1. Aims
- To explore an accurate method to segment the cerebrum in dual-modality PET-CT images into three different tissue, grey matter (GM), white matter (WM) and cerebrospinal fluid (CSF).

2. Introduction
- Dual-modality PET-CT imaging are now a routine component of clinical practice. However, medical image segmentation methods, as listed below, have generally only been applied to single modality images.
  - Expectation-maximisation segmentation (EMS) algorithm [1];
  - Statistical Parametric Mapping (SPM) package (version 8);
  - Voxel-based morphometry (VBM) package (version 5) [2];
- The difficulties of brain PET-CT image segmentation consist of:
  - Low spatial resolution and high levels of noise in positron emission tomography (PET) images
  - Low contrast computed tomography (CT) component
  - Use the complementary functional (PET) and anatomical (CT) information.
- This project proposes a Gaussian mixture model (GMM) based brain PET-CT image segmentation approach, where the prior anatomical knowledge from the probabilistic brain atlas is incorporated into the variational expectation-maximisation (VEM) algorithm to improve the segmentation performance.

3. Method
   **Step 1: Extraction of the Brain Mask**
   - The brain mask can be extracted in two steps: removing the bone and background from the CT image, and combining the result with brain atlas.

   **Step 2: Calculation of Standardised Uptake Value (SUV) for PET**
   - SUV is necessary for quantitative analysis of PET data, and can be calculated as follows
     \[
     \text{SUV} = \frac{c(t) \text{ injected dose (in)}}{\text{body weight (in lb)}}
     \]
     where \( c(t) \) is the ratio of tissue radioactivity concentration at time \( t \), and injected dose at time \( t_0 \).

   **Step 3: Brain Voxel Classification**
   - An observed brain PET-CT image is characterised by the GMM. Thus its likelihood is as follows
     \[
     p(X; \theta) = \prod_{i=1}^{N} \sum_{k=1}^{K} \pi_k p(x_i | \mu_k, \Sigma_k)
     \]
     where \( X = \{x_1, x_2, \ldots, x_N\} \) represents the voxel values in both PET and CT, \( p(x_i | \mu_k, \Sigma_k) \) is a Gaussian distribution with mean \( \mu_k \) and covariance matrix \( \Sigma_k \), and \( \theta = \{\pi_k, \mu_k, \Sigma_k\} \) denotes all model parameters.
   - In the variational Bayes inference, GMM parameters are assumed to be random variables governed by hyper-parameters \( \pi \). Hence, the GMM-based segmentation aims to maximise the log-likelihood of the image \( \ln p(X; \Psi) \).
   - The probabilistic brain atlas is used to initialise the VEM algorithm, to estimate the mixing coefficients \( \pi \), and to correct the intermediate and final classified results.

4. Results
   - The proposed method was compared to the EMS, SPM8, VBM5 algorithms in 30 clinical PET-CT studies acquired on a Siemens Biograph LSO Duo PET-CT scanner in the Department of PET and Nuclear Medicine at Royal Prince Alfred Hospital (Sydney, Australia).
   - Fig. 1 shows two PET-CT slices and their segmentation results obtained by applying the EMS algorithm (3rd column), SPM8 algorithm (4th column), VBM5 algorithm (5th column), proposed algorithm (6th column), and ground truth (7th column).
   - Table 1 gives the average performance of those four segmentation approaches.

5. Conclusion
   - The proposed brain PET-CT image segmentation algorithm substantially outperforms the EMS, SPM8 and VBM5 algorithms, and is capable of providing a satisfying segmentation result.
   - The prior anatomical information implied in the probabilistic brain atlas can facilitate the segmentation approach.

6. Reference