Journal of Neuroradiology 50 (2023) 315–326

Available online at
ScienceDirect
www.sciencedirect.com

Elsevier Masson France
EM|consulte
www.em-consulte.com

Review

The performance of machine learning approaches for attenuation correction of PET in neuroimaging: A meta-analysis

Confidence Raymond[a,b], Michael T. Jurkiewicz[a,b,c], Akintunde Orunmuyi[d], Linshan Liu[b], Michael Oluwaseun Dada[e], Claes N. Ladefoged[f], Jarmo Teuho[g,h], Udunna C. Anazodo[a,b,i,*]

[a] Department of Medical Biophysics, Western University, London, ON, Canada
[b] Lawson Health Research Institute, London, ON, Canada
[c] Department of Medical Imaging, Western University, London, ON, Canada
[d] Kenyatta University Teaching, Research and Referral Hospital, Nairobi, Kenya
[e] Department of Physics, Federal University of Technology, Minna, Nigeria
[f] Department of Clinical Physiology, Nuclear Medicine, and PET, Rigshospitalet, Copenhagen, Denmark
[g] Turku PET Centre, Turku University, Turku, Finland
[h] Turku University Hospital, Turku, Finland
[i] Montreal Neurological Institute, 3801 Rue University, Montreal, QC H3A 2B4, Canada

ARTICLE INFO

Article History:
Available online 3 February 2023

Keywords:
Machine learning
Attenuation correction
Synthetic-CT
Neuroimaging
PET/MRI
PET
Brain PET
Systematic review

ABSTRACT

Purpose: This systematic review provides a consensus on the clinical feasibility of machine learning (ML) methods for brain PET attenuation correction (AC). Performance of ML-AC were compared to clinical standards.
Methods: Two hundred and eighty studies were identified through electronic searches of brain PET studies published between January 1, 2008, and August 1, 2022. Reported outcomes for image quality, tissue classification performance, regional and global bias were extracted to evaluate ML-AC performance. Methodological quality of included studies and the quality of evidence of analysed outcomes were assessed using QUADAS-2 and GRADE, respectively.
Results: A total of 19 studies (2371 participants) met the inclusion criteria. Overall, the global bias of ML methods was 0.76 $\pm$ 1.2%. For image quality, the relative mean square error (RMSE) was 0.20 $\pm$ 0.4 while for tissues classification, the Dice similarity coefficient (DSC) for bone/soft tissue/air were 0.82 $\pm$ 0.1 / 0.95 $\pm$ 0.03 / 0.85 $\pm$ 0.14.
Conclusions: In general, ML-AC performance is within acceptable limits for clinical PET imaging. The sparse information on ML-AC robustness and its limited qualitative clinical evaluation may hinder clinical implementation in neuroimaging, especially for PET/MRI or emerging brain PET systems where standard AC approaches are not readily available.

Introduction

Positron emission tomography (PET) measure metabolic and neurochemical processes in the body and is a versatile imaging tool to diagnose disease and explore disease mechanisms in the brain. Gamma photons emitted after the annihilation of positrons undergo attenuation as they pass through tissues and may create artifacts. Computed tomography (CT) or other approaches to measure tissue density allow for correction of PET photon attenuation. In standalone PET and PET/CT systems, appropriate attenuation correction (AC) is achieved by use of external radioactive source, either by a positron-emitting source or a CT scan, respectively. Integrated PET and magnetic resonance imaging (MRI) systems predict tissue densities by modeling tissue intensities estimated from MRI and relating predicted tissue densities to known tissue attenuation correction factors.

Abbreviations: ML, Machine Learning; DL, Deep Learning; AC, Attenuation correction; QUADAS-2, Quality Assessment for Diagnostic Accuracy Studies 2; CLAIM, Checklist for Artificial Intelligence in Medical Imaging; GRADE, Grading of Recommendations, Assessment, Development, and Evaluation; PROSPERO, Prospective Register of Ongoing Systematic Reviews; PRISMA-DTA, Preferred Reporting Items for a Systematic Review and Meta-analysis of Diagnostic Test Accuracy Studies; CMA, Comprehensive Meta-Analysis; UTE, Ultrashort echo time; ZTE, Zero echo-time; CNN, Convolutional Neural Networks; GAN, Generative Adversarial Networks; SVM, Support Vector Machine; ARF, Alternating Random Forests; MeSH, Medical Subject Headings; RMSE, Relative mean square error; DSC, Dice similarity coefficient; PSNR, Peak signal-to-noise ratio; SSIM, Structural similarity index measure; RE, Relative error; MAE, Mean absolute error; ME, Mean error; I2, Inconsistency index

* Corresponding author at: Udunna C. Anazodo, Montreal Neurological Institute, 3801 Rue University, Montreal, QC H3A 2B4, Canada.
E-mail address: udunna.anazodo@mcgill.ca (U.C. Anazodo).

https://doi.org/10.1016/j.neurad.2023.01.157
0150-9861/