Exploring the potentials and challenges of Artificial Intelligence in supporting clinical diagnostics and remote assistance for the health and well-being of individuals

Andrea Berti[1,2], Rossana Buongiorno[1,2], Gianluca Carloni[1,2], Claudia Caudai[1], Giulio Del Corso[1], Danila Germanese[1], Eva Pachetti[1,2], Maria Antonietta Pascali[1] and Sara Colantonio[1,*]

[1]Institute of Information Science and Technologies, ISTI, National Research Council of Italy, CNR, via G. Moruzzi, 1, Pisa, 56124, Italy
[2]Department of Information Engineering, University of Pisa, Via Caruso 16,56122, Pisa, Italy

Abstract
Innovative technologies powered by Artificial Intelligence have the big potential to support new models of care delivery, disease prevention and quality of life promotion. The ultimate goal is a paradigm shift towards more personalized, accessible, effective, and sustainable care and health systems. Nevertheless, despite the advances in the field over the last years, the adoption and deployment of AI technologies remains limited in clinical practice and real-world settings. This paper summarizes the activities that a multidisciplinary research group within the Signals and Images Lab of the Institute of Information Science and Technologies of the National Research Council of Italy is carrying out for exploring both the potential of AI in health and well- being as well as the challenges to their uptake in real-world settings.

Keywords
Visual intelligence, Medical imaging, Radiomics, Imaging bio-banks, Assistive technologies, Trustworthy AI

1. Introduction

The health and care landscape is changing significantly, thanks to the continuous advances of scientific discoveries and diagnostic and therapeutic procedures. Though undeniably advantageous for the health outcome of individuals, this progress may increase clinicians' and physicians' workload and thus affect the quality of their professional life.

Computerised technologies powered by Artificial Intelligence (AI) have the potential to relieve this issue, thanks to their ability to integrate multi-modal data and provide quantitative insights, particularly when considering those topics whose medical knowledge is not yet well-consolidated as remote monitoring of individuals.

Nevertheless, the adoption and deployment of AI technologies remains still limited in clinical practice. A recent survey carried out in Australia and New Zealand highlights that a large share of clinicians was convinced that AI solutions could improve their specialty, but the vast majority of them (more than 80%) had never used any AI-powered applications in their daily practice and only 5% viewed themselves as having excellent knowledge of AI [1]. Adoption barriers include perceived challenges to human autonomy, accountability and liability issues, potential biases and risks [1, 2], as well as excessive requirements in terms of effort and cognitive load and dissatisfaction with user interfaces [3]. Overall, a general lack of trust is reported and it seems to be also related to the lack of knowledge about the assumptions, limitations and capabilities of the AI-powered tools [4]. It should be noted that the same types of concerns and challenges have been identified along the years in the field of Computer-Aided Diagnosis (CAD) systems [5].

Similarly, several factors seem to hinder the uptake in real-life settings of AI-powered technologies for life-logging and remote assistance to individuals [6]. The classical usability analyses have demonstrated to fall short when considering the eventual acceptance and adoption of assistive technologies by their end beneficiaries (i.e., assisted subjects/patients and their caregivers). The need to take into account other individual concerns, such as trust in technology, data security and privacy, has lately become evident [7].

This paper summarizes the activities that a multidis-

Ital-IA 2023: 3rd National Conference on Artificial Intelligence, organized by CINI, May 29–31, 2023, Pisa, Italy
*Corresponding author.
rossana.buongiorno@isti.cnr.it (R. Buongiorno); gianluca.carloni@isti.cnr.it (G. Carloni); claudia.caudai@isti.cnr.it (C. Caudai); giulio.delcorso@isti.cnr.it (G. D. Corso); danila.germanese@isti.cnr.it (D. Germanese); eva.pachetti@isti.cnr.it (E. Pachetti); maria.antonietta.pascali@isti.cnr.it (M. A. Pascali); sara.colantonio@isti.cnr.it (S. Colantonio)
0009-0001-5190-0223 (R. Buongiorno); 0000-0002-5774-361X (G. Carloni); 0000-0002-1590-7890 (C. Caudai); 0000-0003-4604-2006 (G. D. Corso); 0000-0002-7814-5280 (D. Germanese); 0000-0002-1321-9285 (E. Pachetti); 0000-0001-7742-8126 (M. A. Pascali); 0000-0003-2022-0804 (S. Colantonio)

ciplinary research group within the Signals and Images Lab of the Institute of Information Science and Technologies of National Research Council of Italy is carrying out for exploring both the potential of AI in health and well-being as well as the challenges to their uptake in real-world settings.

2. Visual AI for clinical diagnostics

In the following sections, we briefly overview the works done in the field of AI supporting clinical diagnostics. In most cases, the focus is on medical imaging, as radiology is expected to be the discipline that will most benefit from the late progresses of AI in visual perception. A discussion of the challenges in this domain and the works done to address them concludes this chapter.

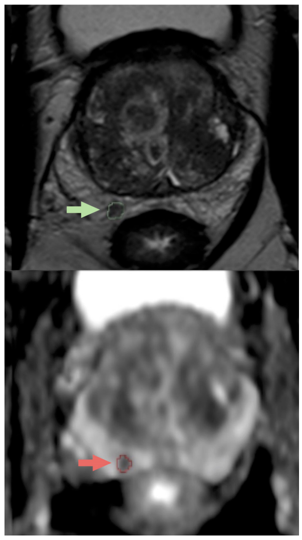

Figure 1: mpMRI of a 76-years old patient: top axial T2-weighted image, bottom ADC map. Both contain the segmented target lesion, pointed by the arrow.

2.1. Visual AI for the prediction of prostate cancer aggressiveness in Magnetic Resonance Imaging

Prostate cancer (PCa) is the most frequent male neoplasm in European men. Assessing PCa aggressiveness, is key to steer patient management. Currently, the gold standard for determining tumour aggressiveness of is biopsy, which is unfortunately an invasive and uncomfortable procedure. Before the biopsy, physicians recommend an investigation by multi-parametric Magnetic Resonance Imaging (mpMRI), which may serve the radiologist to gather an initial assessment of the tumour, based on the visual inspection and evaluation based on the PI-RADS standard.

Quantitative assessment of mpMRI might provide the radiologist with a repeatable and non-invasive tool decreasing intra- and inter-reader variability. In this view, in collaboration with a team from CNR Institute of Physics "Nello Carrara" and the University Hospital of Careggi in Florence, we have initially investigated the potential of high dimensional radiomics analyses to identify the phenotypic differences of tumour traits [8]. We extracted radiomic features of different orders from T2w and ADC map images (see "`figure`" 1), and applied a wrapper, feed-forward feature selection method to select the most relevant ones for distinguishing non aggressive (i.e., low grade according to the biopsy Gleason score) from aggressive (i.e., high grade according to the biopsy Gleason score) PCa. A non-linear SVM classifier, trained in cross-validation on the 57 cases, was able to achieve an accuracy of 93% (sens 90.2%, spec 100%, F-score 94.9%) and an AUC of 99%.

After increasing the sample size to 104 patients, we designed and trained Deep Learning (DL) models without and with an attention mechanism to predict PCa aggressiveness from different pre-processed data, namely on lesion-centred cropped T2w and ADC images, and on lesion- selected T2w and ADC images. Imaging data were acquired in diverse time frame, in accordance with two PI-RADS protocols (i.e., 2.0 and 2.1). We adopted a robust framework to train and test the models, based on nested, stratified, multiple split and bootstrap cross-validation, leaving aside a test set of 14 cases. The DL model with attention trained on lesion-centred cropped T2w images achieved the overall best performance. Nevertheless, the performance consistently dropped when applying the model to data acquired with a different PI-RADS protocol, thus showing limited generalization capacity of the model [9].

For further investigating the potential of the attention mechanism, we designed and trained a 3D Vision Transformer (ViT) able to process volumetric scans, and we optimized it, via a grid search, on the freely available ProstateX-2 challenge dataset by training it from scratch [10]. As a term of comparison, we also designed a 3D Convolutional Neural Network (CNN), and we optimized it in a similar fashion. The results obtained by our preliminary investigations showed that Vision Transformers, even without extensive optimization and customization, can ensure an improved performance with respect to CNN and might be comparable with other more fine-tuned solutions. Trained on 5-fold cross-validation, the ViT reached an average AUC of 77.5% (sens 75%, spec 56.7%, F2-score 52.3%) on the test set.

2.2. Radiomics analyses for discriminating parotid gland tumours

In collaboration with a team from Pisa University Hospital, we investigated the potential of radiomics analyses also for predicting the malignancy of parotic malignant tumours from MRI data [11]. Salivary gland tumours are fortunately rare, with an annual worldwide incidence ranging from 0.05 to 2 cases per 100,000 individuals. Almost 80% of tumours affect parotid glands and most of them are benign (80%), being the pleomorphic adenoma the most frequent neoplasm, then followed by the Warthin tumour. In our study, we evaluated 75 T2-weighted images of parotid gland lesions, of which 61 were benign tumours (32 pleomorphic adenomas, 23 Warthin tumours and 6 oncocytomas) and 14 were malignant tumours. A receiver operating characteristics (ROC) curve analysis was performed to find the threshold values for the most discriminative features and determine their sensitivity, specificity and area under the ROC curve (AUROC). The most discriminative features were used to train an SVM classifier, which was able to distinguish a pleomorphic adenoma from a Warthin tumour (with sensitivity, specificity and a diagnostic accuracy as high as 0.8695, 0.9062 and 0.8909, respectively) and from a malignant tumours (sensitivity, specificity and a diagnostic accuracy of 0.6666, 0.8709 and 0.8043, respectively). Our work, though preliminary, showed that radiomics analyses on lesions extracted from conventional T2-weighted MR images may be a viable instrument to discriminate pleomorphic adenomas from Warthin tumours and malignant tumours with a high sensitivity, specificity and diagnostic accuracy.

2.3. Visual AI for Hepatic Steatosis Estimation from Ultrasound Imaging

Hepatic steatosis is the major histologic feature of Metabolic Disfunction-Associated Fatty Liver Disease (MAFLD), and is due to the accumulation of fat within the liver. When associated with inflammation, steatosis may cause the progression of fibrosis to cirrhosis and hepatocellular carcinoma. An early detection and accurate quantification of steatosis is an essential tasks for preventing disease progression and monitoring its evolution over time.

Ultrasound examinations are the most used technique to non-invasively identify liver steatosis in a screening settings. However, the diagnosis is operator dependent, since quantitative and repeatable image processing techniques have not yet entered clinical practice. In this frame, in collaboration with a team from the IFC-CNR and Pisa University Hospital, we designed and trained a simple CNN model able to predict, from ultrasound images (see an example in "figure" 2), a fat-liver score aligned with the Hepatic fat fraction currently estimated from the Magnetic Resonance Spectroscopy (i.e., H-MRS index). More than 22,000 ultrasound images obtained from a multi-centre dataset of 150 subjects were used to train three regression networks, which were able to predict the fat fraction with a root mean square error of 1.11 in the best case, thus showing to be an effective instrument that might replace the much more expensive MRS [12].

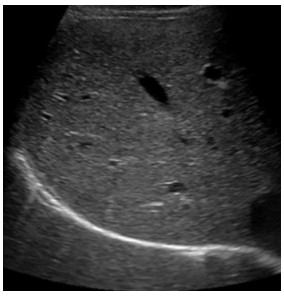

Figure 2: A clip (i.e., frame) taken from an ultrasound examination of an healthy subject.

2.4. Visual AI supporting the management of Idiopathic Pulmonary Fibrosis

A key step of the diagnosis of Idiopathic Pulmonary Fibrosis (IPF) is the examination of high-resolution computed tomography images (HRCT). IPF exhibits a typical radiological pattern, named Usual Interstitial Pneumoniae (UIP) pattern, which can be detected in non-invasive HRCT investigations, thus avoiding surgical lung biopsy. Unfortunately, the visual recognition and quantification of UIP pattern can be challenging even for experienced radiologists due to the poor inter and intra-reader agreement.

In collaboration with the radiology unit of Cisanello Hospital in Pisa, we designed and developed a tool for the semantic segmentation and the quantification of UIP pattern in patients with IPF using a deep-learning method based on a Convolutional Neural Network (CNN), called UIP-net [13]. o train and evaluate the CNN, a dataset of 5000 images, derived by 20 CT scans of different patients, was used. The network performance yielded 96.7% BF-score and 85.9% sensitivity. Once trained and tested, the UIP-net was used to obtain the segmentations of other 60 CT scans of different patients to estimate the volume of lungs affected by the UIP pattern. The measurements were compared with those obtained using the reference software for the automatic detection of UIP pattern, named Computer Aided Lungs Informatics for

Figure 3: Segmentation results of UIP-net. Top: the ground-truth highlighted in yellow; bottom: UIP-net results in red.

Pathology Evaluation and Rating (CALIPER), through the Bland-Altman plot. The network performance assessed in terms of both BF-score and sensitivity on the test-set and resulting from the comparison with CALIPER demonstrated to reliably detect and quantify UIP pattern, thus having the potential to become a supportive tool for radiologists. See "`figure`" 3 for an example of the segmentation results.

Thanks to its promising performance, the UIP-net is being applied also in the detection of COVID-19 radiological manifestations, which are very similar to the UIP pattern.

2.5. Imaging bio-banking in the quest of FAIR AI research

The availability of large volumes of high-quality data is essential in today's AI data-driven research. Bio-banks play a central role in this scenario, as they serve the management and more effective usage of large volumes of data. Besides the more common collections of body fluids and tissues, bio-banks are nowadays advancing to integrate also collections of medical imaging data. Imaging bio-banks are organized repositories of medical images, usually associated with imaging bio-markers. Most of the existing imaging bio-banks focus on cancer-related data and oncology imaging bio-markers collections. Their goal is to exploit the wealth of information hold in imaging data to discover novel diagnostic and prognostic bio-markers, especially when considering cancer phenotypes.

The NAVIGATOR Project, funded by the Tuscany Region, aims to establish the first regional imaging bio-bank, with the goal of boosting precision medicine in oncology. To do this, the Project plans to employ quantitative imaging and multi-omics analyses towards a better understanding of cancer biology, cancer care, and cancer risks [14].

The building block of the bio-bank design is the definition of the data model, which name and organize the relationship between the data elements and real-world entities' properties. For NAVIGATOR, we designed and implemented three separate data models utilized for the storage of imaging and clinical data about colorectal, prostate and gastric cancer [15].

2.6. Challenges to the uptake of AI in clinical practice

Realizing the full potential and benefit of AI solutions in high-stake domains, such as clinical diagnostics, mandates high-quality scientific foundations, technical robustness, and responsible development. This vision is at the core of the European strategy for AI, promoting excellence and trust as the main drivers of a beneficial impact of AI. Undeniably, only those applications that guarantee reliability, stakeholders' trust and acceptance, and total patients' safety can be expected to have a real impact and uptake in clinical practices. Transparency is a key pillar of trustworthiness. Transparency entails to document the entire life-cycle of an AI system as well as the underlying principles of its functioning [16].

Making an AI system transparent by design is key to avoid any grey area in its functioning and use by decision makers in clinical practice. Therefore, it is an overarching principle of the FUTURE-AI guidelines [17], notably touching upon the Traceability, Explainability and Usability principles. Transparency also ensures that the AI system is reproducible and auditable by design, thus laying the bases for accountability and liability.

Our group was actively involved in the definition of the FUTURE-AI guiding principles and is currently working in cooperation with FORTH, within the EU H2020 ProCAncer-I project (GA 952159) on the definition of an AI Model Passport, which is going to include all the relevant of information to document the development lifecycle of AI models.

In cooperation with IMATI-CNR and the Poznań University of Technology, within the EU NoE TAILOR (GA 952215), we contributed to a recent survey of the terminology, recommendations and open issues of the reproducibility of Machine Learning [18].

Moreover, we worked on effective approaches to increase the transparency of AI and ML models' decisions, especially in the Explainable AI for visual AI models. In this regard, the ProtoPNet model, which breaks down an image into prototypes and uses evidence gathered from the prototypes to classify an image, represents an appealing approach. We explored the applicability of

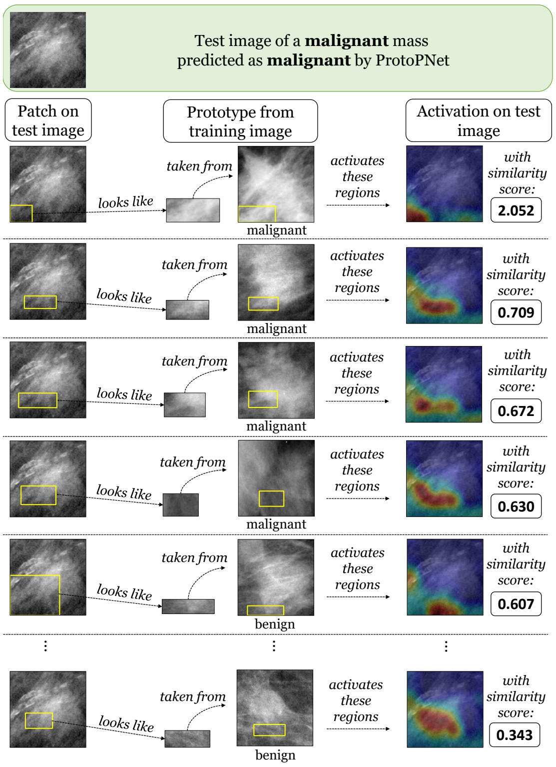

Figure 4: Results of ProtoPNet on a sample malignant mass. Each row represents the activation process of a certain prototype with the corresponding similarity score.

prototypical part learning in medical imaging by experimenting with ProtoPNet on a breast masses classification task (i.e., identification of malignant masses [19]. The two aspects we considered to evaluate the applicability of this approach were the classification capabilities and the validity of explanations. In this respect, an experienced radiologist provided a clinical viewpoint on the quality of the learned prototypes, the patch activations, and the global explanations. We achieved a Recall of 0.769 and area under the receiver operating characteristic curve of 0.719 in our experiments. Even though our findings are non-optimal for entering the clinical practice yet, the radiologist found ProtoPNet's explanations very intuitive, reporting a high level of satisfaction. See "`figure`" 4 for a sample result of ProtoPNet of a malignant mass. Therefore, we believe that prototypical part learning offers a reasonable and promising trade-off between classification performance and the quality of the related explanation.

3. AI for assistive technologies and health promotion

The ability of AI techniques to mine and correlate large amount of data plays a key role in delivering solutions that may support individuals in their daily-life activities through remote monitoring, assistance and care. The goals spam for encouraging individuals towards healthier lifestyles, to assisting them in daily-life activities, to preventing and managing chronic or multi-morbidity health conditions. In the most advanced settings, these systems use different approaches to learn about their users and make automated decisions, for personalizing their services and optimise outcomes. In the following sections, we briefly overview our works in the field, also with respect to the challenges that prevent the acceptance of AI in real-world environments.

3.1. AI for disease prevention

Cardio-metabolic risk assessment in the general population is of paramount importance to reduce diseases burdened by high morbidity and mortality. In collaboration with IFC-CNR, we defined a strategy for cardio-metabolic risk assessment, based on data acquired from contact-less sensors used in real-life settings. We employed Structural Equation Modelling to identify latent clinical variables of cardio-metabolic risk, related to anthropometric, glycolipidic and vascular function factors. Then, we defined a set of sensor-based measurements that correlate with the clinical latent variables.

Our measurements, processed by a Self-Organizing Map model, identified subjects with one or more risk factors in a population of 68 healthy volunteers from the EU-funded SEMEOTICONS project (GA 611516) with accuracy 82.4%, sensitivity 82.5%, and specificity 82.1%. The preliminary results we obtained strengthen the role of AI-powered self-monitoring systems for cardio-metabolic risk prevention.

3.2. AI for Active and Assisted Living

Active and Assisted Living (AAL) technologies usually address older adults or people in needs with diverse types of sensorised AI-powered applications. A comprehensive review of the AAL technologies taking advantage of AI techniques has been recently published by the team [20] as part of the activities within the Cost Action GoodBrother (CA 19121). Within this Action, a collaboration with a team from the University of Castilla-La Mancha delivered a survey about AI-powered solutions for bedtime monitoring to prevent falls in older adults [21].

In this field, we investigated also the use of thermal imaging for stress discrimination [22, 23] and the use of

Figure 5: The e-nose device used to monitor severe liver impairment.

an e-nose for monitoring severe liver impairment (see "figure" 5) [24].

3.3. Challenges to the uptake of AI AAL in real-world settings

AI-powered AAL technologies provide promising solutions for the health and social care challenges, nevertheless they are not exempt from ethical, legal and social issues [25]. From a technical perspective, they need to guarantee robust, accurate, reliable and unobtrusive data acquisition and interpretation in daily-life settings as well as security, privacy-preservation, safety, and usability that may ensure long-term engagement [26]. Nevertheless, an ethical approach and a thorough understanding of all issues pertaining to ethics, social equality, legality, and fairness need to be integrated at their early development phases [25].

Within the Cost Action GoodBrother, we surveyed existing literature for analysing the specific AI models used in AAL systems, the target domains of the models, the technology using the models, and the major concerns from the end-user perspective. Our goal was to consolidate research on this topic and inform end users, health care professionals and providers, researchers, and practitioners in developing, deploying, and evaluating future intelligent AAL systems. Older adults were the primary beneficiaries, followed by patients and frail persons of various ages. Availability was a top beneficiary concern [6, 27].

4. Conclusions

AI has a big potential to ameliorate care and health systems. Nevertheless, future research in the field should involve health care professionals and caregivers as designers and users, comply with health-related regulations, improve transparency and privacy, integrate with health care technological infrastructure, explain their decisions to the users, and establish evaluation metrics and design guidelines [6].

Acknowledgments

This publication is partially based upon work from COST Action GoodBrother—Network on Privacy-Aware Audio- and Video-Based Applications for Active and Assisted Living (CA19121), supported by COST (European Cooperation in Science and Technology); upon the work carried within the EU H2020 projects ProCAncer-I (GA 952159) and TAILOR (GA 952215); and upon the work carried out within the PAR FAS Tuscany Region NAVIGATOR.

References

[1] J. Scheetz, P. Rothschild, M. McGuinness, X. Hadoux, H. P. Soyer, M. Janda, J. J. Condon, L. Oakden-Rayner, L. J. Palmer, S. Keel, P. van Wijngaarden, A survey of clinicians on the use of artificial intelligence in ophthalmology, dermatology, radiology and radiation oncology, Scientific Reports 11 (2021) 1–10. doi:https://doi.org/10.1038/s41598-021-84698-5.

[2] J. R. Voskens, Frank J.and Abbing, A. T. Ruys, J. P. Ruurda, I. A. M. J. Broeders, A nationwide survey on the perceptions of general surgeons on artificial intelligence, Artificial Intelligence Surgery 2 (2022). doi:10.20517/ais.2021.10.

[3] J. Born, D. Beymer, D. Rajan, A. Coy, V. V. Mukherjee, M. Manica, P. Prasanna, D. Ballah, M. Guindy, D. Shaham, P. L. Shah, E. Karteris, J. L. Robertus, M. Gabrani, M. Rosen-Zvi, On the role of artificial intelligence in medical imaging of covid-19, Patterns 2 (2021) 100269. URL: https://www.sciencedirect.com/science/article/pii/S2666389921000957. doi:https://doi.org/10.1016/j.patter.2021.100269.

[4] B. W. Israelsen, N. R. Ahmed, "dave...i can assure you ...that it's going to be all right ..." a definition, case for, and survey of algorithmic assurances in human-autonomy trust relationships, ACM Comput. Surv. 51 (2019). URL: https://doi.org/10.1145/3267338. doi:10.1145/3267338.

[5] J. Yanase, E. Triantaphyllou, The seven key challenges for the future of computer-aided

diagnosis in medicine, International Journal of Medical Informatics 129 (2019) 413–422. URL: https://www.sciencedirect.com/science/article/pii/S1386505619300632. doi:https://doi.org/10.1016/j.ijmedinf.2019.06.017.

[6] M. Jovanovic, G. Mitrov, E. Zdravevski, P. Lameski, S. Colantonio, M. Kampel, H. Tellioglu, F. Florez-Revuelta, Ambient assisted living: Scoping review of artificial intelligence models, domains, technology, and concerns, J Med Internet Res 24 (2022) e36553. URL: https://www.jmir.org/2022/11/e36553. doi:10.2196/36553.

[7] M. Ziefle, W. Wilkowska, Why traditional usability criteria fall short in ambient assisted living environments, PervasiveHealth '14, ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), Brussels, BEL, 2014, p. 218–222. URL: https://doi.org/10.4108/icst.pervasivehealth.2014.255481. doi:10.4108/icst.pervasivehealth.2014.255481.

[8] D. Germanese, L. Mercatelli, S. Colantonio, V. Miele, M. A. Pascali, C. Caudai, N. Zoppetti, R. Carpi, A. Barucci, E. Bertelli, S. Agostini, Radiomics to predict prostate canceraggressiveness: A preliminary study, in: 2019 IEEE 19th International Conference on Bioinformatics and Bioengineering (BIBE), 2019, pp. 972–976. doi:10.1109/BIBE.2019.00181.

[9] E. Bertelli, L. Mercatelli, C. Marzi, E. Pachetti, M. Baccini, A. Barucci, S. Colantonio, L. Gherardini, L. Lattavo, M. A. Pascali, S. Agostini, V. Miele, Machine and deep learning prediction of prostate cancer aggressiveness using multiparametric mri, Frontiers in Oncology 11 (2022). URL: https://www.frontiersin.org/articles/10.3389/fonc.2021.802964. doi:10.3389/fonc.2021.802964.

[10] E. Pachetti, S. Colantonio, M. A. Pascali, On the effectiveness of 3d vision transformers for the prediction of prostate cancer aggressiveness, in: P. L. Mazzeo, E. Frontoni, S. Sclaroff, C. Distante (Eds.), Image Analysis and Processing. ICIAP 2022 Workshops, Springer International Publishing, Cham, 2022, pp. 317–328.

[11] M. Gabelloni, L. Faggioni, S. Attanasio, V. Vani, A. Goddi, S. Colantonio, D. Germanese, C. Caudai, L. Bruschini, M. Scarano, V. Seccia, E. Neri, Can magnetic resonance radiomics analysis discriminate parotid gland tumors? a pilot study, Diagnostics 10 (2020). URL: https://www.mdpi.com/2075-4418/10/11/900. doi:10.3390/diagnostics10110900.

[12] S. Colantonio, A. Salvati, C. Caudai, F. Bonino, L. D. Rosa, M. A. Pascali, D. Germanese, M. R. Brunetto, F. Faita, A deep learning approach for hepatic steatosis estimation from ultrasound imaging, in: K. Wojtkiewicz, J. Treur, E. Pimenidis, M. Maleszka (Eds.), Advances in Computational Collective Intelligence, Springer International Publishing, Cham, 2021, pp. 703–714.

[13] R. Buongiorno, D. Germanese, C. Romei, L. Tavanti, A. De Liperi, S. Colantonio, Uip-net: A decoder-encoder cnn for the detection and quantification of usual interstitial pneumoniae pattern in lung ct scan images, in: Pattern Recognition. ICPR International Workshops and Challenges: Virtual Event, January 10–15, 2021, Proceedings, Part I, Springer-Verlag, Berlin, Heidelberg, 2021, p. 389–405. URL: https://doi.org/10.1007/978-3-030-68763-2_30. doi:10.1007/978-3-030-68763-2_30.

[14] R. Borgheresi, A. Barucci, S. Colantonio, G. Aghakhanyan, M. Assante, et al., Navigator: an italian regional imaging biobank to promote precision medicine for oncologic patients, European Radiology Experimental 6 (2022). URL: https://doi.org/10.1186/s41747-022-00306-9. doi:10.1186/s41747-022-00306-9.

[15] A. Berti, G. Carloni, S. Colantonio, M. A. Pascali, P. Manghi, P. Pagano, R. Buongiorno, E. Pachetti, C. Caudai, D. Di Gangi, E. Carlini, Z. Falaschi, E. Ciarrocchi, E. Neri, E. Bertelli, V. Miele, R. Carpi, G. Bagnacci, N. Di Meglio, M. A. Mazzei, A. Barucci, Data models for an imaging bio-bank for colorectal, prostate and gastric cancer: the navigator project, in: 2022 IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI), 2022, pp. 01–04. doi:10.1109/BHI56158.2022.9926910.

[16] S. Colantonio, The Design of Trustworthy AI System: a Deep Look into the Transparency of Data, Models, and Decisions, 2022. URL: https://doi.org/10.5281/zenodo.7181554. doi:10.5281/zenodo.7181554.

[17] K. Lekadir, R. Osuala, C. Gallin, N. Lazrak, K. Kushibar, G. Tsakou, S. Aussó, L. C. Alberich, K. Marias, M. Tsiknakis, S. Colantonio, N. Papanikolaou, Z. Salahuddin, H. C. Woodruff, P. Lambin, L. Martí-Bonmatí, Future-ai: Guiding principles and consensus recommendations for trustworthy artificial intelligence in medical imaging, 2021. arXiv:2109.09658.

[18] R. Albertoni, S. Colantonio, P. Skrzypczyński, J. Stefanowski, Reproducibility of machine learning: Terminology, recommendations and open issues, 2023. arXiv:2302.12691.

[19] G. Carloni, A. Berti, M. A. Pascali, I. Chiara, S. Colantonio, On the Applicability of Prototypical Part Learning in Medical Images: Breast Masses Classification Using ProtoPNet, 2023. URL: https://doi.org/10.5281/zenodo.7791603. doi:10.5281/zenodo.7791603.

[20] S. Aleksic, M. Atanasov, J. C. Agius, K. Camilleri, A. Cartolovni, P. Climent-Peerez, S. Colantonio,

S. Cristina, V. Despotovic, H. K. Ekenel, E. Erakin, F. Florez-Revuelta, D. Germanese, N. Grech, S. G. Sigurðardóttir, M. Emirzeoglu, I. Iliev, M. Jovanovic, M. Kampel, W. Kearns, A. Klimczuk, L. Lambrinos, J. Lumetzberger, W. Mucha, S. Noiret, Z. Pajalic, R. R. Peerez, G. Petrova, S. Petrovica, P. Pocta, A. Poli, M. Pudane, S. Spinsante, A. A. Salah, M. J. Santofimia, A. S. Islind, L. Stoicu-Tivadar, H. Tellioglu, A. Zgank, State of the art of audio- and video-based solutions for aal, 2022. arXiv:2207.01487.

[21] J. Fernández-Bermejo Ruiz, J. Dorado Chaparro, M. J. Santofimia Romero, F. J. Villanueva Molina, X. del Toro García, C. Bolaños Peño, H. Llumiguano Solano, S. Colantonio, F. Flórez-Revuelta, J. C. López, Bedtime monitoring for fall detection and prevention in older adults, International Journal of Environmental Research and Public Health 19 (2022). URL: https://www.mdpi.com/1660-4601/19/12/7139. doi:10.3390/ijerph19127139.

[22] F. Gioia, M. A. Pascali, A. Greco, S. Colantonio, E. P. Scilingo, Discriminating stress from cognitive load using contactless thermal imaging devices, in: 2021 43rd Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC), 2021, pp. 608–611. doi:10.1109/EMBC46164.2021.9630860.

[23] O. Curzio, L. Billeci, V. Belmonti, S. Colantonio, L. Cotrozzi, C. F. De Pasquale, M. A. Morales, C. Nali, M. A. Pascali, F. Venturi, A. Tonacci, N. Zannoni, S. Maestro, Horticultural therapy may reduce psychological and physiological stress in adolescents with anorexia nervosa: A pilot study, Nutrients 14 (2022). URL: https://www.mdpi.com/2072-6643/14/24/5198. doi:10.3390/nu14245198.

[24] D. Germanese, S. Colantonio, M. D'Acunto, V. Romagnoli, A. Salvati, M. Brunetto, An e-nose for the monitoring of severe liver impairment: A preliminary study, Sensors 19 (2019). URL: https://www.mdpi.com/1424-8220/19/17/3656. doi:10.3390/s19173656.

[25] A. Ake-Kob, A. Blazeviciene, S. Colantonio, L. Colonna, A. Cartolovni, C. Dantas, A. Fedosov, F. Florez-Revuelta, E. Fosch-Villaronga, Z. He, A. Klimczuk, M. Kuźmicz, A. Lukács, C. Lutz, R. Mekovec, C. Miguel, E. Mordini, Z. Pajalic, B. K. Pierscionek, M. J. S. Romero, A. A. Salah, A. Sobecki, A. Solanas, A. Tamò-Larrieux, State of the art on ethical, legal, and social issues linked to audio- and video-based AAL solutions, Technical Report, Alicante, 2021. URL: http://hdl.handle.net/10419/248470. doi:10.13140/RG.2.2.28785.81764.

[26] S. Colantonio, G. Coppini, D. Giorgi, M.-A. Morales, M. A. Pascali, Chapter 6 - computer vision for ambient assisted living: Monitoring systems for personalized healthcare and wellness that are robust in the real world and accepted by users, carers, and society, in: M. Leo, G. M. Farinella (Eds.), Computer Vision for Assistive Healthcare, Computer Vision and Pattern Recognition, Academic Press, 2018, pp. 147–182. URL: https://www.sciencedirect.com/science/article/pii/B978012813445000006X. doi:https://doi.org/10.1016/B978-0-12-813445-0.00006-X.

[27] S. Colantonio, M. Jovanovic, E. Zdravevski, P. Lameski, H. Tellioglu, M. Kampel, F. Florez-Revuelta, Are active and assisted living applications addressing the main acceptance concerns of their beneficiaries? preliminary insights from a scoping review, PETRA '22, Association for Computing Machinery, New York, NY, USA, 2022, p. 414–421. URL: https://doi.org/10.1145/3529190.3534753. doi:10.1145/3529190.3534753.