Machine learning – What it is, how it works, the nuclear medicine data it could be applied to and a live demo.

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Background: With the emerging role of artificial intelligence (AI) in nuclear medicine in its infancy, there are numerous potential applications and multiple approaches by which these can be researched, developed and implemented[1][2][3]. One option is that of developing in-house AI tools using classic machine learning (ML) algorithms applied to local datasets.

Fortunately, ML algorithms, the code libraries and the platforms to implement them are well established, widely available and free to use[4][5][6]. This low technical barrier to use, combined with freely available training in coding and the fundamental principles of ML[7][8] provides the opportunity for departments to easily start developing their own in-house AI solutions. Increasing awareness and knowledge in this will be key to the development of AI in nuclear medicine.

Methods: This work provides an introduction to ML and uses simple, every day, non-medical examples to explain the fundamental principles and process of both classification and regression supervised ML. The various types of nuclear medicine data that supervised ML could be applied to are explored and some key examples from the literature are provided. Finally, a live coding demonstration of a simple supervised ML project applied to breast cancer cell data[9] is given. This uses the Python programming language[4] and associated scikit-learn[6] ML code libraries as implemented in the freely available Google CoLab[10] cloud platform.

Results: By the end of this presentation the audience will:

- Understand the context, fundamental principles and process of supervised ML.
- Understand the differences between classification and regression problems
- Have an awareness of the nuclear medicine data that could be used in supervised ML
- Be familiar with key published examples of supervised ML applied to nuclear medicine
- Be familiar with the level of coding required to perform simple ML investigations

Discussion: This work demonstrates the relative ease with which the basic skills and knowledge to perform simple supervised ML can be acquired. The publications highlight the potential of this approach. The methods used in this work are available at no financial cost.

Conclusion: Developing in-house AI tools using supervised ML applied to local datasets is a relatively easily accessible option for researching, developing and implementing AI in nuclear medicine. The technical barriers to entry are low, availability of educational resources is abundant and cost implications are minimal if any. A growing number of publications in the literature using this approach highlight the potential for future benefits to patient care.

Key references:

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Image reconstruction in PET: from state-of-the-art to AI

Andrew J. Reader

Image reconstruction for positron emission tomography (PET) has been developed over many decades, starting out with filtered backprojection methods, with advances coming from improved modelling of the data statistics and improved modelling of the overall physics of the data acquisition / imaging process. However, high noise and limited spatial resolution have remained major issues in PET, and state-of-the-art methods have started to exploit other medical imaging modalities (such as MRI) to assist in denoising and enhancing the spatial resolution for PET. Nonetheless, there is a drive towards not only improving image quality, but also to reducing the injected radiation dose and reducing scanning times. While the arrival of new PET scanners (such as total body PET) is helping, there is still a need to improve the reconstruction of PET images in terms of quality and speed of reconstruction. Deep learning methods are forming the new frontier of research for PET image reconstruction. They can learn the imaging physics and its inverse, learn the noise and also exploit databases of high-quality reference examples, to provide improvements in image quality. There are a number of approaches: direct data-driven learning of reconstruction operators, direct methods which incorporate known imaging physics, methods which integrate deep learning into existing iterative reconstruction algorithms (unrolled reconstruction) and methods which exploit deep learning as a means of representing the images to reconstruct (e.g. the deep image prior). This talk will only look at just some examples of these methods, their advantages and disadvantages, and then consider some of the recent research directions for deep learning / AI as related to PET imaging and reconstruction in particular.

From training data to clinical implementation: an in-house automated segmentation tool for MUGA scans

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Background

Clinical nuclear medicine processing methods, particularly for 2D data, have changed very little over the last decades. Quantification using regions of interest is still a largely manual process. However, with the advent of accessible deep learning technologies there is scope to better automate such processes. This work summarises the development, testing and implementation of one of the in-house segmentation tools used in Sheffield, for MUGA blood pool scans.

Methods

1793 historical MUGA images and associated 24-frame segmentations were used for algorithm training (80% train, 10% validation, 10% test). An automated segmentation algorithm was created using an open-source platform (niftynet [1]), with an established network architecture (U-net [2]). The algorithm was applied to test data and standalone performance was measured as compared to human operators.

A clinical evaluation study was then conducted: 20 MUGA studies were processed via the existing manual method (using MIM software) and separately using the results from the algorithm as a first guess (with subsequent manual editing, again in MIM). The time taken to process via both methods was measured.

Results

On the test data mean Dice score between manually defined segmentation (across all 24 frames) and automatically generated segmentation was 0.93 (SD 0.05). The clinical evaluation phase produced the following results: Mean processing time of 9.7 mins (manual) vs. 3.4 mins (assisted), mean absolute difference between EF result from manual and assisted segmentation was 0.0 (SD 2.9%).

Discussion

An accurate automated segmentation tool for MUGA scans was created using established deep learning tools. The impressive results are perhaps unsurprising given the large number of training cases available. Using the developed algorithm as part of the scan processing procedure it was shown that staff time could be significantly reduced, without impacting on ejection fraction results.

Arguably, the greatest challenge of this work was in clinical deployment, with no clear solution to creating a safe, sustainable clinical application. The final design involved packaging the algorithm as a remote DICOM service, configured to receive data from and send results back to the Nuclear Medicine archive. Following implementation, algorithm performance in clinic is being continually recorded to enable ongoing surveillance

Conclusion

A machine learning tool created using open-source tools was able to accurately segment MUGA blood pool images. Using the automated segmentation as an initial guess led to a 2/3 reduction in operator processing time, without a significant impact on ejection fraction results. The algorithm is now used clinically and is one of an increasing number of in-house machine learning tools.

References

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Early experiences of research radiographers working in an AI Hub

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Background: While approximately 65% of radiographers say they understand the term artificial intelligence (AI), only 31% said they felt confident using AI technologies [1] suggesting limited involvement in AI and AI research. Therefore, the opportunity to work as radiographers in an AI research hub within a multi-disciplinary team, undertake tasks traditionally completed by a radiologist and contribute to and influence developments in AI in imaging is novel and exciting.

Summary: A short SWOT analysis of radiographers in an AI research team discussing the particular skills and benefits that radiographers can bring and outlining suggestions to mitigate weaknesses that may currently prevent radiographer participation. It will illustrate the analysis with examples from current projects and suggest how radiographers and technologists working in clinical departments can ensure their practice supports future AI development.

Learning points:

- Awareness of AI, its role in medical imaging and how AI applications can inform commissioning of scanners, systems and workflow processes.
- Discussion of the skills that radiographers and technologists can bring to AI and skills that may need to be developed.
- Consideration of factors that can be enhanced in daily clinical practice to facilitate AI development in the future.

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BRAIN AI: An Artificial Intelligence Tool for Dementia Diagnosis

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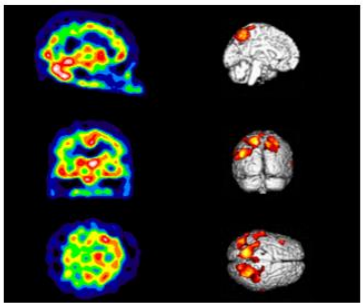
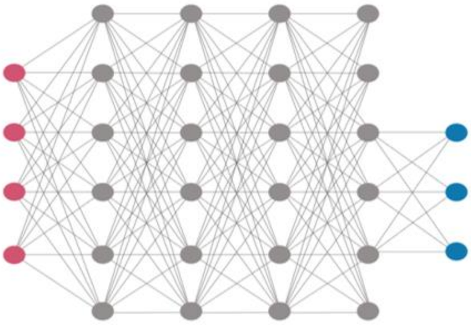
Background. Dementia is a progressive neurodegenerative disease that causes loss of cognitive function resulting in impairment of daily activities, eventually leading to disability and death.
Dementia diagnosis is a complex, subjective and slow process. It is estimated that it takes upwards of 2 years on average from symptom onset to diagnosis. There is a clear need for objective methods for early diagnosis of dementia and prediction of the likelihood of progression.
Functional neuroimaging techniques, including Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) support diagnosis of dementia by identifying subtle changes in brain metabolism and perfusion respectively[1]. Artificial intelligence (AI) can support clinicians for rapid and accurate image interpretation, improve the workflow for healthcare systems and reduce medical errors, ultimately benefiting patient care[2]. Specific to neuroimaging, the use of AI for diagnosis and prognosis in dementia is a rapidly emerging field[3].
In this study we hypothesised that AI methods applied on brain perfusion SPECT scans can provide accurate classification of dementia diagnosis.

Methods. 433 patients brain perfusion SPECT scans from a heterogenous patient cohort where analysed. Statistical Parametric Mapping was used to quantify brain perfusion differences in HMPAO SPECT scans in comparison to a database of healthy controls. The Marseille Region of Interest Toolbox was used for extracting summed t-scores for anatomical brain regions. A minimum redundancy maximum relevance method was used for feature selection. 5-fold cross validation was used for training and testing the AI tool.



Brain Scan



Artificial Intelligence Module

Diagnosis Support Tool

Results. The classification accuracy of the AI tool was 87%. The area under the receiver operator characteristic curve was 0.93

Discussion and Conclusion. Results indicated high classification accuracy for the AI tool. Further validation, using the AI tool for diagnosis support during image interpretation is required to evaluate its' impact to clinical application.

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Title of Study

Artificial Intelligence & Nuclear Medicine: Best Practices and Trustworthy Ecosystems

Integration and implementation of artificial intelligence (AI) applications in the practice of nuclear medicine require careful analysis of potential opportunities and critical challenges. This comprehensive evaluation is inevitable in order to enhance patient care through innovation on one hand and to address concerns of all relevant stakeholders on the other.

The AI ecosystem contains the total life-cycle of the application including data acquisition, model training and prototyping, production/testing, validation/evaluation, implementation and development, and post-deployment surveillance. Attention to all these steps through the lens of trustworthiness is essential. We explore the elements of trust in the healthcare ecosystem in the AI era while reviewing potential opportunities and critical challenges.

This presentation summarizes the discussions of the Society of Nuclear Medicine and Molecular Imaging (SNMMI) AI Task Force, which consists of various stakeholders and experts including physicists, computational imaging scientists, physicians, statisticians, and representatives from industry & regulatory agencies.

The SNMMI AI Task Force has identified valuable opportunities to enhance the practice of nuclear medicine through AI-based innovation. In addition, critical pitfalls that commonly afflict AI algorithm development, evaluation, and implementation have been recognized. In the end, Task Force elaborated on the responsibilities of the nuclear medicine community to ensure the trustworthiness of these tools.

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