation and information to develop the field of medical image processing will be reviewed. The advancement of quantum computation in image processing has proved its outstanding properties for processing and storage capacity compared to the classical methods
SOURCE
IET Quantum medical images processing foundations and applications https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/qtc2.12049?af=R

NUMBER | TITLE
1099 | Large language models make radiology reports more patient friendly
SUGGESTED MATURITY
Close to market (TRL 7-9)
SUMMARY DESCRIPTION
Generative artificial intelligence can significantly improve patients' understanding of their radiology reports, in addition to streamlining communication between referring providers and radiologists. That's according to new research published in Scientific Reports that analyzed the effectiveness of AI-generated reports in simplifying radiologists' imaging interpretations into more easily understandable language, as judged by both radiologists and nonphysicians.
SOURCE
Health Imaging Large language models make radiology reports more patient friendly https://healthimaging.com/topics/health-it/enterprise-imaging/large-language-models-make-radiology-reports-more-patient-friendly

NUMBER | TITLE
1098 | New software could improve diagnosis of lung conditions for patients who cannot tolerate contrast dye
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
New imaging software could provide more accurate diagnoses for patients with lung issues who are unable to receive contrast media during their CT scan. Iodinated contrast media is a valuable tool in imaging, as it offers radiologists a more detailed view of patients' anatomy. But for many people, contrast dye cannot be used due to either an allergy or medical condition that prohibits it. For those people, noncontrast exams are the only option, although they are known to be less accurate. But new software developed by pulmonologist Girish Nair, MD, with Corewell Health William Beaumont University Hospital in Royal Oak, Michigan, and biomedical engineer Edward Castillo, PhD, with the University of Texas at Austin, could address the issue. The machine learning-based software—CT-Derived Functional Imaging, or CTFI—uses a formula called the Integrated Jacobian Formulation to calculate lung volume based on metrics derived from imaging taken during inhalation and exhalation. This sort of image capture is not new, though it is improved with this software, Nair indicated in a release.
SOURCE
Health Imaging New software could improve diagnosis of lung conditions for patients who cannot tolerate contrast dye https://healthimaging.com/topics/artificial-intelligence/new-software-could-improve-diagnosis-lung-conditions-patients-who-cannot-tolerate-contrast-dye

NUMBER | TITLE
1097 | An AI alternative that generates virtual contrast-enhanced images without chemical agents
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
While the use of chemical contrast materials is the gold standard for diagnosing many diseases, increasing numbers of patients, associated costs and potential side effects pose significant challenges. While uncommon, risks to patients include allergic reactions and other short-term adverse reactions. A new non-chemical imaging technique could reduce such risks while also saving time and money. Such a technique could also help alleviate burdens of potential supply chain issues, such as the global shortage of iodinated contrast media in 2022. With a new four-year, $1.125 million grant from the National Science Foundation (NSF), researchers at Case Western Reserve University hope to develop an artificial intelligence (AI) alternative that generates virtual contrast-enhanced images without chemical agents. Their goal: a safer, quicker and cheaper process using non-contrast images only.
SOURCE
MedImaging.net AI Contrast Agent Technology to Make Medical Imaging Safer, Faster and Less Expensive https://www.eurekalert.org/news-releases/1029683

NUMBER | TITLE
1085 | Holistic imaging of human brain tissues at multiple resolutions allows mapping of the human brain
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Researchers developed a technology pipeline to image entire human brain hemispheres at high resolution. This breakthrough allows for detailed analysis of brain structures, offering insights into diseases like Alzheimer's. The study reveals how specific neurons are activated during sleep and how sleep deprivation impacts memory. This advancement paves the way for comprehensive brain mapping and understanding brain function.
SOURCE
Neuroscience News https://neurosciencenews.com/neurotech-brain-mapping-26318/

NUMBER | TITLE
1075 | Epistemic AI
SUGGESTED MATURITY
n/a
SUMMARY DESCRIPTION
Epistemic Artificial Intelligence (AI) in the field of Information and Communication Technology (ICT) is a form of AI that addresses uncertainty in AI predictions, which is known as epistemic uncertainty. This type of AI is capable of learning from accidents in various industrial sectors to prevent similar accidents, primarily by focusing on the relation between human errors and their influencing factors. The AI utilizes a predefined classification scheme to analyse accident reports for organisational, technological, and individual factors that may trigger human errors. It uses Bayesian approaches for probabilistic reasoning to determine the confidence in the probabilities in light of the training data. Epistemic AI also applies Explainable AI (XAI) techniques to provide transparency to machine learning predictions, thus enabling understanding of how features contribute to epistemic uncertainty. The technology is also used in Quantum Machine Learning, providing benefits such as high levels of generalization and epistemic uncertainty estimation. Other applications include estimating failure risks and predictive uncertainties of black-box classification models, and improving communication in human-robot collaborations; The novelty of epistemic AI lies in its ability to address uncertainties in predictions made by AI systems. Traditional AI systems are not designed to handle uncertainties and therefore, may not be reliable in safety-critical domains. Epistemic AI addresses this gap by incorporating uncertainty quantification and explainability in AI models. Furthermore, unlike traditional AI that lacks transparency, epistemic AI uses XAI techniques to provide insights into the decision-making process of AI systems. This technology also surpasses traditional AI by applying Bayesian learning in Quantum Neural Networks, providing greater generalization and uncertainty estimation. Another novelty is that it provides a risk score and decomposes uncertainty estimates into aleatoric and epistemic uncertainty components, offering insights into the sources of uncertainty causing failures. This allows for the distinction between failures caused by data variability, data shifts and model limitations, providing useful guidance on appropriate risk mitigation actions. The technology also enables more natural communication in human-robot collaborations, handling both aleatoric variability and epistemic uncertainty, thus making it suitable for uncertain and noisy environments.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1016/j.ssci.2021.105528; http://doi.org/10.1016/j.ijhcs.2022.102839; http://doi.org/10.1007/978-3-031-16452-1_49; http://doi.org/10.1109/ICASSP49357.2023.10096780; http://doi.org/10.1109/BigData55660.2022.10020687; http://doi.org/10.1039/d3dd00002h; http://doi.org/10.1016/j.ins.2023.119356; http://doi.org/10.1109/TITS.2023.3288507

NUMBER | TITLE
1066 | Trustworthy AI
SUGGESTED MATURITY
n/a
SUMMARY DESCRIPTION
Trustworthy Artificial Intelligence (AI) is a technology that aims to increase trust, safety, interpretability, and accountability in AI systems. It does so through the integration of well-founded knowledge representation, logical reasoning, and deep learning, an approach also known as neurosymbolic computing. The technology further enhances trust in AI through eXplainable AI (XAI) methods, which provide clear reasoning behind the decision-making processes of AI models. Applications of trustworthy AI span across various sectors including healthcare, government, and the Internet of Things (IoT). In healthcare, for instance, it supports medical data analysis and diagnostics, while in government, it assists in policy initiatives. In the IoT sector, trustworthy AI ensures privacy, security, and reliable decision-making in high-risk applications; The novelty of trustworthy AI lies in its ability to address the "black box" nature of traditional AI systems. By integrating neural network-based learning with symbolic knowledge representation and logical reasoning, it provides a clear and understandable explanation of how AI models arrive at their decisions. This is a significant shift from the conventional AI models that provide little or no insight into their decision-making processes. Furthermore, advances in trustworthy AI have led to the development of techniques like federated learning and decentralized blockchain-based learning, enhancing privacy and security in AI applications. The introduction of explainability concepts such as model and data explainability, post-hoc explainability, and assessment of explanations further distinguishes trustworthy AI from established technologies. Additionally, the technology offers a multidimensional measure of trust, factoring in human-like trust and functionality trust, unlike traditional AI systems.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1080/10447318.2022.2050543; http://doi.org/10.4324/9780429262081-19; http://doi.org/10.1007/s10462-023-10448-w; http://doi.org/10.1109/KST57286.2023.10086917; http://doi.org/10.1016/j.inffus.2023.101805; http://doi.org/10.1109/SaTML54575.2023.00039; http://doi.org/10.1145/3593013.3594067; http://doi.org/10.1016/j.eswa.2023.121220

NUMBER | TITLE
1065 | Ethical AI
SUGGESTED MATURITY
n/a
SUMMARY DESCRIPTION
Ethical AI is a technology that aims to ensure fairness, transparency, and respect for individual persons in the application of artificial intelligence (AI), particularly in machine learning algorithms used in healthcare (HMLA). It involves a conceptual redefinition of fairness beyond non-discrimination and absence of biases, adding a distributive and socio-relational dimension. Transparency in AI systems involves a clear understanding of the different aspects of AI, enabling better human-technology interaction and human agency. Ethical AI also seeks to integrate ethical principles into AI design practices, considering the motivations and barriers faced by AI practitioners. Furthermore, it involves the strategic management of AI-powered service innovation capability, taking into account AI-market capability, AI-infrastructure capability, and AI-management capability, including AI ethics; Ethical AI is a novel approach compared to established technologies, primarily due to its focus on the ethical implications of AI. While previous technologies have primarily focused on the technical aspects of AI, Ethical AI brings a new dimension of fairness, transparency, and respect for individuals into the picture. It goes beyond the traditional focus on non-discrimination and absence of biases, introducing a more comprehensive notion of fairness. Additionally, it provides a framework for navigating the complexities of human-technology interactions, and proposes a detailed field scan of the AI audit ecosystem to ensure algorithmic accountability. It also addresses the need for ethical principles to be directly applied to private actors in AI governance, and suggests a shift from abstract ethical theories to more practical and implementable design practices. This technology also acknowledges the need for increased focus on ethical analysis grounded in concrete use-cases, people's experiences, and sensitivity to structural and historical power asymmetries
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1007/978-3-030-81907-1_2; http://doi.org/10.1080/17439884.2021.2010094; http://doi.org/10.1145/3531146.3533213; http://doi.org/10.1109/WACV56688.2023.00142; http://doi.org/10.3390/socsci12030148; http://doi.org/10.1109/ICIDCA56705.2023.10099747; http://doi.org/10.4018/978-1-6684-7164-7.ch014; http://doi.org/10.1145/3544548.3580959

NUMBER | TITLE
1064 | 2D memristor for neuromorphic computing
SUGGESTED MATURITY
n/a
SUMMARY DESCRIPTION
The technology, 2D memristor for neuromorphic computing, refers to the application of two-dimensional materials in memristor construction - a type of resistor with memory effect that is crucial for neuromorphic computing, a form of computing that mimics the neural structure of the human brain. Researchers have recently been investigating the use of atomically thin 2D materials, such as transition metal dichalcogenide (TMD) monolayers and hexagonal boron nitride (hBN), to construct these memristors. These 2D material memristors, especially when built in a vertical form, can achieve lower switching voltages, an important factor in memristor research. Additionally, these memristors can exhibit synapse-like learning behavior, making them promising for low-power neuromorphic computing and potentially enabling direct interfacing with mammalian neuronal networks; The novelty of this technology lies in its use of 2D materials to construct memristor devices for neuromorphic computing, which have demonstrated unique memristive characteristics and synaptic functionalities. The use of 2D materials allows for the construction of atomic-scale filaments, which can significantly lower switching voltages. This technology also allows for the demonstration of spike-timing dependent plasticity (STDP), a first in 2D-material-based vertical memristors, and offers the potential to build neural networks for emulating ionic interactions among neurons. Furthermore, the use of 2D materials in memristor construction provides the potential for high-density, fast, low power consumption memory devices. This technology has also led to the development of gate-tunable 2D-oxide memtransistors, an integrated device of a memristor and a transistor, which offers additional degrees of freedom in neuromorphic device design
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1021/acsnano.8b03977; http://doi.org/10.1021/acs.nanolett.8b05140; http://doi.org/10.1002/aelm.201901335; http://doi.org/10.1002/adma.202002092; http://doi.org/10.1021/acsami.1c18329; http://doi.org/10.1002/adom.202202378; http://doi.org/10.35848/1882-0786/acc8b6; http://doi.org/10.1002/adma.202303737; http://doi.org/10.1088/2053-1583/acdfe1; http://doi.org/10.1002/adfm.202309058

NUMBER | TITLE
1063 | AI generated synthetic data for training AI, inc for medical imaging
SUGGESTED MATURITY
n/a
SUMMARY DESCRIPTION
AI-generated synthetic data is a technology in the field of ICT that involves the creation of artificial data sets for training machine learning models. This is achieved through processes such as interactive machine teaching, generative adversarial networks, or the use of software like Unreal Engine 4 to create realistic synthetic environments. Applications of this technology range from training AI agents for online classes, predicting and mitigating tokamak plasma disruption, detecting anomalies in operating environments such as airfields, policy evaluation in data-driven cities, improving machine learning methodologies in medicine, enhancing industrial robotic tasks, wavefront sensing, optical design parameter modeling, business decision-making, and object recognition in production processes; The novelty of AI-generated synthetic data technology lies in its ability to overcome the challenges of data scarcity, data diversity, and time-consuming training processes associated with traditional machine learning models. By generating unlimited, diverse, and realistic synthetic data sets, AI models can be trained more efficiently and effectively. Additionally, the use of synthetic data allows for a wider exploration of policy interventions, improved decision-making support based on patient data in medicine, more accurate prediction of super modes in optical design, and the creation of reliable and consistent classification systems. Furthermore, this technology enables real-time, cost-effective solutions and reduces the need for real-world damage or disruption for training purposes, thus offering significant cost and time savings.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1016/S0167-9236(02)00110-0; http://doi.org/10.1117/12.2564070; http://doi.org/10.1117/12.2586046; http://doi.org/10.3390/jpm12081278; http://doi.org/10.1109/TNB.2022.3221104; http://doi.org/10.1002/ctpp.202200051; http://doi.org/10.2196/40589; http://doi.org/10.1038/s41746-023-00834-7; http://doi.org/10.1109/SmartNets58706.2023.10215825

NUMBER | TITLE

1060 | Wearable sweat sensor

SUGGESTED MATURITY

n/a

SUMMARY DESCRIPTION

The wearable sweat sensor is a cutting-edge biotech device that enables continuous, non-invasive health monitoring by analyzing sweat. Using either laser-engraved sensors or flexible electronics, these devices can detect and monitor physical and chemical biomarkers, such as temperature, respiration rate, and concentrations of substances like uric acid and glucose, which are associated with various health conditions. They function by collecting sweat through microfluidic channels and analyzing the sweat for biomarkers using a variety of methods, including electrochemical sensing and surface-enhanced Raman spectroscopy. With the unique ability to provide real-time, continuous data, these sensors hold significant potential in personalized medicine, disease diagnostics, fitness tracking, and drug monitoring; The novelty of the wearable sweat sensor technology lies in its ability to continuously and non-invasively monitor health status through sweat analysis, addressing the limitations of conventional health monitoring techniques that are invasive and intermittent. These sensors can detect a wide range of analytes at low concentrations, which has been a challenge for existing sensors. Additionally, unlike traditional sensors, these devices can be fabricated at a large scale using techniques such as roll-to-roll gravure printing. The integration of advanced materials and techniques, such as inorganic-nanomaterials-based active layers, nanowire transistor arrays, liquid metals, and molecularly imprinted polymers, further enhance the sensor's flexibility, sensitivity, and stability. Another groundbreaking development is the incorporation of self-powered modules, such as enzymatic biofuel cells and perovskite solar cells, which eliminates the need for external power supplies. Furthermore, the use of flexible electronics and soft materials enhances the device's conformability and comfort, making it suitable for long-term wear. These innovative aspects make the wearable sweat sensor a leap forward in the realm of personalized health monitoring.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1021/acs.accounts.8b00500; http://doi.org/10.1038/s41587-019-0321-x; http://doi.org/10.1126/sciadv.abn1736; http://doi.org/10.1038/s41378-022-00443-6; http://doi.org/10.1021/acssensors.2c02016; http://doi.org/10.1016/j.nanoen.2023.108212; http://doi.org/10.1016/j.snb.2023.133451; http://doi.org/10.1021/acs.chemrev.2c00823; http://doi.org/10.1016/j.bios.2023.115360; http://doi.org/10.1038/s41928-023-00996-y

NUMBER | TITLE

1059 | AI for macular degeneration

SUGGESTED MATURITY

n/a

SUMMARY DESCRIPTION

The technology of AI for macular degeneration entails the use of artificial intelligence (AI) and machine learning (ML) models to detect and diagnose age-related macular degeneration (AMD), a leading cause of vision loss in the elderly. AI models can automatically detect AMD through training data from large sets of fundus or OCT images, providing a cost-effective, simple, and fast diagnosis. The high accuracy of these models allows them to differentiate controls and AMD patients and predict responsiveness to anti-VEGF therapy in nAMD patients. Furthermore, AI-based tools are beneficial for facilitating early treatment, improving health care quality, and enhancing medical workflow. This technology is also being explored for use in telemedicine, offering a cloud-based tool for remote diagnosis and proposed treatment of AMD; The novelty of this technology lies in its application of AI and ML algorithms for AMD detection and diagnosis. While AI has been applied in various medical fields, its use in ophthalmology, particularly for AMD, marks a significant advancement. These AI models are trained on large datasets of retinal images and are capable of achieving a diagnostic accuracy comparable to human experts. Moreover, the technology offers a more transparent and interpretable diagnosis by highlighting the regions recognized by the neural network. The integration of this technology into a cloud-based platform for telemedicine also represents a novel approach, enabling remote AMD diagnosis and treatment recommendations. This technology not only outperforms traditional methods in terms of accuracy and efficiency but also addresses the limitations of availability of retina specialists and trained human graders.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1016/j.cell.2018.02.010; http://doi.org/10.1111/ceo.13381; http://doi.org/10.7150/thno.28447; http://doi.org/10.22608/APO.2018479; http://doi.org/10.1016/S2589-7500(21)00055-8; http://doi.org/10.1038/s41433-021-01540-y; http://doi.org/10.1016/j.eclinm.2021.100875; http://doi.org/10.1097/APO.0000000000000397; http://doi.org/10.3389/fmed.2022.875242; http://doi.org/10.3389/fcell.2023.1174936

NUMBER | TITLE
1058 | AI for disease prediction
SUGGESTED MATURITY
n/a
SUMMARY DESCRIPTION
AI disease prediction is a rapidly evolving technology that leverages artificial intelligence (AI), machine learning, and deep learning techniques to predict and diagnose diseases. This technology uses vast amounts of data from electronic health records and various other sources, which is then processed using big data analytics. The application of AI in disease prediction has shown promising results in numerous areas, including the screening of COVID-19 patients, the prediction of heart disease, and the early detection of stroke symptoms. Additionally, the integration of AI with emerging technologies like blockchain, 5G, and the metaverse, enhances data security, real-time monitoring, and provides immersive healthcare experiences. In essence, AI disease prediction has the potential to transform healthcare services by improving accuracy, speed, and security of disease diagnosis and prediction; AI disease prediction represents a significant advancement over traditional disease diagnosis methods. Unlike conventional methods, AI-based models can analyze vast amounts of data and identify patterns that may be too complex for human analysis. These models can predict disease outcomes with high accuracy and in real-time. Furthermore, the incorporation of explainable AI (XAI) approaches enhances the transparency and interpretability of these models, addressing the 'black box' nature of AI. The novelty also lies in the integration of AI with other advanced technologies. For instance, the use of blockchain ensures data security and integrity, while the metaverse provides an immersive healthcare experience. The combination of AI and these technologies pushes the boundaries of disease prediction, making it more accurate, secure, and user-friendly.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1109/ACCESS.2021.3062687; http://doi.org/10.3390/s23020565; http://doi.org/10.1016/j.measen.2023.100695; http://doi.org/10.1109/IT57431.2023.10078464; http://doi.org/10.1117/12.2655266; http://doi.org/10.1109/ASET56582.2023.10180650; http://doi.org/10.4018/978-1-6684-8913-0.ch013; http://doi.org/10.1109/ICBDS58040.2023.10346275; http://doi.org/10.11591/eei.v13i1.5999

NUMBER | TITLE
1056 | Digital twins for personalized medicine
SUGGESTED MATURITY
n/a
SUMMARY DESCRIPTION
The technology of Digital Twin Personalized Medicine (DTPM) involves creating a virtual model of a patient, which is continuously updated based on real-time health and lifestyle data. Utilizing artificial intelligence (AI), deep learning algorithms, and omics sciences, the technology can support personalized healthcare, precise diagnosis, and personalized treatment processes. It has the potential to revolutionize disease detection and management. Applications include virtual clinical trials, population studies, and personal health management. Further, the technology is anticipated to be key in enabling precision healthcare, which focuses on intelligent, data-centric healthcare models tailored to individual patient outcomes; The novelty of DTPM lies in its ability to create a live, continuously updated model of a patient's health status. Unlike traditional medical approaches that rely on periodic health check-ups and static data, DTPM integrates real-time data from various sources like electronic health records, wearable biosensors, and genome and microbiome sequencing. The integration of AI and deep learning technologies allows DTPM to surpass the accuracy of medical practitioners in some cases. Furthermore, DTPM is beginning to be deployed in areas such as cardiovascular diagnostics and insulin pump control, demonstrating its potential to transform various areas of healthcare. However, challenges remain, particularly in data collection, fusion, and accurate simulation. Despite these hurdles, DTPM represents a groundbreaking shift from established healthcare models, signifying a new era in personalized medicine and healthcare services.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1007/978-3-030-35746-7_8; http://doi.org/10.1007/s10916-020-01623-5; http://doi.org/10.1109/JIOT.2021.3051158; http://doi.org/10.1109/ETFA52439.2022.9921533; http://doi.org/10.1007/978-3-031-21333-5_4; http://doi.org/10.1109/ACCESS.2023.3249116; http://doi.org/10.1117/12.2667794; http://doi.org/10.1145/3576842.3589163; http://doi.org/10.5220/0011859400003476

NUMBER | TITLE

1053 | Digital biomarker remote monitoring

SUGGESTED MATURITY

n/a

SUMMARY DESCRIPTION

The technology of digital biomarker remote monitoring involves the collection and analysis of healthcare data through the integration of biosensors, clinical information systems, and electronic health records to create digital biomarkers. This technology allows for continuous, passive, and real-time monitoring of patient health, enabling the early detection and prevention of health deterioration. It employs various devices such as smartphones, wearable sensors, and other IoT devices to capture a wealth of data, including motor activities, sleep patterns, and other physical and physiological parameters. The technology can be used in a variety of healthcare contexts, including managing chronic conditions like Parkinson's disease, assessing physical frailty in older adults, monitoring patient health during or after cancer treatment, and detecting anomalies indicative of adverse health conditions in people living with dementia; The novelty of digital biomarker remote monitoring technology lies in its capacity to provide high-resolution, real-time, and continuous data, going beyond traditional healthcare monitoring strategies that rely on intermittent clinical visits and self-reported patient data. It also leverages advanced data analytics to derive meaningful insights from complex, multivariate data. Unlike traditional methods, this technology can detect subtle changes in health status even in the absence of visible clinical symptoms. Furthermore, it offers the potential for personalized care, early intervention, and improved patient outcomes. Notably, the technology also addresses some of the challenges posed by the COVID-19 pandemic, such as the need for remote patient monitoring and telemedicine. However, it also faces challenges, including issues related to data management and security, patient engagement, integration into existing healthcare systems and workflows, and ethical and privacy concerns. Novel approaches are being developed to address these issues and improve the utility and applicability of this technology in healthcare settings

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1002/mds.27376; http://doi.org/10.1038/s41746-020-00351-x; http://doi.org/10.1159/000512977; http://doi.org/10.1016/j.jss.2021.01.023; http://doi.org/10.1002/jac5.1382; http://doi.org/10.1109/PerComWorkshops51409.2021.9431000; http://doi.org/10.3390/s21165289; http://doi.org/10.1016/j.cjca.2021.11.014; http://doi.org/10.2196/38211; http://doi.org/10.1017/S1092852923002225

NUMBER | TITLE

1052 | Digital Twin continuous monitoring technology

SUGGESTED MATURITY

n/a

SUMMARY DESCRIPTION

Health - DT continuous monitoring technology refers to a novel approach towards healthcare where a Digital Twin (DT), a virtual representation of a patient, is used for long-term continuous monitoring. This approach combines the easy measurability of photoplethysmogram (PPG) and the rich clinical knowledge of electrocardiogram (ECG) for comprehensive cardiac monitoring. By integrating data-driven methods such as machine learning, the technology can track patients' health continuously and evaluate the efficacy of treatments virtually. The potential applications of this technology span precision medicine, chronic disease management, healthcare service design, and even the optimization of entire production processes in healthcare; The novelty of Health - DT continuous monitoring technology lies in its ability to construct a virtual representation that reflects real-time status of a patient's health, enabling a live model for healthcare services. This differs from traditional healthcare monitoring methods that rely on intermittent data. The new approach employs advanced dictionary learning frameworks to improve ECG inference quality and enrich PPG-based diagnosis knowledge. Furthermore, the concept of Digital Twin in healthcare represents a major advancement towards improving interactions between systems, caregivers, and patients. The technology also addresses key challenges such as cybersecurity and privacy, which are critical in the context of sensitive health data. The use of a Digital Twin, combined with machine learning and artificial intelligence, introduces a new level of personalization and precision in healthcare, making it a groundbreaking innovation in the field

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1007/978-3-030-35746-7_8; http://doi.org/10.1007/s10916-020-01623-5; http://doi.org/10.1109/JIOT.2021.3051158; http://doi.org/10.1109/ETFA52439.2022.9921533; http://doi.org/10.1007/978-3-031-21333-5_4; http://doi.org/10.1109/ACCESS.2023.3249116; http://doi.org/10.1117/12.2667794; http://doi.org/10.1145/3576842.3589163; http://doi.org/10.5220/0011859400003476

NUMBER | TITLE
1050 | AI therapy response prediction
SUGGESTED MATURITY
n/a
SUMMARY DESCRIPTION
AI therapy response prediction is a transformative approach in healthcare that leverages artificial intelligence (AI) and machine learning (ML) to predict patient responses to various treatments. The technology uses multimodal deep learning frameworks and graph neural networks to extract and analyze data from modalities like 2D echocardiography and cardiac magnetic resonance, histology images, and biochemical biomarker data. It enables the prediction of therapy responses in cardiac resynchronization therapy, cancer treatment, and various other diseases. It also provides interpretability of predictive outcomes through quantifying data and model uncertainty, fostering trust in clinical settings. Moreover, AI therapy response prediction can assist in precision treatment by stratifying patients based on the most effective tumor characteristics for therapy response prediction. The novelty of AI therapy response prediction lies in its ability to provide personalized, precise, and effective treatment plans based on individual patient data. Unlike traditional methods that mainly rely on cancer subtypes and presence of genetic mutations, this technology uses machine learning algorithms to predict therapeutic responses, even considering the complex heterogeneity in tumor tissue. It represents the first multimodal deep learning approach for therapy response prediction, offering improved accuracy and sensitivity. The technology also integrates structural and functional imaging biomarkers with clinical data, providing a comprehensive view of the patient's health status. Furthermore, this approach offers a level of interpretability often missing in AI models, by quantifying uncertainty in its predictions, thereby enhancing its reliability and acceptance in clinical settings. The technology also demonstrates potential for large-scale application in clinical diagnostics, providing an efficient and cost-effective solution for therapy response prediction.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1117/12.2510037; http://doi.org/10.1038/s41416-020-01122-x; http://doi.org/10.1080/10408363.2020.1857681; http://doi.org/10.1016/j.csbj.2021.07.003; http://doi.org/10.1016/j.media.2021.102264; http://doi.org/10.1007/978-3-030-93722-5_21; http://doi.org/10.1016/j.media.2022.102465; http://doi.org/10.1109/NSS/MIC44867.2021.9875936; http://doi.org/10.1002/cnr2.1796; http://doi.org/10.1016/j.media.2023.102861

NUMBER | TITLE
997 | Brain mapping device for safer neurosurgery
SUGGESTED MATURITY
Novel (TRL 1-3)
SUMMARY DESCRIPTION
A flexible film bristling with tiny sensors could make surgery safer for patients with a brain tumor or severe epilepsy. The experimental film, which looks like Saran wrap, rests on the brain's surface and detects the electrical activity of nerve cells below. It's designed to help surgeons remove diseased tissue while preserving important functions like language and memory.
SOURCE
NPR https://www.npr.org/sections/shots-health-news/2024/06/13/nx-s1-4985906/high-resolution-brain-mapping-device-neurosurgery-safer

NUMBER | TITLE
985 | AI supported interventional radiology
SUGGESTED MATURITY
Close to market (TRL 7-9)
SUMMARY DESCRIPTION
AI-supported interventional radiology integrates artificial intelligence (AI) and machine learning algorithms to enhance the efficiency and accuracy of radiological procedures. It offers the potential to reduce diagnostic errors and optimize radiologists' workload by automating complex tasks such as image interpretation and patient data analysis. This technology can be used in various capacities, including the early diagnosis of diseases like COVID-19, aiding in treatment planning, and improving patient care through predictive models. It also has potential applications in training tools and imaging simulations for procedural planning. Furthermore, AI can assist in material decomposition, scatter estimation, and noise injection in 3D and 2D imaging, thereby enhancing the quality and utility of the images for diagnostic and interventional procedures; The novelty of AI-supported interventional radiology lies in its ability to learn from and process vast amounts of data, enabling more accurate and efficient diagnosis, treatment planning, and patient care. Unlike traditional radiological practices, it can handle large datasets, discern patterns beyond human perception, and continuously redefine its logic based on the data it processes. This technology can simulate fluoroscopy-guided procedures from 3D diagnostic CT, thereby providing a learning platform for interventional radiology. It also enables the development of predictive models for patient selection and treatment planning. AI models like the fast-track COVID-19 classification network (FCONet) have been developed to diagnose COVID-19 pneumonia from CT scans, demonstrating the potential of AI in rapid and accurate diagnosis. AI's integration in interventional radiology has the potential to revolutionize radiology service and improve patient care. However, this technology is still emerging, and its widespread adoption requires further validation and appropriate regulation.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1007/978-3-030-00937-3_12; http://doi.org/10.1186/s41747-020-0145-y; http://doi.org/10.1007/s11547-020-01205-y; http://doi.org/10.1007/s11547-020-01197-9; http://doi.org/10.2196/19569; http://doi.org/10.1016/j.diii.2022.11.004; http://doi.org/10.1177/08465371231170133; http://doi.org/10.1007/s11547-023-01634-5; http://doi.org/10.5194/isprs-archives-XLVIII-2-W3-2023-21-2023; http://doi.org/10.1016/j.jvir.2023.05.037

NUMBER | TITLE
984 | Tensor-valued diffusion encoding
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Tensor-valued diffusion encoding is an advanced technique used in medical imaging, particularly in diffusion MRI, to characterize the complexities of human brain connectome and other tissue microstructures. This technology uses multidimensional diffusion encoding strategies to acquire data at multiple echo-times, enhancing the amount of information encoded into the signal. Through a nonparametric Monte Carlo inversion process, it generates 5D relaxation-diffusion distributions, separating contributions from different sub-voxel tissue environments with minimal assumptions on their microscopic properties. This facilitates the derivation of fiber-specific metrics that can be mapped throughout the imaged brain volume or other tissue structures. Tensor-valued diffusion encoding can also be combined with gradient waveform design to counteract the effects of tissue motion, improving data quality and accuracy. By isolating and combining different pieces of diffusion information, this technology provides robust estimations of various statistical descriptors of tissue content. Potential applications of tensor-valued diffusion encoding include the preoperative prediction of meningioma characteristics, non-invasive assessment of breast tumor microstructure, and the characterization of white matter fibers in the brain. This technology can also be used to estimate compartment-specific fractions, diffusivities, and T2 values within a two-compartment model of white matter, providing valuable insights into tissue microstructure and potential pathological changes. The novelty of tensor-valued diffusion encoding lies in its ability to tease apart diffusion anisotropy and orientational order, a feature not accessible by conventional diffusion encoding. It introduces the 'shape of the b-tensor' as a new encoding dimension, allowing control over the sensitivity to microscopic diffusion anisotropy. This technology also incorporates motion compensation in the design of gradient waveforms, improving efficiency and reducing signal bias and image artifacts caused by concomitant gradients. Furthermore, tensor-valued diffusion encoding enables the simultaneous quantification of relaxation and diffusion using MR fingerprinting in a clinically feasible time, enhancing the efficiency of medical imaging processes. As such, tensor-valued diffusion encoding represents a significant advancement over established technologies in medical imaging, offering increased depth of microstructural characterization and greater precision in parameter estimation.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1002/mrm.27828; http://doi.org/10.1002/mrm.28216; http://doi.org/10.1002/hbm.25224; http://doi.org/10.1002/mrm.28551; http://doi.org/10.1039/9781788019910-00068; http://doi.org/10.1016/j.jneumeth.2020.109007; http://doi.org/10.1002/mrm.28604; http://doi.org/10.1016/j.nicl.2021.102912; http://doi.org/10.1002/mrm.29352; http://doi.org/10.1093/braincomms/fcaa077

NUMBER | TITLE
983 | Deuterium metabolic imaging
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Deuterium Metabolic Imaging (DMI) is a non-invasive technique that measures tissue metabolism by using deuterium-labeled substrates like glucose. The relatively low detection sensitivity of these substrates is compensated by their short T1 values, which allow rapid signal acquisition without significant signal saturation. DMI can thus create three-dimensional metabolic maps, providing valuable insights into tissue metabolism and cell death. It is also capable of revealing glucose metabolism beyond mere uptake and can be used with other deuterated substrates. This technology has potential applications in diagnosing and monitoring metabolic disorders, cancers, neurodegenerative diseases, and other conditions that involve alterations in tissue metabolism; The novelty of DMI lies in its ability to provide detailed metabolic information without the need for ionizing radiation, unlike established imaging techniques like positron emission tomography (PET). Unlike conventional magnetic resonance imaging (MRI) which mainly provides anatomical information, DMI provides metabolic information, adding a new dimension to the imaging contrasts. Moreover, DMI can seamlessly be integrated with clinical MRI protocols, offering a metabolic component without increasing patient discomfort or scan time. The use of deuterium-labeled substrates makes DMI more versatile and informative than other imaging techniques that solely rely on glucose uptake. Furthermore, the ability to generate high-contrast metabolic maps depicting specific metabolic pathways, such as the Warburg effect in cancer, makes DMI a promising tool for precision medicine.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1126/sciadv.aat7314; http://doi.org/10.1016/j.neuroimage.2021.118639; http://doi.org/10.1016/j.neuroimage.2022.119284; http://doi.org/10.1158/1078-0432.CCR-21-4418; http://doi.org/10.1002/mrm.29439; http://doi.org/10.1016/j.pnmrs.2023.02.002; http://doi.org/10.1002/nbm.4926; http://doi.org/10.1002/mrm.29696; http://doi.org/10.1097/RLI.0000000000000953; http://doi.org/10.1016/j.neuroimage.2023.120250

NUMBER | TITLE
982 | Neurofluid imaging
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Neurofluid imaging is a novel technology used in medical imaging to study the dynamics of interstitial fluids (neurofluids) in the brain's parenchyma and cerebrospinal fluid (CSF) in the ventricle and subarachnoid space. This technology is based on the glymphatic system hypothesis, which describes how waste products are cleared from the brain. Using techniques such as magnetic resonance imaging (MRI), neurofluid imaging can visualize the movement of CSF, which is guided to the perivascular space around the arteries and enters the brain tissue via aquaporin-4 water channels to clear waste proteins. Potential applications include the study of diseases such as Alzheimer's, Chiari malformations, and hydrocephalus, where abnormalities in neurofluids have been implicated. Additionally, this technology can be used to evaluate the effects of surgery on neurofluid dynamics; The novelty of neurofluid imaging lies in its ability to non-invasively study the dynamics of neurofluids in the brain and spine, an area that has been difficult to investigate due to limited imaging modalities. Traditional imaging technologies focus on static structures, whereas neurofluid imaging captures the motion and passage of neurofluids, providing a dynamic view of the brain's waste clearance system. This technology offers a more comprehensive understanding of brain physiology, potentially contributing to early diagnosis and treatment of neurodegenerative diseases. Furthermore, the integration of neurofluid imaging with other techniques like phase-contrast MRI and PET imaging can provide a more detailed characterization of neurofluid dynamics and their association with pathological conditions.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.3348/kjr.2020.0042; http://doi.org/10.1111/jon.12837; http://doi.org/10.1016/j.mric.2021.01.002; http://doi.org/10.1002/mrm.28806; http://doi.org/10.3390/jcm11185343; http://doi.org/10.1093/braincomms/fcad128; http://doi.org/10.1016/j.sleep.2023.07.021; http://doi.org/10.1186/s12987-023-00467-8; http://doi.org/10.1259/bjr.20230016

NUMBER | TITLE
981 | Optoretinography
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Optoretinography (ORG) is an advanced technology in medical imaging that uses optical coherence tomography (OCT) to non-invasively assess retinal function. By detecting stimulus-evoked movement or changes in retinal photoreceptor cells, ORG measures the physiological response to visible light. The technology can capture nanometer-scale light-induced optical path length changes in retinal cells, enabling the recording of retinal responses to light. This high-speed, high-resolution imaging technique can provide insight into both retinal structure and function. Potential applications of ORG include early detection of photoreceptor dysfunction in diseases like age-related macular degeneration and inherited retinal degenerations. It can also be utilized as a critical biomarker for testing the safety and efficacy of new therapies and their translation to the clinic; Compared to established technologies like electroretinography (ERG), ORG offers several advantages. Unlike ERG that provides an aggregated measure of photoreceptor function, ORG can measure function at the individual photoreceptor level, providing a more granular understanding of retinal health. Moreover, ORG is non-invasive and objective, offering a more comfortable and reliable way to assess retinal function. Recently, velocity-based approaches have been introduced, which monitor the velocity of subcellular features in the retina instead of their positions, thereby simplifying the process and eliminating the need for costly and laborious aspects of position-based approaches. These innovations underline the novelty and potential of ORG in transforming ophthalmic care and clinical trials for novel therapeutics.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1364/BOE.399034; http://doi.org/10.1364/BOE.399334; http://doi.org/10.1364/OE.409193; http://doi.org/10.1002/jbio.202000462; http://doi.org/10.1117/12.2577605; http://doi.org/10.1117/12.2576897; http://doi.org/10.1073/pnas.2107444118; http://doi.org/10.1038/s41598-022-06562-4; http://doi.org/10.1364/BOE.444567; http://doi.org/10.1117/12.2650676

NUMBER | TITLE
979 | 2-D shear wave elastography
SUGGESTED MATURITY
Close to market (TRL 7-9)
SUMMARY DESCRIPTION
2-D shear wave elastography (2D-SWE) is a medical imaging technology utilized for the non-invasive evaluation of tissue elasticity. It works by generating shear waves and assessing their speed, providing a quantitative shear-wave speed measure that correlates with tissue stiffness. In the field of liver disease, particularly in nonalcoholic fatty liver disease (NAFLD), 2D-SWE is employed to identify inflammation, steatosis, and fibrosis, thus offering a potential non-invasive alternative to liver biopsy. Additionally, it can be used in combination with other parameters, such as dispersion slope and attenuation coefficient, to improve the diagnosis of nonalcoholic steatohepatitis (NASH). Another innovative application is its use within deep learning radiomics elastography (DLRE) for the accurate prediction of liver fibrosis stages in chronic hepatitis B patients; The novelty of 2D-SWE lies in its ability to non-invasively assess and quantify tissue stiffness, which is beneficial in diagnosing and monitoring the progression of liver diseases such as NAFLD and NASH. Compared to other established technologies like magnetic resonance elastography (MRE) and vibration-controlled transient elastography (VCTE), 2D-SWE exhibits comparable diagnostic accuracy, especially for advanced fibrosis. Moreover, it has been integrated into a multiparametric ultrasound approach that combines it with attenuation imaging for a comprehensive evaluation of NAFLD. The combination of 2D-SWE with DLRE also offers enhanced diagnostic performance in predicting liver fibrosis stages, demonstrating its potential in advancing non-invasive liver disease diagnostics.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1002/hep.29179; http://doi.org/10.1136/gutjnl-2018-316204; http://doi.org/10.2214/AJR.19.21267; http://doi.org/10.1148/radiol.2020192665; http://doi.org/10.1136/gutjnl-2020-323419; http://doi.org/10.1016/j.cgh.2020.05.034; http://doi.org/10.1016/j.cgh.2020.12.016; http://doi.org/10.1007/s00261-021-03269-4; http://doi.org/10.1136/gutjnl-2022-327498; http://doi.org/10.1097/RLI.0000000000000972

NUMBER | TITLE
978 | Flash radiotherapy
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Flash radiotherapy is a novel technique in radiation oncology that involves the delivery of ultra-high dose rates of radiation in very short times, which has shown promising results in reducing damage to healthy tissues while maintaining tumor control. This method, characterized by its 'FLASH effect', is being studied for optimization in various treatment planning scenarios, including pencil beam scanned proton therapy and high-energy X-ray therapy. The protective FLASH effect is believed to be linked to reduced production of reactive oxygen species. Current research is focusing on understanding the biological mechanisms underlying this effect and the optimal parameters for its delivery. Potential applications of flash radiotherapy include treatment of invasive and treatment-resistant brain tumors, and other cancers where large irradiation volumes with high cytotoxic doses are required; Flash radiotherapy represents a significant shift from conventional radiotherapy techniques, which typically involve lower dose rates and longer treatment times. Its novelty lies in its ability to deliver high doses of radiation in a very short time - often less than a second - without increasing damage to healthy tissue. This has the potential to reduce treatment time, minimize toxicity, and increase the number of patients who can be treated. However, the technology also presents new challenges, including the need for accurate dosimetry at ultra-high dose rates and understanding the biological basis of the FLASH effect. While promising, flash radiotherapy is still in the early stages of development and requires further investigation and clinical trials to fully realize its potential.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1158/1078-0432.CCR-17-3375; http://doi.org/10.1016/j.radonc.2019.06.019; http://doi.org/10.1158/1078-0432.CCR-20-0894; http://doi.org/10.1002/mp.15649; http://doi.org/10.1109/SC41404.2022.00008; http://doi.org/10.1001/jamaoncol.2022.5843; http://doi.org/10.1038/s41571-022-00697-z; http://doi.org/10.1088/1742-6596/2420/1/012087; http://doi.org/10.2196/41812; http://doi.org/10.1007/978-3-031-26066-7_21

NUMBER | TITLE
977 | Biology-guided radiotherapy
SUGGESTED MATURITY
Close to market (TRL 7-9)
SUMMARY DESCRIPTION
Biology-guided radiotherapy (BgRT) is a novel technology that amalgamates real-time positron emission tomography (PET) imaging with linear accelerator (Linac) technology to deliver targeted radiation therapy. BgRT leverages PET images and radiopharmaceutical tracers to track and treat one or more tumors in real time. The RefleXion™ X1 system, a specific example of BgRT, is designed for image-guided radiotherapy and tracks tumor motion using real-time positron emission signals. This technology can be used for a range of radiotherapy regimens, including IMRT, SBRT, SRS, and BgRT, with the potential to deliver highly conformal treatments to malignant lesions while minimizing dose to surrounding healthy tissues. BgRT is especially promising for advanced and metastatic disease states, where it can enable the treatment of multiple targets in a single session; The novelty of BgRT lies in its ability to transform tumors into their own fiducials after intravenous injection of a radiotracer, enabling real-time tracking and treatment of tumors. This represents a significant evolution from traditional radiation therapy systems, which do not offer real-time tracking capabilities. The integration of PET detectors, rapid beam-station delivery, real-time tracking, and high-frequency multi-leaf collimation are unique features of BgRT that offer improved precision and efficiency in cancer treatment. Furthermore, BgRT has potential for use with novel dose painting and fractionation schemes and new radiotracers, which may further enhance its utility in clinical practice.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1259/bjr.20200873; http://doi.org/10.1016/j.ctro.2021.04.003; http://doi.org/10.1002/acm2.13607; http://doi.org/10.1177/15330338221100231; http://doi.org/10.1016/j.ctro.2022.05.005; http://doi.org/10.1259/bjr.20220387; http://doi.org/10.1016/j.ctro.2023.100608; http://doi.org/10.1016/j.radonc.2023.109592; http://doi.org/10.3389/fonc.2023.1134884; http://doi.org/10.1016/j.phro.2023.100438

NUMBER | TITLE
975 | Pix2Pix GAN
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Pix2Pix GAN (Generative Adversarial Network) is a deep learning technology that has shown significant potential in the field of medical imaging. Its primary function is to translate images from one form to another, for instance, transforming label-free microscopy images such as Coherent Anti-Stokes Raman Scattering (CARS) into more familiar histopathological images. This translation ability is crucial for real-time, spectrally resolved label-free imaging in clinical diagnosis. The technology works by training on pairs of images and learning to map the input to the output image. It utilizes a UNet+ structure for enhanced pattern extraction and gradient richness. This new Pix2Pix GAN model addresses the problem of incorrect content identification during image translation by integrating it with seg-cGAN and applying partial regularization strategy. This enables the model to correctly identify content categories during image translation, thus improving the quality of the generated images. Potential applications of Pix2Pix GAN include resolution enhancement in microscopic imaging, retinal blood vessel segmentation, denoising low dose SPECT images, and lymph node segmentation from CT scans The novelty of Pix2Pix GAN lies in its ability to overcome the limitations of previous GAN models which were criticized for lacking precision and often misinterpreting image information. By integrating UNet+ with seg-cGAN and applying partial regularization, Pix2Pix GAN can correctly identify content categories during image translation, thus significantly improving the quality of the generated images. This precision enhancement is a major advancement over established technologies. Additionally, Pix2Pix GAN also stands out for its potential to be used in generating realistic images for data augmentation, which is particularly useful when collection of real data for specific applications is challenging. The technology also addresses the problem of requiring large amounts of paired datasets for training the networks, which is often costly and time-consuming. By utilizing a small amount of unpaired experimental microscopic images, Pix2Pix GAN can generate paired data for supervising learning in resolution enhancement, effectively replacing the need for experimental paired data and broadening the application of deep learning in optical fields.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1117/12.2512004; http://doi.org/10.1002/mp.14624; http://doi.org/10.1109/MED51440.2021.9480169; http://doi.org/10.21037/qims-21-1042; http://doi.org/10.1007/s11042-023-14437-7; http://doi.org/10.1007/s11119-023-10001-3; http://doi.org/10.1007/978-981-19-5191-6_51; http://doi.org/10.1259/dmfr.20230007; http://doi.org/10.1109/ICECAI58670.2023.10176715; http://doi.org/10.1109/IVCNZ61134.2023.10343548

NUMBER | TITLE
974 | Radiomics nomogram
SUGGESTED MATURITY
Close to market (TRL 7-9)
SUMMARY DESCRIPTION
Radiomics nomogram is a predictive technology used in medical imaging, particularly in the field of oncology. It uses machine learning algorithms to extract high-dimensional data from standard medical images, such as computed tomography (CT) and magnetic resonance imaging (MRI). These data, known as radiomic features, are then combined with clinical risk factors to create a predictive model or 'nomogram'. The radiomics nomogram can be used to predict various outcomes, such as the likelihood of lymph node metastasis in colorectal cancer, disease-free survival in non-small cell lung cancer, and the axillary lymph node status in breast cancer. It can also predict the MSI status in colorectal cancer, the invasiveness of solitary pulmonary nodules, and the recurrence of soft tissue sarcomas following surgical resection; The novelty of radiomics nomogram technology lies in its ability to extract more information from medical images than traditional radiological evaluation methods, and its capacity for personalized prediction. Traditional methods are limited to evaluating morphological changes and cannot provide high-dimensional data. Radiomics nomogram, on the other hand, leverages machine learning to extract and analyze high-dimensional data, which allows for more accurate and personalized predictions. For example, it can predict the likelihood of lymph node metastasis in individual colorectal cancer patients, which can inform preoperative decision-making. Furthermore, it can predict disease-free survival in non-small cell lung cancer patients, which may enable a step forward in precision medicine.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1200/JCO.2015.65.9128; http://doi.org/10.1148/radiol.2016152234; http://doi.org/10.1093/annonc/mdz001; http://doi.org/10.1007/s00330-021-08167-3; http://doi.org/10.1016/j.eclinm.2022.101348; http://doi.org/10.1007/s00330-022-09051-4; http://doi.org/10.1007/s00330-022-09109-3; http://doi.org/10.1002/cncr.34540

NUMBER | TITLE
972 | AI supported flow imaging
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
AI supported flow imaging is a technology that leverages deep learning techniques to analyze image sequences and extract high-level representations of data for medical imaging. This technology has been applied in areas such as crowd behavior recognition, cardiovascular disease assessment, cell sorting and counting, cerebral blood flow analysis, ultrasound image reconstruction, blood velocity measurement, and kidney fibrosis prediction. The technology works by training deep neural networks on datasets of medical images, resulting in systems capable of performing tasks such as automated ventricular segmentation, identifying cell morphology, enhancing MRI-derived velocity fields, and predicting kidney tubulointerstitial fibrosis. The technology has been demonstrated to improve the accuracy of imaging results, decrease post-processing time, reduce inter-observer variability, and provide high-resolution flow images; Comparatively, AI supported flow imaging presents novelty in the field of medical imaging by integrating handcrafted and Conv-LSTM-AE methods with optical flow images, applying neuromorphic imaging cytometry, combining computational fluid dynamics (CFD) informed neural networks with MRI data, and using support vector machine (SVM) to assess the value of shear wave elastography (SWE). Compared to traditional methods, this technology has shown to be more effective in extracting high-level representations of data and solving the problem in an end-to-end pipeline. It also unbinds applications from the constraints of framerate, provides a cost-efficient, reproducible, high-throughput imaging mechanism, and improves the accuracy of physiological flow fields. Furthermore, the technology also shows promise in enhancing the diagnostic performance of traditional kidney ultrasound in predicting different kidney tubulointerstitial fibrosis grades among CKD patients.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1109/ULTSYM.2019.8925595; http://doi.org/10.1016/j.cmpb.2020.105729; http://doi.org/10.1016/j.jfma.2021.08.011; http://doi.org/10.1109/TUFFC.2022.3152689; http://doi.org/10.1109/TMI.2022.3222541; http://doi.org/10.1007/s00348-022-03554-y; http://doi.org/10.1186/s40001-022-00975-7; http://doi.org/10.1007/s10554-023-02815-z; http://doi.org/10.1038/s42003-023-04656-x; http://doi.org/10.1148/RADIOL.223008

NUMBER | TITLE
971 | Multimodal image fusion
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Multimodal image fusion is a technology in medical imaging that merges images from various systems to provide a detailed view of specific organs or diseases. This process includes anatomical and physiological data, simplifying the diagnosis process. The fusion techniques are categorized into six primary types: frequency fusion, spatial fusion, decision-level fusion, deep learning, hybrid fusion, and sparse representation fusion. This technology is applicable in combining preoperative, intraoperative, and postoperative imaging and multi-sensor fusion for disease detection. Moreover, it can significantly improve segmentation, help reduce metal artifacts in CT images, and enhance the fusion quality of Regions of Interest (ROIs) relevant to medical implications; The novelty of multimodal image fusion lies in its ability to merge different imaging modalities, thereby providing a comprehensive understanding of the disease or organ under study. This technology has been further enhanced through the integration of deep learning-based methods, which have demonstrated superior performance in image classification, segmentation, and object detection. Similarly, the use of generative adversarial networks (GANs) in reducing metal artifacts in CT images underscores the innovative nature of this technology. Furthermore, the application of transformers to multimodal medical image classification is a breakthrough in the field, helping to establish long-range dependencies between modalities effectively. Lastly, the integration of structured medical knowledge into medical vision-and-language pre-training (Med-VLP) methods signifies a major advancement in multimodal image fusion technology.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1109/TMI.2013.2265603; http://doi.org/10.3390/diagnostics11081384; http://doi.org/10.1007/s00521-021-06490-w; http://doi.org/10.1016/j.neucom.2022.01.005; http://doi.org/10.1016/j.compbiomed.2022.105253; http://doi.org/10.1016/j.array.2019.100004; http://doi.org/10.1145/3503161.3547948; http://doi.org/10.1186/s40779-023-00458-8; http://doi.org/10.1016/j.eswa.2023.121574; http://doi.org/10.1109/ICCV51070.2023.00742

NUMBER | TITLE

970 | Use of AI for Joint and Cartilage Segmentation

SUGGESTED MATURITY

Emerging (TRL 4-6)

SUMMARY DESCRIPTION

Joint and Cartilage Segmentation technology in the field of medical imaging involves the use of advanced algorithms and techniques to accurately segment and classify anatomical structures within medical images, such as MRI or X-ray scans. This technology primarily employs deep learning systems, such as convolutional neural networks (CNNs), and more recently Transformer-based techniques, which autonomously learn from the images to categorize and segment the structures within. Novel approaches include the use of memory-efficient Transformers, self-training frameworks, or joint segmentation and registration methods, aiming to improve segmentation accuracy and computational efficiency. These technologies can be applied to various medical scenarios, such as glaucoma screening, arthritis diagnosis, and tumor identification. Furthermore, with the integration of IoT frameworks, these technologies can be utilized remotely, providing promising tools for large-scale clinical screenings and early disease detection;

The novelty of Joint and Cartilage Segmentation technology lies in its application of Transformer-based and deep learning approaches, which surpass traditional pixel classification methods in both segmentation accuracy and computational efficiency. Specifically, the development of memory-efficient Transformers, such as iSegFormer, addresses the challenge of limited memory in 3D medical image segmentation. The use of self-training frameworks and joint segmentation and registration methods also represents a significant innovation, offering simultaneous improvements in segmentation and registration accuracy, even with limited training data. Furthermore, the integration of these technologies into an IoT framework provides a new avenue for remote application, enhancing accessibility and practicality for clinical use. These advancements mark a significant step forward from established technologies, demonstrating the potential for substantial improvements in medical imaging segmentation and the broader field of medical diagnosis and treatment.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1007/978-3-642-40763-5_31; http://doi.org/10.1109/ISBI.2017.7950685; http://doi.org/10.1109/ISBI.2018.8363705; http://doi.org/10.1007/978-3-030-32245-8_47; http://doi.org/10.1093/bioinformatics/btab154; http://doi.org/10.1109/CVPR46437.2021.01545; http://doi.org/10.1088/1742-6596/2234/1/012008; http://doi.org/10.1038/s41598-022-27089-8; http://doi.org/10.1016/j.bspc.2023.104906

NUMBER | TITLE

967 | AI supported Instance Segmentation

SUGGESTED MATURITY

Emerging (TRL 4-6)

SUMMARY DESCRIPTION

AI-supported Instance Segmentation in medical imaging leverages deep learning methods such as Convolutional Neural Networks (CNNs) to process and interpret imaging data. It enables detailed analyses of Regions of Interests (ROIs) in medical images, such as CT scans and MRI, by precisely delineating organ boundaries for surgical planning, volumetric estimation, and pathology monitoring. The core principle revolves around automatic pixel-level labeling of images with classes and instances, which can be crucial for detecting and measuring specific features or objects within the images. The technology can also be adapted to handle noises in images, such as those in ultrasound images, and bridge the domain gap observed between images from different organs and collections;

The novelty of AI-supported Instance Segmentation technology lies in its capability for simultaneous instance segmentation and tracking, which offers superior performance in distinguishing ambiguous pixels on boundaries and overlaps. It also utilizes innovative techniques like unsupervised learning for denoising of medical ultrasound images, and the integration of a generator and discriminator into the segmentation pipeline with adversarial training to generalize nuclei instances and texture patterns. Furthermore, the technology has been adapted for use with multi-channel imagery, which has shown to improve performance. Recent developments also include methods for zero-shot instance segmentation, which can segment all seen and unseen instances, a crucial feature in fields where data collection and labeling can be challenging.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1109/TIP.2019.2919937; http://doi.org/10.1016/j.knosys.2020.106062; http://doi.org/10.1109/TPAMI.2021.3059968; http://doi.org/10.1016/j.media.2021.102048; http://doi.org/10.1148/rg.2021200210; http://doi.org/10.1007/s00330-022-09355-5; http://doi.org/10.1016/j.media.2023.102750; http://doi.org/10.3390/diagnostics13020223; http://doi.org/10.1016/j.bspc.2023.105299; http://doi.org/10.1007/s12652-020-01680-1

NUMBER | TITLE

966 | Explainable AI in medical imaging

SUGGESTED MATURITY

Emerging (TRL 4-6)

SUMMARY DESCRIPTION

Explainable AI (XAI) in medical imaging is an advanced technology that aims to provide transparent and understandable explanations for the decisions made by machine learning models in medical imaging analysis. This technology uses feature attribution maps or heatmaps, which highlight the important features of AI models' prediction, thereby aiding clinicians in interpreting AI decisions. It also includes a predictive module for learning image registration and uncertainty simultaneously, contributing to improved accuracy. New developments in this field involve utilizing a modality-specific feature importance (MSFI) metric, which encodes clinical image and explanation interpretation patterns. Additionally, topology-aware networks are proposed for accurately separating densely clustered and severely deformed glands in histopathology images. This technology is also being employed to explain image retrieval, specifically in detecting COVID-19 in chest X-rays and skin lesions;
Compared to conventional AI techniques, XAI in medical imaging introduces a new level of transparency and interpretability in AI decision-making, especially in multi-modal medical images. Traditional AI models are often considered "black boxes, " making it difficult for clinicians to understand the basis for the AI's decisions. XAI, on the other hand, not only improves the accuracy of medical imaging analysis but also explains its decision-making process in a way that is understandable to clinicians. This is achieved through the introduction of novel techniques like empirical randomness, registration error-based uncertainty prediction, and the MSFI metric. The novelty lies in the ability of XAI to provide both technically sound and clinically useful explanations, therefore, increasing trust in AI systems and potentially leading to greater integration of these tools into routine clinical practice. However, it's worth noting that some reports suggest that the explanations generated by XAI are volatile to changes in model training, raising questions about the underlying reliability of these models.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1117/12.2549298; http://doi.org/10.1038/s42256-021-00338-7; http://doi.org/10.1109/WACV51458.2022.00161; http://doi.org/10.1016/j.inffus.2021.07.016; http://doi.org/10.1016/j.media.2022.102684; http://doi.org/10.3390/s23020634; http://doi.org/10.1016/j.compbiomed.2023.106668; http://doi.org/10.1016/j.ejrad.2023.110786; http://doi.org/10.1109/ICACCS57279.2023.10113001

NUMBER | TITLE

962 | Lesion network mapping

SUGGESTED MATURITY

Emerging (TRL 4-6)

SUMMARY DESCRIPTION

Lesion network mapping is a technology application used in the field of medical imaging to better understand the impact of brain lesions on functional networks within the brain. This analytical approach uses data from healthy subjects to map the network effects of brain lesions in patients, moving beyond the limitations of traditional lesion mapping which focuses on the lesion site itself. This method has been successfully applied in the study of various neurological symptoms and disorders, including hallucinations, tics, and cervical dystonia, revealing common brain network involvement despite diverse lesion locations. Furthermore, it has been used to predict post-stroke cognitive and motor outcomes based on the lesion location and associated network disruption, offering potential guidance for treatment and rehabilitation strategies;
The novelty of lesion network mapping lies in its shift from a region-centric to a network-centric view of brain function and dysfunction. Traditional approaches have focused on identifying overlaps in lesion location across patients with similar symptoms, falling short when symptoms do not localize to a single region or are caused by network disruptions rather than the lesion site itself. Lesion network mapping overcomes these limitations by leveraging healthy connectome data to identify common brain circuits impacted by diverse lesion locations. This approach provides more comprehensive and precise insights into the neuroanatomical substrates of various neurological symptoms and disorders, and opens up new possibilities for identifying potential therapeutic targets for neuromodulation treatments.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1093/brain/awv228; http://doi.org/10.1093/brain/awz112; http://doi.org/10.1038/s41380-019-0565-3; http://doi.org/10.1093/brain/awac010; http://doi.org/10.1093/brain/awac361; http://doi.org/10.1038/s41562-022-01501-9; http://doi.org/10.1016/j.biopsych.2023.02.007; http://doi.org/10.1093/braincomms/fcad071; http://doi.org/10.1093/brain/awac009; http://doi.org/10.1001/jamaneurol.2023.1988

NUMBER | TITLE
960 | Attention mechanisms in Convolutional Neural Networks
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Attention mechanisms in Convolutional Neural Networks (CNN) have emerged as powerful tools in the field of medical imaging. They integrate CNN and Transformer structures to effectively analyze medical images, overcoming the inherent limitations of CNNs in modeling long-range relations, while also addressing the need for large-scale datasets in Transformer structures. The attention mechanisms help to extract both local and global features from medical images, enabling better image segmentation, disease diagnosis, and accuracy in detecting irregularities such as tumors or lesions. They also show promise in the segmentation of 3D images, and in applications such as Visual Question Answering in Medical imaging (VQA-Med); The novelty of attention mechanisms in CNN lies in their ability to combine the strengths of CNNs and Transformers, overcoming individual limitations of both. Unlike traditional CNNs, these mechanisms can model long-range dependencies in images, enhancing the understanding of the image beyond local details. They also overcome the dependency of Transformers on large-scale datasets for performance, which is often a limitation in medical imaging applications. Furthermore, they introduce additional controls in the self-attention module and use strategies like Local-Global training to improve performance on medical images. They also present an efficient way to process high-resolution 3D feature maps, which was previously a challenge. These advancements make attention mechanisms in CNN a significant leap from existing technologies used for the same purpose.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1016/j.media.2019.01.012; http://doi.org/10.1007/978-3-030-58595-2_30; http://doi.org/10.1007/978-3-030-87199-4_16; http://doi.org/10.1007/978-3-030-87193-2_4; http://doi.org/10.1007/978-3-030-87193-2_11; http://doi.org/10.1007/978-3-030-87199-4_6; http://doi.org/10.1093/jmicro/dfac051; http://doi.org/10.1016/j.compbiomed.2023.106791; http://doi.org/10.1109/TIP.2023.3293771; http://doi.org/10.1109/ISBI53787.2023.10230337

NUMBER | TITLE
959 | Few-shot learning for use with limited data
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Few-shot learning is a machine learning technique designed to yield accurate results with limited data. In medical imaging, it presents an efficient solution to challenges such as the high cost and difficulty of obtaining large, annotated datasets. Few-shot learning has been applied in various areas, such as the segmentation of lung and infection in COVID-19 CT scans, detection of COVID-19 in chest X-ray images, skin lesion segmentation in dermoscopic images, abdominal organ segmentation, and classification of multiple medical images. In addition to segmentation and classification tasks, few-shot learning methods also facilitate the development of deep learning models for efficient diagnosis and screening, even in data-scarce situations. The technique is particularly useful in instances where collecting abundant seen-class data is difficult, as it can leverage learning from the natural domain to facilitate rare-disease skin lesion segmentation with limited data; Few-shot learning is a novel technology compared to established techniques used to achieve similar purposes in medical imaging. Traditional methods often require large amounts of annotated data, which are difficult and costly to obtain, especially in a single institution. In contrast, few-shot learning allows models to rapidly adapt to unseen classes with few labeled samples, making it especially valuable in medical scenarios where data is limited. This technology has demonstrated significant improvements in accuracy and efficiency, as seen in COVID-19 detection and skin lesion segmentation. Furthermore, few-shot learning has been combined with other technologies such as Siamese networks and auto-encoders, leading to the development of new models like the Siamese few-shot network (SFN) and multi-learner based few-shot learning methods. These advancements contribute to its novelty and potential for future applications in medical imaging.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1109/ISBI.2019.8759182; http://doi.org/10.1007/978-3-030-58583-9_8; http://doi.org/10.1002/mp.14676; http://doi.org/10.1117/12.2581496; http://doi.org/10.1109/TNNLS.2022.3190452; http://doi.org/10.1016/j.patcog.2022.109108; http://doi.org/10.1109/JBHI.2022.3215147; http://doi.org/10.1007/978-3-031-21014-3_28; http://doi.org/10.1109/WACV56688.2023.00252; http://doi.org/10.1109/ICEIC57457.2023.10049899

NUMBER | TITLE

958 | AI image correction for improved accuracy

SUGGESTED MATURITY

Emerging (TRL 4-6)

SUMMARY DESCRIPTION

AI image correction in medical imaging is a technology that uses deep learning algorithms to enhance and correct images, increasing their overall quality and making them more accurate. This technology is used for various purposes, such as mitigating the effects of poor exposure settings, correcting inaccuracies in mask images, reducing phase error in 4D flow MRI, and improving the spatial resolution of satellite hyperspectral imagery. Deep learning algorithms are specifically designed to enhance image quality by predicting missing details in unexposed images, correcting the speed of sound aberrations in photoacoustic imaging, and correcting image-based phase error. Other applications include organ-at-risk contouring in radiotherapy and color research in dentistry;
The novelty of AI image correction lies in its ability to automate and enhance traditionally manual and complex processes. Traditional systems often have limitations like poor spatial resolution, phase errors, and inaccurate exposure settings that can affect the quality and accuracy of images. AI image correction bypasses these limitations by using deep learning algorithms to predict and correct errors, improving the accuracy and quality of images. Furthermore, the technology is capable of continuous learning and improvement, adapting to new data and refining its algorithms over time. This represents a significant advancement over existing technologies, offering potential for increased efficiencies and more accurate outcomes in medical imaging.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1109/EMBC.2018.8512336; http://doi.org/10.1117/12.2543440; http://doi.org/10.1111/jerd.12844; http://doi.org/10.1109/TGRS.2021.3135501; http://doi.org/10.1007/s10278-022-00721-9; http://doi.org/10.1002/mp.16119; http://doi.org/10.1088/1361-6560/ac9a97; http://doi.org/10.1117/12.2660084; http://doi.org/10.1109/ECTI-CON58255.2023.10153365; http://doi.org/10.1016/j.phro.2023.100482

NUMBER | TITLE

957 | Weakly/Self Supervised Segmentation

SUGGESTED MATURITY

Emerging (TRL 4-6)

SUMMARY DESCRIPTION

Weakly or Self Supervised Segmentation is a technology in the field of medical imaging that utilizes deep learning and neural networks to enhance the accuracy and efficiency of image segmentation. This method reduces the reliance on pixel-level annotation, thereby improving computer-aided diagnosis. The technology can handle large deformations in images and addresses the issues of under- and over-segmentation often encountered with traditional methods. It uses an attention-guided fusion of multi-scale deformation fields, a separately trained segmentation network, and a novel dense registration network. This allows it to remove interference from uninterested areas, predict deformation fields, and combine them for final registration. The technology can be used in a variety of applications such as lesion segmentation on thoracic CT for rapid quantitative analysis of lung involvement in COVID-19 infections, nodule size differentiation in thyroid ultrasound images, and histopathological image segmentation, among others;
Compared to established technologies, Weakly or Self Supervised Segmentation is novel in its use of advanced deep learning techniques and neural networks for image segmentation. The use of an attention-guided fusion of multi-scale deformation fields and a dense registration network distinguishes this technology from traditional methods. It introduces a new approach to image segmentation that overcomes the limitations of class activation maps and handles large deformations in images. Furthermore, it enhances the sensitivity of the neural network to the nodule scale size and improves the nodule edge segmentation effect. Additionally, it alleviates the strenuous data-collecting/annotating labor while enhancing the generalization ability and robustness of the segmentation model. It also incorporates regularization, data augmentation, and consistency across scales to boost robustness against annotation noise, making it more effective in noisy and imperfect annotation environments. This technology has shown significant performance improvement over state-of-the-art methods, demonstrating its novelty and potential for wide adoption in the medical imaging field.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1007/978-3-319-66179-7_65; http://doi.org/10.1016/j.compbiomed.2022.105347; http://doi.org/10.1109/CVPR52688.2022.00263; http://doi.org/10.1109/CVPR52688.2022.01138; http://doi.org/10.1016/j.cmpb.2023.107398; http://doi.org/10.1109/BigDataSecurity-HPSC-IDS58521.2023.00013; http://doi.org/10.1109/TMI.2023.3290356

NUMBER | TITLE

956 | AI-supported oncologic image analysis

SUGGESTED MATURITY

Emerging (TRL 4-6)

SUMMARY DESCRIPTION

AI-supported oncologic image analysis utilizes machine learning and deep learning methodologies to evaluate a vast array of data from medical imaging technologies, such as computed tomography (CT), electrocardiograms, echocardiograms, and magnetic resonance imaging (MRI). These AI algorithms can identify patterns and features in the imaging data that may be indicative of cancer or its potential complications. Such technology has shown promising results in various aspects of oncology care, including risk stratification, treatment monitoring, clinical outcome assessment, early detection of metastases, and even intraoperative identification of cancerous tissue. Moreover, AI has been employed in radiogenomics, which combines radiological data with genomic information to create predictive models for patient risk and treatment outcomes;

The novelty of AI-supported oncologic image analysis lies in its ability to process vast amounts of complex imaging data at a far greater speed and precision than traditional methods, uncovering "hidden" biomarkers and quantitative features that would be difficult, if not impossible, to detect manually. The use of AI in oncologic imaging also allows for more personalized treatment plans and may lead to improved patient outcomes. In addition, AI advances the field of cardio-oncology by analyzing cardiovascular data to identify cancer patients at risk for cardiovascular complications. However, it is crucial to acknowledge that while the results of these AI technologies are promising, they are still being developed and are not yet widely implemented in clinical settings. Thus, while AI-supported oncologic image analysis builds upon existing technologies, it represents a significant advancement in the precision, scope, and potential applications of medical imaging analysis.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1007/s00259-019-04372-x; http://doi.org/10.1007/s00261-020-02624-1; http://doi.org/10.1016/j.ejmp.2021.03.009; http://doi.org/10.1007/s11547-022-01512-6; http://doi.org/10.3390/diagnostics13010100; http://doi.org/10.1117/12.2652661; http://doi.org/10.3390/cancers15041174; http://doi.org/10.3389/fmed.2023.1133269; http://doi.org/10.1177/03009858231189205; http://doi.org/10.1007/s00405-023-08326-w

NUMBER | TITLE

954 | Explainable segmentation

SUGGESTED MATURITY

Close to market (TRL 7-9)

SUMMARY DESCRIPTION

Explainable segmentation is a technology in medical imaging that uses deep learning techniques, such as convolutional neural networks (CNNs), to analyze and interpret medical images. The technology focuses on distinguishing and explaining features within images, helping medical practitioners to understand and trust the AI's diagnosis. It is especially useful in diagnosing diseases such as COVID-19, where rapid and reliable diagnosis is crucial. Explainable segmentation achieves this by implementing image enhancement, image segmentation, and ensemble models to classify images. It incorporates visualizations such as Grad-CAM to establish trust in the AI system. Additionally, the technology can handle the difficulties of small datasets and low-resolution images by generating synthetic samples of medical images;

The novelty of explainable segmentation lies in its ability to provide an explainable AI model for medical imaging. Unlike traditional AI models that focus solely on achieving high performance, explainable segmentation also provides insight into the decision-making process of the model. It integrates domain knowledge into the modeling process, quantifies the importance of different brain regions, and visualizes the most relevant features. The use of attention maps and multiple attentions in a CNN architecture allows the technology to focus on the most important spatial positions, channels, and scales. This approach not only enhances the accuracy of medical image segmentation but also improves the explainability of the AI system. Furthermore, the technology provides a novel strategy for eliciting explainability, such as synthesizing images that span the range of a CNN's principal embedded features. The advancements in explainable segmentation show a significant step towards transparent and trustworthy AI models in medical imaging.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1109/TNNLS.2017.2766168; http://doi.org/10.1016/j.mri.2019.05.043; http://doi.org/10.3390/su13031224; http://doi.org/10.1109/TMI.2020.3035253; http://doi.org/10.1007/s11548-022-02619-x; http://doi.org/10.3390/math11061489; http://doi.org/10.1109/ECCE57851.2023.10101503; http://doi.org/10.4018/978-1-6684-7524-9.ch003; http://doi.org/10.1201/9781003333425-2; http://doi.org/10.1109/ACCESS.2024.3359698

NUMBER | TITLE
952 | AI for X-Ray protocol optimization
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
AI for X-Ray protocol optimization utilizes deep learning techniques to enhance the analysis and interpretation of X-ray images, particularly in thoracic disease diagnosis and protein structure refinement. The technology incorporates domain-ensemble learning with cross-domain mixup (DELCOM), creating virtual samples by mixing up pairs of samples from source domains. This approach helps to counteract performance degradation often experienced when applying trained deep learning models to unseen data, a common issue in clinical practice due to domain shifts. Accuracy predictions for X-ray structures are used to refine protein structure models, demonstrating the potential of AI in biomolecular research. Additionally, transfer learning with convolutional neural networks has shown promise in various medical image analysis tasks, including those involving X-rays. Moreover, AI is also being used to generate synthetic images for augmenting limited data, particularly for COVID-19 detection from X-ray images; The novelty of AI for X-Ray protocol optimization lies in its ability to address the issue of performance degradation in applying trained deep learning models to unseen data. The use of domain-ensemble learning with cross-domain mixup to construct virtual samples is a distinctive approach. The technology also offers the potential for improved accuracy in protein structure refinement, an area not traditionally associated with X-ray imaging. Furthermore, the ability to generate synthetic images for data augmentation, especially in the context of limited data such as COVID-19 X-ray images, is a significant advancement. Finally, the widespread application of transfer learning with convolutional neural networks in medical image analysis represents a departure from traditional X-ray interpretation methods.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1007/s10858-010-9433-9; http://doi.org/10.1016/j.compbiomed.2020.104115; http://doi.org/10.1016/j.compbiomed.2020.104181; http://doi.org/10.1038/s41467-021-21511-x; http://doi.org/10.1117/12.2580886; http://doi.org/10.1007/s40747-021-00405-x; http://doi.org/10.1109/JBHI.2021.3117575; http://doi.org/10.1186/s12903-022-02170-w; http://doi.org/10.1109/JIOT.2023.3288678; http://doi.org/10.1016/j.compbiomed.2023.107789

NUMBER | TITLE
949 | AI supported Point of Care diagnostics
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
AI-supported Point-of-Care (POC) diagnostics integrates artificial intelligence (AI) and medical imaging to improve the efficiency, accuracy, and speed of disease detection and diagnosis. It employs deep learning techniques and machine learning algorithms for analyzing medical images, such as radiographs, CT scans, and MRI data. These AI models can identify and classify lesions, cancer cells, infectious diseases, and other medical conditions. They are also used in microfluidic label-free separation of different blood cell components and non-traditional biomarker identification. Additionally, they can be embedded into portable imaging devices for POC diagnostics, and can be used in remote diagnostic systems, enabling prompt treatment of conditions like breast cancer in remote areas. AI models can also be integrated with blockchain and federated learning for secure misbehavior detection in Internet of Medical Things (IoMT) devices, ensuring privacy and security; The novelty of AI-supported POC diagnostics lies in its ability to overcome the shortcomings of traditional diagnostic methods through AI and deep learning models. It offers a more comprehensive health profiling by analyzing intrinsic cellular properties and biophysical phenotypes, along with standard blood count analysis. It resolves the object position offset problem and the degradation problem of IoU-based loss in medical lesion detection models. It also provides an efficient framework for resource allocation in medical AI systems, which is crucial when processing large volumes of medical data within a limited time. Moreover, by leveraging new GPU virtualization technology, it achieves superior performance in disease detection tasks and converges more quickly than existing IoU-based losses. Furthermore, this technology can be implemented on mobile hardware, potentially enabling point-of-care diagnostics for personalized cancer treatment.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1016/B978-0-12-818318-2.00005-2; http://doi.org/10.1038/s43018-020-0087-6; http://doi.org/10.1111/1346-8138.15683; http://doi.org/10.3390/diagnostics11020241; http://doi.org/10.1109/JBHI.2022.3187037; http://doi.org/10.1039/d2lc00904h; http://doi.org/10.3389/fbioe.2023.1049555; http://doi.org/10.1016/j.medj.2023.06.007; http://doi.org/10.1109/CVPRW59228.2023.00312; http://doi.org/10.1109/EMBC40787.2023.10340508

NUMBER | TITLE
946 | Automated ultrasound image analysis
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Automated ultrasound image analysis is a technology that employs artificial intelligence (AI) and deep learning algorithms to interpret ultrasound images, a crucial tool in medical imaging. It works by training AI algorithms on large datasets of ultrasound images, enabling them to identify and categorize different health conditions ranging from breast cancer to lung diseases, cardiac issues, and placental diseases. The technology can extract meaningful features associated with specific pathological conditions, assess image quality for more accurate analysis, segment images for detailed examination, and even estimate gestational age and fetal weight in obstetrics. It is designed to reduce the time and resource demands of manual analysis, while also mitigating the issue of inter-reader variability. Its applications include early disease detection, diagnosis, monitoring, and predicting the development of symptoms; The novelty of automated ultrasound image analysis lies in its use of advanced AI and deep learning techniques to automate what has traditionally been a manual, time-consuming and expertise-dependent process. Unlike traditional methods, this technology can process large volumes of images swiftly and accurately, and its performance can continually improve as it learns from more data. Furthermore, it delivers high levels of accuracy in detecting various health conditions across different medical fields, often surpassing currently used state-of-the-art methods. Its ability to provide interpretable results, rather than an inscrutable diagnosis, makes it a more trustworthy and practical tool for clinicians. Moreover, the use of synthetic tissue phantom models for training AI algorithms represents a significant advancement, as it circumvents the need for large animal models or clinical testing. The technology also stands out for its potential to operate effectively in resource-scarce environments, where access to expert interpretation may be limited.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1109/EMBC.2018.8513063; http://doi.org/10.1088/1742-6596/1964/4/042019; http://doi.org/10.1109/EMBC46164.2021.9630169; http://doi.org/10.1016/j.compbiomed.2022.105221; http://doi.org/10.1001/jamacardio.2022.0183; http://doi.org/10.1038/s41598-022-12367-2; http://doi.org/10.1152/ajpheart.00208.2022; http://doi.org/10.3390/diagnostics12092229; http://doi.org/10.1007/s11517-022-02758-y; http://doi.org/10.1016/j.heliyon.2023.e13577

NUMBER | TITLE
945 | AI and IoT to improve patient monitoring
SUGGESTED MATURITY
Close to market (TRL 7-9)
SUMMARY DESCRIPTION
AI-supported patient monitoring in the field of medical imaging combines machine learning (ML), Internet of Things (IoT), and healthcare to improve patient monitoring. This approach utilizes smart devices that gather body measurements, which are then processed and analyzed using ML techniques for risk assessment and management. AI can support perioperative risk monitoring, postoperative care planning, diagnosis of diseases like diabetes, and rehabilitation. It can also facilitate health surveillance and prediction of disease trends. AI can be used in real-time applications, providing valuable decision-making support for clinicians and personalized healthcare for patients. Notably, the use of AI has been proposed for home monitoring of patients with COVID-19 through the Internet of Medical Things (IoMT), using a combination of fog computing and blockchain technology for secure information processing and storage; The novelty of AI-supported patient monitoring lies in its ability to integrate and analyze vast amounts of patient data from various sources in real time. Unlike traditional patient monitoring systems, AI can learn from past data, adapt to changes, and make predictions with high accuracy. This technology provides opportunities for personalized, efficient, and proactive healthcare. However, issues such as data security, patient privacy, and the need for continuous monitoring and tuning of ML algorithms to overcome data drift are challenges that need to be addressed. The use of edge cloud technology to identify malicious nodes in the IoT network is another innovative aspect. Despite its potential, the adoption of AI in some areas, such as oncology, has been slower due to challenges such as lack of incentives and support, and missing standardized infrastructure to implement digital innovations.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1038/sdata.2018.178; http://doi.org/10.1002/ett.4245; http://doi.org/10.1007/s40747-020-00244-2; http://doi.org/10.1016/B978-0-12-818438-7.00002-2; http://doi.org/10.1007/s10462-022-10304-3; http://doi.org/10.3934/math.2023629; http://doi.org/10.1109/ICSCSS57650.2023.10169505; http://doi.org/10.1109/INCET57972.2023.10170738; http://doi.org/10.1109/IC0SEC58147.2023.10275890

NUMBER | TITLE
944 | AI for Tumor Heterogeneity Analysis
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
AI for Tumor Heterogeneity Analysis is a novel technological application that combines advanced machine learning algorithms and computational pathology to analyze tumor heterogeneity in cancer patients. The technology employs deep learning models such as survival convolutional neural networks (SCNNs) to integrate information from histology images and genomic biomarkers. This unified approach enables accurate prediction of patient outcomes, surpassing current clinical paradigms. Furthermore, it uses statistical sampling techniques to overcome challenges posed by tumor heterogeneity and the need for large training cohorts. The technology also encompasses the development of algorithms for segmentation of nuclei and classification of tissue images, the use of liquid biopsy for the detection of cancer and underlying tissue origin, and the construction of deep learning models combining both radiomic and clinical features for overall survival prediction; This technology presents a significant novelty in its integrative approach to analyzing tumor heterogeneity, combining histological, genomic, and clinical data for improved outcome prediction. Traditional methods have often relied on separate analyses of these data types, leading to fragmented and potentially inconsistent results. The AI for Tumor Heterogeneity Analysis overcomes this limitation by harmonizing these data within a single analytical framework. Furthermore, the use of deep learning models and machine learning algorithms enhances the precision and accuracy of the analysis, enabling the detection of subtle patterns and associations that may be overlooked by conventional methods. The technology also addresses challenges in tumor heterogeneity analysis, such as the need for large training cohorts and the complexity of tissue morphology. Through these advancements, the AI for Tumor Heterogeneity Analysis represents a significant innovation in the field of medical imaging and has the potential to transform the practice of pathology and the treatment of cancer.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1016/j.ebiom.2017.12.026; http://doi.org/10.1073/pnas.1717139115; http://doi.org/10.3389/fbioe.2019.00053; http://doi.org/10.1016/j.media.2020.101772; http://doi.org/10.3390/diagnostics12081899; http://doi.org/10.23736/S1824-4785.20.03227-6; http://doi.org/10.1007/s00330-023-09869-6; http://doi.org/10.1097/JS9.0000000000000441

NUMBER | TITLE
942 | AI supported radiogenomics
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
AI-supported radiogenomics involves the application of artificial intelligence (AI) and machine learning to analyze the relationships between radiomic features (extracted from medical images) and genomic data. This technology can infer the genomic features of tumors from radiogenomic associations using non-invasive imaging techniques. It provides a bridge between two areas of research, potentially improving clinical treatment planning and patient outcomes. Recent advancements have led to the development of various models predicting the genetic subtypes of tumors, such as glioblastoma, and other diseases. These predictive models combine information about the spatial distribution and size of tumorous structures with radiomic features, leading to high accuracy in determining the methylation status of patients, which is crucial for their treatment planning. Additionally, AI-supported radiogenomics can assist in identifying the hypoxic pattern in ovarian cancer, which is essential for patient prognostication; The novelty of AI-supported radiogenomics lies in its ability to bridge the gap between radiomics and genomics, providing a new perspective for cancer diagnosis and treatment. Traditional methods focus mainly on the relationship between ultrasonic features and the most popular cancer genes, missing many-to-many relationships and confounding group-specific associations with whole sample associations. AI-supported radiogenomics overcomes these issues by offering an omics-to-omics view and addressing tumor heterogeneity. It uses advanced machine learning algorithms to extract information directly from raw data, eliminating the need for human-engineered features. The application of the rejection algorithm is also a novel approach, effectively selecting and isolating negative training instances from the original dataset. This technology represents a significant advance over established technologies, improving the standard of diagnosis, prognosis, and treatment planning in the medical field.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1148/radiol.2016161382; http://doi.org/10.1148/radiol.2019190613; http://doi.org/10.1002/nbm.4792; http://doi.org/10.1093/noajnl/vdac060; http://doi.org/10.3390/jcm12020419; http://doi.org/10.1016/j.compbiomed.2023.106672; http://doi.org/10.1038/s41598-023-30309-4; http://doi.org/10.3390/ijms24054615; http://doi.org/10.1007/s00330-023-09645-6

NUMBER | TITLE

941 | Improved bowel pathology analysis through AI

SUGGESTED MATURITY

Emerging (TRL 4-6)

SUMMARY DESCRIPTION

AI bowel pathology analysis utilizes machine learning algorithms and artificial intelligence to improve the detection and assessment of bowel diseases such as colorectal cancer, ulcerative colitis, and Crohn's disease. This technology analyzes imaging data from endoscopic procedures, radiographs, and histopathologic images to identify disease markers, predict disease recurrence, and assess disease severity. It also assists in the classification of bowel obstructions and the identification of gut microbiota profiles associated with disease severity in ulcerative colitis. AI-assisted colonoscopy tools have shown potential in enhancing the detection of precancerous polyps, leading to a significant reduction in colorectal cancer incidence and mortality. Furthermore, AI bowel pathology analysis has demonstrated its ability to predict postoperative complications in high-risk ulcerative colitis patients, and to identify specific biomarkers in Crohn's disease for improved diagnosis and treatment;
The novelty of AI bowel pathology analysis lies in its application of artificial intelligence and machine learning to improve the accuracy, precision, and predictive power in bowel disease detection and assessment, overcoming the limitations of subjectivity and variability in traditional methods. Unlike established technologies, AI-assisted tools have demonstrated an incremental gain in colorectal cancer detection and a cost-saving advantage in screening procedures. Furthermore, the integration of machine learning approaches with genetic expression data and gut microbiota profiling offers new insights into disease pathogenesis and prognosis. The ability of this technology to identify specific biomarkers and immune infiltration patterns also opens up new avenues for personalized treatment strategies in bowel diseases.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1016/j.gie.2019.11.012; http://doi.org/10.1016/S2589-7500(22)00042-5; http://doi.org/10.1007/s00330-022-09171-x; http://doi.org/10.1093/ecco-jcc/jjac137; http://doi.org/10.1016/j.lfs.2022.121272; http://doi.org/10.1016/j.eclinm.2022.101805; http://doi.org/10.1109/ICAIS56108.2023.10073766; http://doi.org/10.1053/j.gastro.2023.05.032; http://doi.org/10.1126/science.add1250; http://doi.org/10.1186/s12859-024-05639-3

NUMBER | TITLE

939 | AI classified histopathology images

SUGGESTED MATURITY

Close to market (TRL 7-9)

SUMMARY DESCRIPTION

AI classified histopathology images technology leverages advanced machine learning algorithms, such as Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), and Bidirectional Long Short-Term Memory (BiLSTM), to analyze and classify histopathological images for disease prediction and diagnosis. The technology extracts features from these images, learns from them, and applies the knowledge to accurately identify diseases such as breast cancer and lung and colon cancer. The technology is particularly successful in the early detection of breast cancer, with accuracy levels as high as 98.8%. It can also classify cancer as benign or malignant, thus aiding in treatment decisions. Additionally, the technology can be employed in Internet of Medical Things (IoMT) enabled healthcare technologies for real-time disease identification;
The novelty of AI classified histopathology images technology lies in its integration of advanced machine learning techniques and image processing to improve the accuracy and efficiency of disease prediction and diagnosis. Unlike traditional techniques that relied solely on visual inspection by experts or basic machine learning models, this technology uses deep learning algorithms and feature extraction techniques that can learn and improve over time. It also avoids the issue of overfitting through data augmentation methods. Furthermore, the technology is also designed to be lightweight, making it suitable for IoMT imaging devices. This advancement in medical imaging technology not only increases diagnosis accuracy but also enhances the speed of processing large datasets, making it a considerable improvement over established technologies.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1038/s41598-017-04075-z; http://doi.org/10.1007/s10278-019-00182-7; http://doi.org/10.1109/ACCESS.2021.3056516; http://doi.org/10.1007/s11063-021-10555-1; http://doi.org/10.1007/978-981-16-2641-8_8; http://doi.org/10.1016/j.ipm.2022.103225; http://doi.org/10.1016/j.bspc.2022.104534; http://doi.org/10.1109/ICCCI56745.2023.10128352; http://doi.org/10.1016/j.eswa.2023.122418; http://doi.org/10.1007/s41060-024-00507-y

NUMBER | TITLE

938 | AI-supported differential diagnosis

SUGGESTED MATURITY

Close to market (TRL 7-9)

SUMMARY DESCRIPTION

AI-supported differential diagnosis is an innovative technology that uses artificial intelligence to assist in the diagnosis of diseases. This technology leverages machine learning algorithms to analyze vast amounts of data, including gene expression, methylation data, and medical imaging such as CT scans and MRI, to distinguish between similar diseases and predict the origin of diseases. In the field of medical imaging, AI-supported differential diagnosis uses neural networks to map large-scale neural network function and dysfunction, helping to differentiate between diseases such as Alzheimer's and frontotemporal dementia. It also employs deep learning algorithms to provide a differential diagnosis for cancer of unknown primary origin using routinely acquired histology slides. Moreover, this technology can be used to detect depression based on large-scale acoustic characteristics, identify lung nodules, and even predict potential risks of heart, lung, and mental illnesses;
The novelty of AI-supported differential diagnosis lies in its ability to analyze complex, multidimensional data to detect patterns that might be overlooked by human clinicians. Unlike traditional methods, which rely on the clinician's expertise and understanding of disease symptoms and progression, AI-supported differential diagnosis can process and interpret vast amounts of data rapidly and accurately. This technology also goes beyond binary symptoms and antecedents, considering categorical and multi-choice symptoms and antecedents as well, and even organizing some symptoms in a hierarchy for logical interaction. Furthermore, it uses self-supervised transfer learning and visual attention to overcome challenges such as insufficient labeled samples and interferences of background tissues. As this technology continues to evolve, it holds the potential to provide simple, inexpensive, and non-invasive biomarkers for dementia differential diagnosis, disease monitoring, and even the prediction of depression status.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1109/TMI.2016.2535865; http://doi.org/10.1148/radiol.2017170706; http://doi.org/10.1016/j.ijcard.2022.11.021; http://doi.org/10.3390/ijerph20043378; http://doi.org/10.1201/9781003328780-6; http://doi.org/10.2196/48568; http://doi.org/10.5858/arpa.2021-0518-OA; http://doi.org/10.2196/48659; http://doi.org/10.1007/s00405-023-08219-y; http://doi.org/10.1007/s40123-023-00805-x

NUMBER | TITLE

937 | MRI-based radiomics

SUGGESTED MATURITY

Close to market (TRL 7-9)

SUMMARY DESCRIPTION

MRI-based radiomics is a cutting-edge technology in the field of medical imaging that involves the extraction and analysis of a large quantity of advanced quantitative features from medical images. It leverages machine learning algorithms to identify patterns within these data, which can be used for disease diagnosis, prognosis, and predicting treatment response. This method has been applied to a variety of clinical scenarios, including predicting the response to neoadjuvant chemotherapy in breast cancer, predicting Gleason scores in prostate cancer, identifying germinomas in the pineal region, and preoperative prediction of vessels encapsulating tumor clusters and patient prognosis in hepatocellular cancer. It also has potential applications in predicting surgical outcomes, assessing the risk of radiotherapy-induced injury, and predicting survival in glioma patients;
The novelty of MRI-based radiomics lies in its ability to extract and analyze a multitude of data from medical images, going beyond the information that can be gleaned through traditional visual assessment. This provides a more comprehensive understanding of disease characteristics and progression, enabling personalized treatment planning. Compared to established imaging technologies, MRI-based radiomics offers a non-invasive, objective, and reproducible method for disease characterization and prediction. While traditional imaging methods rely on subjective interpretation by radiologists, MRI-based radiomics harnesses the power of machine learning to identify complex patterns within imaging data, potentially increasing diagnostic and prognostic accuracy. Furthermore, this technology has the potential to be integrated into routine clinical practice, enhancing patient management and outcomes.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1093/brain/awab340; http://doi.org/10.1148/RADIOL.211986; http://doi.org/10.1016/j.acra.2022.04.004; http://doi.org/10.1007/s00330-022-08952-8; http://doi.org/10.1002/jmri.28441; http://doi.org/10.1097/RLI.0000000000000927; http://doi.org/10.1136/ijgc-2023-004313; http://doi.org/10.1109/ISBI53787.2023.10230328

NUMBER | TITLE
935 | Vesical Imaging-Reporting and Data System
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Vesical Imaging-Reporting and Data System (VI-RADS) is a novel technology in the field of medical imaging, specifically for bladder cancer (BC). It is a scoring system that standardizes multiparametric magnetic resonance imaging (mpMRI) interpretation and reporting for BC. VI-RADS leverages T2-weighted MRI, diffusion-weighted imaging, and dynamic contrast enhancement. The goal is to enhance patient care by offering better imaging resolution than computed tomography and without radiation exposure. Besides aiding in the diagnosis of muscle-invasive bladder cancer (MIBC), potential applications of VI-RADS include risk stratification of non-muscle-invasive BC, monitoring therapy response, and possibly predicting post-treatment outcomes. It is expected to improve communication among clinicians and facilitate patient comparison, thus optimizing BC management; The novelty of VI-RADS lies in its standardized approach to imaging and reporting mpMRI for BC, which addresses the staging dilemma often faced when results from different tests conflict. Unlike traditional imaging technologies, VI-RADS incorporates a scoring system that suggests risks of muscle invasion, thereby enhancing diagnosis accuracy. It has demonstrated good diagnostic efficacy and repeatability even among less experienced radiologists, indicating its robustness. Furthermore, recent developments suggest the possibility of using VI-RADS for preoperative staging in post-treatment patients and for distinguishing non-muscle-invasive BC from muscle-invasive BC. It also shows potential in grading bladder tumors, which is a significant advancement in the field of medical imaging for bladder cancer.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1016/j.eururo.2018.04.029; http://doi.org/10.1007/s00330-019-06117-8; http://doi.org/10.1016/j.eururo.2019.03.012; http://doi.org/10.1148/radiol.2019182506; http://doi.org/10.1016/j.eururo.2019.09.029; http://doi.org/10.1002/jmri.27361; http://doi.org/10.1007/s00261-021-03365-5; http://doi.org/10.1016/j.acra.2022.04.014; http://doi.org/10.1007/s00330-022-09272-7; http://doi.org/10.1016/j.euo.2022.07.006

NUMBER | TITLE
934 | AI supported Imaging Protocols
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
AI-supported Imaging Protocols involve the use of machine learning models to automatically segment and analyze medical images, such as X-rays, MRIs, and cardiac imaging, for disease diagnosis and prognosis. These protocols leverage techniques such as domain-ensemble learning, self-adaptive normalization networks, U-Net architectures, and image-to-image translation to overcome challenges such as domain shifts and inter-site discrepancies caused by variations in scanner vendors, imaging protocols, and patient demographics. These AI models can be trained to generalize across different clinical centers and scanner vendors, adapt to new datasets, and maintain the natural appearance of images, thus improving diagnostic accuracy and reducing the need for manual annotation; The novelty of this technology lies in its ability to learn from both source and virtual domains, adapt to unseen datasets, and handle different imaging protocols and patient demographics, which are significant challenges in medical imaging. AI-supported Imaging Protocols use advanced techniques like cross-domain mixup to construct virtual samples, masked adaptive instance normalization to minimize inter-site discrepancies, and data augmentation techniques to improve domain generalizability. This technology also includes the development of variational networks that integrate the structure of variational models with deep learning, and the application of adversarial neural networks for unsupervised domain adaptation. These advancements enhance the robustness, accuracy, and generalizability of medical imaging analyses, making AI-supported Imaging Protocols a significant upgrade over traditional imaging protocols.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1007/978-3-319-59050-9_47; http://doi.org/10.1007/978-3-319-66179-7_59; http://doi.org/10.1002/mrm.26977; http://doi.org/10.1016/j.nicl.2018.101645; http://doi.org/10.1109/TMI.2021.3090082; http://doi.org/10.1038/s41596-023-00806-x; http://doi.org/10.1109/ISBI53787.2023.10230409; http://doi.org/10.1117/12.2651430; http://doi.org/10.1117/12.2653251; http://doi.org/10.1097/SLA.0000000000005465

NUMBER | TITLE
933 | Diagnosis of eye-related disease based on automated analysis of retinal images
SUGGESTED MATURITY
Close to market (TRL 7-9)
SUMMARY DESCRIPTION
Diagnosis based on retinal images involves using advanced computational and machine learning methods to automate the analysis of retinal images for detecting various eye-related diseases such as diabetic retinopathy, macular degeneration, and glaucoma. This technology involves several stages including pre-processing of images to reduce noise and improve contrast, segmentation to extract key features such as blood vessels, and the application of deep learning algorithms for accurate classification and diagnosis. Recent advancements include the integration of convolutional neural networks, transformers, and ensemble learning techniques for improved feature extraction and diagnostic accuracy. Furthermore, these systems are designed to leverage large datasets for training, resulting in high precision and recall scores. The technology also offers the potential for faster diagnosis, reducing the workload on healthcare professionals and enabling earlier detection and treatment of eye diseases;b) The novelty of this technology lies in its use of advanced machine learning techniques and the integration of multiple models to improve diagnostic accuracy. Traditional methods involve manual grading of retinal images which is time-consuming, prone to errors, and highly dependent on the skill of the grader. In contrast, the new technology automates this process and negates the need for human intervention, thereby increasing efficiency and consistency in diagnosis. Additionally, the use of deep learning algorithms allows for the extraction of complex and abstract features that may not be easily identifiable by human graders. The incorporation of advanced techniques such as attention blocks, label smoothing, and cost-sensitive regularization further enhance the performance of these systems, making them superior to existing methods. Furthermore, some of these models are designed to maintain privacy by not transferring patient data between healthcare organizations, thus addressing potential legal and ethical issues surrounding data sharing in healthcare.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1016/j.ophtha.2017.10.031; http://doi.org/10.1001/jamaophthalmol.2018.1934; http://doi.org/10.1016/B978-0-12-817440-1.00003-6; http://doi.org/10.1109/TCYB.2022.3194099; http://doi.org/10.1109/ICAIC57335.2023.10044122; http://doi.org/10.1007/s11042-023-15045-1; http://doi.org/10.1109/ICEARS56392.2023.10085616; http://doi.org/10.1109/ICEARS56392.2023.10085273; http://doi.org/10.1109/ICICT57646.2023.10134388; http://doi.org/10.1109/ICICT57646.2023.10133943; http://doi.org/10.1038/s41586-023-06555-x

NUMBER | TITLE

929 | Transparent ultrasound transducer

SUGGESTED MATURITY

Emerging (TRL 4-6)

SUMMARY DESCRIPTION

Transparent ultrasound transducers (TUTs) are innovative devices in the field of medical imaging that offer new potential for multimodal imaging applications. These devices, fabricated from materials such as indium tin oxide coated lithium niobate, offer both transparency and piezoelectric properties. This transparency allows for the co-alignment of optical illumination and ultrasound receiving fields, overcoming the limitations of conventional, opaque ultrasound transducers. This facilitates a simplified and miniaturized setup, enabling integration with other imaging modalities. TUTs have shown promising applications in endoscopy, microscopy, computed tomography systems, and photoacoustic imaging. They can be used to image areas of the body such as the cerebral vasculature and lymph nodes, and can also be used in applications such as tumor imaging and monitoring responses to injuries;
The novelty of TUTs lies in their transparent nature, which offers several advantages over conventional ultrasound transducers. This transparency allows for the seamless integration of optical and ultrasound imaging, overcoming the need for complex arrangements of optical components. It also allows for co-axial alignment of the ultrasound and optical signal paths, which results in higher signal-to-noise ratios. Furthermore, TUTs enable miniaturization of the imaging head and can be easily integrated into different imaging geometries, facilitating high-throughput imaging applications. Despite these advancements, challenges remain in matching the acoustic sensitivity of TUTs to conventional transducers, and in optimizing their signal to noise ratio. However, ongoing research and development are paving the way for breakthroughs in these areas, promising significant advancements in the field of medical imaging.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1364/OL.44.005326; http://doi.org/10.1109/JSEN.2019.2952971; http://doi.org/10.1117/12.2544037; http://doi.org/10.1073/pnas.1920879118; http://doi.org/10.1117/12.2579056; http://doi.org/10.1117/12.2610187; http://doi.org/10.1016/j.pacs.2022.100417; http://doi.org/10.1109/JSEN.2023.3247969; http://doi.org/10.1016/j.pacs.2023.100548; http://doi.org/10.1002/lpor.202300652

NUMBER | TITLE

927 | Red Dichromatic Imaging

SUGGESTED MATURITY

Close to market (TRL 7-9)

SUMMARY DESCRIPTION

Red Dichromatic Imaging (RDI) is a novel type of image-enhanced endoscopy technology that leverages two long wavelengths to visualize deep submucosal vessels in the gastrointestinal wall. This technology offers the capability to clearly identify and visualize bleeding points, even in cases of massive bleeding where traditional white light imaging (WLI) may be inadequate. RDI has been shown to effectively predict esophageal varices depth, decrease recurrence rates, and enhance the visibility of bleeding points in acute gastrointestinal bleeding. It also demonstrated its value in reducing the incidence of bleeding and hematoma formation during submucosal injection in esophageal endoscopic submucosal dissection (ESD), and in reducing the psychological stress on endoscopists during hemostatic treatments;
The novelty of RDI technology lies in its ability to use longer wavelengths to visualize deeper vessels, improving the identification and treatment of bleeding points, and potentially shortening treatment times. Compared to established technologies like white light imaging, RDI enhances the visibility of deep-lying blood vessels and bleeding areas, making it more effective in diagnosing and treating gastrointestinal disorders. Moreover, RDI has been found to be safe to use for hemostatic procedures and reduces the psychological stress experienced by endoscopists when they perform hemostatic treatment during ESD. This technology, therefore, presents significant advancements over traditional methods in terms of efficiency, accuracy, and practitioner ease of use.

SOURCE

TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1002/jhbp.894; http://doi.org/10.1111/den.14011; http://doi.org/10.1111/den.14191; http://doi.org/10.1016/j.gie.2021.10.031; http://doi.org/10.1007/s00464-022-09244-4; http://doi.org/10.1007/s00464-022-09543-w; http://doi.org/10.1055/a-1929-9038; http://doi.org/10.1055/a-1948-2182; http://doi.org/10.1007/s00464-022-09852-0; http://doi.org/10.1038/s41598-023-35564-z

NUMBER | TITLE
923 | Positronium imaging
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Positronium imaging is a ground-breaking advancement in the field of medical imaging, specifically in positron emission tomography (PET), which leverages the properties of positronium, a short-lived system of an electron and its anti-particle, a positron. When positronium decays within the body, it is sensitive to the nanostructure and metabolism of tissues, providing unique diagnostic markers for cancer therapy. The technology enhances the sensitivity and specificity of PET scans by measuring the mean lifetime and production probability of positronium in healthy and cancerous tissues, providing potential indicators for in-vivo cancer classification. The total-body PET scanners, like the J-PET tomography system, can be used for positronium imaging, offering a more cost-effective solution for broad clinical applications. This technology could significantly improve the specificity of PET diagnostics and provide crucial insights into disease progression at the initial stages of molecular alterations; The novelty of positronium imaging lies in its ability to capitalize on the properties of positronium, a phenomenon that has not been recorded or used in traditional PET techniques. While current PET systems provide information on the density distribution of a radiopharmaceutical in the body, positronium imaging can provide additional insights about the inter- and intra-molecular structure of the tissue and the concentration of bio-active molecules. This enhanced level of information could be instrumental in understanding the tissue microenvironment in vivo, studying disease mechanisms, and selecting appropriate treatments. Additionally, the development of the J-PET tomography system, which is based on low-cost plastic scintillator strips, represents a significant advancement in making total-body PET more accessible and cost-effective. Lastly, positronium imaging also opens up the possibility of performing quantum entanglement imaging, exploiting the quantum properties of the surrounding tissue environment, and potentially developing novel prognostic indicators for cancer diagnostics.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1088/1361-6560/aafe20; http://doi.org/10.1109/NSSMIC.2018.8824622; http://doi.org/10.1109/NSS/MIC42101.2019.9059856; http://doi.org/10.1186/s40658-020-00307-w; http://doi.org/10.1016/j.cpet.2020.06.009; http://doi.org/10.1126/sciadv.abh4394; http://doi.org/10.1109/NSS/MIC44867.2021.9875524; http://doi.org/10.1016/j.zemedi.2022.11.001; http://doi.org/10.1103/RevModPhys.95.021002; http://doi.org/10.1186/s40658-023-00543-w

NUMBER | TITLE
922 | Line-field confocal opt coherence tomography
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
Line-field Confocal Optical Coherence Tomography (LC-OCT) is a cutting-edge imaging technique in medical diagnostics. It provides high-resolution, real-time, in vivo images in both vertical and horizontal planes and in three dimensions. This technology allows for a deep imaging up to 400 µm, making it an excellent tool for evaluating skin lesions. Its application has been evaluated for diagnosing various skin conditions like melanocytic lesions, basal cell carcinomas (BCCs), pustular skin disorders, and other inflammatory skin diseases. LC-OCT has shown high correlation with histopathology and reflectance confocal microscopy, demonstrating its potential to provide precise diagnosis at the cellular level. It can also assist in differentiating between benign and malignant lesions, and even between different subtypes of a particular skin cancer; The novelty of LC-OCT lies in its ability to combine the advantages of both reflectance confocal microscopy and optical coherence tomography. Unlike these two established technologies, LC-OCT can create both vertical and horizontal images in real-time with high cellular resolution. This gives it superior diagnostic capabilities, allowing for a more accurate identification of skin lesions and their subtypes. The LC-OCT's ability to provide three-dimensional imaging is another significant advance, as it allows for a better understanding of the architecture of skin lesions. Furthermore, studies have shown that LC-OCT can achieve high sensitivity and specificity in diagnosing skin cancers, surpassing the performance of dermoscopy alone. This makes it a promising tool for non-invasive early detection and diagnosis of skin cancers.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1111/srt.12949; http://doi.org/10.1111/jdv.17078; http://doi.org/10.1111/cup.14321; http://doi.org/10.1002/lsm.23613; http://doi.org/10.1111/srt.13215; http://doi.org/10.3390/diagnostics13030361; http://doi.org/10.1111/jdv.19149; http://doi.org/10.23736/S2784-8671.23.07634-X; http://doi.org/10.23736/S2784-8671.23.07639-9; http://doi.org/10.1117/12.2670911

NUMBER | TITLE
921 | Stimulated Raman Histology
SUGGESTED MATURITY
Close to market (TRL 7-9)
SUMMARY DESCRIPTION
Stimulated Raman Histology (SRH) is a novel technology in medical imaging that leverages stimulated Raman scattering microscopy to generate rapid, high-resolution, label-free images of tissue samples. This technique allows for intraoperative analysis of tissue samples, providing real-time data to inform surgical decisions. SRH images can be processed to simulate traditional hematoxylin-and-eosin stained slides, revealing key diagnostic features. Furthermore, deep learning models can be trained on SRH images to automate interpretation and speed up diagnoses. SRH has been successfully used in various clinical contexts, including brain and spinal tumor resections, gastric cancer diagnosis, and skull base tumor analysis; The novelty of SRH lies in its capacity to expedite intraoperative histopathological decision-making without sacrificing accuracy. Traditional methods for intraoperative histopathology, such as the frozen section technique, are labor-intensive, time-consuming, and require specialized resources. In contrast, SRH allows for rapid acquisition and interpretation of diagnostic histological images at the bedside, significantly reducing the time to diagnosis. Moreover, with the integration of artificial intelligence, SRH can provide automated, accurate diagnoses within minutes, further accelerating the surgical workflow. The ability to reliably differentiate tumor from non-tumorous tissue, predict brain tumor subtypes, and even anticipate molecular alterations in diffuse gliomas positions SRH as a promising alternative to traditional histopathological methods.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1038/s41551-016-0027; http://doi.org/10.3171/2019.9.JNS192075; http://doi.org/10.1007/s10143-021-01712-0; http://doi.org/10.1007/s10143-021-01711-1; http://doi.org/10.1227/neu.0000000000001929; http://doi.org/10.1038/s41467-022-31339-8; http://doi.org/10.1186/s40478-022-01411-x; http://doi.org/10.1038/s41591-023-02252-4; http://doi.org/10.3389/fonc.2023.1146031; http://doi.org/10.1016/j.modpat.2023.100219

NUMBER | TITLE
907 | Enhanced minimally-invasive patient monitoring with a new peripheral nerve interface technology
SUGGESTED MATURITY
Novel (TRL 1-3)
SUMMARY DESCRIPTION
Researchers from the University of Cambridge combined flexible electronics and soft robotics techniques to develop the devices. They could be used to diagnose and treat a range of disorders, including epilepsy and chronic pain, or to control prosthetic limbs. Current tools for interfacing with the peripheral nerves – the 43 pairs of motor and sensory nerves that connect the brain and the spinal cord – are outdated, bulky, and carry a high risk of nerve injury. The robotic nerve 'cuffs' developed by the Cambridge team are sensitive enough to grasp or wrap around delicate nerve fibers without causing any damage. The researchers say the combination of soft electrical actuators with neurotechnology could be an answer to minimally invasive monitoring and treatment for a range of neurological conditions. The results are reported in the journal Nature Materials.
SOURCE
University of Cambridge Researchers have developed tiny, flexible devices that can wrap around individual nerve fibres without damaging them. https://www.cam.ac.uk/research/news/robotic-nerve-cuffs-could-help-treat-a-range-of-neurological-conditions

NUMBER | TITLE
737 | Quadratic support vector machines to identify medical conditions
SUGGESTED MATURITY
n/a
SUMMARY DESCRIPTION
Quadratic Support Vector Machines (Q-SVM) are advanced machine learning models extensively used in various fields of quantum technology for classification and prediction tasks. The distinguishing feature of Q-SVMs is their kernel-free structure, which eliminates challenges associated with finding suitable kernel functions or adjusting hyperparameters. Q-SVMs also have the ability to utilize Universum data points, external data not belonging to any class, to incorporate prior knowledge and improve overall model performance. This technology has shown promising results in several applications, such as automatic arrhythmia diagnosis using Electrocardiogram signals, external disturbance detection in buried pipeline monitoring systems, and brain computer interface models for understanding brain disorders. Furthermore, Q-SVMs have been successfully used in classifying skin cancer lesions, detecting power quality disturbances, and forecasting electrical load demands in microgrid systems. With high accuracy, computational efficiency, and robustness, Q-SVMs offer significant advancements in quantum technology and its various applications.
SOURCE
TIM signals. Sources used in the signal's detection and description include, but are not limited to: http://doi.org/10.1007/s00521-020-05212-y ; http://doi.org/10.1016/j.rico.2023.100219 ; http://doi.org/10.1016/j.foodcont.2021.108479

NUMBER | TITLE
313 | Inhalable nanosensors used for cancer detection
SUGGESTED MATURITY
Novel (TRL 1-3)
SUMMARY DESCRIPTION
A new diagnostic tool such as inhalable sensors. These nanosensors can be delivered by an inhaler or a nebulizer. If the sensors encounter cancer-linked proteins in the lungs, they produce a signal that accumulates in the urine, where it can be detected with a simple paper test strip. This is significant because it has the potential to make lung cancer screening accessible worldwide.
SOURCE
MIT News Inhalable sensors could enable early lung cancer detection https://news.mit.edu/2024/inhalable-sensors-early-lung-cancer-detection-0105

NUMBER | TITLE
264 | Cancer-fighting nanoparticles
SUGGESTED MATURITY
Close to market (TRL 7-9)
SUMMARY DESCRIPTION
Researchers are developing a groundbreaking method for early tumor detection using injectable nanoparticles. These nanoparticles, designed to locate microscopic tumors undetectable by traditional imaging, were detailed in a recent study. The technique involves guiding cancer-detecting nanoparticles to tumors more efficiently, using minimal resources. The challenge of using 'nanoswimmers' lies in efficiently dispersing them throughout the body while ensuring they accumulate at the cancer site. Historically, only 0.7% of injected nanoparticles reach their target. To improve targeting, researchers propose combining two known solutions using a fleet of semi-autonomous nanoswimmers that instinctively move towards cancer cells. By periodically measuring their speed and aggregation pattern, researchers can identify their general convergence area. This information allows for more precise magnetic guidance, directing the swarm towards the tumor. Simulations demonstrate that this "spot sampling technique" can accurately steer the nanoswimmers with 90% fewer monitoring resources, making it a promising approach for early cancer detection.
SOURCE
IEEE IEEE SPECTRUM https://spectrum.ieee.org/nanoparticles-in-cancer-treatment

NUMBER | TITLE
239 | Hyperspectral imaging
SUGGESTED MATURITY
Emerging (TRL 4-6)
SUMMARY DESCRIPTION
A technique which combines spectroscopy with imaging that analyses a wide spectrum of light, the light striking each pixel is broken down into many different spectral bands to provide much better information about the image. With the advent of imaging beyond the visible light, we can see how we could get more precise on fingerprinting an exact object or technology, precision agriculture is one potential application.
SOURCE
Innovate UK 50 UK's Emerging Technologies https://www.ukri.org/wp-content/uploads/2023/12/IUK-05122023-IN00617_Emerging-Tech-Report_AW2-final.pdf

NUMBER | TITLE
211 | Paper-based wearable electronics
SUGGESTED MATURITY
Novel (TRL 1-3)
SUMMARY DESCRIPTION
Skin-interfaced wearable electronics can find a broad spectrum of applications in healthcare, human-machine interface, robotics, and others. The state-of-the-art wearable electronics usually suffer from costly and complex fabrication procedures and nonbiodegradable polymer substrates. Paper, comprising entangled micro- or nano-scale cellulose fibers, is compatible with scalable fabrication techniques and emerges as a sustainable, inexpensive, disposable, and biocompatible substrate for wearable electronics. Given various attractive properties (e.g., breathability, flexibility, biocompatibility, and biodegradability) and rich tunability of surface chemistry and porous structures, paper offers many exciting opportunities for wearable electronics.
SOURCE
https://www.sciencedirect.com/science/article/pii/S2589004221007045

Getting in touch with the EU

In person

All over the European Union there are hundreds of Europe Direct centres. You can find the address of the centre nearest you online (european-union.europa.eu/contact-eu/meet-us_en).

On the phone or in writing

Europe Direct is a service that answers your questions about the European Union. You can contact this service:

— by freephone: 00 800 6 7 8 9 10 11 (certain operators may charge for these calls),

— at the following standard number: +32 22999696,

— via the following form: european-union.europa.eu/contact-eu/write-us_en.

Finding information about the EU

Online

Information about the European Union in all the official languages of the EU is available on the Europa website (european-union.europa.eu).

EU publications

You can view or order EU publications at op.europa.eu/en/publications. Multiple copies of free publications can be obtained by contacting Europe Direct or your local documentation centre (european-union.europa.eu/contact-eu/meet-us_en).

EU law and related documents

For access to legal information from the EU, including all EU law since 1951 in all the official language versions, go to EUR-Lex (eur-lex.europa.eu).

EU open data

The portal data.europa.eu provides access to open datasets from the EU institutions, bodies and agencies. These can be downloaded and reused for free, for both commercial and non-commercial purposes. The portal also provides access to a wealth of datasets from European countries.

Science for policy

The Joint Research Centre (JRC) provides independent, evidence-based knowledge and science, supporting EU policies to positively impact society.

EU Science Hub
Joint-research-centre.ec.europa.eu

Publications Office
of the European Union