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Deep learning-based Automated Localisation of Anterior Commissure and Posterior Commissure Landmarks in 3D space from three-plane 2D MRI localiser slices of the brain

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Abstract

The operator first performs the three-plane MRI localiser slices acquisition protocol during brain MRI scan acquisition. Based on various anatomical landmarks such as anterior commissure AC), posterior commissure (PC), and mid-sagittal plane (MSP), the operator plans MRI position and orientation before a full brain MRI scan which is essential for good quality MRI. Automatic localisation of these landmarks is vital to automatise the process and minimise operator error. Prior approaches focused on automated AC and PC detection on 2D mid-sagittal MRI slices. However, improper head positioning leads to improper 2D mid-sagittal MRI slice; therefore, it may impact the localisation error, and the localisation is not in 3D space with respect to brain volume. In the present work, the AC and PC landmarks' locations were predicted in 3D space from three-plane 2D MRI localiser slices using a convolutional neural network-based approach. Six publically available brain MRI datasets were used. The mean AC and PC localisation error obtained was less than 2mm in a within-dataset evaluation and less than 3mm in a cross-dataset evaluation.

Keywords: Brain MRI, Scout scan, anterior commissure, Posterior Commissure, convolutional neural network (CNN)

1. Introduction

Proper head positioning in an MRI scanner is crucial for obtaining a good quality brain MRI scan. Frequently, MRI scanned with different resolutions in different orientations where there is a good "in-plane" resolution and lower "out-of-plane" resolution. A larger deviation from the desired orientation of the head may cause difficulties in

interpreting the image[1][2]. For example, the clinical practitioner often views MRI scans as 2D slices; therefore, improper head orientation can impact the interpretation of the MRI slices. Therefore, the radiographer first performs a three-plane localiser MR scan (scout scan) in sagittal, coronal or horizontal planes before performing a full-fledged MRI scan [3][4]. In the scout scan, the operator commonly looks for the various anatomical landmarks such as anterior commissure (AC), posterior commissure (PC), and mid-sagittal plane (MSP). These landmarks are significant for identifying the current head position and determining the correct position and orientation of the MR slices for a whole-brain MR scan. A radiographer has to do this task manually. However, manual positioning is a tedious task and susceptible to operator error. Therefore, automatic MR slice positioning and orientation may minimise the inter-operator variability, reduces the total scan duration and improve the accuracy [2].

AC, PC and MSP are important anatomical landmarks in the brain. They are often used for characterising brain anatomical coordinate systems [5]–[7] and have significant applications in various neuro-surgical procedures, functional brain mapping, deep brain stimulation, etc. [8]–[10]. Many different approaches have been proposed for automated localisation of these fiducial landmarks in a 3D brain MRI volume or a 2D mid-sagittal slice. Mary prior such techniques used a model-based approach in which AC and PC locations were detected by reference template matching [11]–[14]. Deep learning approaches have recently become more prevalent in various medical image analyses [15]–[17]. In line with it, machine learning/deep learning-based approaches have also been used for the AC and PC anatomical landmark detection in a 3D MRI volume [14], [18] or a 2D MRI scan [2], [19].

One has three 2D brain MRI slices in sagittal, coronal and axial planes in a three-plane MRI localiser (scout) scan. Therefore, one needs to localise AC and PC in a mid-sagittal brain MRI slice. Prior studies used a deep learning model to predict AC and PC landmarks in the mid-sagittal MRI slice [2][19]. However, obtaining a proper mid-sagittal MRI slice is essential. The radiologist may not get a proper mid-sagittal plane MRI localiser sequence due to improper head positioning. Consequently, one may not get perfect AC and PC landmark positions in that 2D slice and also their positions in 3D space. In the present work, we directly predicted AC and PC landmarks' location in 3D space from three-plane MRI localiser slices using a deep learning-based approach. Deep learning-based approaches are susceptible to data bias [20], [21]. Moreover, data variability and reproducibility of deep learning is the key concern for medical imaging applications [22], [23]. Therefore, cross-dataset analysis was also performed to evaluate the model's generalisation capabilities.

2. Methods

AC, PC and Inter Hemispheric (IH) anatomical landmarks were manually identified in each brain MRI volume. MSP plane passes through the AC, PC and IH landmarks. Each MRI volume was aligned to the SPM coordinate system. In an SPM coordinate system, AC is the origin, Y-axis is running from PC to AC location, the X-axis is orthogonal to the MSP plane from left to right, and Z-axis is orthogonal to X- and Y-axis in an upward direction. Each MRI volume was resized to 256x256x256 with isotropic 1mm resolution. An affine transformation (with 9 DOF; translation, rotation, scaling) was randomly generated in which translation ranged from -10 mm to 10 mm, rotation ranged from -30º to 30º, and scaling factor ranged from 0.8 to 1.2. Ten random affine transformations were computed for each MRI scan and applied to the MRI volume. Therefore, ten brain MRI volumes were generated from a single brain MRI volume. After that, three-plane MRI localiser slices were extracted by slicing the MRI volume at the centre in each of the three axes. Consequently, AC and PC anatomical landmarks variably go off from mid-sagittal planes. Therefore, such affine transformation of brain MRI volume and extraction of three-plane localiser slices from it, simulates the head positioning error in an MRI scanner.

A convolutional neural network (CNN) is widely used for image data classification, segmentation and regression analysis [24]. In the present work, inputs were three brain MRI localiser slices, and output was the 3D coordinates of the AC or PC anatomical landmarks in a brain MRI volume. A custom CNN model with four parallel convolutional branches, as shown in Fig.1 was used. We used the linear activation function in the output layer and ReLu activation function in all hidden layers. Mean square error (MSE) was the loss function. Each model was trained for 200 epochs using the 'adam' optimiser.

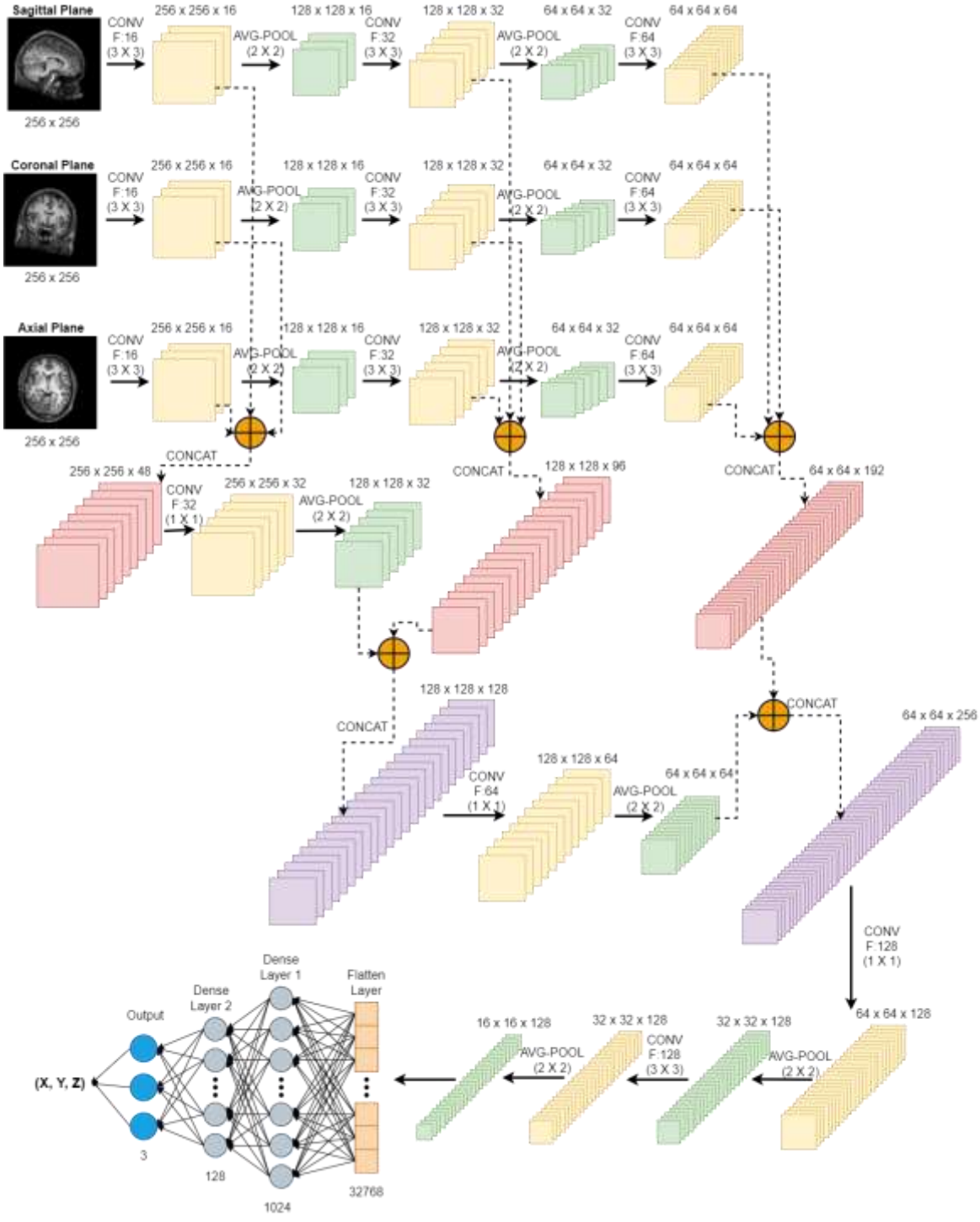

Fig. 1. Custom CNN architecture for AC and PC landmarks' location prediction from three-plane brain MRI localiser slices.

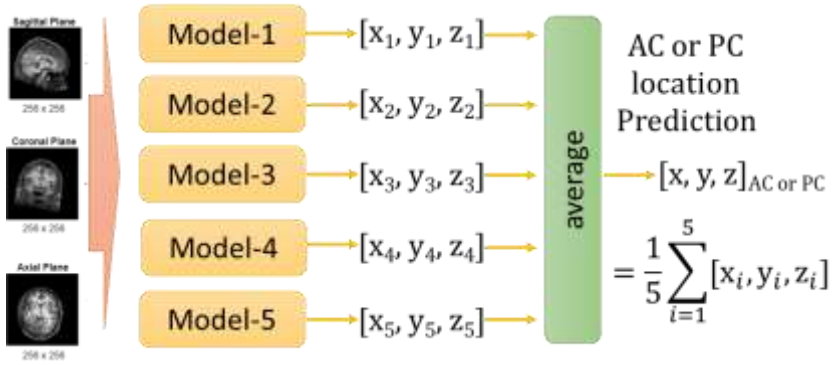

Fig. 2. Homogenous Ensemble Approach. A model is the custom CNN architecture, as shown in Fig.1.

Ensemble learning uses multiple similar or different models to improve the prediction accuracy and generalisation performance[25], [26]. In the present work, a homogenous ensemble approach was used in which five similar models were trained independently. AC or PC coordinated were predicted from each of these five models and then averaged them to obtain the final predicted AC or PC coordinate(Fig. 2). Note that different models were trained separately for AC and PC coordinate prediction.

3. Experiment and results

3.1. Dataset

Six publically available MRI datasets were used for the evaluation (Table. 1.). Few scans from these datasets were discarded based on data quality grounds.

Table. 1. Information about datasets that were used for the evaluation.

Datasets	Number of MRI scans Used(Available)	Demography	Reference
DS1	35 (36)	mean age 20.12, SD : 1.73 ; 18 females	[27]
DS2	34 (34)	Age: 19 - 35	[28]
DS3	34 (35)	Age:19-31; 21 females	[29]
DS4	30 (36)	Age:18-32, 24 females	[30]
DS5	50 (52)	Age:18-42yrs; 30 females	[31]
DS6	48 (49)	Age:19-29; 24 females	[32]

3.2. Evaluation

In the present work, we performed the within-dataset and cross-dataset evaluation. Randomly 20 MRI scans were selected from each of the datasets DS1, DS2 and DS3 for the training, and the remaining MRI scan were used for the testing for a within-dataset evaluation. For the cross-dataset evaluation, the model was tested on MRI scans from DS4, DS5 and DS6. As ten three-plane MRI localiser slices were simulated from each Brain MRI scan, we had ten

times of data for training and testing. Euclidian distance between actual and predicted anatomical landmarks' location in 3D space was used as an error measure.

3.3. Outcome

Mean AC and PC landmark localisation error is below two mm in a within-dataset evaluation and below three mm in a cross-dataset evaluation (Table 2).

Table 2. AC and PC landmarks localisation error in mm (mean±std).

	AC	PC
Within-Dataset Evaluation	1.60 ± 0.13	1.71 ± 0.21
Cross-Dataset Evaluation	2.09 ± 0.37	2.71 ± 0.80

4. Discussion and Conclusion

Many prior studies focused on automatic AC, PC and MSP anatomical landmarks location prediction in the 3D brain MRI volume, and they showed promising results [11], [14], [18]. In the present work, we predicted AC and PC locations in 3D space from the three-plane MRI localiser slices. The AC and PC location prediction accuracy obtained are comparable to that of prediction accuracy obtained using 3D MRI brain volume in [11], [14]. Moreover, prior studies focused on AC and PC detection in mid-sagittal MRI slices can only provide the 2D location with respect to that slice [2], [19]. However, as mentioned earlier, head positioning errors also result in improper mid-sagittal MRI slice, which may affect the AC or PC prediction accuracy in a mid-sagittal MRI slice. Note that majority of prior studies did not perform the cross-dataset analysis [2], [14], [19]. It is essential as a deep learning-based model subject to data bias [20], [21]. In line with it, our outcomes also show that the prediction error in the cross-dataset analysis is higher than in the within-dataset analysis. It shows that it is essential to perform cross-dataset analysis to access the generalisation capabilities of the models. In conclusion, the proposed approach can efficiently localise the AC and PC anatomical landmarks in 3D space from three-plane brain MRI localiser slices. It can help in automated MRI slice positioning and orientation for a full-fledged MRI scan.

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Response to Reviewers' Comments

(ICMLDE 2022 / Paper ID: 3907)

Deep learning-based Automated Localisation of Anterior Commissure and Posterior Commissure Landmarks in 3D space from 2D three-plane MRI localiser slices of the brain

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Reviewing: 1

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The authors of this manuscript would like to thank the reviewer for their valuable comments. Efforts have been made to improve the quality of work and a manuscript by addressing their various suggestions and comments.

Comments:

The authors' motivation behind using a homogenous ensemble approach with five similar models is unclear.

Response:

Ensemble modelling uses multiple similar or different learning models to improve the prediction accuracy and generalisation performance. Related reference has been incorporated in the revised manuscript.

(In the manuscript, 3rd para in method section) "Ensemble learning uses multiple similar or different models to improve the prediction accuracy and generalisation performance[25], [26]. In the present work, a homogenous ensemble approach was used in which five similar models were trained independently. AC or PC coordinated were predicted from each of these five models and then averaged them to obtain the final predicted AC or PC coordinate(Fig. 2). Note that different models were trained separately for AC and PC coordinate prediction."

In the current context, coordinate prediction errors from different models are likely to be in different orientations and magnitude; by averaging them, an error is partly cancelled out. Therefore, we may improve the performance of AC or PC coordinate prediction accuracy and generalisation.

Comments:

A comparison of their model with other state-of-the-art methods proposed for AC and PC landmark location prediction should be provided.

Response:

Yes, there were plenty of studies aimed at predicting **AC or PC landmark location in 3D space** in **3D MRI volume**. Here, full MRI scan is available. Similarly, there were different studies aimed at predicting AC or PC landmark location in **2D space** in a **2D sagittal plane MRI slice**. It is only relevant when a correctly oriented sagittal plane MRI slice is available. However, obtaining a proper mid-sagittal MRI slice during the MRI localiser sequence is challenging due to improper head positions.

Related information and references are present in the manuscript in the introduction section

Key contribution of the present study is a prediction of AC and PC landmark location in **3D space** from a **2D three-plane MRI localiser (scout) sequence.** Therefore, we can not compare it with other state-of-the-art methods proposed for AC and PC landmark location in 3D space in 3D MRI.

As the goal and perspective of the prior studies of AC and PC landmark detection differ from the current work, we did not perform a comparative examination. Moreover, we are not claiming any methodological novelty (e.g. deep learning architecture) in the present work.

Of course, a lower prediction error is expected when predicting AC and PC from 3D MRI compared to the **2D three-plane MRI localiser (scout) sequence.** Prior studies reported AC and

PC prediction errors of about lower than one mm in **3D MRI** [14], [18]. Note that these studies used within-dataset analysis for their evaluation.

Comments:

The authors have proposed a cross-data analysis to evaluate their proposed model's generalisation capabilities. Such analysis is critical in medical imaging as they are susceptible to data bias. Authors should discuss how cross dataset evaluation errors can be used to address bias in the data for generalised model training.

Response:

Data variability is a critical issue and challenge for deep learning-based medical image analysis [22], [23]. A deep learning model trained on one dataset may not work well if tested on another dataset from a similar imaging modality. Therefore, we performed the cross-data analysis to check the expected performance on unseen data from different setups and ethnicities. However, most prior studies (about AC and PC prediction) performed within-dataset analysis evaluation only; therefore, it does not provide an idea about the generalisation capabilities of the model.

Comments:

Proposed CNN architecture can be explained in detail in tabular form for better understanding.

Response:

The majority of technical details about the custom CNN model architecture used for the present study is shown in the figure. 1. Placement of these detail in tabular form will add redundant information. Therefore, we have not provided the CNN architecture details in tabular form.

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Reviewing: 2

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The authors of this manuscript would like to thank the reviewer for their valuable comments. Efforts have been made to improve the quality of work and a manuscript by addressing their various suggestions and comments.

Comments:

The technical contribution of this study needs to be strengthened.
Information on the experimental setup is missing
Need additional information about the proposed methodology
Additional comparisons with more criteria are necessary in the 3. Experiment and results

Response:

As the comments are not specific, it is difficult for us to incorporate them into the manuscript. We have made some modifications considering the other reviewer's comments, which may resolve some of your concerns.

Comments:

Remove the word like "we" from the manuscript

Response:

We have reduced the use of "we" in the revised manuscript.

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Reviewing: 3

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Comments:

The primary contribution has to be clarified more
The paper's structure must be explained towards the conclusion of the introduction section
What inspired you to write it? Are there any knowledge gaps in it?

Response:

Prior studies aimed to predict AC or PC landmark locations **in 3D space** in **3D MRI volume**. In their study, a full MRI scan is available. Similarly, there were different studies aimed at predicting AC or PC landmark location in **2D space** in a **2D sagittal plane MRI slice**. It is only relevant when a correct midsagittal MRI plane slice is available.

Key contribution of the present study is the prediction of AC and PC landmark locations in **3D space** from a **2D three-plane MRI localiser (scout) sequence.**

This information is already present in the introduction section and discussed in the discussion section.

Comments:

A comparative examination is necessary in light of recent publications

Response:

As the goal and perspective of the prior studies of AC and PC landmark detection differ from the current work, we did not perform a comparative examination. Moreover, we are not claiming any methodological novelty (e.g. deep learning architecture) in the present work.

Comments:

Only a few references follow the rules
cite some recent works

- Singh, V.; Asari, VK; Rajasekaran, R. A Deep Neural Network for Early Detection and Prediction of Chronic Kidney Disease. Diagnostics 2022, 12, 116, https://doi.org/10.3390/diagnostics12010116
- Priyanka Rastogi, Vijendra Singh, and Monika Yadav, Deep Learning and Big Data Technologies in Medical Image Analysis,5th IEEE International Conference on Parallel, Distributed and Grid Computing (PDGC-2018), 20-22 Dec, 2018, Solan, India, 978-1-5386-6026-3

- Priyanka Rastogi, Kavita Khanna, Vijendra Singh, LeuFeatx: Deep learning–based feature extractor for the diagnosis of acute leukemia from microscopic images of peripheral blood smear, Computers in Biology and Medicine, Volume 142,2022

Response:

We have included the following recent publications in the revised manuscript at appropriate places.

- Priyanka Rastogi, Vijendra Singh, and Monika Yadav, Deep Learning and Big Data Technologies in Medical Image Analysis,5th IEEE International Conference on Parallel, Distributed and Grid Computing (PDGC-2018), 20-22 Dec, 2018, Solan, India, 978-1-5386-6026-3
- Priyanka Rastogi, Kavita Khanna, Vijendra Singh, LeuFeatx: Deep learning–based feature extractor for the diagnosis of acute leukemia from microscopic images of peripheral blood smear, Computers in Biology and Medicine, Volume 142,2022
- J. Shi et al., "Applications of deep learning in medical imaging: a survey," Journal of Image and Graphics, vol. 25, no. 10. pp. 1953–1981, 2020.

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Below is the list of newer references have been added in the revised manuscript to address various review concerns.

[15] P. Rastogi, K. Khanna, and V. Singh, "LeuFeatx: Deep learning–based feature extractor for the diagnosis of acute leukemia from microscopic images of peripheral blood smear," *Comput. Biol. Med.*, 2022.

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