



Deep Learning Approaches Applied to Image Classification of Renal Tumors: A Systematic Review

Sandra Amador¹ · Felix Beuschlein^{2,3} · Vedant Chauhan⁴ · Judith Favier⁵ · David Gil¹ · Phillip Greenwood⁴ · R. R. de Krijger⁶ · Matthias Kroiss⁷ · Samanta Ortuño-Miquel⁸ · Attila Patocs⁹ · Anthony Stell⁴ · Axel Walch¹⁰

Received: 26 April 2023 / Accepted: 19 August 2023
© The Author(s) 2023

Abstract

Renal cancer is one of the ten most common cancers in the population that affects 65,000 new patients a year. Nowadays, to predict pathologies or classify tumors, deep learning (DL) methods are effective in addition to extracting high-performance features and dealing with segmentation tasks. This review has focused on the different studies related to the application of DL techniques for the detection or segmentation of renal tumors in patients. From the bibliographic search carried out, a total of 33 records were identified in Scopus, PubMed and Web of Science. The results derived from the systematic review give a detailed description of the research objectives, the types of images used for analysis, the data sets used, whether the database used is public or private, and the number of patients involved in the studies. The first paper where DL is applied compared to other types of tumors was in 2019 which is relatively recent. Public collection and sharing of data sets are of utmost importance to increase research in this field as many studies use private databases. We can conclude that future research will identify many benefits, such as unnecessary incisions for patients and more accurate diagnoses. As research in this field grows, the amount of open data is expected to increase.

1 Introduction

Renal cancer is one of the ten most common cancers in the population [1]. Angiomyolipoma (AML) or Small Renal Masses (SRMs) are mostly benign and usually detected during a health examination or evaluation of

other diseases due to their asymptomatic nature. Although malignant forms of AML (aka epithelioid angiomyolipoma (EAML)) exist, the most common malignant tumor in the kidney is Renal Cell Carcinoma (RCC). It affects 65,000 new patients a year [2]. There are 3 major RCC subtypes,

✉ Sandra Amador
sam77@alu.ua.es

David Gil
david.gil@ua.es

¹ Department of Computer Science Technology and Computation, University of Alicante, Alicante, Spain

² Medizinische Klinik und Poliklinik IV, Ludwig-Maximilians-Universität München, D-80336 Munich, Germany

³ Endokrinologie, Diabetologie und Klinische Ernährung, UniversitätsSpital Zürich (USZ) und Universität Zürich (UZH), Zurich, Switzerland

⁴ School of Computing and Information Systems, University of Melbourne, Melbourne, Australia

⁵ Université Paris cité, PARCC, INSERM, Equipe Labellisée par la Ligue contre le Cancer, Paris, France

⁶ Dept. of Pathology, University Medical Center Utrecht, Utrecht, The Netherlands and Princess Máxima Center for pediatric oncology, Utrecht, The Netherlands

⁷ University Hospital Munich, Ludwig-Maximilians-Universität München, Munich, Germany

⁸ Health and Biomedical Research Institute of Alicante, Alicante, Spain

⁹ ELKH Hereditary Cancer Research Group, Department of Laboratory Medicine, Semmelweis University and Department of Molecular Genetics, National Institute of Oncology, Budapest, Hungary

¹⁰ Research Unit Analytical Pathology, Helmholtz Zentrum München, Oberschleissheim, Germany

including clear cell (ccRCC), chromophobe (chRCC) and papillary (pRCC) [3–5].

Nearly 20% of patients who undergo surgery to remove the mass are reported to be benign, which is an invasive solution to this problem [2]. That is because AML with minimal fat is difficult to differentiate from RCC and there is no validated imaging- or biomarker-based screening for diagnosis. Several criteria can be used to help predict malignancy, such as tumor size, necrosis, round shapes and atypical mitotic figures [6]. These features were carefully selected to make sure the proper sensitivity and specificity of the prediction.

Nowadays, the imaging techniques used in this field, are mainly Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). MRI is less feasible, overpriced, and tedious compared to CT. Although, both have limited sensitivity and specificity to achieve the proper diagnosis [2]. Another thing to take into consideration is the time-consuming expert knowledge of radiologists that are needed in both approaches. Further analysis cannot be based on standard imaging technology exclusively, as comprehensive laboratory analyses, as well as endocrinological investigations, are required. Therefore, if the image studies combined with Artificial Intelligence (AI) will help in the more precise of these lesions, this would be a huge success.

For these reasons and with the widespread use of imaging procedures, it is mandatory to improve accuracy to differentiate AML from RCCs by combining standard procedures with AI algorithms to avoid unnecessary resections. The AI converts images into metadata for further exploitation, helping the clinician to make decisions. To go even further, an innovative technique that links imaging with the spatial distribution of molecules along a tissue section, which is Matrix-assisted laser desorption/ionization (MALDI) mass spectrometry imaging (MSI), allows to classify metabolic profiles and find biomarkers [7].

Currently, Deep Learning (DL) methods have tremendous performance in medical fields. The advent of graph processing units and large training datasets have proven the capabilities of Convolutional Neural Networks (CNNs) to extract high-throughput features, deal with segmentation tasks, also to building models (V-Net, U-Net, ANU-Net, ImageNet, ResNet...) to predict pathology or classify the tumor [8]. Unfortunately, medical data is not always adequate or easily available, for that reason Transfer Learning (TL) using a data-augmentation strategy is used to tackle them [9].

To summarise, the purpose of this study is to better understand the predictive models based on DL in renal tumors to be used in other types. Specifically, one of them is the diagnosis of adrenal tumors that have been covered until now by only a few studies.

2 Methods

To perform the systematic review of the literature on renal tumor detection with deep learning in images, the instructions of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 have been followed. The following sections describe the specific methodology followed.

2.1 Eligibility Criteria

This review has focused on the different studies related to the application of deep learning techniques for the detection or segmentation of renal tumors in patients based on image analysis.

The search for related articles was not restricted by sample size, gender, age, study location, type of renal cancer, type of image analyzed, or applied deep learning algorithms.

The inclusion criteria applied to the studies that have been selected are (1) to be related to the classification or segmentation of renal tumor images; (2) to apply deep learning techniques on those images.

The studies included in this review, in addition to meeting the two features mentioned, had to meet a series of eligibility requirements regarding the characteristics of the report: (1) in terms of language, the report had to be published in English; (2) As for the type, it had to be a scientific article, it could not be a review.

2.2 Information Sources

We conducted electronic searches for eligible studies within the Scopus, PubMed, and Web of Science reference databases. The search was carried out in September 2022.

2.3 Search Strategy

Search keywords were selected according to the review framework. As primary concepts for the search, “renal tumor”, “deep learning” and “image” were selected. In addition to them, synonyms of the term “renal tumor” were also considered, namely “renal carcinoma”, as they are often used interchangeably in this area of research. The exclusion criteria applied to the search were by language (English). Below are the resulting queries that are ultimately run on Scopus, PubMed and Web of Science as they are the world’s two main databases for bibliographic references and periodical citations.

Scopus TITLE-ABS-KEY (“deep learning” AND “image” AND (“renal tumor” OR “renal carcinoma”)) AND (LIMIT-TO (LANGUAGE, “English”))

Web of Science (TS=(“deep learning” AND “image” AND (“renal tumor” OR “renal carcinoma”)) AND LA=(“ENGLISH”))

PubMed (Deep learning[Title/Abstract]) AND (image[Title/Abstract]) AND (renal tumor[Title/Abstract] OR renal carcinoma[Title/Abstract]) AND (English[Language])

2.4 Selection Process

Once the records were obtained from the databases and the manual search, they were imported into the Mendeley web library to browse through the records and reports. Duplicate records were manually identified by the authors by comparing the title and authors of the article. These reviewers further analyzed each article retrieved by the search, assessed its eligibility, and finally selected the set of studies that have been included in the review after reaching a majority consensus.

2.5 Data Collection Process

Reviewers participated in the scrutiny and assessment of the included studies. A Google spreadsheet was used to collect data from included studies. The document obtained consists of a state-of-the-art matrix where each row represents a study and the columns indicate the data elements to be analyzed.

2.6 Data Items

The columns defined in the collaborative spreadsheet corresponded to the outcomes for which data were sought. The specific columns defined were: title, authors, type of article, research objectives, name of the data set used, whether the data set is open access or not, number of patients, and number of images analyzed.

3 Results

In this section, we present the results derived from the systematic review of the application of deep learning in medical images with patients diagnosed with renal carcinoma. The rest of the section provides a detailed description of the research objectives, the types of images used for the analysis, the data sets used, whether the database employed is public or private, and the number of patients used in the studies.

3.1 Study Selection

From the bibliographic search carried out, a total of 33 records (manuscripts) were identified. The Scopus search obtained a total of 21 records, PubMed 5 while for Web of Science only 7. After reviewing all the selected articles, 10 duplicates were deleted. Taking into account the remaining 23 records, these were reviewed according to the title and abstract which resulted in 5 records that were excluded based on the selection criteria. Four of these five records were removed for being systematic reviews and one of them was eliminated for not being able to obtain the full version of the article before the final selection. The workflow with the detailed process is shown in Fig. 1.

3.2 Research Goal

The goals for conducting renal tumor research with the application of deep learning techniques differ between studies (Fig. 2). 50% (9/18) of the studies aim at the segmentation of renal tumors images [1, 10–17] while around 50% (9/18) aim at the classification of benign or malignant renal tumors [2, 3, 9, 18–23].

3.3 Image Types

In the 18 selected articles, the most commonly used imaging modality in studies for the segmentation/classification of renal tumors with the application of deep learning techniques (Fig. 3) are computed tomography images with a percentage of 72.22% (13/18) [1, 9–15, 17, 18, 20–22]. The second most used images in the studies are magnetic resonance imaging with a total of 22.22% (4/18) [2, 3, 16, 19]. The least used image was the macroscopic cross-section with only one article (1/18), representing 6% [23].

3.4 Data Origin

In the 18 articles selected, there are 5 different origins of the image databases used in the studies (Fig. 4). The most common data source is from hospitals or departments with a total of 61.11% (11/18) [1, 3, 10, 11, 14, 15, 18–20, 22, 23]. The public databases used are The 2019 renal and renal Tumor Segmentation Challenge (KiTS19) with a total of 16.67% (3/18) [12, 16, 17], followed by ImageNet with a total of 11.11% (2/18) [2, 9]. Only one study each used The 2021 renal and renal Tumor Segmentation Challenge (KiTS21) [13] and The Cancer Imaging Archive (TCIA) (1/18) [21].

3.5 Open Access Database

The articles selected, all use a database to perform the analysis and apply deep learning techniques. We

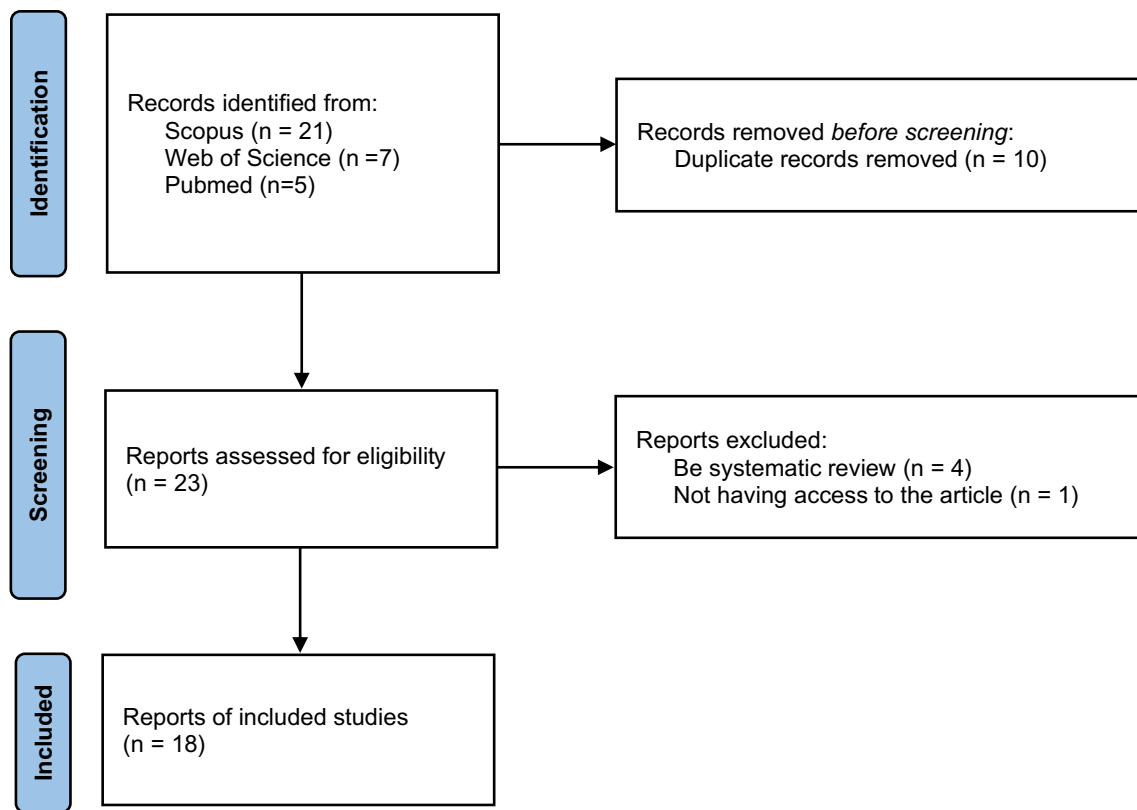


Fig. 1 Flow of information through the different phases of a systematic review (PRISMA methodology)

PURPOSE OF THE ARTICLE

- Renal tumor segmentation
- Classification of benign or malignant renal cyst

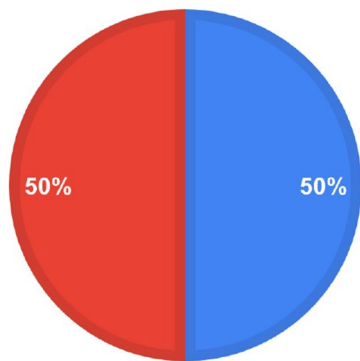


Fig. 2 Research goal

IMAGE USED IN THE STUDY

- Magnetic resonance
- Computed tomography
- Macroscopic cross-section

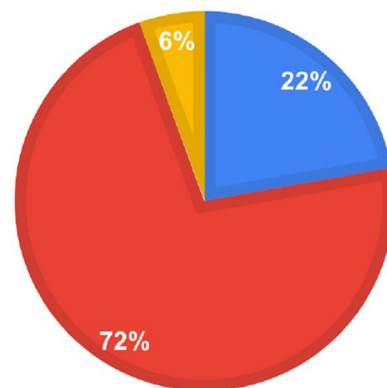


Fig. 3 Images used in the study

differentiate two types of databases: open-access databases and private databases (Fig. 5). The private databases included the databases obtained from hospitals or local departments. Taking into account the above, the studies analyzed use more private databases than open

access, with a total of 61.11% (11/18), [1, 3, 10, 11, 14, 15, 18–20, 22, 23] compared to 38.89% (7/18) [2, 9, 12, 13, 16, 17, 21].

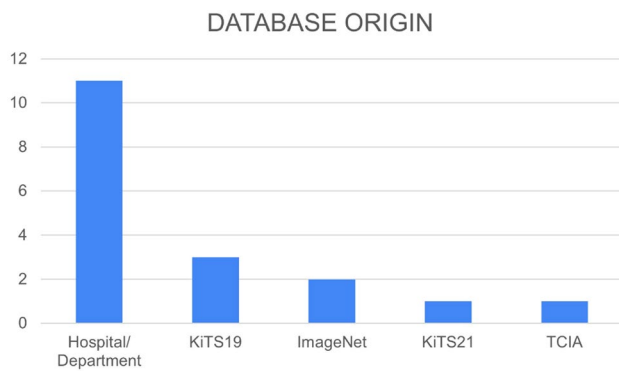


Fig. 4 Database origin

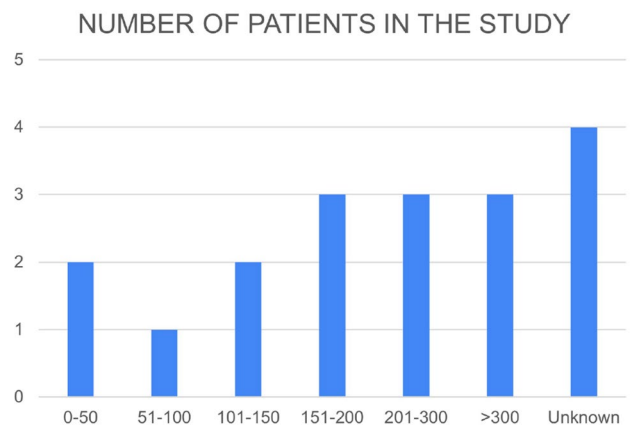


Fig. 6 Number of patients

OPEN ACCESS DATABASE

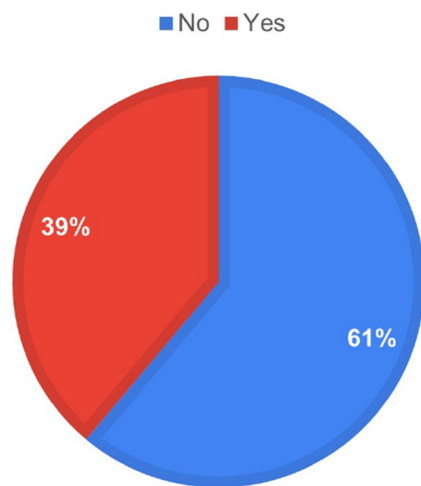


Fig. 5 Open access database

3.6 Number of Patients

Taking into account everything, the number of patients in each study has been divided by ranges (Fig. 6). Despite having four articles where they mention the number of images used but not the number of patients, 22.22% (4/18), most of the studies use a sample between 151 and 300 patients, 33.33% of the studies (6/18). To be more exact, 16.67% (3/18) [11, 17, 19] use a sample between 201 and 300 patients and another 16.67% (3/18) [1, 3, 9] use a subsample of the population between 151 and 200 patients. 16.67% (3/18) of the studies [14, 22, 23] analyzed greater than 300 patients. Finally, 11.11% (2/18) used a sample between 101 and 150 patients [15, 20] and 11.11% (2/18) used a sample between 0 and 50 patients [10, 18]. In the end, only 6% (1/18) use a sample between 51 and 100 patients [16].

3.7 Summary results

Table 1 summarises the parameters described in the preceding sections.

4 Discussion

The use of deep learning techniques applied to research problems is on the rise as it improves the performance of systems in various areas. It is true that in the field of renal tumors, the application of deep learning on images has only started very recently. It should be highlighted that the first paper applying deep learning techniques to renal tumors was in 2019. This date is very recent compared to other types of tumors. The first paper published for tumor detection with deep learning on images was for the detection of invasive ductal carcinoma [24].

Therefore, the objective of this work focuses on the bibliographic review process of the articles that have applied deep learning to the study of renal tumors using images. Thus, a total of 18 studies that used different deep learning techniques in the investigation of renal tumors were identified and reviewed.

Considering our results, there are only two objectives in the selected papers: renal tumor segmentation and classification of benign or malignant renal cyst, without having a significant difference in the number of articles that have each objective.

The image most analysed by the studies is computed tomography (hereinafter, CT). The reason for this may be the availability in all hospitals of CT scan used to supplement conventional X-ray imaging and ultrasonography. This machine allows obtaining detailed internal images of the body of the patients with metallic implants or pacemakers in contrast to MRI which is contraindicated.

Table 1 Summary of criteria used to classify the studies

Criteria for classifying studies				
Research goal	Image types	Data origin	Open access database	Number of patients (in ranges)
50% (9/18) Segmentation of renal tumors images	72.22% (13/18) Computed tomography	61.11% (11/18) Hospitals or departments	61.11% (11/18) Private databases	11.11% (2/18) 0–50 Patients
50% (9/18) Classification of benign or malignant renal tumors	22.22% (4/18) Magnetic resonance	16.67% (3/18) KiTS19	38.89% (7/18) Public databases	5.56% (1/18) 51–100 patients
		6% (1/18) Macroscopic cross-section	11.11% (2/18) ImageNet	11.11% (2/18) 101–150 patients
		6% (1/18) KiTS21		16.67% (3/18) 151–200 patients
		6% (1/18) TCIA		16.67% (3/18) 201–300 patients
				16.67% (3/18) > 300 patients
				22.22% (4/18) unknown

The vast majority of studies use private hospital or departmental databases (61%). This may be due to the fact that usually when such data are obtained, they are protected by the ethics committee, which does not allow these data to be published openly. Studies that create their own databases tend to use smaller numbers of patients. Sometimes it is not easy to have the opportunity and the permission of the ethics committee to work with a large number of patients. The most widely used databases of renal tumors are KiTS2019, ImageNet, KiTS21 and TCIA. As mentioned above, more than half of the databases are private. Also, there are limited number of datasets with the proper labels to train an effective model. The increase of public databases and open data in general will benefit future research, although this is progressing slowly.

As for the number of patients analysed in each study, there are certain studies (in this case 5) that do not mention in their papers the number of patients utilized, but simply mention the number of images analysed. These papers have therefore been set as Unknown. In the other papers, the most common is to analyse a sample between 151 and 300 patients.

4.1 Limitations

We did a preliminary check by performing an unrestricted search by title, abstract, and keywords, but the articles we found were not relevant and did not meet our search criteria. A broad search strategy was followed where articles on kidney tumors were sought, but this search was also restricted to studies where deep learning was applied to images. Although this search is very specific, it is possible that some interesting studies have been left out of the search.

5 Conclusions

In this work, we have carried out a systematic review of the literature on renal tumor detection with deep learning in images. It is well known that the application of artificial intelligence, specifically deep learning, in the field of health is increasing by leaps and bounds. However, as our review shows, the application in renal tumors is limited and insufficiently validated. The number of papers analysed is not very large (18 in total) because the first paper where deep learning techniques are applied to renal tumors was in 2019. This fact rather than a limitation is a challenge and an opportunity for much more research in the area, not only in this field of renal tumors but also in others.

As has been observed, a large number of studies use private databases, created by the hospitals themselves or departments based on their own patients. Collecting and publicly sharing datasets that are related to renal tumors is considered of utmost importance in order to increase research in the field. There are currently very few public image-based data sets of renal tumors. During the research, these databases should be somehow made available for researchers and for computing experts, which means that they fulfill the ethical and legal issues related to data sharing. This topic needs to be addressed with documents to protect knowledge. We face serious problems with these issues and in the future, it may be more problematic. At the end of the investigations of the group, will be mandatory to publish the database or repositories in an open access format to reach reproducibility and accessibility of the data to the scientific community.

We will use dedicated repositories for sharing, we will sign ethical documents to protect our data. In addition, in the group's upcoming research, it will be mandatory to publish

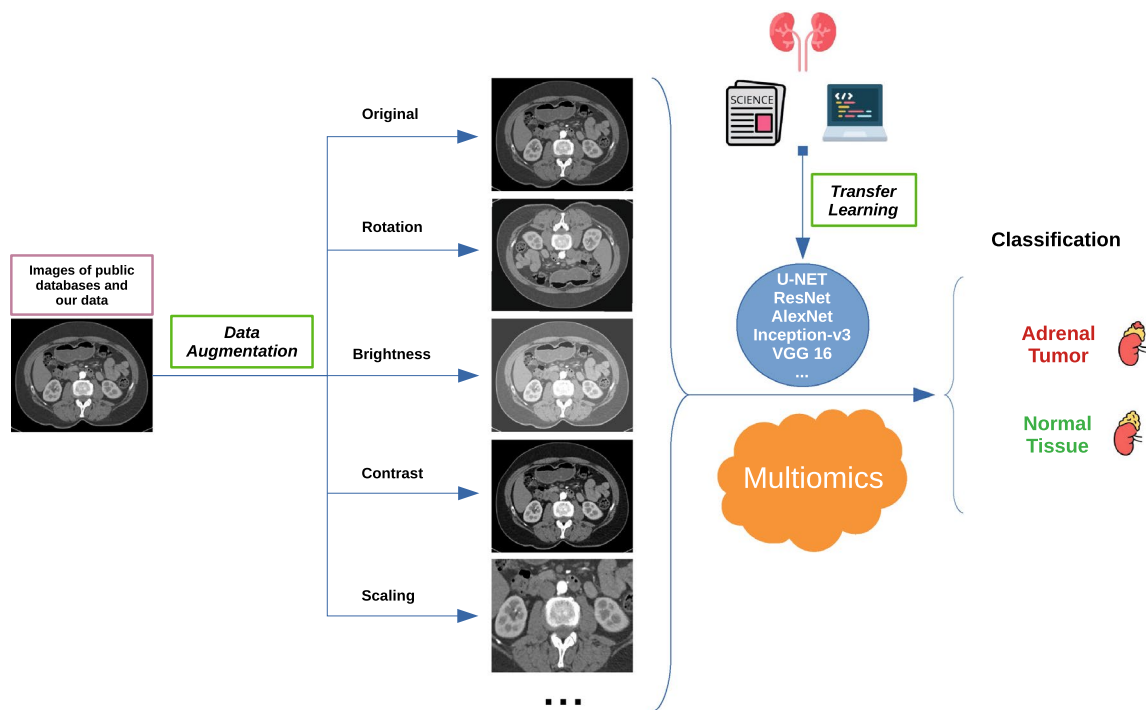


Fig. 7 Scheme of the workflow that is going to be used

the database or repositories in an open access format to achieve reproducibility and accessibility of the data to the scientific community.

As future lines, it is proposed to carry out a deep learning method, specifically convolutional neural networks, to predict the pathology or classify the adrenal tumor. Unlike the literature, Data Augmentation would be carried out to increase the number of data since it is difficult to find a large number of quality medical images [25]. As regards, TL will be used to train an effective models, reducing time and cost. The next step, we would like analyse the synergism between multiomics and morphometry based on the following references [26, 27] (Fig. 7). Furthermore, a server dedicated exclusively to artificial intelligence, recently acquired by Health and Biomedical Research Institute of Alicante,¹ will be a perfect infrastructure for the application of deep learning in this area.

We can conclude that future deep learning research in the above areas will identify many benefits. As deep learning tools become more accessible to many people, it is expected that the field will continue to grow and new applications for renal tumor detection and classification will emerge, as well as the publication of new open repositories.

¹ 512 GB RAM, 5 NVIDIA A30 GPUs of 24 GB each, 2 AMD Milan 7413 24-cores processors at 2.65 Ghz, 15 TB SSD disk in total with Linux-based operating system.

Acknowledgements This article is based upon work from COST Action HARMONISATION (CA20122). This research has been partially funded by the Spanish Government by the project PID2021-127275OB-I00, FEDER “Una manera de hacer Europa”.

Funding Open Access funding provided thanks to the CRUE-CSIC agreement with Springer Nature.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article’s Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article’s Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

1. Yang G, Wang C, Yang J, Chen Y, Tang L, Shao P, Dillenseger J-L, Shu H, Luo L (2020) Weakly-supervised convolutional neural networks of renal tumor segmentation in abdominal CTA images. *BMC Med Imaging* 20(1):1–12
2. Xi I, Zhao Y, Wang R, Chang M, Purkayastha S, Chang K, Huang R, Silva A, Vallières M, Habibollahi P, Fan Y, Zou B, Gade T, Zhang P, Soulen M, Zhang Z, Bai H, Stavropoulos S (2020) Deep learning to distinguish benign from malignant renal lesions based on routine MR imaging. *Clin Cancer Res* 26(8):1944–1952

3. Zheng Y, Wang S, Chen Y, Du H-Q (2021) Deep learning with a convolutional neural network model to differentiate renal parenchymal tumors: a preliminary study. *Abdom Radiol* 46(7):3260–3268
4. Wang K, Sun Y, Tao W, Fei X, Chang C (2017) Androgen receptor (AR) promotes clear cell renal cell carcinoma (CCRCC) migration and invasion via altering the circRNAs/mir-195-5p/29a-3p/29c-3p/cdc42 signals. *Cancer Lett* 394:1–12
5. Schieda N, Van der Pol CB, Moosavi B, McInnes MD, Mai KT, Flood TA (2015) Intracellular lipid in papillary renal cell carcinoma (PRCC): T2 weighted (t2w) MRI and pathologic correlation. *Eur Radiol* 25(7):2134–2142
6. Jian L, Liu Y, Xie Y, Jiang S, Ye M, Lin H (2022) MRI-based radiomics and urine creatinine for the differentiation of renal angiomyolipoma with minimal fat from renal cell carcinoma: a preliminary study. *Front Oncol* 12:876664
7. Murakami M, Sun N, Greunke C, Feuchtinger A, Kircher S, Deutschbein T, Papathomas T, Bechmann N, Wallace PW, Peitzsch M et al (2021) Mass spectrometry imaging identifies metabolic patterns associated with malignant potential in pheochromocytoma and paraganglioma. *Eur J Endocrinol* 185(1):179–191
8. Siddique N, Paheding S, Elkin CP, Devabhaktuni V (2021) U-net and its variants for medical image segmentation: a review of theory and applications. *IEEE Access* 9:82031–82057
9. Zhou L, Zhang Z, Chen Y-C, Zhao Z-Y, Yin X-D, Jiang H-B (2019) A deep learning-based radiomics model for differentiating benign and malignant renal tumors. *Transl Oncol* 12(2):292–300
10. Roblot V, Giret Y, Mezghani S, Auclin E, Arnoux A, Oudard S, Duron L, Fournier L (2022) Validation of a deep learning segmentation algorithm to quantify the skeletal muscle index and sarcopenia in metastatic renal carcinoma. *Eur Radiol* 32(7):4728–4737
11. Tanimoto R, Higuchi K, Ishiguro T, Mori K, Kojo K, Kojima T, Kakeya H (2022) Segmentation of renal tumors in CT images by 3d u-net preserving rotational symmetry in axial slices. *OSA Continuum* 1(2):297–305
12. Kang L, Zhou Z, Huang J, Han W (2022) Renal tumors segmentation in abdomen CT images using 3d-CNN and CONVLSTM. *Biomed Signal Process Control* 72:10334
13. Li D, Chen Z, Hassan H, Xie W, Huang B (2022) A cascaded 3d segmentation model for renal enhanced CT images. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol 13168 LNCS, pp 123–128
14. Lin Z, Cui Y, Liu J, Sun Z, Ma S, Zhang X, Wang X (2021) Automated segmentation of kidney and renal mass and automated detection of renal mass in CT urography using 3d u-net-based deep convolutional neural network. *Eur Radiol* 31(7):5021–5031
15. He Y, Yang G, Yang J, Ge R, Kong Y, Zhu X, Zhang S, Shao P, Shu H, Dillenseger J-L, Coatrieux J-L, Li S (2021) Meta grayscale adaptive network for 3d integrated renal structures segmentation. *Med Image Anal* 71:102055
16. Barbera G, Gori P, Boussaid H, Belucci B, Delmonte A, Goulin J, Sarnacki S, Rouet L, Bloch I (2021) Automatic size and pose homogenization with spatial transformer network to improve and accelerate pediatric segmentation. volume 2021-April, pp 1773–1776
17. Türk F, Lüy M, Barışçi N (2020) Kidney and renal tumor segmentation using a hybrid v-net-based model. *Mathematics* 8(10):1–17
18. Zhu X-L, Shen H-B, Sun H, Duan L-X, Xu Y-Y (2022) Improving segmentation and classification of renal tumors in small sample 3d CT images using transfer learning with convolutional neural networks. *Int J Comput Assist Radiol Surg* 17(7):1303–1311
19. Xu Q, Zhu Q, Liu H, Chang L, Duan S, Dou W, Li S, Ye J (2022) Differentiating benign from malignant renal tumors using t2- and diffusion-weighted images: a comparison of deep learning and radiomics models versus assessment from radiologists. *J Magn Reson Imaging* 55(4):1251–1259
20. Osowska-kurczab A, Markiewicz T, Dziekiewicz M, Lorent M (2021) Multi-feature ensemble system in the renal tumour classification task. *Bull Pol Acad Sci* 69(3)
21. Mohammed Akhil, P. and Yadav, M. (2021). Computer-aided classifier for identification of renal cystic abnormalities using Bosniak classification. *Lecture Notes in Electrical Engineering*, vol 749, pp 439–457
22. Pedersen M, Andersen M, Christiansen H, Azawi N (2020) Classification of renal tumour using convolutional neural networks to detect oncocytoma. *Eur J Radiol* 133:109343
23. Lin Z, Yang W, Zhang W, Jiang C, Chu J, Yang J, Yuan X (2023) Recognizing pathology of renal tumor from macroscopic cross-section image by deep learning. *Biomed Eng Online* 22(1):1–20
24. Cruz-Roa A, Basavanthally A, González F, Gilmore H, Feldman M, Ganesan S, Shih N, Tomaszewski J, Madabhushi A (2014) Automatic detection of invasive ductal carcinoma in whole slide images with convolutional neural networks, vol 9041. *All Open Access, Green Open Access*
25. Chanchal AK, Lal S, Kumar R, Kwak JT, Kini J (2023) A novel dataset and efficient deep learning framework for automated grading of renal cell carcinoma from kidney histopathology images. *Sci Rep* 13(1):5728
26. Hanczar B, Bourgeais V, Zehraoui F (2022) Assessment of deep learning and transfer learning for cancer prediction based on gene expression data. *BMC Bioinform* 23(1):262
27. Prade VM, Sun N, Shen J, Feuchtinger A, Kunzke T, Buck A, Schraml P, Moch H, Schwamborn K, Autenrieth M et al (2022) The synergism of spatial metabolomics and morphometry improves machine learning-based renal tumour subtype classification. *Clin Transl Med* 12(2):e666

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.