Adnan Ahmad, Drew Parker, Suhani Dheer, Zahra Riahi Samani, Ragini Verma

Computerized Medical Imaging and Graphics 2023

- Quality control (QC) is crucial for artifact detection in diffusion MRI before any analysis
- Manual QC is time-consuming and subjective
- Need for automated QC pipeline

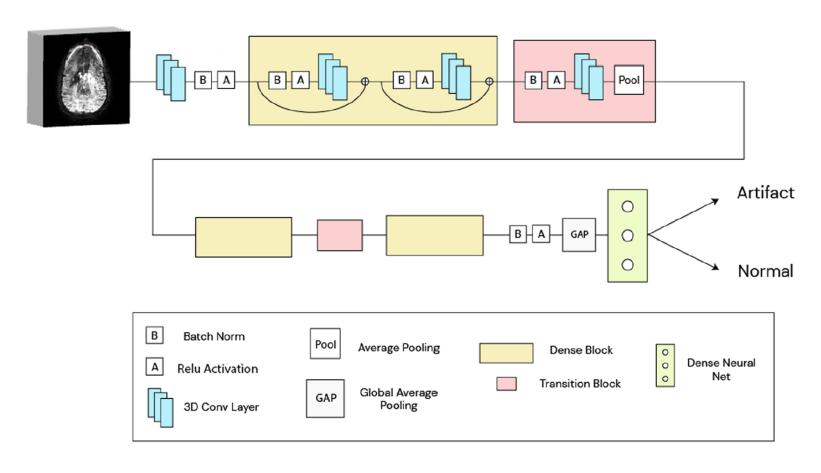
Goal of the paper:

Proposing an automated deep learning pipeline for artifact detection in dMRI volumes



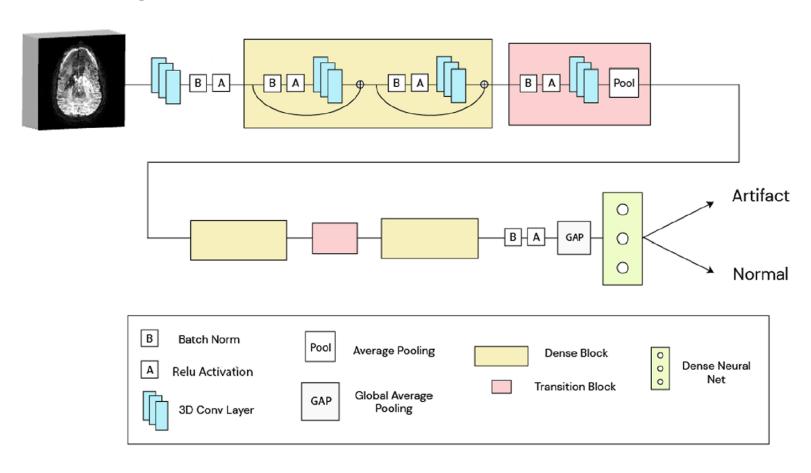
Using 3D-DenseNet across diverse dMRI datasets

Model architecture



- 3D-DenseNet with 3 dense blocks
- Transition layers for downsampling
- Global Average Pooling + softmax classifier
- Input volumes resized to 96×96×70

Training details:



Batch size: 5

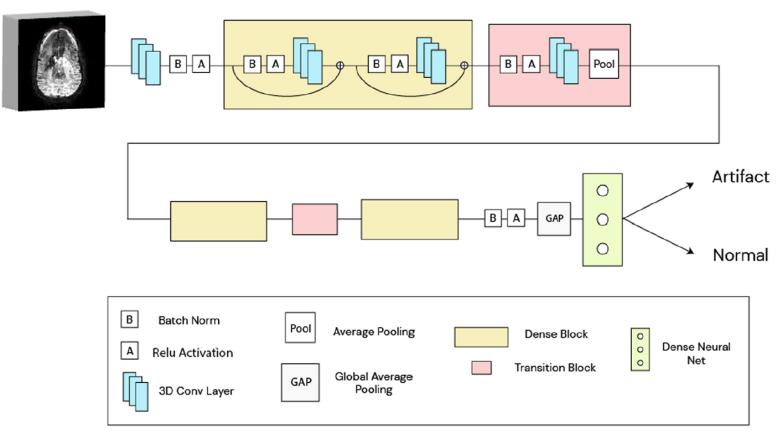
epochs: 20

Optimizer: Adam

Cross entropy loss

■ Training time ~3h on NVIDIA 1080 GPU

Inference pipeline:



- Accepting dMRI scans, preprocessing each 3D volume to a fixed size
- Running in inference mode, providing the user with predicted artifact / normal label for each volume, calculating and reporting performance metrics
- Generating a QC report listing flagged volumes so users can drop them before further analyses

Dataset

> 7 datasets: 3 for training / validation, 4 for testing

> Total 9258 volumes from 678 subjects

5619 training volumes

1292 validation volumes

2347 test volumes

- Heterogeneous in scanners and protocols
- Annotating by an expert with 8 years of experience identifying artifacts in diffusion scans

Results

Results – 3D-QCNet Model.

	Dataset	Accuracy	Precision	Recall
	Dataset 1	97	95	80
	Dataset 2	81	91	66
	Dataset 3	89	90	82
Validation Set	Average	89	92	76
	Dataset 4	97	84	81
	Dataset 5	92	86	98
	Dataset 6	96	81	100
	Dataset 7	92	95	89
Test Set	Average	94	87	92

Defining "artifacts" as the positive class

✓ Consistent across 4 unseen datasets

images

Results

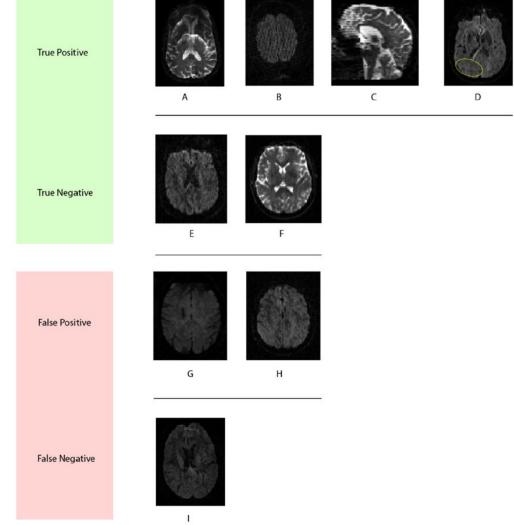


Fig. 3. Scans from the test set illustrated to demonstrate 3D-QCNet's model performance with respect to ground-truth. True Positive samples – A Ghosting artifact, B Herringbone artifact, C Motion/interslice instability artifact, D Faint Chemical artifact (marked in yellow). True Negative samples – E Weighted Image is noisy but is correctly marked as normal. F BO image with no artifacts. False Positive samples – G Abnormal anatomy of the brain may be affecting the classifier. H Weighted image is noisy but there are no visible artifacts; the model may be too sensitive. False Negative samples – I Chemical shift artifact alongside instability and susceptibility.

Results

False Positive

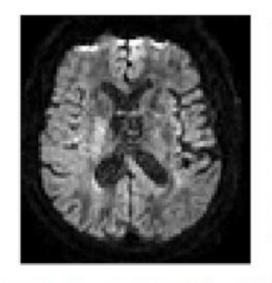




Fig. 4. These scans are from a volume that was marked as normal by our annotator but 3D-QCNet labelled it as having an artifact. Later, on closer inspection it was found to have ghosting artifacts in the ventricles and subcortical regions along with some interslice instability.

Results

Results on Dataset 5 when using labels from different annotators.

	Ground Truth	Comparison	Accuracy	Precision	Recall
8 + years of experience	= Annotator 1	3D-QCNet	92.75	86.5	98.85
A month's training on identifying artifacts	= Annotator 2	3D-QCNet	76	75.6	75.6

- ✓ The inherent inaccuracy of Annotator 2 given their relative inexperience
- ✓ Due to the data it was trained on, the model is more akin to Annotator 1 and learns their expertise as well as biases

Conclusion

- ✓ End-to-end automation of dMRI QC
- ✓ Robust generalization across diverse data

- × Binary output only. It flags "artifact" vs "normal" but doesn't identify artifact type
- × Fixed input size (96×96×70)
- × Not training on data annotated by multiple experts with similar experience

Thank you