TranSOP: Transformer-based Multimodal Classification for Stroke Treatment Outcome Prediction

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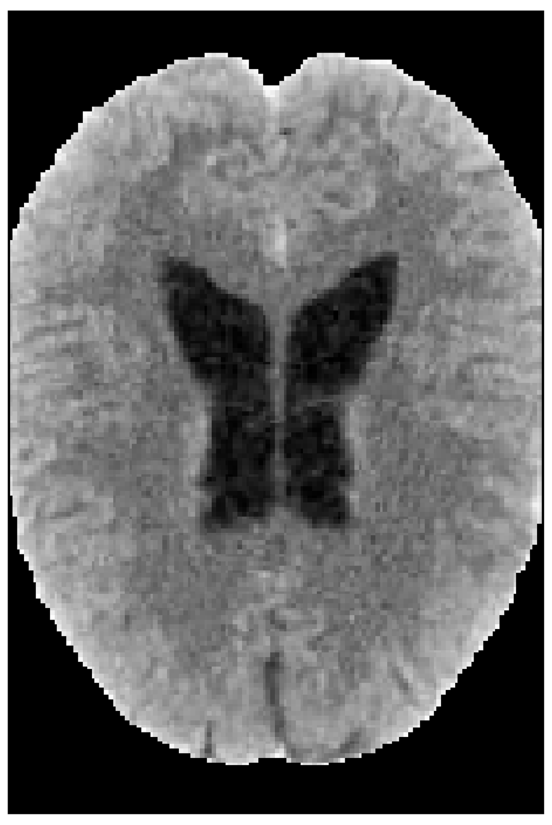
1. Motivation

- Acute ischaemic stroke, caused by an interruption in blood flow to brain tissue, is a leading cause of disability and mortality worldwide.
- The selection of patients for the most optimal ischaemic stroke treatment is a crucial step for a successful outcome, as the effect of treatment highly depends on the time to treatment.
- Avoiding treatment where risks are highest

3. Dataset

- MR CLEAN trial dataset [1]
- 500 patients from 16 medical centers, NCCT volumes
- Clinical metadata comprises, such as patient demographics, medical history and the stroke metrics



2. Contributions

Problem: predict the successful rate (functional outcome) of ischaemic stroke treatment (thrombectomy) from baseline 3D non-contrast computed tomography (NCCT) volume (the first scan when the patient was admitted to hospital) and clinical metadata.

- A transformer-based multimodal network (TranSOP) to predict the functional outcome of stroke treatment.
- A fusion module to efficiently combine NCCT features and clinical information.
- Achieve a state of the art AUC score of 0.85.

4. Proposed Method

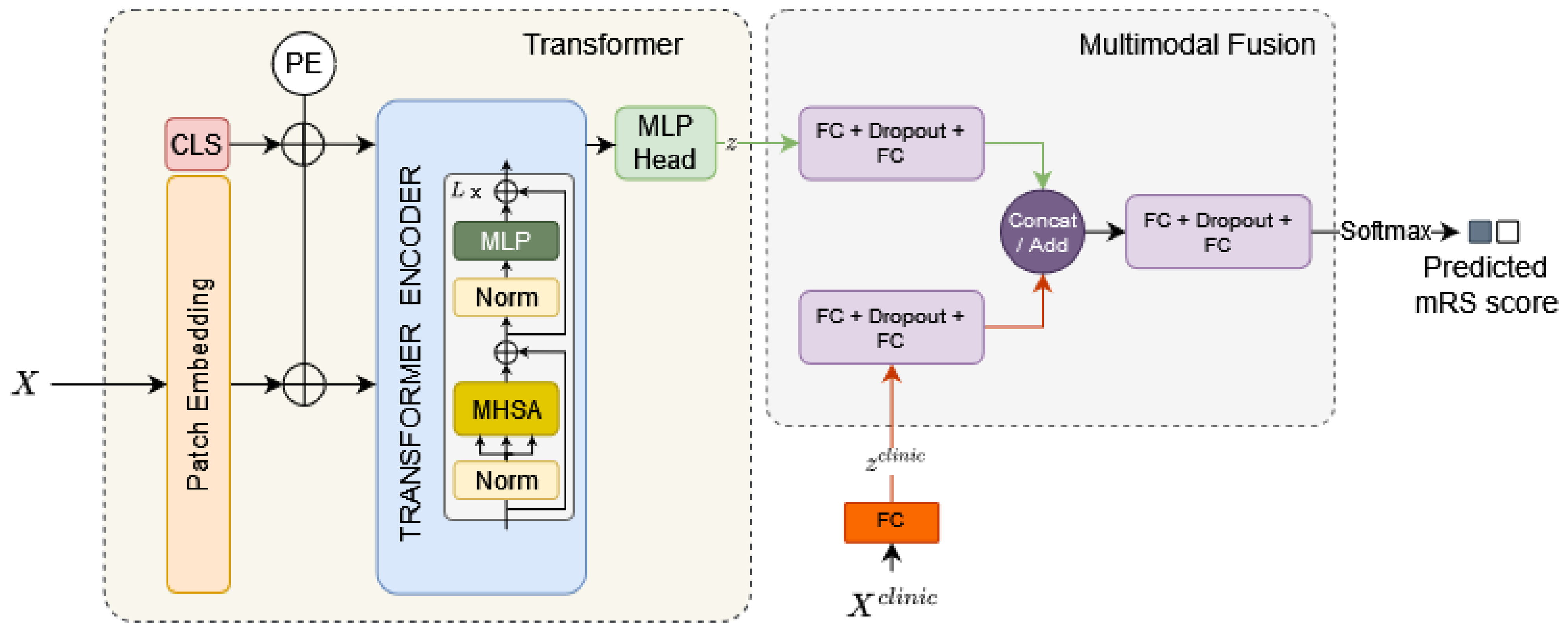


Figure 1: Overview of our proposed transformer-based multimodal architecture, TranSOP. PE: positional encoding, CLS: a token/vector that represents the input volume for classification, MHSA: Multi-head self-attention, MLP; multi-layer perceptron, FC: fully connected layer.

5. Results

	w/o Clinical Records				with Clinical Records		
Method	ACC (95% CI)	F1-score (95% CI)	AUC (95% CI)	Fusion	ACC (95% CI)	F1-score (95% CI)	AUC (95% CI)
ClinicDNN*	-	-	-	-	0.75 (0.65-0.85)	0.44 (0.19-0.64)	0.73 (0.57-0.86)
Samak et al[2]	<u>0.72</u> (0.62-0.82)	0.33 (0.09-0.53)	0.63 (0.44-0.81)	concat	0.77 (0.66-0.87)	0.47 (0.18-0.67)	0.78 (0.63-0.91)
				add	<u>0.79</u> (0.69-0.89)	0.44 (0.17-0.67)	0.71 (0.51-0.88)
Bacchi et al[3]	**0.75** (0.65-0.85)	0.40 (0.16-0.60)	<u>0.66</u> (0.48-0.80)	concat	0.73 (0.62-0.83)	0.51 (0.29-0.68)	0.78 (0.62-0.90)
				add	0.73 (0.62-0.83)	0.51 (0.29-0.68)	0.78 (0.62-0.90)
TranSOP$_{ConViT}$	0.58 (0.46-0.69)	0.40 (0.21-0.56)	**0.67** (0.46-0.85)	concat	0.77 (0.68-0.87)	<u>0.58</u> (0.36-0.74)	0.83 (0.72-0.93)
				add	0.77 (0.68-0.87)	<u>0.58</u> (0.36-0.74)	0.82 (0.71-0.92)
TranSOP$_{DeiT}$	0.58 (0.46-0.69)	0.40 (0.21-0.56)	0.63 (0.44-0.80)	concat	0.77 (0.68-0.86)	0.53 0.30-0.71)	0.82 (0.68-0.93)
				add	<u>0.79</u> (0.69-0.89)	0.52 (0.27-0.71)	<u>0.84</u> (0.71-0.94)
TranSOP$_{ViT}$	0.58 (0.46-0.69)	0.40 (0.21-0.56)	0.60 (0.40-0.78)	concat	**0.80** (0.70-0.89)	0.53 (0.28-0.74)	<u>0.84</u> (0.72-0.94)
				add	**0.80** (0.70-0.89)	**0.59** (0.35-0.76)	0.83 (0.71-0.93)
TranSOP$_{SwinT}$	0.58 (0.46-0.69)	0.40 (0.21-0.56)	0.64 (0.44-0.82)	concat	0.76 (0.66-0.86)	0.54 (0.32-0.71)	0.83 (0.71-0.93)
				add	<u>0.79</u> (0.69-0.89)	0.55 (0.31-0.73)	**0.85** (0.75-0.94)

* A method that uses only clinical metadata information.

Table 1: Results of the models with and without clinical records. The best and second best results are shown in bold and underlined respectively. The second and third rows are convolutional-based models. CI is confidence interval.

6. Conclusions

- Transformer models outperformed convolutional architectures in multimodal settings.
- The transformer models, although not performing as well on only imaging data, can learn better complementary imaging information when combined with clinical metadata.
- In future work, we plan to investigate and explore a data-efficient transformer model for small image datasets

7. References

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