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Research Article

Using INTRPRT Guideline to Assess Human-Centric AI Design in CT Tissue Growth Detection

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Abstract

Manual analysis of lesions in serial Computed Tomography (CT) scans is often performed in 2D, making it time-consuming and error-prone. There is a growing need for automated, explainable tools that support radiologists in clinical environments. This study presents a novel, human-centric Artificial Intelligence (AI) framework that combines classical computer vision for automatic alignment, machine learning and deep learning for tissue sectioning, and unsupervised learning techniques for lesion detection. These were used to create a Proof-of-Concept Graphical User Interface tool. Developed over a 12-week period in collaboration with George Eliot Hospital (GEH) and ROKE as part of the National Health Service (NHS) AI Skunkworks programme. The proposed framework offers a novel contribution by integrating explainable AI techniques with human-centred design to improve CT scan analysis. It advances current research by focusing on clinical usability, transparency, and co-development with healthcare professionals.

Keywords: Human-Centred AI; Alignment; Lesion Detection; CT Comparison; Human Health

Introduction

The healthcare industry is potentially on the cusp of a transformative giant step driven by Artificial Intelligence (AI) models that assist clinical stakeholders, particularly in radiology departments [1]. There remains, however, a chasm between the hype of AI and what is really being delivered in terms of clinical benefit at the patient's bedside [2].

Trustworthiness and clinical reliability of AI algorithms are some of the key issues preventing wider adoption, which could then become the standard of care [3]. AI is a tool that needs to be used to assist the human expert and evaluation should be of the outcomes achieved by the integrated working of the combination of the human-AI expert rather than of the AI algorithm in isolation [4]. Thus, unless there is a strong emphasis on embedding a culture of human-centred AI (HCAI) throughout the design, implementation, deployment, optimisation, and evaluation processes, AI will fail to realise its potential [5].

We describe herein the development of a novel AI algorithm to assist the radiologist and critically evaluate the human-centricity of the project. We share the lessons learnt as we attempt to interweave a human-centric focus into all aspects of the project.

The problem we address is that of the current manual process for radiology assessments, which relies on a laborious, time-intensive, error-prone process of serial measurement and analysis of CT scan lesions over time in 3D. Because of human-centred factors, 2D measurements are usually taken by the reporting radiologists. The actual lesional change is in 3D, which is in turn a proxy for the evaluation of disease (cancer) progression, which then forms the basis for clinical decision-making of treatment options.

Our project looked to develop an AI model with a human-centred approach to speed up the analysis of CT scans. The NHS AI Skunkworks team funded this 12-week research project, and GEH clinicians and ROKE, an AI company that provided the technical expertise, collaborated to deliver it. The project utilised various techniques, including classical computer vision for automatic alignment, machine learning and deep learning for tissue sectioning and unsupervised learning techniques for lesion detection.

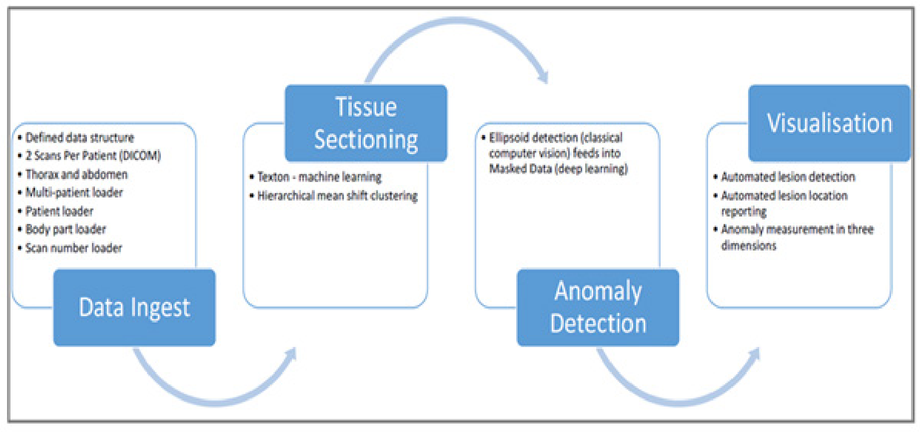

Figure 1: Project techniques.

Methods

Overview

The project was delivered using an agile methodology in twelve weeks and was split into six two-week sprints. Data of 2 CT scans each (a baseline scan and a subsequent follow-up) from 100 patients, all of whom had developed lesions, was used. Figure 2 shows the data flow.

To create a Proof-of-Concept Graphical User Interface tool, three techniques were used: data ingest, classical computer vision, and deep learning. The features built in each stage fed into the Graphical User Interface (GUI) tool, as shown in Figure 3.

The INTRPRT Guideline [6] was used to retrospectively analyse the human-centricity of the project. The guideline consists of six themes: incorporation (IN), interpretability (IN), targets (T), reporting (R), priors (PR), and task (T). Incorporation is the inclusion of clinical experts in the project's team. Interpretability is the type of technique used (including visualisation and human-understandable features). Targets define the end users. Reporting is evaluating the model's performance in human factor goals. Priors include the previous information used to define the algorithm. Finally, the task is evaluating how the algorithm fulfils the required clinical tasks. The aim of the evaluation using the guideline was to determine how human-centric the design and application of the algorithm were. This is explored further in the discussion.

The methods have been split into four sections: alignment, tissue sectioning, lesion detection, and GUI development.

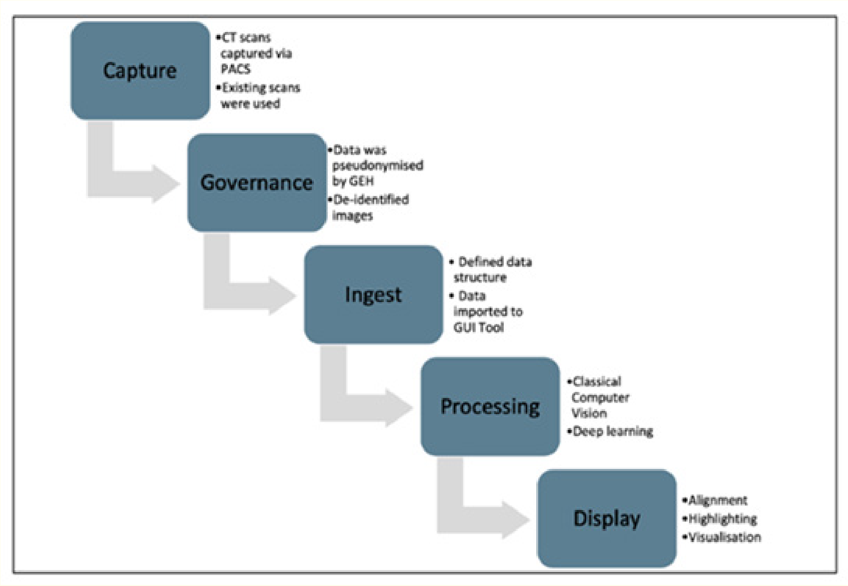

Figure 2: Data flow.

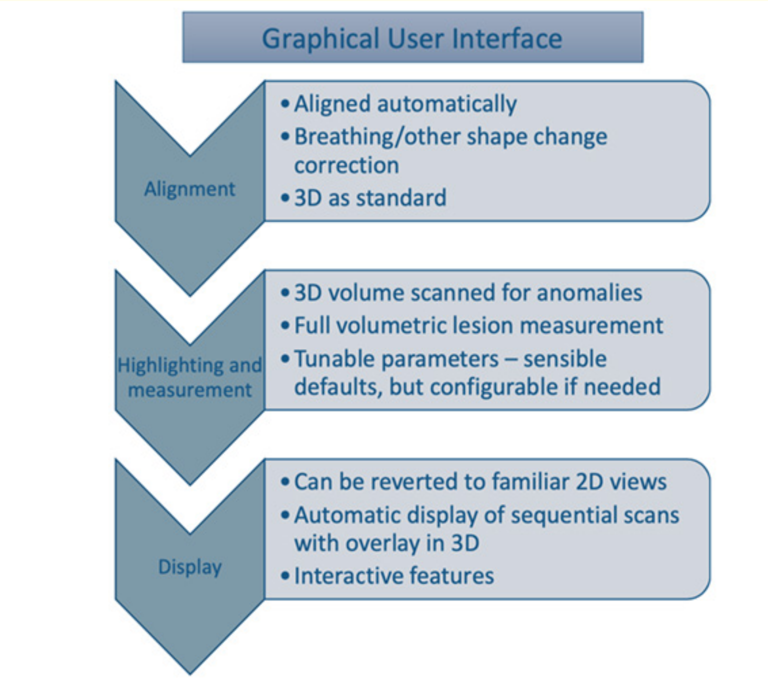

Figure 3: GUI tool overview.

Alignment

Accurate assessment of whether a suspicious cancer lesion has increased in volume or not requires alignment of the lesion in the 3D body habitus across multiple scans done over a period of time. This is to account for the dynamic anatomy of the lesion relative to the body parts because the lesion takes up different positions relative to adjoining other body parts, for example, when breathing or when there are changes in body composition. Thus, there needs to be a system of intelligent and automated alignment of this lesion to accurately determine how it has changed over time. Three alignment techniques of Phase correlation, keypoint detection, and Coherent Point Drift (CPD) were tested. An example of how this was achieved is illustrated in the following patient, where an algorithm was implemented to find the location of the table in a scan based on the observation that the table appears as a vertical line when viewed in the sagittal plane (Figure 4).

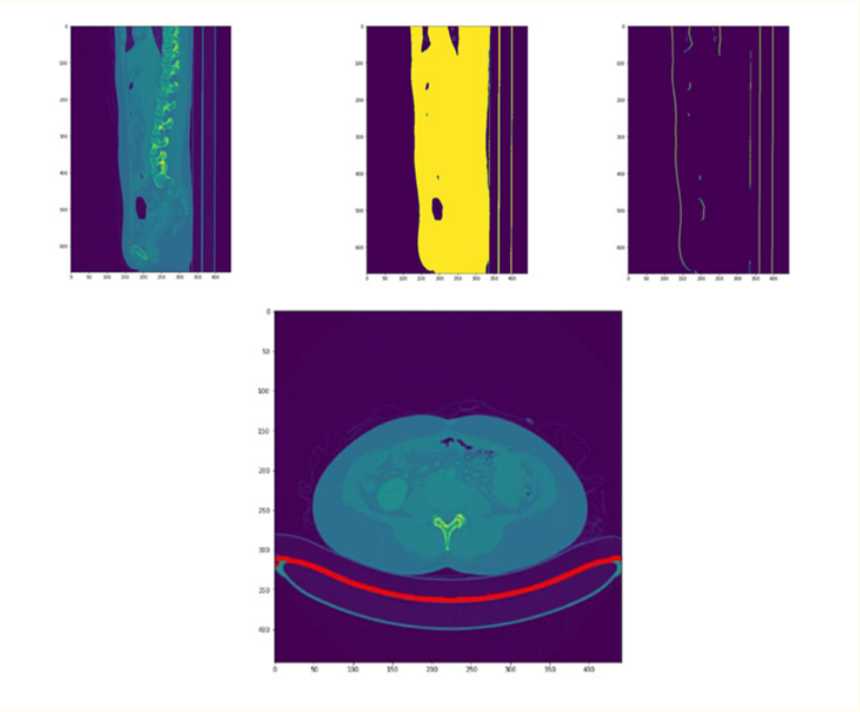

Figure 4: The key steps in the algorithm used to detect the table in a full 3D scan.

The key steps in the algorithm used to detect the table in a full 3D scan. The top row of Figure 4 illustrates that the first image is the original sagittal slice, the second image is a binary version where pixels above a threshold are retained, and the third image then relates to a Hough transformation, being used to find vertical lines. The lower image then shows the surface of the table identified. Pixels vertically below the highlighted red points are then trivially removed, such that the table has been filtered out.

The first method of Phase correlation [7] calculated shifts of pixels of images between two sequential scans. An algorithm was then created using algebraic matrix transformation methods to enable 3D alignment by shifting and overlaying a sequential second scan onto the previous scan.

The keypoint detection method was to extract and match keypoints and descriptors, filter the matched keypoints, estimate the homography of the matching, and finally, apply this to the 2D slice to produce an aligned scan.

The CPD [8] allows non-rigid transformations of certain points in the sequential images to be aligned in a controlled manner using probability density estimations of the prevalence of these points in the images. This was then done iteratively through a machine learning algorithm and tested for accuracy.

Tissue sectioning

Tissue sectioning is the process of automatically differentiating between different types of tissue (e.g., 'bone' and 'fat') or simply determining arbitrary classes (e.g., 'class 1' and 'class 2') and assigning a per-pixel label to all 2D and 3D pixels with which tissue type they belong to. Two techniques were used. Firstly, the Textons [9] pre-processing technique and subsequently, three different clustering algorithms were used. Secondly, a simple self-supervised method called DINO [10] was used.

Lesion detection

This used an unsupervised deep learning technique to detect and signpost any abnormal lesions to the radiologist. As it is unsupervised, it does not need vast numbers of abnormal images but uses lots of normal tissue from few images to train itself. For the ellipsoid detection, various open-source computer vision methods for contour detection and processing were used [11,12] to develop a method that would return a set of ellipses with geometric information for each 2D slice. Figure 5 shows the result for a 2D axial slice.

As the unsupervised technique did not yield the required accuracy, a Density-Based Spatial Clustering of Applications with Noise

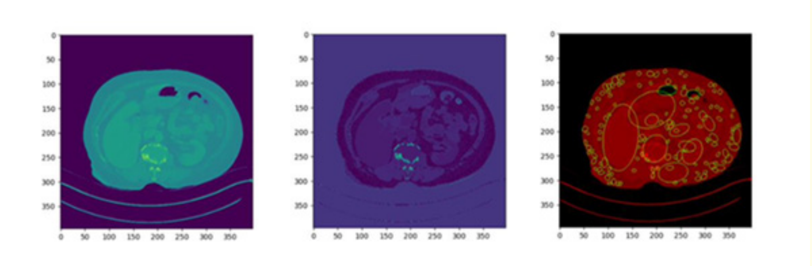

Figure 5: 2D ellipses detected in a single axial slice. (Left) the original image, (middle) the sectioned image, and (right) found ellipses drawn on the image. A high number of non-lesion ellipses are present in most axial views, which motivated moving to full 3D ellipsoidal triggering.

(DBSCAN) supervised clustering algorithm was superimposed on the initial unsupervised technique and developed to provide the 3D centre of the lesion, a 3D bounding box, a volumetric measurement, the number of ellipses in each axis that supported that ellipsoid, and the tissue class (given by the texton tissue sectioner) [14]. When compared to the actual scan, if any differences were detected, then this would signify an anomaly. Checking associated ellipses across axes aided in eliminating false positives.

A rudimentary GUI-based demonstrated system was built using Qt5 with Python binding from PySlide2. Desired functionality to its full complexity was not achieved. However, a prototype was built adequate for end-user testing.

Results

Alignment

Regarding edge detection, performance with preprocessing showed greatly improved robustness as compared to the trial of methods without this preprocessing step. Results from the phase correlation method showed the best alignment.

The second method of Keypoint-based methods was applied to only full 2D slices, not localised regions. This is because there was a challenge in ensuring enough matching key points were extracted to estimate a homography and the results were inferior to the phase correlation approach.

Figure 6 shows the results of keypoint alignment on scans from patient 1. The overall alignment is strong, despite misalignment for the axial slice (around the edge of skin tissue and the bones at the bottom) and the ORB technique [16] (Orientated FAST and Rotated BRIEF) of key points in the sagittal plane (alignment becomes worse for the top and bottom).

Figure 7 shows the results of alignment on slices from scan 2. There was a high magnitude of change to the patient between the two scans.

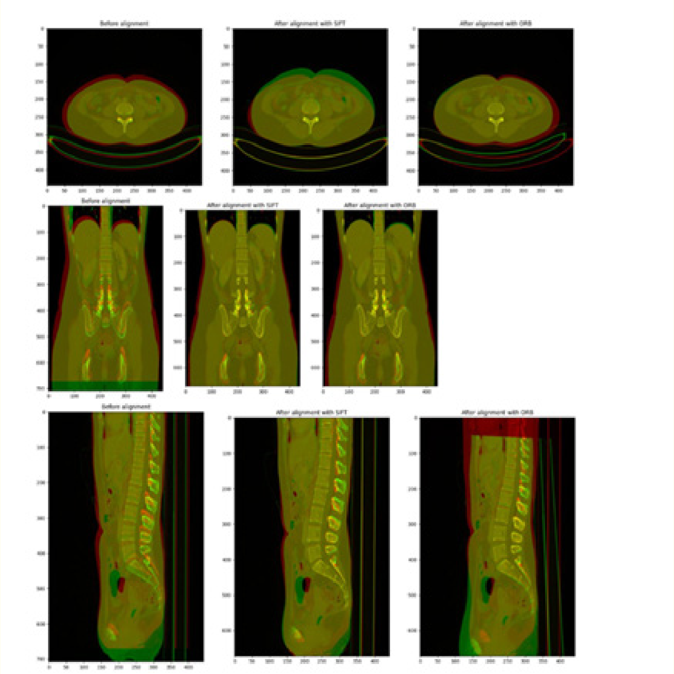

Figure 6: Keypoint alignment of the 2D central Axial (top) Coronal (middle), and Sagittal (bottom) slice from patient 1 using both SIFT feature extraction algorithm and ORB feature detector.

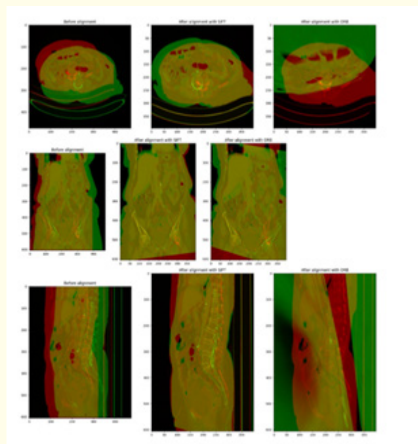

Figure 7: Keypoint alignment of the 2D central axial (top), coronal (middle), and sagittal (bottom) slices from patient 2 using both SIFT and ORB feature detectors [16].

Coherent point drift quickly showed promise on 2D slices. Patient 1 had little body shape change, such that a naïve overlay achieved good alignment. Patient 2 had severe body shape changes as well as severe changes in the orientation of his bones. Thus, they were used comparatively for the results across the project.

While some minor displacements remain, the results in this case (Figure 9) are impressive. The hyperparameters of the CPD algorithm [8] required tuning for this particular patient and took approximately an hour to complete. However, applying this to other patients resulted in inconsistencies and the initially accurate results were not achieved when we had a higher number of more varied image samples.

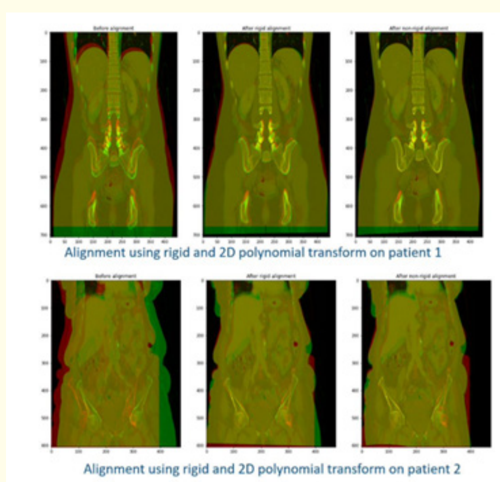

Figure 8: CPD rigid and non-rigid methods, compared to no alignment for two patients.

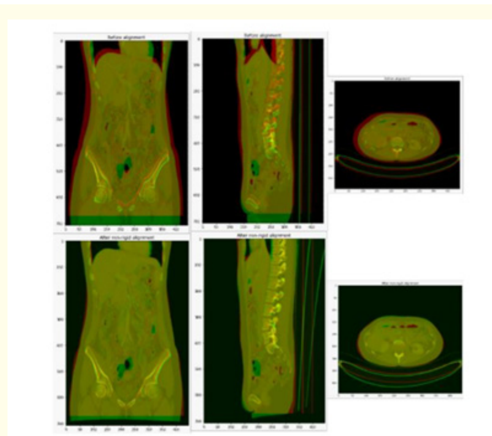

Figure 9: Before and after full 3D non-rigid CPD-based alignment.

Tissue sectioning

Figure shows results for three clustering algorithms with the preprocessing texton step. The results were not as robust as expected.

The colour maps are arbitrary, with a distinct colour only meaning that a distinct class has been found relative to other colours in each image. In the upper right and lower left images, the relevant clusterers were instructed to seek 27 separate tissue classifications, i.e., 27 separate clusters.

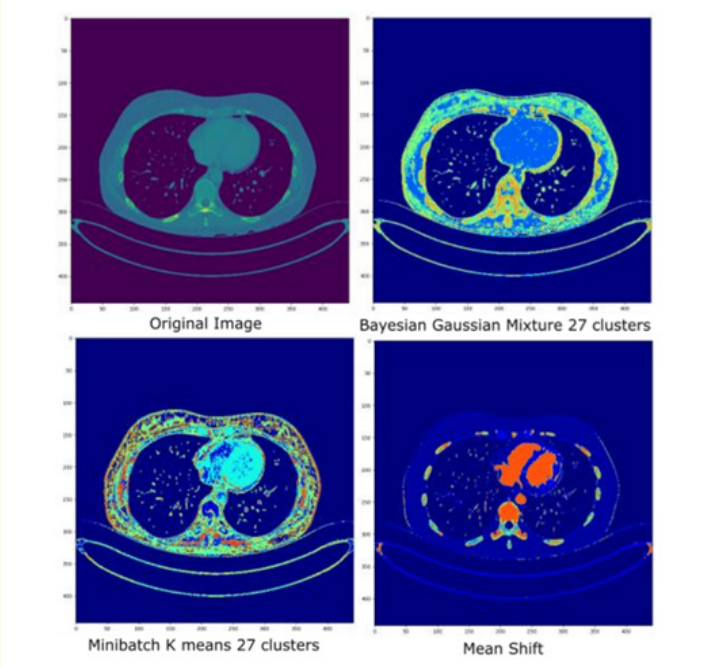

Figure 10: Tissue class labelled image from some of the clusterers trialled on texton features using Gabor kernels.

Figure shows the results of the three clustering algorithms without the preprocessing step. The results of this led to superior sectioning results. The BGM and Mean Shift algorithms proved to achieve a more robust tissue separation. This was validated by a senior Consultant Radiologist.

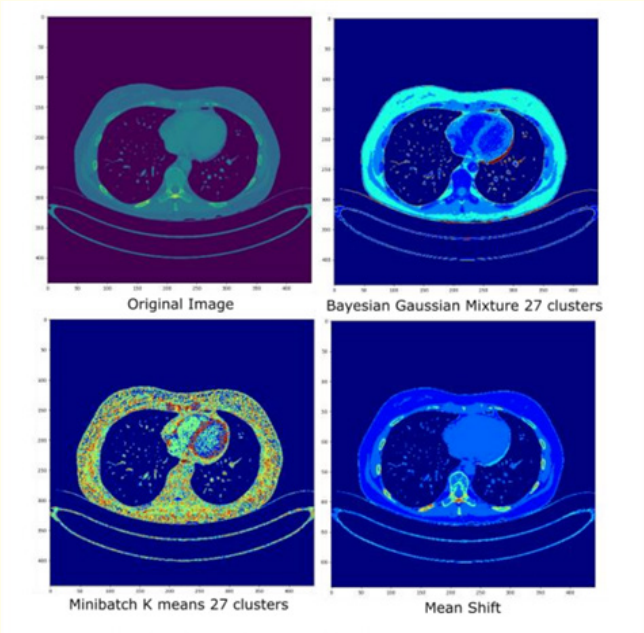

Figure 11: Tissue class labelled images from some of the clusterers trialled on raw intensity values.

The above figure, the colour maps are arbitrary, with a distinct colour only meaning that a distinct class has been found relative to other colours in each image. The DINO techniques were also trialled; however, the results were not as robust as expected. This, combined with the high cost in terms of time (the training time for the models was 8 days), meant that the DINO technique was not feasible and thus little value was seen in progressing with DINO-based methods in this project.

Lesion Detection – prompts radiologist to look at lesion—techniques were explored—unsupervised learning

For ellipsoid detection, the outlines of ellipses found in 2D were used to detect the presence of dense regions in 3D. One of around 30 detected ellipsoids corresponded to the true lesion in each scan. There was clearly a higher density of perimeter points around the true lesion than in other ellipsoids. In Figure 10, an ellipsoid has been accurately identified, and it triggered an accurate masked data prediction, which in turn accurately highlighted a lesion.

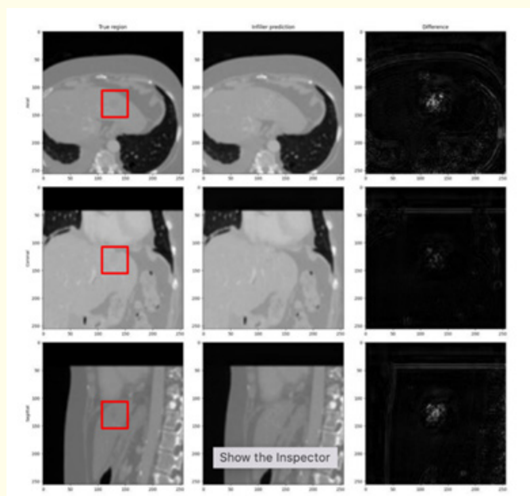

Figure 12: The masked infill method applied to a detected ellipsoid, which coincided well with the known lesion location on patient 17, abdominal scan 1.

For lesion detection, the project provided 'ground truth' data from nine patients, whose scans were marked up by radiologists and radiographers, identifying lesions using existing methods.

Table 1 shows the results of the ellipsoid detector and/or highlighting via masked data prediction for the 9 patients in the validation set. Table 2 summarises this into a per-patient level. These results were produced using a single set of parameters. The validation concluded that, for the nine patients, either ellipsoid detection or masked data prediction was useful in seven cases for at least one lesion.

Patient	Scan	Slice	Lesion	Detected	Ellipsoid Detection	Masked Data
11	Abdo2	60	Large liver lesion	Yes	Yes	Yes
11	Thorax2	317	Lung nodule	Yes	No	Yes
11	Abdo1	615	Bone lesion	Yes	No	Yes
12	Abdo1	100	Multiple liver lesions	Yes	Yes	No
12	Abdo2	220	Renal Cyst	No	No	No
13	Abdo1	135	Liver cyst	Yes	No	Yes
14	Abdo2	281	Fibroid uterus	Yes	Yes	Yes
15	Abdo1	322	Right ureteral lesion	Yes	No	Yes
16	Thorax1	259	Left hilar nodule	No	No	No
17	Abdo1	88	Liver lesion	Yes	Yes	Yes
17	Abdo1	207	liver lesion	Yes	Yes	Yes
18	abdo1	47	liver lesion	No	No	No
18	Abdo1	142	liver lesion	No	No	No
18	Abdo1	165	liver lesion	No	No	No
18	Abdo1	135	Pancreatic cyst	No	No	No
19	Thorax1	19	lymph node	Yes	Yes	Yes
19	Thorax1	130	thoracic mass	No	No	No

Table 1: Result of ellipsoid/detection/masked data highlighting against true lesions.

Patient	Lesion(s) Detected
11	Yes
12	Yes
13	Yes
14	Yes
15	Yes
16	No
17	Yes
18	No
19	Yes

Table 2: Result of whether the ellipsoid detector or masked data highlighting was found to be useful on a per-patient basis in the validation set.

Fully labelling the total of 100 patients in the dataset or a second round of validation was not possible due to time constraints.

Discussion

A simple overlay of two images, as is current radiology practice, for manual discovery and measurement of unexpected features is often not an accurate comparison method. This is due to differences in patient position, body shape changes between sequential scans, and differing lung volumes during each of the scans. Thus, radiologists often must manually reposition scans, deciding on position manually using trial and error, which is tedious, time-consuming, and prone to human error. There is little to no recourse when the patient is misaligned in coronal and sagittal directions. In many cases, there are shifts of several millimetres, leading to disparate structures appearing at the same slice indices.

Thus, we identified this clinical need of the radiologist and patients for time-efficient CT scan analysis and more precise tissue growth/regression detection for the benefit of the end users, i.e., clinicians and patients. We worked in conjunction with Roke and created a proof-of-concept that supports radiologists in achieving a more time-efficient analysis of CT scans. Our project goes beyond just the technical aspects of creating an algorithm; it embodies a human-centric approach from the outset and throughout the design process. Other studies that have used a human-centric process to build a clinician-AI team where the AI acts as an intelligent assistant to improve the clinician's workflow are examples of our strategy. Introduction of a human-centric AI assistant to aid radiologists in multimodal breast image classification [15].

For alignment, 3D methods aim to align all body parts simultaneously or follow a 'rigid' approach where they don't stretch any part of the image. Our project has experimented with a mixture of both. As a result, alignment showed strong promise, with phase correlation and coherent point drift techniques being particularly promising. Phase correlation achieved robust local 3D alignment but did not correct for patient body shape changes or lung volume problems. Non-rigid alignment methods were used to tackle lung volume and body shape issues. Keypoint-based methods showed promise for global alignment over 2D slices, but their success rate was lower than phase correlation. The coherent point drift algorithm achieved excellent global alignment for some patients but would benefit from automated tuning on a per-patient basis.

The tissue sectioning work achieved assumable results using a custom clustering algorithm and deep learning models, but the results were less convincing and required higher engineering effort. Lesion detection also showed some success, particularly with the validated set of nine patients. However, more robust and thorough validation was required to improve results. Finally, the GUI development was used to demonstrate the Proof of Concept. For implementation, it needed to be integrated into the current software used by radiologists so it could seamlessly work with the radiologists' workflow.

In many other studies, there was a gap between designers and end users, which led to challenges related to transparency and user-centred interaction in real practice [17]. To analyse this, we have used the INTRPRT Framework [6].

Incorporation

Our aim was to foster a sense of collaboration between the technology and the users. As a result, end users and designers drove and co-produced this project. During the project's 12 weeks, designers established weekly meetings under the direction of clinicians. During these regular meetings, the researchers investigated the end users' needs. This played a vital role in ensuring the end users' willingness to adopt the technology in real practice. We emphasise that the collaboration between radiologists and developers needs to be improved in order to increase the viability and usability of this technology in the radiologist's real-time workflow.

Interpretability

According to Explainable medical imaging, AI needs human-centred design. Guidelines and evidence from a systematic review [6] confirmed that transparency is viewed as an affordance from an AI and human-centred design perspective, or the interaction between an algorithm and its users, rather than as a feature of the machine learning model.

There are various methods of ensuring transparency with regard to interpretability: attention mechanisms, human factors, deep neural networks, visualisation, clustering, uncertainty measurement, and relation analysis between input features and output. Our project mainly utilised visualisation. Incorporation of human factors as well would have been ideal and the lack of this proves to be a limitation of this project. This could be an avenue for future work.

Targets

The primary end user targeted for this technology (encompassed in the GUI) is the radiologist. Therefore, radiologists assisted in the data collection and validation processes, with a senior radiologist overseeing the entire project. The secondary end users are other clinicians, and the ultimate beneficiary is the patient. Exploring and quantifying the benefits to patients would be an avenue for future work.

Reporting

The reporting step ensures that evaluation directly corresponds to the needs of all the end users, whether it be the radiologist, clinician, or patient. There are four approaches: metrics based on human perception, quantification of the quality of explanations for a specific purpose, qualitative validation of transparent systems, and finally, user studies on target populations. We conducted the third approach. This approach lacked numbers for validation; the project provided 'ground truth' data from only nine patients, whose scans were marked up by radiologists and radiographers identifying lesions using existing methods. A limitation: the ground truth lacks quantitative metrics of success, instead having qualitative measures.

Priors

There are two different types of prior knowledge that can contribute to the development of a transparent ML algorithm: prior documented clinical knowledge informed by the end user and prior computer vision techniques. Our project used, in the majority, the latter. Previous 'edge detection' algorithms [18], phase correlation [7] techniques, keypoint detection methods [19], and CPD [8] methods were used to inform alignment. Various methods [11,12] were used for lesion detection as well. Using robust prior documented clinical knowledge would have been a possible improvement that would have improved affordability and usability for the end user. As prior documented clinical knowledge has not been fully utilised, it is a limitation of this project.

Task

This technology was designed with the aim of integrating into the radiologists' workflow in real time. Its end goal is to aid radiologists with the detection of changes in lesions. While the methods of alignment, tissue sectioning, and lesion detection have the potential to improve the time taken by the radiologist, they currently do not produce a percentage change in the volume of a lesion. This could be a key limitation for future work; the percentage change plays a key role in the clinical outcomes of radiology.

The GUI needed to be able to seamlessly integrate into the radiologists' workflow. Thus, to ensure this, it should have been integrated into the current technology used by the radiologist. This was not possible due to the time constraints of the project and thus is a limitation. It would be a useful and vital avenue for future work. The INTRPRT Guideline [6] was applied to our project retrospectively. The application of the INTRPRT framework simultaneously to the 12-week project would have been an improvement, and any future work should carry this out.

Our project designers emphasise that collaboration with radiologists is necessary for further extension. As the field of radiography is already beginning to use artificial intelligence, to prepare the radiography workforce and other clinicians for a future with AI, prospective research projects for the design, validation, implementation, and evaluation of AI models should be launched with the workforce to generate the required evidence base. According to literature [20], this will lead to a combined design of a model according to the needs of end users, identify any potential bias and confirm that the model transparency technique is consistent with flow-appropriate validation procedures and a regulatory framework.

To put it simply, our vision for the use of AI in healthcare goes beyond technology and instead focuses on creating a mutually beneficial partnership between these technological designers and end users. The quest for an AI model that is more human-centric is more than just a technical aim; it is a commitment to integrating empathy into the core of care innovation and building a future in which cutting-edge technology is skilfully integrated into patient care.

Conclusions and Recommendations

In summary, our project's CT analysis product has made improvements in alignment and overlay methods. It has demonstrated a human-centric process of designing a radiology AI algorithm. The design process right at the outset and throughout incorporated the end-user clinician trio of a radiologist, a radiographer, and also a clinician (a urologist) who is the end user for the radiologist report in terms of providing care for the patient acts according to the outcome of the radiology diagnostic report. Interpretability or transparency could be better, but the alignment algorithm was simpler to understand with less of a "black box" component to it. Apart from the patient, all target end users were made aware of the outcome and its applicability was tested in a clinical setting. This was a pilot project and validation needed more numbers. Time motion studies to analyse the workflow of the tasks were limited and could be done in the future. Further work is required to develop promising AI techniques beyond this 12-week project. Whilst there is much work still to do to make this a useable solution and more human-centric, it is clear the technology has the potential to provide a much-needed 'support tool' needed by Radiologists across the NHS.

Ethical Approval

All procedures were performed in compliance with relevant laws and institutional guidelines. No ethical approval was required because we did a data protection impact assessment and because we used retrospective data.

Conflict of Interest Statement

There are no conflicts of interest from the authors. However, ROKE was paid for this work.

Credit Statement

Sid Singh: Methodology, Writing – Review and Editing, Project Administration, Supervision, Funding Reham Ahmad: Formal Analysis, Investigation, Writing Kimaya Garg: Formal Analysis, Investigation, Writing, Visualisation Paolo Melissa: Methodology, Resources, Data Curation, Writing, Supervision Mena Kumari: Formal Analysis, Investigation, Writing, Supervision Manoj Srivastava: Conceptualisation, Validation, Resources, Supervision, Funding

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