Development of a Deep Learning Network using a Pre-Trained Convolutional Neural Network

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Abstract

The use of machine and deep learning is rising in oncology. Discrimination of tissue types using texture analysis is a long standing technique. Texture features are often used to train machine learning models. Deep learning, a subfield of machine learning, overcomes the need to calculate features by allowing the machine to learn directly from the image. However, a large amount of labelled image data is required to train deep learning models, this is a difficulty in oncology. Transfer learning is the process of taking a trained model and adapting it for use on a new task, this allows for rapid progress or improved performance when modelling the new task. In this work, transfer learning has been used to classify diseased tissue from healthy prostate with the hypothesis being that the convolutional neural network (CNN) would identify generic features common to most images such as colour, contrast and repetitive patterns. This was compared to a typical machine learning approach where features are derived from the image set and used for later classification. Through the development of these models on three data sets, results showed that a pre-trained CNN can be successfully adapted for use on medical images. Transfer learning was successful in identifying prostate from surrounding structures in T2 prostate MRI images. The development of an accurate model would enable automatic segmentation of focal disease which could be used to aid clinical decisions and guide treatment strategies. Additionally, if successful, this model could be integrated into an adaptive radiotherapy framework.

Introduction

'Images are more than pictures, they are data'. There is an expanding interest in extracting quantitative features from medical images to do just that [1].

Machine learning is showing great promise in automated tumour segmentation / detection. This will be key to speed up the radiotherapy process and aid adaptive radiotherapy.

Machine learning requires distinctive features to be derived and selected, meaning the most distinguishable features may be missed.

Deep learning has rapidly developed since the success of Krizhevsky et al [2] in 2012 who developed AlexNet, a high performing CNN capable of classifying images in 1000 object categories. This overcomes the issue of feature extraction by enabling the machine to learn features which are important to the problem at hand.

Methods

Using Matlab, three workflows were investigated, Figure 1. Firstly, 32 texture features were calculated to characterise the image properties of healthy and diseased tissue and used to train machine learning algorithms. Secondly AlexNet, was used as a feature extractor for later classification. Lastly, AlexNet was adapted for use o MRI images using transfer learning.

Each was initially developed on brodatz images containing strong textural features. This was then translated onto a set of 40 prostate MRI images published as part of a MICCAI grand challenge, to test performance on a set of medical images, Figure 2. The models were assessed in terms of accuracy, sensitivity, specificity and AUC.

Finally, T2 MRI studies of 16 patients with localised prostate cancer were analysed using all three workflows. Each image was contoured by a consultant radiation oncologist, defining the healthy and diseased prostate classes.

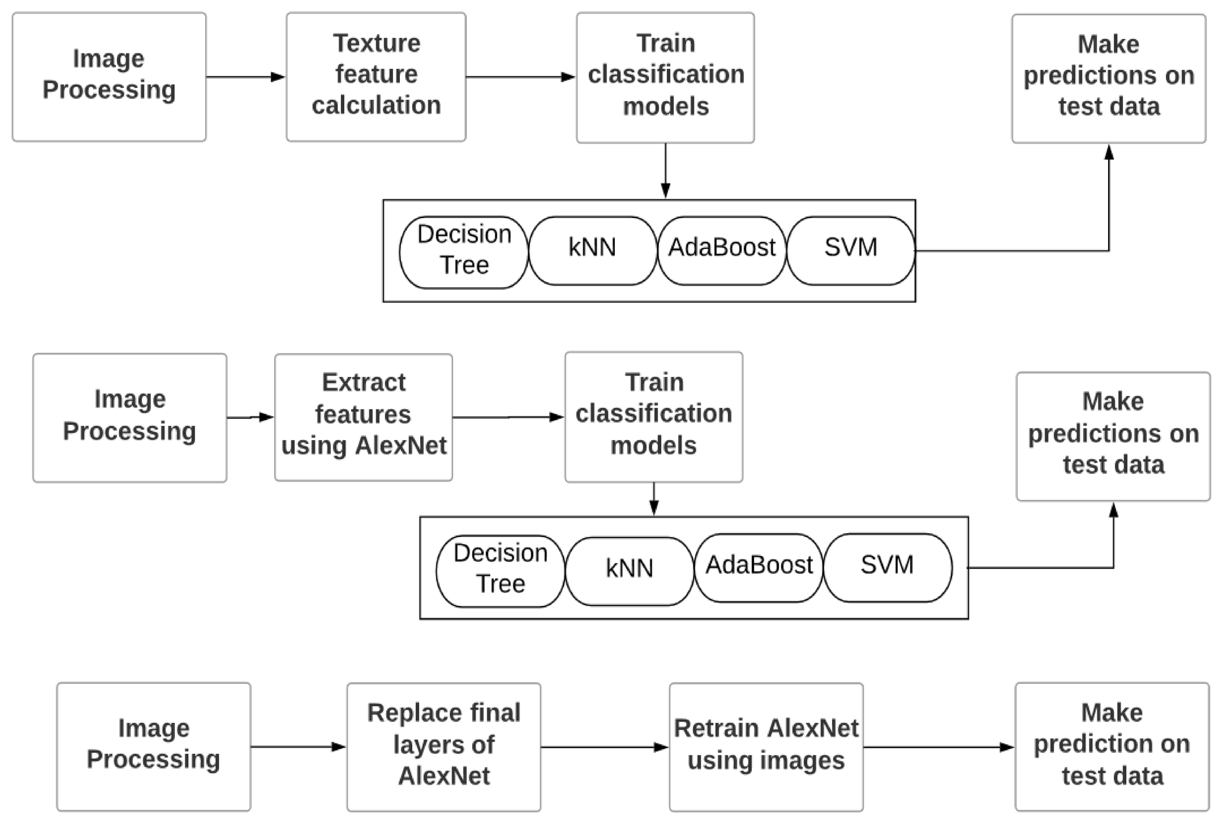

Figure 2: A flow chart of the processes used in this work

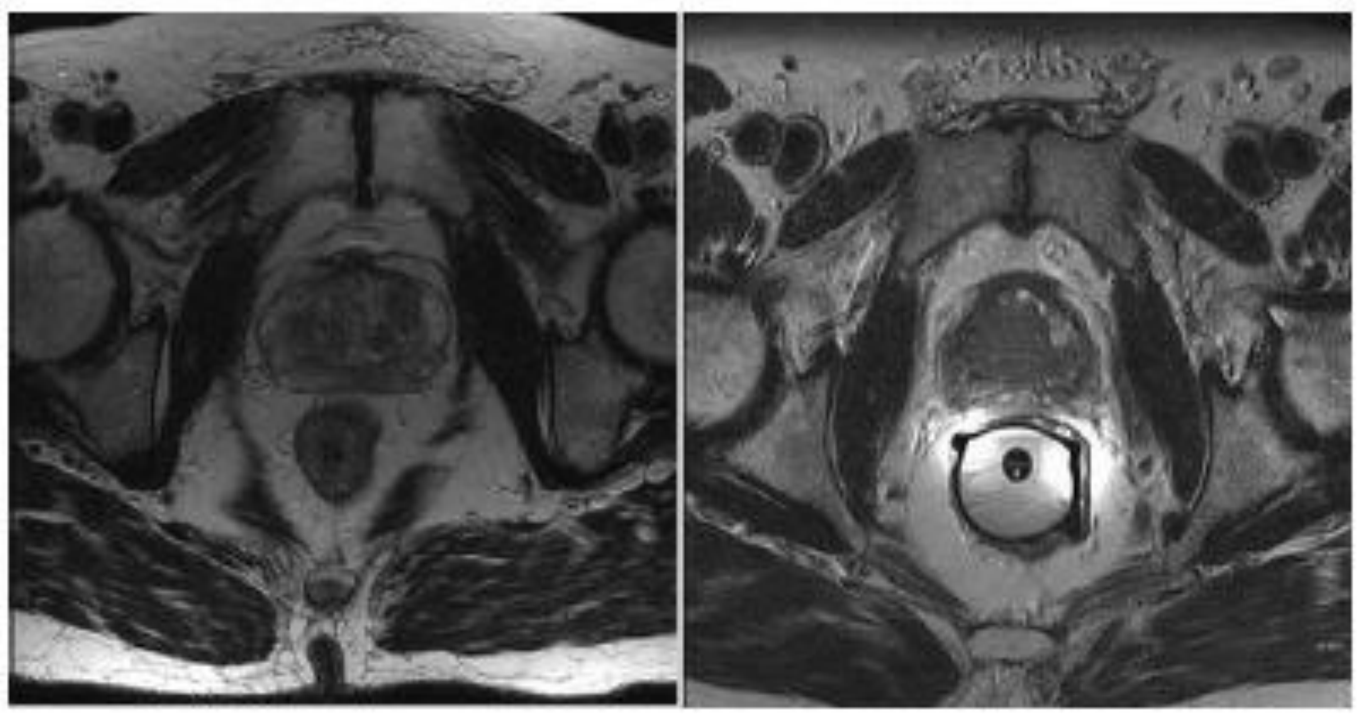

Figure 2: An example of the T2 MRI images included in the MICCAI dataset with and without an endorectal coil, only cases without an endorectal coil were considered.

Aims

The aim of this work was to investigate the feasibility of applying a pre-trained CNN to a set of medical T2 MRI images with the intent to identify areas of disease in the prostate using texture analysis as a baseline.

Results

The key findings from this work have been summarised in Table 1 with the performance of the fine-tuned CNN has been highlighted in each case.

Data Set	Method	Accuracy	Sensitivity	Specificity	AUC
Brodatz	Texture Features	0.924	0.924	0.924	0.978
	CNN Derived Features	0.818	0.701	0.867	0.899
	Fine-tuned CNN	**0.966**	**0.918**	**0.989**	**0.996**
MICCAI	Texture Features	0.595	0.492	0.716	0.651
	CNN Derived Features	0.529	0.241	0.867	0.568
	Fine-tuned CNN	**0.593**	**0.830**	**0.367**	**0.635**
T2 Prostate Cancer Positive	Texture Features	0.682	0.454	0.710	0.641
	CNN Derived Features	0.674	0.632	0.679	0.682
	Fine-tuned CNN	**0.783**	**0.227**	**0.852**	**0.663**

Table 1: Summary of results

- Findings from Brodatz images show the ability to obtain high levels of classification accuracy using texture analysis and CNNs.
- Progression to the MICCAI data set showed that texture features derived from T2 images have shown an ability to distinguish prostate from other tissue in the pelvic area.
- Feature extraction using the CNN yielded mixed results, with an average decrease in accuracy of 11% compared to classification using texture features.
- Application to the local dataset showed promise. Using AlexNet, the results were on par with those of machine learning but low sensitivity was observed. This is likely due to the high level of imbalance inherent to this data type.

Conclusion and Future work

Overall, the AUC indicated that the performance of the CNN is on par with machine learning methods. These data strengthen the claim that pre-trained CNN's are suitable to identify prostate cancer on MRI images.

The results show that different classification algorithms behave differently with different data sets and that no gold standards should be assumed.

Transfer learning is clearly a suitable method for analysis of MRI images, as is proved by the high sensitivity of the network. This may be of benefit to those who wish to develop classification algorithms without a large amount of training data available.

References

[1] Robert J. Gillies, Paul E. Kinahan, and Hedvig Hricak. Radiomics: Images are more than pictures, they are data. Radiology, 278(2):563–577, 2016. PMID: 26579733.
[2] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. Imagenet classification with deep convolutional neural networks. In Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume 1, NIPS'12, pages 1097–1105, USA, 2012. Curran Associates Inc.

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