Radiomic evaluation of treatment response in patients with glioblastoma: a preliminary study

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Aims and objectives

Background

Assessment of treatment response in brain tumours is one of the most important issues in oncology. After chemo-radiotherapy (CRT), glioblastoma, the most common aggressive primary brain tumour, increases in size in one third of patients. It appears that treatment is not working and in about half of these cases, the growth is transient and due to treatment itself, known as 'pseudoprogression', rather than true progression.[1] In clinical practice, it is impossible to differentiate between true progression and pseudoprogression. Conventional MRI scans also cannot distinguish between the two (Fig. 1 on page 4).

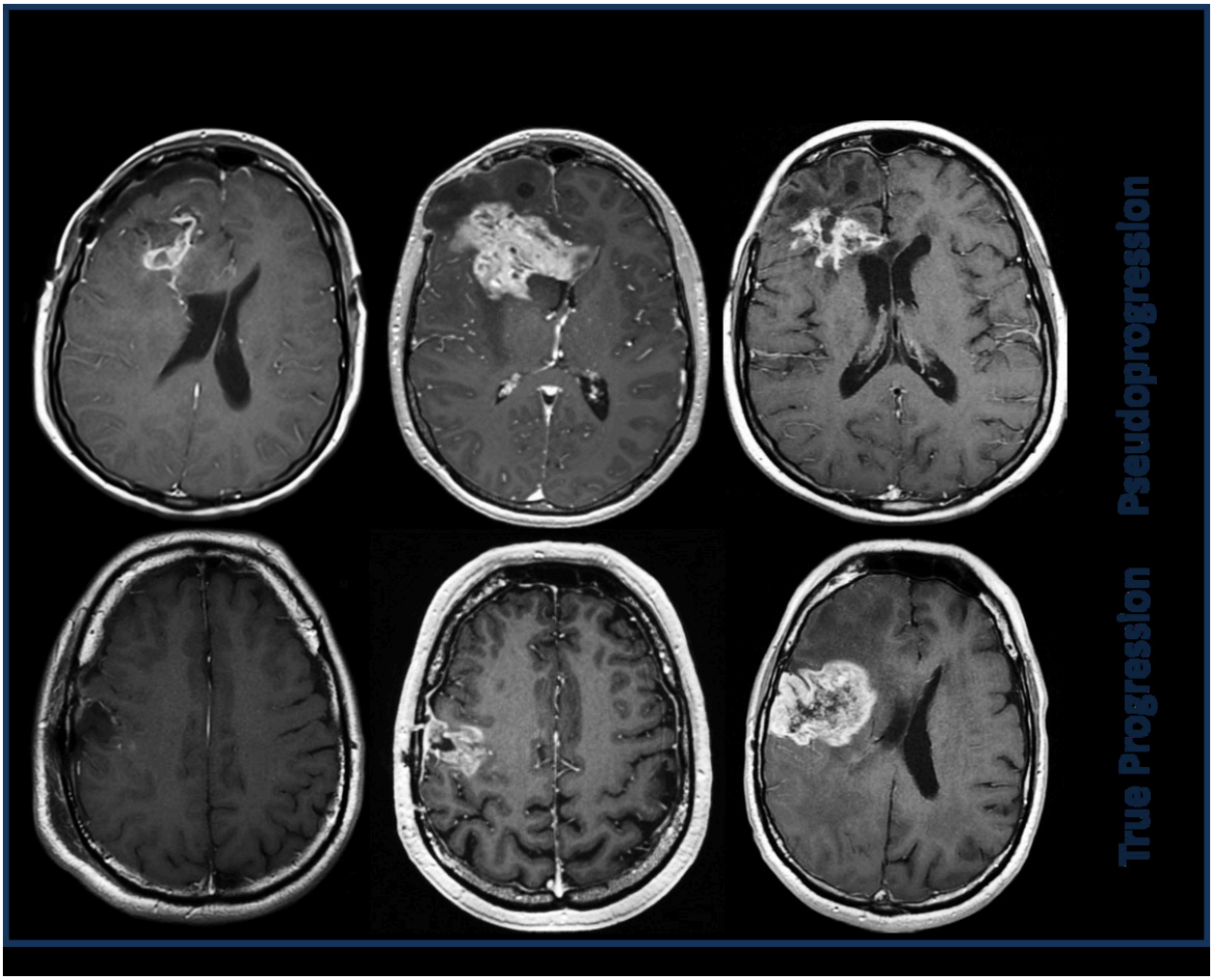


Fig. 1: Examples of pseudoprogression and true progression in two patients. At the first follow-up MRI scan at six weeks after chemo-radiotherapy treatment, there is an

increase in enhancing disease. At this time it is impossible to differentiate between the two pathologies. Scans at 6-9 months make the distinction.
References: - Birmingham/UK

Computer vision can be used to read images of tumours and detect hundreds of features invisible to the human eye, known as 'radiomics'.[2] Machine learning can also be used to create a prediction model from the features and clinical data to predict clinical outcome.[3]

Aim

The aim of this pilot study was to see if we could use computer vision to identify radiomic features, not visible to the human eyes, to distinguish between early true progression and pseudoprogression in glioblastoma.

Images for this section:

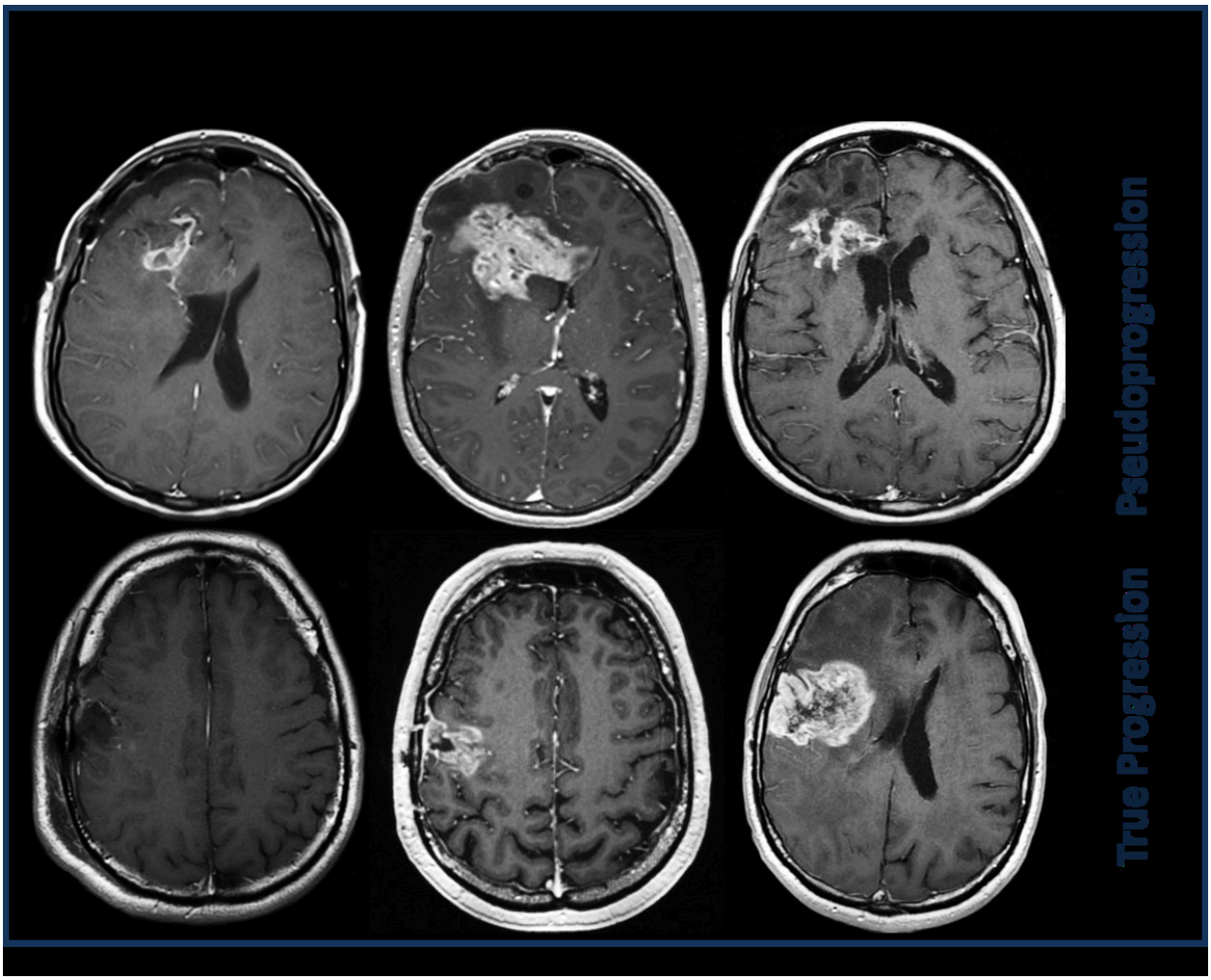


Fig. 1: Examples of pseudoprogression and true progression in two patients. At the first follow-up MRI scan at six weeks after chemo-radiotherapy treatment, there is an increase in enhancing disease. At this time it is impossible to differentiate between the two pathologies. Scans at 6-9 months make the distinction.

Methods and materials

We retrospectively analysed 20 MRI studies of patients with biopsy-proven glioblastoma who had standard chemo-radiotherapy treatment and early progressive enhancing disease. Studies were labelled as true progression (n=11) if there was progression or death within six months or pseudoprogression (n=9) if there was no further progression within six months.

The T1-weighted post-contrast and T2-weighted sequences were co-registered to allow segmentation of tumour components. Enhancing disease and perilesional oedema were segmented from the two sequences respectively to create volumes of interest (Fig. 2 on page 6) using ITK-SNAP open-source software[4] with a semi-automatic method with manual adjustment.

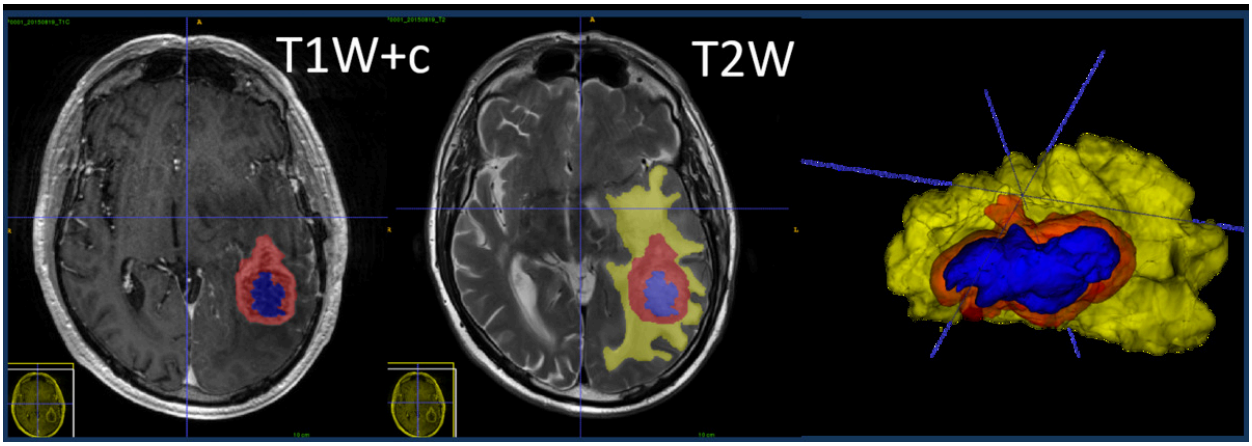
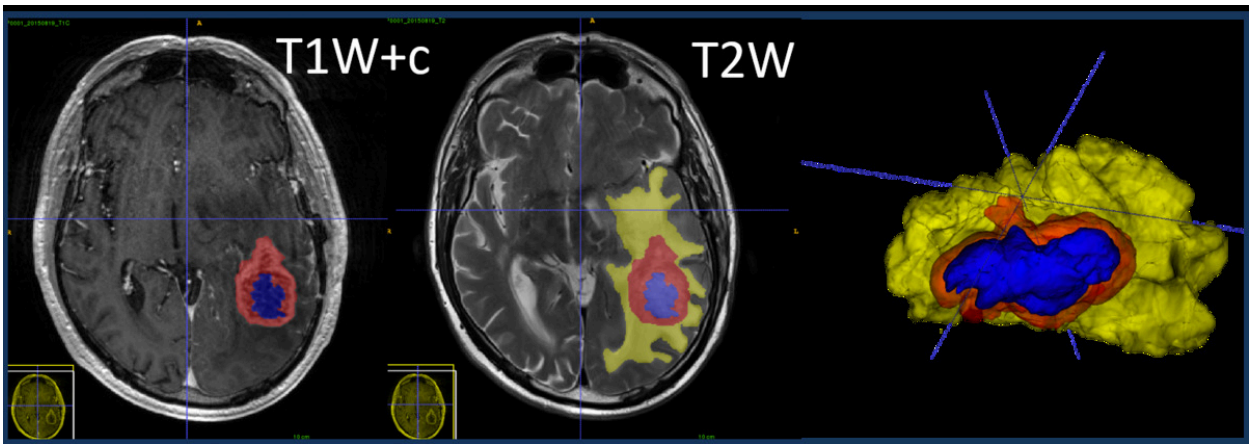


Fig. 2: Co-registration of T1-weighted post-contrast and T2-weighted MRI images with segmentation of enhancing tumour (red) and peritumoural oedema (yellow). Volumes of interest created (right).
References: - Birmingham/UK

Radiomic texture features were extracted from the volumes of interest using CaPTk software[5] and more than 280 features were extracted per MRI sequence. The features included morphological, grey level co-occurrence matrix (GLCM), grey level run length matrix (GLRLM), neighbouring grey tone difference matrix (NGTDM) and grey level size-zone matrix (GLSZM) features. Statistical analysis was performed using SPSS software to calculate the differences between the true progression and pseudoprogression groups.

Images for this section:



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Results

Results showed several features demonstrating significant difference between the true progression and pseudoprogression groups. For enhancing disease on T1W imaging, the significant GLCM features were contrast and homogeneity, and significant GLRLM features were grey level non-uniformity and run length non-uniformity. For perilesional oedema, the significant GLRLM features were grey level non-uniformity and run length non-uniformity. There were also significant differences in the volume of enhancing disease and perilesional oedema between both groups. Results are summarised in Table 1 (Fig. 3 on page 8).

			Features				
ROI	**Sequence**		Contrast	Homogeneity	Grey Level Non-Uniformity	Run Length Non-Uniformity	Volume
Contrast-Enhancing Tumour	Post-contrast T1W	tPD	2.81 ± 0.76	0.52 ± 0.04	3903 ± 2324	15127 ± 7014	27562 ± 13996
		psPD	4.27 ± 1.51	0.45 ± 0.08	1335 ± 797	6306 ± 2793	14992 ± 10237
		p-value	**0.022***	**0.014***	**0.005***	**0.002***	**0.037***
Oedema	T2W	tPD			10735 ± 8384	28015 ± 11516	100730 ± 53446
		psPD			2646 ± 841	11914 ± 4189	37661 ± 18300
		p-value			**0.010***	**0.001***	**0.003***

** significant at level p < 0.05*

Fig. 3: Results table demonstrating the significant features and differences between the true progression (tPD) and pseudoprogression (psPD) groups.
References: - Birmingham/UK

The results suggest that computer vision can detect differences between tumours demonstrating early true progression, despite there being no discernible differences to oncologists and radiologists, both clinically and on imaging.

Images for this section:

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Conclusion

- This pilot study has shown that radiomic texture features can differentiate between early true progression and pseudoprogression in glioblastoma.
- The most significant radiomic features distinguishing pseudoprogression from true progression were contrast, homogeneity, grey level non-uniformity and run length non-uniformity. The volumes of enhancing disease and perilesional oedema were also significantly different between both groups.
- Big data incorporating machine learning is required to produce strong prediction models for earlier prediction of treatment response.

References

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